INFORMATION CASCADES IN THE BRAZILIAN FARMLAND MARKET

by

BRADY E. BREWER

B.S., Oklahoma State University, 2010
M.S., Kansas State University, 2012

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2015

Abstract

Farmland values have reached all-time highs and have significantly risen over the last few years. This has caused much debate about whether farmland prices are currently on a bubble and ready to burst, much like the earlier 1980s. Much research has been done on farmland values; however, work done outside of agricultural economics, looking at general asset values, can be incorporated into models of farmland value. Information cascades, or herding, are phenomenon where information in the market is sent between investors and this information is bid into the asset price, thus resulting in boom and bust periods. By using a Vector Autoregression (VAR) model, farmland price dynamics are modeled and analyzed for spatial dependencies from one region to the next. VAR allows for no a priori specification of network typology. This allows for the examination of the existence of information cascades and what form the network takes among spatially located farmland markets. This method is then compared to two other spatial estimation techniques. The first is a Spatial Autoregressive (SAR) model where network typology is imposed prior to estimation. The second is a VAR model where no network is modeled, and only the region's own asset prices can influence future periods. It is found that information cascades exist and network typology is somewhat random.

These results caution the current direction of the literature of imposing network or spatial structure. However, due to data requirements, SAR models are easier to estimate since they require less data and if network structure, which the SAR model inherently imposes by the weight matrix, could be determined by an autoregressive process instead of an adjacency rule it could prove to be the most accurate forecasting method.

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Approved by:

Co-Major Professor
Dr. Allen Featherstone

Approved by:

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Dr. Christine Wilson

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These results caution the current direction of the literature of imposing network or spatial structure. However, due to data requirements, SAR models are easier to estimate since they require less data and if network structure, which the SAR model inherently imposes by the weight matrix, could be determined by an autoregressive process instead of an adjacency rule it could prove to be the most accurate forecasting method.

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Chapter 1 - Introduction

Farmland values have reached all-time highs and have significantly risen over the last four years. This can be attributed to high commodity prices, high net returns for the agriculture sector and low interest rates. Farmland represents a major portion of a farmer's balance sheet, thus a change in value can greatly influence the solvency and liquidity position of a farmer, further influencing a farmer's ability to obtain credit for production purposes. A fall 2014 survey found that agricultural lenders expect farmland prices to decrease from their current high levels in both the short- and long-term (Brewer, et al. 2014).

The farm financial crisis of the 1970s and 1980s began with high farmland values that later led to the credit crisis when farmland values declined. This credit crisis involved farmers defaulting on loans and banks tightening restrictions on future credit. Implications like these are why an understanding of the current farmland price situation is essential in predicting the financial health of farms and the agricultural economy as a whole (Briggeman, Gunderson and Gloy 2009). An understanding of farmland prices is needed to examine where we are currently from a financial perspective and to explore what could happen in the future.

The importance of farmland prices in determining financial health of a farm has understandably drawn much attention from the academic community. Previous studies have used hedonic price analysis, capitalization rates, growth models, and vector autoregression to analyze farmland prices. Each of these studies sheds new light on pricing schemes, value of certain types of farmland attributes, or measuring the propensity for boom and bust cycles; however, one area that has not been explored in the farmland markets is that of herding or information cascades within the farmland market.

Each of the aforementioned types of studies focuses on different empirical methods in an attempt to estimate what one would expect farmland to be priced at or the value of particular characteristics of a parcel of land. An assumption of each of these methods is that all relevant market information is used in an efficient manner when determining the price of the farmland. A contrasting view is that investment is also driven by group psychology, which weakens the link between information and market outcomes (Scharfstein and Stein 1990). This group psychology is what is commonly called the herding effect or information cascade. For this study, this effect is referred to as an information cascade.

Information cascades arise when certain players in a market receive a market signal and take the information received from this signal (e.g., prices are going up) as truth (Shiller 1995). Shiller (1995) discusses how information cascades arise, "The kinds of opinions where [information cascade] behavior is prominent are not matters of plain fact but subtle matters, where many pieces of information are relevant, and where limitations of time and natural intelligence prevent each individual from individually discovering all relevant information." This market signal is used as factual information by the market participants own decision making process, creating a mimicking effect (Graham 1999). This concept of cascading has been explored more in depth in the general finance literature to look at investing patterns in capital asset pricing or stock market valuation. Behavioral economics/finance have turned to networks to try and model these mimicking investor patterns (Scharfstein and Stein 1990). Network typology gives insight into how the interactions between agents cause the information cascade to spread.

Examples of these information cascade effects are numerous and the effects can be slow to spread, or in some cases that receive high profile attention, the signals are sent rapidly through the market. For instance, when news went public that Warren Buffett increased his shareholding in two particular companies, prices for those companies stocks rose 4.3% and 3.6% (Hirshleifer and Hong Teoh 2001). This same effect can happen in other capital asset markets and could explain part of the recent increase in farmland prices across much of the United States.

Capital asset values, and more specifically farmland values, may be driven by a number of factors. Ricardian rent theory states that farmland values are set by the expected return of the future payments from the land. In the case of farming, the future payments from the land include the expected net income generated by the crop or cash rental payments. This idea is captured by the Gordon Growth Model (net present value model) where the present value of a perpetually lived asset is the sum of all future cash flows discounted back to time period zero. In finance theory, the Gordon Growth Model captures the expected cash flows from an asset and provides the value of the asset.

If this valuation held perfectly, then there would be no cascading within the market. That is to say, the price always reflects the true value of the asset. However, the true market value cannot be determined as it is unknown since the value expectations from one agent to another may be different. The transaction price of the asset is what is observed. And if the efficient market hypothesis holds, then the transaction price is always the best estimate of market value (Fama, Efficient Capital Markets: II 1991). This is where farmland prices may be of use to test the effect of network and market signals on an asset's price.

There exists a clear lack of empirical data in most studies as individual investor expectations are hard to track and relationships within a network are hard to map. Which investors are receiving each particular market signal and how they affect the aggregate price level is not known. Farmland is spatially located, which means that ties within a farmland market network might be assumed to follow a spatial pattern perhaps allowing for the estimation of these network ties. If the network is assumed to follow a pattern, and market signals are sent spatially, which is to say farmers receive signals in a pattern related to where the farmland is located, then the effect of these signals can be analyzed. However, the agricultural market is global. Thus, it is possible that information from a distinctly different region is important in price determination.

Using data from Informa Economics FNP on Brazil's farmland values, the existence of information cascades is tested using a Vector Autregression (VAR) model where each region is a variable in the system and may affect other regions in subsequent periods. This methodology, to the author's knowledge, has not been used in the literature and takes into account the dynamic nature of the farmland prices of the different regions. This framework allows for forecasting of farmland values where a shock to one region may affect other regions for the analysis of how signals containing information on farmland values are sent through a network.

Objectives

The overall objective of this study is to examine how market signals sent within the farmland market affect farmland prices. This objective could be analyzed using a wide array of empirical or modeling techniques, thus, some specific objectives and goals for this research are needed. The specific objectives for the research are as follows:

- Compare current farmland prices to historical returns;
- Test for existence of market signals influencing farmland price within a spatial network using Brazilian survey data on farmland values;
- Analyze the network structure's effect on farmland prices;

- Examine the effect these market signals have on boom/bust cycles in the farmland market.

The organization for the rest of this study is as follows. A review of previous literature will cover past farmland valuation and network studies. A theoretical discussion of how farmers value farmland are next. Data and empirical models used for the analysis are discussed, then results and conclusions are examined.

Chapter 2 - Literature Review

This chapter will cover research relating to farmland valuation. It is divided into past studies looking at the value of farmland and also address literature from the broader finance area that covers asset valuation and information cascades.

Past Farmland Valuation Studies

Past studies that have analyzed farmland values use a wide variety of data and techniques to examine farmland values. Each approach offers various insights into the farmland market from a different perspective. These approaches include using farmland price to rent ratios, dividend growth models, hedonic price analysis, and times series approaches. Each method offers advantages and disadvantages when analyzing farmland value. The specifics of each method are discussed later in this study; however, a comprehensive knowledge of these past studies is helpful. This section can be divided into two categories: those studies that have looked at historical land values and compared them to another measure (e.g., cash rental rates or some return for an investment) and those studies that have attempted to quantify farmer expectations of farmland prices. This section will examine past literature relating to farmland values for the two categories previously mentioned.

Trend Perspective

The capitalization rate[1] is the ratio of cash rent to land value. Analyzing the capitalization rate shows how the rental price to farmland value may vary from year to year. The lower this ratio is, the higher farmland value is relative to cash rental rates. What the capitalization rate

[1] The capitalization rate can be used when referring to the discount rate in the dividend valuation model. In this paper, the capitalization rate will refer to the cash rent to land value ratio.

provides is an earnings per price ratio similar to a stock price earnings ratio. This ratio can then be interpreted as a measure to look at historical trends when tracked over time. Paulson and Schnitkey (2013) compared the capitalization rate of farmland to the 10 year treasury rate. They found that the capitalization rate fell below the 10 year treasury rate during the 1980s credit crisis, but has been relatively well aligned from the 1990s forward indicating that current farmland prices may not be over stated.

Baker et al., (2014) use the farmland price to rent ratio to examine farmland values. They compare the price to rent ratio to a reciprocal 10-year treasury and the S&P 500 price to earnings ratio. It is found that the current farmland price to rent ratio is well above its historical average. Though, when compared to the reciprocal 10-year treasury and the S&P 500 price to earnings ratio, it is only slightly higher. The authors caution about comparing the farmland to price ratio and the price to earnings ratio of the dividend paying companies as they are not an exact comparison. A more appropriate ratio to compare to would be the price to dividend ratio; however, due to variance in dividends paid this measure is not used.

A contention in the literature is whether cash rents are a leader or follower to farmland values. While it might seem intuitive to think of farmland values being a derivation of the potential income stream that the farmland can offer, some argue that cash rental rates are actually derived from the farmland value. Ibendahl and Griffin (2013) state that one reason for cash rent to follow farmland value is that farmland prices can adjust immediately while many cash rents are multi-year. Given the nature of multi-year contracts for rental agreements, this can make the rental price slow adjusting (Paulson and Schnitkey 2013). For this argument, Ibendahl and Griffin claim that net income is capitalized into land value instead of cash rent. Featherstone and Baker (1988) argue that the residual returns of the land determine cash rental rate and then the farmland value is determined by the cash rental rate. Ibendahl and Griffin (2013) examine lags between the change in farmland value and the change in farmland rental rates. They posit that there is a lag between the change in farmland prices and the change in cash rental prices due to cash rental contracts being multi-year agreements. They find that when land values are decreasing, lagging the land value does explain some variation in the capitalization ratio. While this evidence of sticky rental rates does not invalidate any previous studies, it is something that should be considered when there are large swings in the farmland price to rent ratio.

Global farmland values have also been analyzed as Informa Economics publishes a "Global Farmland Survey and Outlook" (Informa 2014). This survey of global farmland prices reports that farmland values have increased across major farmland supply regions including the United States, Brazil and Australia. The report does cite "current fundamentals" of the market have given observers cause for concern with the rapid increase in prices.

Farmers Expectations of Farmland Prices

The dividend valuation model has been widely used as the underlying theoretical framework for how farmers value farmland where the price of farmland is the sum of all expected future cash flows discounted according to the risk of these cash flows (Goodwin, Mishra and Ortalo-Magne 2003). However, through the studies of farmland variation, it has been shown that many factors affect this valuation. Factors such as the variance of returns to the farmland, government subsidies, arms length transactions, buildings on the land, potential for on-farm capital gains, and distance to markets have all been examined to find how these factors affect farmland values.

Castle and Hoch (1982) posit that expected net income from the land is only one component that farmers analyze when valuing farmland. They claim that a farmer also takes into account future real capital gains when looking to invest in farmland. This concept is then integrated into the dividend valuation model framework. They conclude that expected income from productivity alone cannot explain farmland value.

Featherstone and Baker (1987) analyze farmer expectations by looking at how time sensitive data affect asset values, returns to land, and interest rates. Vector autoregression (VAR) is used to estimate three equations using lags of one through five years allowing each of the lags to affect each of the dependent variables. They argue that information that is newer will have a larger influence on asset values as individuals overweight recent information. They also argue that when quasi-rational agents develop expectations of future capital gains based upon past capital gains, this can lead to a bubble. Similar to this study, Falk and Lee (1998) use a VAR approach and find similar results to Featherstone and Baker (1987). Falk and Lee find that the farmland market is prone to fads and overreactions in the short run but the market converges in the long run.

Clark et. al (1993) criticize previous studies and suggests that land rents and land prices do not have the same time-series representations. They find that the data do not justify explosive roots (price bubbles) since land prices only have one or two unit roots. They conclude that more complex models that allow for rational bubbles, risk aversion and expectations of future government policies should be included to make the capital asset pricing model accurate.

Simulation has also been used to analyze farmland value. Featherstone and Baker (1988) use a simulation of corn and soybean markets and alternative policy choices. Using these simulations, the resulting farmland value and distribution is calculated. The calculation of the distributions results in confidence intervals of expected farmland values. While no technical predictive model exists, this analysis is unique in that it is a forward looking analysis into the nature of the farmland distributions.

An issue that arises in the valuation of farmland is the effect of U.S. farm policies on farmland values. Not surprisingly, much attention has been paid to examine the effect of U.S. farm policy on farmland values in the literature (Goodwin, Mishra and Ortalo-Magne 2003; Patton, et al. 2008; Kirwan 2009). Most of these studies have focused on the effect that subsidies pass through to the farmland value. Kirwan (2009) finds that farmers that rent their farmland only pass 25% of the subsidy to the landowner. Patton, et al. (2008) find that the amount of pass through to the landowner is dependent on the type of payment and the nature of the production characteristics associated with the commodity grown on the farmland. Goodwin, Mishra and Ortalo-Magne (2003) perform an econometric analysis; however, due to limitations of their data they do not make any firm conclusions.

With the changing of U.S. farm policy, this literature provides key knowledge in how farmland values respond. Farm policy either increases or decreases the revenue potential of the land, affecting the cash rental rates. These policies can be discontinued at any moment, and new policies can take their place, creating variability in the expected revenue stream. The extent to which farm subsidies are capitalized into rental payments can affect farmland value.

Hedonic models have also been used to model farmland values. Nivens et al. (2002) used a hedonic price model to analyze Kansas farmland value with an inclusion of a satellite imagery variable. The satellite imagery measured the "greenness" of the parcel of land. Featherstone et al. (1993) also used a hedonic model when examining Kansas farmland values. They used the hedonic model to analyze the effect of bank repossessions, and quality characteristics in determining farmland value. Tsoodle et al. (2006) use a hedonic model to examine Kansas farmland prices; however, this study looks specifically at the effect of personal relationships of the buyer and seller and how that affects the transaction. While hedonic models are useful in examining the components that determine a price, the time dimension is often not taken into account in these models.

Vantreese et al (1986) use a capital asset pricing model to look at parcel specific attributes and how they are capitalized into farmland value. A unique aspect of their study is that all the attributes are multiplied by the discount factor.

Huang et al., (2006) use a hedonic model to examine factors that influence Illinois farmland values, incorporating productivity characteristics, neighborhood characteristics, location, and environmental characteristics of the land to model farmland prices. A unique aspect of this study is the use of the spatial autoregressive (SAR) model. This uses a weighted spatial and temporal matrix that is instrumented against a right hand endogenous price variable. This allows for the concept that prices in a region move together. The economic interpretation of this type of model is that farmland prices in neighboring counties affects farmland prices of each county (indirect effects) in addition to the explanatory variables of a parcel of land (direct effects) (Huang, et al. 2006).

General Finance Literature

Farmland has unique attributes, that, when attempting to model, present problems for the researcher. While much research has been done concerning farmland values, research that has been done in the general finance literature that furthers the explanation of asset values and could prove helpful in the valuation of farmland exists. While the basic dividend valuation model has been used in the valuation of farmland, theories and modeling approaches that have been used in the finance literature could be applied to farmland values.

Expectations of Future Dividends

A major modeling goal within the literature is to capture how investors take past information and use this information to adjust his/her expectations for future earnings. Miller and Modigliani (1961) look at the expectation of future dividends by first analyzing what investors actually capitalize into the stock price and then by including a stochastic component to the model. In this study, the dividend is divided into different components that the authors felt investors capitalize differently into the price of the stock. They then assume that dividends in future periods can go up, stay the same, or decline and investors base their expectations on characteristics of the firms.

Hurley and Johnson (1994) develop a dividend valuation model with a Markov process. The Markov process uses economic information to predict the probability that the value of the asset will increase or stay the same. This probability is then used in the dividend valuation model in conjunction with the expected growth rate of the future cash flows. This model is important to the current study because it incorporates an expectation of what future dividends will do into the dividend valuation model.

Asset Price Bubbles and Information Cascades

The debate over the existence of asset price bubbles has received a lot of attention. Within the farmland market particularly, much attention has been paid to whether a bubble exists with the recent increase in farmland prices. Case and Shiller (2003) define a bubble as a time where "excessive public expectations of future price increases cause prices to be temporarily elevated." For a price bubble to occur, the efficient market hypothesis must be violated for a time. Recently, the literature has used behavioral economics to answer why an investor would deviate from so called rational behavior when deciding to invest. Specifically, studies looking at herd mentality and information cascades among investors have received a lot of attention. The ability to predict a price bubble can help in determining characteristics that set farmland value.

Shiller (1995) argues that herd behavior can lead to asset price bubbles. In his theory, an investor receives a signal from other investors in the market and he/she assumes that the other investors have information that justifies those actions. For example, one investor pays a higher amount for an asset than the current market equilibrium, this sends a signal to other investors that they have information that the asset should be worth that higher amount.

Before delving too deep into the literature, a definition of herding and information cascades would be prudent as the terms are used loosely in the literature. Graham (1999) states that "Herd behavior is often said to occur when many people take the same action, perhaps because some mimic the actions of others." Graham (1999) attempts to categorize herding into four categories: 1) information cascades, 2) reputational herding, 3) investigative herding, and 4) empirical herding, though this list is hardly exhaustive nor mutually exclusive. Graham (1999) then goes on to describe information cascades as when:

> "…individuals choose to ignore or downplay their private information and instead jump on the bandwagon by mimicking the actions of individuals who acted previously. Information cascades occur when the aggregate information becomes so overwhelming that an individual's single piece of private information is not strong enough to reverse the decision of the crowd. Therefore, the individual chooses to mimic the action of the crowd, rather than act on his private information."

This mimicking behavior is attributable to an asset price bubble as investors mimic other investors actions despite what private information may say about the price of an asset. An example would be if farmland values are increasing, a farmer might reason that all land values are increasing even though his/her private information says that a particular piece of land should not be valued any higher. A farmer witnesses farmland in his/her region increasing in price and because of this aggregate information, the farmer adjusts his/her valuation of a particular parcel of land to be in line with the aggregate trend. This action by the farmer only adds to the aggregate trend.

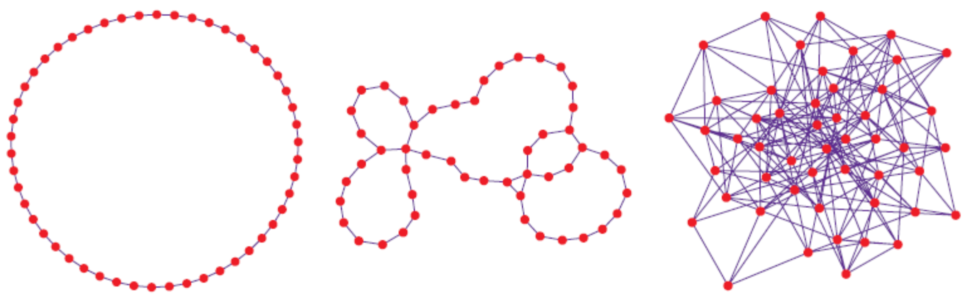
Case and Shiller (2003) argue that the notion of a bubble is really defined in terms of people's thinking and their expectation of future prices. Using data on housing prices, the potential for a bubble is analyzed. Comparing the growth of home prices to that of income growth, it is found that for 40 U.S. states, the growth in housing prices did not exceed the growth of income. It was found that the amount of personal debt relative to personal income was relatively high in 2003, concluding that this led to a high probability of future defaults. Featherstone and Baker (1987) use farmland values, real returns to assets and real interest rates to analyze movements in value. They find that a shock creates a continued buildup that exaggerates the movement in the value of the asset, thus creating a bubble. The low amount of transactions that took place in the housing market also contributed to this herd mentality. Case and Shiller (2003) point out that when market participants have limited experience in the market, they have a harder time deciding what is fact about the price of an asset and what is informational noise. This can amplify the effect of the market signals sent through the network.

Scharfstein and Stein (1990) study herd behavior in investors and find that managers mimic other investor decisions even when they have private information that contradicts that decision. The model that they propose separates investors into two categories of "smart" and "dumb." A smart investor receives a market signal but does not take it as given evidence as they still use private information. A dumb investor receives a market signal and assumes that the other investor who sent the signal has information that supports their investment decision. Reputational herding is a theoretical justification for this behavior.

Though the existence of asset price bubbles is debated. Fama (1970) concludes that the efficient market hypothesis holds when testing the market equilibrium. Fama (1991) revisits this proposition with the same conclusion in his later paper; however, this time certain causes that may cause abnormal deviations are acknowledged in the paper.

While the concept of herding and information cascades has been researched in relation to causing asset price bubbles, a fairly new topic is how the information within a cascade is transmitted. To explain this phenomenon, social networks have been used. Alfarano and Milakovic (2008) develop a probabilistic herding model that is dependent on interactions between agents. Networks are categorized into regular networks, random networks, small-world networks, and scale-free networks. Regular networks resemble a lattice framework where every agent interacts with a constant number of neighbors. In a random network, an agent has the same probability of interacting with a respective agent across the entire network. The small-word networks are based on the idea that geographical proximity plays an important role in the formation of social networks. Scale-free networks are larger networks with a power-law degree distribution. A power-law degree distribution is where there are two quantities and one is a power of another. In this case, it is the number of nodes in the network that is a function of the connections of the network, meaning that as the network grows larger the degree distribution remains unchanged. It is found that in the probabilistic herding model, the type of network, or network heterogeneity, affects the outcome of the model. However, the system is also dependent on the number of agents in the model, which the authors label N-dependence. Figure 2.1 below illustrates the circle network where each agent knows their neighbor on either side, a small-world network with shortcuts, and a random network with linking probability of p=0.15. This illustration shows how market signals would spread in each of the different networks.

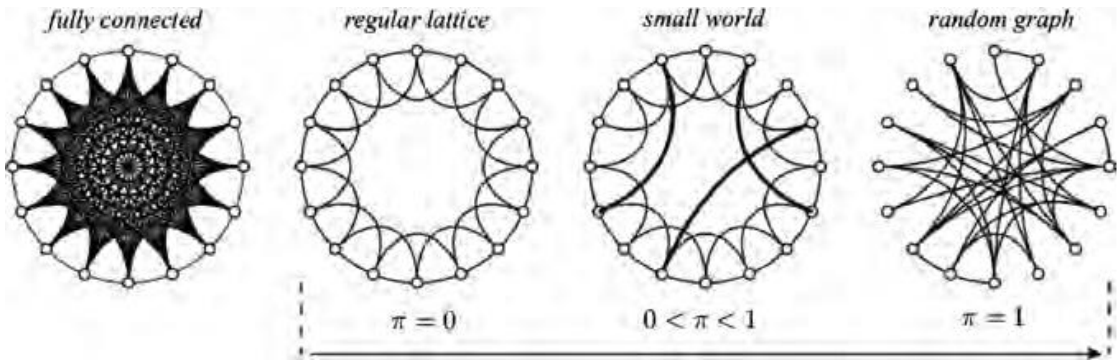
Figure 2.1, Network Structures (from left to right): a circle with neighborhood two; a small-world network with shortcuts; and a random network with linking probability p=0.15



(Alfarano and Milakovic, 2008)

Panchenko et al. (2013) look at how network structure affects the dissemination of information across the network and how this affects variance of prices of stocks. Network typology affects how market signals are sent within the network. It is unrealistic to assume that every market participant has access to the signals that are sent by every other participant in the market. Figure 2.2 below, from Panchenko et al. (2013), shows the lattice structure for four different network structures. Each of these structures spread information across a network differently and at a different pace. The authors note that even in the regular lattice where a node is only connected to those immediately surrounding it, it is still only a few connections away from the complete opposite side of the network allowing for signals to have a rapid effect on overall asset prices.

Figure 2.2, Small Network Structures



(Panchenko et al., 2013)

Panchenko et al. (2013) find that the more connected a network is, the higher the propensity the network has to create a herding effect within the market. It is also concluded that the small world network produced results closest to real financial markets. The conclusion is that network typology affects market outcomes and must be taken into account when modeling social interactions. Panchenko et al. (2013) is similar to this study in that it tested for the effect of network type on the spread of information through a market.

Chapter 3 - Conceptual Model

Valuation of farmland, since it is a non-depreciable infinitely lived asset, represents a unique valuation problem. Traditionally, the value of an asset can be represented by the net present value of all future cash flows discounted according to the risk of these cash flows. Given a finite life span of the asset, the expectation of the cash flows can be fairly certain. However, given the indefinite nature of land and the non-predictability of the income stream resulting from the land, the valuation of farmland is a difficult topic.

Dividend Valuation Model

The dividend valuation model says that the present value of an asset is the sum of all future dividends[2] discounted back to present day. This can be represented by

(3.1) $$PV_0 = \int_{t=0}^{T} e^{-rt} V(t)dt,$$

where PV_0 is the present value of the farmland at present time, r is the cost of capital, t is the time period and $V(t)$ is the income from the farmland in time period t. Since farmland is an infinitely lived asset, T equals infinity:

(3.2) $$PV_0 = \sum_{t=0}^{\infty} \frac{V_t}{(1+r)^t}.$$

This equation is the sum of all expected future cash flows discounted back to present day. However, a problem arises in that a farmer only knows the current income from the land. To solve this problem, we assume that a farmer uses present day income expectation and assumes a constant growth rate. This results in:

(3.3) $$PV_0 = \sum_{t=0}^{\infty} \frac{V_t(1+g)^t}{(1+r)^t},$$

[2] For a farmer, the dividend is the sum of all net income generated by the land for a given year.

where g is the growth rate of the income from the farmland. It is assumed that the interest rate is greater than the growth rate: $r > g$. By removing the summation and equating t equal to zero, this equation further simplifies to

(3.4) $$PV_0 = \frac{V_0(1+g)}{r-g}.$$

To further simplify the identity

(3.5) $$V_{t+1} = V_t(1+g)$$

which says that next year's income from the land is equal to this year's income multiplied by the expected growth rate. This simplifies the numerator to

(3.6) $$PV_0 = \frac{V_1}{r-g}.$$

and creates the common dividend valuation model.

The present value of this model is also assumed to be the market equilibrium price as well. If the price is the present value of all future cash flows, then a buyer will not accept since this would result in a loss, and if the price is below the present value of future cash flows, then the seller would not accept since they would make more money by keeping the farmland.

The next component that needs to be addressed is that a farmer does not take the components of this model as given, many factors go into a farmers expectations of $V_1, r,$ and g. This can be represented by

(3.7) $$PV_0 = \frac{E(V_1)}{E(r)-E(g)}$$

where $E(V_1), E(r),$ and $E(g)$ are the farmers expectations of net income, cost of capital, and growth rate for the parcel of land. Thus, the main question that needs addressed is what factors affect a farmer's expectations of income from the land, interest rate and growth rate.

Previous trends in net income, interest rate, and growth rate may form the basis of a farmer's expectations. A farmer has access to his/her own private information, and forms a forward looking outlook based on what he/she has experienced in the past. While a farmer certainly remembers the last one to two years, any information further in the past will need to be considered as expectations are formed. Featherstone and Baker (1987) explain that information gathered will affect expected growth in returns which has an impact on $(r-g)^{-1}$ which can lead to movements in the price of farmland. Farmers will consider previous trends and future expectations to form the overall price expectation expectations (Featherstone and Baker, 1987).

These past trends are not all created equal. A trend in a farmers region may have a greater impact on a farmer's expectation than a trend happening away from the farmer's home region, or in other cases a trend in a region that has similar production capabilities may have a greater impact. This spatial effect of trends being considered by market participants may explain how movements in farmland price spreads throughout a geographic region, much like how farmland prices were increasing rapidly in the Midwest and spread to outside regions. These trends send signals to nearby farmers that receive the signal, incorporate the new information, whether valid or not, into their expectations of farmland price and then create a new signal.

Signals that get sent throughout the market and are received by a respective farmer and passed on can distort expectations causing information cascades. When a farmer receives a signal, a land sale happened on a neighboring farm where the buyer paid a higher than expected price, it can be interpreted as hidden market information. In the case of higher than expected prices, the farmer receiving the signal would assume that the buyer has information concerning the future income from the land that no one else has. If the receiver of the signal takes it as given, this influences his/her expectations of farmland prices. This then sends a signal to other market participants which has the same effect. The interactions between market participants will affect how these signals are sent and received in the market.

Various other factors may also affect the magnitude of these signals. Time considerations such as the amount of time that has passed between the signal being sent in the network and the actions of the market participant could cause a signal to be stronger or weaker. Distance within a network may also affect the signal. If the signal has to travel farther it may weaken the impact. However, technology makes signals travel faster than ever. University publications, internet reports, and news published on available websites makes information available to farmland buyers more assessable. These factors all play a role in the magnitude of the information cascade and how the connections within a network contribute to the rise/fall in farmland values.

The dividend valuation model has been used extensively in the literature. If the farmers' expectations of returns to the land, interest and growth rates can be determined, then an accurate model will result to predict farmland prices. However, to date, the problem has been estimating the ever changing and dynamic nature of farmer expectations. The incorporation of a spatial component capturing the spread of market signals may help in explaining how information and trends in the market shape farmer expectations.

Chapter 4 - Data

Several data are used for this study. These data were selected as they have location properties allowing for the testing of the spatial properties of agricultural land prices and income generation properties as well. This chapter will give an overview of the data used in this study.

The first data are Brazilian land values (Wohlenberg, 2014). These data are from a survey of land prices that is conducted by Informa Economics-FNP company. The survey is bi-monthly and expressed in Brazilian Reais per Hectare for each particular region of Brazil. There are two different types of regions within the data: macro and micro. Macro regions are determined by larger political boundaries. Micro regions are subsets within the macro regions and are homogenous by land type and production quality (FNP 2013). A visual representation of these regions is found in Figure 4.1. In this figure the macro regions are divided by color with the numbers outlining each particular micro region.

The FNP data are bi-monthly for all regions included in the data. The data begin in November to December in 2001 and end in September to October in 2013. Micro regions selected for this study only include agricultural producing regions. Regions that are largely rain forest or other non-agricultural use were not included in the study. All macro regions were included in the study except for those dominated by rain forest: Amazonas, Acre, Rondônia, Roraima, and Amapá.

The survey data are appropriate for this analysis as it represents land owners expectations of the current value of farmland. While survey bias may be present in the data such as a farmer responding with a value for farmland that is not what that respective farmer would actually pay in an auction or a private transaction exactly, it does represent the buyers expectations for the current value of farmland. If an information cascade is affecting farmland value, it would be incorporated into this expectation.

In addition to the price of farmland, income potential of the farmland and an interest rate are obtained for this study. For real returns per hectare in Brazil, soybean price and yield are used. Soybean price is expressed in Brazilian Reais per bag and is from the Safras & Mercado (2013) daily price survey. Soybean yield is a state average provided by CONAB (2014). Soybean is a major crop grown in Brazil and acts as a proxy for income potential of farmland within Brazil. Nominal interest rate and Consumer Price Index (CPI) data are from the St. Louis's Federal Reserve Bank (Federal Reserve Bank, 2015). The CPI was used to calculate an inflation rate for Brazil. The real interest rate used in the study is calculated using the following formula:

$$Real\ Interest\ Rate = \frac{1+Nominal\ Interest}{1+Inflation\ Rate} - 1. \tag{4.1}$$

In addition to finding the real interest rate, the farmland values were deflated as well. All farmland values were put in 2013 Brazilian dollars (R$) using the following formula:

$$Deflated\ Farmland\ Value = \frac{Nominal\ Farmland\ Value}{CPI\ Index}. \tag{4.2}$$

These data were chosen for this study due to its spatial properties and trends in farmland prices similar to that observed in the United States. Much like the trend in farmland prices observed in the United States, Brazil has experienced a steady increase in farmland prices during the time period measured by the data (Figure 4.2). Also, while the overall trend of the data are upward during the time period measured by the data, the data do include a period of falling prices. This addition of the falling prices is key since boom/bust cycles in the farmland market do not always follow a linear path and could help in finding the relationship in market signals to the overall value of farmland. The nominal and real interest rates for Brazil expressed in a yearly basis are graphed in Figure 4.3. Gross returns to Brazilian farmland as measured by the soybean yield and soybean price are graphed in Figure 4.4.

A statistical overview of the data in this study can be in the tables and figures at the end of this chapter. Table 4.1 shows the mean, standard deviation, minimum, and maximum for the variables. Parana had the highest average farmland value of the macro regions at R$19,639, and Para had the lowest average farmland value of the macro regions at R$3,827. The regions selected for this study vary in production capabilities and that is reflected in the average farmland values. The average gross return for the regions was R$153,687 and the average real interest rate was 7.49%.

Figure 4.1, Informa Economics-FNP Survey Regions

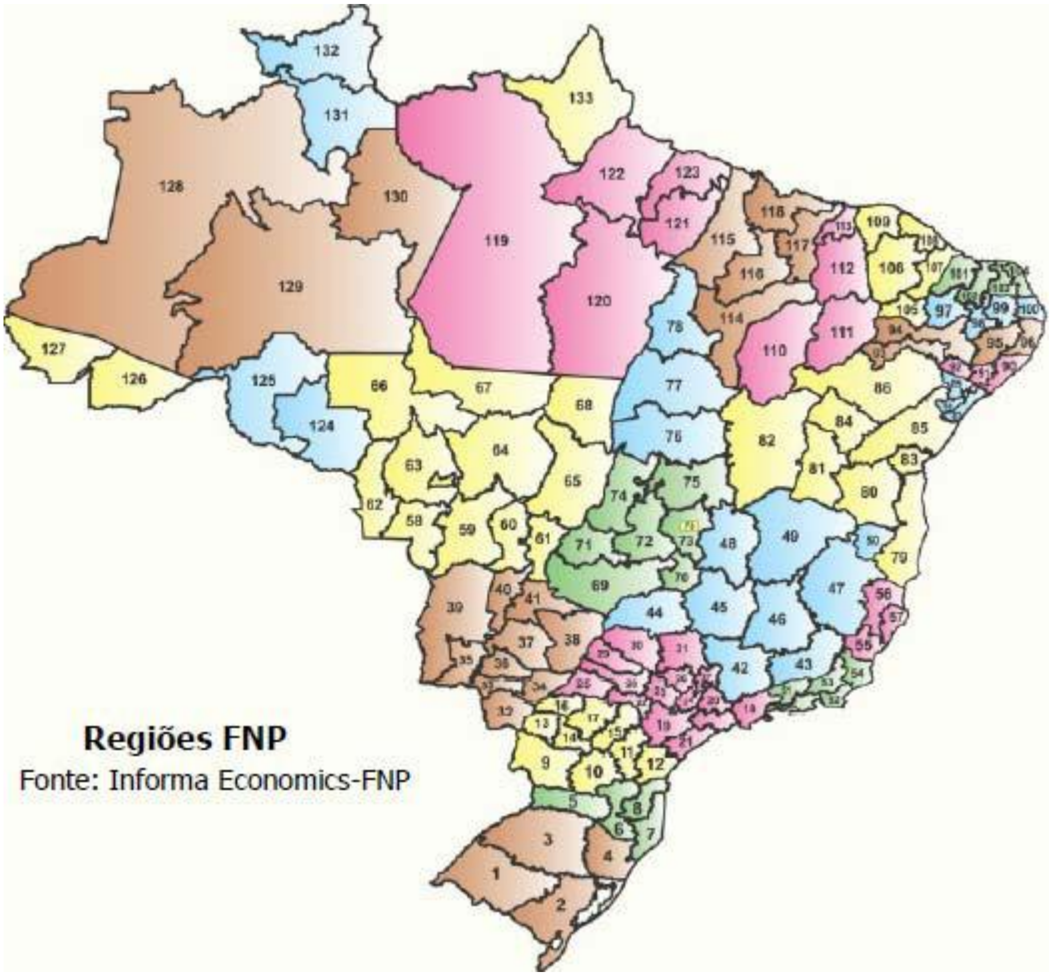


Figure 4.2, Real Brazil Farmland Values by Macro Region, Bi-Monthly

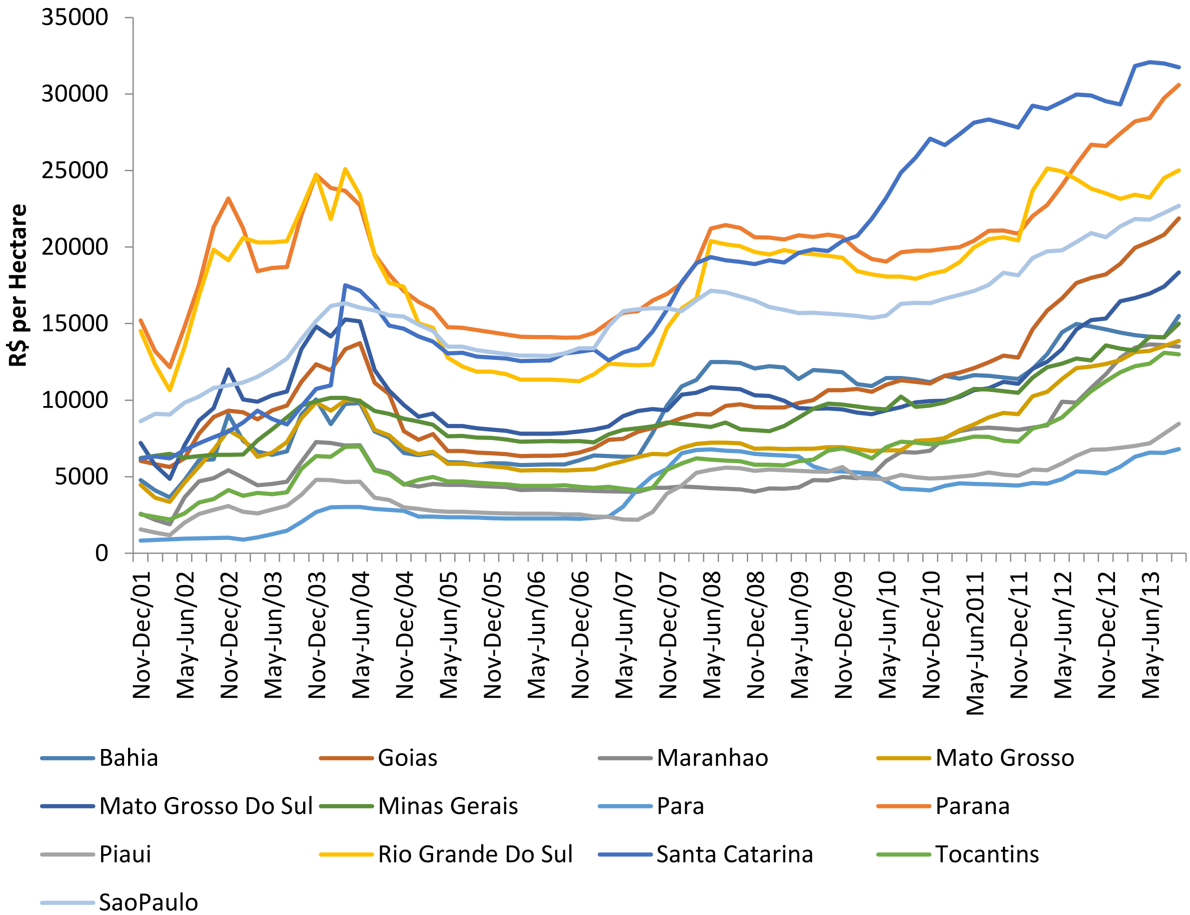
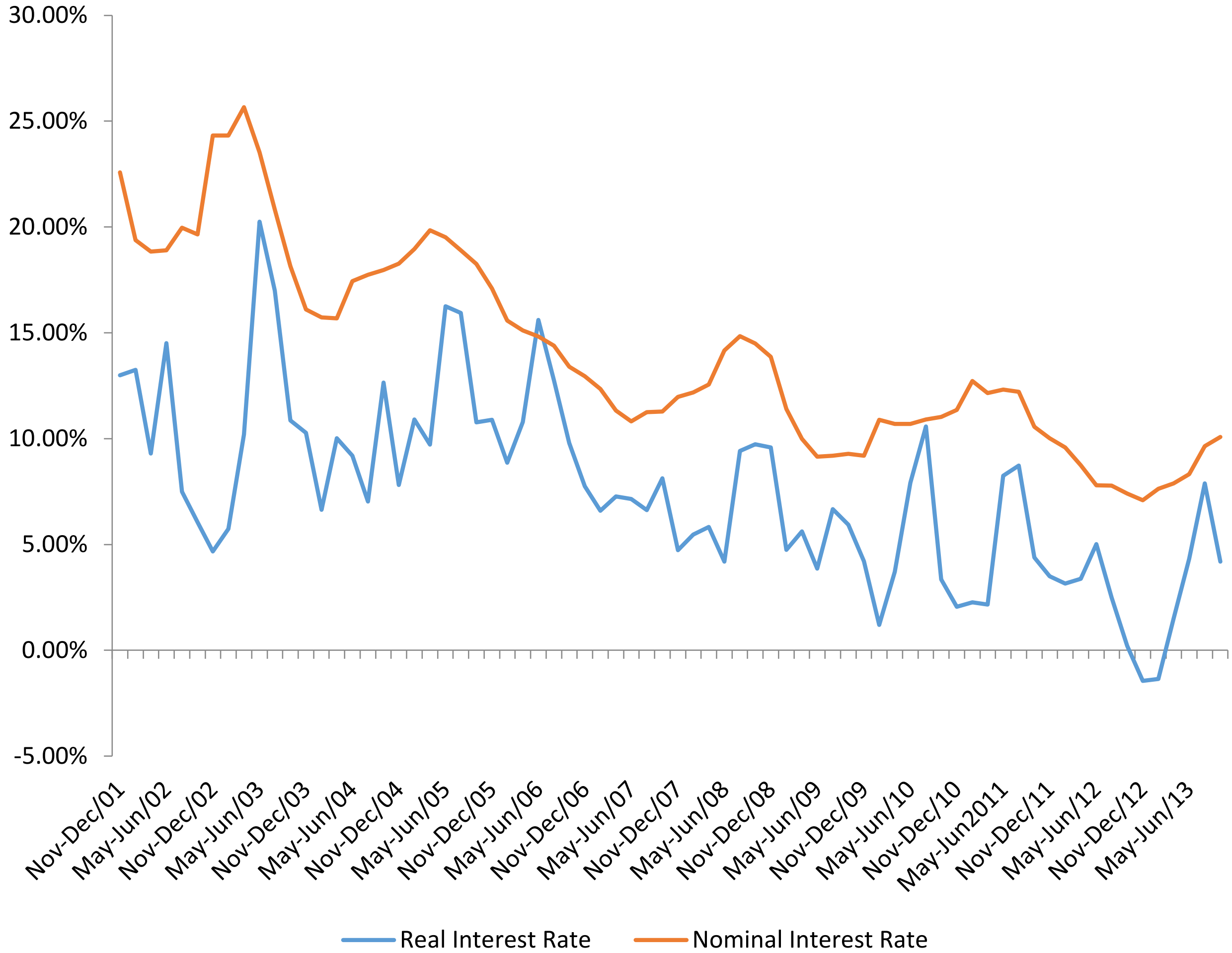


Figure 4.3, Brazil Nominal and Real Yearly Interest Rate, Bi-Monthly



*Interest rates for real and nominal are expressed on a yearly basis.

Figure 4.4, Gross Returns to Farmland in Brazilian Reais per Hectare, Brazil

Table 4.1 Descriptive Statistics, Brazil FNP Data

Variable	N	Mean	Std Deviation	Min	Max
Bahia	72	9516.99 (R$)	3230.97	3654.29	15500.00
Goiás	72	10607.39 (R$)	3996.88	5644.35	21875.00
Maranhão	72	6006.90 (R$)	2790.65	1903.28	13640.18
Mato Grosso	72	7665.17 (R$)	2405.72	3352.02	13877.78
Mato Grosso Do Sul	72	10606.39 (R$)	2830.99	4872.38	18350.00
Minas Gerais	72	9179.55 (R$)	2111.52	6225.91	15000.00
Pará	72	3827.96 (R$)	1909.45	830.12	6800.00
Paraná	72	19639.85 (R$)	4240.48	12147.36	30600.00
Piauí	72	4232.65 (R$)	1662.83	1180.03	8450.00
Rio Grande Do Sul	72	18137.15 (R$)	4410.00	10658.34	25131.79
Santa Catarina	72	18180.78 (R$)	7826.85	6174.02	32079.68
Tocantins	72	6160.62 (R$)	2498.63	2202.72	13098.35
São Paulo	72	15536.95 (R$)	3205.16	8629.23	22687.50
Returns to Land	72	153687.06 (R$)	35852.28	81216.48	254008.47
Real Interest Rate	72	7.49%	4.36	-1.45%	20.25%

(R$) stands for Brazilian Reais

All values are the deflated values in 2013 Brazilian Reais (R$)

Chapter 5 - Empirical Model

This chapter will discuss the approaches used to analyze the data. First, a Vector Autoregression model that allows for an information cascade will be discussed, followed by a series of Vector Autoregression models without information cascades. Then a pseudo-spatial autoregressive model will be discussed.

Vector Autoregression

The first estimation approach used is Vector Autoregression (VAR). VAR estimates the expectations of farmland values, returns from the farmland, and the interest rate in a dynamic framework. Following Featherstone and Baker (1987), VAR is used to estimate three equations simultaneously. The key difference between this study and Featherstone and Baker is that this study allows for spatial signals by distinguishing between different regions allowing asset prices in one region to influence asset prices in other regions.

The system for the VAR model allows for interest rates (r_t), real returns to land (R_t), and asset prices in each region (A_{tl}) to effect each other and is shown by equations 5.1 through 5.3 below:

(5.1) $$r_t = k_1 + a_1 s + \sum_{i=1}^{n} b_{1i} r_{t-i} + \sum_{i=1}^{n} c_{1i} R_{t-i} + \sum_{i=1}^{n} \sum_{l=1}^{m} d_{1il} A_{tl-i} + e_{1t}$$

(5.2) $$R_t = k_2 + a_2 s + \sum_{i=1}^{n} b_{2i} r_{t-i} + \sum_{i=1}^{n} c_{2i} R_{t-i} + \sum_{i=1}^{n} \sum_{l=1}^{m} d_{2il} A_{tl-i} + e_{2t}$$

(5.3) $$A_{tl} = k_{3l} + a_{3l} s + \sum_{i=1}^{n} b_{3il} r_{t-i} + \sum_{i=1}^{n} c_{3il} R_{t-i} + \sum_{i=1}^{n} \sum_{l=1}^{m} d_{3il} A_{tl-i} + e_{3tl}$$

where t is an index of time period; l is the index of spatial region; i is the lag length where $i \in \{1,2\}$; k is an intercept; s is a linear time trend; and $b, c,$ and d are parameter estimates of the system. The above equations represent reduced form equations. A time trend is included to achieve trend stationarity. The time trend is an assumption in a VAR framework is that there are no seasonal patterns or trends in the data.

The VAR model treats the entire system as endogenous. Following the discussion earlier on how a farmer sets expectations of interest, returns to land, and farmland prices simultaneously based on past and current trends, a VAR model allows for forecasting of these variables in a dynamic framework.

The VAR model requires no a priori specification of network typology in testing for information cascades. Previous studies examining network typology and how it affects information cascades test predetermined network types when examining their effect. Using a VAR removes pre-specification of network typology that might bias results.[3] This methodology of regions being allowed to affect other regions with no specification on structure of the network has yet to be done in the literature.

Due to the high number of lagged variables in a VAR model, correlation among right hand side variables can be a problem. This can cause the variance estimates to be unreliable. (Featherstone et al. 1988). To solve this, Granger causality tests are performed on each subgroup of variables. That is, all asset variables, returns to farmland, and interest rate variables at all lags are tested for each independent variable. These tests are shown in equations 5.5, 5.6, and 5.7 below: for interest rates

[3] This freedom from pre-specification of network type is why the author chose not to use a Spatial Autoregressive model (SAR). SAR models require the researcher to specify a spatial weight matrix based on some adjacency relationship. Two types of SAR models for this application would be appropriate: the Spatial Lag Model and the Spatial Error Model.

(5.5) $$b_{zi} = 0 \; \forall \, \{z, i: z \in (1,2,3); i \in (1,2)\}$$

returns to farmland

(5.6) $$c_{zi} = 0 \; \forall \, \{z, i: z \in (1,2,3); i \in (1,2)\}$$

and asset prices

(5.7) $$d_{zil} = 0 \; \forall \, \{z, i, l: z \in (1,2,3); i \in (1,2)\}.$$

Each one of these tests are performed for each dependent variable in the VAR system. Granger causality does not imply a causal relationship between two particular variables, rather, a variable "Granger-causes" another variable if the respective variable helps improve the forecast of the variable in question.

From the conceptual model, farmland price should not be found to cause farmland prices if returns to farmland and interest are entirely accounted for in the model. If farmland prices are found to influence farmland prices, specifically if farmland prices in one region are found to influence farmland prices in another region, it can be inferred that market signals from one region influence another region's farmland price. To test for robustness of the model, two models using equation 5.1, 5.2, and 5.3 are estimated. A model aggregating all data to the macro region level and a model where micro regions of selected macro regions are analyzed. The micro region model will include similar micro regions in Brazil's soybean producing area.

To compare, a VAR model is estimated individually for each of Brazil's macro regions. In this case, only the asset prices for each respective region are allowed to influence each region. Thus, this framework specifies that no information cascade exists and only those farmland values within each respective region are allowed to influence future farmland values. This restricted VAR model is represented by equations 5.4, 5.5, and 5.6 below:

(5.4) $$r_t = k_1 + a_1 s + \sum_{i=1}^{n} b_{1i} r_{t-i} + \sum_{i=1}^{n} c_{1i} R_{t-i} + \sum_{i=1}^{n} d_{1i} A_{t-i} + e_{1t}$$

(5.5) $$R_t = k_2 + a_2 s + \sum_{i=1}^{n} b_{2i} r_{t-i} + \sum_{i=1}^{n} c_{2i} R_{t-i} + \sum_{i=1}^{n} d_{2i} A_{t-i} + e_{2t}$$

(5.6) $$A_t = k_3 + a_3 s + \sum_{i=1}^{n} b_{3i} r_{t-i} + \sum_{i=1}^{n} c_{3i} R_{t-i} + \sum_{i=1}^{n} d_{3i} A_{t-i} + e_{3t}.$$

To test for prediction accuracy, the prediction errors of the VAR model that allows for information cascades are compared to the prediction errors of the VAR model that do not allow for information cascades. However, the region's own farmland prices may affect subsequent time periods. Thus, while no network is allowed to exist with signals between regions, information cascades within the respective region are allowed in this model.

Impulse Response Functions

To test for information cascades within the Brazilian farmland market, the VAR framework allows for the testing of shocks in an impulse response function. An impulse response function analyzes the response of asset prices, returns to farmland, and interest rate as an exogenous change in one of the variables. This measures the time profile of the effect of shocks at a given point in time on the expected future values of variables in the dynamic system (Pesaran and Shin 1998).

Each variable is positively shocked one standard deviation. The correlations between the variables are included in the calculation. Thus a shock in one region may cause farmland prices in other regions to react. This process allows for feedback once the shock is introduced. Two types of impulse response functions are simple impulse response functions and orthogonal impulse response functions. Simple impulse response functions only allow for one variable to initially be shocked. This assumption can be restrictive as it may be assumed that shocks are correlated amongst variables. Orthogonal impulse response functions remedy this problem by converting the process to a Moving Average (MA) and makes the errors recursive. For this calculation to occur, the error correlation matric (Σ) needs to be transformed. Sims (1980) does this by using Cholesky Decomposition such that

(5.7) $$\sum = PP'$$

where P is a lower triangular matrix. However, problems arise with this method as the system is now subject to the ordering of the variables within the system (Sims 1980).

In small systems this may not be a problem as there may be theoretical justifications for how the variables affect each other. However, for the purpose of this study, sequencing of the variables would affect the no a priori specification of network type and may bias results. Thus, for this study, simple impulse response functions will be used. As stated, this method restricts the shock to one variable initially. This may seem restrictive; however, it is not unreasonable to hypothesize that the information cascades begin in a region smaller than one of Brazil's macro regions.

The impulse response functions are forecast for 24 bi-monthly periods or for four years. Confidence intervals of 95% statistical significance above and below the forecast are also calculated. If the forecast and the range of confidence intervals do not include zero, then the impulse response function is statistically significant at the 95% significance level.

Forecast Error Decomposition

The impulse response functions can be used to derive the forecast error variance decompositions. This is the proportion of the forecast in each variable that is accounted for by the innovation in another variable. An example of this is the proportion of the forecast for one region being attributed to a shock in another region. This allows for the examination of market leaders. If a region accounts for a significant portion of another regions error, then it may be inferred that the connection between the two regions is of significance.

Pseudo-Spatial Autoregressive Model

Current literature uses the SAR model as a technique to account for spatial correlations in data. The difference between the VAR model and the SAR model is the lack of a priori specification of network typology in the VAR model that is needed for the SAR model. This model is estimated to compare how the specification of network type affects prediction accuracy.

The SAR model is expressed as:

$$A_t = \rho(W \otimes I_T)A_{t-1} + \beta_1 R_{t-1} + \beta_2 r_{t-1} + e_t \quad (5.8)$$

where A_t is the asset price for year t, W is a row normalized spatial weight matrix, I_T is an identity matrix, ρ is the coefficient for the spatially weighted lagged prices, R_{t-1} is the lagged real returns to farmland, r_{t-1} is the lagged interest rate, and β_1 and β_2 are coefficients. For this model, w, the weight matrix is a set of binary weights based on queen adjacency. Queen adjacency, whose name comes from the game chess and the movements the queen can make, means that a 1 is placed in the matrix for any two regions that share a border. Other forms of adjacency include rook and castle adjacency rules. If the signals are assumed to travel in a spatial manner, then any two regions that share borders could send a market signal to each other.

Since the SAR model and VAR model are both used in this study, it is important to discuss the difference between an information cascade and a spatial market. An information cascade is where asset prices in one time period affect asset prices in subsequent time periods. A spatial market is when exogenous factors cause prices in a region or regions to move together. To examine information cascades in the farmland market, the spatial lag in equation 5.7 is also lagged by one time period. This clarification is important since many spatial autoregressive models are only lagged spatially. This type of model is only correcting for exogenous variable that cause prices in a region or nearby regions to move together.

As in the case where no information cascade is allowed, the predicted errors of the SAR model are compared by region to those of the full VAR model and the restricted VAR models.

Forecast Error

To test for the prediction accuracy of each of the models, the forecast error will be analyzed. A metric for forecast accuracy is out-of-sample prediction accuracy. To test for this, each model described previously, will be estimated excluding the final six periods of data. The models will then be used to forecast those six periods that were not included in the estimation of the models. This provides an out-of-sample estimation to examine which model performed the best in terms of forecasting farmland values.

Chapter 6 - Results

This chapter will present the results. The results are presented in three different sections. The first section is a descriptive analysis of the data. The second set of results will examine information cascades within the Brazilian farmland market.

Descriptive Perspective

Before any econometric model is examined, it is important to examine the descriptive nature of the farmland markets. Descriptive analysis, whether it is simply analyzing asset price movements or using capitalization ratios, gives perspective on the overall performance of farmland compared to previous years.

Brazilian Farmland Values

Brazilian farmland values have been steadily increasing from November/December 2001 to May/June of 2013 (Figure 4.2). This increase has occurred in all macro regions; however, some have experienced a larger increase than others. The region of Santa Catarina experienced the largest increase of this time period, increasing from R$6,174 at the beginning of 2002 to over R$28,000 at the end of 2012 (Figure 4.2). Also of note is that during the time period studied, Brazil experienced a period of declining farmland values from mid-2004 to the end of 2005.

Along with the rising farmland values in Brazil, returns to acres of farmland have also increased. This is shown in Figure 4.4. As discussed earlier, returns to farmland are a critical component of farmland values. Gross returns per hectare of farmland has varied from a low of R$87,442 in March/April of 2006 to a high of R$254,008 in July/August of 2012. However, despite the large variation, there is no trend for the gross returns to farmland as the beginning value is R$193,796 in November/December 2001 and ending value is R$190,995 for May/June

2013 (Figure 4.4). A farmland price to income ratio, similar to a stock P/E ratio shows how the relationship between the price and returns may have changed over time. If this ratio were to increase, it would indicate farmland is being valued more relative to the income the farmland generates, and if the ratio were to decrease it would indicate farmland is being valued less relative to the income it generates. As it is shown in Figure 6.1, this ratio for Brazilian farmland and returns, remains fairly steady over the time period of the study. While a positive relationship does exist for the ratio, it is not large enough to conclude that farmland is being overvalued.

Information Cascades

The next section of results focuses on the existence of information cascades within the farmland market and the network typology. The data previously discussed are analyzed using different econometric methods to analyze the existence of the information cascades, and where possible, the network typology that leads to each respective information cascade.

To test the existence of information cascades in the Brazilian farmland market, a dynamic framework is used. As mentioned above, if farmland returns affect farmland values and farmland values affect farmland returns, then a dynamic framework can be employed to solve the endogeneity problem. Two models were estimated for Brazil farmland: one for Brazil's macro regions and one on a subset of Brazil's micro regions. The micro regions selected are in Brazil's soybean producing region as this provides regions that are similar in crops produced and income potential.

A Vector Autoregression (VAR) model was used to analyze Brazilian farmland prices. Sims (1980) states that due to the high number of lagged variables within a VAR system, individual parameter estimates cannot be interpreted. Coefficients can switch sign from one lag to the next, making the direction of the feedback hard to determine. Thus, the best descriptive analysis of a VAR model is the response of the system to a shock. These responses are called impulse response functions, and detail the response of dependent variable to a one standard deviation shock.

Since the many lags of a VAR system can be correlated, Sims (1980) takes note that the variance estimates of the system may also be unreliable. To correct for this, Granger causality tests can be performed for groups of variables. A Granger causality test is a pooled F-Test. It should be noted, that Granger causality tests imply statistical significance between a group of variables. For this study, farmland values, returns to farmland, and interest rate are tested for Granger causality. In addition to the parameter estimates and Granger causality results, a complete set of impulse response functions are found in Appendix A for all VAR models. Those results discussed in depth are found at the end of this chapter.

To test for the number of lags in each model, the Akaike Information Criterion (AIC) is used (Akaike 1974). For each macro region and micro region model, the number of lags within the model was varied. The model that minimizes AIC is chosen. For each of the models, lags from one to three were ran. Models with four or more lags were not estimated as there were not enough degrees of freedom. The AIC increased after two lags, thus the model with two lags was chosen. It is possible for the AIC to decline after more lags are included in the model past the three lags; however, the signals sent within the network would fade as they are replaced by new signals and lose impact. This supports the justification that it is unlikely that the AIC would decrease after more lags are added to the model.

The rest of this section discusses the following: first the existence of information cascades are examined using the VAR models on Brazil’s macro regions and soybean producing micro regions. Then, if applicable, the network typology of how the market signals are sent in the farmland market are discussed.

Brazil Macro Regions

Parameter estimates for the VAR system examining the dynamics between Brazil's macro regions, returns to farmland, and interest are shown in Table 6.1. The Granger causality results are found in Table 6.2. Granger causality is also shown in map form in Figure 6.2 through Figure 6.13. Each of these figures is a map of Brazil's macro regions. The region shaded in red is the region of interest and any region shaded in blue is statistically significant at the 90% level to Granger cause prices in the region of interest. In addition to testing Granger causality for each individual region, all regions were pooled together and tested for causality with returns and interest rates. These results are at the top of Table 6.2.

The pooled Granger causality tests show that returns cause farmland values, and farmland values cause both returns and interest rates. Interest rate was found to not affect either farmland value or returns. This result for interest rate concurs with that of Featherstone and Baker (1988). To test for Granger causality of farmland values causing farmland values, each macro region of Brazil is examined for Granger causality causing farmland values in other regions.

Examining the Granger causality for the interactions between Brazil's macro regions is where the existence of information cascades can be analyzed. From the theoretical model discussed earlier, information cascades occur when market signals are sent through a network, received by an investor or buyer of farmland, affecting farmland price. If myopic capitalization theory were to hold, then farmland price movements in one region should not affect farmland prices in another. It was found that regions do cause farmland prices in other regions.

Graphing of the Granger causality shows which regions have been found to cause asset prices in other regions. A cursory analysis of the graphs shows that a spatial proximity pattern does not clearly emerge (Figures 6.2 to 6.13). In some instances, the statistical significance is spatially explained (Figure 6.10, Figure 6.12, Figure 6.13), others the production crop may be a better explanation of the statistical significance (Figure 6.2, Figure 6.4, Figure 6.9) as different soybean producing regions or sugar cane producing regions are found to cause each other.

In addition to Granger causality, impulse response functions were also used. Impulse response functions allow for the analysis of direction and magnitude of the dynamic relationships within the model. It should be noted, that not all of the impulse response functions are discussed in depth, with fifteen endogenous variables, this makes a total of 225 impulse response functions for the macro region model. The major themes from the impulse response functions are discussed. For a complete presentation of all impulse response function please see Appendix A.

The impulse response functions correspond with the Granger causality results. Farmland values in one region affect farmland values in other regions according to the positive shock administered. Figure 6.14 shows the response to a positive shock in farmland values in Goiás for Mato Grosso do Sul, Minas Gerais, Para, and Paraná. It is shown that the positive shock in Goiás causes farmland prices in Mato Grosso do Sul, and Paraná to increase and farmland prices in Minas Gerais and Pará to slightly increase. Goiás was found to Granger cause Mato Grosso do Sul, Minas Gerais, and Paraná. The responses to positive shocks indicate potential information cascades where an increase or shock to farmland price in one region leads to an increase in prices in other regions. The positive shock to Goiás above is only one example of the existence of the information cascade where an increase in farmland price in one region affects prices in other regions. These results show that an increase in farmland price, analogous to a buyer in one region paying more or less than the historical average, sends a signal to other regions that increase or decrease the price in each respective region that receives the signal. This is, by definition, the process of an information cascade.

It is also found that a shock to returns causes an increase in farmland prices. This is shown in the impulse response function in Figure 6.15 which shows the response in Bahia, Goiás, Maranhão and Mato Grosso to a positive shock in farmland returns. Shocks to returns to farmland are caused by price changes and yield shocks. In each of the impulse response functions in Figure 6.15, returns causes farmland prices to increase. Given the covariance of the innovations or errors of the dynamic system, a shock to returns also leads to increased farmland prices for a finite period before returning to its normal price level.

Decomposition of the forecast error also reveals the presence of information cascades. Figure 6.16 to Figure 6.30 show the percentage of forecast error attributable to each variable in the VAR model for every period of the forecast from two bi-monthly periods out to 24 bi-monthly periods. Decomposing the forecast error in this manner allows for the analysis of which regions are contributing to the forecast error in a respective region.

Figure 6.16 shows that for the bi-monthly forecast 2 periods ahead, the region Bahia accounts for approximately 85% of the forecast error for itself. This proportion dissipates as the forecast lead grows longer and more of the forecast error is attributable to other regions. Other regions, besides Bahia, exhibited more impact from other regions. Figure 6.27 shows the decomposition of the forecast error for Tocantins. Goiás contributes less in the first two to three periods and grows more impactful to the forecast error the longer the forecast is made. This would indicate that a shock to Goiás would not have an immediate impact on Tocantins but would eventually have a stronger influence as time passed. Overall what these figures of the decomposed forecast error show is that the proportion of a forecast error attributable to other regions is economically significant and is shows that shocks in one region will affect asset prices in other regions.

Leaders in the market emerge from the decomposition as well. Table 6.20 shows the total percentage of forecast error accounted for by each region and return and interest. These percentages are ranked from one to fifteen. Goiás accounts for the most forecast error with 28.31% attributable to Goiás. This percentage is more than double the second ranked region of Bahia which accounts for 10.96% of the forecast error. Goiás is centrally located in Brazil and is located in the main soybean producing region. In regions that are not spatially close to Goiás, such as Piauí, Goiás does not account for a significant portion of the forecast error till 5 bi-monthly periods from the initial forecast (Figure 6.20). This delayed signal and impact on forecast error is also experienced for Goiás's impact on Santa Catarina. In this instance, Goiás accounts for 0.41% of the forecast error for the first forecast. By the 12 bi-monthly forecast (two years lead) Goiás accounts for 15.15% of the forecast error (Figure 6.18). This indicates that the market signals may take time to reach from one region to another, but that Goiás is a market leader once the signals are received.

Brazil Micro Regions

A subset of the larger micro regions was chosen for additional analysis. These micro regions are located in Mato Grosso, Goiás, and Mato Grosso do Sul. These regions were selected due to their similarity in production capabilities and homogeneity in soybean production. The parameter estimates for this model are in Table 6.3. Granger causality for this model is located in Table 6.4. This model is a robustness check on the macro region model. Brazil's agriculture is diverse and climate from one macro region to another can be diverse as well. Since returns to farmland in the data are measured by the soybean prices and yields, this model uses only those regions that are in Brazil's soybean producing area making returns to farmland more consistent.

This model also suggests the potential for information cascades within the farmland market. Of the 400 possible Granger causality relationships, 142 are statistically significant at the 95% level and another 186 at the 90% level for farmland values affecting farmland values. This shows the significance of how farmland values affect farmland values and confirms the macro region model of the presence of information cascades within the farmland market.

Network Typology of the Information Cascade

The previous section examined the existence of farmland prices in one region affecting farmland prices in another region. However, the next question that needs to be addressed is if there is a definitive network type or structure that these market signals adhere to? One could hypothesize that the spread of signals would follow a nearest neighbor approach where only those regions bordering each other would have an effect on each other. However, with the onset of technology that allows for farmers to monitor market prices and news from all regions of the global agricultural markets, they may not respond to a nearest neighbor but farther regions. Thus, the question of whether market signals follow a spatial pattern or are there other factors for why one region was found to cause another regions farmland prices is the focus of this section.

Before the results of the models estimated in this study are examined for network typology, a brief overview of the direction of current literature would prove useful. In recent literature, the SAR model has become increasingly popular. With lower data requirements since only one equation is estimated, the spatial correlation of regions are accounted for in this type of model. An example of this is Huang, et al., (2006) where the spatial weights are inserted into a hedonic price analysis model. Dachary-Bernard et al., (2014) is another example that incorporates this process into a hedonic pricing model of farmland prices. While this method is not a dynamic framework like that estimated in this study, the authors of these two papers attempt to control for exogenous factors affecting all counties for the respective states in a given year.

To test for network typology and subsequent prediction accuracy of models the results from the macro region VAR are analyzed along with results from individual VAR model where only the respective region is allowed to influence its own farmland prices, and a SAR model using the nearest neighbor or queen adjacency rule for construction of the weight matrix are analyzed. As stated previously, the VAR model for Brazil's macro regions allowed for estimation of an endogenous relationship without a priori specification of a spatial weight matrix, which is required by the Spatial Autogressive (SAR) model. Mapping the Granger causality results shows which regions were found to cause other regions. Figure 6.2 to Figure 6.13 show that the VAR may be the more appropriate in most cases than the nearest neighbor rule.

For instance, Figure 6.13 shows the causality for Tocantins. Farmland values in Maranhão, Mato Grosso, Goiás, and Minas Gerais are found to cause farmland values in Tocantins. The regions that are found to cause farmland values in Tocantins all border Tocantins. However, Figure 6.5 shows the regions that cause Bahia values are Rio Grande do Sul, Paraná, and Piauí, where only Piauí borders Bahia. If an adjacency rule were to be used for Bahia, the network which influences Bahia would be incorrect. Some of the seemingly random Granger causality results can be explained via other factors besides spatial proximity. Those regions found to cause Mato Grosso, Mato Grosso do Sul and Tocantins are Brazil's main soybean producing regions (Figure 6.9, Figure 6.10, and Figure 6.13). It should be noted that while these results can be explained by the crops grown in the region, not all regions that have the same crops are found to cause the farmland prices in other regions. Granger causality for Maranhão, which was found to be caused by Minas Gerais, a result that at present time is difficult to explain by crops produced or spatial dependency.

These results suggest that a flexible form with no a priori specification of network may be the best. To test this proposition that no a priori specification may be best, a SAR model that imposes network structure and a set of VAR models that impose no network were estimated to compare prediction results. If a SAR model were to be used, some criteria for spatial dependency would have to be established. In this case, it is the a binary matrix matching nearest neighbors or a queen adjacency rule. The results for this SAR model are in Table 6.5 and the results of the region specific VAR models where no network is imposed are in Table 6.6 through Table 6.18.

The prediction error by region for each of the three types of models is in Table 6.19. From the prediction errors, it is shown that the worst predictor of farmland prices is the Pseudo-SAR model, next best are the region specific VAR models with no network or information cascade, and the best predictor of farmland prices is the VAR model with no a priori specification of network type. While these models do not offer a direct comparison since the error terms are treated differently from the VAR to Pseudo-SAR models and the number of lags is also different, the result of prediction error increasing when imposing network structure should be an indication that researchers should explore network type more in depth before imposing it.

These results indicate that the current direction of the literature should show caution when using SAR based models when examining farmland prices. Allowing the data to determine network typology seems to be the best method for prediction of farmland prices. However, it would be prudent to mention that since SAR models do require less data, they have an estimation advantage over the VAR procedure employed in this study.

Figure 6.1, Real Brazil Farmland Price to Income Ratio

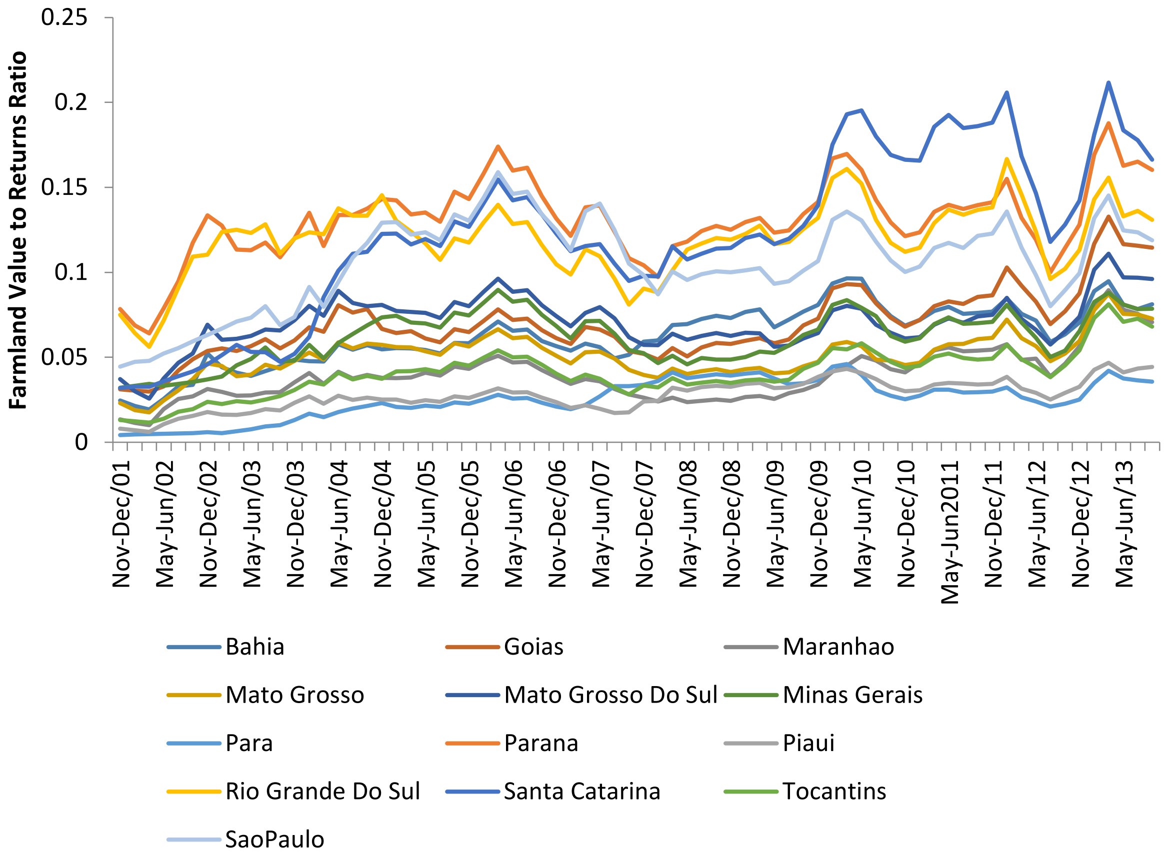
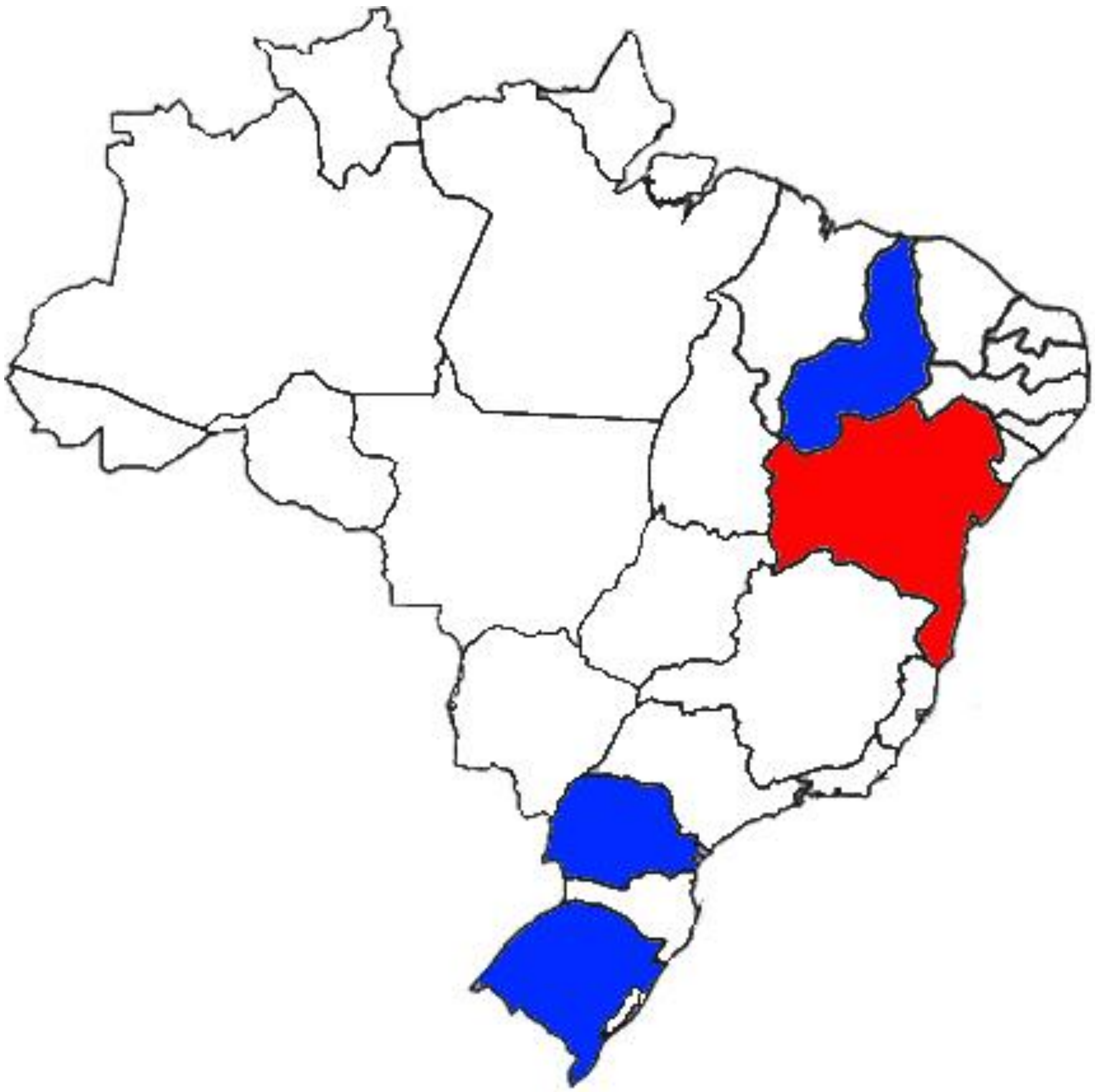
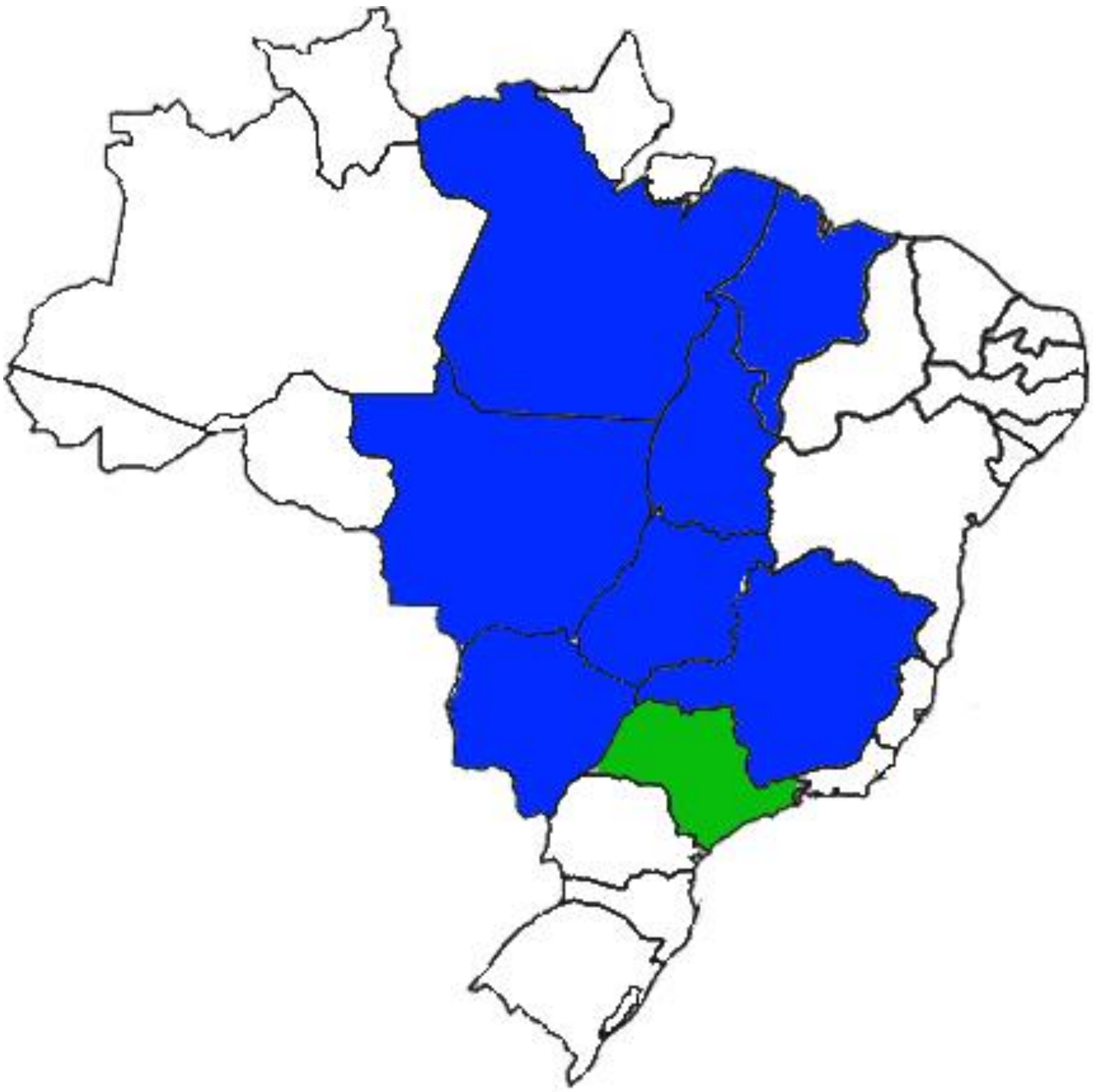


Figure 6.2, Brazil Macro Region, Granger Causality Map, Bahia



Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.3, Brazil Macro Region, Granger Causality Map, São Paulo



Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.4, Brazil Macro Region, Granger Causality Map, Santa Catarina

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.5, Brazil Macro Region, Granger Causality Map, Rio Grande do Sul

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.6, Brazil Macro Region, Granger Causality Map, Piauí

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.7, Brazil Macro Region, Granger Causality Map, Paraná

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.8, Brazil Macro Region, Granger Causality Map, Minas Gerais

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.9, Brazil Macro Region, Granger Causality Map, Mato Grosso

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

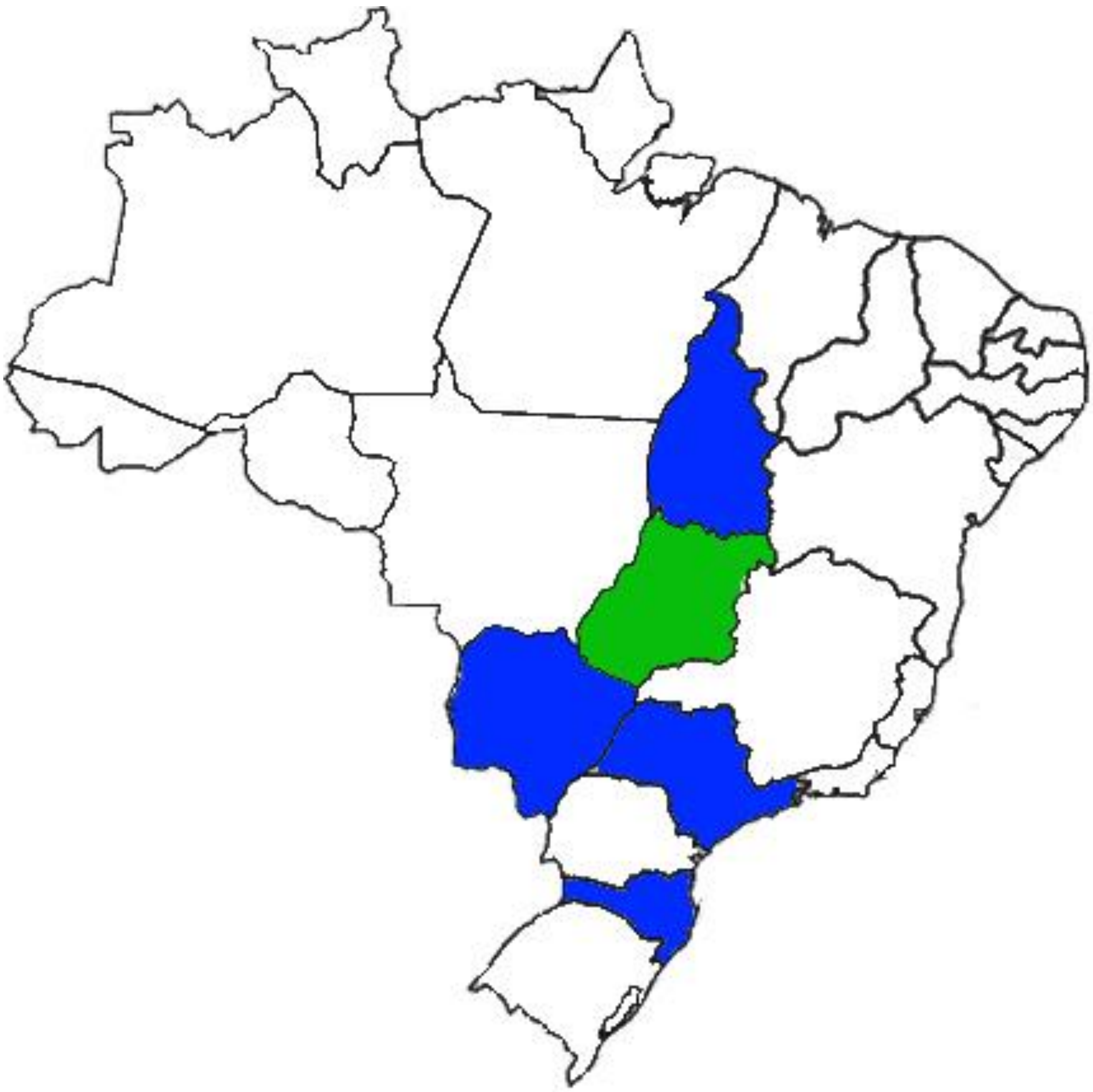
Figure 6.10, Brazil Macro Region, Granger Causality Map, Mato Grosso do Sol

Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.11, Brazil Macro Region, Granger Causality Map, Maranhão

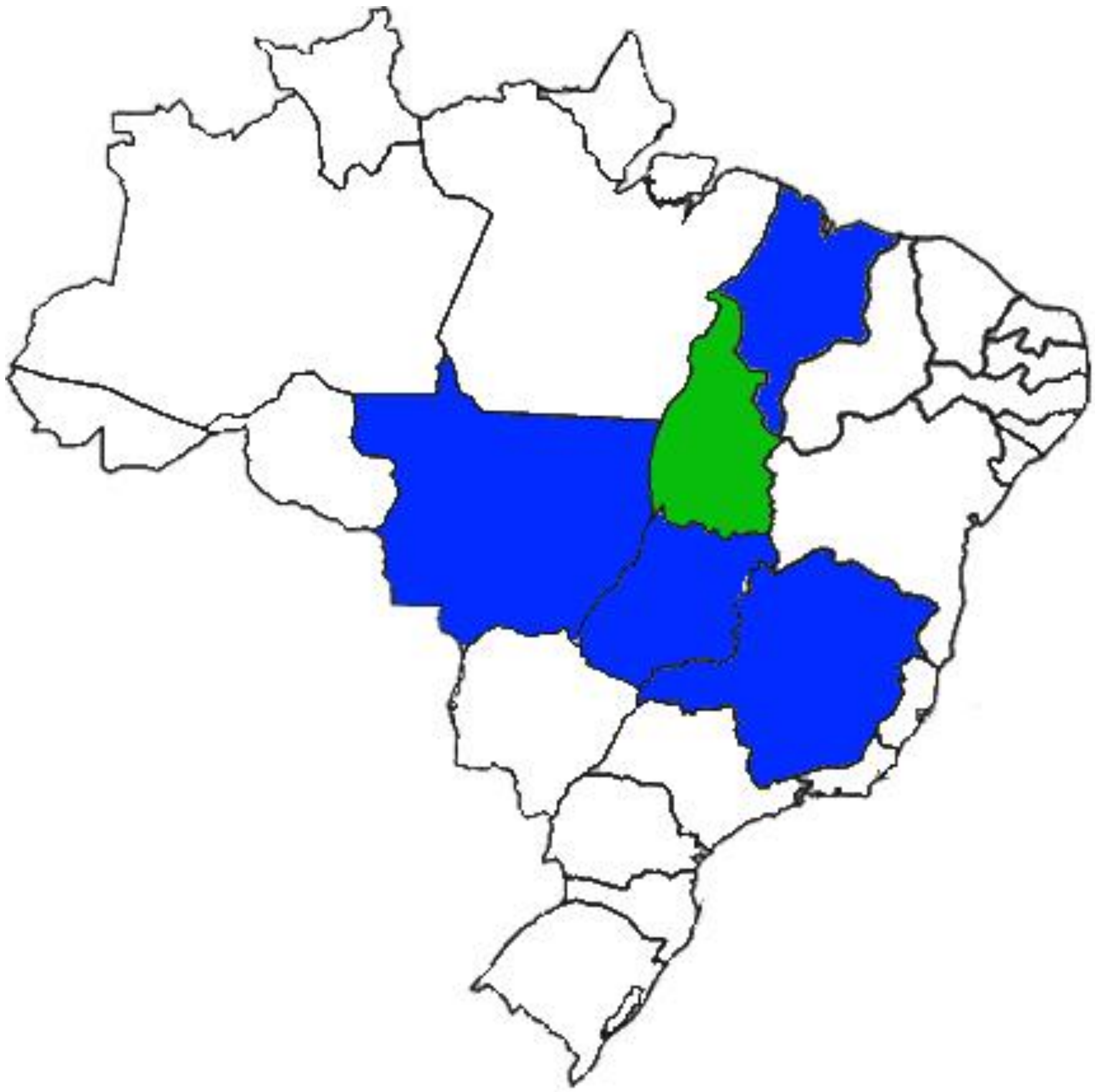
Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.12, Brazil Macro Region, Granger Causality Map, Goiás



Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.13, Brazil Macro Region, Granger Causality Map, Tocantins



Region in red or green signifies it is the region being analyzed with red representing it was not statistically significant at the 90% level to Granger cause itself and green indicating the respective region was statistically significant at 90% to Granger cause itself. Regions in blue signify it is statistically significant at the 90% level to Granger cause the region being analyzed.

Figure 6.14, Impulse Response Function to Goiás for Mato Grosso do Sul, Minas Gerais, Pará, and Paraná

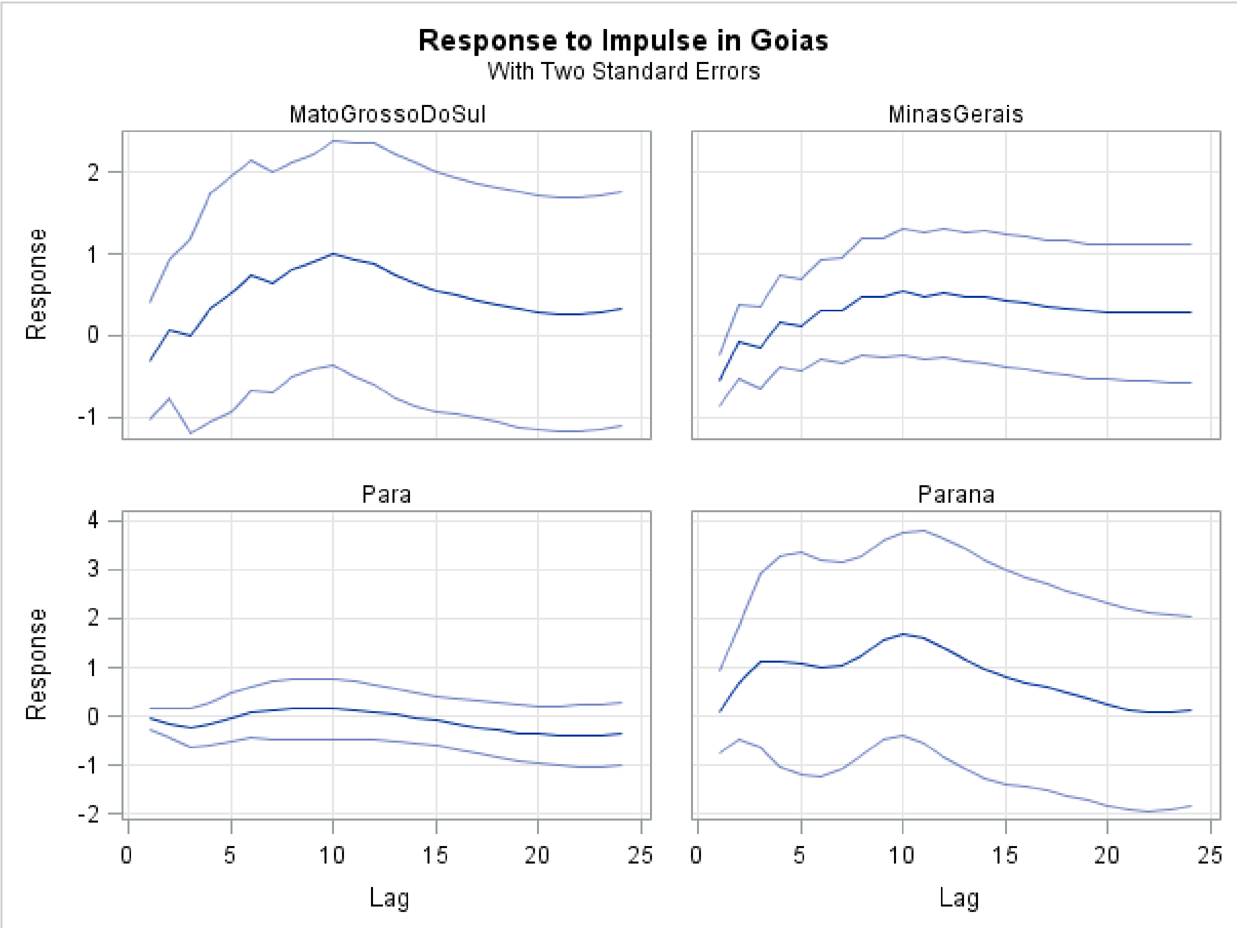


Figure 6.15, Impulse Response Function to Returns for Bahia, Goiás, Maranhão and Mato Grosso

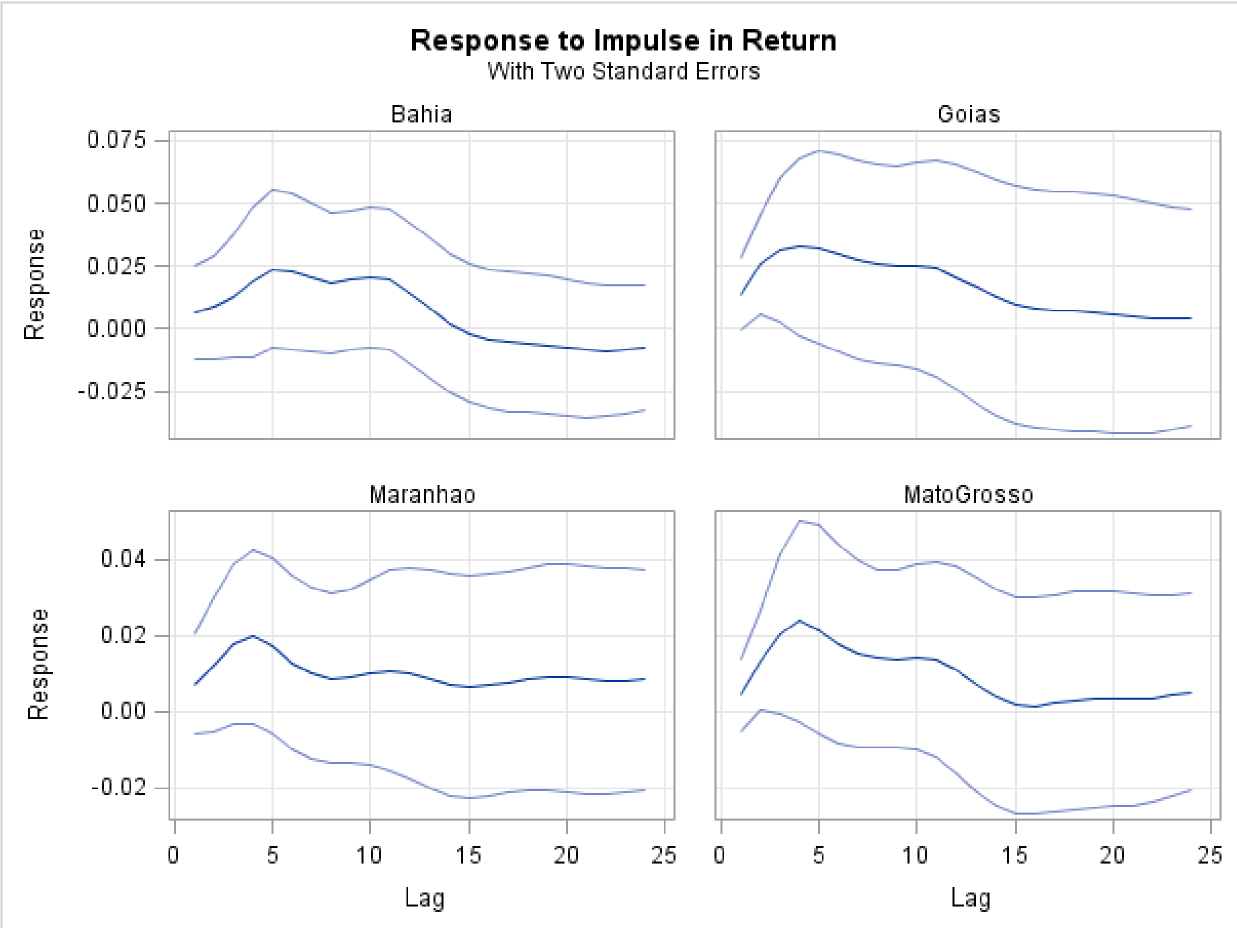


Figure 6.16, Decomposition of Forecast Error, Bahia

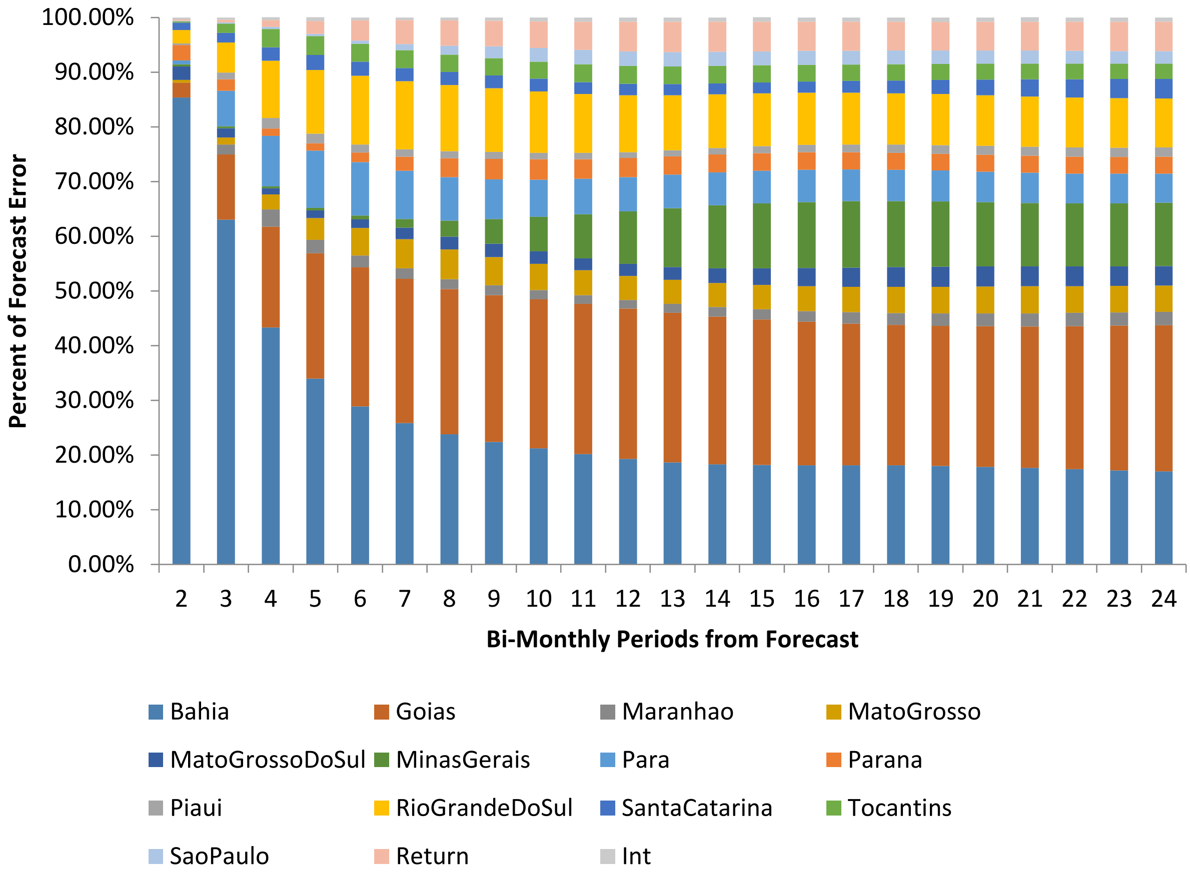


Figure 6.17, Decomposition of Forecast Error, São Paulo

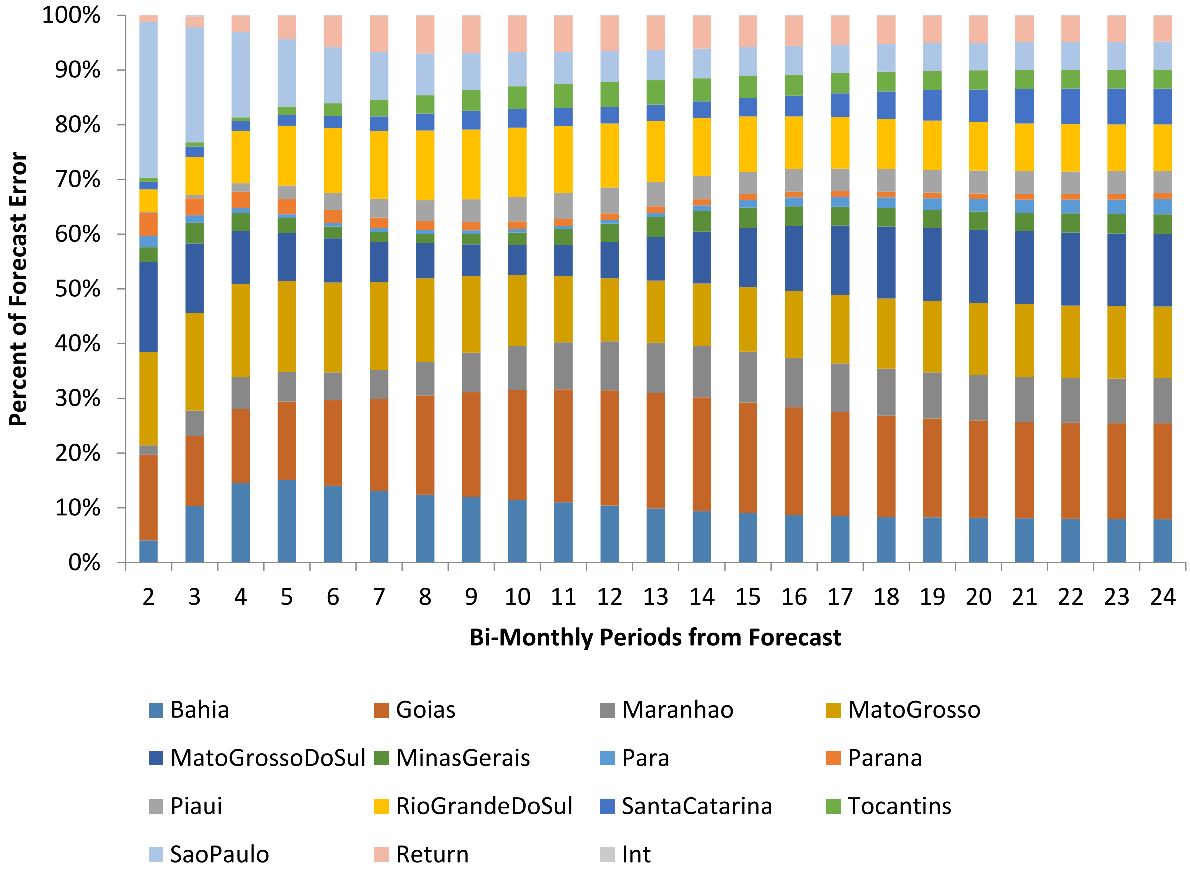


Figure 6.18, Decomposition of Forecast Error, Santa Catarina

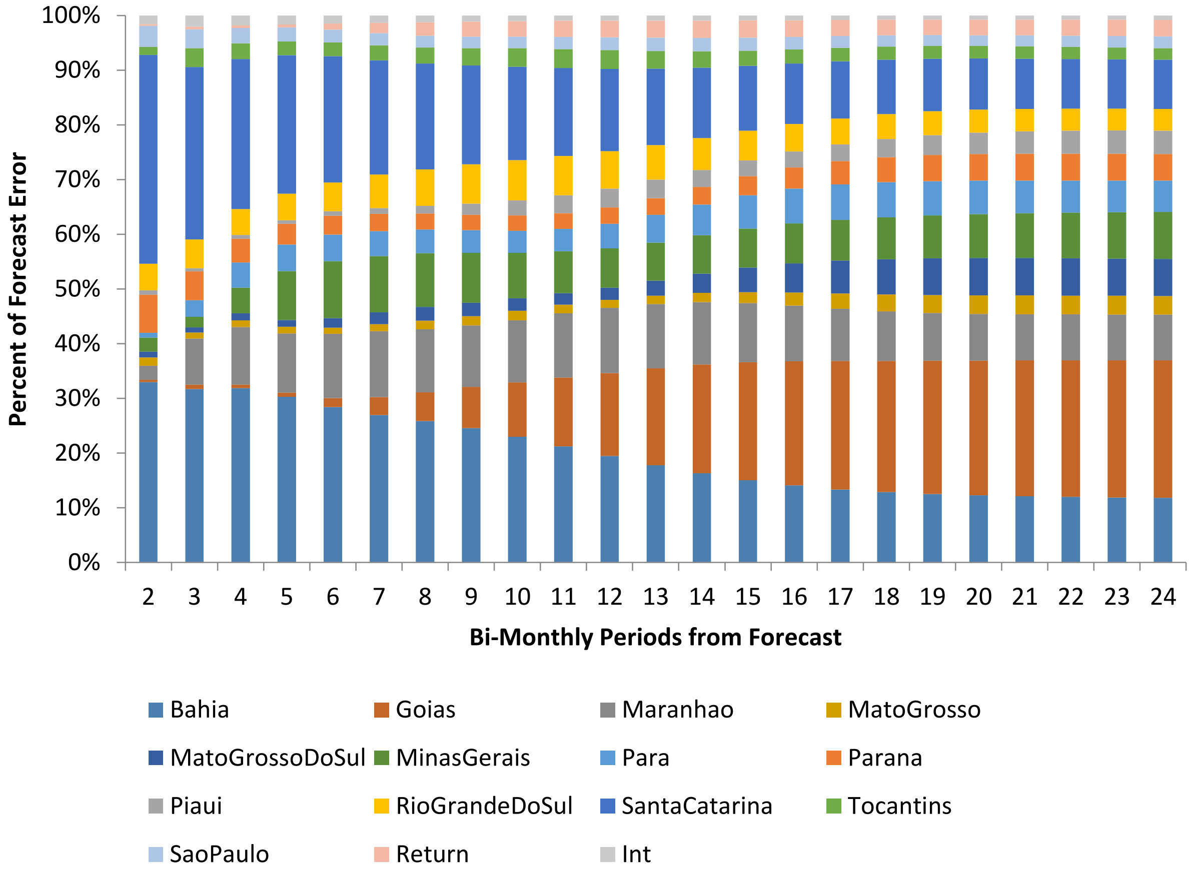


Figure 6.19, Decomposition of Forecast Error, Rio Grande do Sul

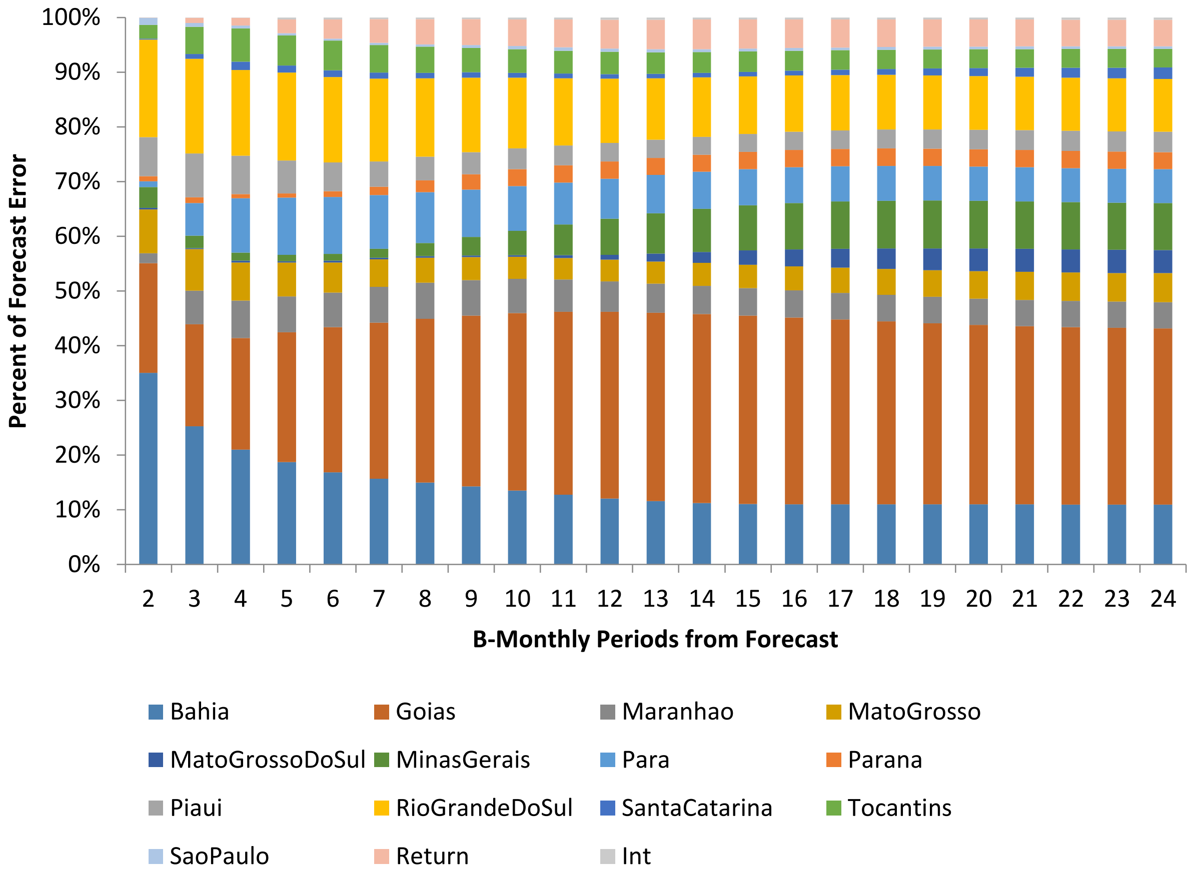


Figure 6.20, Decomposition of Forecast Error, Piauí

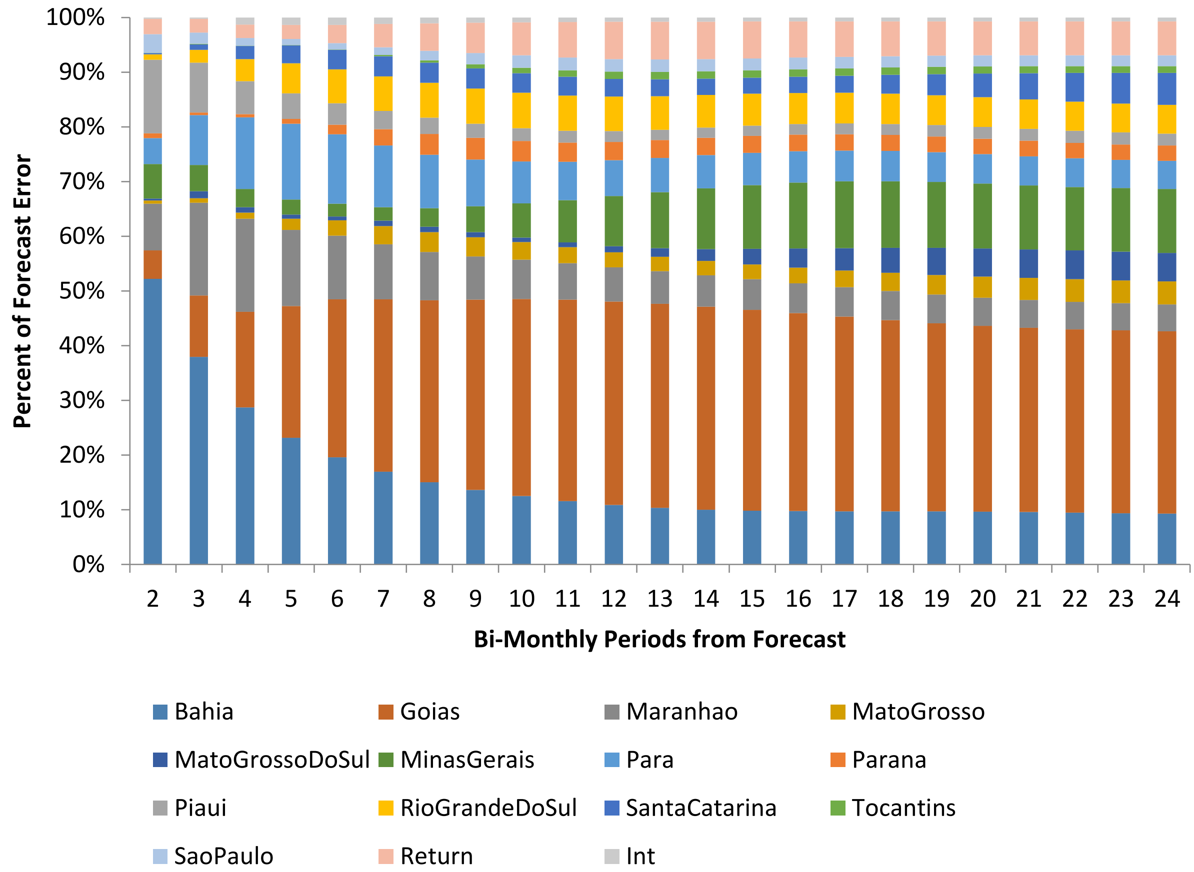


Figure 6.21, Decomposition of Forecast Error, Paraná

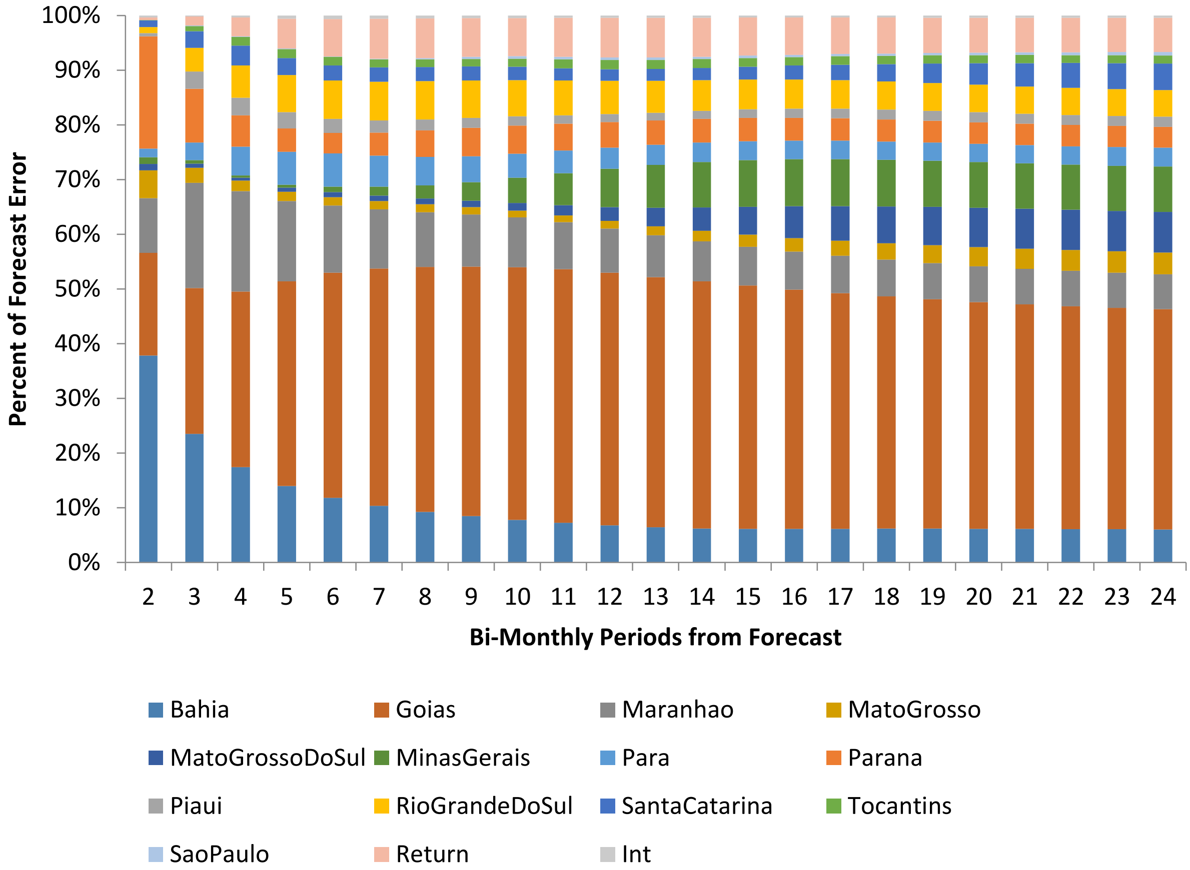


Figure 6.22, Decomposition of Forecast Error, Minas Gerais

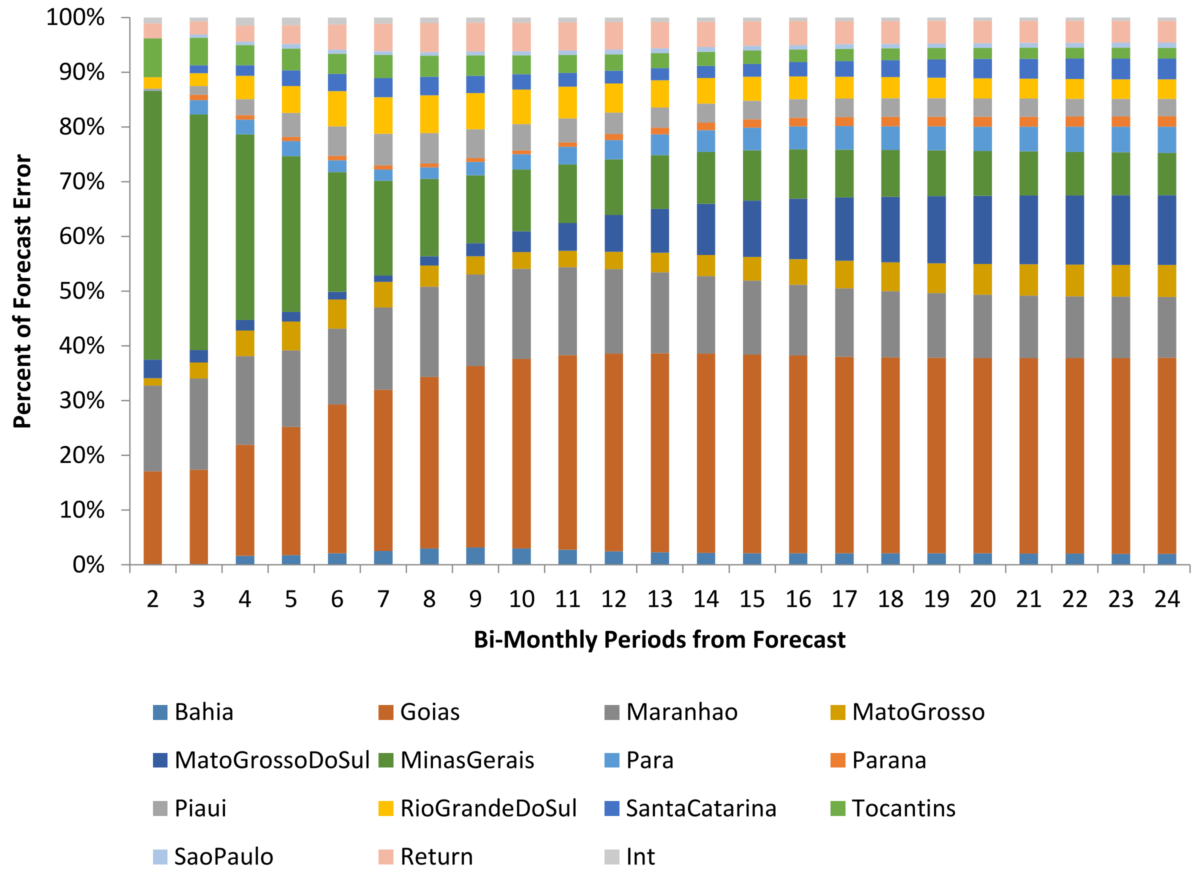


Figure 6.23, Decomposition of Forecast Error, Mato Grosso

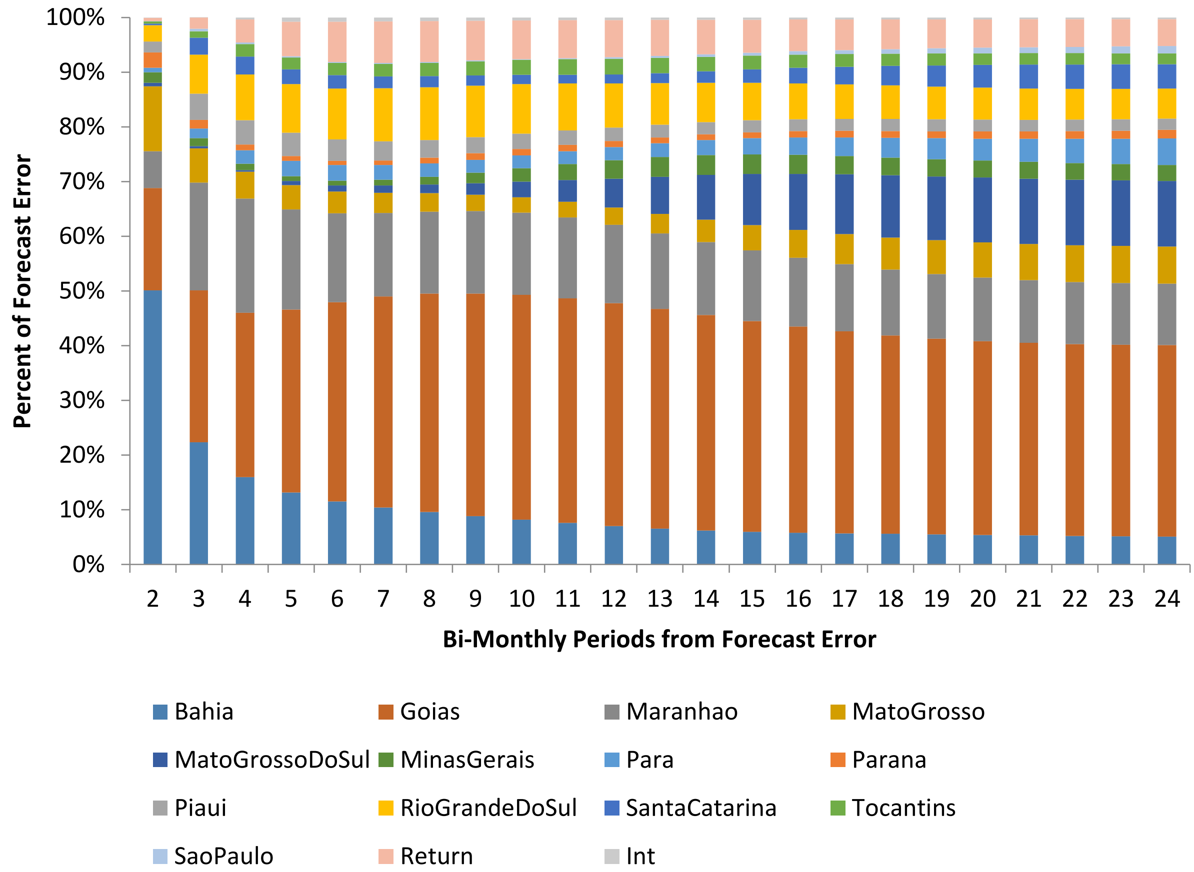


Figure 6.24, Decomposition of Forecast Error, Mato Grosso do Sul

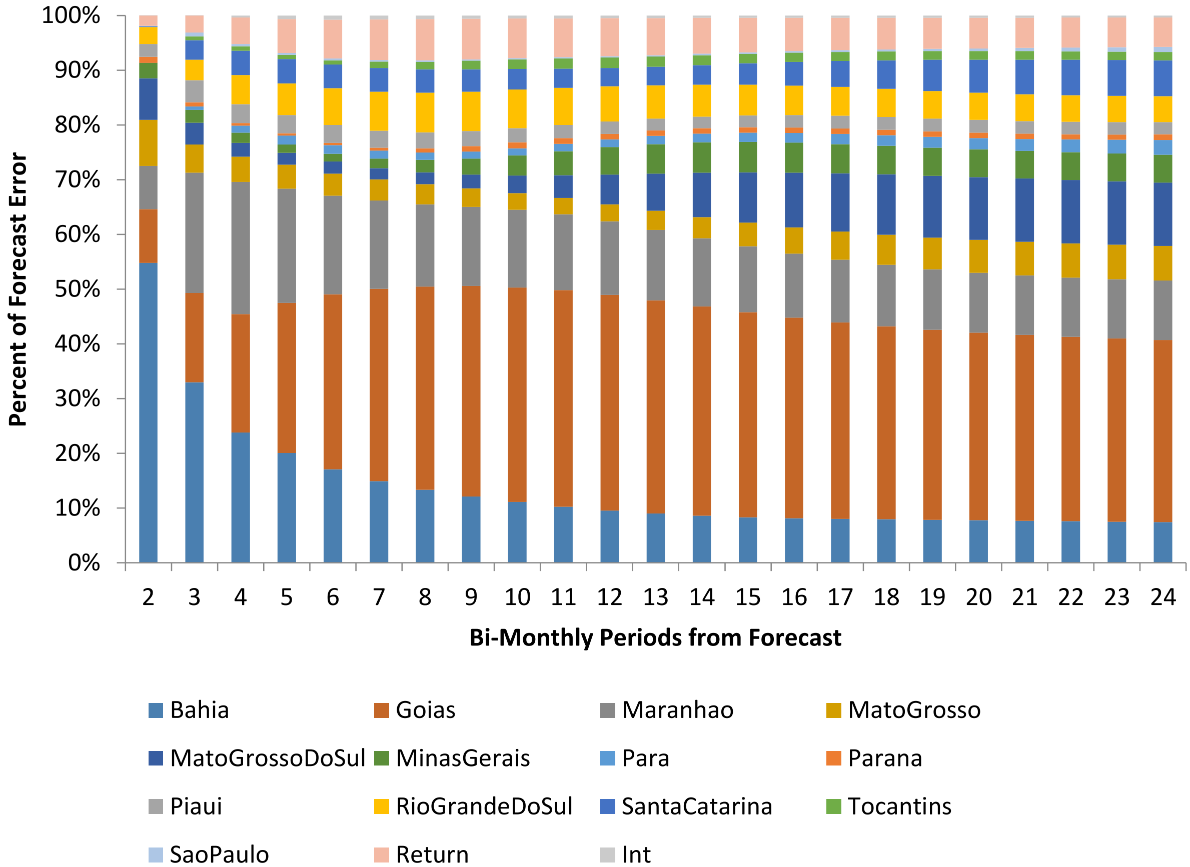


Figure 6.25, Decomposition of Forecast Error, Maranhão

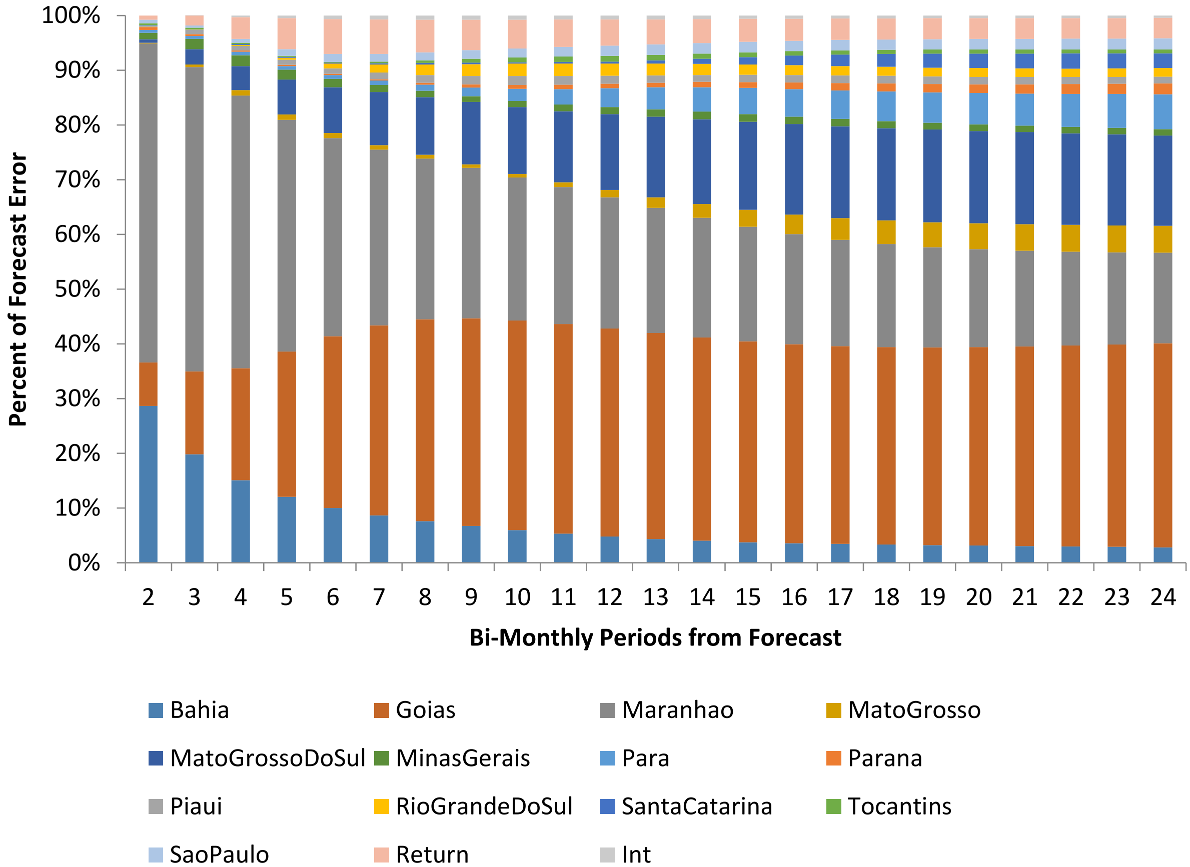


Figure 6.26, Decomposition of Forecast Error, Goiás

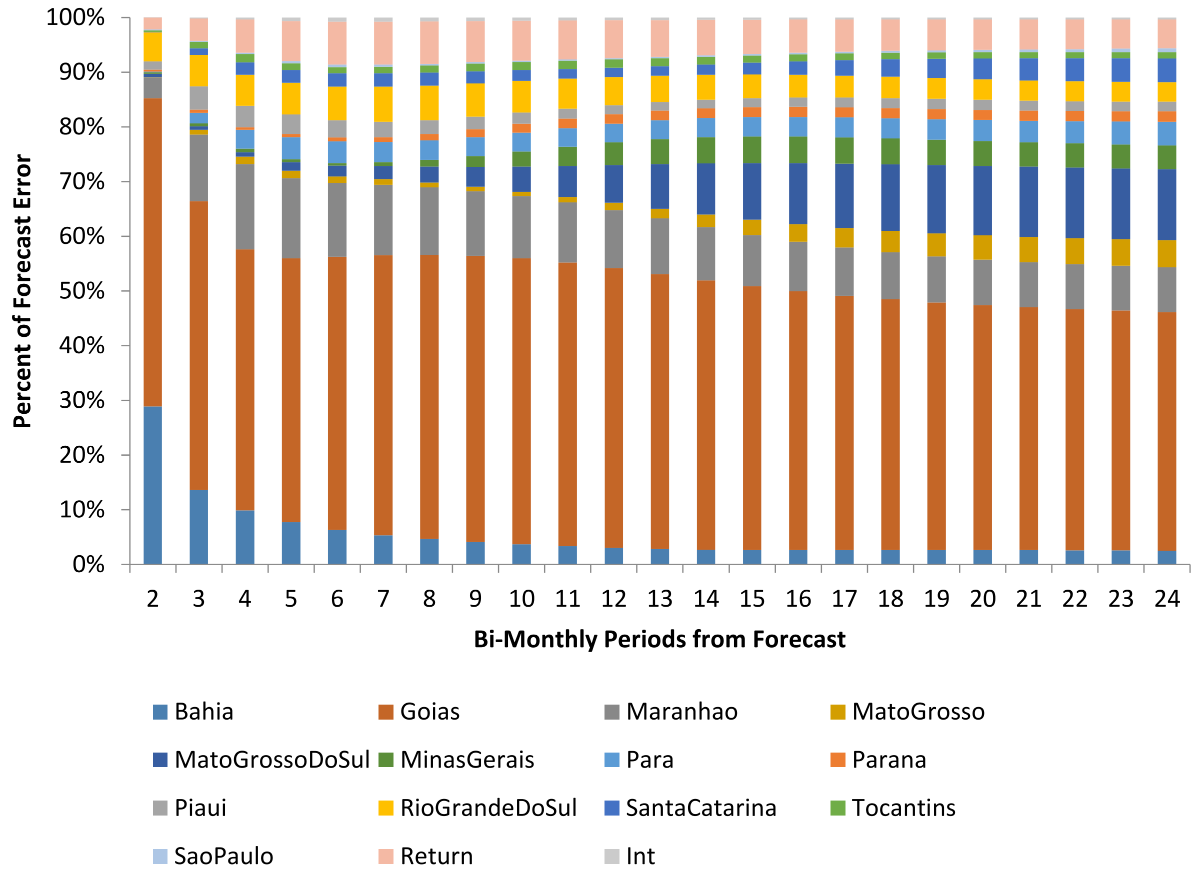


Figure 6.27, Decomposition of Forecast Error, Tocantins

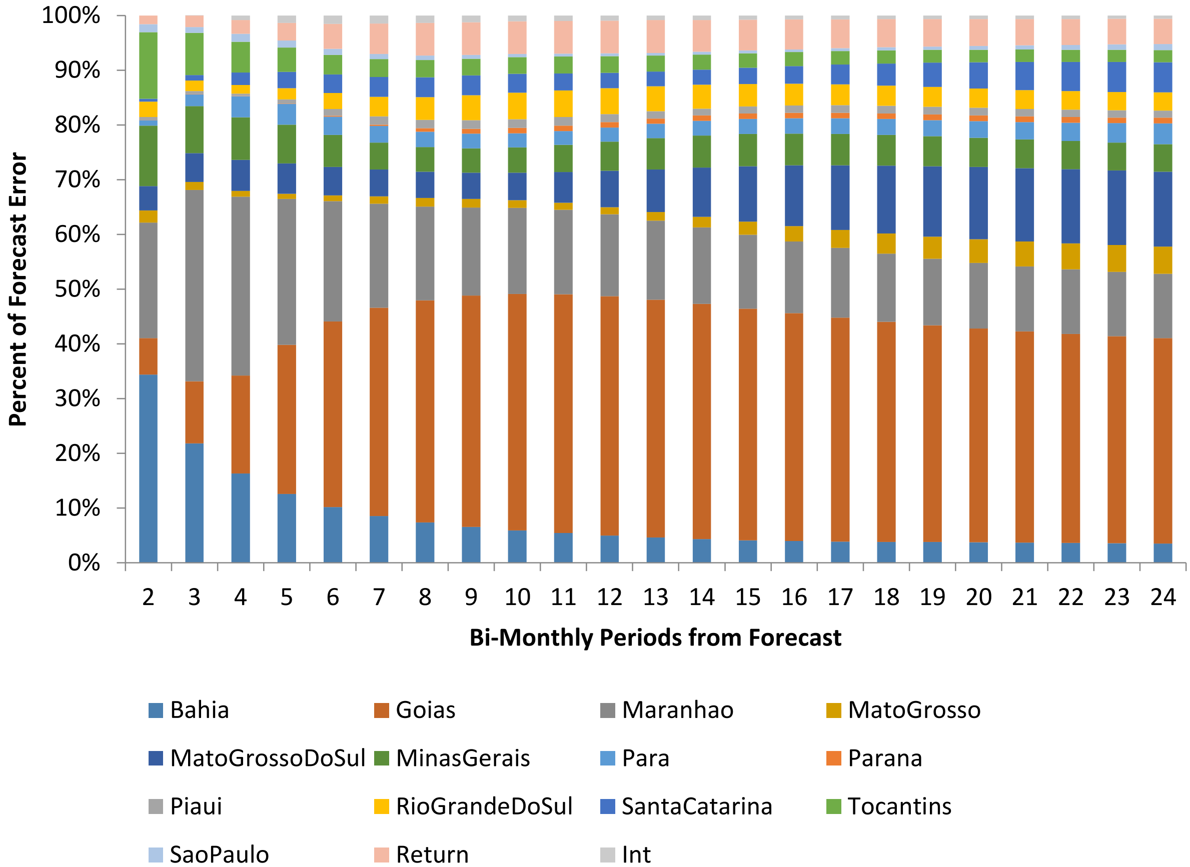


Figure 6.28, Decomposition of Forecast Error, Pará

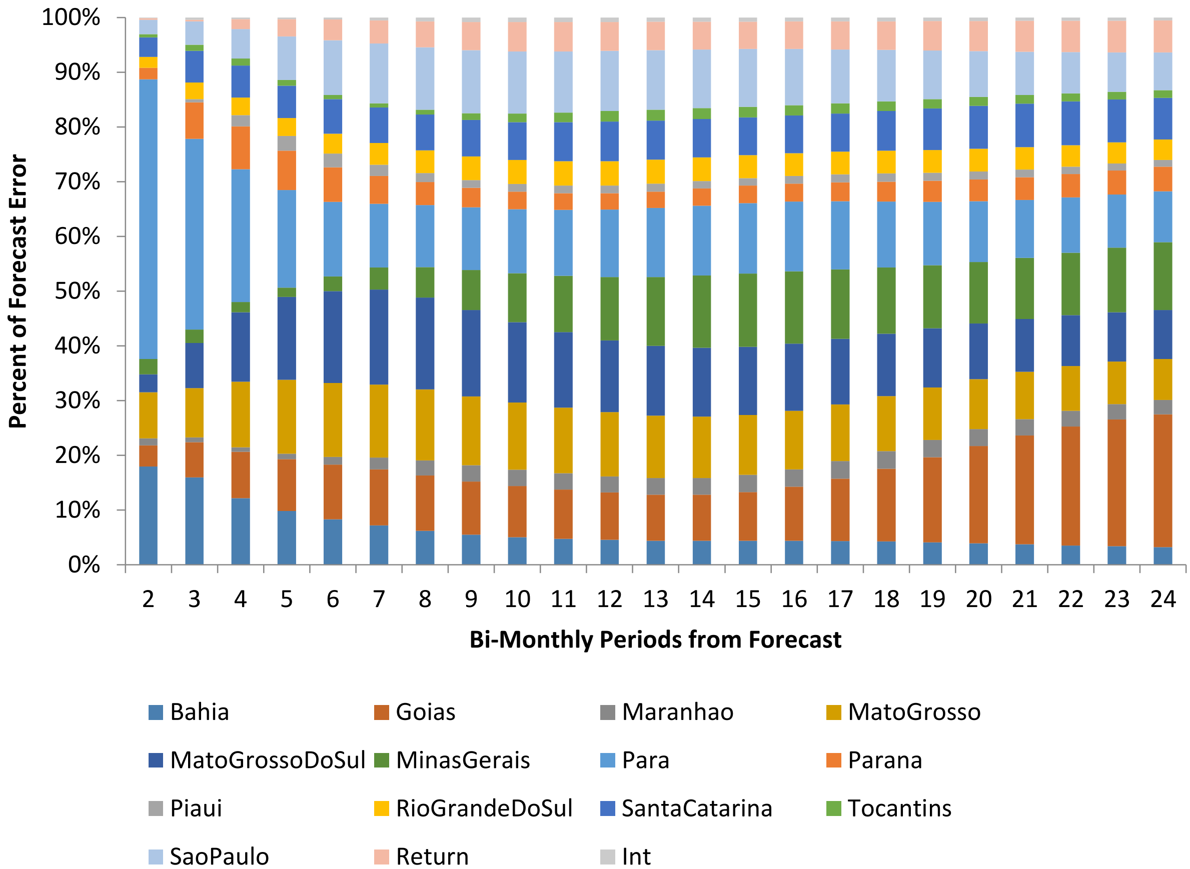


Figure 6.29, Decomposition of Forecast Error, Returns

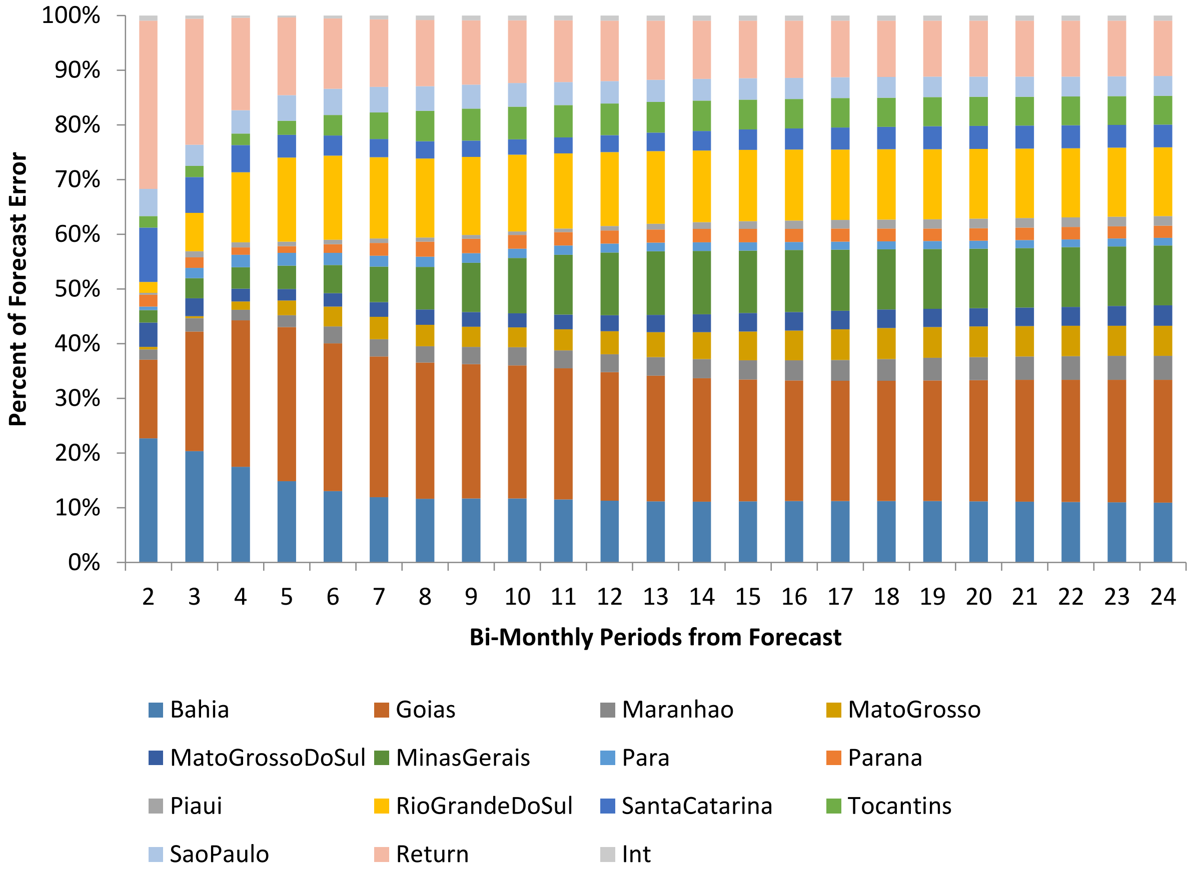


Figure 6.30, Decomposition of Forecast Error, Interest

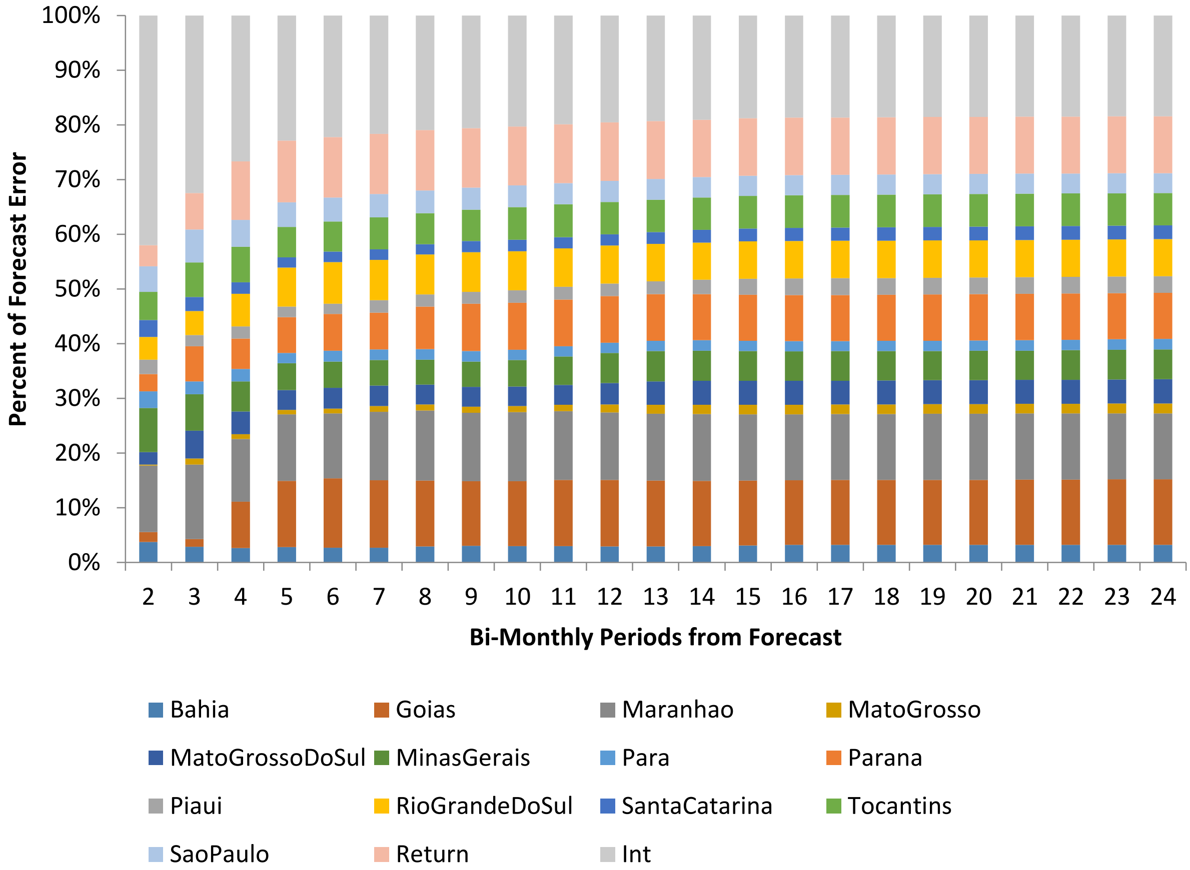


Table 6.1 Brazil Macro Regions, Vectorautoregression Parameter Estimates

	Dependent Variables														
Independent Variable	Bahia	Goiás	Maranhoa	Mato Grasso	Mato Grosso Do Sul	Minas Gerais	Pará	Paraná	Piauí	Rio Grande Do Sul	Santa Catarina	Tocantins	São Paulo	Returns	Interest
Intercept	1665.28	1569.58	1097.53	1572.92	2320.41	2928.94*	-2761.22*	10105.23*	675.21	10203.3*	688.63	4277.63	583.75*	83357.38	0.23*
Time Trend	120.08*	145.5*	34.95	64.11*	88.44*	114.64*	32.36*	47.09	25.01	-9.62	3.02	77.04*	50.84*	979.66	0.00
$Bahia_{t-1}$	0.16	-0.18	-0.17	0.08	-0.23	-0.34*	0.28*	-0.07	0.01	0.05	0.22	-0.01	-0.02	-0.64	0.00
$Goias_{t-1}$	-0.24	0.42	-0.10	-0.07	-0.32	-0.55*	-0.05	0.08	-0.14	0.32	0.34	-0.33	-0.26	-3.38	0.00
$Maranhoa_{t-1}$	0.05	0.61*	1.03*	0.3**	0.50	0.33*	-0.04	0.78*	0.24**	0.90	1.08*	0.11*	0.50	16.76*	0.00
$Mato\ Grasso_{t-1}$	0.17	-0.15	-0.10	0.28	0.38	0.51**	-0.25	-0.27	-0.12	0.35	-0.86	0.39	0.16	17.41	0.00
$Mato\ Grasso\ Do\ Sul_{t-1}$	-0.45	-0.25	-0.13	-0.30	0.09	-0.34*	-0.13	-0.08	0.00	-0.12	-0.14	0.24	-0.21	-19.94*	0.00
$Minas\ Gerais_{t-1}$	-0.11	-0.29	0.20	0.02	-0.07	0.26	0.00	0.04	0.09	0.15	-0.06	0.03	0.29	-18.24*	0.00
$Para_{t-1}$	0.26	0.03	0.29	0.16	-0.17	0.46**	1.16*	0.19	0.39**	0.50	0.52	-0.05	-0.04	3.72	0.00
$Parana_{t-1}$	0.28	-0.24	0.08	0.04	-0.22	-0.19	-0.02	0.49	-0.01	-0.70	-0.29	-0.33	-0.03**	-8.31	0**
$Piaui_{t-1}$	0.22	0.50	-0.34	0.40	0.68	-0.31	-0.24	0.38	0.29	3.34*	1.65	-0.10	0.05	1.08	0**
$Rio\ Grande\ Do\ Sul_{t-1}$	0.23	0.28*	0.08	0.14**	0.31*	0.24*	0.12*	0.32**	0.12*	0.51**	-0.32	0.15	0.05	2.80	0*
$Santa\ Catarina_{t-1}$	0.11	-0.09	-0.02	-0.08	-0.20	-0.09	-0.11*	-0.35**	-0.08	-0.17	0.8*	-0.22	-0.02*	-0.26	0.00
$Tocantins_{t-1}$	0.27	0.05	0.37	-0.08	0.26	1.09*	0.18	-0.08	0.18	-1.65	-1.02	0.19**	0.57	12.58	0.00
$Sau\ Paulo_{t-1}$	-0.09	0.34	-0.11	0.14	0.34	0.21	0.2**	0.10	-0.17	0.85	0.73	0.90	-0.13*	22.73*	0.00
$Returns_{t-1}$	0.01	0.01**	0.01	0.00	0.02**	0.01**	0.00	0.01	0.01*	0.00	0.00	0.01	0.01	0.95*	0.00
$Interest_{t-1}$	-2899.64	-552.69	-72.75	678.52	-1056.21	2692.46	636.81	-4162.44	1195.94	-3121.74	-8186.96	-76.92	-27.82	-109659.27	0.20

AIC= 172.37, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.1 Continued, Brazil Macro Regions, Vectorautoregression Parameter Estimates

Independent Variable	Bahia	Goiás	Maranhoa	Mato Grasso	Mato Grosso Do Sul	Minas Gerais	Pará	Paraná	Piauí	Rio Grande Do Sul	Santa Catarina	Tocantins	São Paulo	Returns	Interest
$Bahia_{t-2}$	-0.28	-0.67*	-0.05	-0.38*	-0.08	-0.39*	-0.16	-0.07	-0.04	-0.56	0.16	0.06	-0.02	-7.45	0.00
$Goias_{t-2}$	0.39	0.35	0.30	0.28	0.51	0.56*	0.02	0.73**	0.18	0.50	-0.33	0.31**	0.31	8.68	0.00
$Maranhoa_{t-2}$	0.28	0.30	-0.14	0.64*	0.67	-0.36*	0.14	1.11*	0.16	1.00	0.57	0.31	0.03	-1.17	0.00
$Mato\ Grasso_{t-2}$	-0.36	0.05	0.19	-0.04	-0.90	-0.44	-0.27	-0.61	0.03	-0.28	-0.02	-0.73	0.03**	-23.78**	0.00
$Mato\ Grasso\ Do\ Sul_{t-2}$	0.33	-0.13	-0.13	-0.01	0.19	0.55*	0.2*	-0.34	-0.01	-0.43	0.02	0.34	0.02**	7.84	0**
$Minas\ Gerais_{t-2}$	-0.17	-0.05	-0.16	-0.28	-0.30	0.08	-0.04	-0.59	0.06	-0.40	1*	0.07	-0.08	-4.84	0.00
$Para_{t-2}$	0.45	0.10	-0.40	-0.30	0.11	-0.30	-0.39**	0.44	0.05	-0.27	-0.59	0.20	0.21	14.23	0.00
$Parana_{t-2}$	-0.49**	-0.08	-0.23	-0.44*	-0.32	0.07	0.05	-0.78*	-0.11	0.29	0.22	-0.10	-0.15	1.60	0.00
$Piaui_{t-1}$	-0.29	0.64	0.84	0.64	0.26	0.63**	-0.29	0.98	0.31	1.11	0.35	0.07	0.32	-26.53	0.00
$Rio\ Grande\ Do\ Sul_{t-2}$	0.27	0.20	-0.01	0.19*	0.15	0.06	-0.03	0.20	-0.02	0.05	0.17	0.04	0.02	12.56*	0.00
$Santa\ Catarina_{t-2}$	-0.3**	-0.31*	-0.08	-0.23*	-0.33*	0.01	-0.01	-0.20	-0.01	-0.01	-0.14	0.06*	-0.18	-5.25	0.00
$Tocantins_{t-2}$	-0.22	-0.10	-0.31	-0.25	-0.28	-0.83*	0.14	-0.71	-0.37	-1.93	-1.39**	-0.39	-0.27	4.20	0.00
$Sau\ Paulo_{t-2}$	0.13	-0.11	0.13	0.3**	0.29	-0.4*	0.09	0.35	0.04	-0.57	-0.43	-0.26	0.16	-14.57*	0.00
$Returns_{t-2}$	0.00	0.01	0.00	0.01	0.00	0.00	0.01*	0.00	0.00	0.00	-0.01	0.00	0.00	-0.25	0**
$Interest_{t-2}$	976.30	-2339.94	-92.71	-1189.00	-1663.69	-2626.20	828.86	112.11	407.34	-4666.62	-2212.34	-4036.82	-236.91**	111402.30	-0.15

AIC= 172.37, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.2, Brazil Macro Regions, Vectorautoregression Granger Causality Results, Wald Test Statistics

Independent Variable	Dependent Variables		
	All Farmland	Returns	Interest
All Farmland[a]	--	50.78*	48.33*
Returns	112.06*	--	10.11*
Interest	29.81	.78	--

Independent Variable	Bahia	Goiás	Maranhoa	Mato Grasso	Mato Grosso Do Sul	Minas Gerais	Pará	Paraná	Piauí	Rio Grande Do Sul	Santa Catarina	Tocantins	São Paulo	Returns	Interest
Bahia	--	0.207	0.854	0.9736	0.1448	0.7449	0.146	0.1147	8.26*	8.33*	2.18*	2.78*	0.3355	0.1188	0.249
Goiás	0.3198	--	0.8943	0.167	0.331	3.78*	0.151	0.2866	0.143	0.159	0.2749	0.1823	9.08*	2.58*	0.22**
Maranhoa	0.6802	0.424	--	0.53*	0.7661	0.209	3.2*	0.2015	0.678	0.5997	0.31*	0.8605	0.8554	0.1804	0.315
Mato Grasso	0.3381	7.71*	0.7143	--	5.07*	13.15**	3.71*	0.1564	0.111	0.2869	0.1505	0.7762	0.8135	3.79*	0.63
Mato Grosso Do Sul	0.2062	12.84*	0.7687	9.49*	--	14.83*	3.27*	0.1948	4.86*	4.29**	0.91**	0.1171	0.6343	5.61*	0.124
Minas Gerais	0.8491	11.43*	0.547	7.53*	3.74*	--	2.16*	0.3396	0.35**	0.8391	0.4747	0.99**	0.7639	0.1406	0.608
Pará	0.5932	0.893	0.9284	0.8199	0.9639	0.9747	--	0.1*	0.949	0.3399	0.8701	0.6529	0.1758	0.2243	0.377
Paraná	0.7242	8.84*	0.5803	0.2984	0.7593	0.9571	1.43*	--	2*	0.3679	0.08*	0.4303	0.9598	0.5302	0.468
Piauí	0.676	0.138	0.9978	0.54	0.4339	0.434	8.11**	3.24*	--	2.85*	0.96*	0.2409	0.6185	0.6206	0.568
Rio Grande Do Sul	0.8502	0.506	3.21*	0.6772	0.6438	0.9922	0.235	0.3108	0.795	--	1.66*	0.6219	0.7386	6.4*	0.676
Santa Catarina	0.3224	0.346	0.7417	0.2008	4.41**	8.24**	0.215	0.529	3.98**	8.88*	--	3.33*	0.4358	5.92**	3.39**
Tocantins	0.1686	14.72**	0.1837	6.79**	0.1383	0.1104	3.42*	0.2318	1.49*	0.1369	1.12**	--	1.4*	8.07**	0.19
São Paulo	0.5358	7.14*	0.8278	9.3*	8.57*	9.27*	6.57*	2.2*	0.333	0.1761	0.1741	0.3828	--	3.5*	0.38**
Returns	0.9723	1.36*	0.9275	0.88*	0.02*	0.4875	2.34*	0.181	0.298	0.4758	0.61*	0.5083	0.5708	--	--

*Indicates significance at 95% level

**Indicates significance at 90% level

[a] All Farmland is all macro regions pooled together

Table 6.3, Brazil Micro Region Vectorautoregression Model, Soybean Producing Regions, Parameter Estimates

Independent Variable	Catalao	Entorno de Brasilia	Entorno de Goiania	Rio Verde	Alta Floresta	Alto Araguaia	Aripuana	Barra do Garcas	Rondonopolis	Sinop (Diamantino)	Sinop (Sorriso)
Intercept	-681.01	-61.23	116.23	3829.52	-254.6	2929.96*	1622.52*	-2073*	2636.24	1622.75	5399.97*
Trend	99.77*	73.82	65.39*	94.04	14.8	67.92**	58.48*	3.27	87.74**	35.29	15.48
$Catalao_{t-1}$	-0.24	0.72**	0.32**	1.1*	0	0.73*	0.26*	0.05	0.89*	0.93*	1.29*
$Entomo\ de\ Brasilia_{t-1}$	-0.57*	-0.15	-0.24**	-0.94*	-0.08	-0.43*	-0.31*	-0.22*	-0.72*	-0.38*	-0.59*
$Entorno\ De\ Goiania_{t-1}$	0.23	-0.01	0.4**	-0.22	-0.16**	-0.21	-0.04	-0.22*	-0.29	-0.29	-0.73**
$Rio\ Verde_{t-1}$	0.22	0.41	-0.22	0.63	-0.02	-0.15	-0.01	-0.11	-0.04	0.16	0.02
$Alta\ Floresta_{t-1}$	-0.36	1.97	-0.47	0.42	0.37	-1.8**	0.24	-0.57	-2.05	0.45	-1.24
$Alto\ Araguaia_{t-1}$	-0.06	-0.02	0.37	0.11	0.19	1.45*	0.11	0.34*	0.92**	0.35	0.61
$Aripuana_{t-1}$	0.18	-0.32	-1.16*	-2.89**	-0.55*	-1.69*	-0.35	-0.32	-1.81*	-3.23*	-2.03*
$Barra\ do\ Garcas_{t-1}$	0.2	-0.98	0.33	0.85	0.05	1.12*	-0.02	0.86*	0.87	-0.57	1.2
$Rondonopolis_{t-1}$	0.33	-0.78	-0.11	-0.89	0.03	-0.66*	-0.14	0.14	-0.5	-0.93*	-0.72
$Sinop\ (Diamantino)_{t-1}$	-0.1	-0.18	-0.19	0.29	-0.02	-0.54*	-0.01	-0.17**	-0.33	0.96*	-0.05
$Sinop\ (Sorriso)_{t-1}$	0.53	1.12*	-0.08	0.94	-0.19**	0.72*	0.29*	-0.21**	0.72**	0.1	0.79**
$Tangara\ da\ Serra_{t-1}$	-0.33	-0.45	0.13	-0.3	0.1**	-0.08	0.07	0.15**	-0.11	0.13	0.03
$Vila\ Rica_{t-1}$	0.82*	-0.44	0.06	0.66	0.2*	0.23	0.17**	0.13	1*	-0.2	0.04
$Bodoquena_{t-1}$	-1.54*	-1.12	-0.21	-1.37	-0.1	-0.64	-0.7*	-0.22	-0.5	0.11	-0.48
$Chapadao\ do\ Sul\ (Chapada)_{t-1}$	-0.05	0.16	0.11	0.7**	0.11**	0.15	0.19*	0.17*	0.13	0.15	0.71*
$Chapadao\ do\ Sul\ (Sonora)_{t-1}$	0.67*	-0.1	0.4	0.27	0.17**	0.56**	-0.06	0.33*	0.9*	0.58**	0.28
$Dorados_{t-1}$	-0.2	-0.45	0.66*	0.76	-0.06	-0.36	-0.03	0.26	-0.66	-0.05	-0.27
$Navirai_{t-1}$	-0.17	0.36	-0.04	0.54	0.22*	0.91*	0.55*	-0.11	0.83*	0.8*	1.55*
$Rio\ Brilhante_{t-1}$	0.42	0.51	-0.4	-0.77	-0.09	-0.52	-0.37*	-0.19	-0.03	-0.18	-1.03**
$Returns_{t-1}$	-0.01	0	0.01	-0.01	0	0.02	0	0.01*	0.01	-0.01	0
$Interest_{t-1}$	214.33	-3169.71	-552.93	-172.17	705.34	3736.39	1207.44	-753.93	248.68	1854.74	680.94

AIC=254.57, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.3 Continued, Brazil Micro Region Model, Soybean Producing Regions, Parameter Estimates

Independent Variable	Tangara da Serra	Vila Rica	Bodoquena	Chapadao do Sul (Chapadao)	Chapadao do Sul (Sonora)	Dourados	Navirai	Rio Brilhante	Returns	Interest
Intercept	5086.4*	-2014.6*	919.3	8365.9*	4201*	2891.6	185.21	4078*	60191.58	0.31*
Trend	86.48*	48.48*	27.28	6.28	77.98*	33.61	68.1	14.35	1335.05	-0.01*
$Catalao_{t-1}$	0.62*	0.01	0.17	1.05*	0.72*	0.64*	0.62*	0.62*	-0.11	0*
$Entomo\ de\ Brasilia_{t-1}$	-0.57*	-0.29*	-0.32*	-0.92*	-0.49*	-0.59*	-0.63*	-0.53*	-7.24	0
$Entorno\ De\ Goiania_{t-1}$	-0.22	-0.14	-0.5*	-0.41	-0.28	-0.44	-0.3	-0.61**	1.36	0
$Rio\ Verde_{t-1}$	-0.13	0.14	-0.11	0.65**	0.12	0.17	0.16	0.15	13.83*	0
$Alta\ Floresta_{t-1}$	-0.08	-0.26	-1.91*	-0.07	-0.03	-1.26	-1.76	-2.43*	63.36*	0
$Alto\ Ariguaia_{t-1}$	0.49	0.03	0.84*	0.56	0.07	0.62	0.96**	1.25*	-8.04	0
$Aripuana_{t-1}$	-1.34**	-0.16	-0.59	-2.19	-2.24*	-0.9	-1.25	-1.36**	-41.58*	0
$Barra\ do\ Garcas_{t-1}$	-0.19	-0.06	1.5*	1.09	0.44	1	1.02	1.46*	-32.28*	0
$Rondonopolis_{t-1}$	0.1	0	-0.17	-0.64	-0.23	-0.54	-0.72**	-0.53	-12.67	0
$Sinop\ (Diamantino)_{t-1}$	-0.34	0.2	-0.27**	0	0.01	-0.06	-0.19	-0.46	14.45*	0
$Sinop\ (Sorriso)_{t-1}$	0.92*	-0.32**	0.03	1.11**	0.6**	0.24	-0.15	0.13	-0.55	0
$Tangara\ da\ Serra_{t-1}$	0.33	0.13	-0.1	0.09	0.1	0.23	0.29	0.05	-0.38	0
$Vila\ Rica_{t-1}$	0.59*	0.65*	0.7*	0.83	0.48**	0.4	0.53	1.01*	4.05	0**
$Bodoquena_{t-1}$	-1.6*	0.16	-0.15	-0.83	-0.51	-1.01	-0.71	-0.95	2.51	0**
$Chapadao\ do\ Sul\ (Chapada)_{t-1}$	0.3	0.2*	0.19	0.29	0.17	0.19	0.38	0.24	4.08	0
$Chapadao\ do\ Sul\ (Sonora)_{t-1}$	-0.1	0.1	0.57*	0.17	0.46	0.21	0.42	0.66**	-8.22	0
$Dorados_{t-1}$	-0.22	-0.2	-0.38	-1.36**	-0.2	-0.22	-0.54	-1.27*	16.89	0
$Navirai_{t-1}$	1.18*	-0.06	0.41*	1.34*	1.08*	1.49*	1.65*	1.48*	-4.99	0*
$Rio\ Brilhante_{t-1}$	-0.83*	0.05	-0.18	-0.24	-0.61**	-0.42	-0.36	0.14	-0.58	0
$Returns_{t-1}$	-0.01	0	0.02*	-0.01	-0.01	0.01	0.01	0.02	-0.2	0
$Interest_{t-1}$	5818.09	752.56	998.91	1982.05	5756.18	-1528.06	-432.5	772.5	-65339.5	0.29

AIC=254.57, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.3 Continued, Brazil Micro Region Model, Soybean Producing Regions, Parameter Estimates

Independent Variable	Catalao	Entorno de Brasilia	Entorno de Goiania	Rio Verde	Alta Floresta	Alto Araguaia	Aripuana	Barra do Garcas	Rondonopolis	Sinop (Diama-ntino)	Sinop (Sorriso)
$Catalao_{t-2}$	-0.02	0.33	0.37*	0.74	0.11	0.19	0.21*	0.22*	0.56**	0.7*	0.64**
$Entomo\ de\ Brasilia_{t-2}$	-0.09	0.2	-0.03	0.09	0.02	0.41*	-0.04	-0.01	0.36*	0.19	0.31
$Entorno\ De\ Goiania_{t-2}$	-0.04	0.3	0.05	0.77	0.18	0.23	-0.09	0.31*	0.66	0.45	0.48
$Rio\ Verde_{t-2}$	0.08	0.07	0.11	0.13	0.02	0.12	0.04	0.03	0.03	-0.11	0.03
$Alta\ Floresta_{t-2}$	-0.01	-0.53	0.34	2.77	0.17	1.57*	-0.01	0.41	2.72*	1.94*	2.27*
$Alto\ Ariguaia_{t-2}$	0.51	-0.27	-0.37	-0.36	-0.26*	-0.7*	-0.07	-0.29*	-0.59	-0.25	-0.72
$Aripuana_{t-2}$	1.14	-0.29	-0.02	-0.45	0.08	-0.26	0.16	-0.29	0.07	-0.53	-0.64
$Barra\ do\ Garcas_{t-2}$	0.48	0.84	0.02	-2.52	-0.25	-1.32*	0.01	-0.19	-2.08*	-0.78	-1.83**
$Rondonopolis_{t-2}$	-0.46*	-0.01	-0.55*	-1.01*	-0.03	-0.53*	-0.26*	-0.17*	-0.68*	-0.82*	-0.54**
$Sinop\ (Diamantino)_{t-2}$	0.04	0.16	0.4*	0.34	0.12	1*	0.09	0.13	0.66*	0.15	0.4
$Sinop\ (Sorriso)_{t-2}$	0.12	0.13	-0.17	0.84	0	-0.02	0.41*	-0.21**	0.2	0.37	0.47
$Tangara\ da\ Serra_{t-2}$	-0.44**	-0.36	-0.1	-0.1	0.02	-0.23	-0.37*	0.17**	-0.42	-0.03	-0.55
$Vila\ Rica_{t-2}$	-0.1	0.15	-0.01	-0.38	-0.32*	0.17	0.23	-0.43*	-0.81**	-0.02	-0.11
$Bodoquena_{t-2}$	-0.33	1.39	0.13	0.83	0.17	0.79	-0.26	0.28	0.32	1.25*	0.75
$Chapadao\ do\ Sul\ (Chapada)_{t-2}$	-0.31	-0.84*	0.21	-0.81	0.03	-0.41**	-0.16**	0.18*	-0.46	0.07	-0.57**
$Chapadao\ do\ Sul\ (Sonora)_{t-2}$	0.01	0.43	0.06	-0.35	-0.14	-0.46	0.2	-0.1	-0.72**	-1.17*	-0.33
$Dorados_{t-2}$	-0.07	0.15	0.26	-0.07	0.1	0.14	-0.13	-0.04	0.2	1.17*	0.12
$Navirai_{t-2}$	-0.04	-0.83	-0.07	-0.34	0.17	0.03	-0.08	0.22	0.02	-0.35	-0.02
$Rio\ Brilhante_{t-2}$	0.51	0.28	0.05	0.71	-0.14	0.43	0.28**	0.01	1**	-0.56	0.42
$Returns_{t-2}$	0.02*	0	-0.01	0	0	-0.01	0	-0.01**	-0.01	0	0
$Interest_{t-2}$	-5611.6**	-4575.7	-7850.06*	-1282.65	-1301.59	-4112.53	-1711.66	-462.67	-4674.65	-3263.56	-907.77

AIC=254.57, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.3 Continued, Brazil Micro Region Model, Soybean Producing Regions, Parameter Estimates

Independent Variable	Tangara da Serra	Vila Rica	Bodoquena	Chapadao do Sul (Chapadao)	Chapadao do Sul (Sonora)	Dourados	Navirai	Rio Brilhante	Returns	Interest
$Catalao_{t-2}$	0.15	0.25*	0.29**	1.1*	0.57*	0.66*	0.7*	0.91*	13.93*	0
$Entomo\ de\ Brasilia_{t-2}$	-0.1	-0.02	0.17*	0.55*	0.23**	0.12	0.19	0.22	-7.98*	0
$Entorno\ De\ Goiania_{t-2}$	-0.3	-0.03	0.12	0.02	-0.07	0.37	0.23	-0.05	18.82**	0
$Rio\ Verde_{t-2}$	0.39*	-0.05	-0.06	0.5	-0.06	-0.22	-0.41*	-0.13	-2.67	0
$Alta\ Floresta_{t-2}$	0.92	0.35	0.77	1.52	1.03	1.05	1.23	1.77*	19	0
$Alto\ Ariguaia_{t-2}$	-0.18	-0.13	-0.51*	-0.89	-0.18	-0.35	-0.59	-0.6**	3.85	0
$Aripuana_{t-2}$	-1.34**	0.89*	0.16	-0.32	-0.45	0.12	0.22	-0.51	-6.63	0
$Barra\ do\ Garcas_{t-2}$	0.43	0.26	-0.85**	-1.6	-0.89	-0.97	-1.27	-1.63*	-25.55	0
$Rondonopolis_{t-2}$	-0.18	-0.04	-0.16	-0.72**	-0.47*	-0.48**	-0.34	-0.3	-7.28	0
$Sinop\ (Diamantino)_{t-2}$	0.34	-0.15	0.35*	0.41	0.23	0.14	0.28	0.6*	-13.19*	0
$Sinop\ (Sorriso)_{t-2}$	0.86*	-0.04	-0.01	0.85	0.49**	0.39	0.25	0.01	21.34*	0
$Tangara\ da\ Serra_{t-2}$	-0.88*	-0.5*	-0.28**	-0.56	-0.34	-0.55**	-0.46	-0.36	-0.2	0
$Vila\ Rica_{t-2}$	0.35	-0.54*	-0.31	-0.68	0.03	-0.23	-0.54	-0.54	-13.09	0
$Bodoquena_{t-2}$	-0.79	0.43	0.07	1.15	-0.04	0	0.17	-0.01	5.98	0
$Chapadao\ do\ Sul\ (Chapadao)_{t-2}$	-0.35	0.08	-0.13	-1.06*	-0.14	-0.36	-0.09	-0.15	1.02	0
$Chapadao\ do\ Sul\ (Sonora)_{t-2}$	0.34	0.05	0.09	-0.58	0.04	0.27	-0.02	-0.27	-17.33**	0
$Dorados_{t-2}$	-0.49	-0.03	0.01	-0.29	0.54	-0.21	0.18	-0.15	10.47	0
$Navirai_{t-2}$	-0.15	0.59*	0.28	-0.11	-0.39	-0.09	0.14	1.06**	6.42	0
$Rio\ Brilhante_{t-2}$	0.87*	-0.4*	0.26	1.05	-0.23	0.79	0.37	0.26	-13.63	0**
$Returns_{t-2}$	0	0	-0.01	-0.01	0.01**	0	0.01	0	0.34	0
$Interest_{t-2}$	-953.69	1229.01	-616.57	-3958.24	-5745.28*	-2089.08	-1905.31	-1587.45	42956.81	-0.14

AIC=254.57, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.4, Brazil Micro Region Model, Soybean Producing Regions, Granger Causality Wald Statistics

Independent Variable	Catalao	Entorno de Brasilia	Entorno de Goiania	Rio Verde	Alta Floresta	Alto Araguaia	Aripuana	Barra do Garcas	Rondonopolis	Sinop (Diama-ntino)	Sinop (Sorriso)
Catalao	--	5.81**	2.07	2.16	1.13	3.49	13.4*	1.56	11.81*	4.04	15.03*
Entorno de Brasilia	0.74	--	0.52	0.68	1.56	0.88	1.58	0.14	2	0.45	2.96
Entorno de Goiania	7.26*	2.17	--	2.17	5.96**	2.22	9.84*	1.78	9.38*	2.42	15.12*
Rio Verde	18.31*	15.37*	7.04*	--	6.33*	4.38	21.57*	2.22	8.82*	1.28	24.53*
Alta Floresta	5.08**	8.11*	1.42	0.37	--	0.9	5.35**	0.52	6.32*	0.73	10.31*
Alto Araguaia	11.9*	2.7	1.6	0.21	6.11*	--	6.68*	1.65	10.17*	0.2	7.62*
Aripuana	8.43*	4.77**	0.89	6.46*	0.94	8.41*	--	5.95**	0.33	11.74*	0.71
Barra do Garcas	9.02*	1.76	7.79*	1.54	1.32	0.29	11.95*	--	6.27*	1.49	12.33*
Rondonopolis	7.64*	2.37	0.57	5.3**	2.74	8.23*	3.88	3.48	--	6.62*	5.14**
Sinop (Diama-ntino)	10.63*	2.67	6.51*	4.33	6.01*	6.64*	9.27*	2	8.74*	--	9.13*
Sinop (Sorriso)	10.82*	9.02*	0.79	4.51	1.88	5.18**	4.72**	3.3	2.22	4.6	--
Tangara da Serra	4.46	2.1	1.68	4.7**	0.86	8.94*	2.45	3.53	0.04	14.96*	0.58
Vila Rica	11.99*	2.91	1.93	17.25*	9.04*	6.44*	7.59*	8.75*	20.92*	4.27	7.21*
Bodoquena	10.12*	7.51*	1.26	6.69*	0.33	4.86**	0.99	8.26*	0.51	3.36	3.91
Chapadao do Sul (Chapadao)	10.36*	10.26*	0.98	9.05*	3	4.58	4.77**	4.5	1.45	9.57*	8.52*
Chapadao do Sul (Sonora)	7.04*	9.97*	0.65	0.79	1.74	0.59	0.95	3.67	0.93	0.35	1.93
Dourados	14.94*	5.66**	2.1	4.25	4.09	4.6	4.04	5.75**	2.5	3.86	5.33**
Navirai	17.91*	9.16*	1.5	5.08**	7.67*	6.59*	10.74*	4.92**	4.8**	4.46	12.91*
Rio Brilhante	13.34*	7.39*	0.49	5**	2.28	8.09*	3.85	3.17	2.49	8.58*	3.33
Returns	5.39**	18.62*	0.99	0.44	3.69	3.12	7.79*	4.27	5.49**	2.65	6.95*
Interest	0.36	0.56	4.39	2.14	1.32	0.69	0.33	1.25	1.87	0.12	0.36

* Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.4 Continued, Brazil Micro Region Model, Soybean Producing Regions, Granger Causality Wald Statistics

Independent Variable	Tangara da Serra	Vila Rica	Bodoquena	Chapadao do Sul (Chapadao)	Chapadao do Sul (Sonora)	Dourados	Navirai	Rio Brilhante	Returns	Interest
Catalao	18.31*	6.4*	8.75*	3.98	0.84	8.18*	8.32*	12.64*	0.31	0.77
Entorno de Brasilia	2.23	1.43	1.96	0.7	1.16	0.64	1.51	0.6	0.73	19.54*
Entorno de Goiania	18.45*	6.6*	11.7*	9.2*	1.37	7.38*	6.43*	7.38*	2.14	0.41
Rio Verde	27.69*	5.85**	13.81*	39.44*	12.27*	8.28*	8.69*	13.47*	1.76	3.99
Alta Floresta	11.56*	4.46	5.3**	5.16**	2.06	3.23	2.84	4.62**	5.37**	1.13
Alto Araguaia	10.81*	5.48**	6.09*	7.49*	0.85	2.76	3.46	7.17*	1.88	10.96*
Aripuana	1.52	7.11*	1.51	2.26	2.94	0.21	0.99	0.01	0.02	9.27*
Barra do Garcas	30.43*	17.45*	14.19*	10.75*	3.01	11.81*	11.12*	8.16*	2.49	0.87
Rondonopolis	6.4*	3.04	2.33	2.45	4.2	0.81	0.08	0.81	0.17	9.96*
Sinop (Diama-ntino)	15.26*	4.28	6.57*	13.62*	2.66	3.53	4.53	7.6*	0.95	17.41*
Sinop (Sorriso)	5.12**	3.08	3.32	3.08	6.33*	0.19	0.09	1.35	0.51	15.4*
Tangara da Serra	--	2.03	1.29	2.78	4.16	0.09	0.34	0.14	0.12	11.04*
Vila Rica	9.58*	--	24.57*	17.04*	17.03*	8.2*	8.05*	16.09*	8.43*	1.04
Bodoquena	3.25	8.17*	--	3.38	6.32*	1.64	2.08	0.27	0.27	3.57
Chapadao do Sul (Chapadao)	19.53*	6.1*	4.11	--	2.2	1.48	2.88	2.53	0.03	9.01*
Chapadao do Sul (Sonora)	2.1	3.23	2.45	0.35	--	3.03	4.15	1.55	0.22	6.63*
Dourados	6.67*	3.28	1.82	0.54	1.1	--	3	0.09	0.65	5.39**
Navirai	12.67*	4.77**	4.68**	3.7	6.37*	13.14*	--	5.77**	0.55	3.13
Rio Brilhante	6.2*	3.5	1.67	1.51	2.4	0.35	2.8	--	0.07	5.27**
Returns	4.05	0.37	6.6*	6.94*	7.88*	3.08	2.96	4.4	--	10.11*
Interest	0.76	9.17*	2.57	1.04	0.11	0.32	0.11	0.46	0.78	--

* Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.5, Spatial Autoregressive Model (SAR), Brazil

Variable	Parameter Estimate	Standard Deviation	Test Stat	P-Value
Intercept	-994.00	478.07	-2.08	0.04
ρ	1.08	0.02	65.35	<.0001
$Returns_{t-1}$	0.00	0.00	0.52	0.60
$Interest_{t-1}$	2699.34	2099.80	1.29	0.20
R^2 o f 0.8421				

Table 6.6, Brazil VAR Model, By Region, Bahia

Independent Variables	Dependent Variable		
	Bahia	Returns	Interest
Intercept	-278.33	6082.8	0.15*
Trend	38.19*	317.22	0.00*
$Bahia_{t-1}$	0.78*	0.38	0.00**
$Returns_{t-1}$	0.02*	1.07*	0.00
$Interest_{t-1}$	-66.09	37766.01	0.43*
$Bahia_{t-2}$	-0.08	-1.27	0*
$Returns_{t-2}$	1347.63	33107.22	-0.26*
$Interest_{t-2}$	0.00	-0.16	0.00*

AIC=25.43, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.7, Brazil VAR Model, By Region, Goiás

Independent Variable	Dependent Variable		
	Goiás	Returns	Interest
Intercept	-530.58	10275.86	0.14*
Trend	11.33	96.41	0.00*
$Goias_{t-1}$	1.22*	3.32	0.00**
$Returns_{t-1}$	0.01	1.03*	0.00
$Interest_{t-1}$	-151.22	23672.89	0.45*
$Goias_{t-2}$	-0.26**	-2.54	0.00*
$Returns_{t-2}$	0.00	-0.21	0.00
$Interest_{t-2}$	1044.16	46688.93	-0.27*

AIC=25.35, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.8, Brazil VAR Model, By Region, Maranhão

Independent Variable	Dependent Variable		
	Maranhão	Returns	Interest
Intercept	-378.1	9694.57	0.13*
Trend	6.07	156.11	0.00*
$Maranhao_{t-1}$	1.24*	3.4	0.00*
$Returns_{t-1}$	0.01*	1.07*	0.00
$Interest_{t-1}$	-1883.58	25638.76	0.48*
$Bahia_{t-2}$	-0.28*	-3.07	0.00*
$Returns_{t-2}$	0.00	-0.22	0.00
$Maranhao_{t-2}$	2207.94	40731.33	-0.28*

AIC=24.73, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.9, Brazil VAR Model, By Region, Mato Grosso

Independent Variable	Dependent Variable: Mato Grosso	Returns	Interest
Intercept	-597.22	8340.01	0.13*
Trend	11.03**	165.52	0.00*
$Mato\ Grosso_{t-1}$	1.21*	3.59	0.00*
$Returns_{t-1}$	0.01	1.04*	0.00
$Interest_{t-1}$	1668.14	35449.39	0.43*
$Mato\ Grosso_{t-2}$	-0.3*	-3.14	0.00*
$Returns_{t-2}$	0.00	-0.19	0.00**
$Interest_{t-2}$	1458.75	32847.11	-0.22*

AIC=24.69, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.10, Brazil VAR Model, By Region, Mato Grosso Do Sul

	Dependent Variable		
Independent Variable	Mato Grosso Do Sul	Returns	Interest
Intercept	-732.28	6258.57	0.13*
Trend	13.47	196.43	0.00*
$Mato\ Grosso\ Do\ Sul_{t-1}$	1.09*	0.17	0.00
$Returns_{t-1}$	0.01	1.09*	0.00
$Interest_{t-1}$	1567.22	32091.9	0.44*
$Bahia_{t-2}$	-0.2	-0.05	0.00*
$Returns_{t-2}$	0.00	-0.22	0.00
$Mato\ Grosso\ Do\ Sul_{t-2}$	2590.58	37853.92	-0.25*

AIC=25.76, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.11, Brazil VAR Model, By Region, Minas Gerais

Independent Variable	Dependent Variable		
	Minas Gerais	Returns	Interest
Intercept	85.85	9244.56	0.14*
Trend	5.74	161.65	0.00*
$Minas\ Gerais_{t-1}$	1.14*	9.37**	0.00
$Returns_{t-1}$	0.00	1.02*	0.00
$Interest_{t-1}$	1116.18	14824.72	0.43*
$Minas\ Gerais_{t-2}$	-0.19	-9.11	0.00
$Returns_{t-2}$	0.00	-0.18	0.00
$Interest_{t-2}$	-1630.57	50361.5	-0.27*

AIC=24.37, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.12, Brazil VAR Model, By Region, Pará

Independent Variable	Dependent Variable: Pará	Returns	Interest
Intercept	-63.14	3683.47	0.15*
Trend	6.2*	295.5	0.00*
$Para_{t-1}$	1.63*	10.55	0.00
$Returns_{t-1}$	0.00	1.02*	0.00
$Interest_{t-1}$	566.53	54002.07	0.47*
$Para_{t-2}$	-0.69*	-11.26**	0.00
$Returns_{t-2}$	0.00	-0.15	0.00
$Interest_{t-2}$	237.02	38493.99	-0.28*

AIC=23.47, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.13, Brazil VAR Model, By Region, Paraná

Independent Variable	Dependent Variable		
	Paraná	Returns	Interest
Intercept	-310.67	5140.92	0.12*
Trend	28.61*	163.34	0.00*
$Parana_{t-1}$	1.32*	1.28	0.00*
$Returns_{t-1}$	0.01	1.05*	0.00
$Interest_{t-1}$	3111.24	34512.89	0.42*
$Parana_{t-2}$	-0.5*	-0.87	0.00*
$Returns_{t-2}$	0.00	-0.22	0.00**
$Interest_{t-2}$	3757.17	38672.67	-0.21**

AIC=25.82, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.14, Brazil VAR Model, By Region, Piauí

Independent Variable	Dependent Variable		
	Piauí	Returns	Interest
Intercept	-327.98	11067.4	0.13*
Trend	10.35*	312.99	0.00*
$Piaui_{t-1}$	1.1*	6.77	0.00**
$Returns_{t-1}$	0.01*	1.02*	0.00
$Interest_{t-1}$	774.79	26166.92	0.5*
$Piaui_{t-2}$	-0.25*	-8.87	0.00*
$Returns_{t-2}$	-0.01*	-0.14	0.00
$Interest_{t-2}$	-104.11	32433.57	-0.27*

AIC=23.55, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.15, Brazil VAR Model, By Region, Rio Grande Do Sul

Independent Variable	Dependent Variable: Rio Grande Do Sul	Returns	Interest
Intercept	-39.97	5007.69	0.14*
Trend	18.17	144.16	0.00*
$Rio\ Grande\ Do\ Sul_{t-1}$	1.05*	0.57	0.00
$Returns_{t-1}$	0.01	1.07*	0.00
$Interest_{t-1}$	8.77	22106.53	0.42*
$Rio\ Grande\ Do\ Sul_{t-2}$	-0.24**	0.15	0.00
$Returns_{t-2}$	0.01	-0.25**	0.00
$Interest_{t-2}$	2386.89	46009.51	-0.26*

AIC=26.63, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.16, Brazil VAR Model, By Region, Santa Catarina

Independent Variable	Dependent Variable		
	Santa Catarina	Returns	Interest
Intercept	434.79	6350.49	0.15*
Trend	58.39*	500.03	0.00*
Santa Catarina_{t-1}	1.07*	-0.54	0.00
Returns_{t-1}	-0.01	1.09*	0.00
Interest_{t-1}	-4225.27	43701.76	0.43*
Santa Catarina_{t-2}	-0.24**	-0.28	0.00
Returns_{t-2}	0.01**	-0.19	0.00
Interest_{t-2}	2988.48	32591.15	-0.28*

AIC=26.10, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.17, Brazil VAR Model, By Region, Tocantins

Independent Variable	Dependent Variable		
	Tocantins	Returns	Interest
Intercept	-371.96	7912.34	0.14*
Trend	8.64	334.53	0.00*
$Tocantins_{t-1}$	1.09*	2.39	0.00
$Returns_{t-1}$	0.01*	1.04*	0.00
$Interest_{t-1}$	-165.92	43208.86	0.44*
$Tocantins_{t-2}$	-0.15	-3.84	0.00**
$Returns_{t-2}$	0.00	-0.16	0.00
$Interest_{t-2}$	499.64	31156.8	-0.26*

AIC=24.43, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.18, Brazil VAR Model, By Region, São Paulo

Independent Variable	Dependent Variable		
	São Paulo	Returns	Interest
Intercept	-276.86	5536.58	0.61
Trend	6.99	-38.40	0.00
$Sao\ Paulo_{t-1}$	1.31	12.46	0.00
$Returns_{t-1}$	0.00	1.13	0.00
$Interest_{t-1}$	45.31	-914.87	0.43
$Sao\ Paulo_{t-2}$	-0.35	-10.47	0.00
$Returns_{t-2}$	0.00	-0.39	0.00
$Interest_{t-2}$	145.59	1549.56	0.19

AIC=25.43, * Indicates Significance at 95% level, ** Indicates Significance at 90% level

Table 6.19, Out-of-Sample Prediction Errors, By Region and Model

Independent Variable	VAR W/Network	SAR	VAR W/O Network
Bahia	372.58	790.42	509.58
Goiás	453.27	4883.89	809.96
Maranhão	557.19	3711.55	736.40
Mato Grosso	253.23	452.34	620.98
Mato Grosso Do Sul	355.50	2397.48	655.79
Minas Gerais	384.04	3688.75	253.42
Pará	219.31	4761.52	1607.96
Paraná	541.59	3271.23	407.34
Piauí	193.57	4313.31	1003.62
Rio Grande Do Sul	731.93	4737.29	917.26
Santa Catarina	412.62	2304.92	813.12
Tocantins	208.12	1174.90	446.13
São Paulo	547.73	222.81	509.58

Last six periods of data forecasted using models estimated with prior data.

Table 6.20, Ranking of Forecast Error Decomposition

Variable	Rank	Average Forecast Error Attributable
Goiás	1	28.31%
Bahia	2	10.96%
Maranhão	3	10.40%
Rio Grande Do Sul	4	6.60%
Mato Grosso Do Sul	5	6.29%
Minas Gerais	6	6.26%
Returns	7	5.75%
Mato Grosso	8	4.60%
Pará	9	4.55%
Santa Catarina	10	4.07%
Paraná	11	2.66%
Tocantins	12	2.64%
São Paulo	13	2.47%
Piauí	14	2.41%
Interest	15	2.01%

Chapter 7 - Conclusions

The purpose of this study was to analyze spatial dependency in the Brazilian farmland market. First, literature relating to farmland valuation and information cascades was reviewed, a conceptual model was discussed, empirical models were detailed, and the results were analyzed.

Data from Informa Economics FNP was analyzed for autoregressive dependencies using a VAR model to examine whether Brazilian farmland prices affect farmland prices. Using a VAR model allowed for no a priori network specification. It was found that farmland prices in one region affect farmland prices in other regions. However, no distinct pattern emerged as to which region affected which region as some Granger causality results could be explained while others could not. To analyze how network type affects prediction of farmland prices, two other types of models were estimated: a SAR model that imposed network structure and a set of VAR models that did not allow for farmland prices to affect farmland prices in other regions. It was found that allowing for a network, but not imposing network structure via an adjacency rule resulted in the most accurate in-sample prediction. This emphasizes the need for network flexibility when analyzing spatial autoregressive dependency as any technique that specifies a weight or distance structure would be restrictive.

Overall, the presence of information cascades within the farmland market was found. This implies that farmland values in one region affect farmland values in other regions the next period. The information cascade may be a significant determinant of the boom/bust cycles. The network type for how signals are sent in the market not found to follow a spatial pattern and point to forecasting techniques that do not impose a priori specification of spatial dependence or network type for better in-sample fit.

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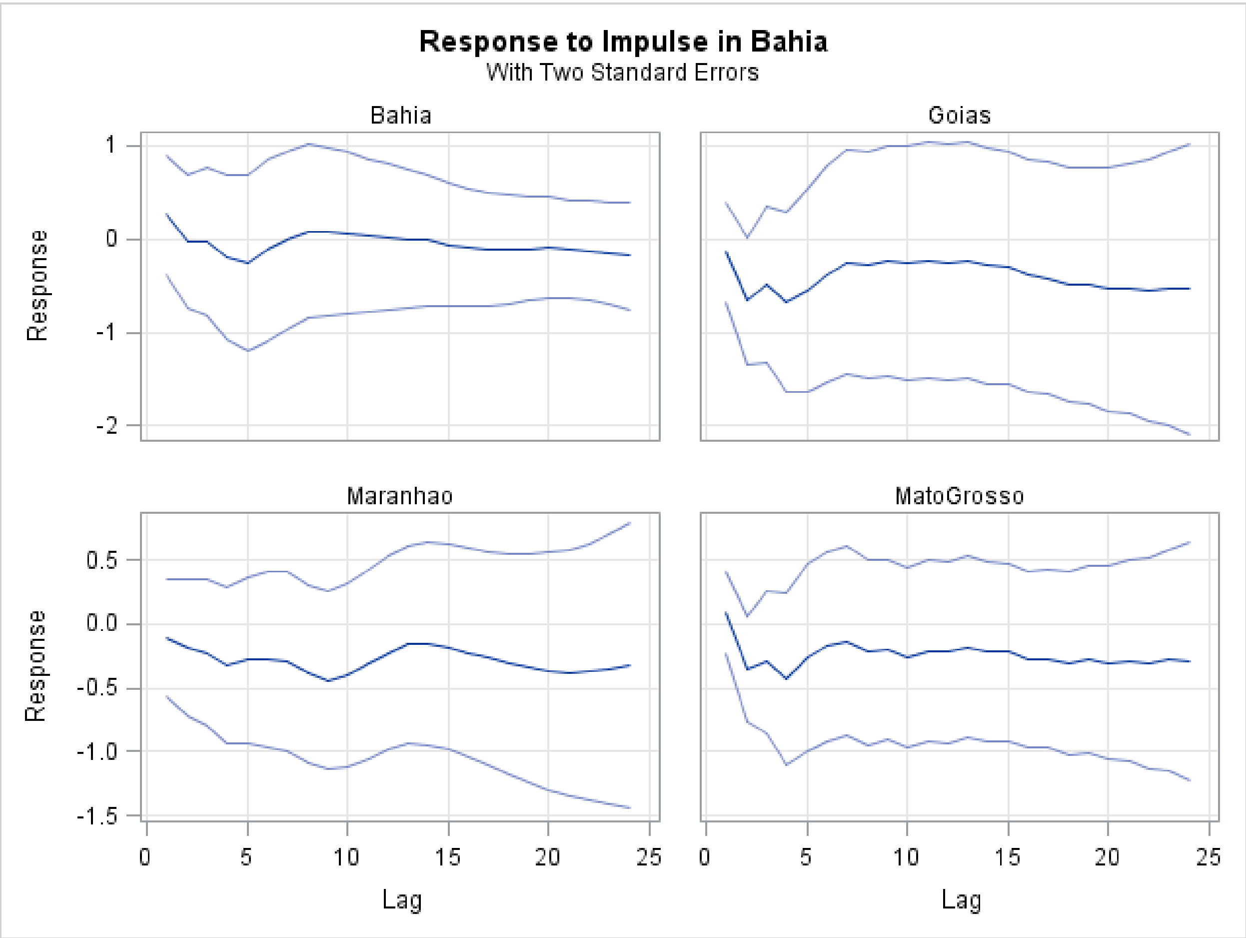
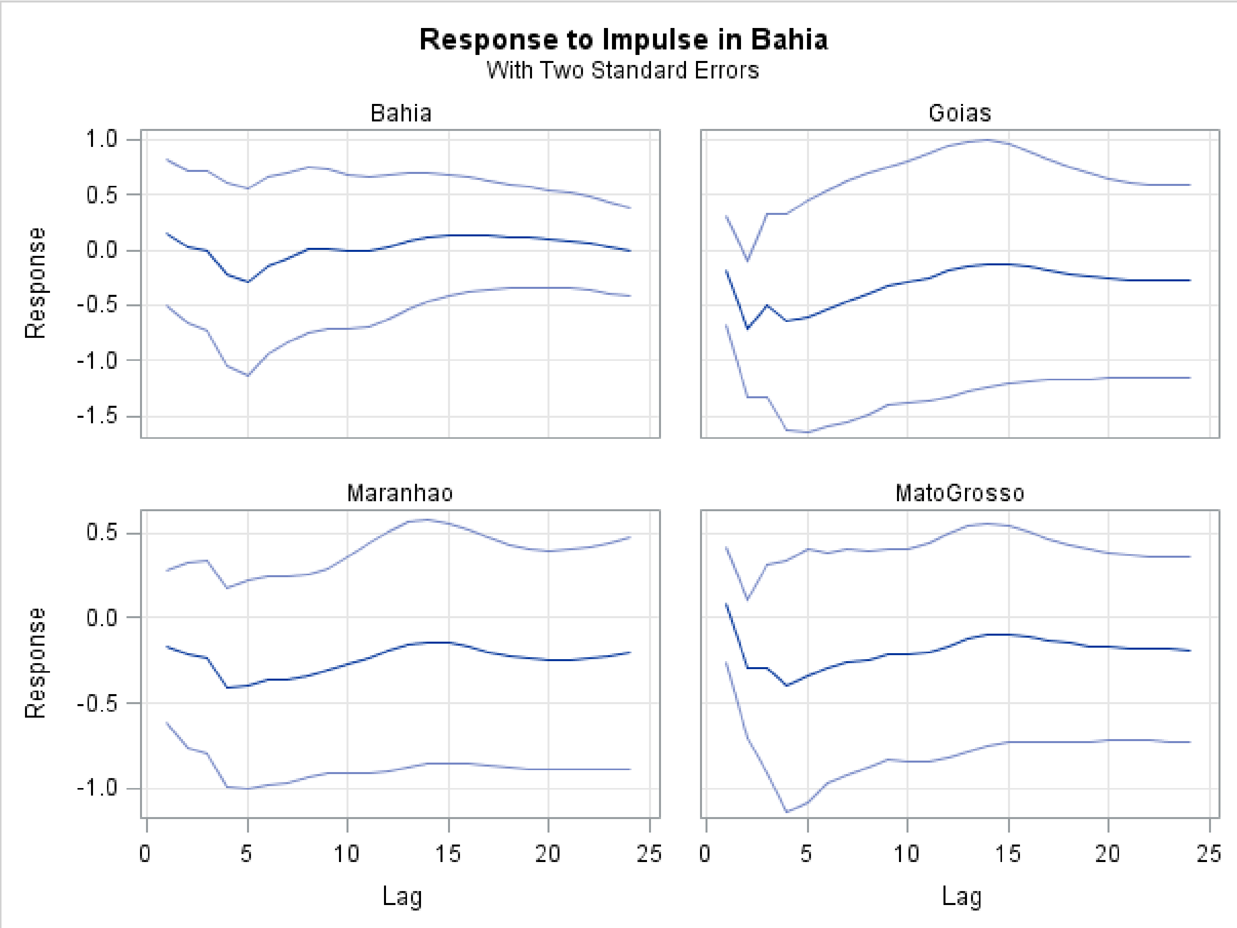
Appendix A - Brazil Vectorautoregession

Impulse Response Functions-Macro Region Model

The following contains the complete set of impulse response function for the Vector Autoregression models used in the analysis. Those impulse response functions used in the analysis can also be found at the end of Chapter 6




Response to Impulse in Bahia
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Lag
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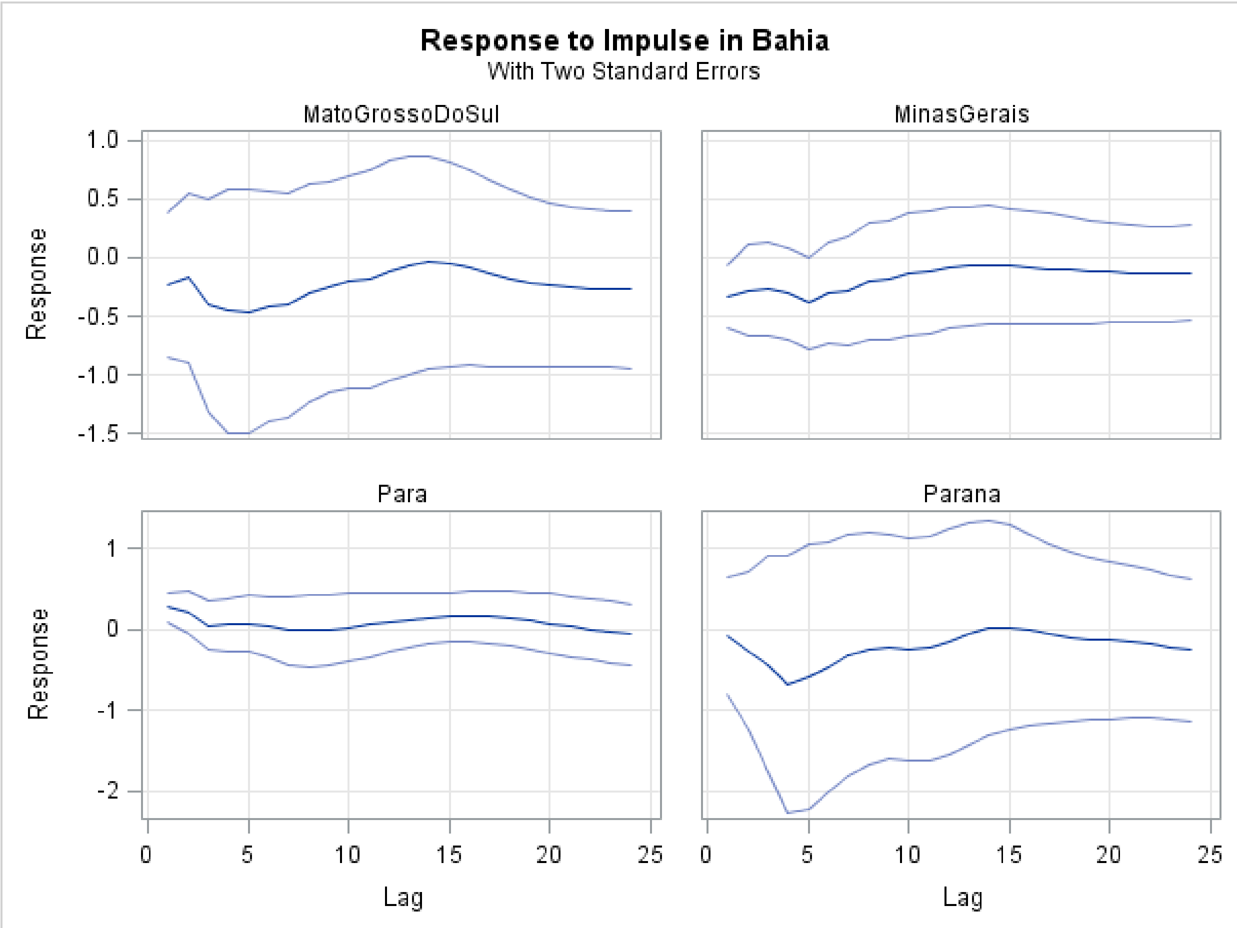
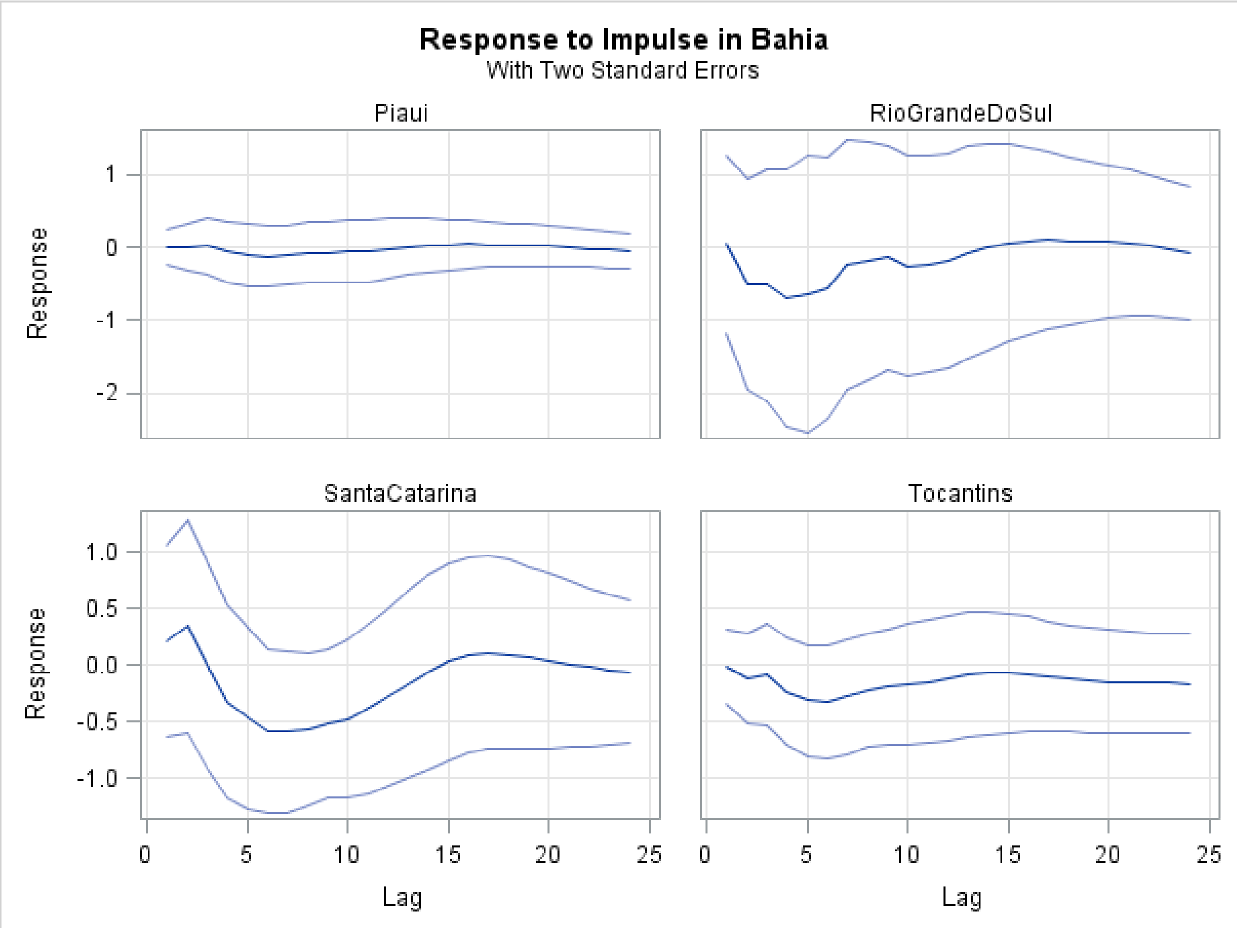
-0.5
-1.0
-1.5
0
5
10
15
20
25


Response to Impulse in Bahia
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag


Response to Impulse in Bahia
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag
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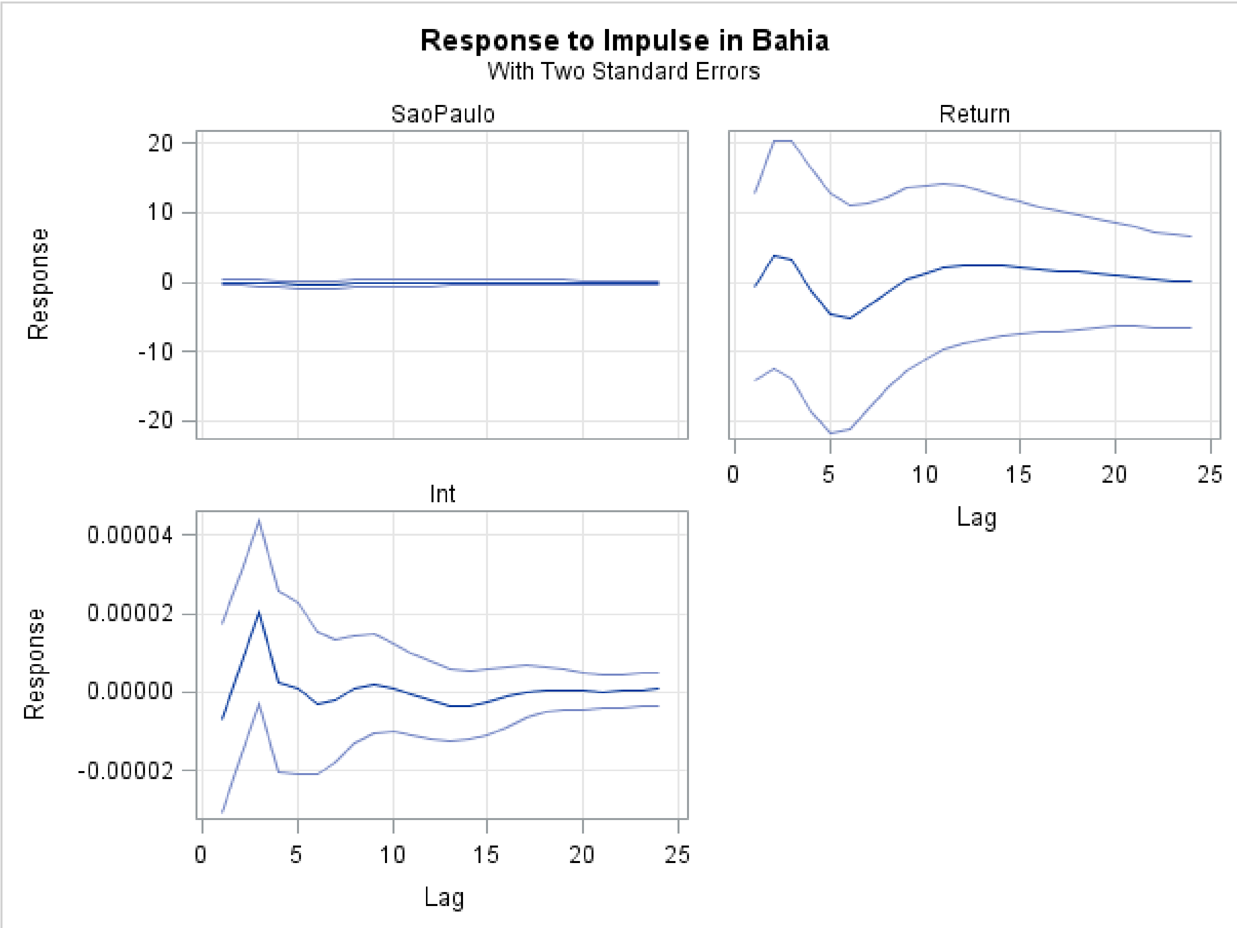
0
-1
-2
1.0
0.5
0.0
-0.5
-1.0
0
5
10
15
20
25


Response to Impulse in Bahia
With Two Standard Errors
SaoPaulo
Return
Int
Response
Response
Lag
Lag
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-10
-20
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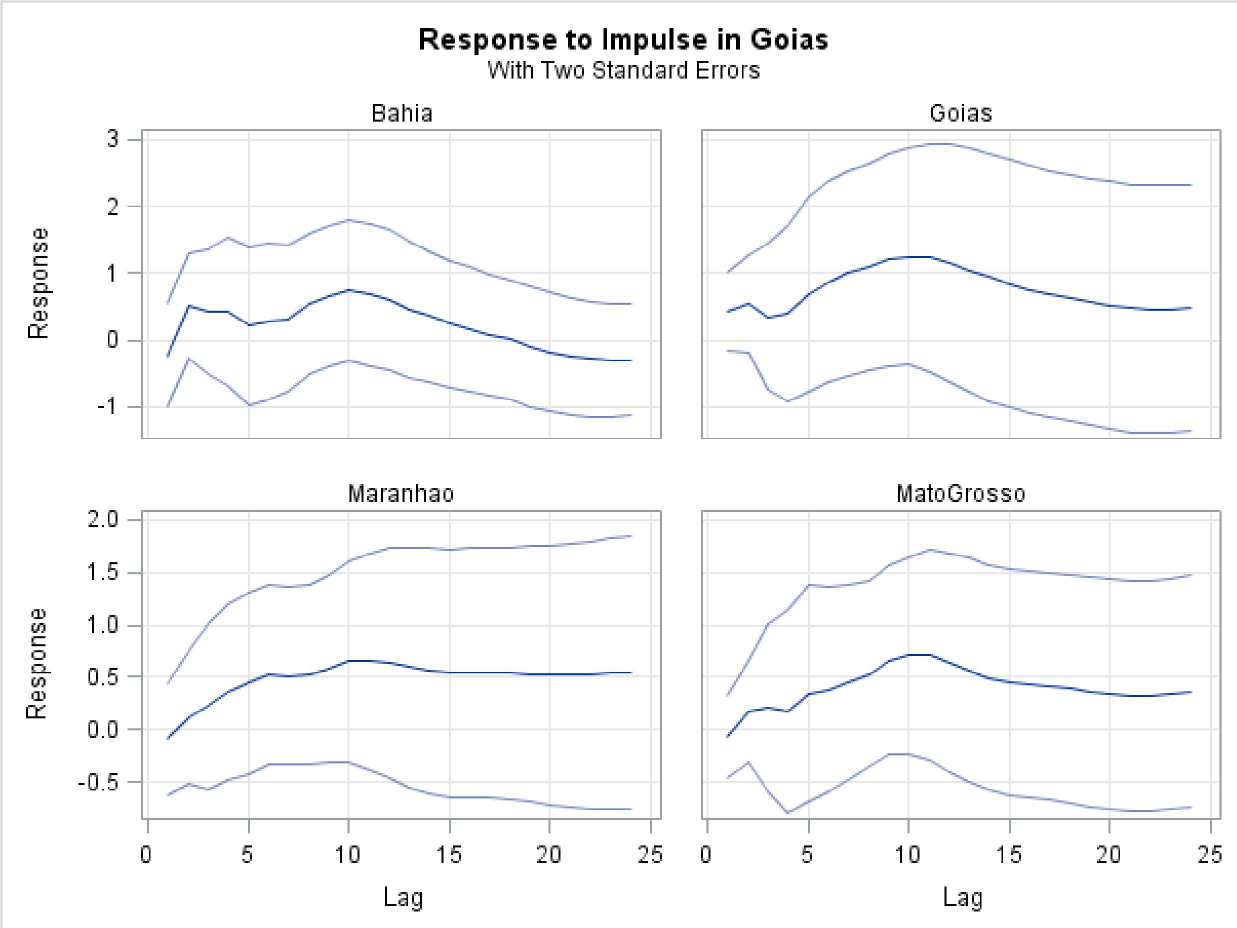
0.00002
0.00000
-0.00002
0
5
10
15
20
25


Response to Impulse in Goias
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
Lag
3
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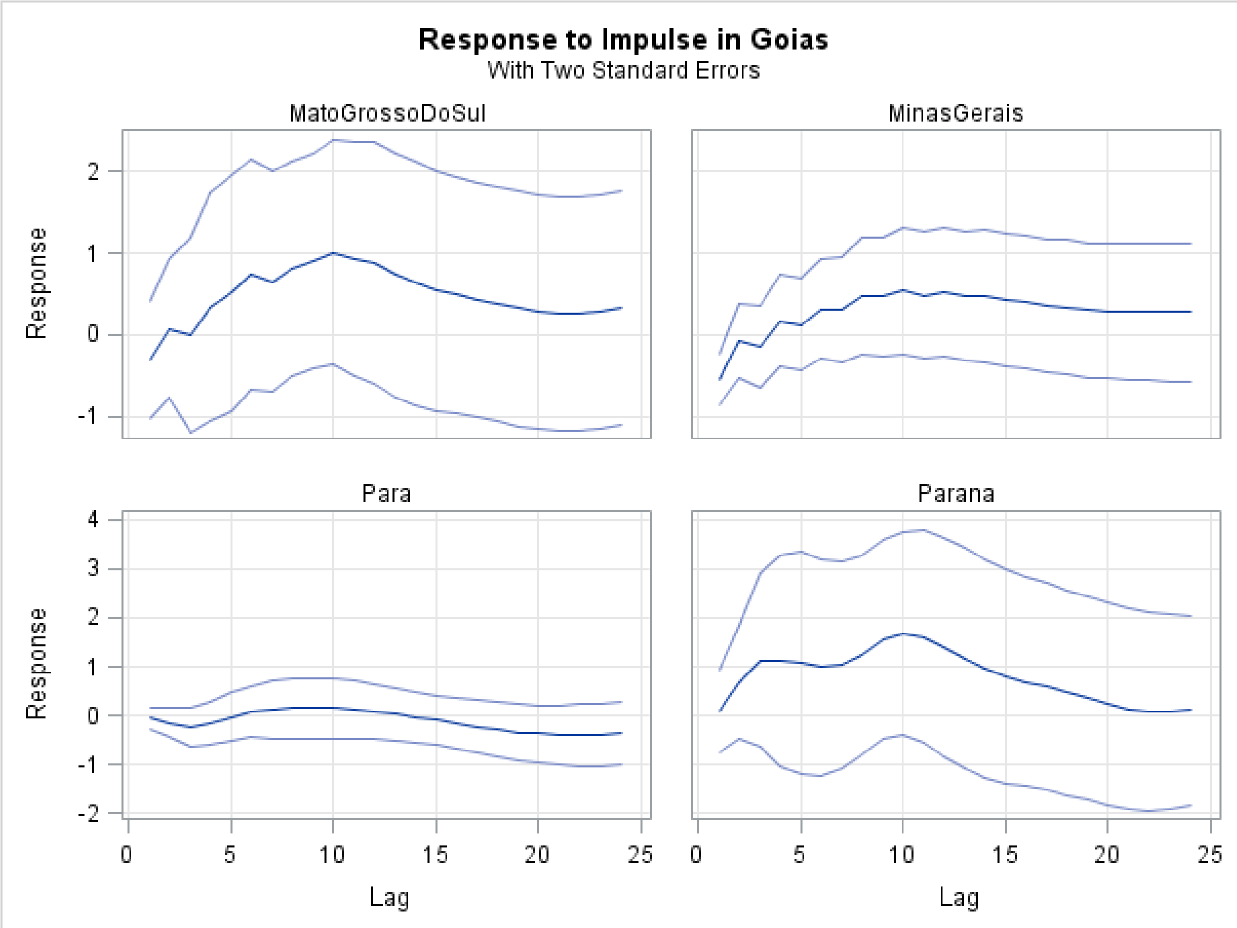
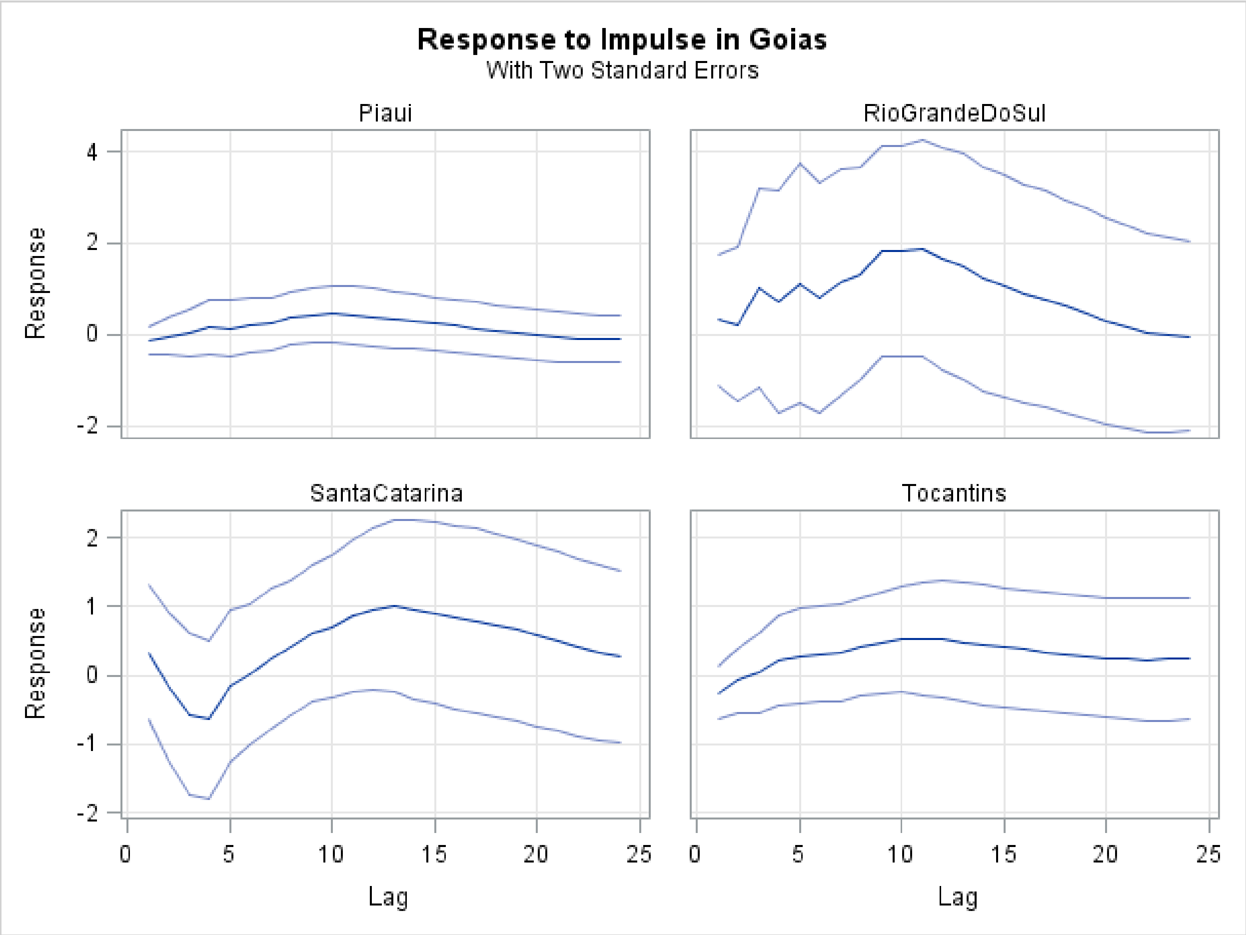
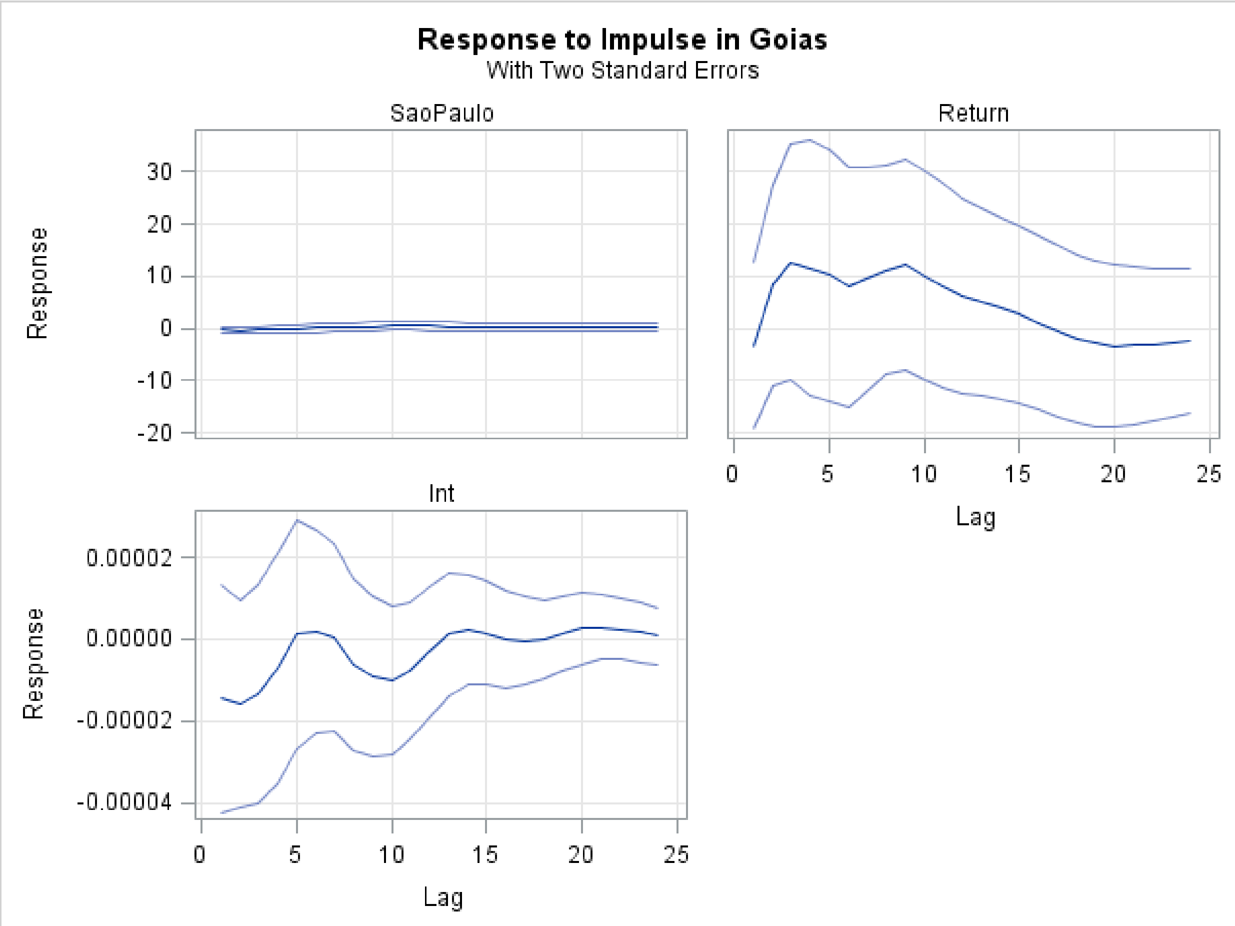
-1
2.0
1.5
1.0
0.5
0.0
-0.5
0
5
10
15
20
25


Response to Impulse in Goias
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag



Response to Impulse in Goias
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
Lag
Lag
4
2
0
-2
2
1
0
-1
-2
0
5
10
15
20
25


Response to Impulse in Goias
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
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-20
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-0.00004
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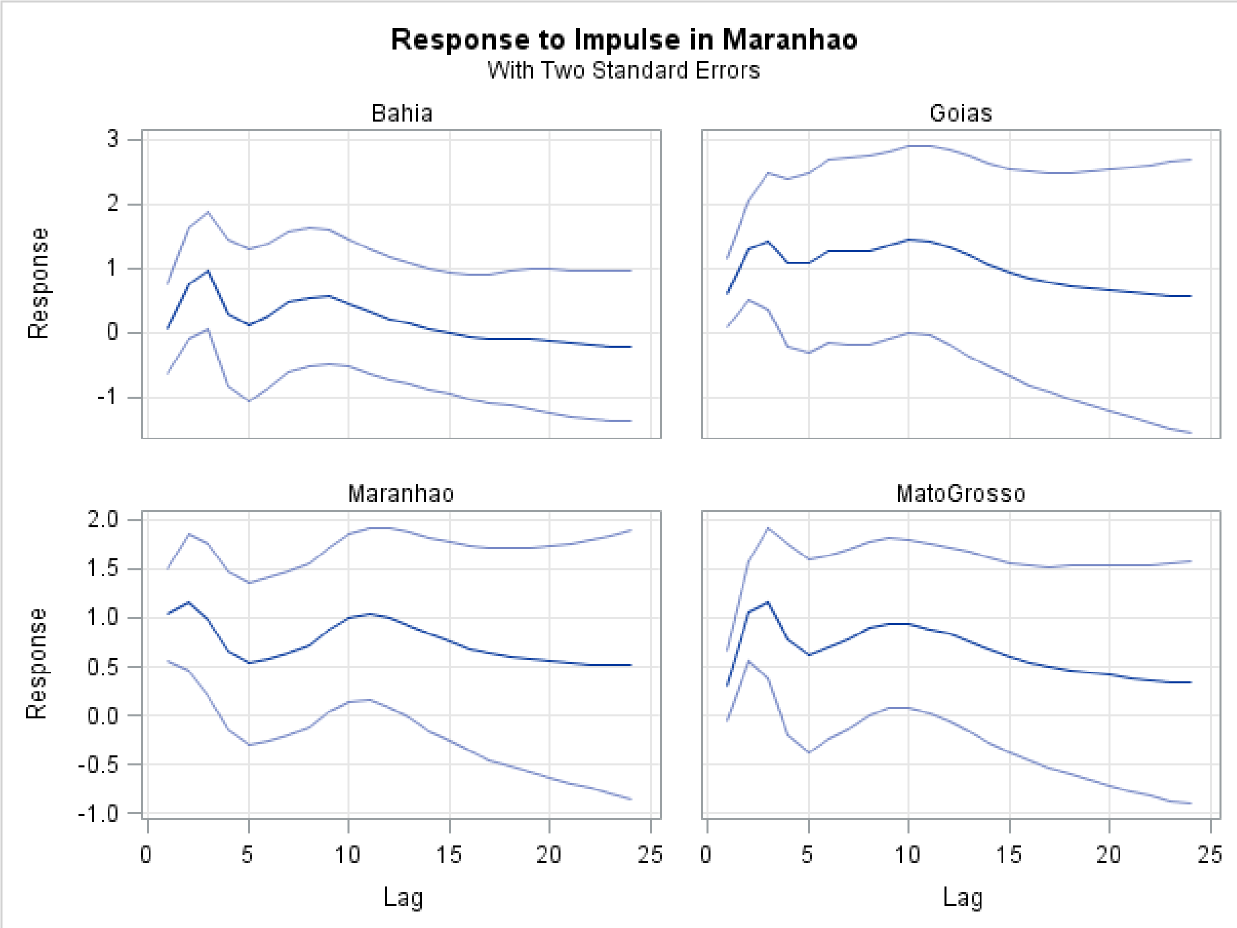
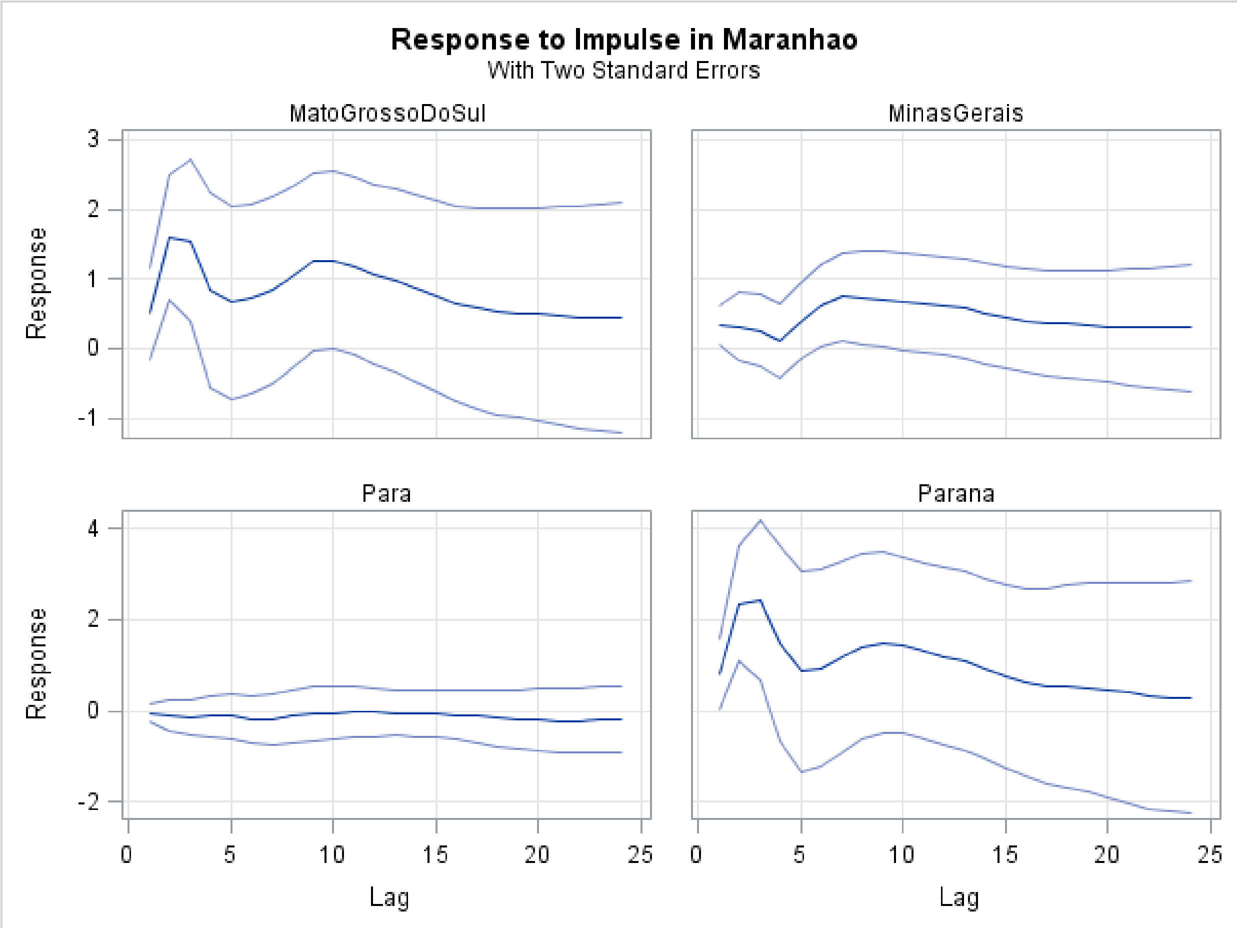
5
10
15
20
25


Response to Impulse in Maranhao
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
Lag


Response to Impulse in Maranhao
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Response
Lag
Lag
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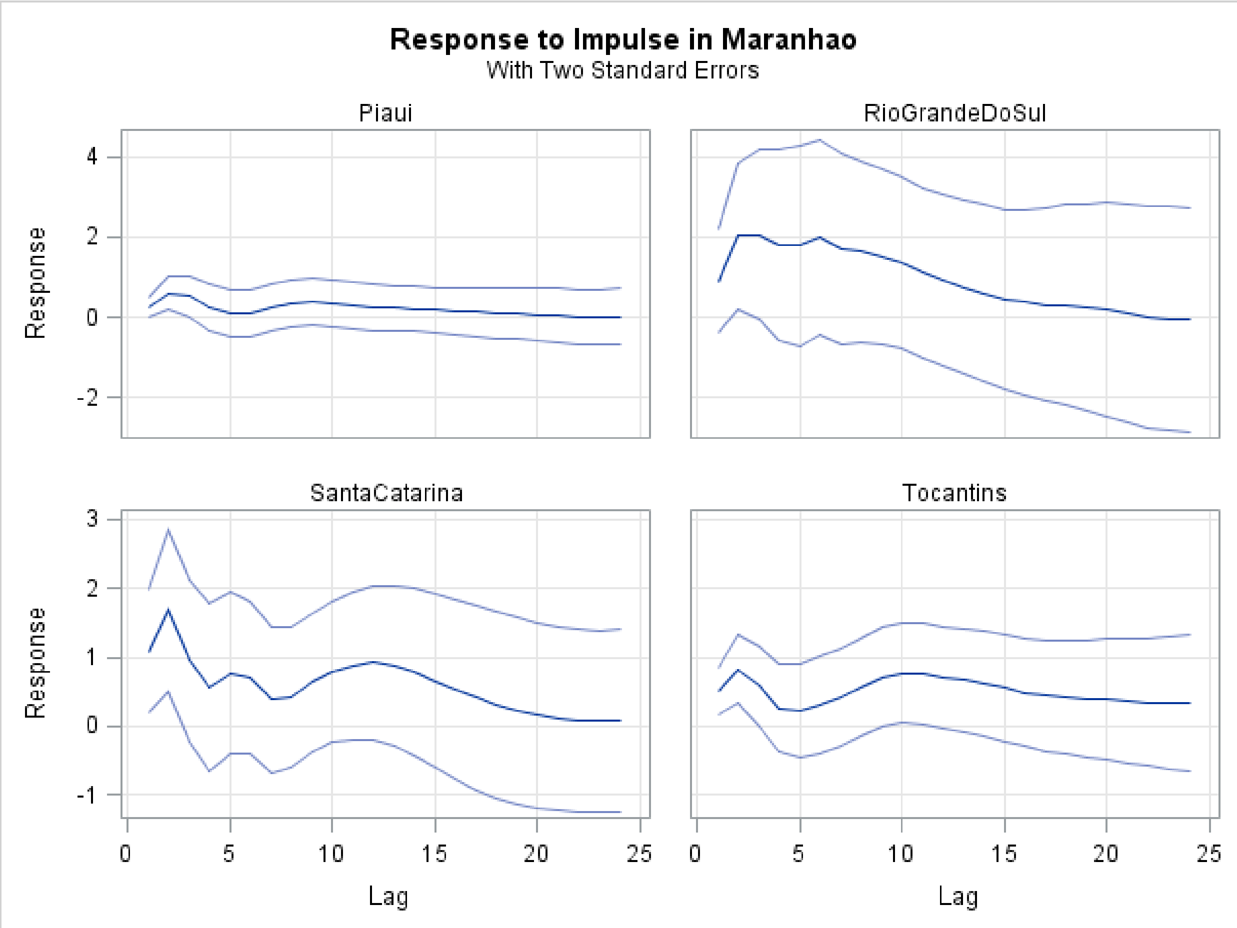
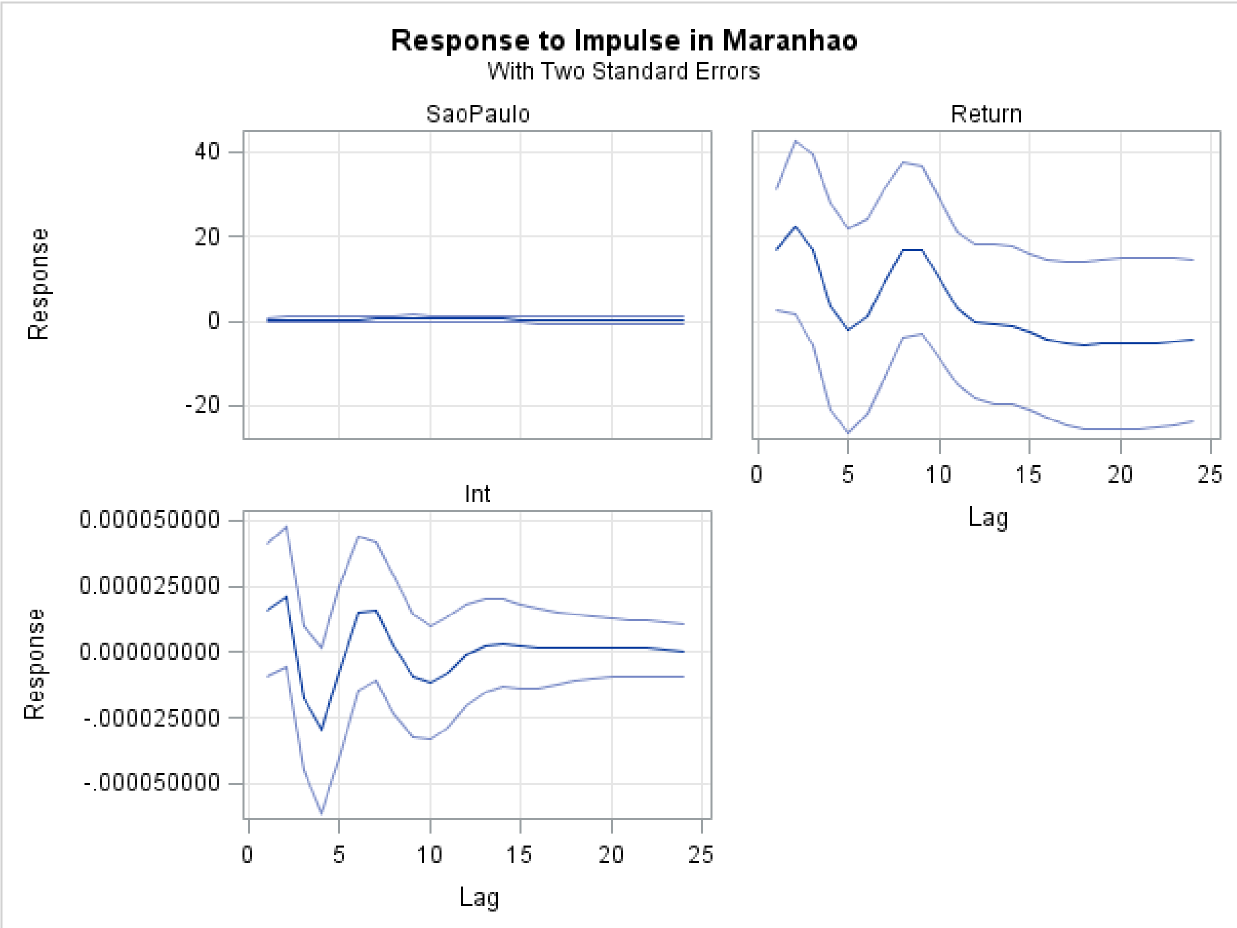
2
1
0
-1
4
2
0
-2
0
5
10
15
20
25


Response to Impulse in Maranhao
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
Lag
Lag



Response to Impulse in Maranhao
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
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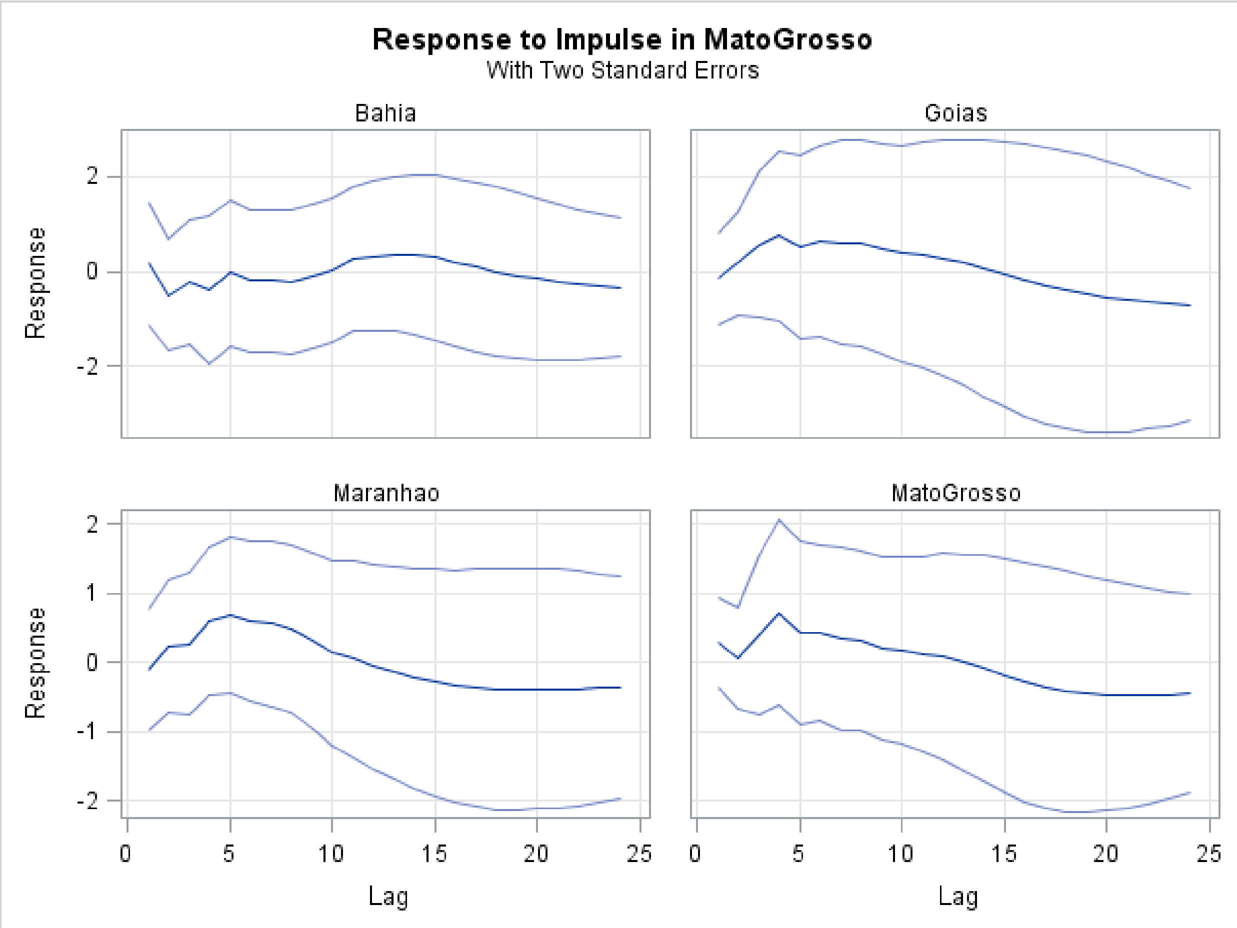
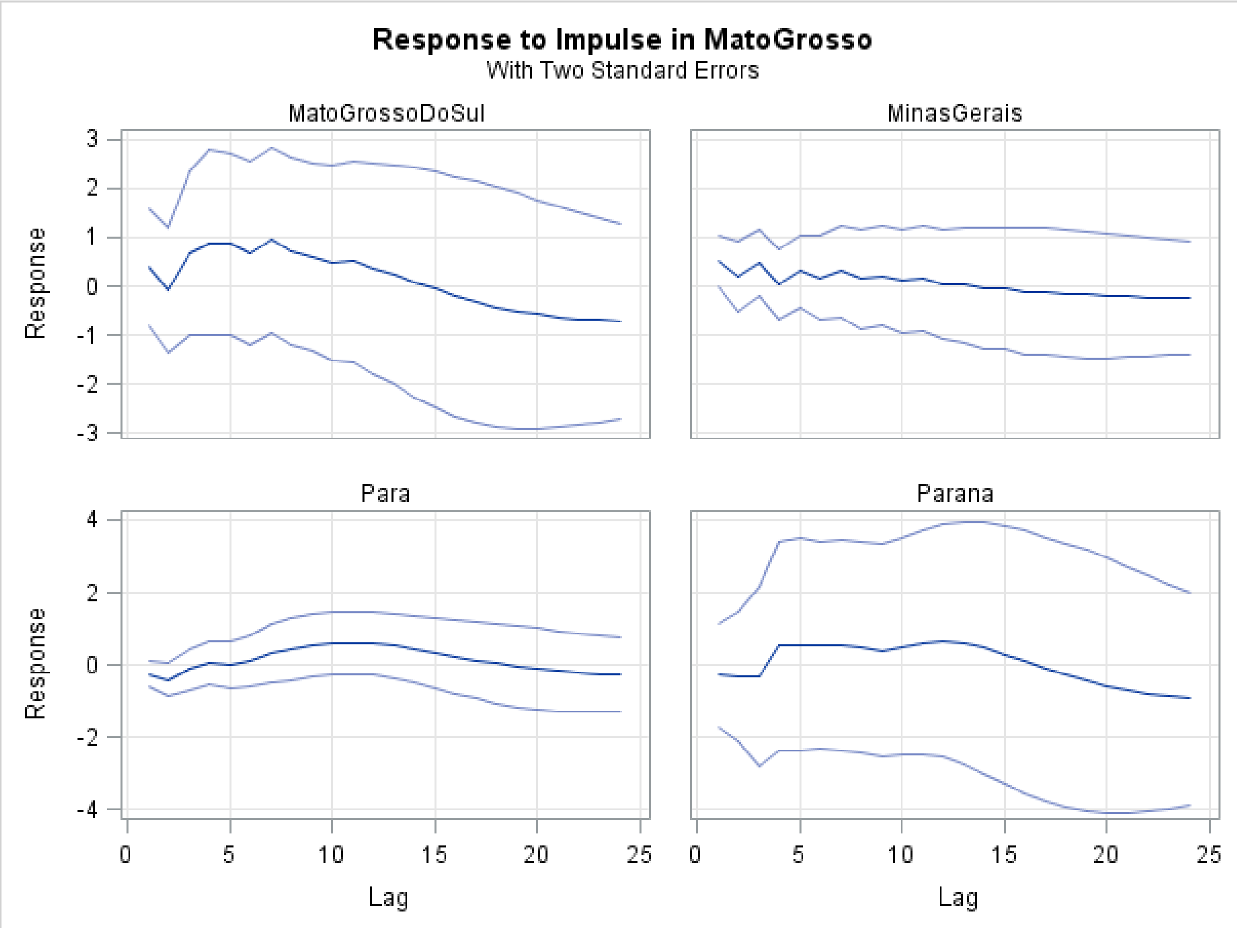
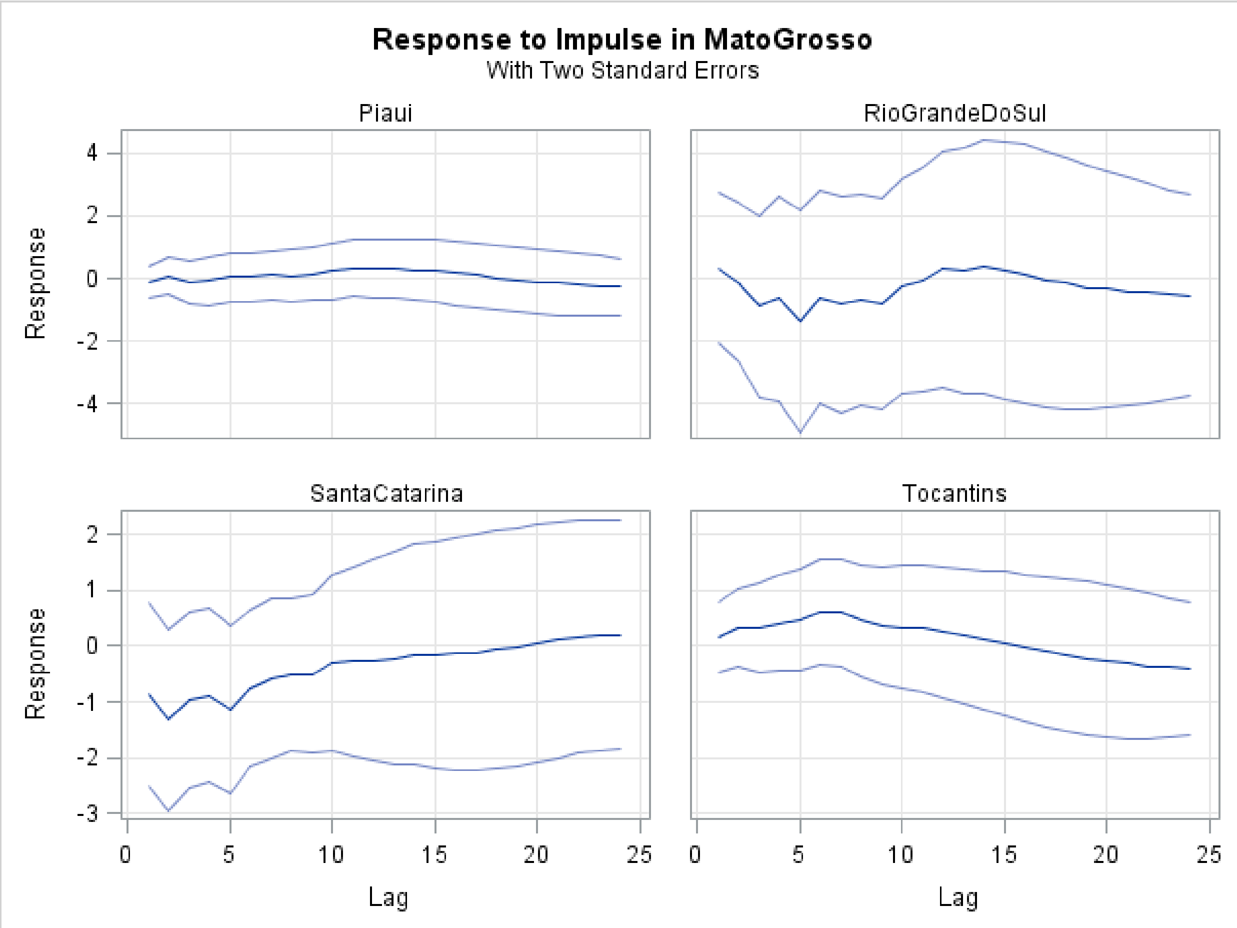
0.000025000
0.000000000
-.000025000
-.000050000
0
5
10
15
20
25



Response to Impulse in MatoGrosso
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
Lag
2
0
-2
2
1
0
-1
-2
0
5
10
15
20
25


Response to Impulse in MatoGrosso
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag


Response to Impulse in MatoGrosso
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag
4
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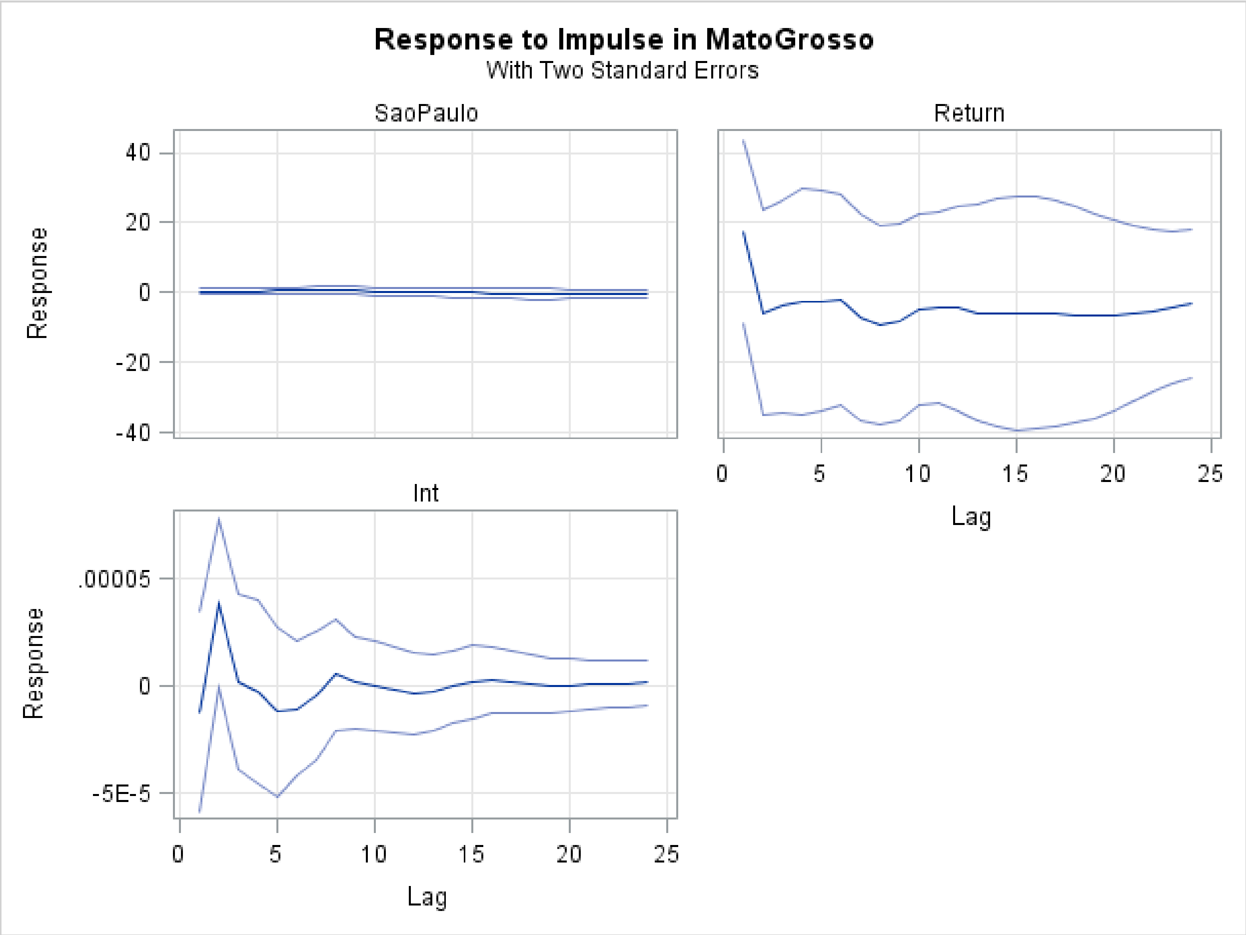
0
-2
-4
1
-1
-3
5
10
15
20
25



Response to Impulse in MatoGrosso
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
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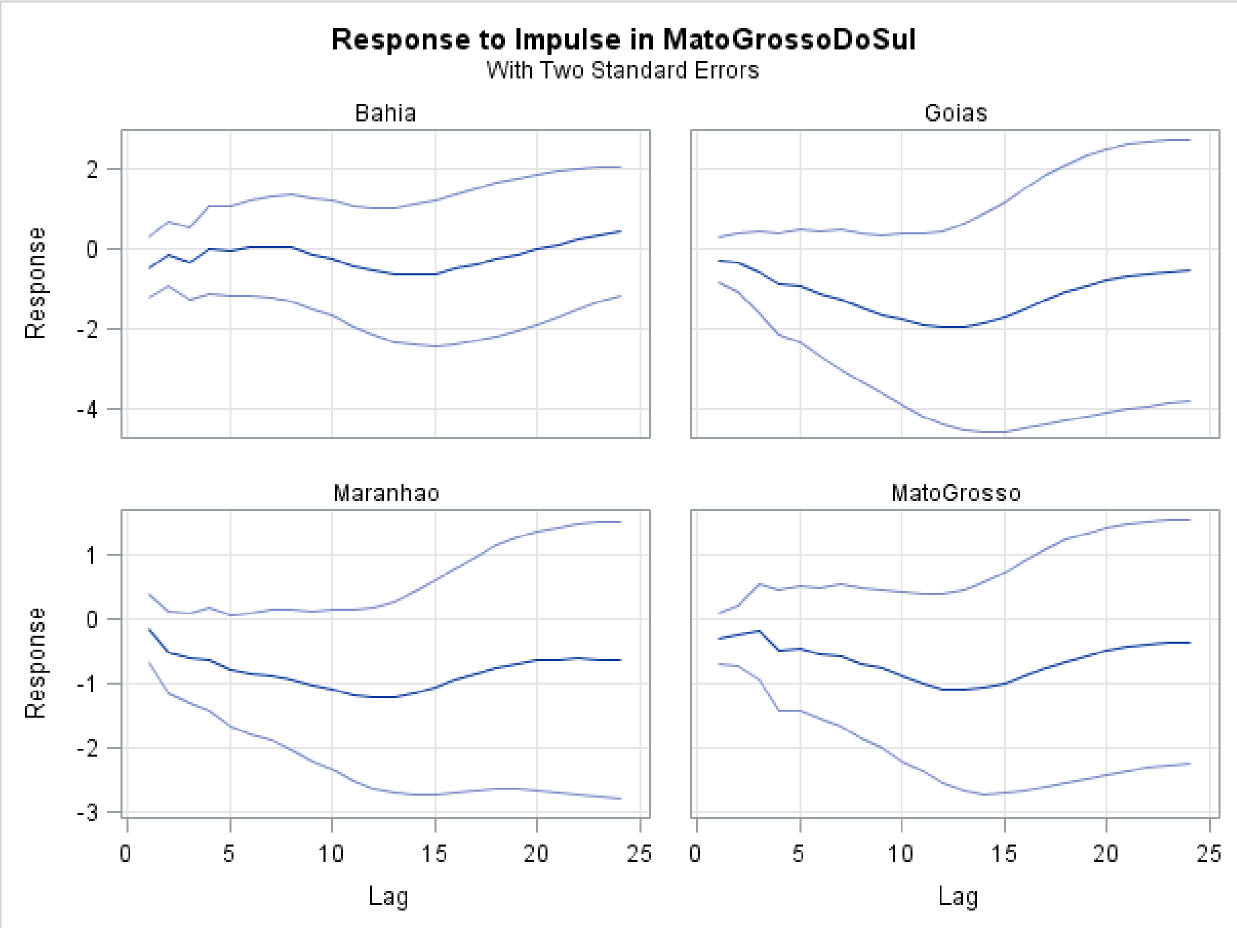
-5E-5
5
10
15
20
25


Response to Impulse in MatoGrossoDoSul
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
Lag
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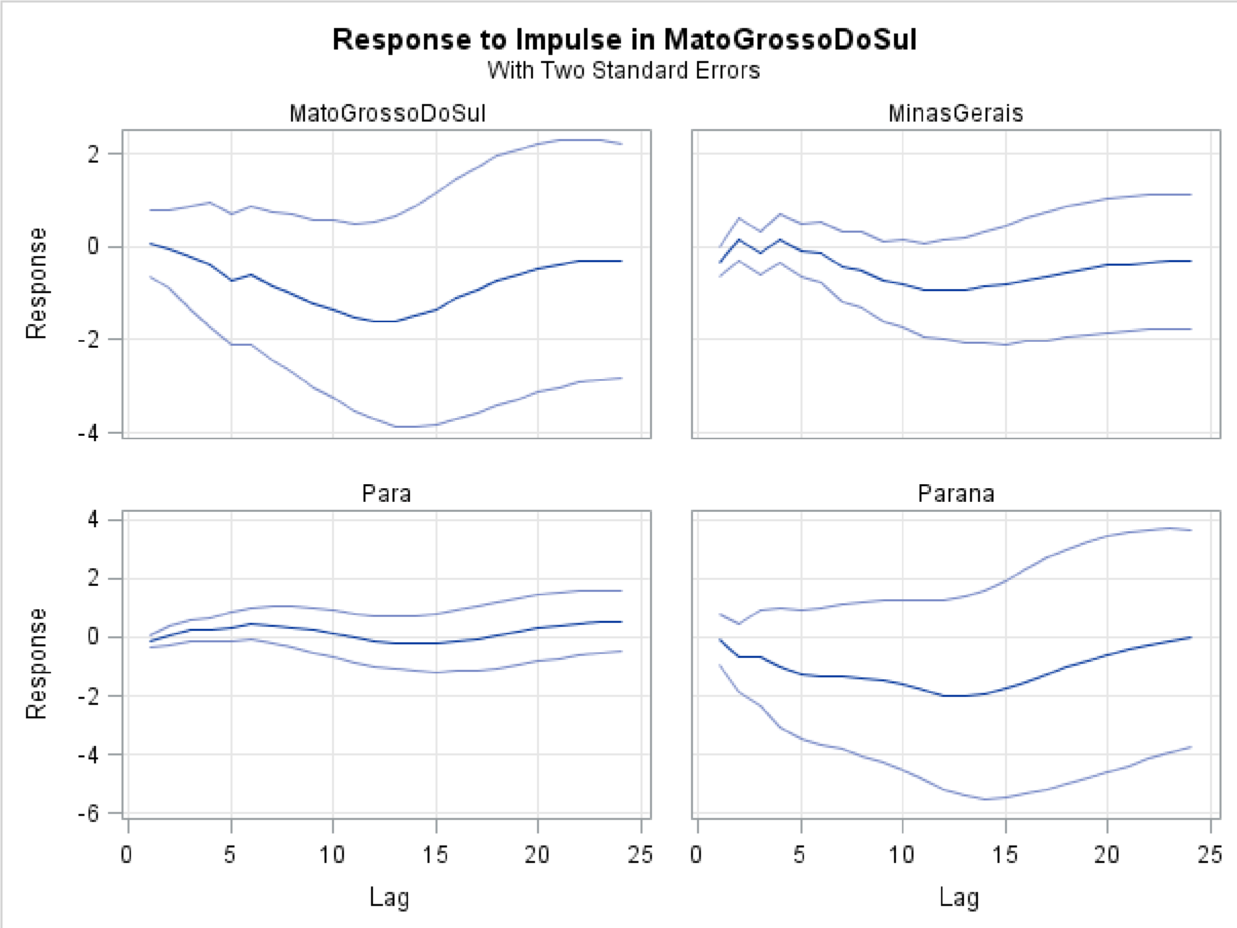
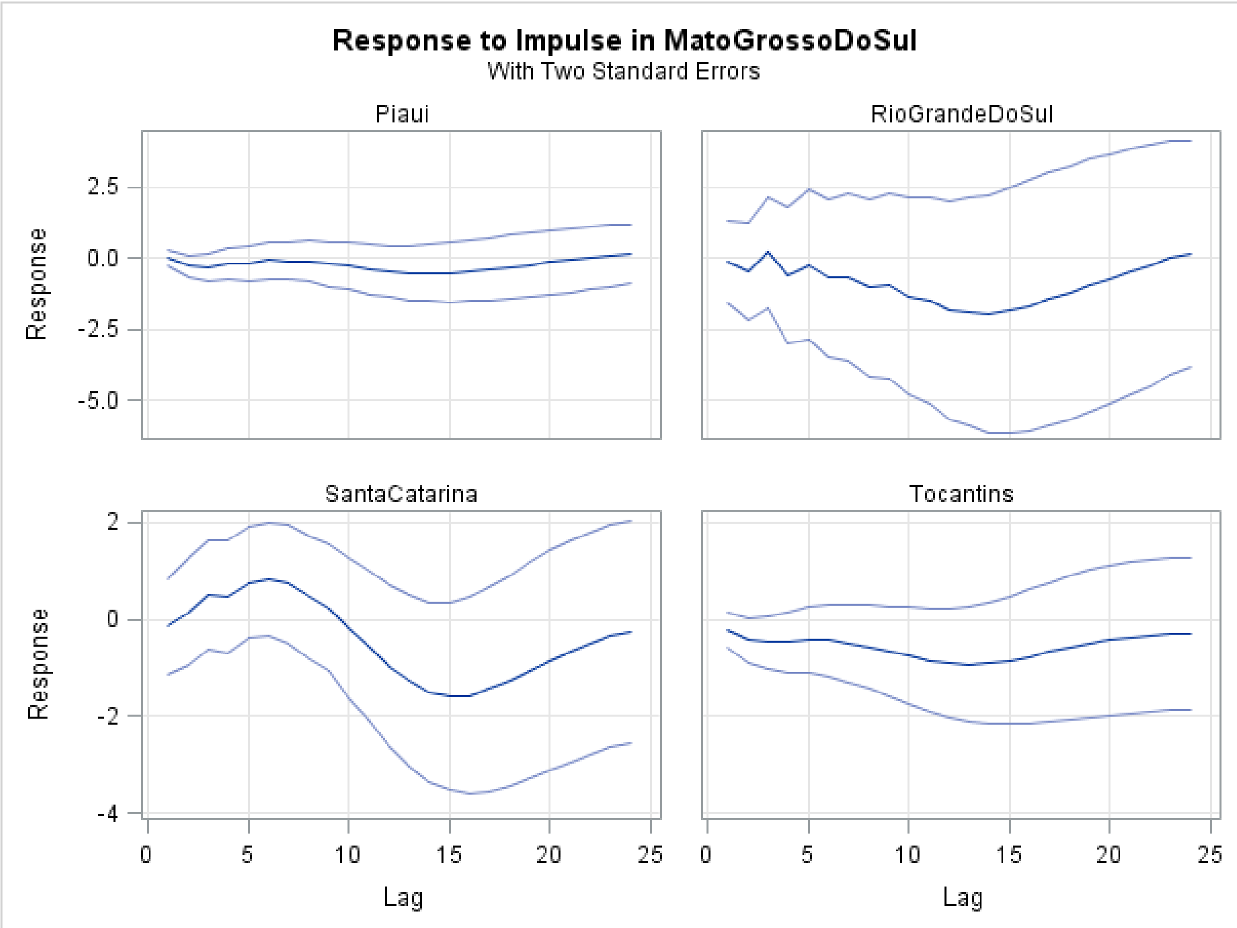
0
-2
-4
1
0
-1
-2
-3
0
5
10
15
20
25



Response to Impulse in MatoGrossoDoSul
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag



Response to Impulse in MatoGrossoDoSul
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
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-2.5
-5.0
2
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-2
-4
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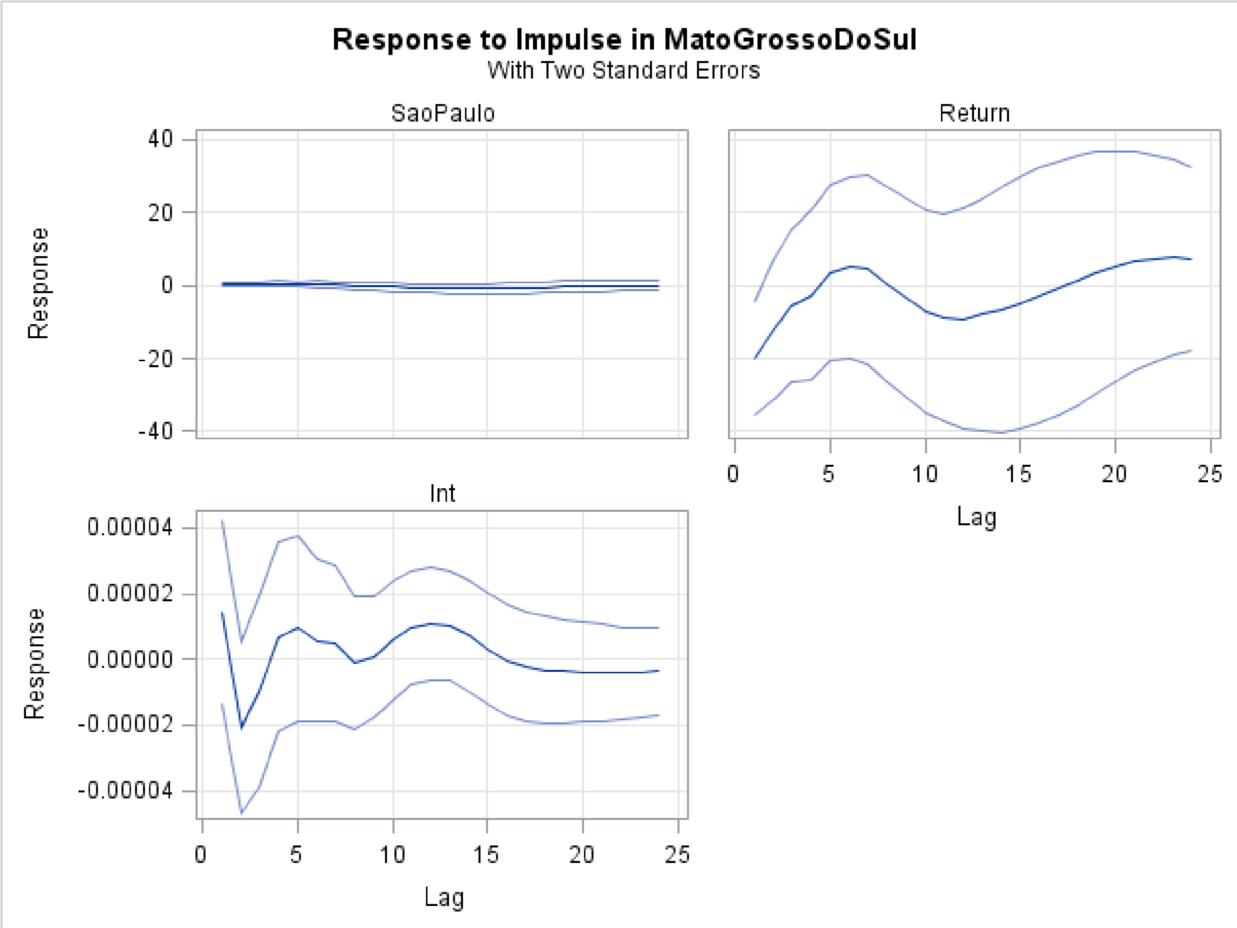
10
15
20
25


Response to Impulse in MatoGrossoDoSul
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
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0.00002
0.00000
-0.00002
-0.00004
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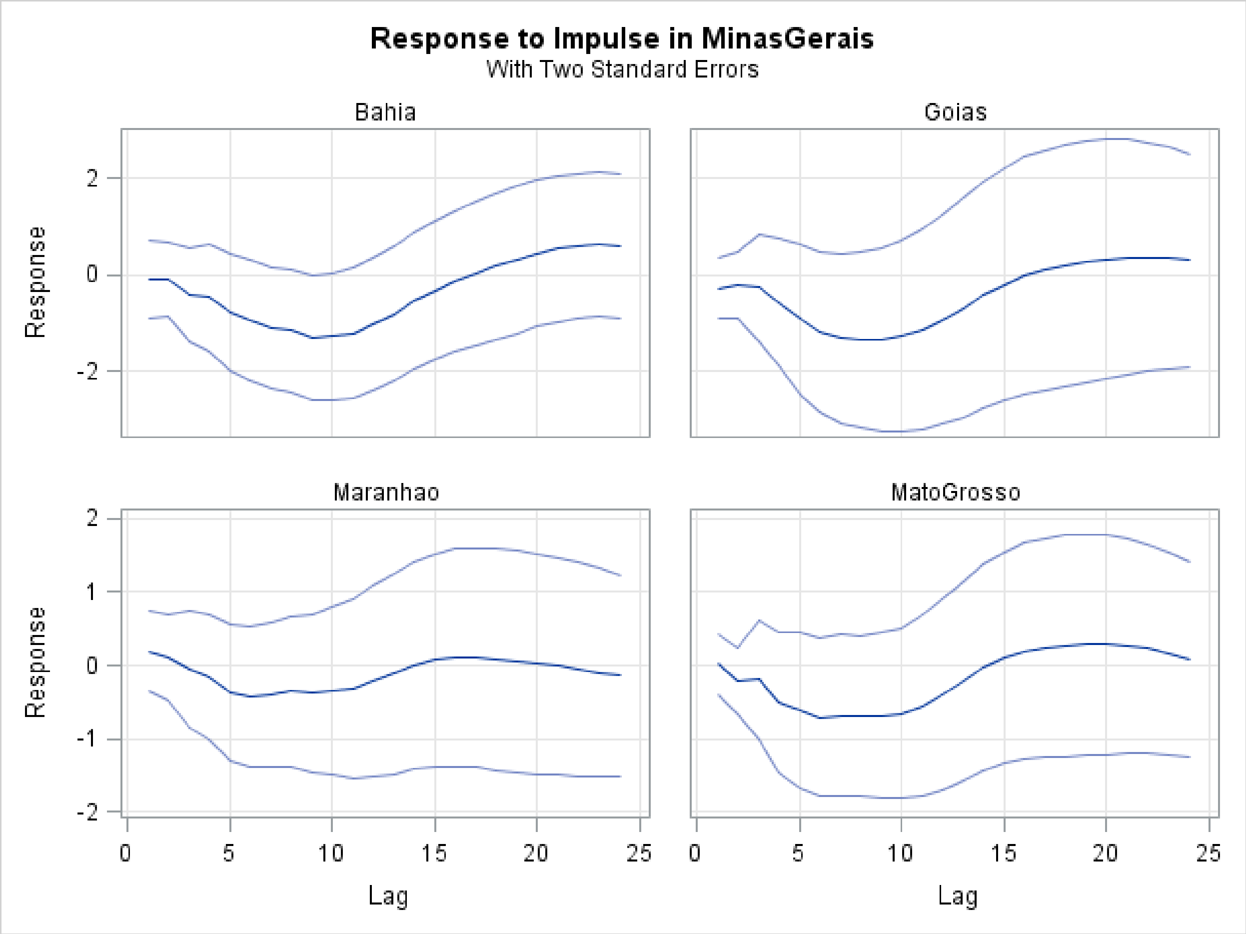
5
10
15
20
25


Response to Impulse in MinasGerais
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Lag
2
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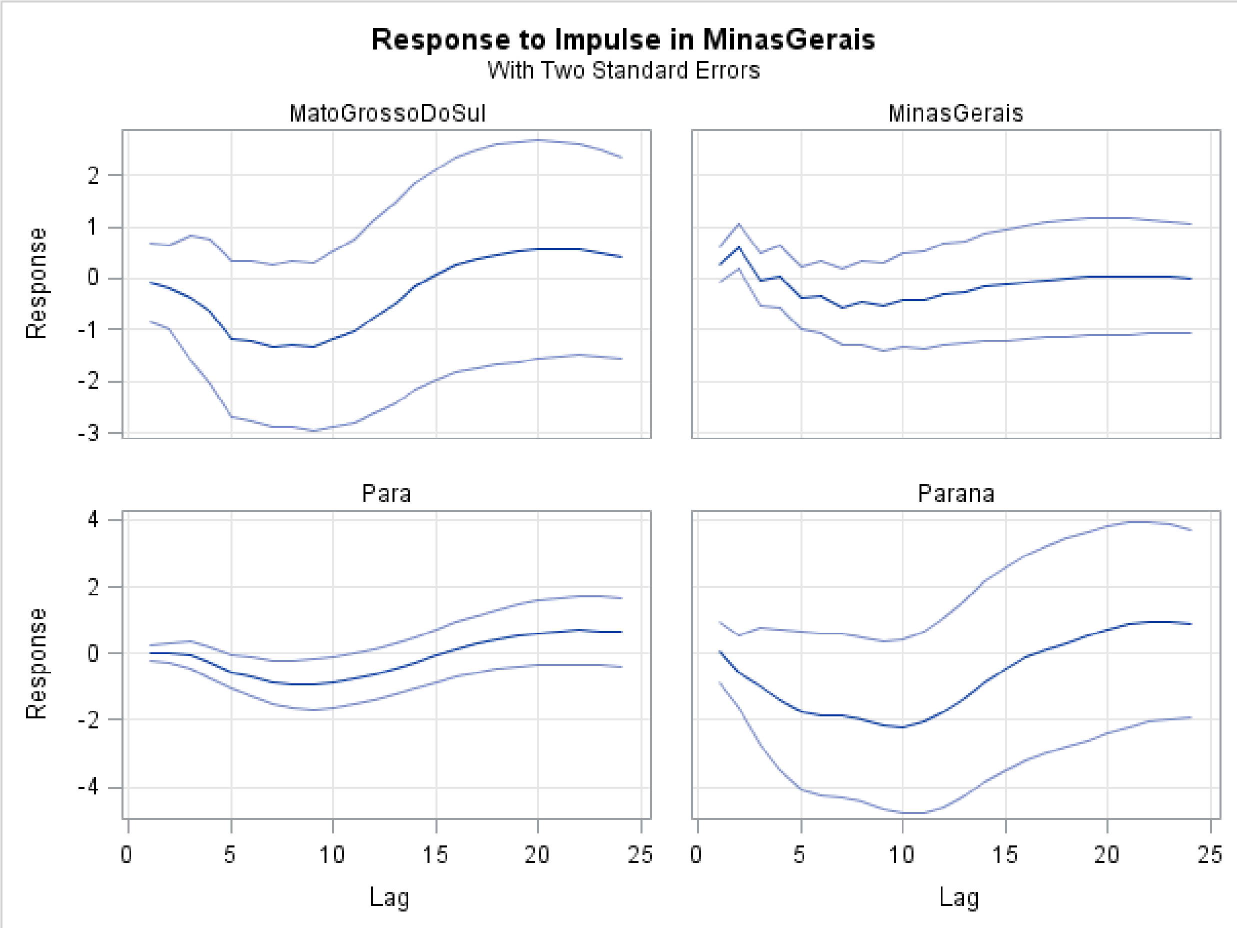
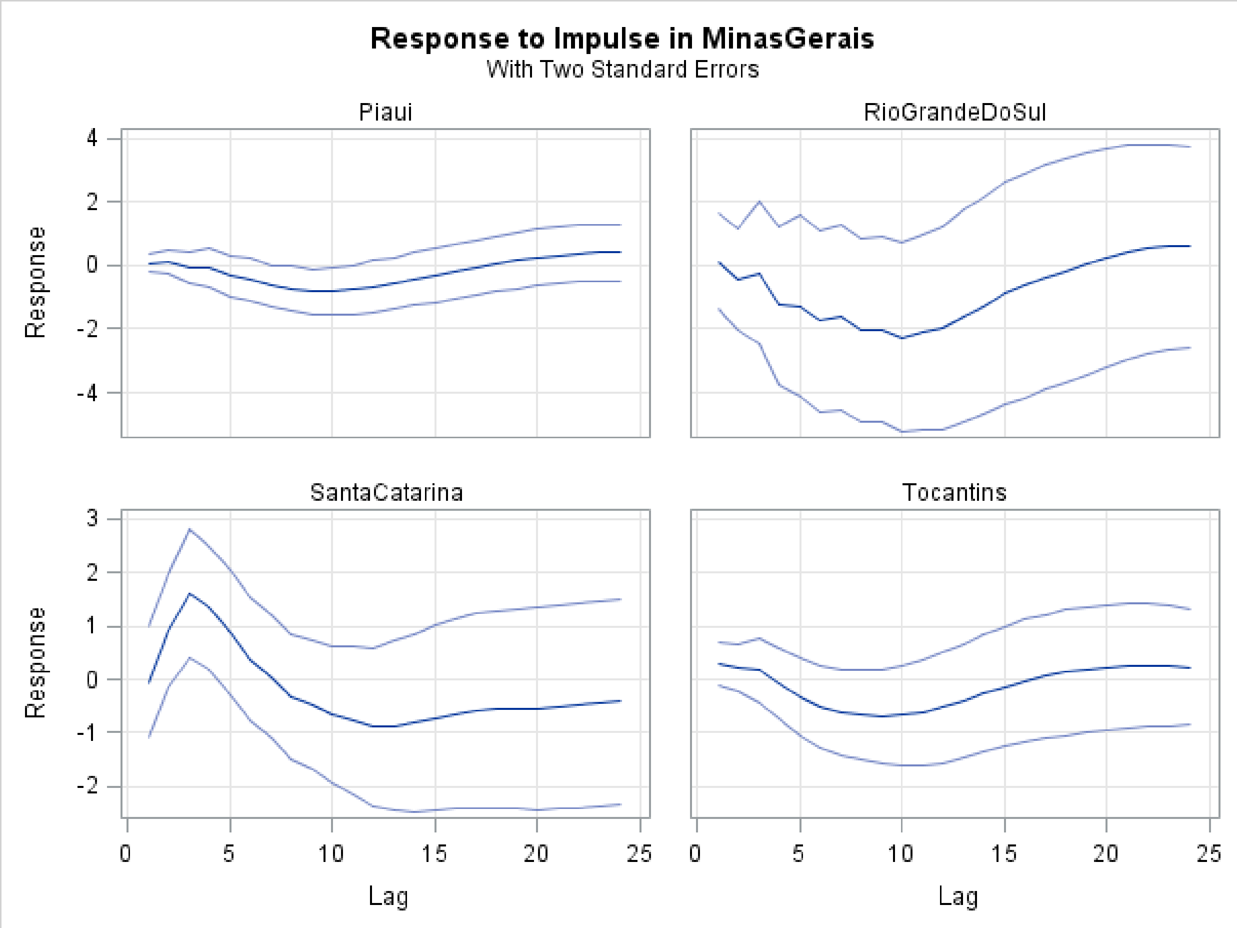
-2
1
-1
5
10
15
20
25


Response to Impulse in MinasGerais
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag



Response to Impulse in MinasGerais
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag
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-2
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3
1
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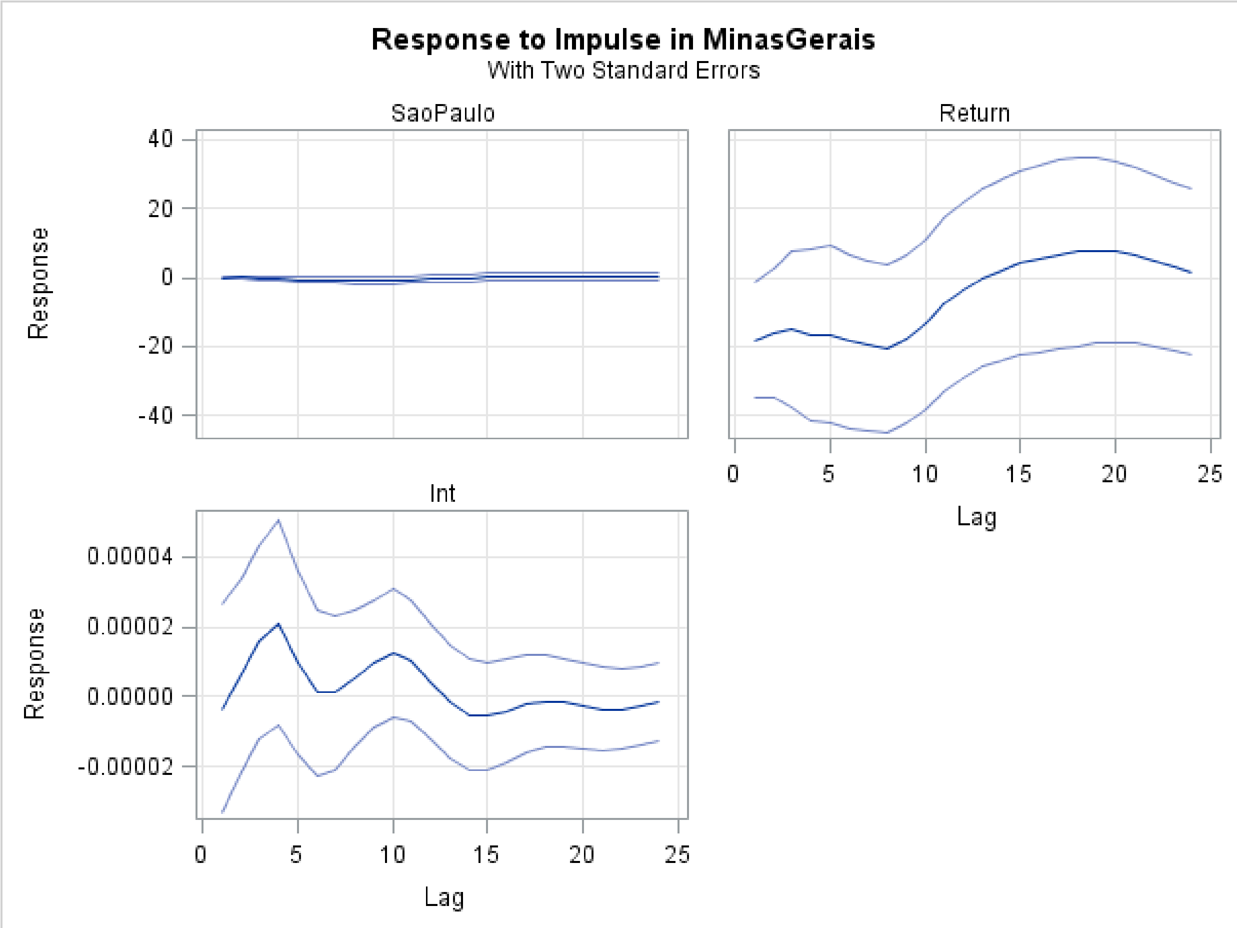
5
10
15
20
25


Response to Impulse in MinasGerais
With Two Standard Errors
SaoPaulo
Return
Int
Response
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20
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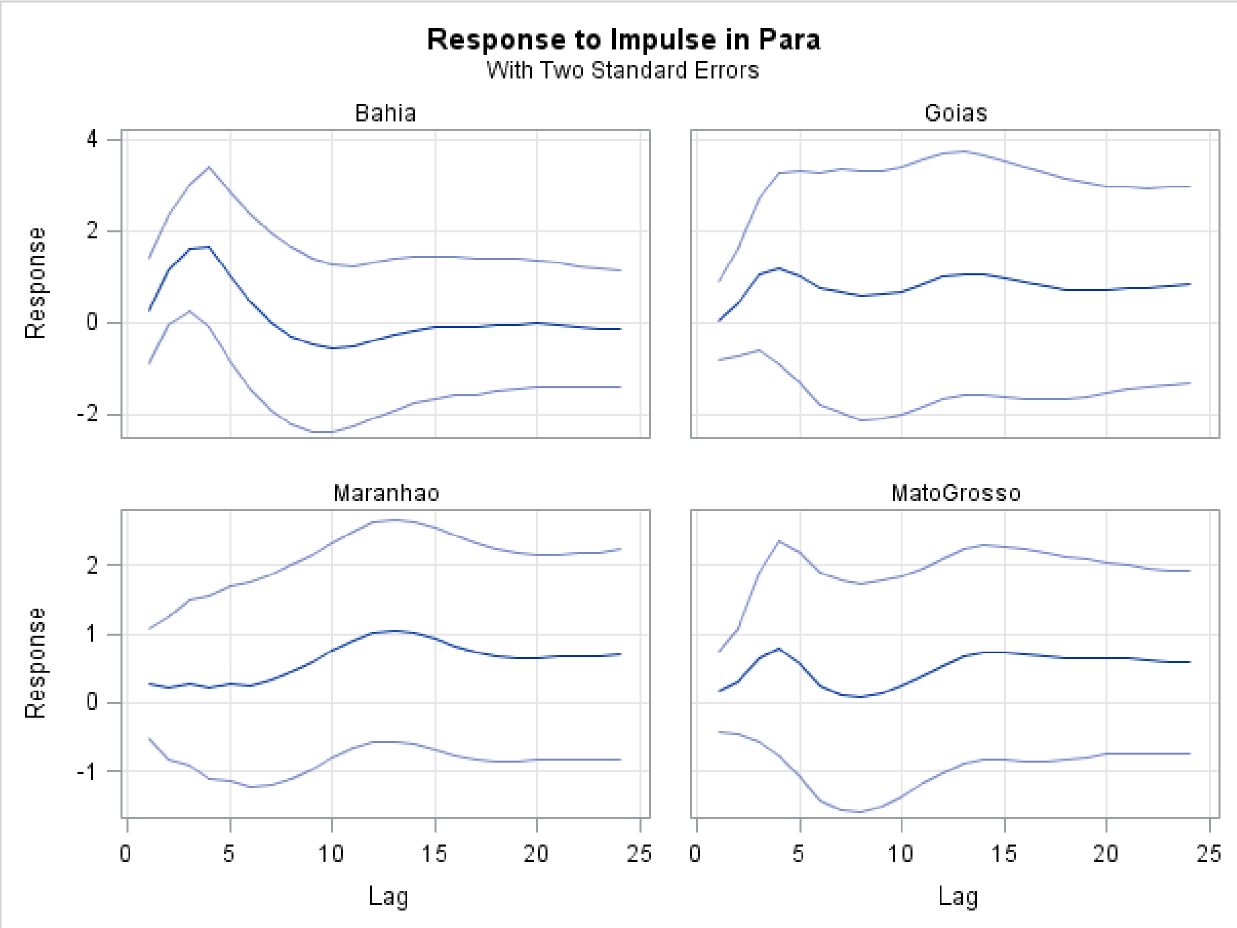
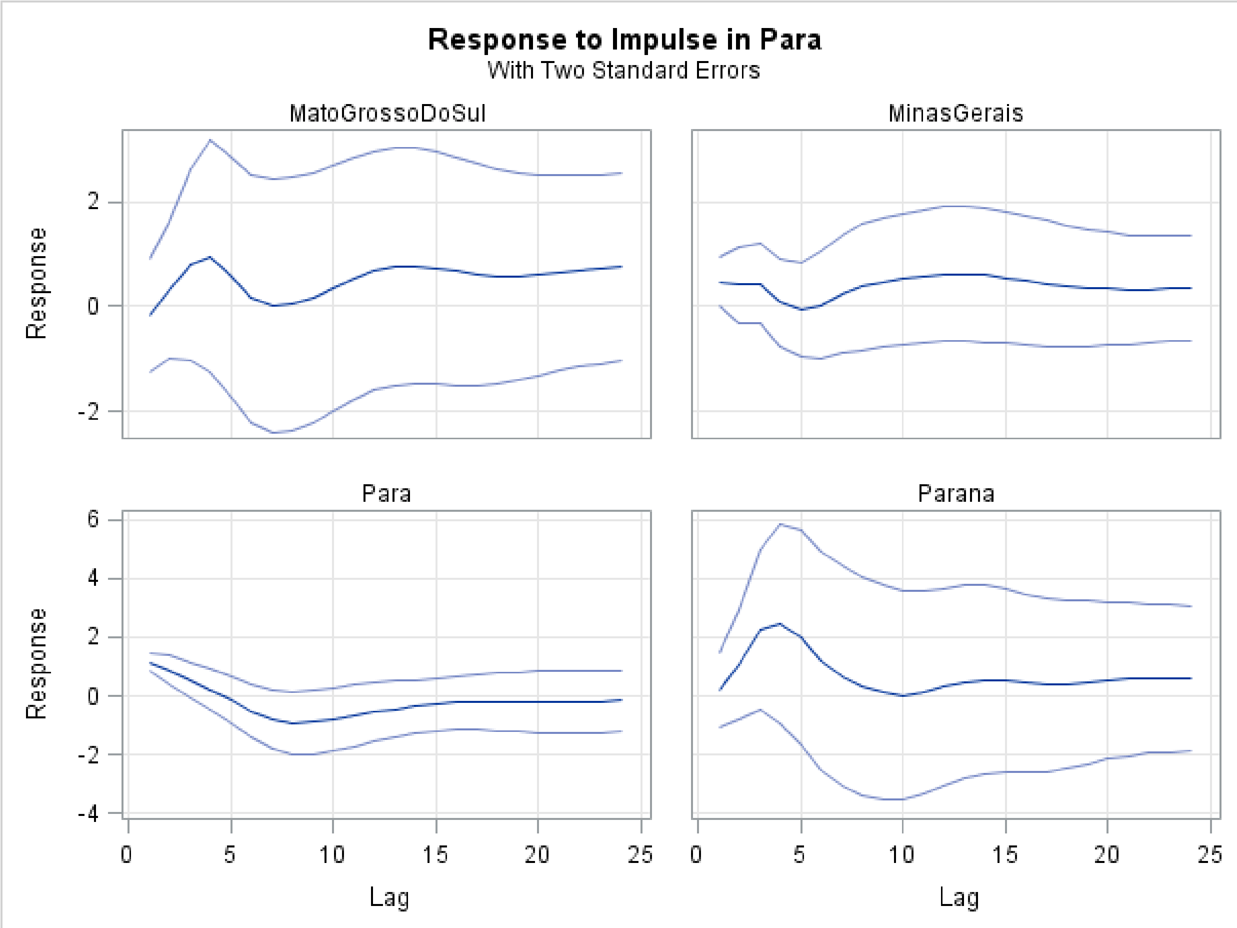


Response to Impulse in Para
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
Lag


Response to Impulse in Para
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
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20
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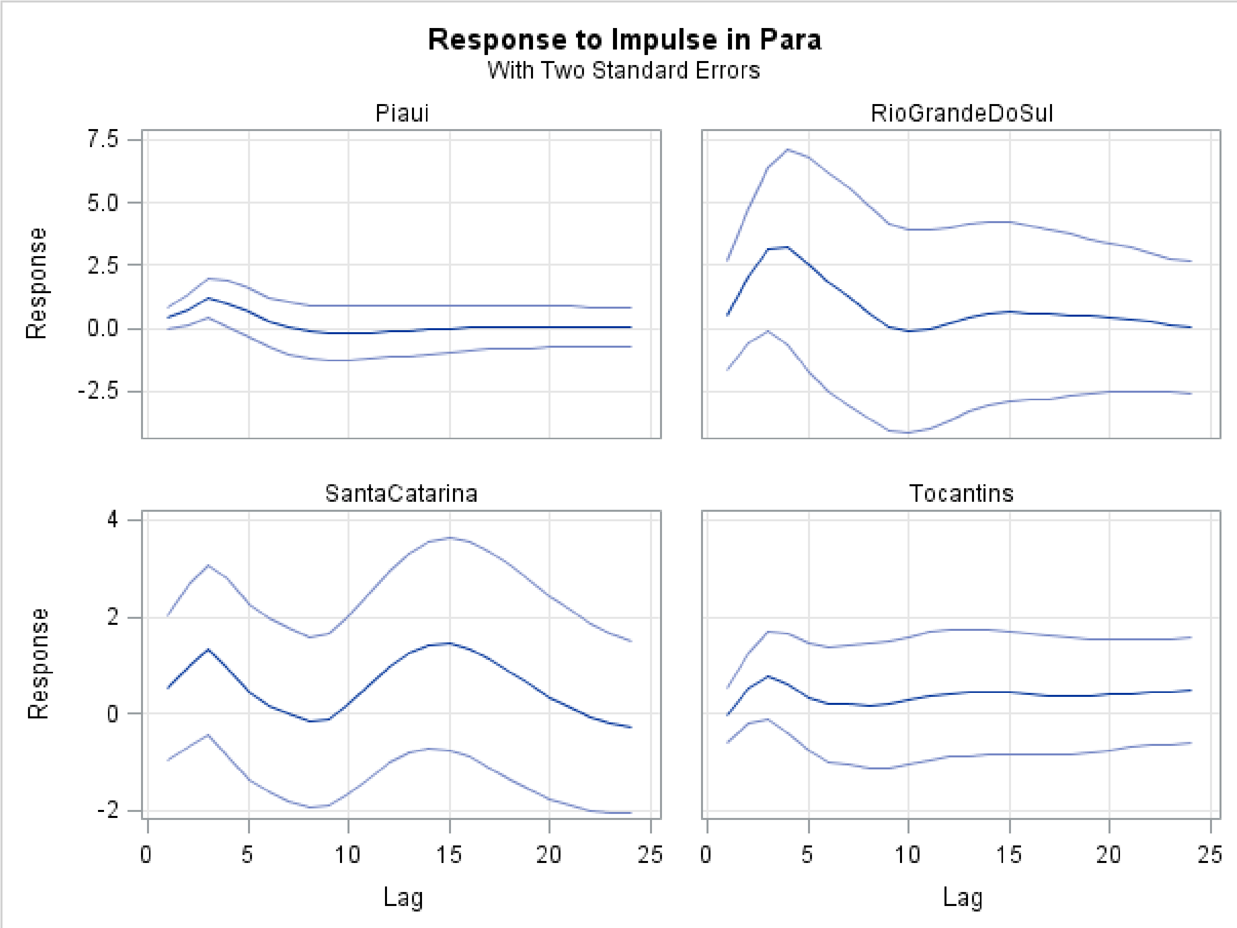
Response to Impulse in Para
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
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4
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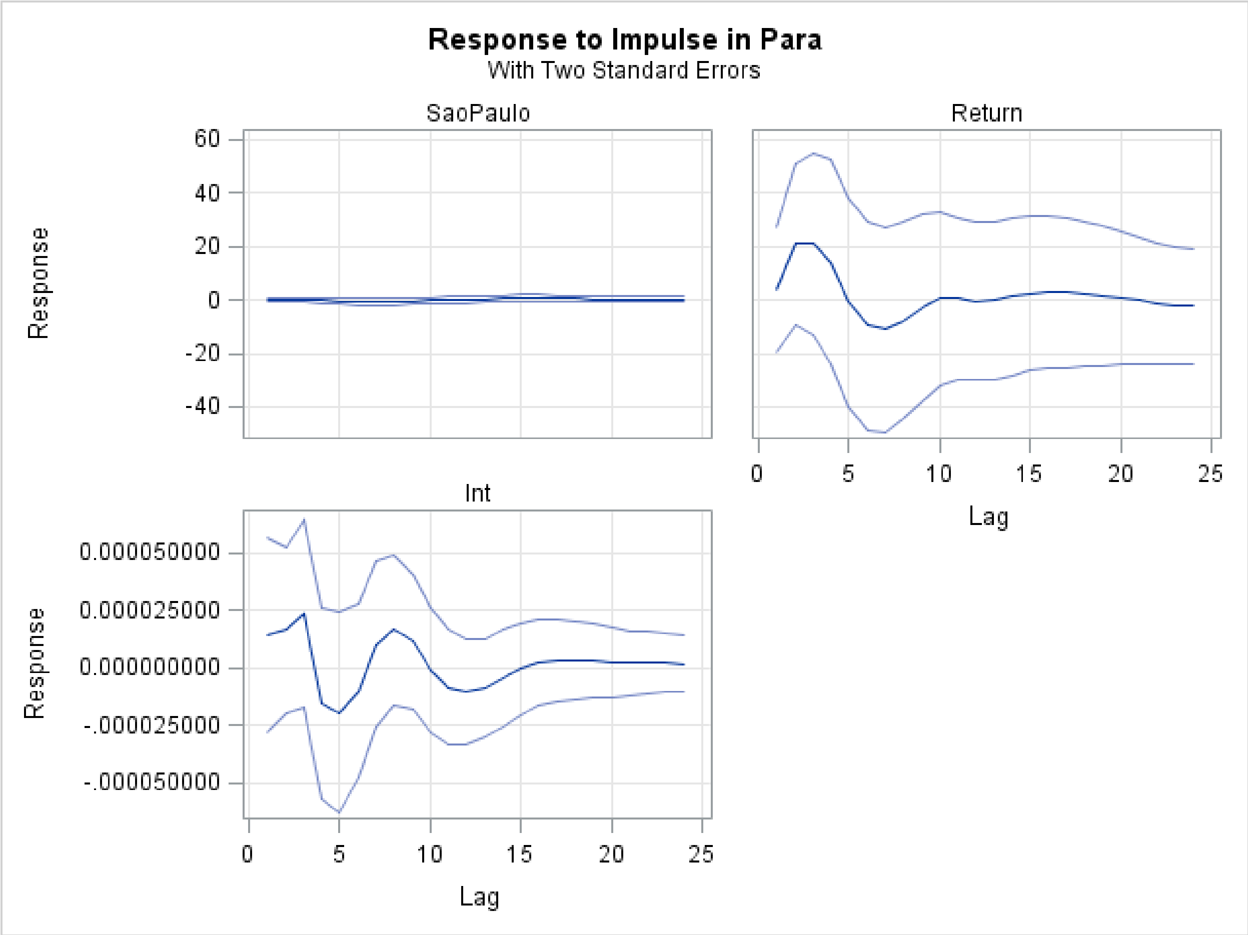
Lag
Lag



Response to Impulse in Para
With Two Standard Errors
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Response
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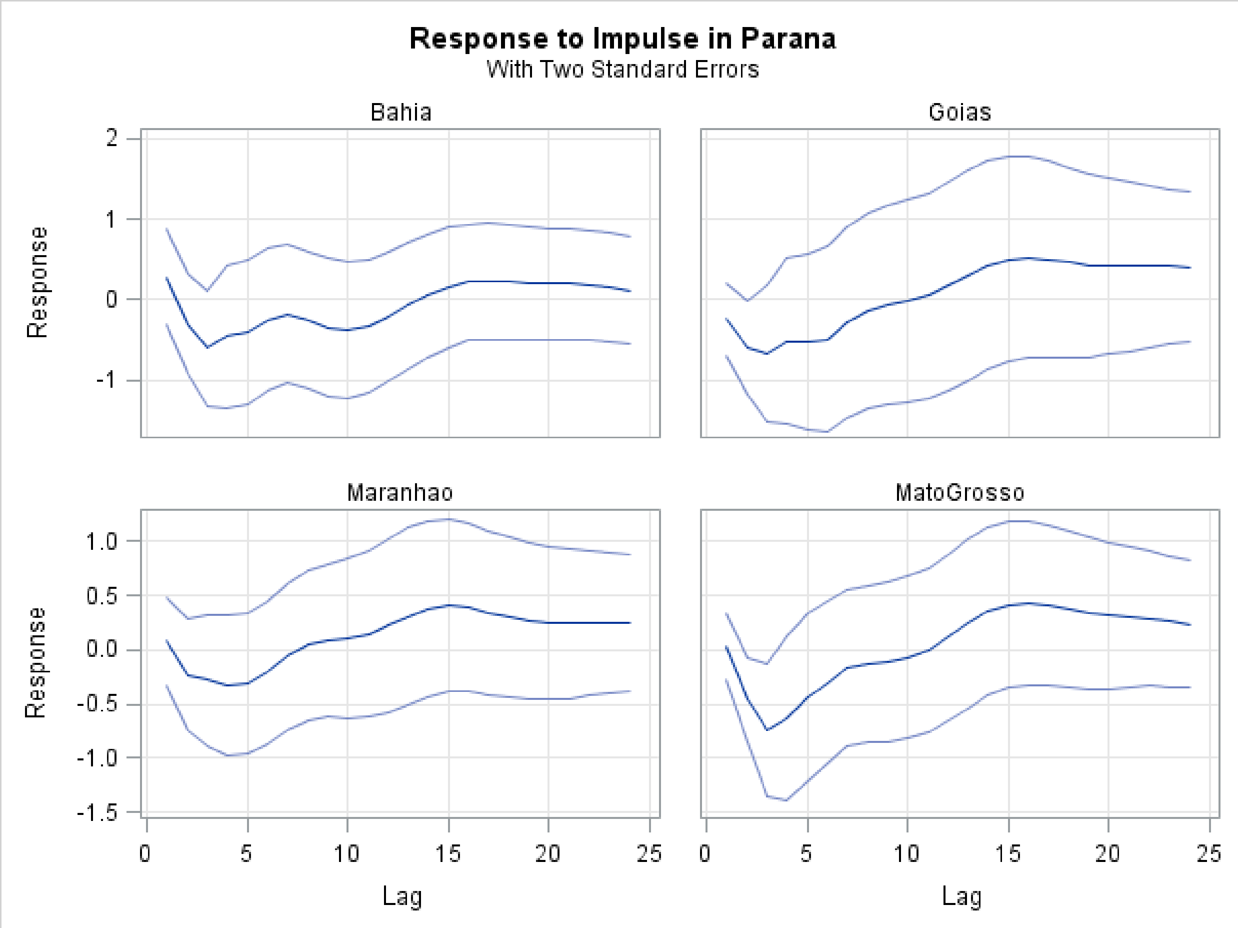
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With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
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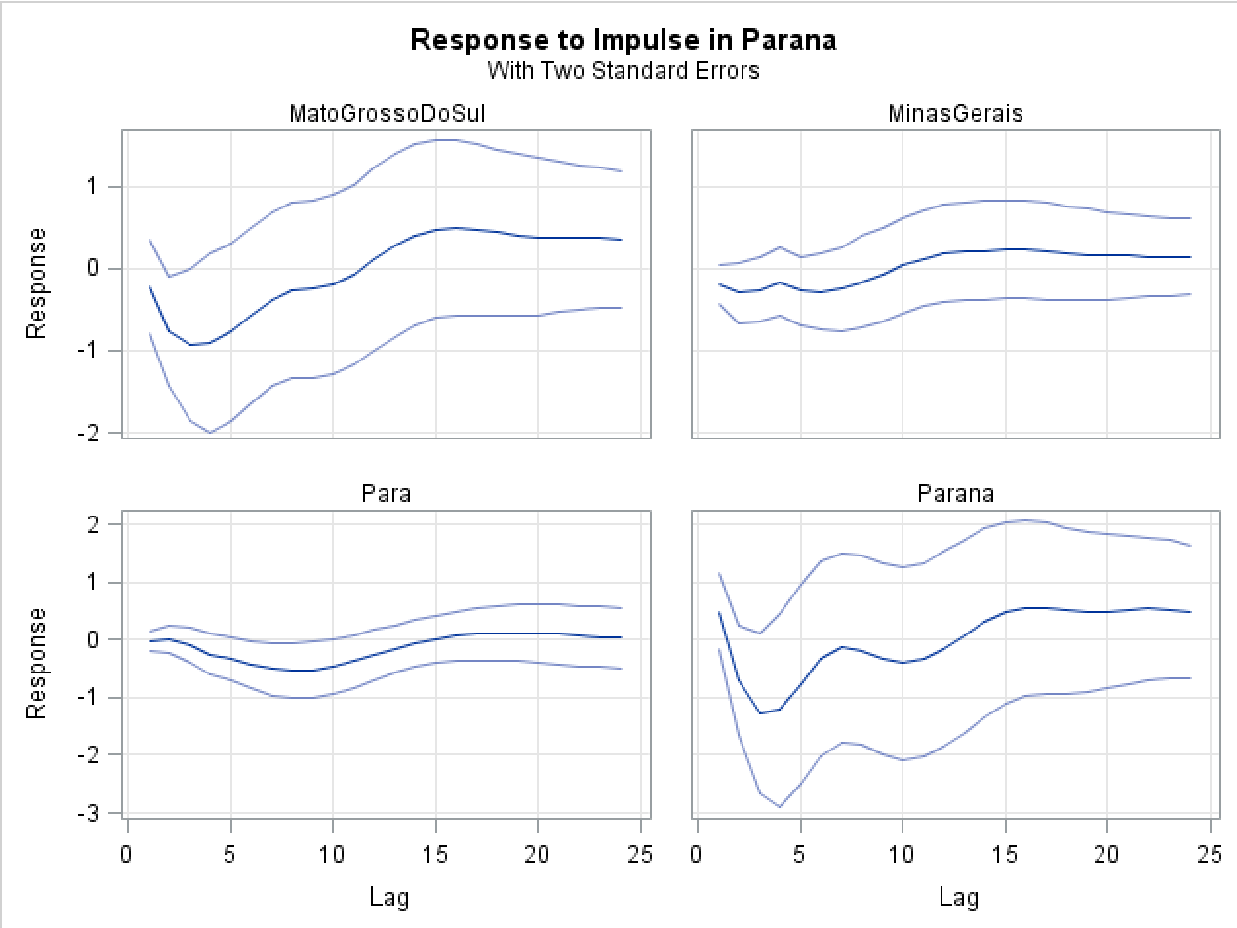
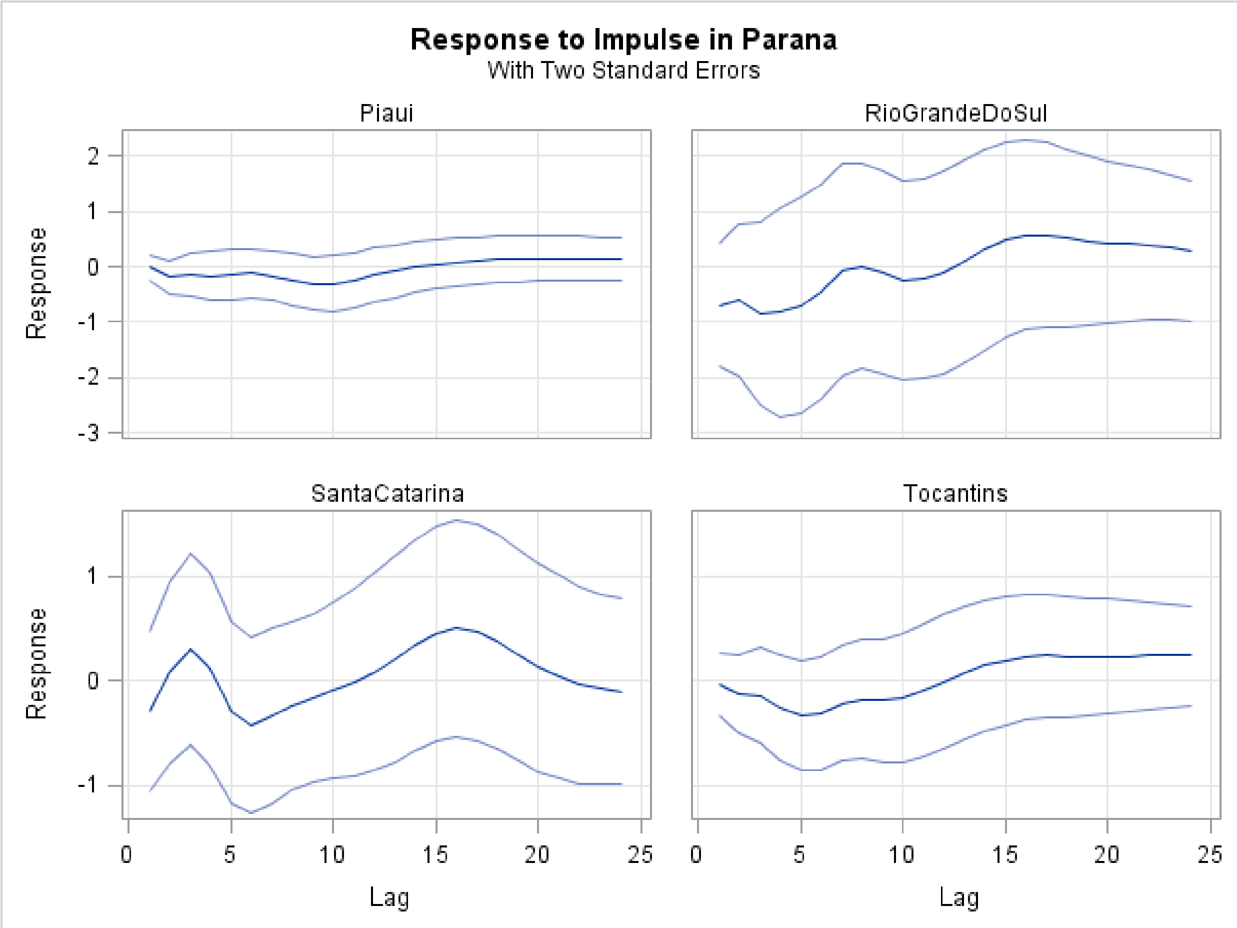
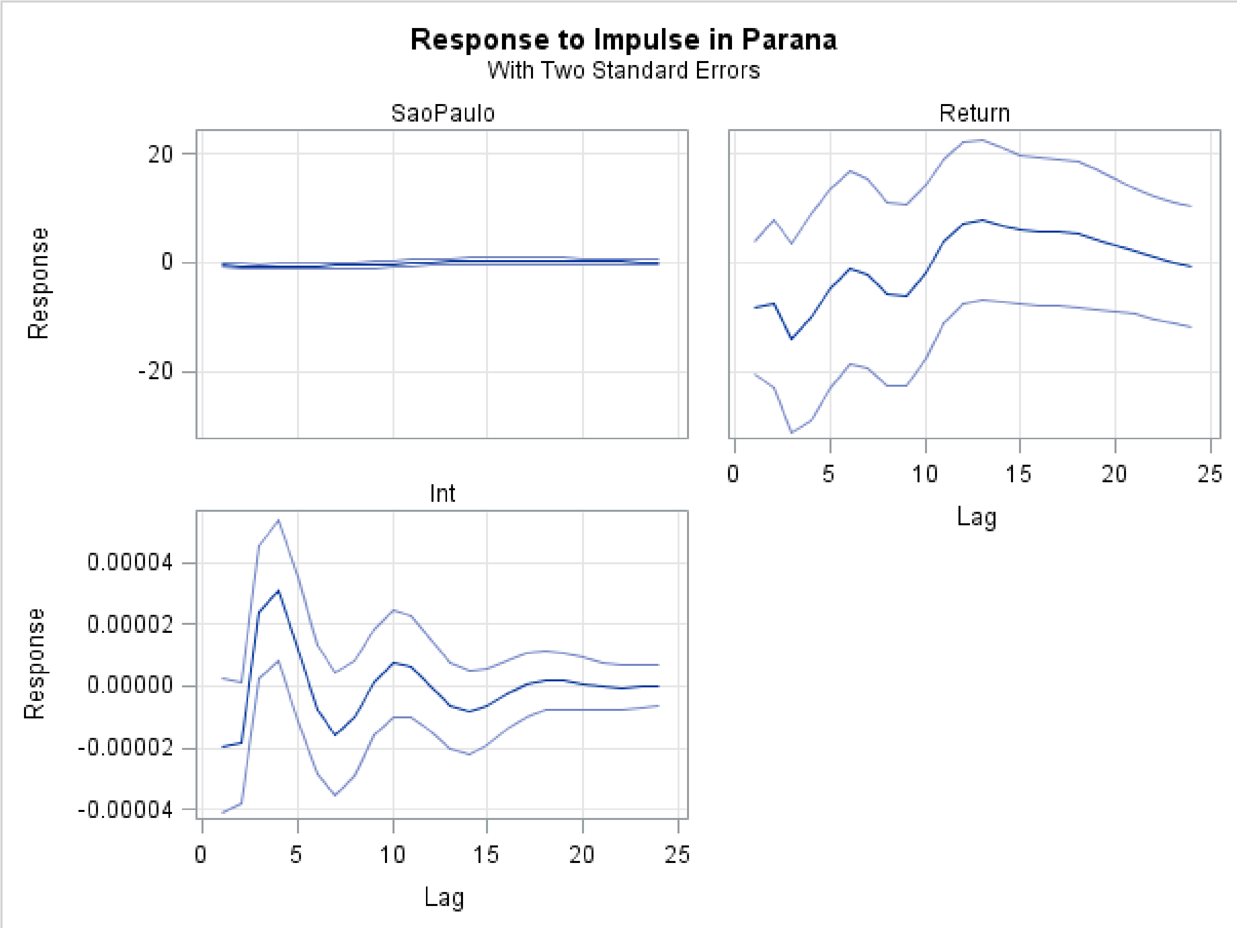
15
20
25


Response to Impulse in Parana
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag


Response to Impulse in Parana
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag


Response to Impulse in Parana
With Two Standard Errors
SaoPaulo
Return
Int
Response
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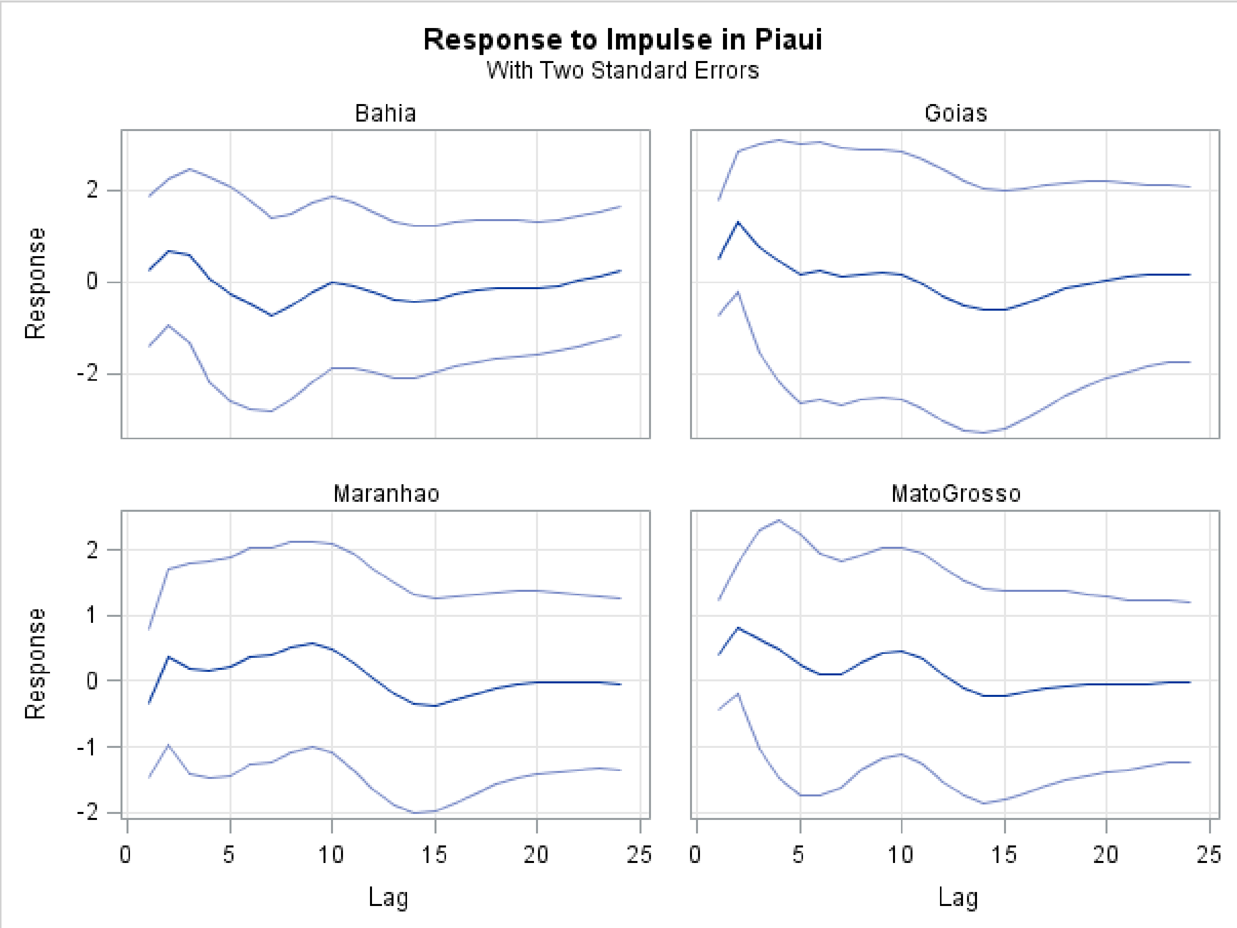
Response to Impulse in Piaui
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Lag
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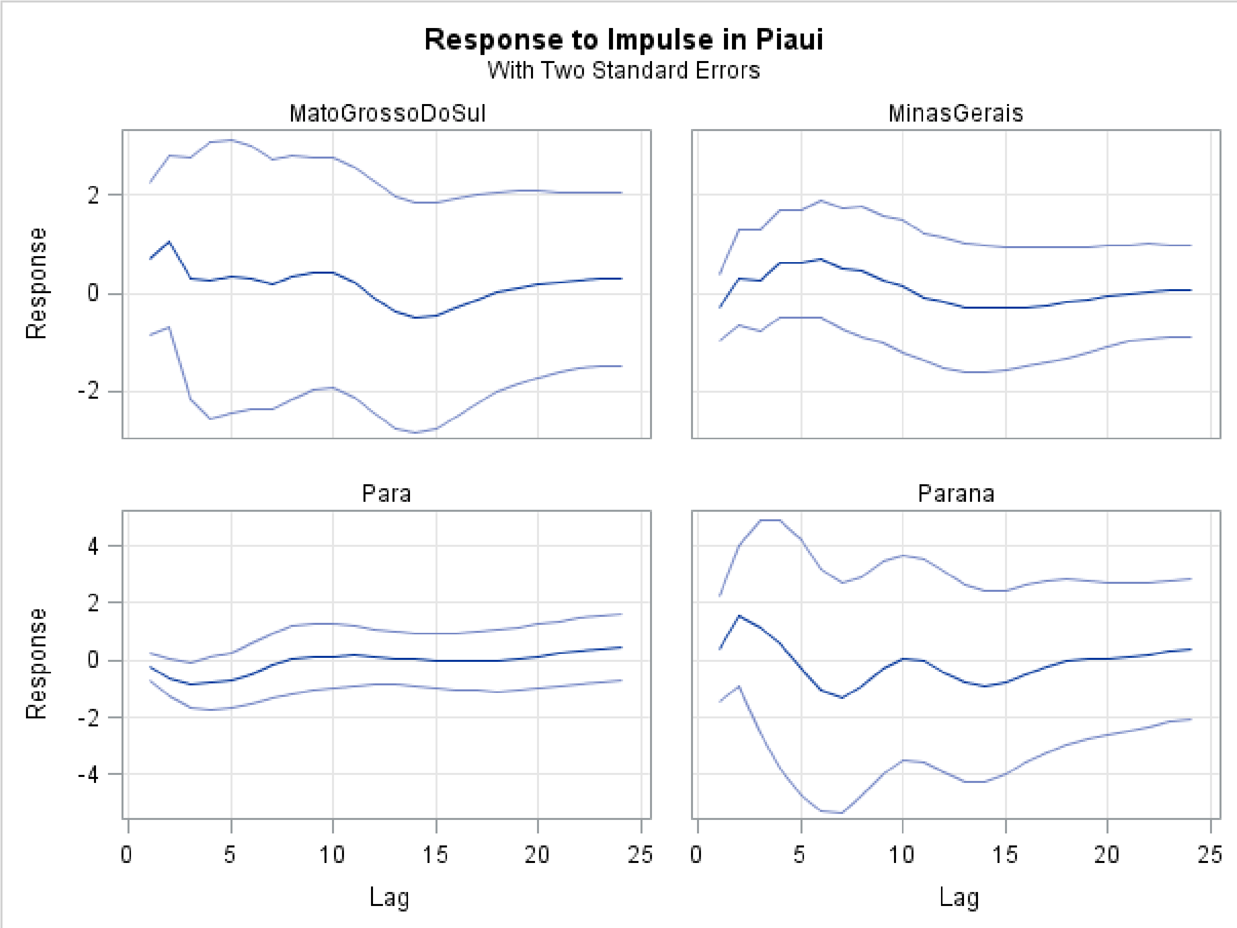
1
-1
5
10
15
20
25


Response to Impulse in Piaui
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Response
Lag
Lag
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-2
4
2
0
-2
-4
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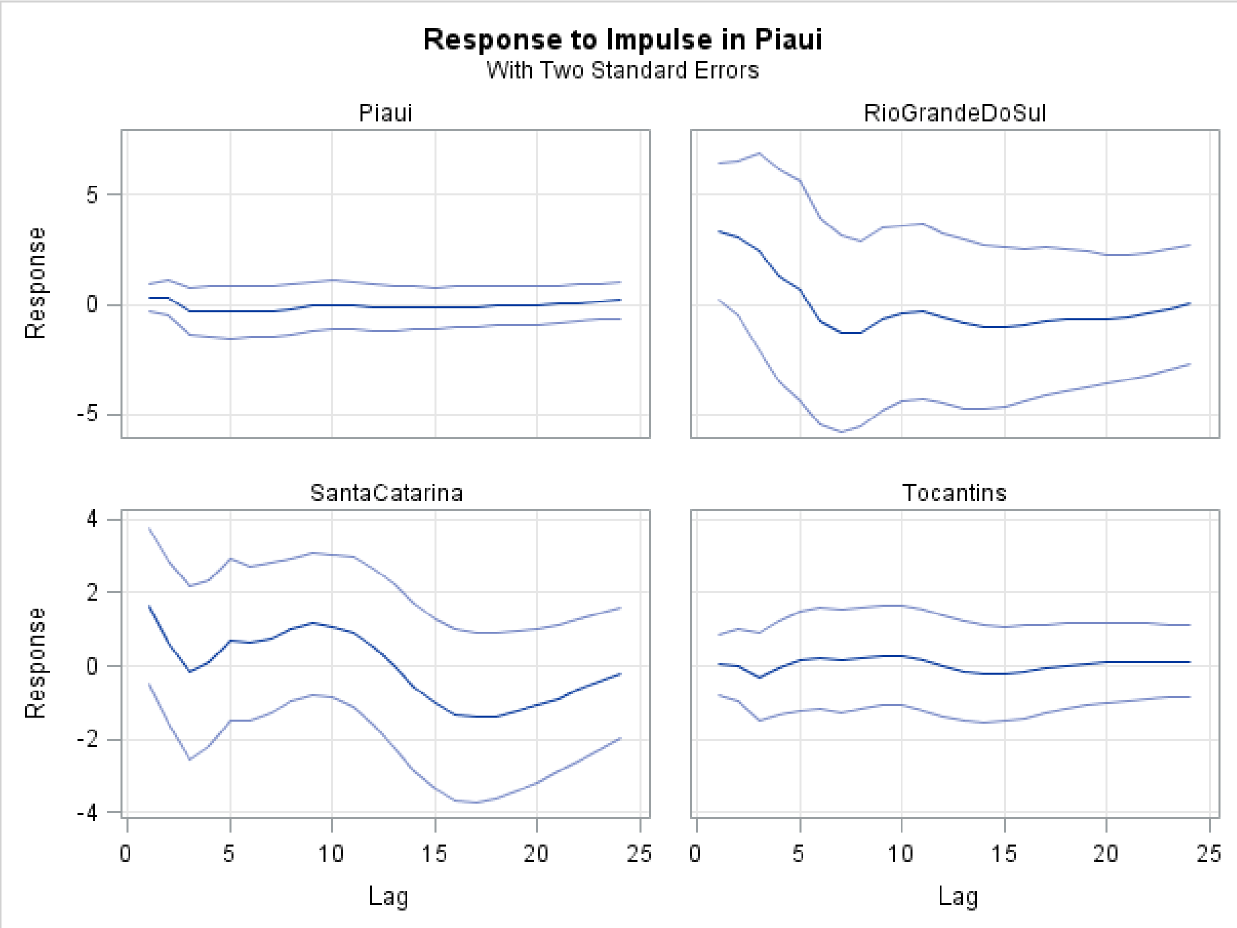
10
15
20
25


Response to Impulse in Piaui
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
Lag
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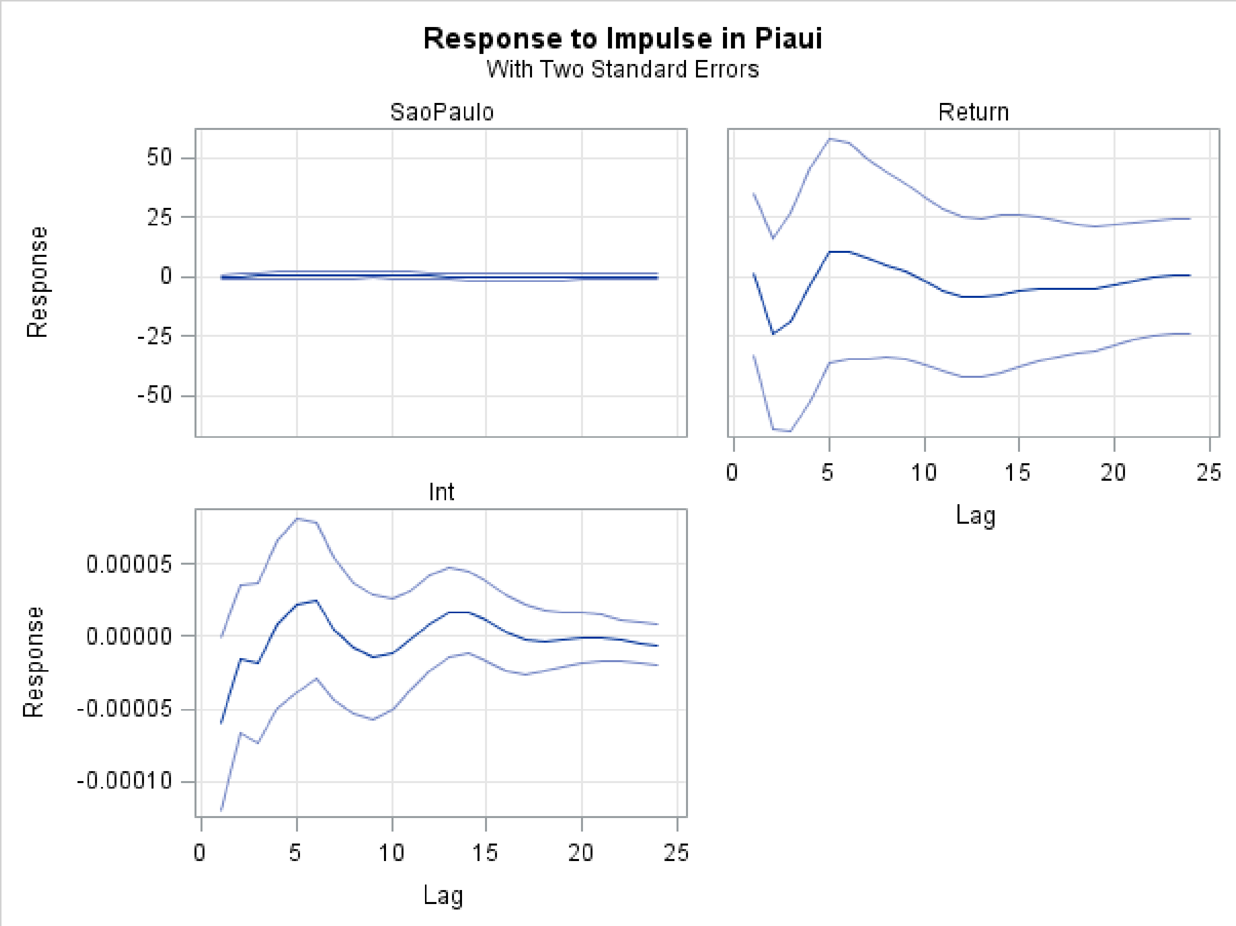
25


Response to Impulse in Piaui
With Two Standard Errors
SaoPaulo
Return
Int
Response
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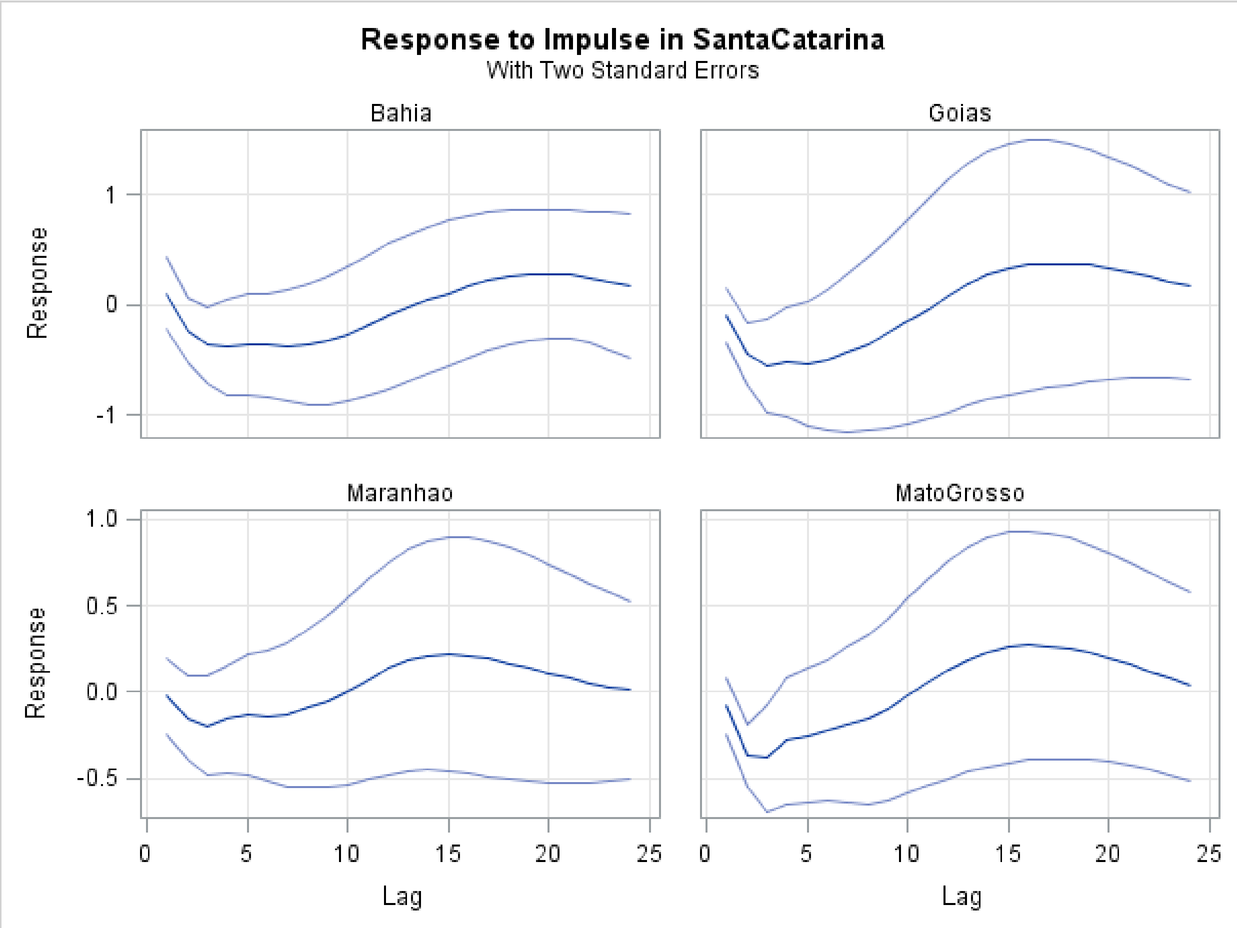
Response to Impulse in SantaCatarina
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
Lag
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-1
1.0
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0.0
-0.5
0
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10
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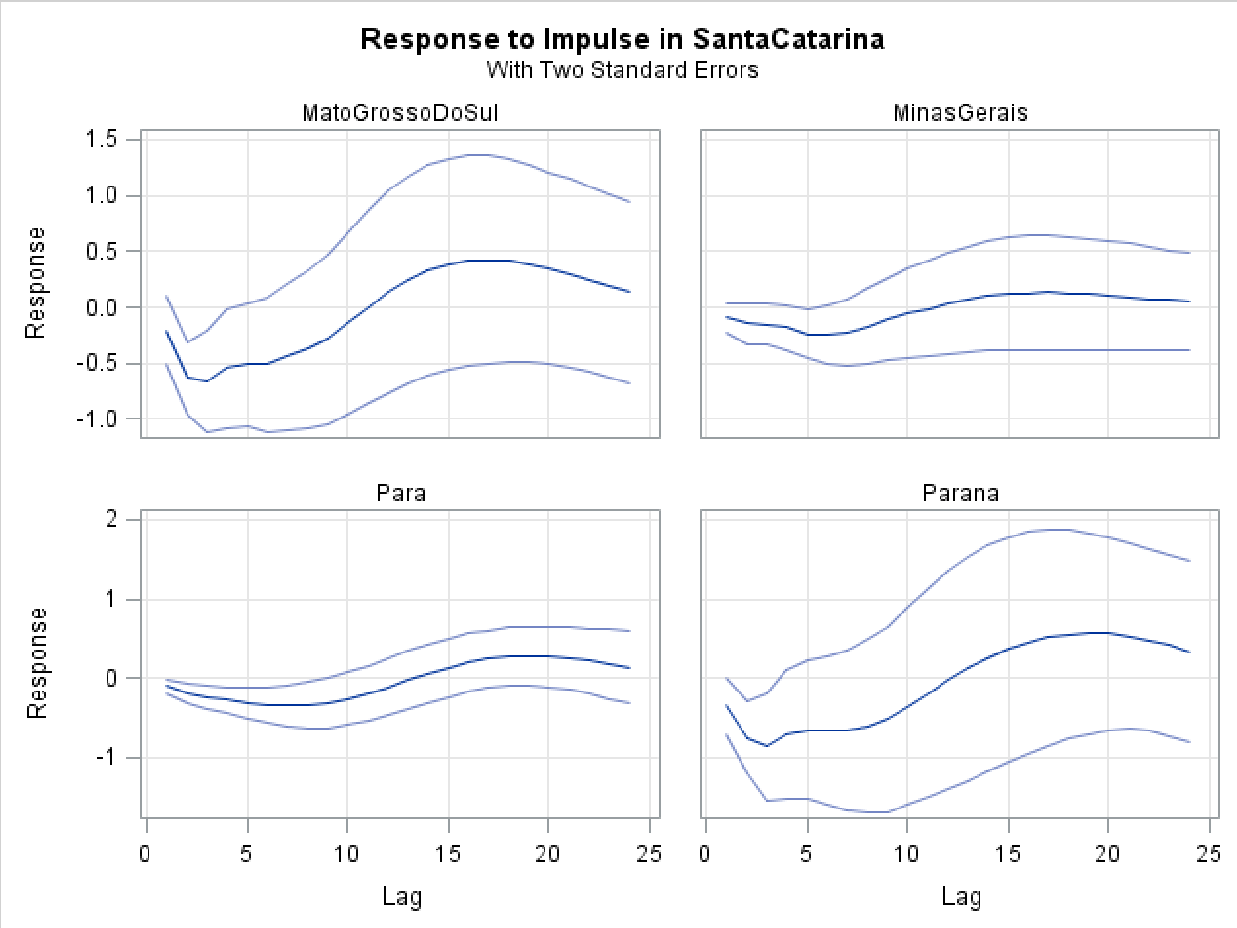
20
25


Response to Impulse in SantaCatarina
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Response
Lag
Lag
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-0.5
-1.0
2
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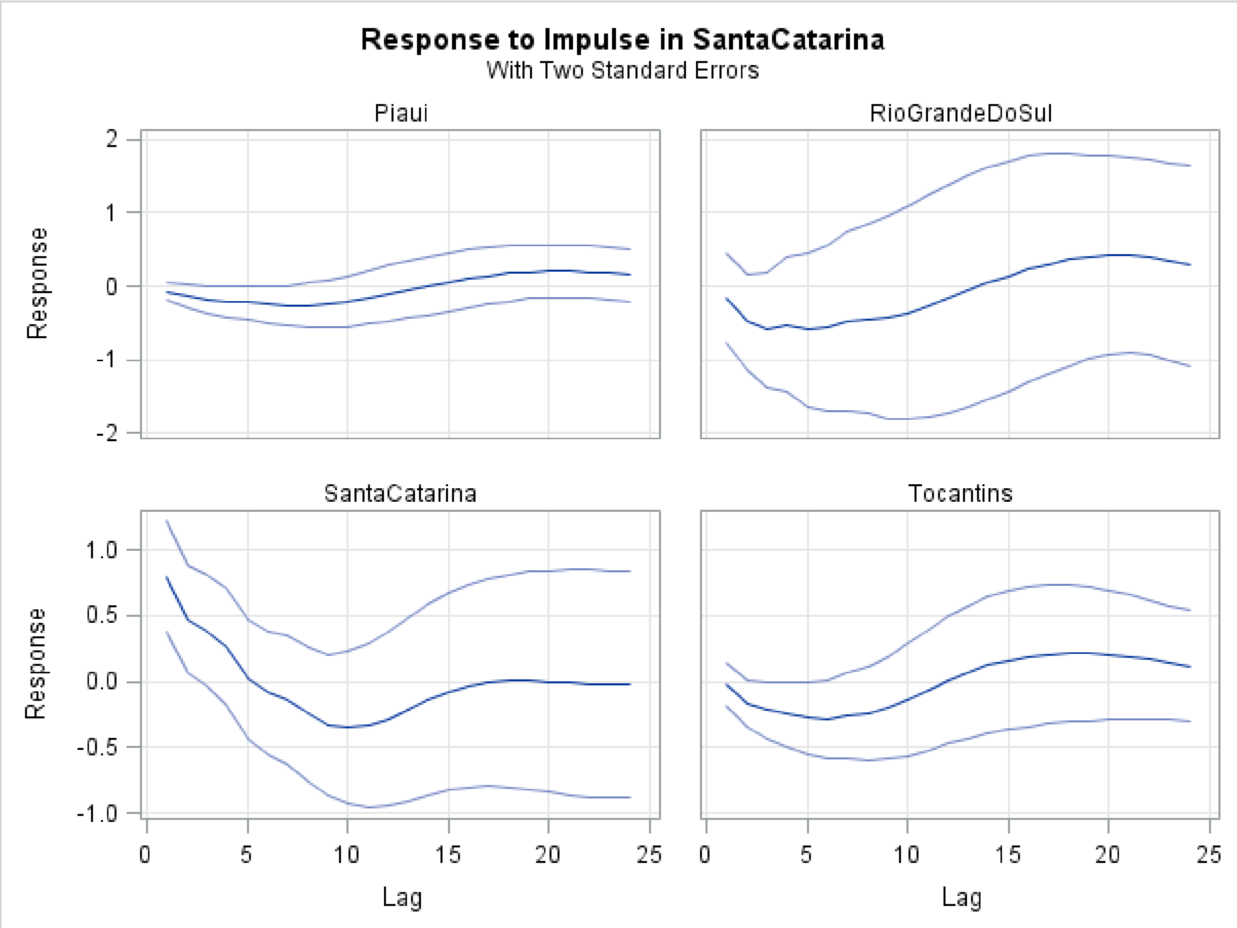
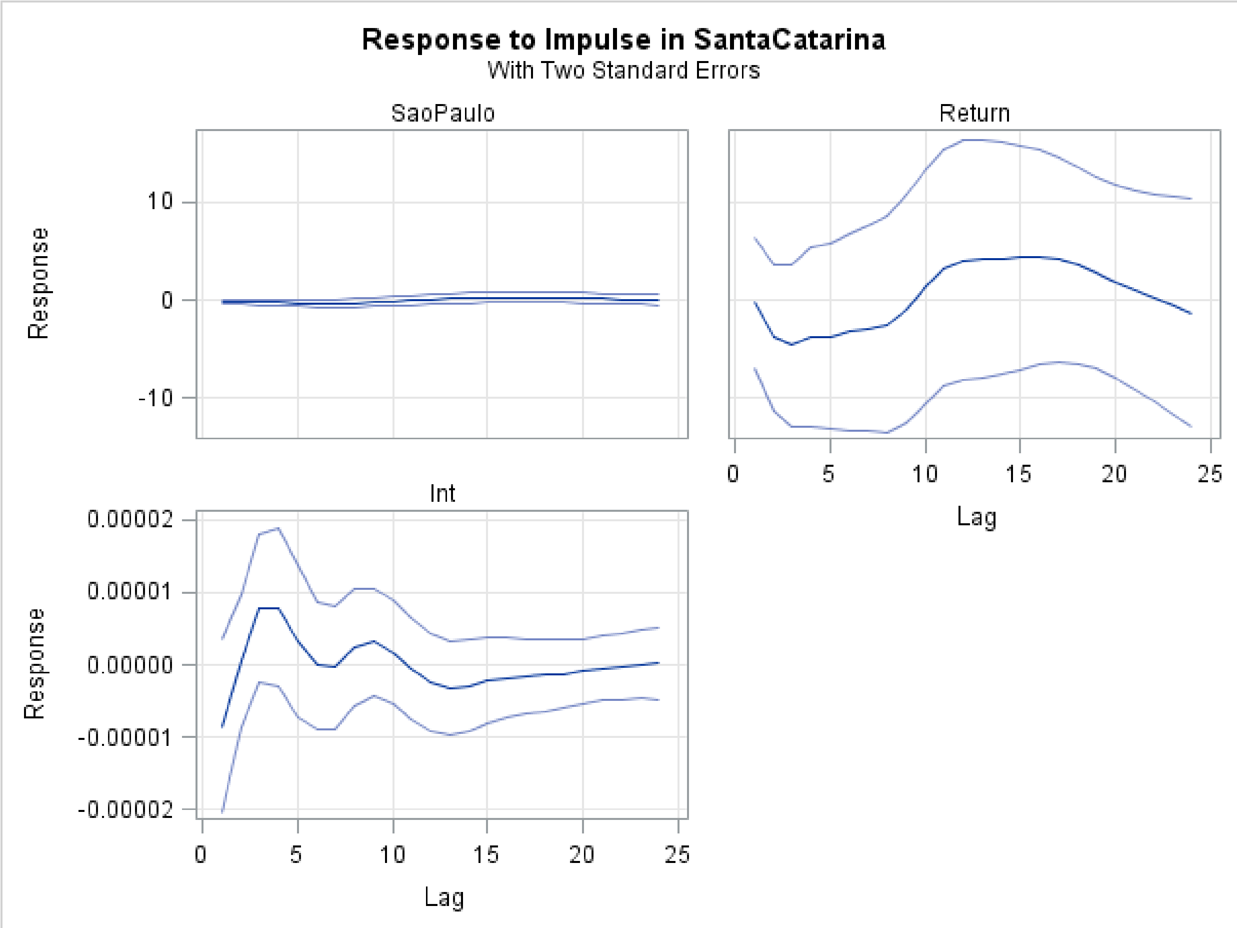
-1
0
5
10
15
20
25


Response to Impulse in SantaCatarina
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag


Response to Impulse in SantaCatarina
With Two Standard Errors
SaoPaulo
Return
Int
Response
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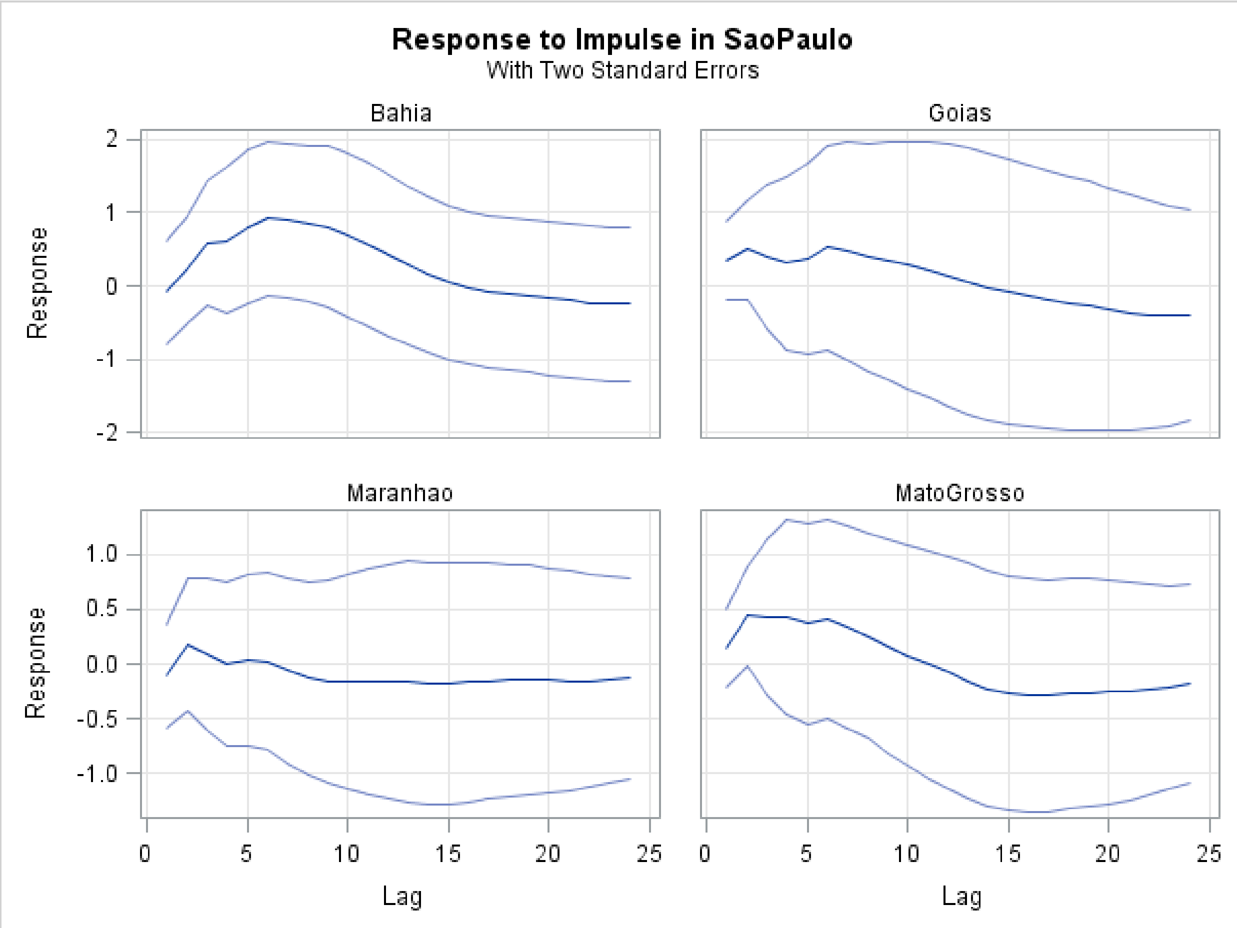
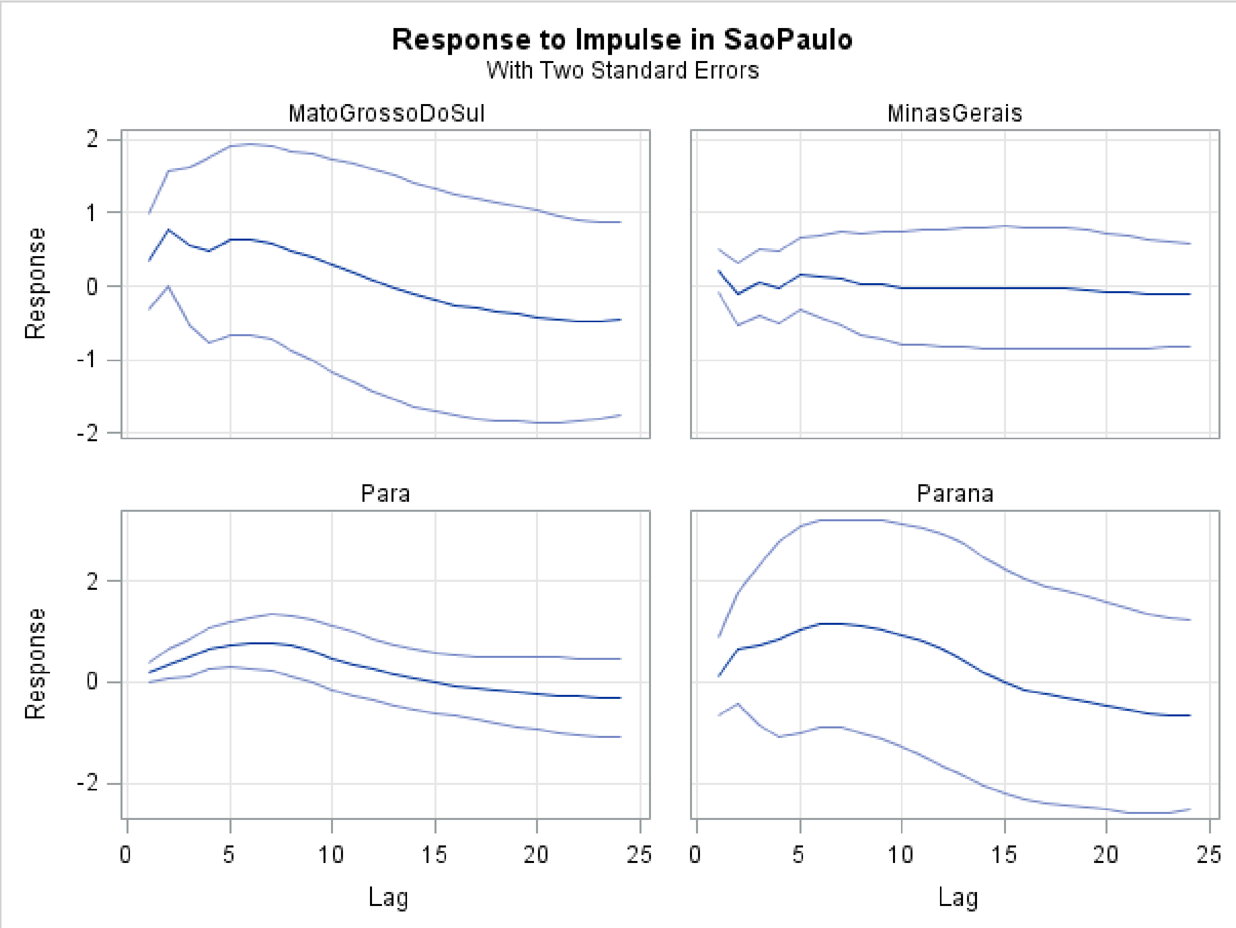
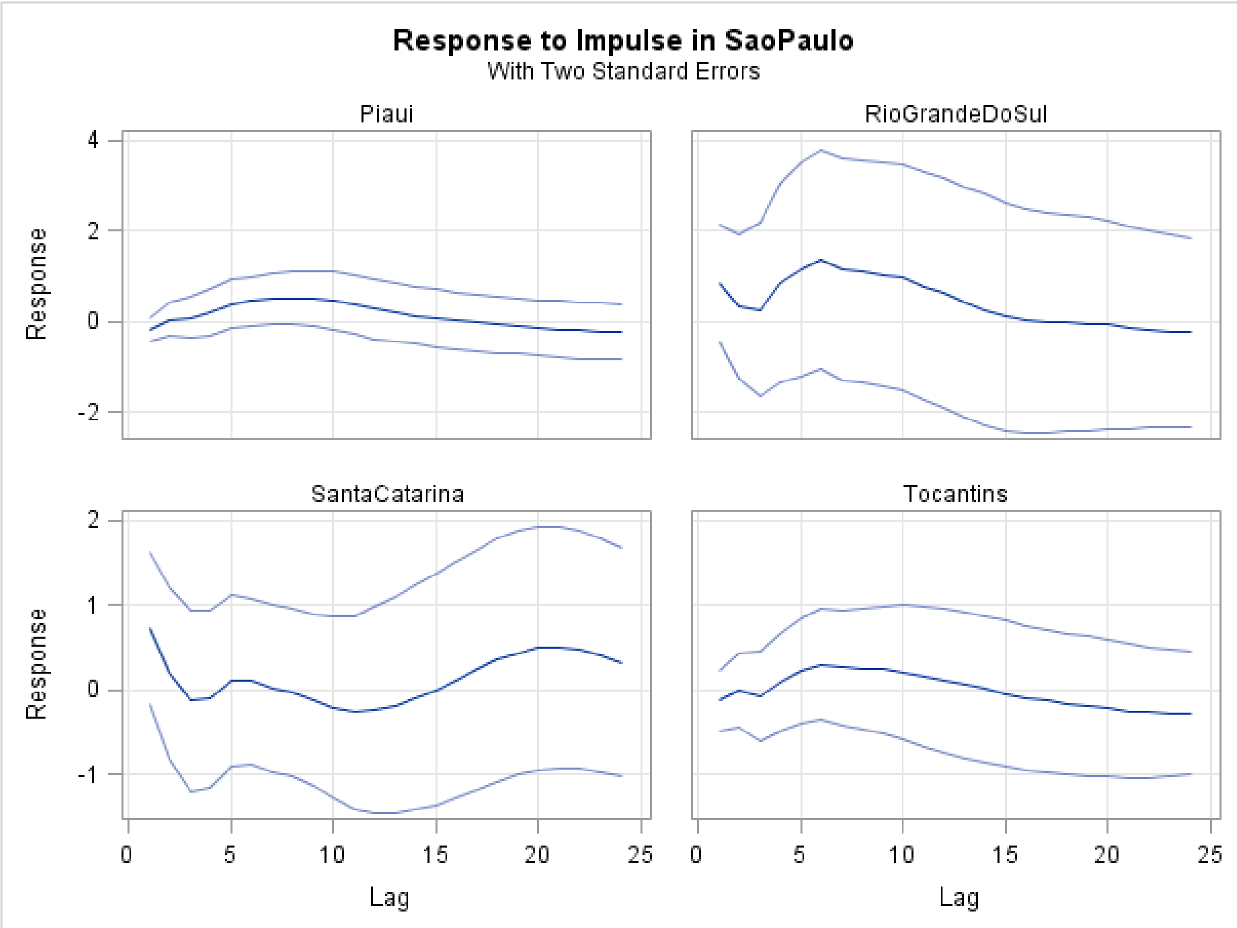
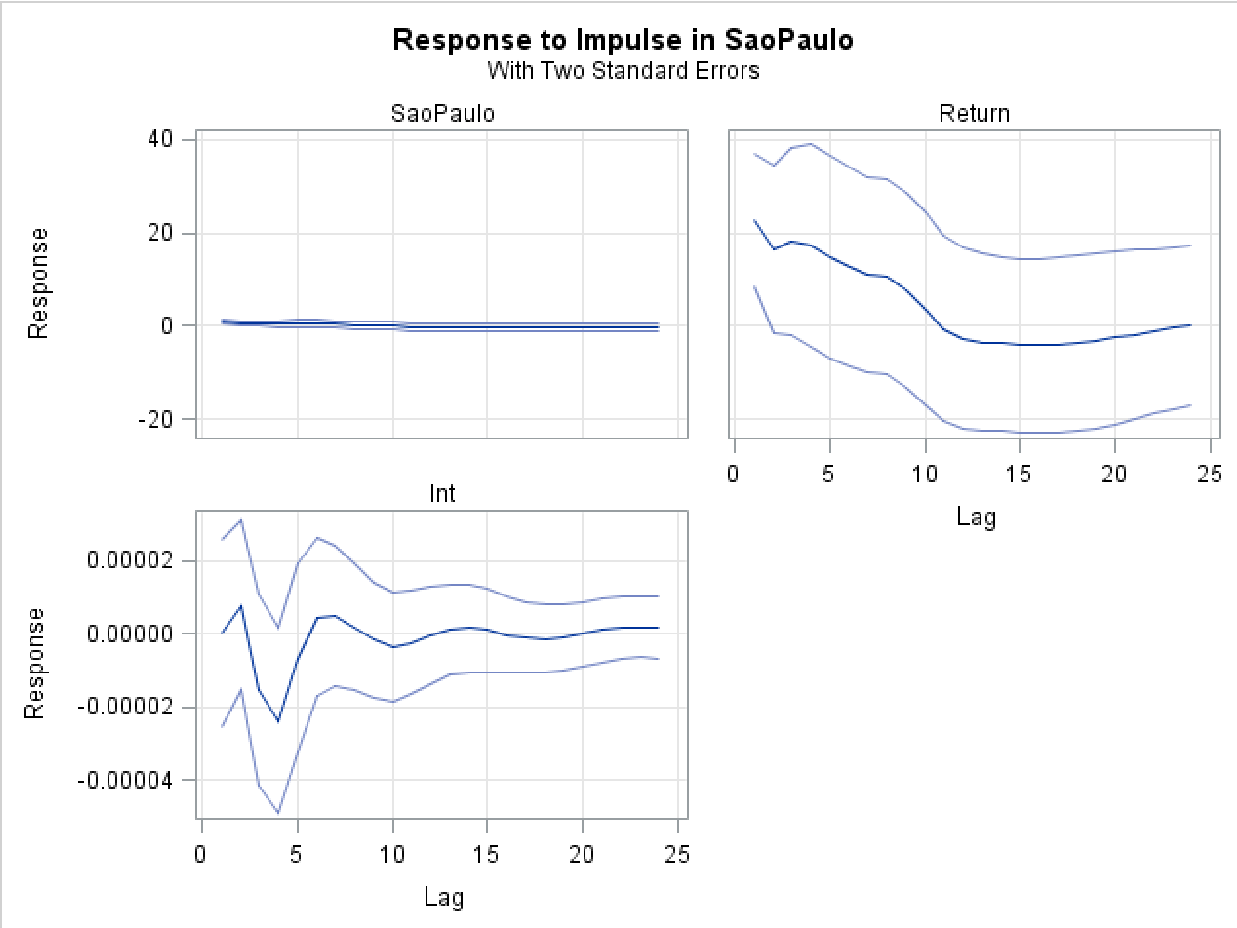
5
10
15
20
25



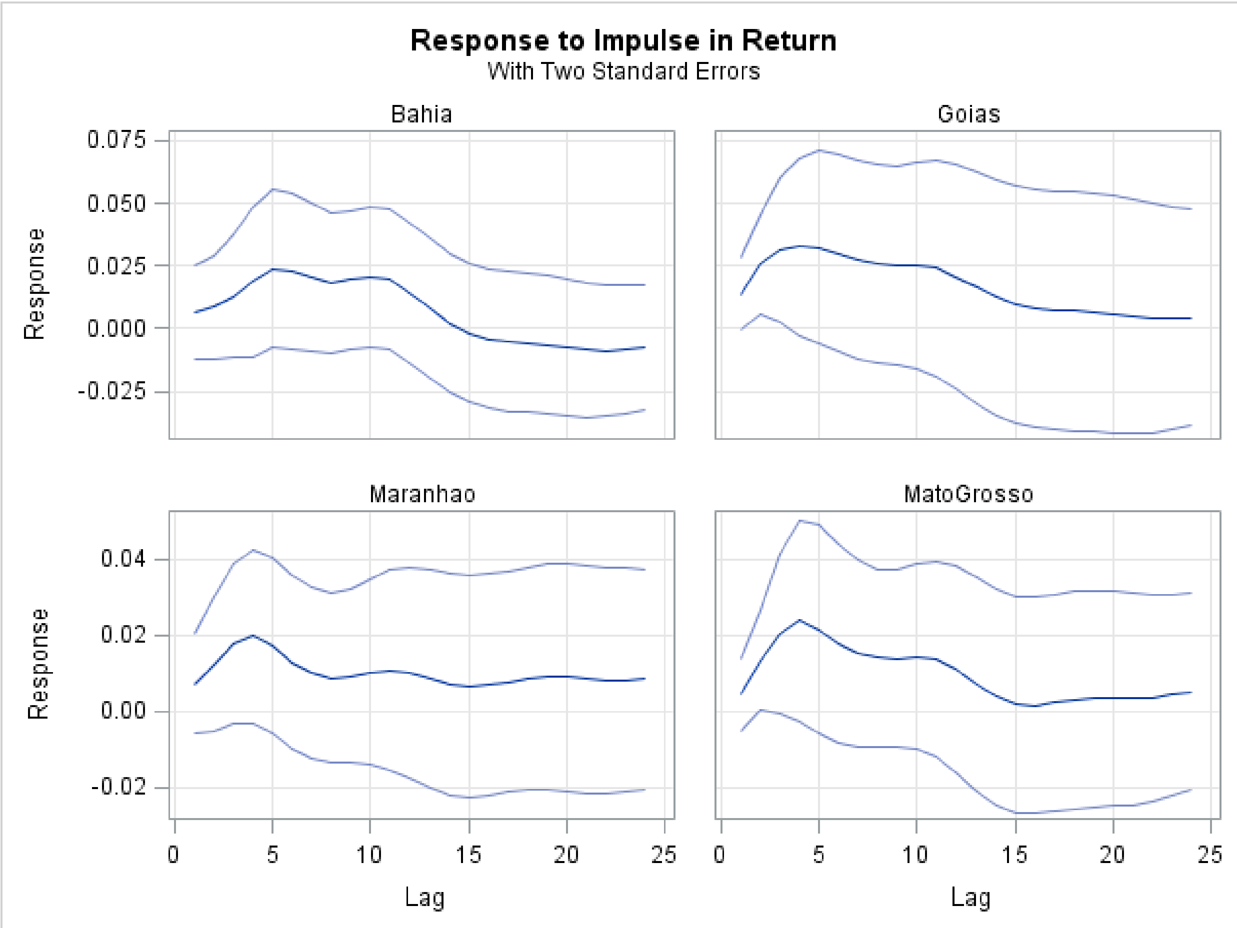
Response to Impulse in SaoPaulo
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Lag

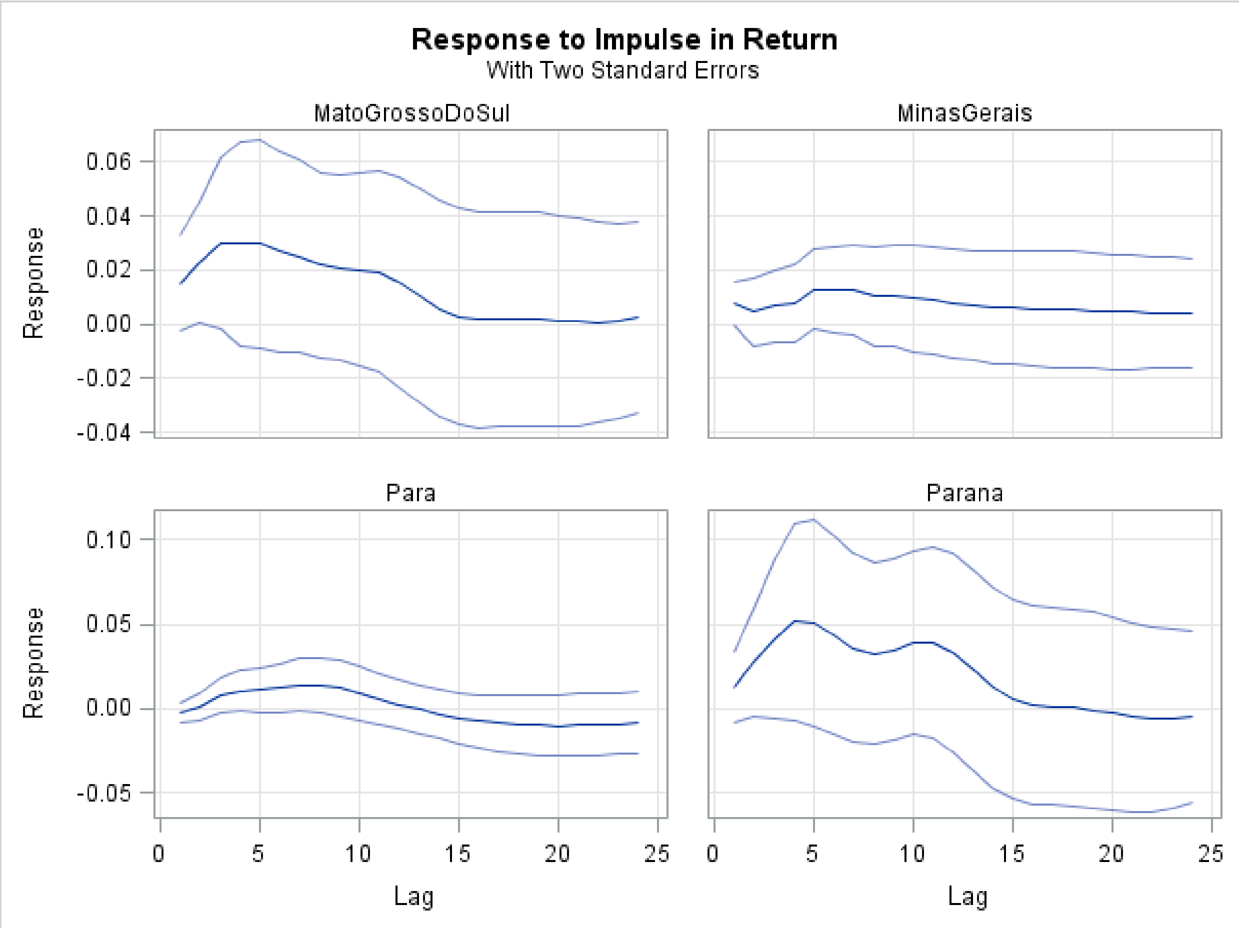

Response to Impulse in SaoPaulo
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Response
Lag
Lag
2
1
0
-1
-2
2
0
-2
0
5
10
15
20
25
0
5
10
15
20
25

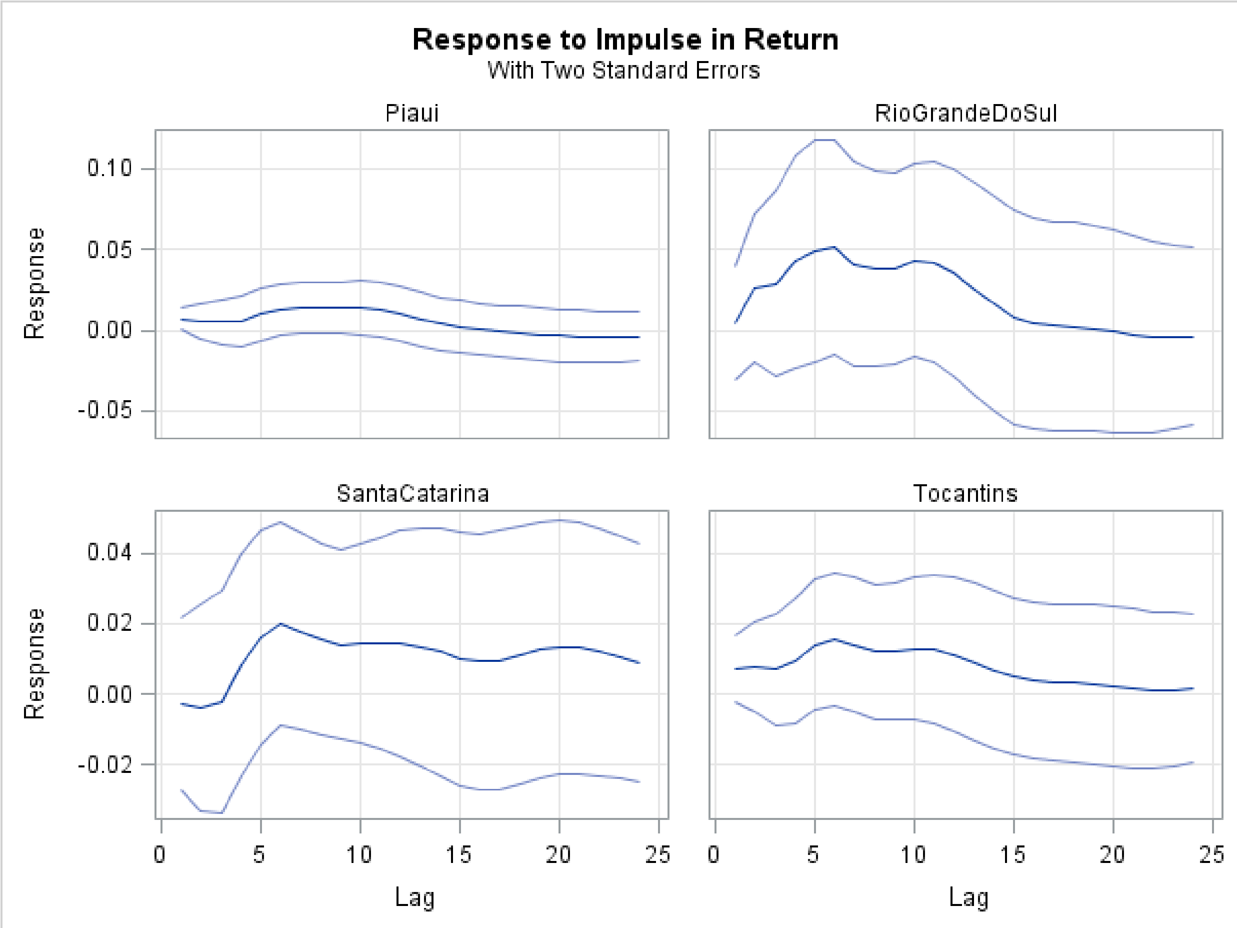

Response to Impulse in SaoPaulo
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
Lag
Lag
4
2
0
-2
2
1
0
-1
0
5
10
15
20
25



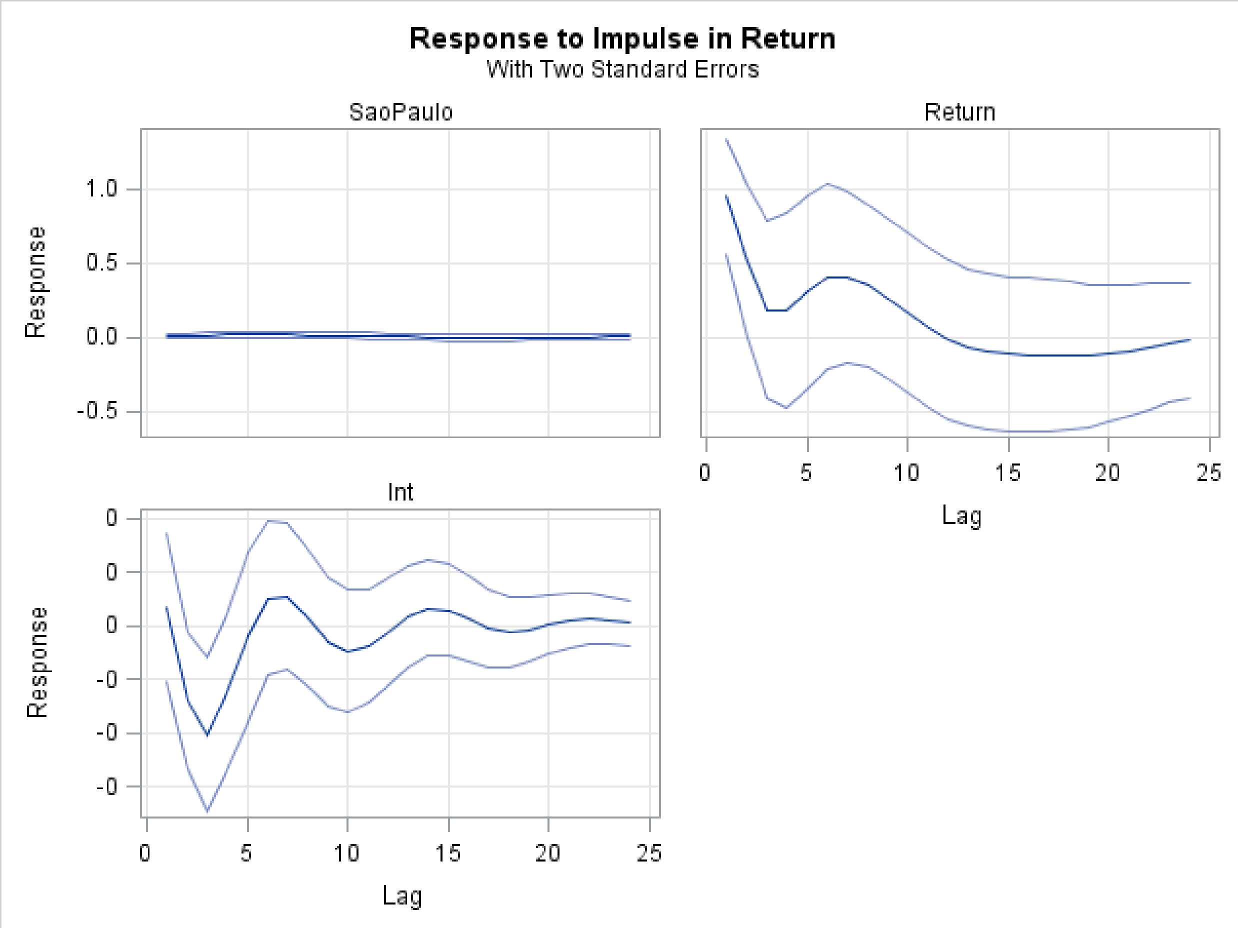
Response to Impulse in SaoPaulo
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
40
20
0
-20
0.00002
0.00000
-0.00002
-0.00004
0
5
10
15
20
25

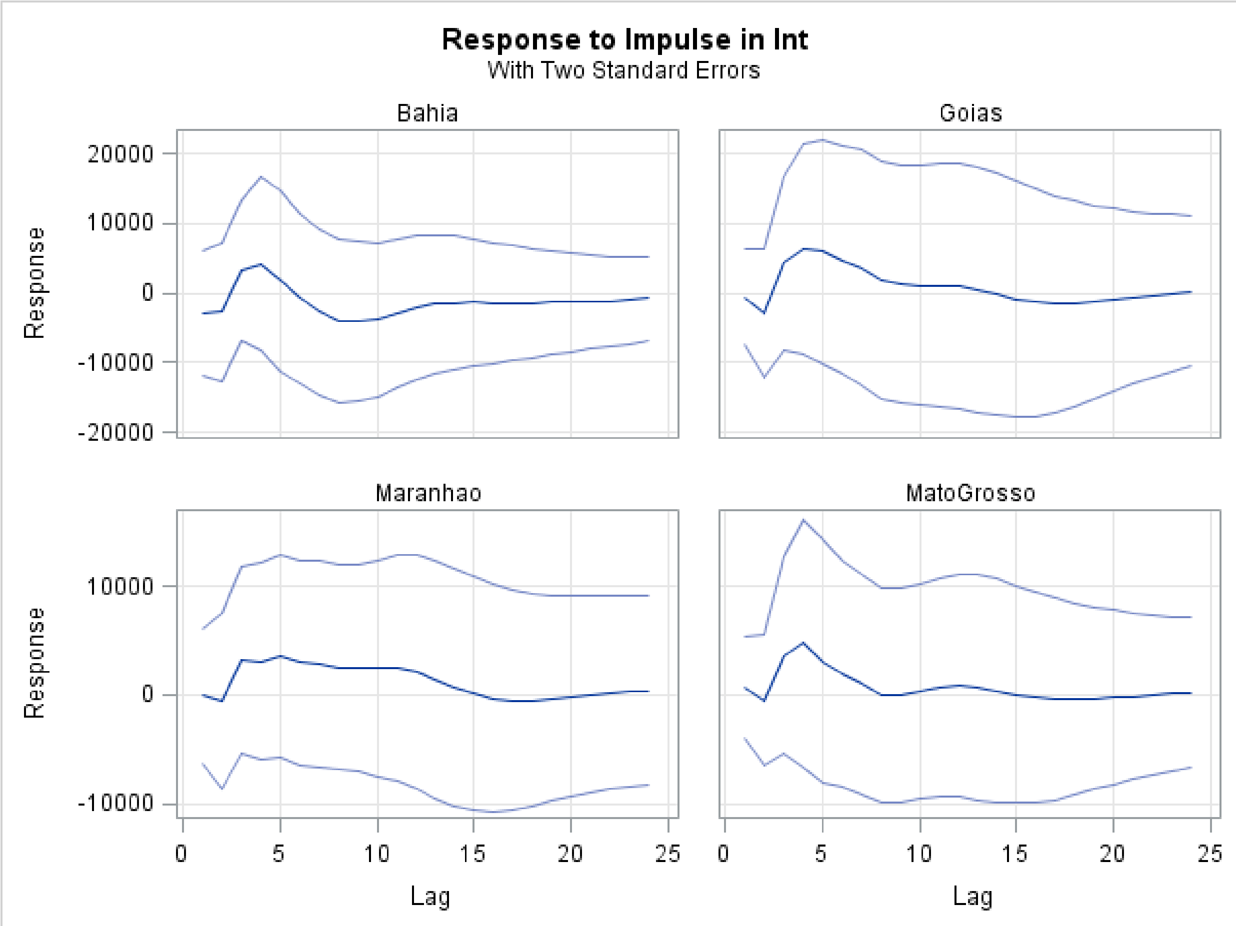

Response to Impulse in Return
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
0.075
0.050
0.025
0.000
-0.025
0.04
0.02
0.00
-0.02
0
5
10
15
20
25
Lag
Lag


Response to Impulse in Return
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Lag
0.06
0.04
0.02
0.00
-0.02
-0.04
0.10
0.05
0.00
-0.05
0
5
10
15
20
25

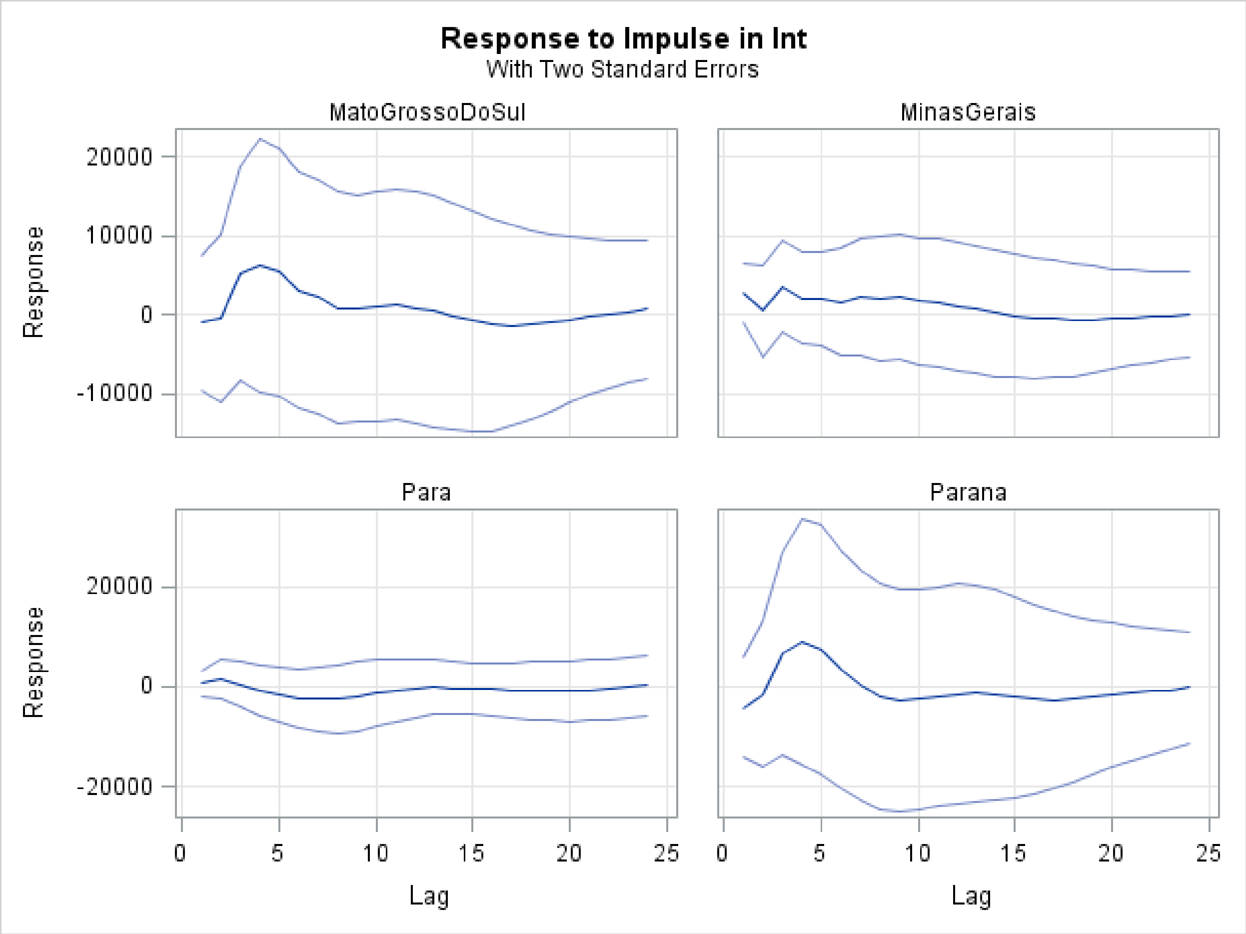


Response to Impulse in Return
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Response
0.10
0.05
0.00
-0.05
0.04
0.02
0.00
-0.02
0
5
10
15
20
25
Lag
Lag

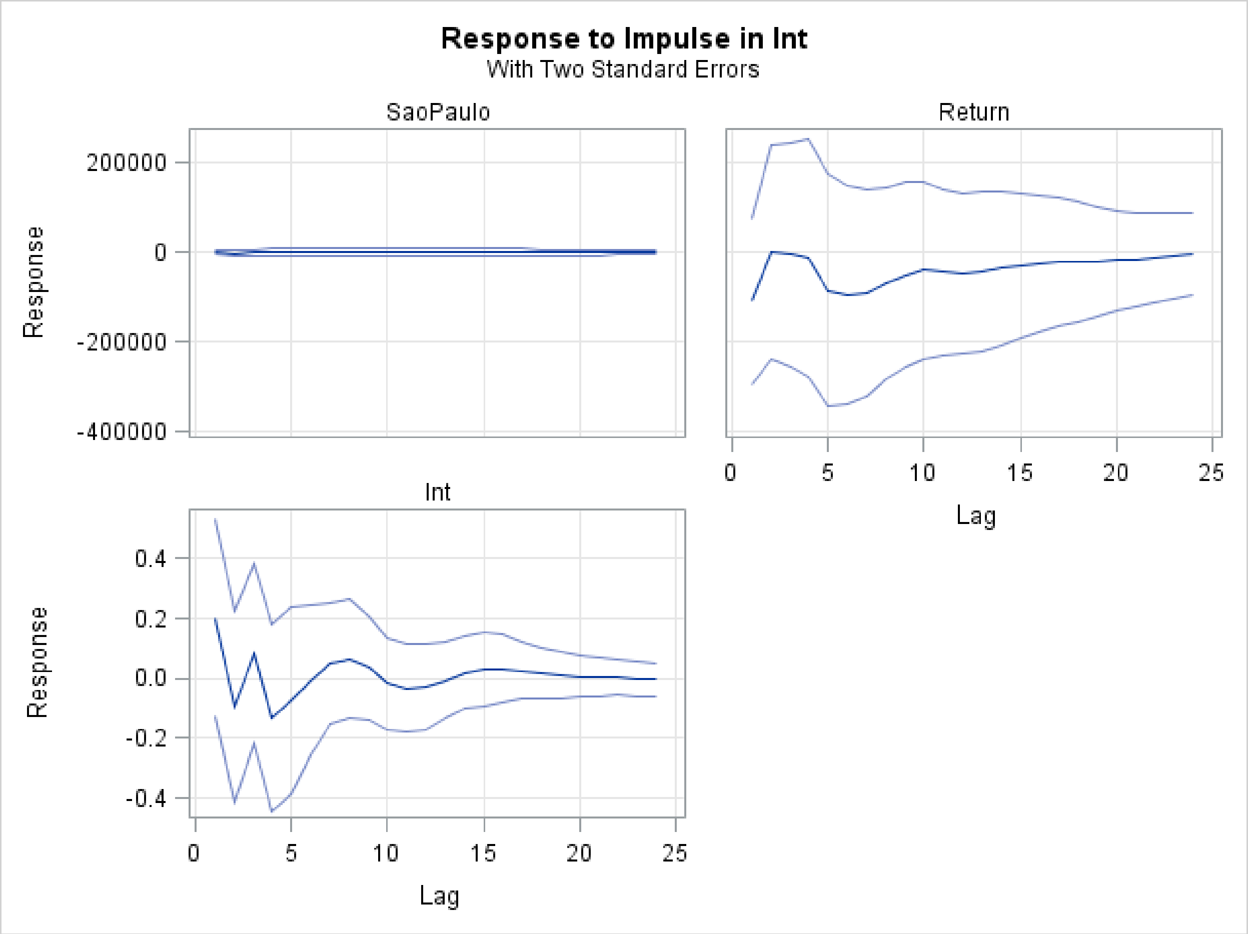

Response to Impulse in Return
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
1.0
0.5
0.0
-0.5
0
5
10
15
20
25
0
-0



Response to Impulse in Int
With Two Standard Errors
Bahia
Goias
Maranhao
MatoGrosso
Response
Response
20000
10000
0
-10000
-20000
10000
0
-10000
0
5
10
15
20
25
Lag
Lag

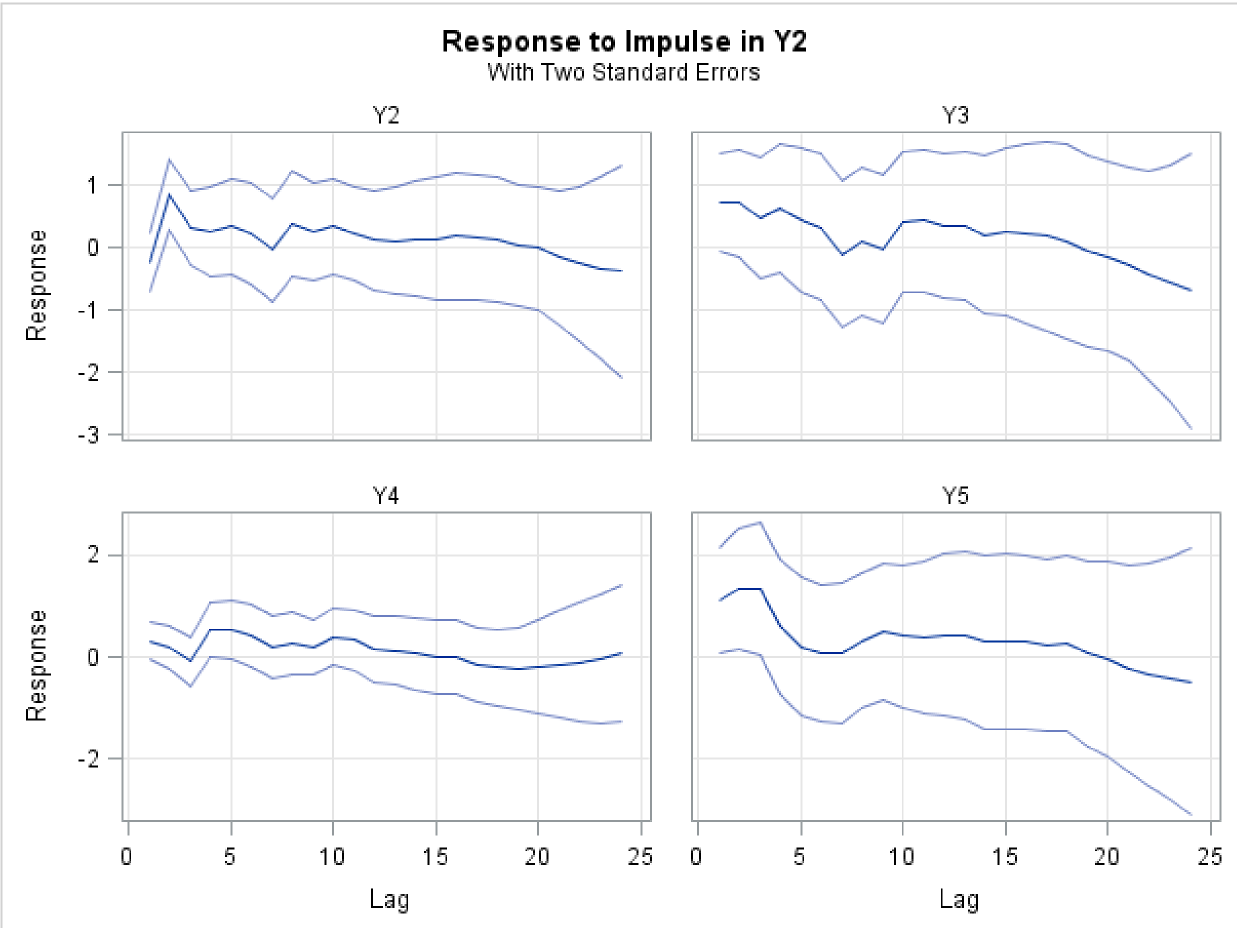

Response to Impulse in Int
With Two Standard Errors
MatoGrossoDoSul
MinasGerais
Para
Parana
Response
Response
Lag
Lag
20000
10000
0
-10000
20000
0
-20000
0
5
10
15
20
25

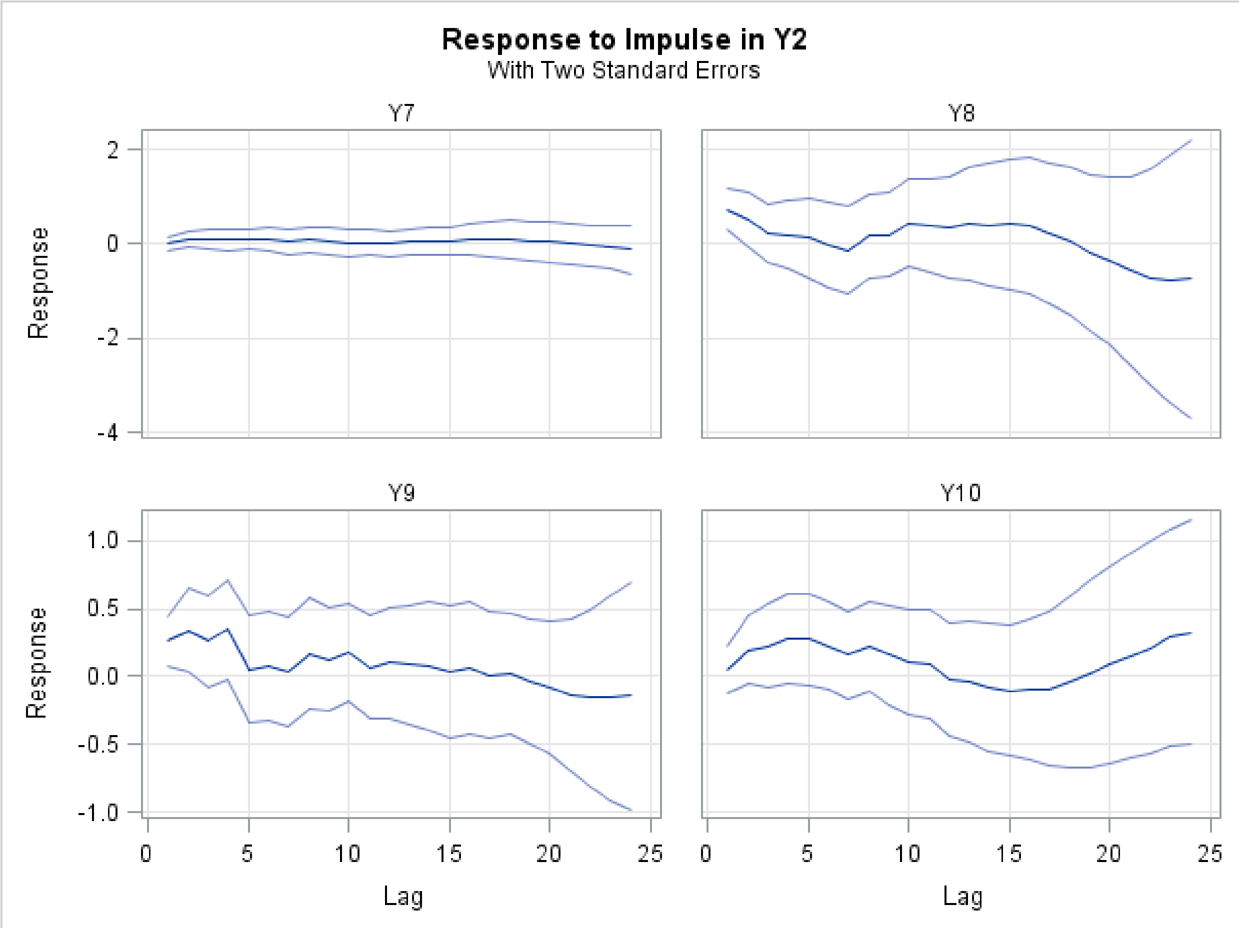

Response to Impulse in Int
With Two Standard Errors
Piaui
RioGrandeDoSul
SantaCatarina
Tocantins
Response
Lag
40000
20000
0
-20000
10000
-10000
0
5
10
15
20
25


Response to Impulse in Int
With Two Standard Errors
SaoPaulo
Return
Int
Response
Lag
200000
0
-200000
-400000
0.4
0.2
0.0
-0.2
-0.4
0
5
10
15
20
25

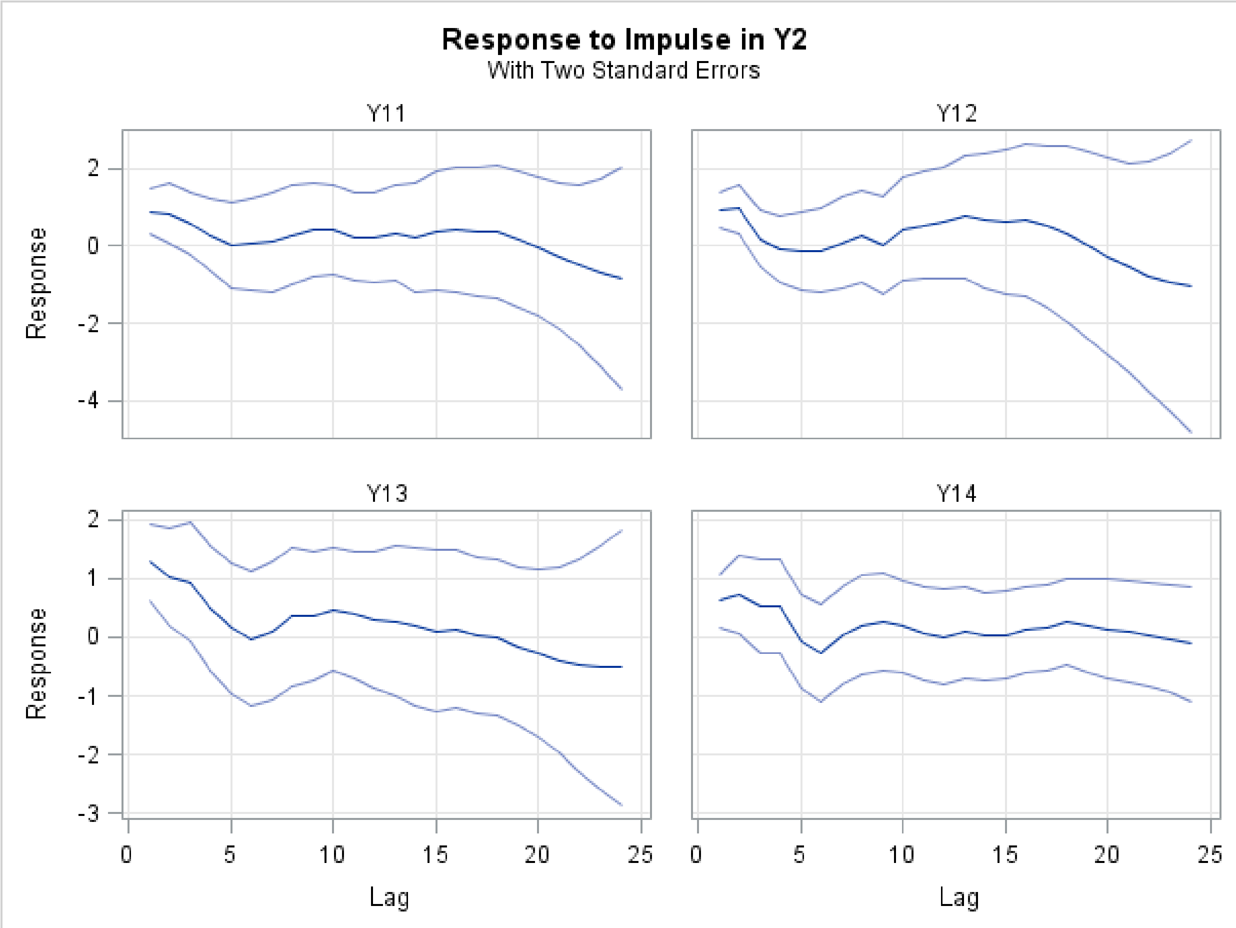
Impulse Response Functions-Micro Region Model

The following contains the complete set of impulse response function for the Vector Autoregression models used in the analysis. Those impulse response functions used in the analysis can also be found at the end of Chapter 6

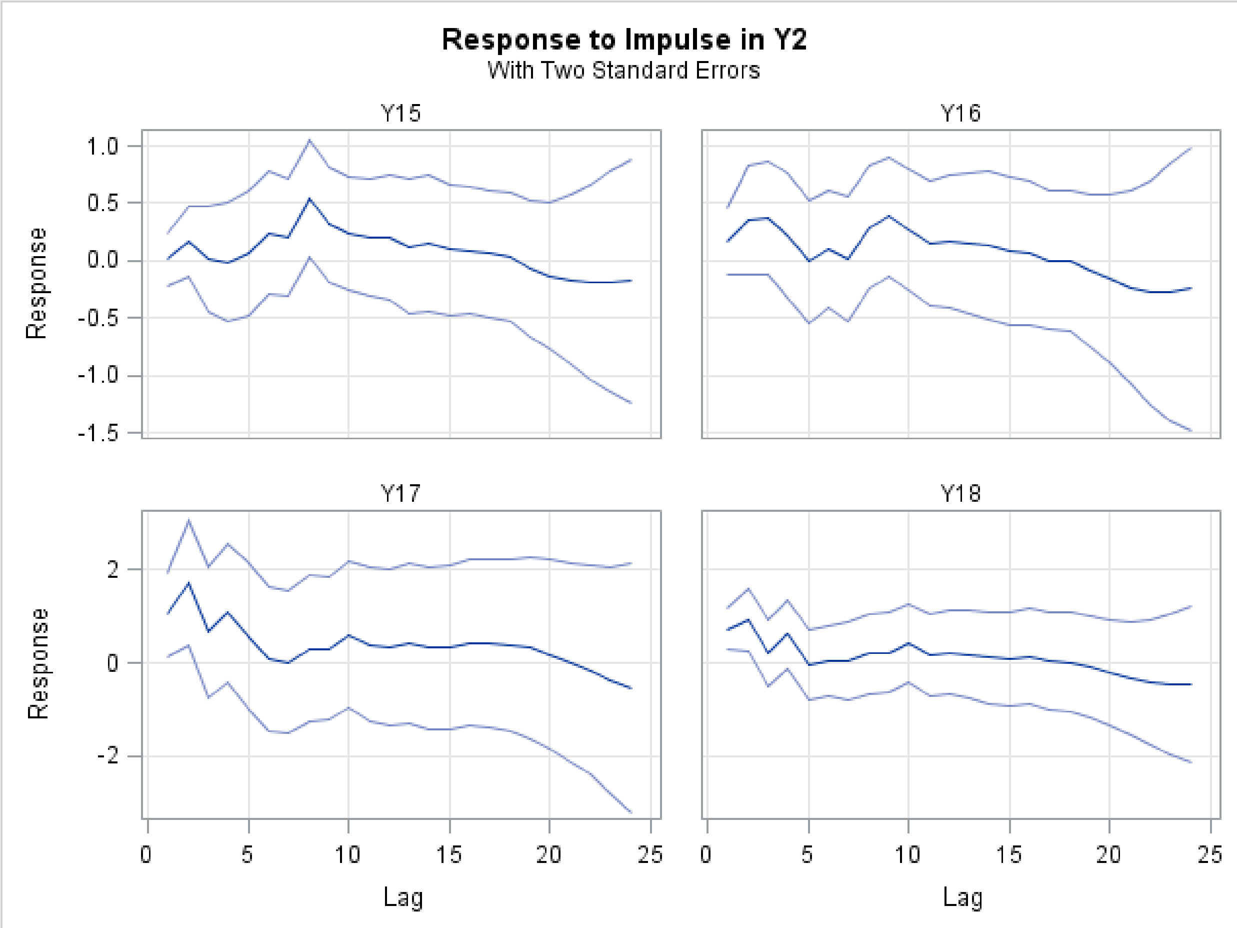


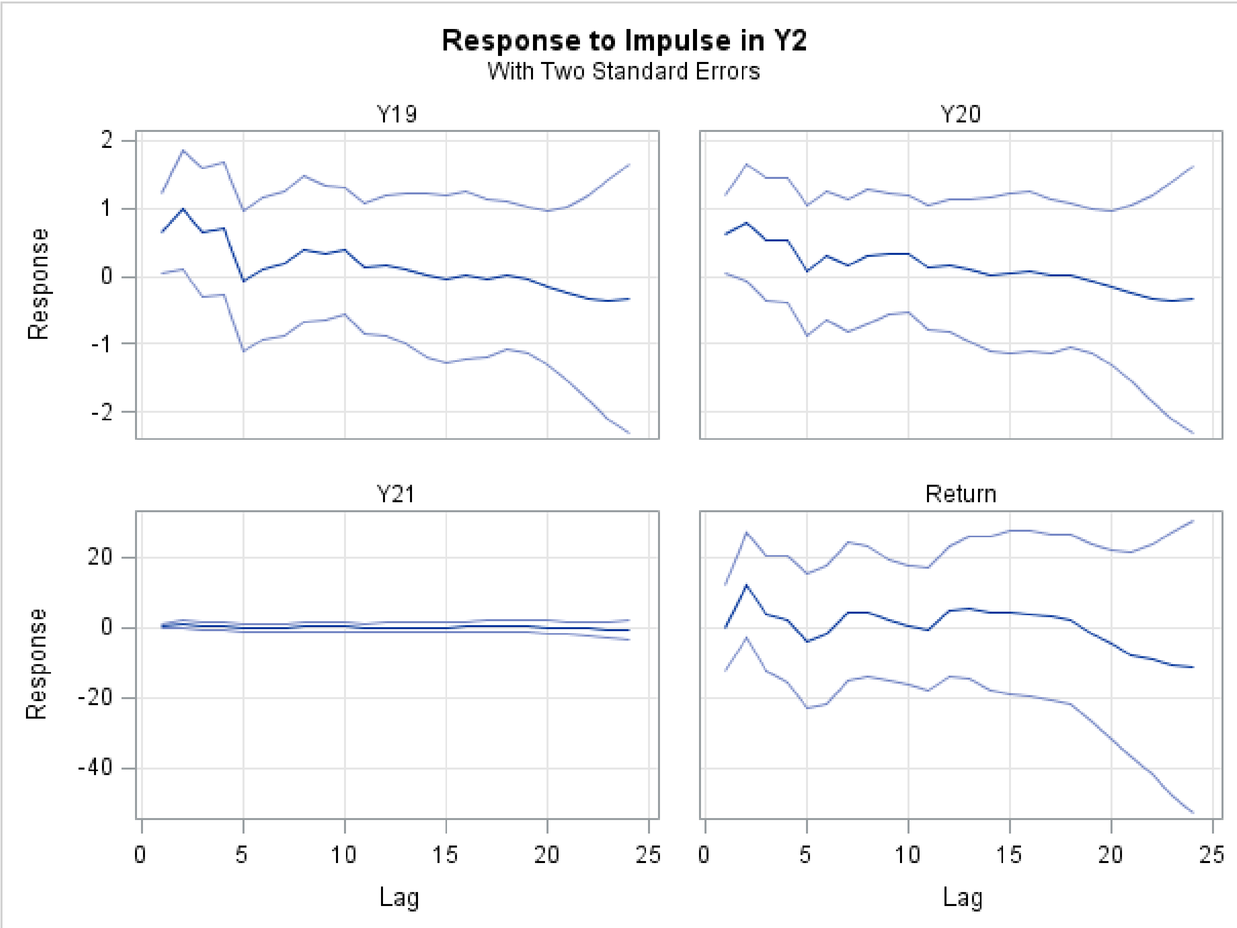


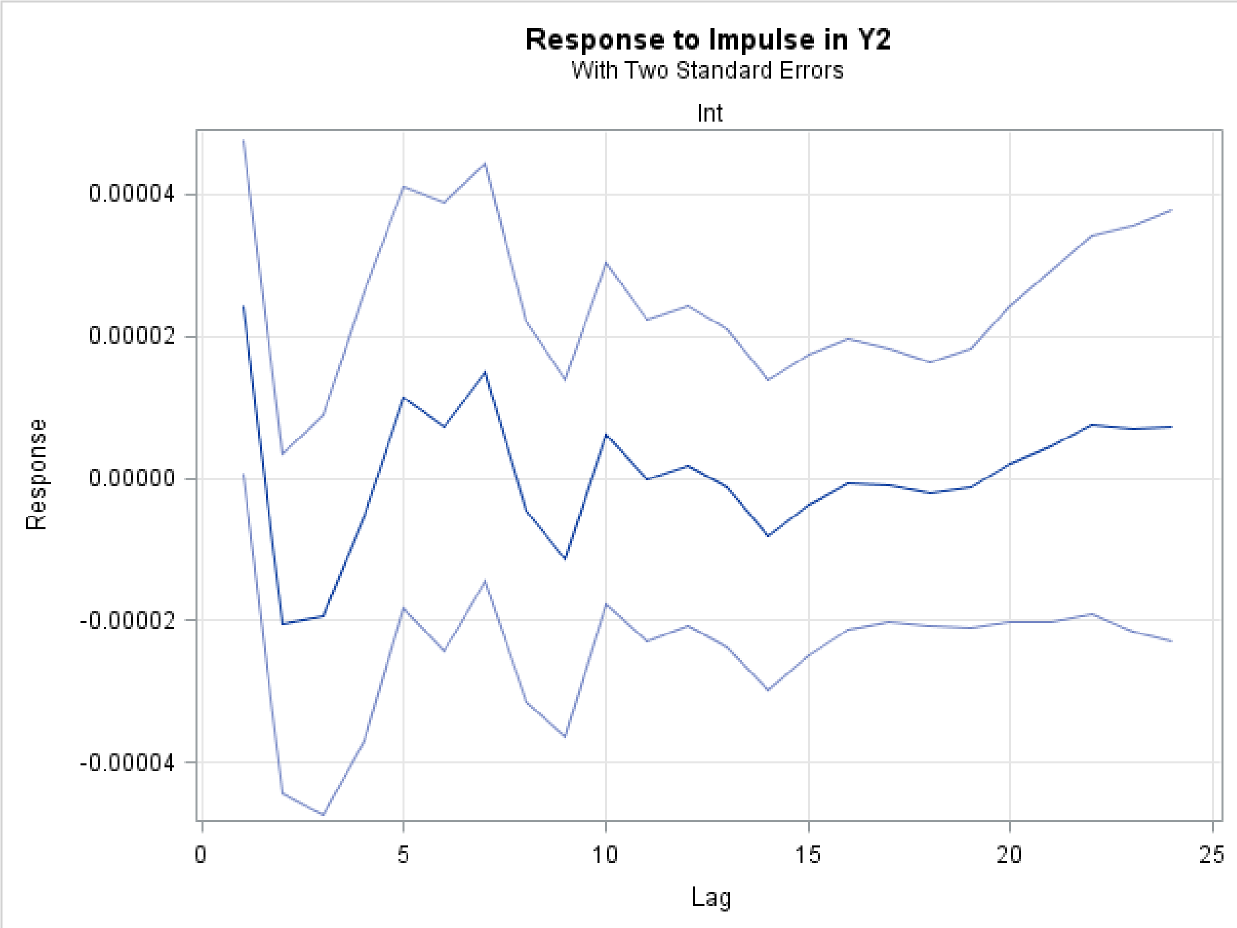
Response to Impulse in Y2
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
2
0
-2
-4
1.0
0.5
0.0
-0.5
-1.0
0
5
10
15
20
25

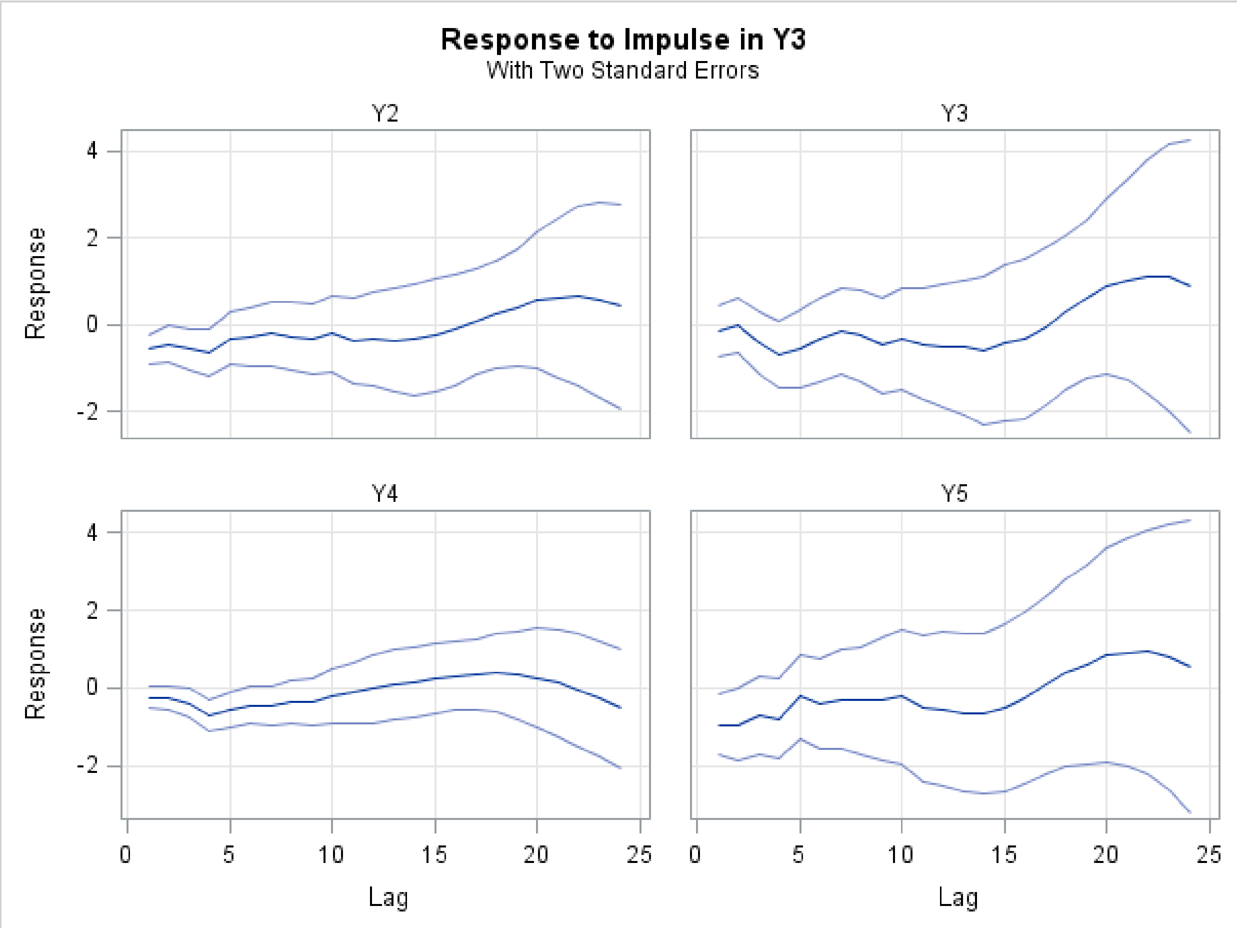


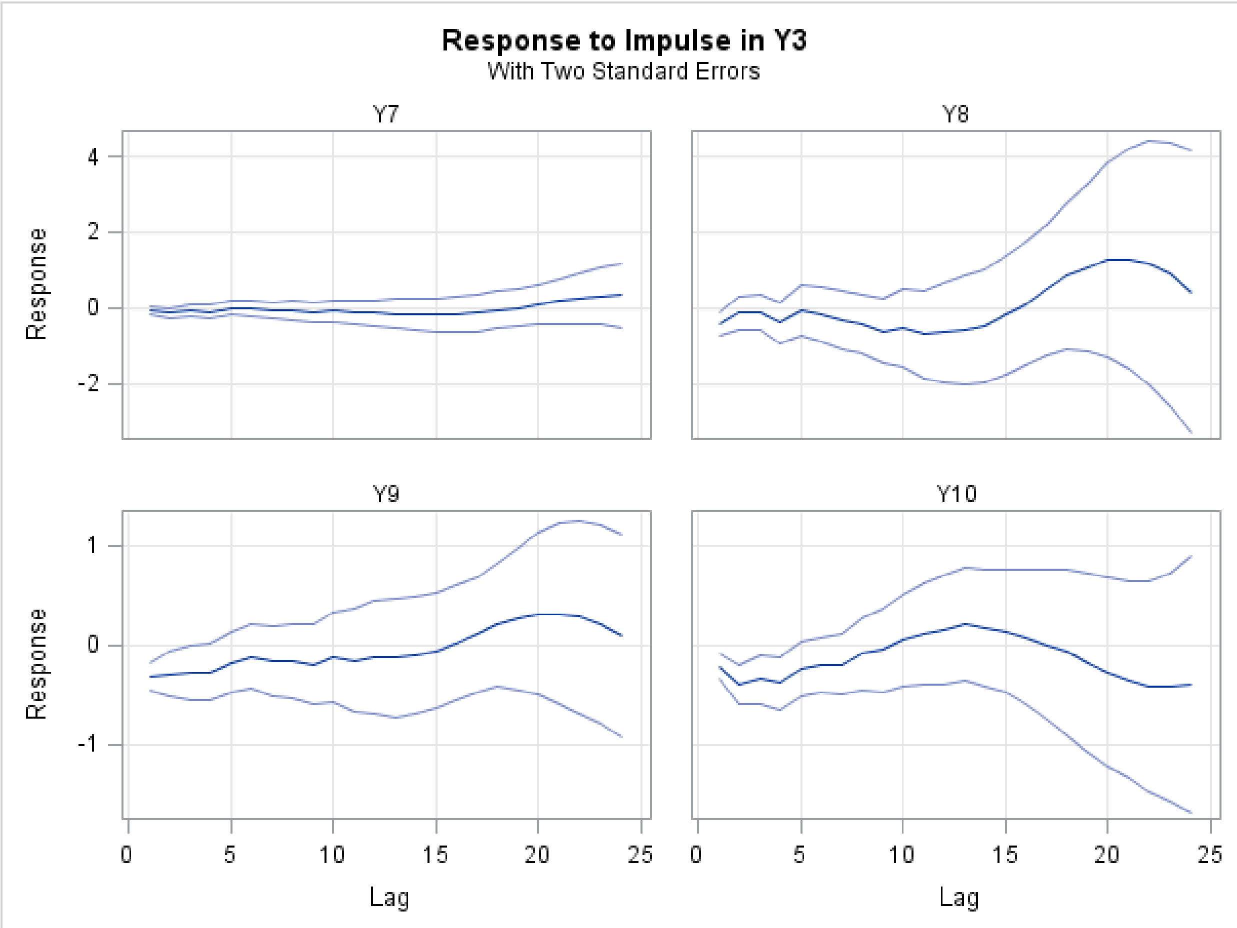
Response to Impulse in Y2
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag

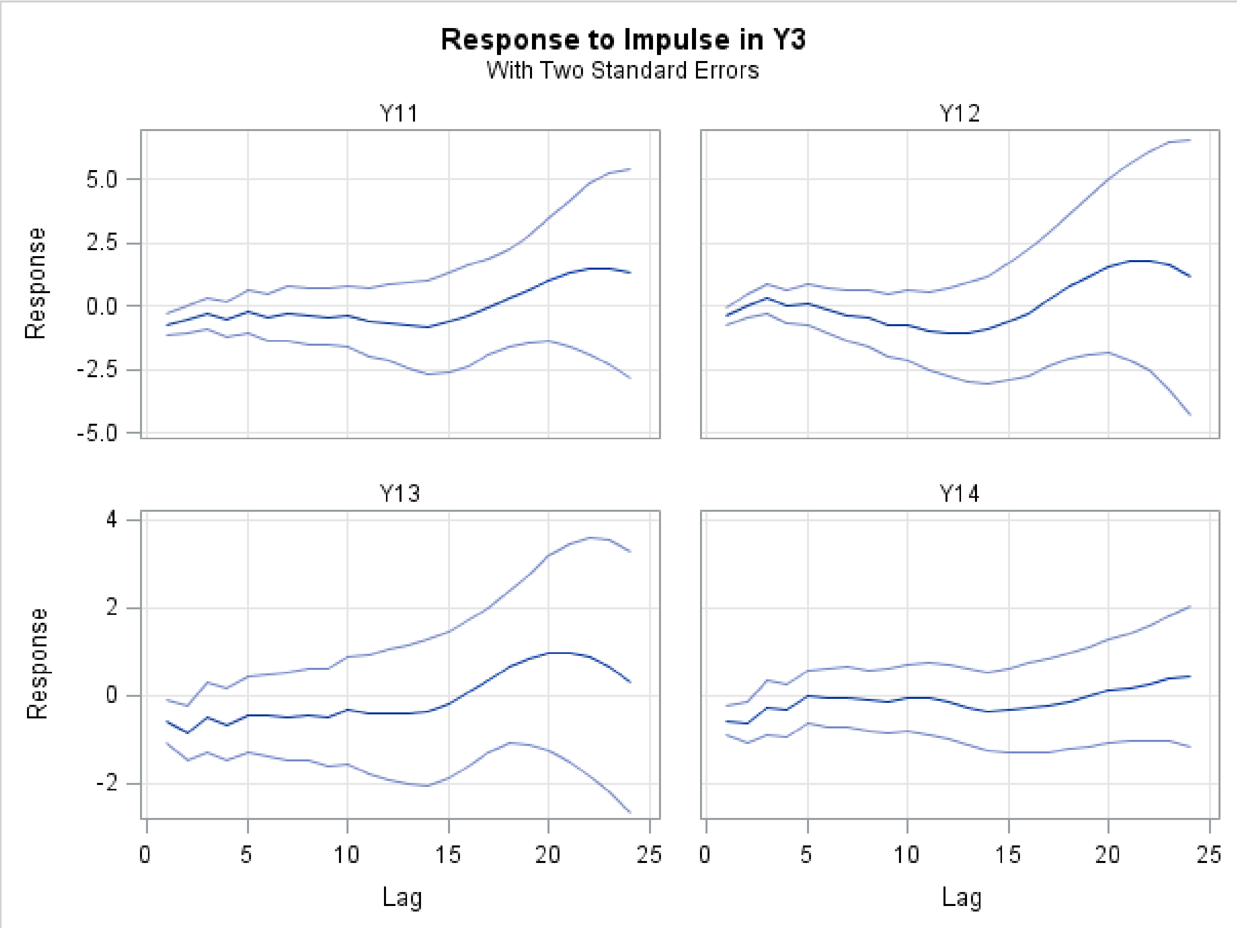

Response to Impulse in Y2
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
1.0
0.5
0.0
-0.5
-1.0
-1.5
2
0
-2
0
5
10
15
20
25
Lag
Lag

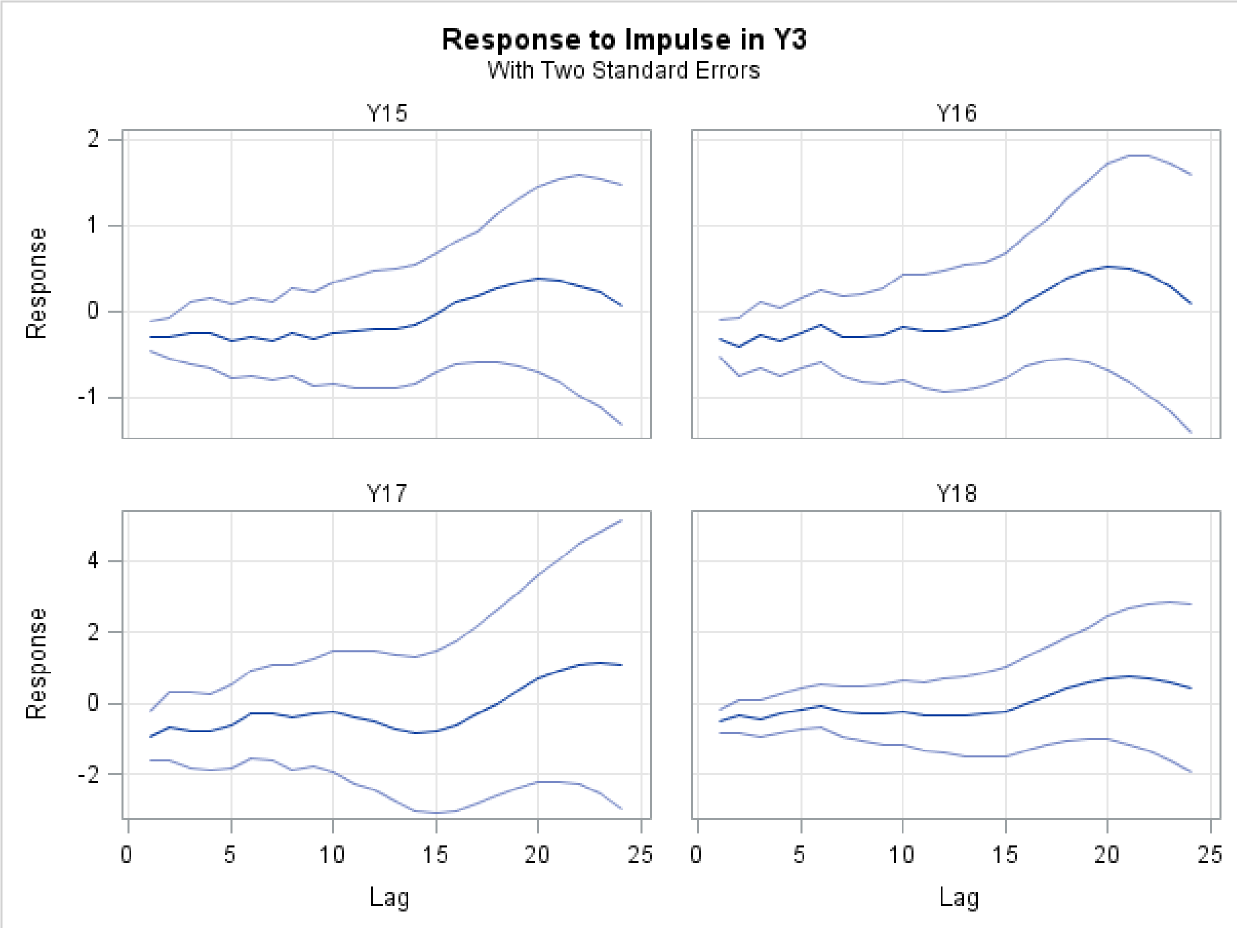

Response to Impulse in Y2
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag

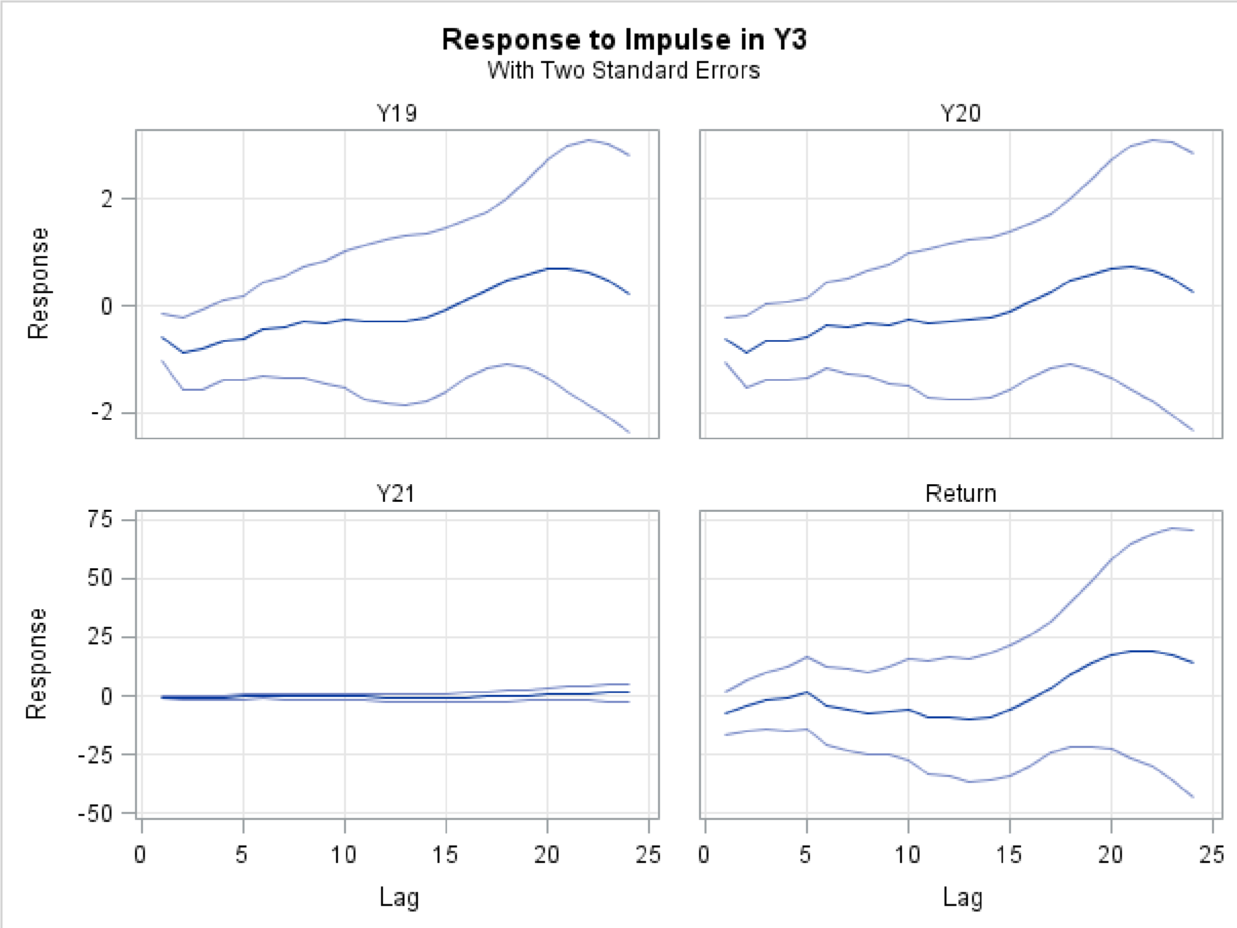

Response to Impulse in Y2
With Two Standard Errors
Int
0.00004
0.00002
0.00000
-0.00002
-0.00004
Response
0
5
10
15
20
25
Lag

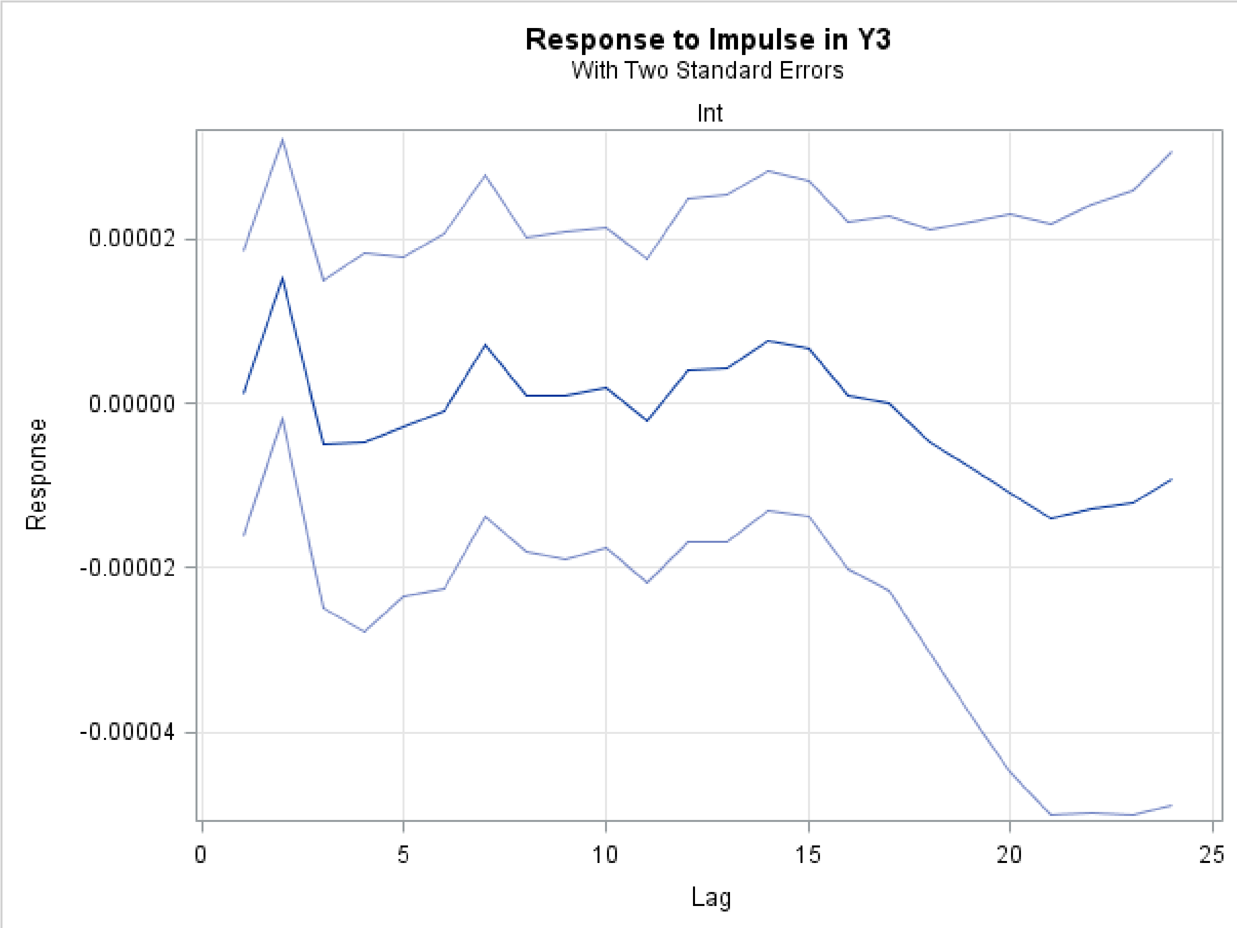

Response to Impulse in Y3
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Lag
4
2
0
-2
0
5
10
15
20
25

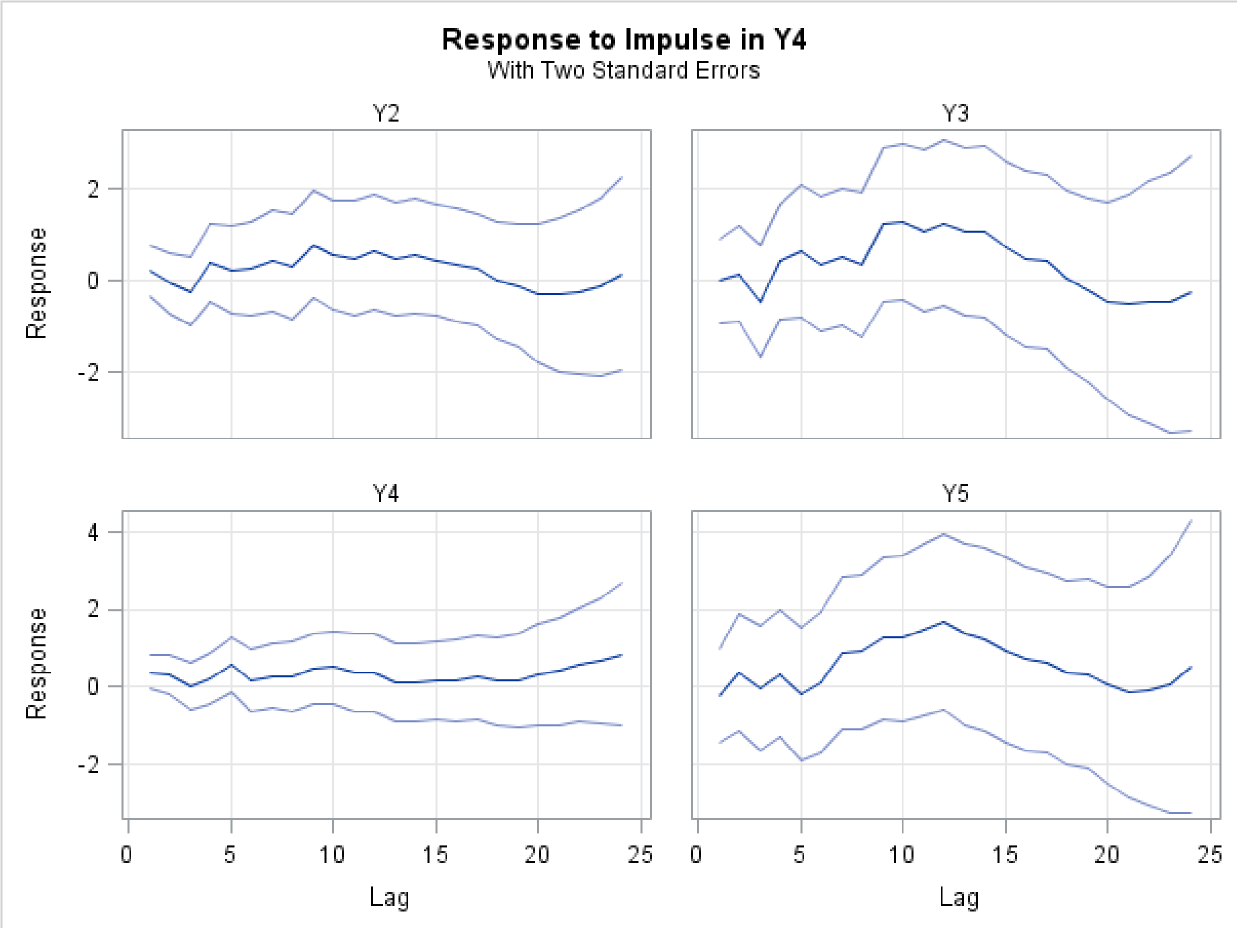

Response to Impulse in Y3
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
4
2
0
-2
1
0
-1
0
5
10
15
20
25

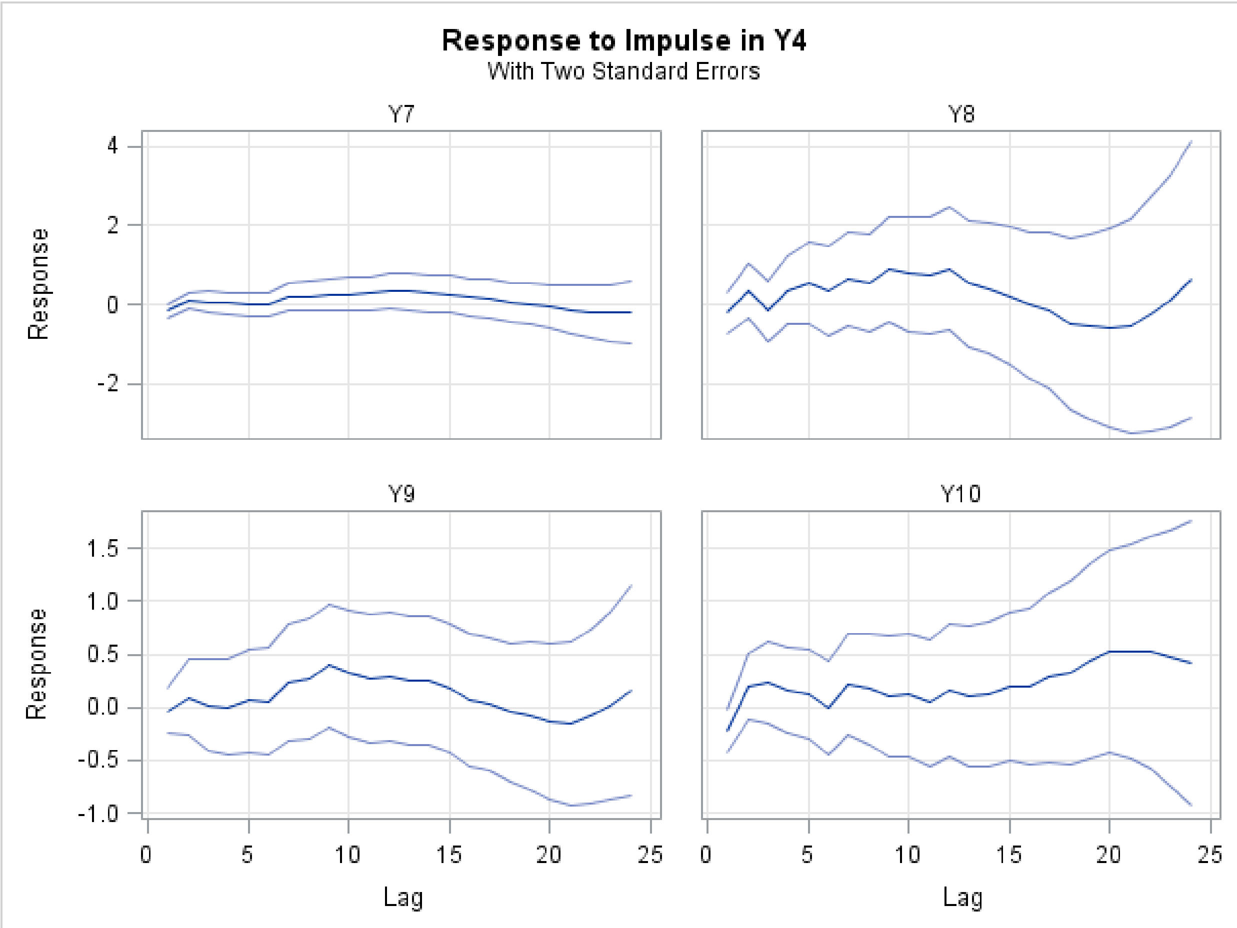

Response to Impulse in Y3
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5.0
2.5
0.0
-2.5
-5.0
4
2
0
-2
0
5
10
15
20
25

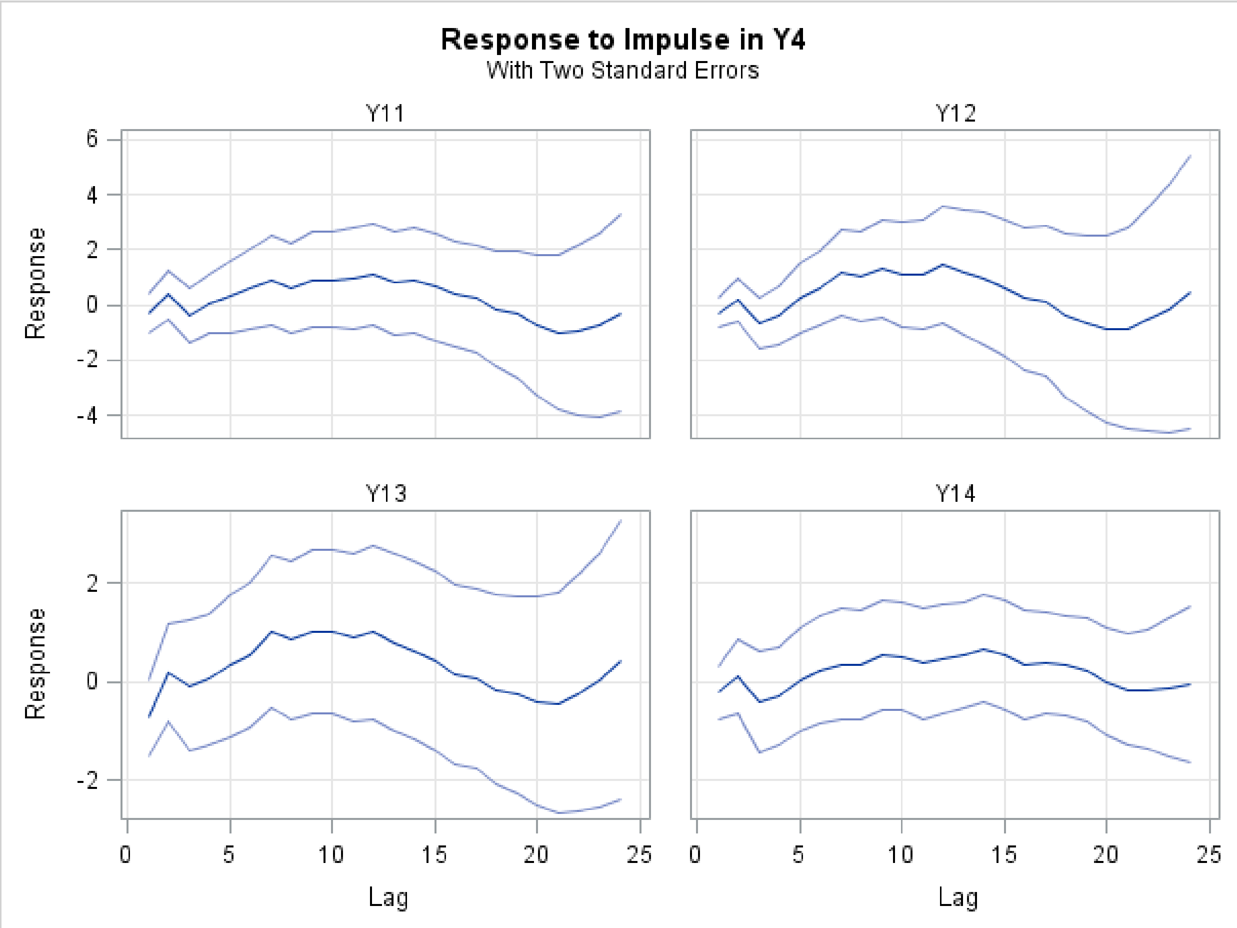

Response to Impulse in Y3
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
2
1
0
-1
4
2
0
-2
0
5
10
15
20
25


Response to Impulse in Y3
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
2
0
-2
75
50
25
0
-25
-50
0
5
10
15
20
25

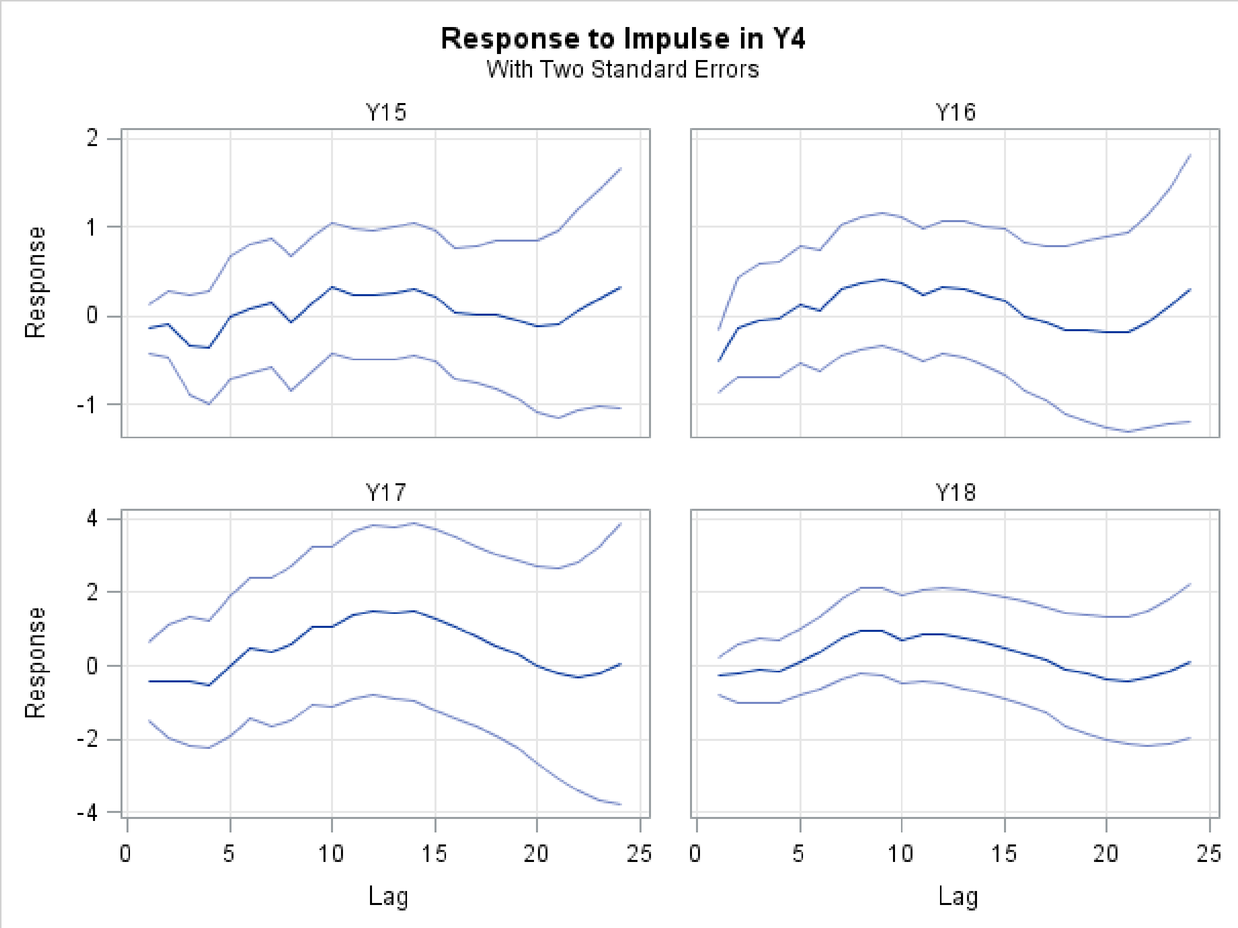

Response to Impulse in Y3
With Two Standard Errors
Int
0.00002
0.00000
-0.00002
-0.00004
Response
0
5
10
15
20
25
Lag

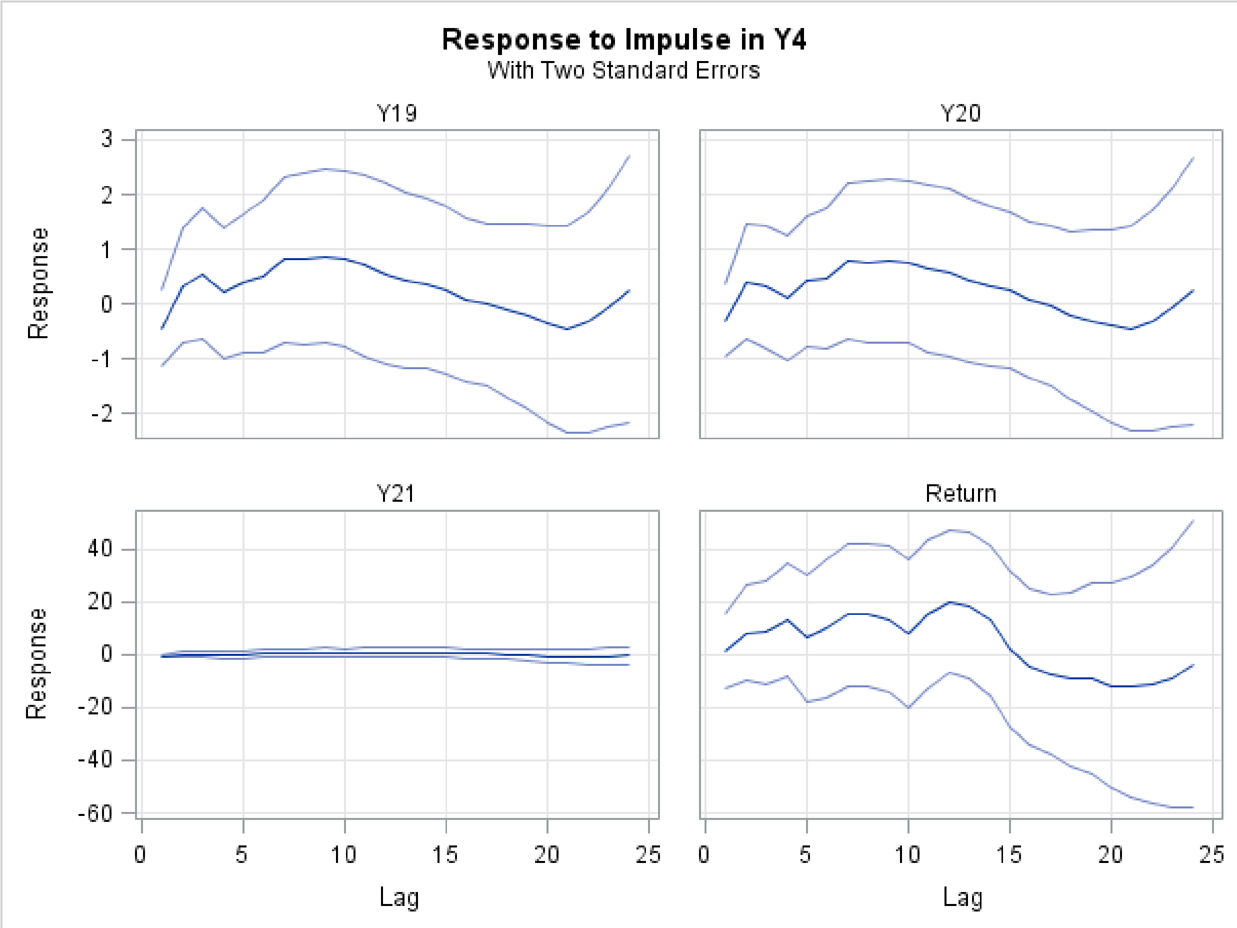

Response to Impulse in Y4
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
2
0
-2
4
2
0
-2
0 5 10 15 20 25
0 5 10 15 20 25

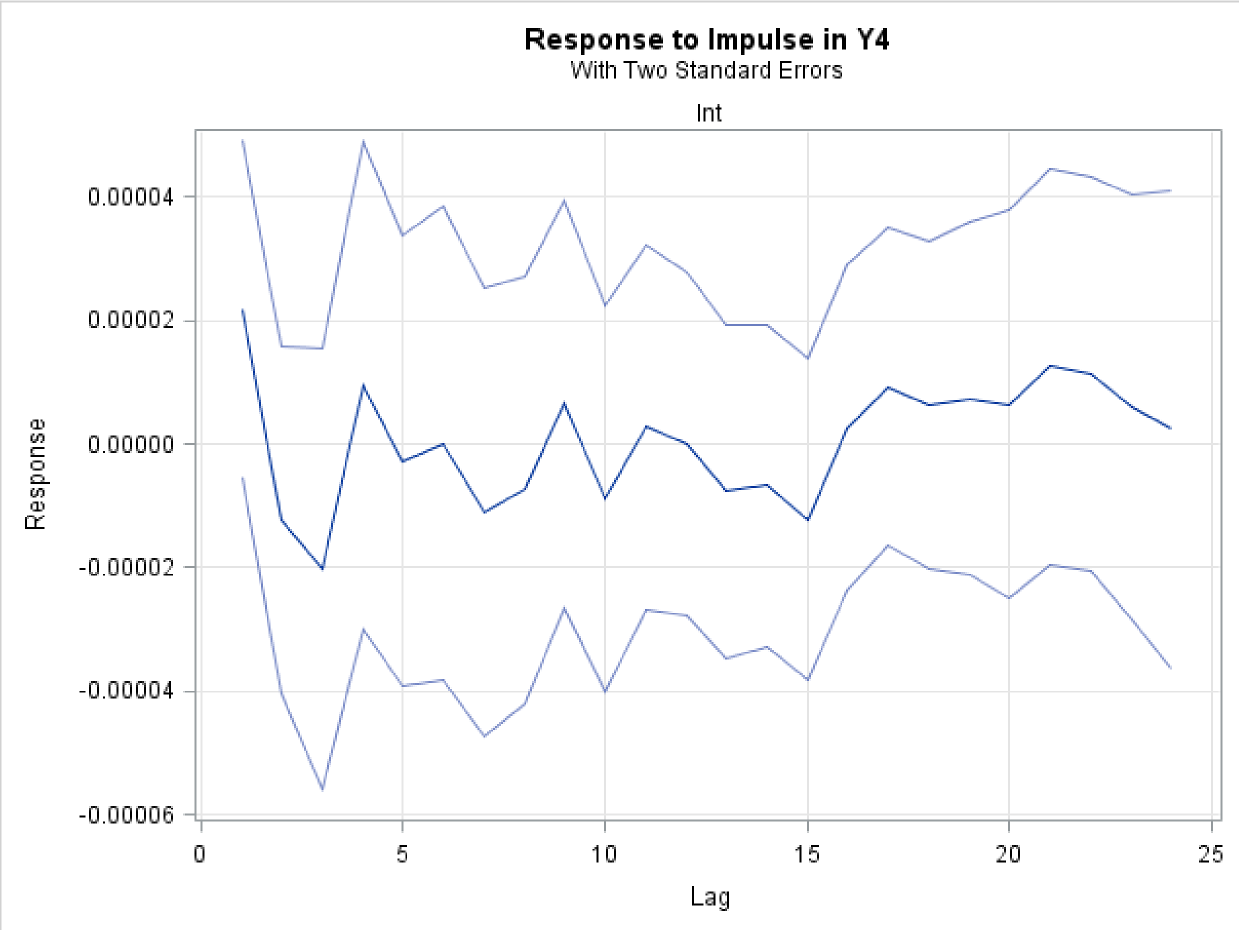

Response to Impulse in Y4
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
4
2
0
-2
1.5
1.0
0.5
0.0
-0.5
-1.0
0
5
10
15
20
25



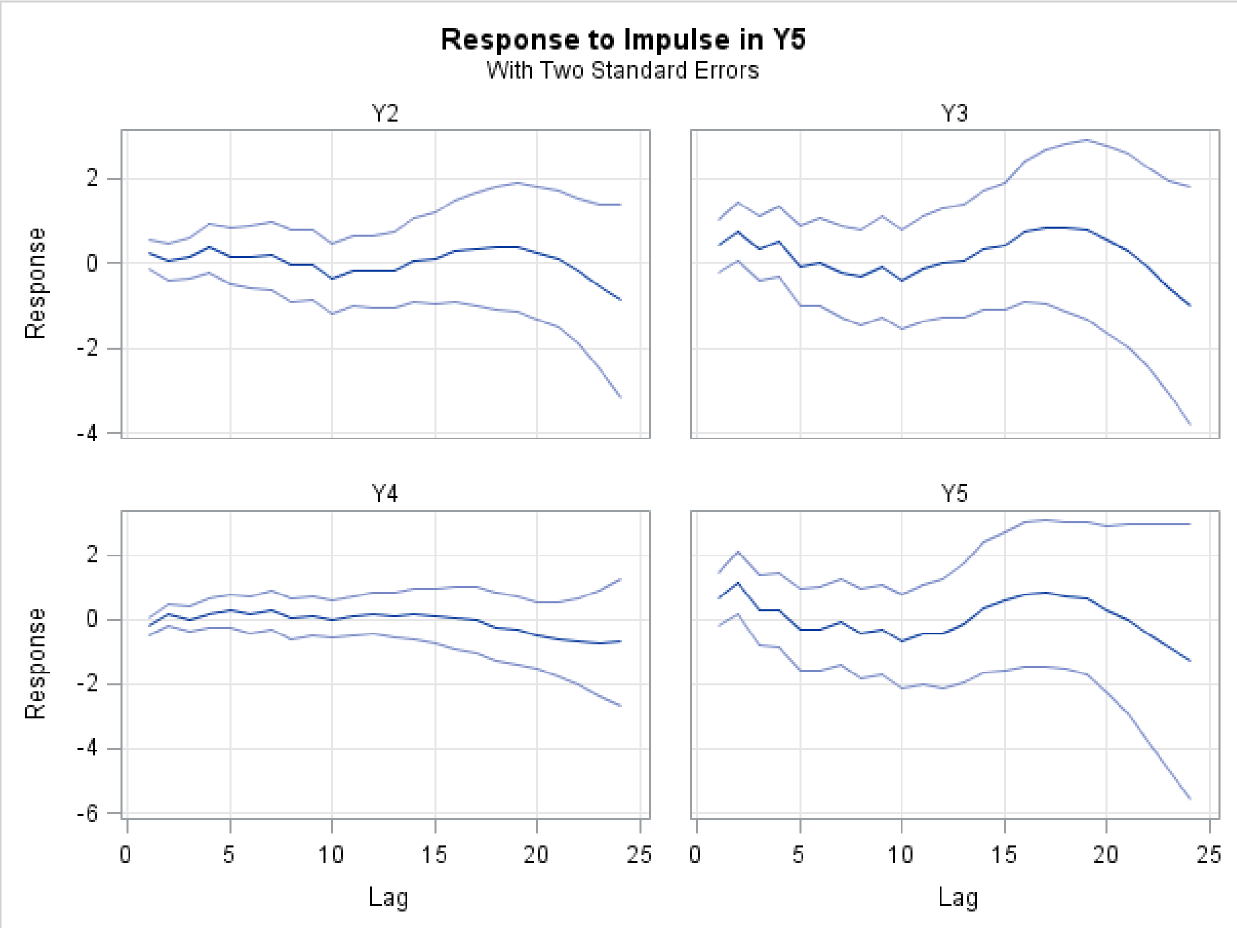
Response to Impulse in Y4
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
6
4
2
0
-2
-4
2
0
-2
0
5
10
15
20
25

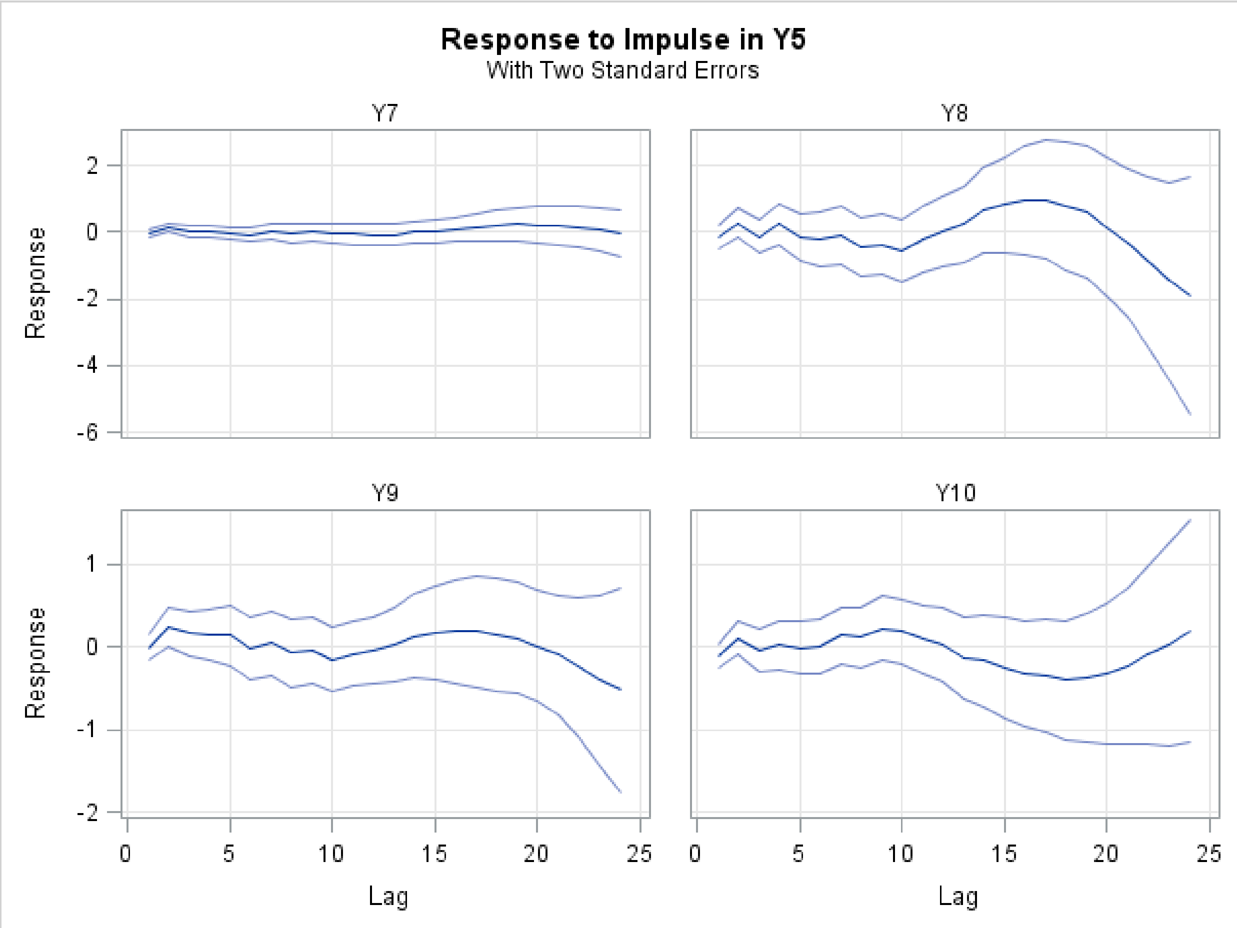

Response to Impulse in Y4
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
2
1
0
-1
4
2
0
-2
-4
0
5
10
15
20
25

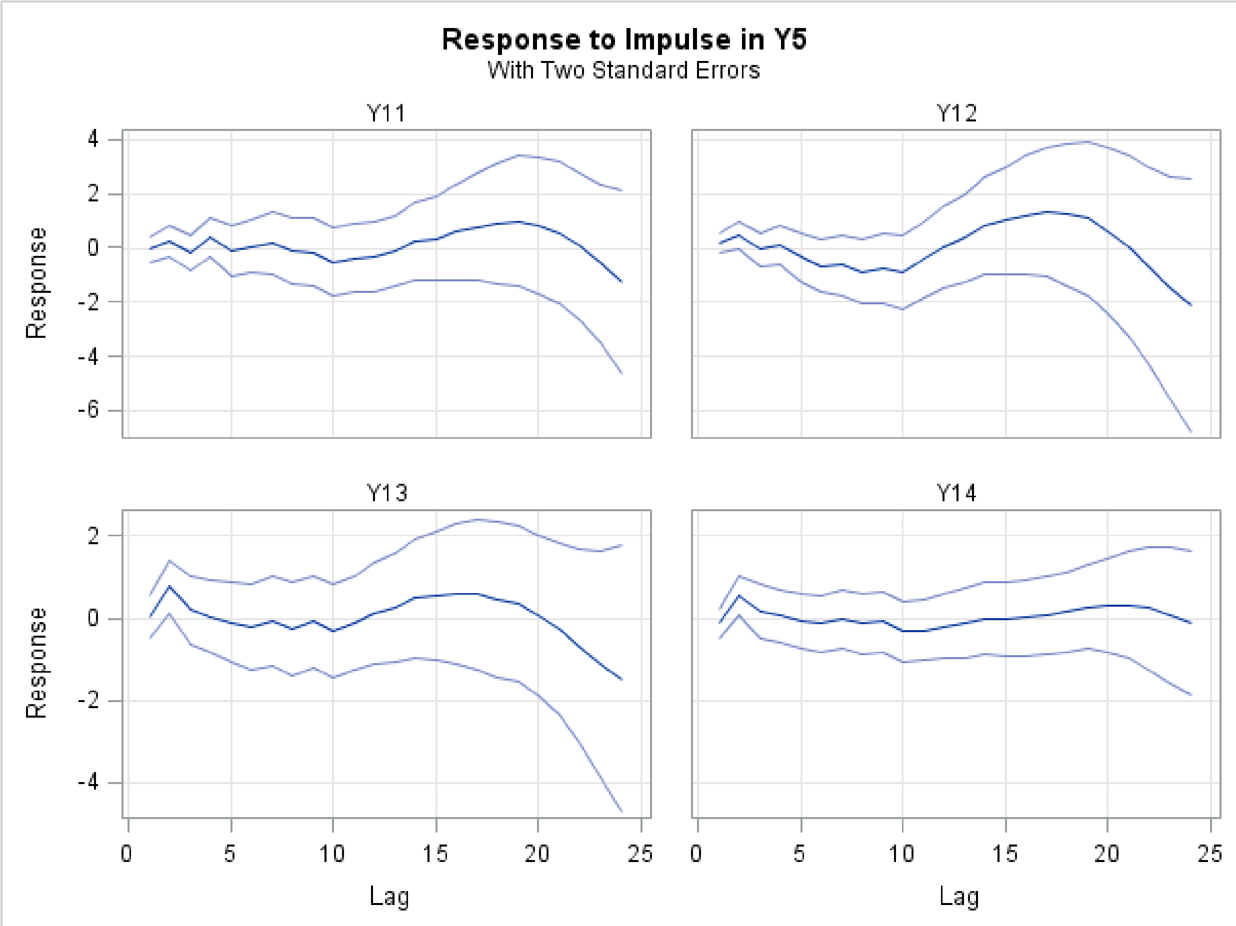

Response to Impulse in Y4
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
3
2
1
0
-1
-2
40
20
0
-20
-40
-60
0
5
10
15
20
25

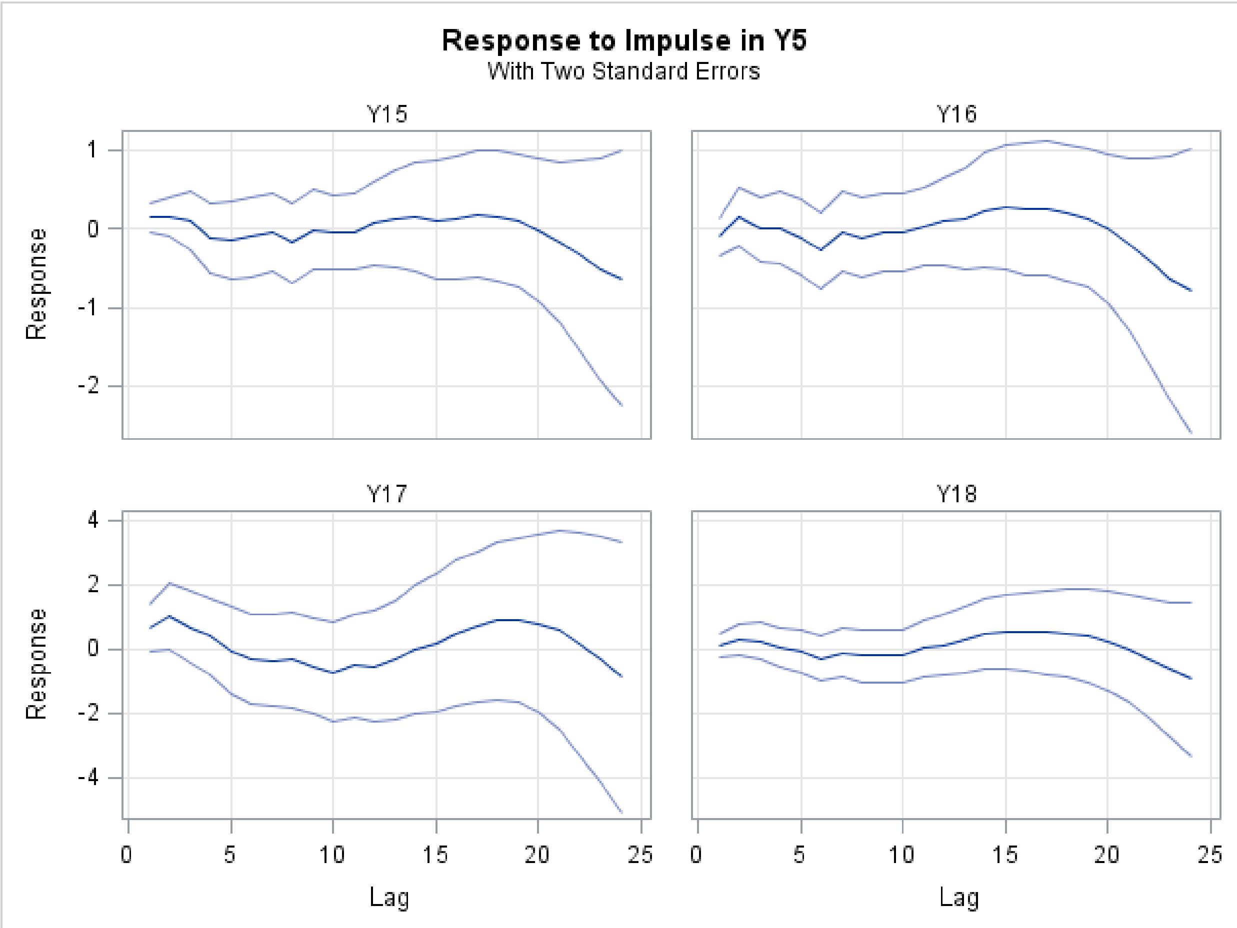


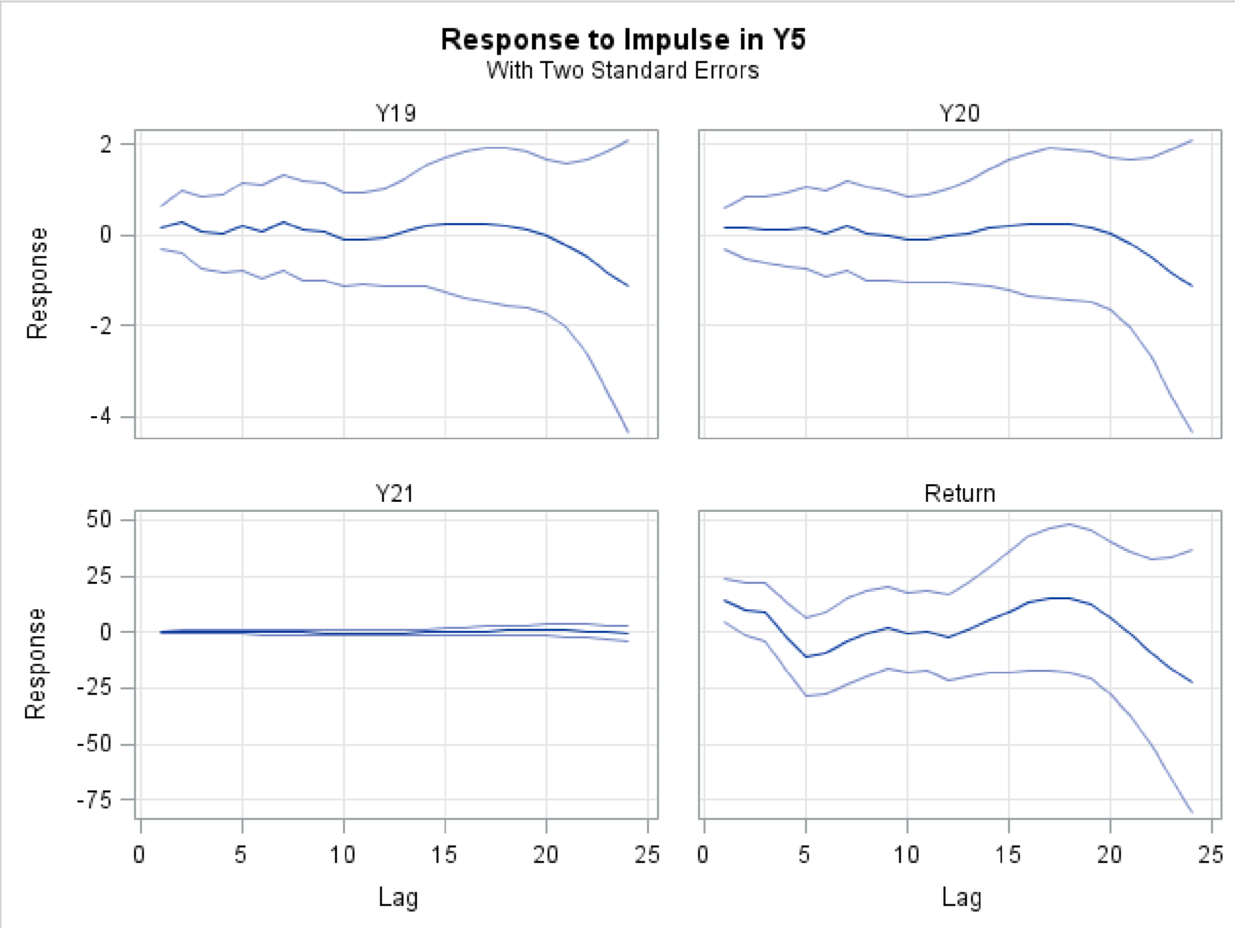
Response to Impulse in Y4
With Two Standard Errors
Int
0.00004
0.00002
0.00000
-0.00002
-0.00004
-0.00006
Response
0
5
10
15
20
25
Lag

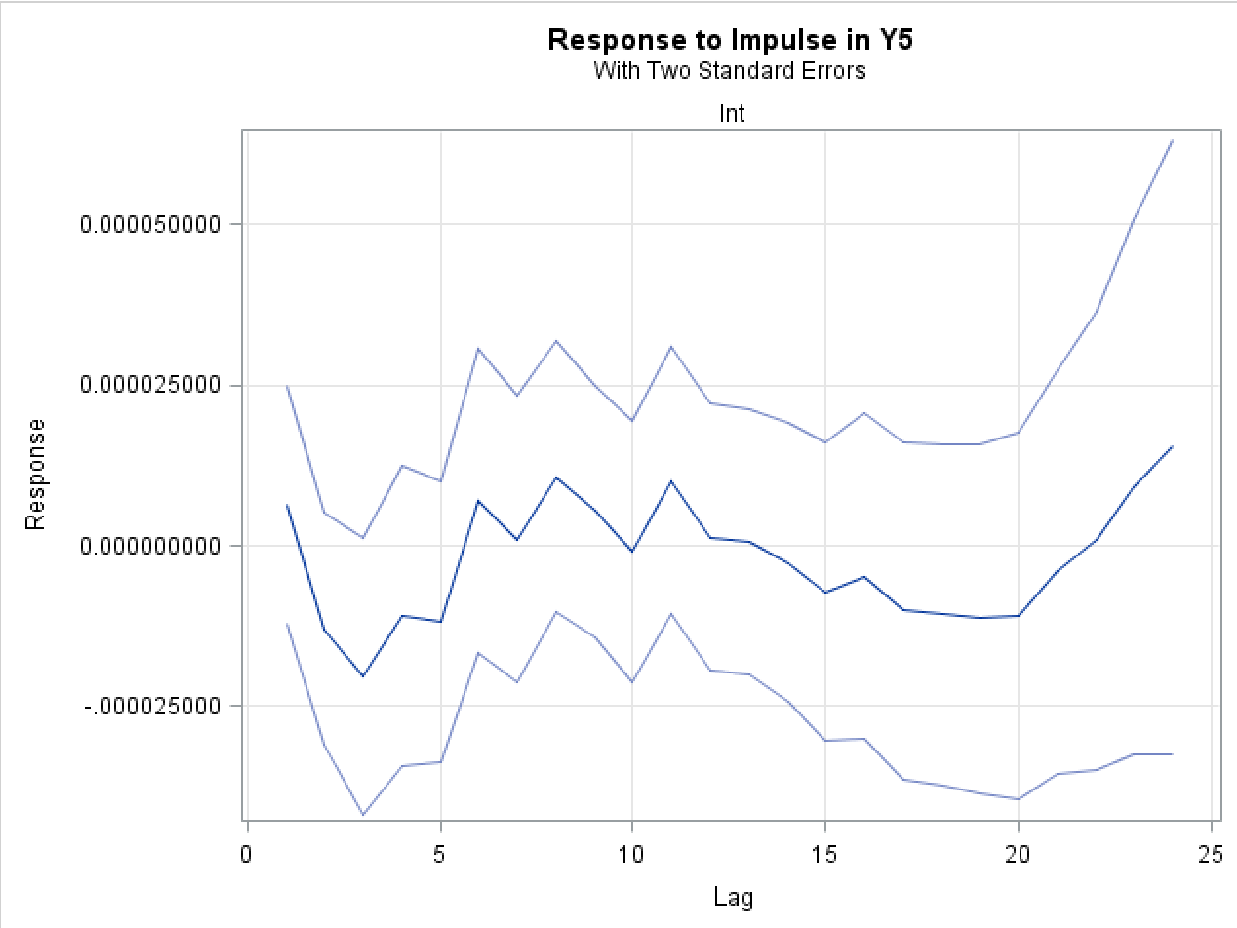

Response to Impulse in Y5
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
2
0
-2
-4
-6
0
5
10
15
20
25

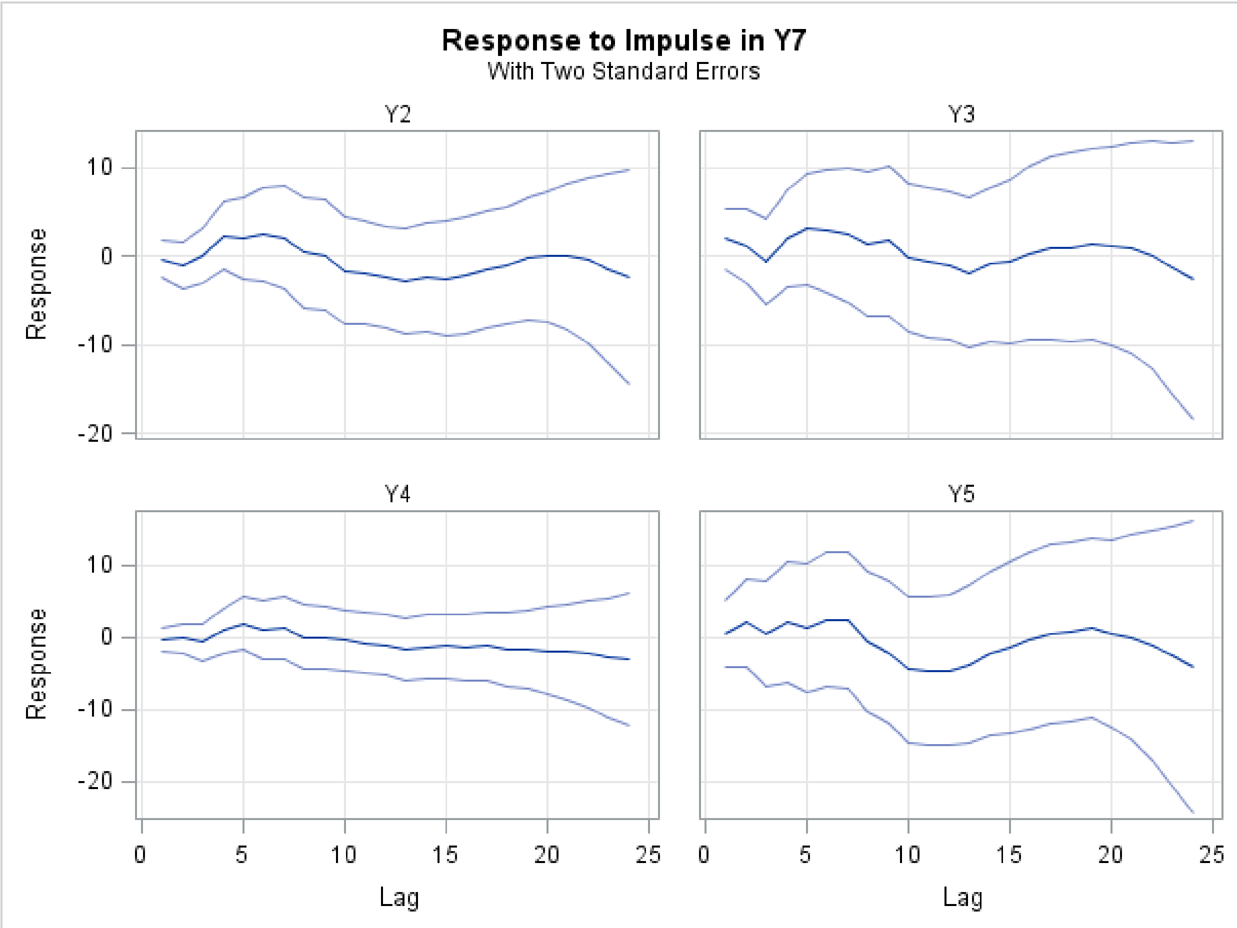

Response to Impulse in Y5
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
2
0
-2
-4
-6
1
0
-1
-2
0
5
10
15
20
25

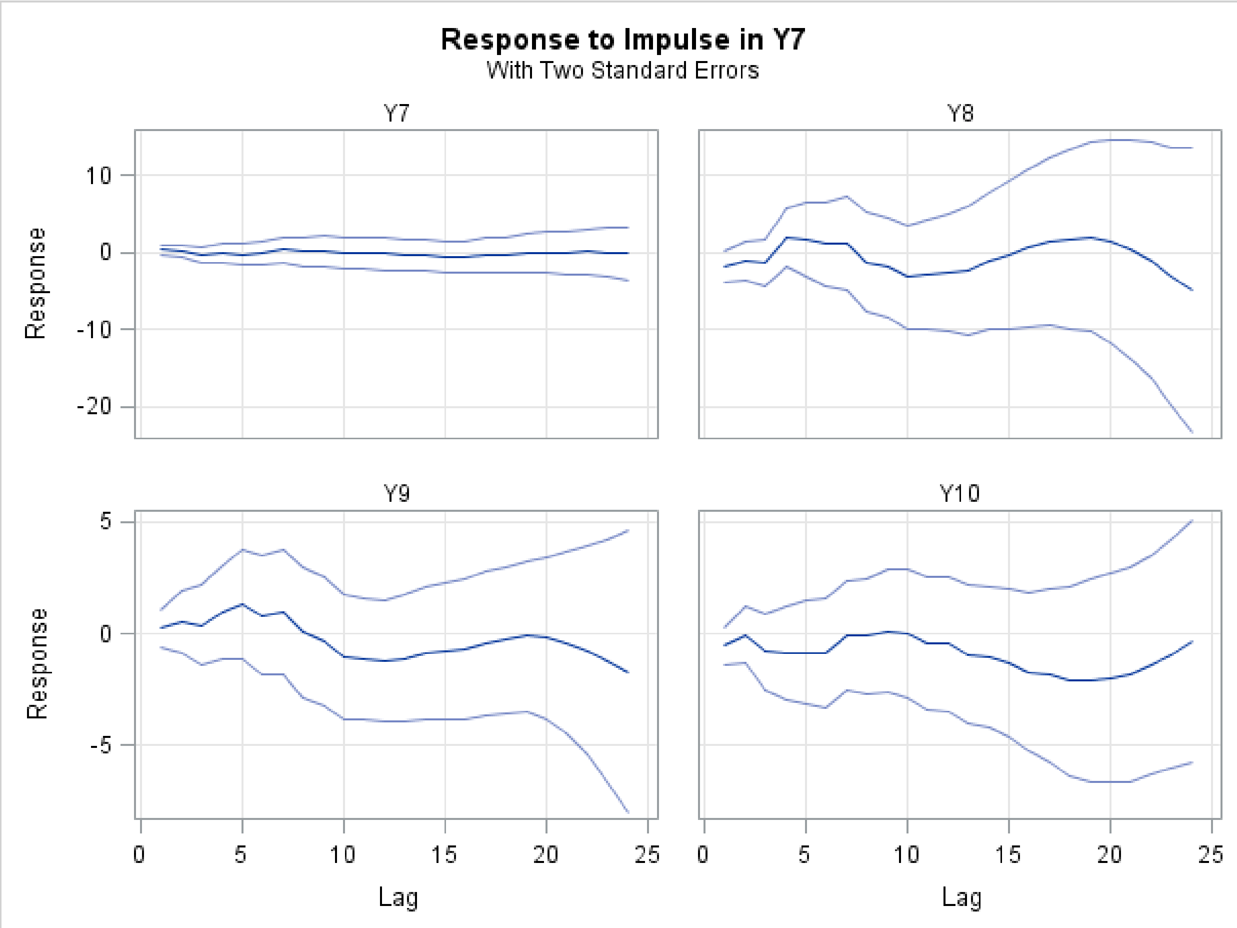

Response to Impulse in Y5
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Lag
4
2
0
-2
-4
-6
0
5
10
15
20
25

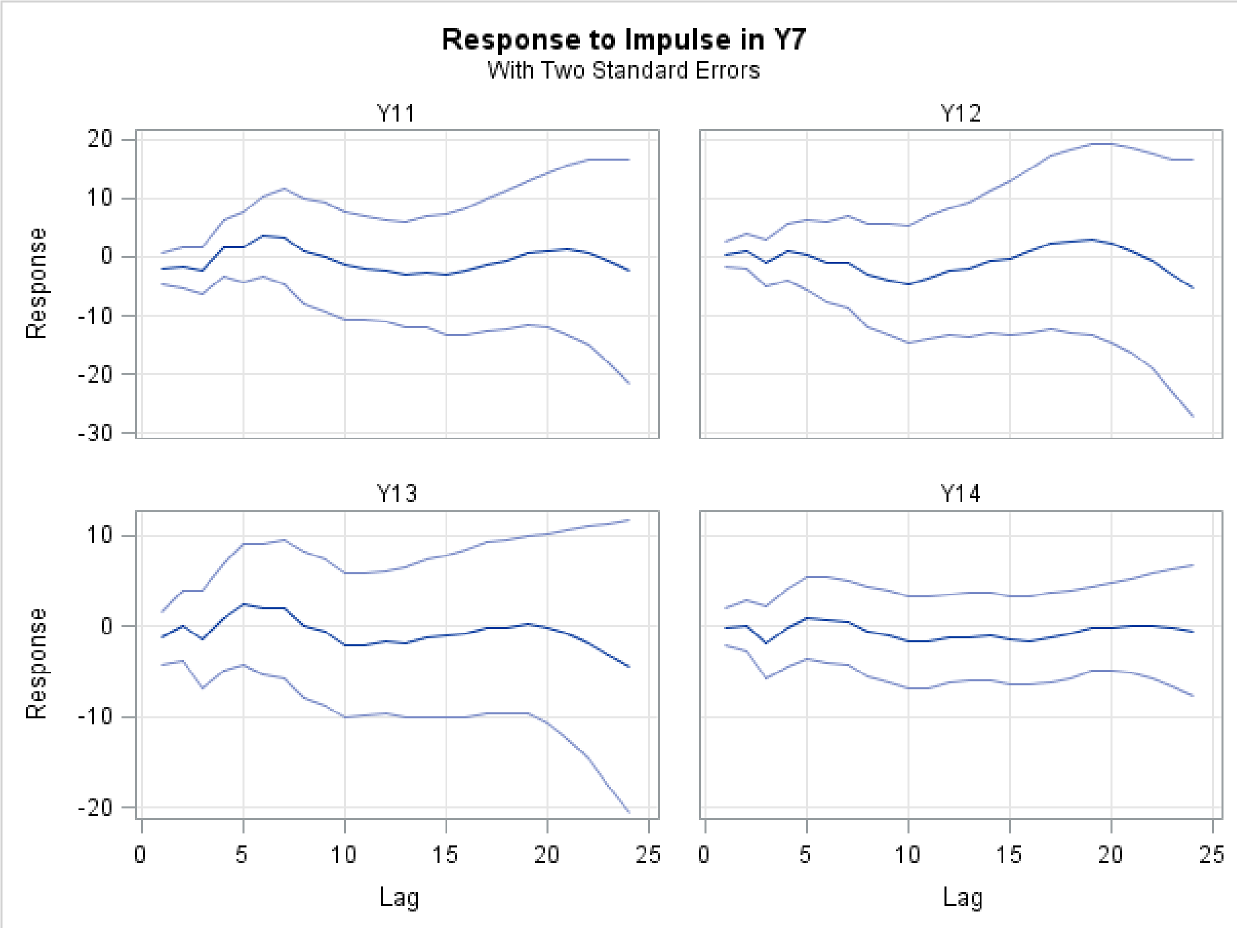

Response to Impulse in Y5
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
1
0
-1
-2
4
2
0
-2
-4
0
5
10
15
20
25


Response to Impulse in Y5
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
2
0
-2
-4
50
25
0
-25
-50
-75
0
5
10
15
20
25

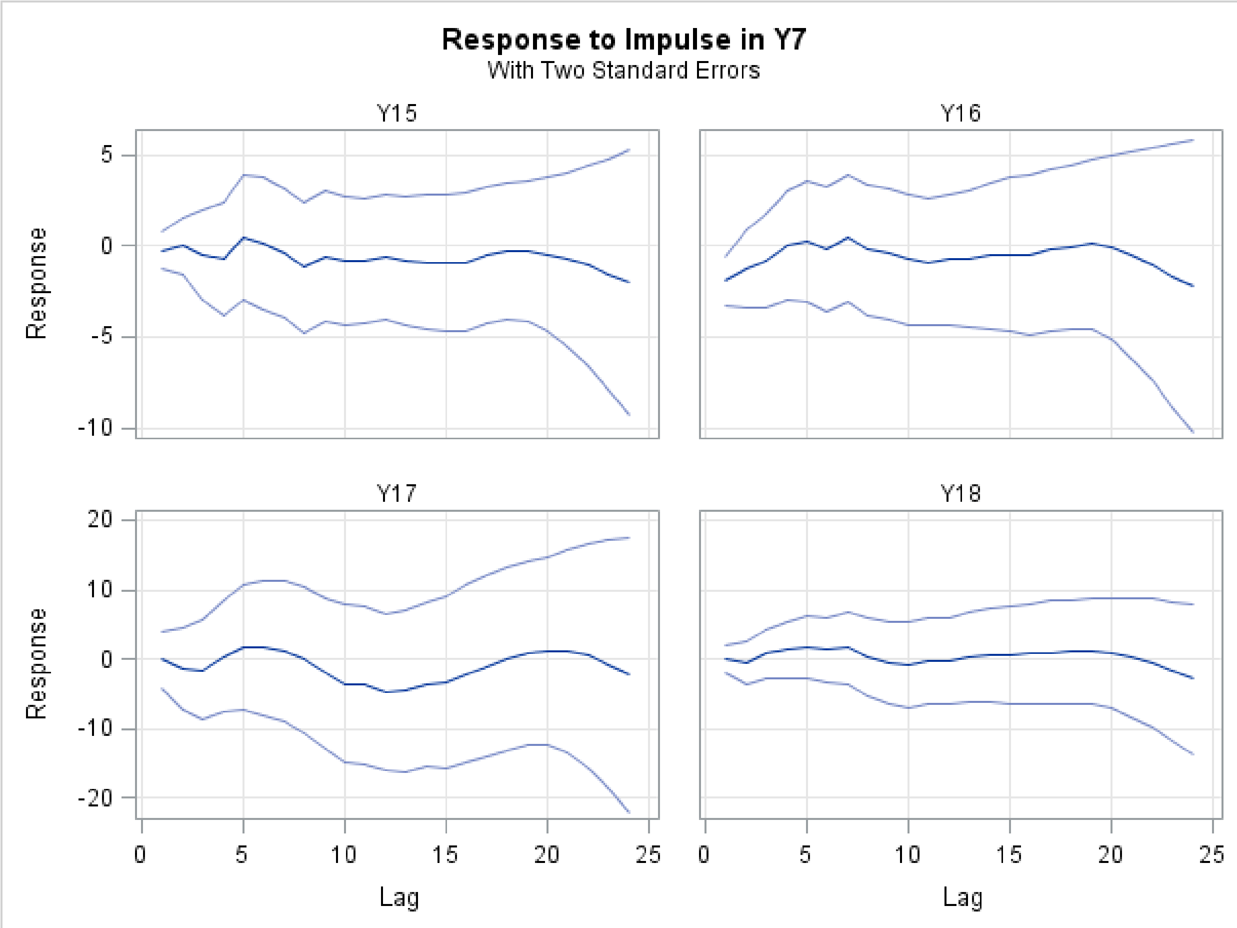

Response to Impulse in Y5
With Two Standard Errors
Int
0.000050000
0.000025000
0.000000000
-.000025000
Response
0
5
10
15
20
25
Lag


Response to Impulse in Y7
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
10
0
-10
-20
10
0
-10
-20
0
5
10
15
20
25
0
5
10
15
20
25
Lag
Lag

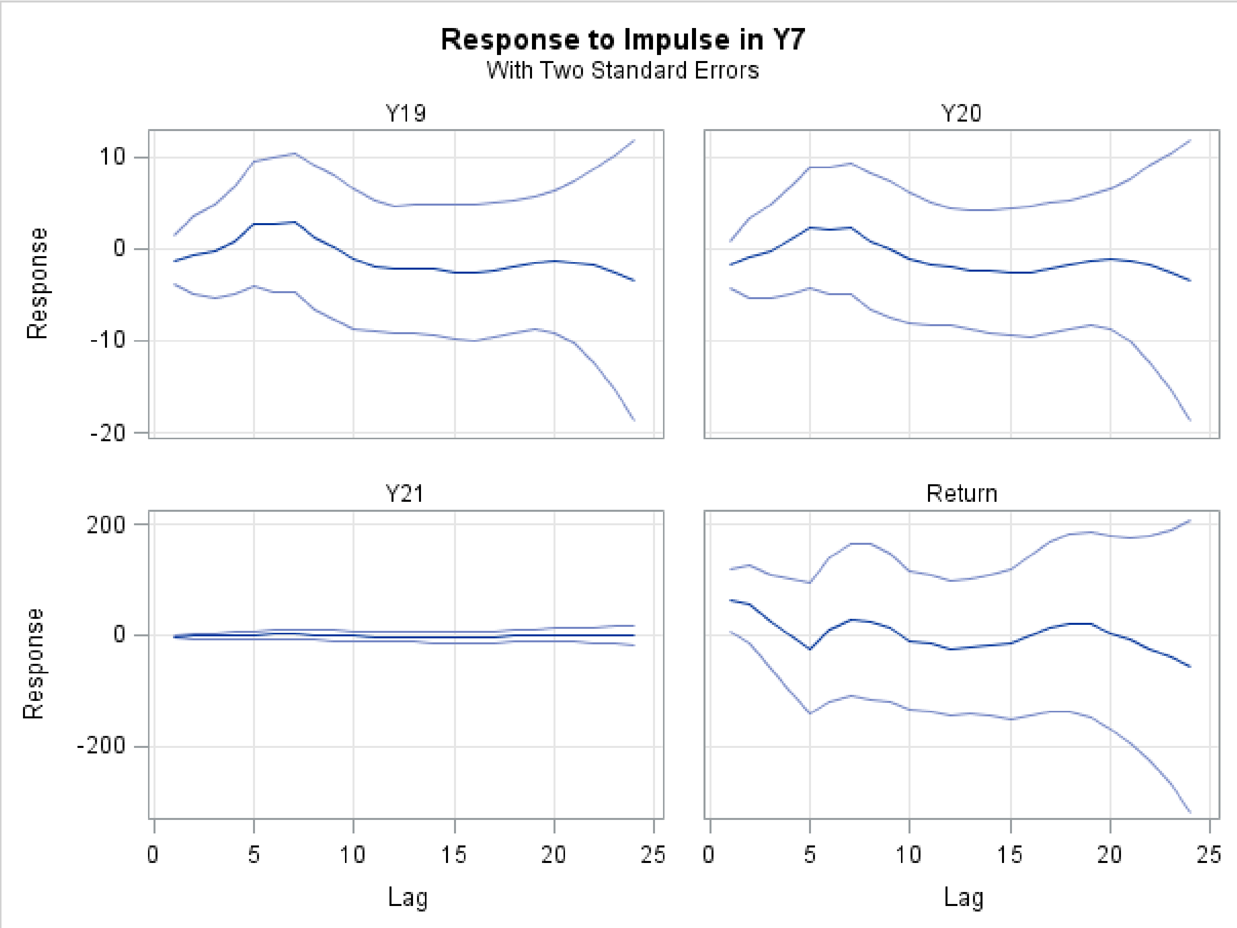

Response to Impulse in Y7
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Lag
10
0
-10
-20
5
-5
15
20
25

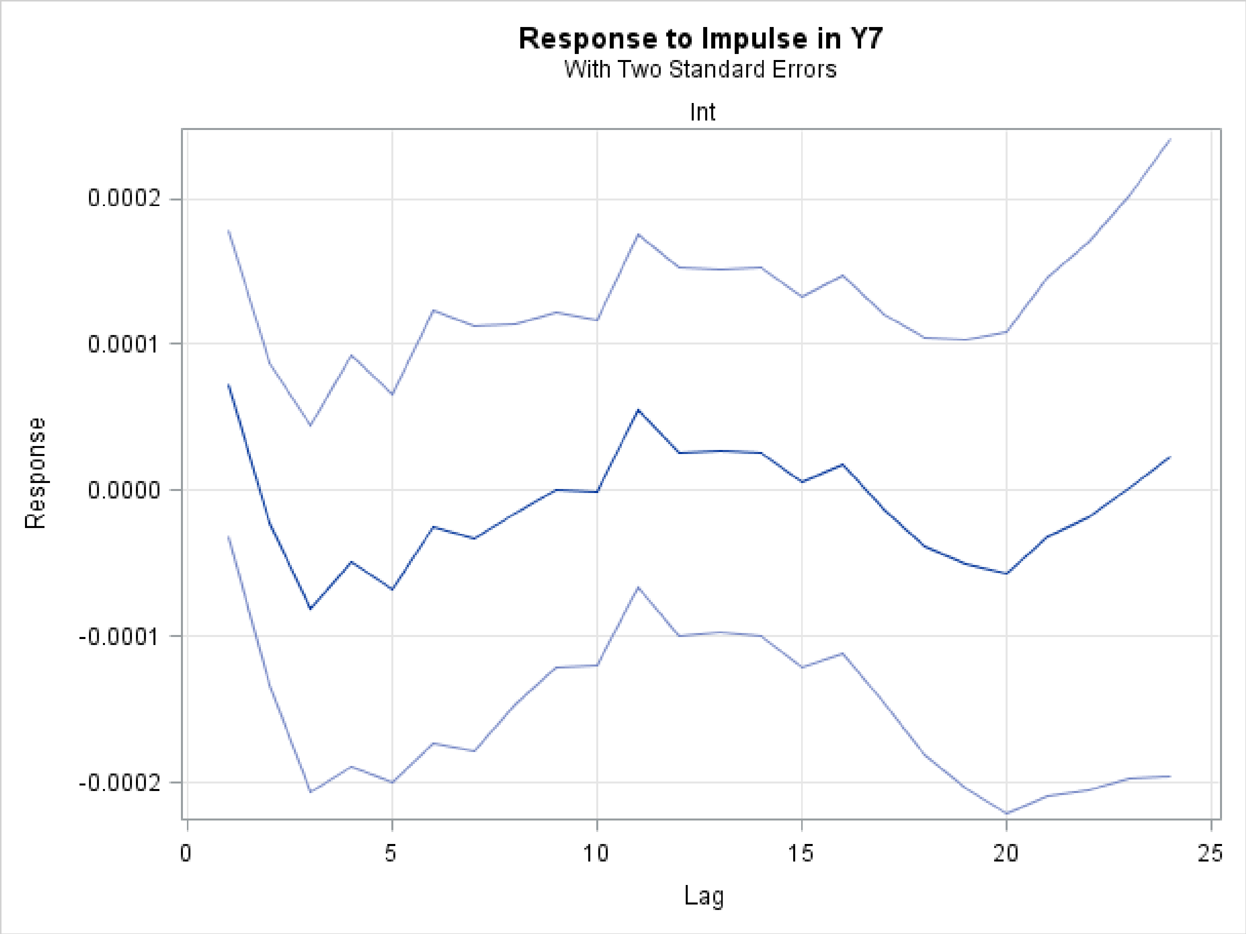


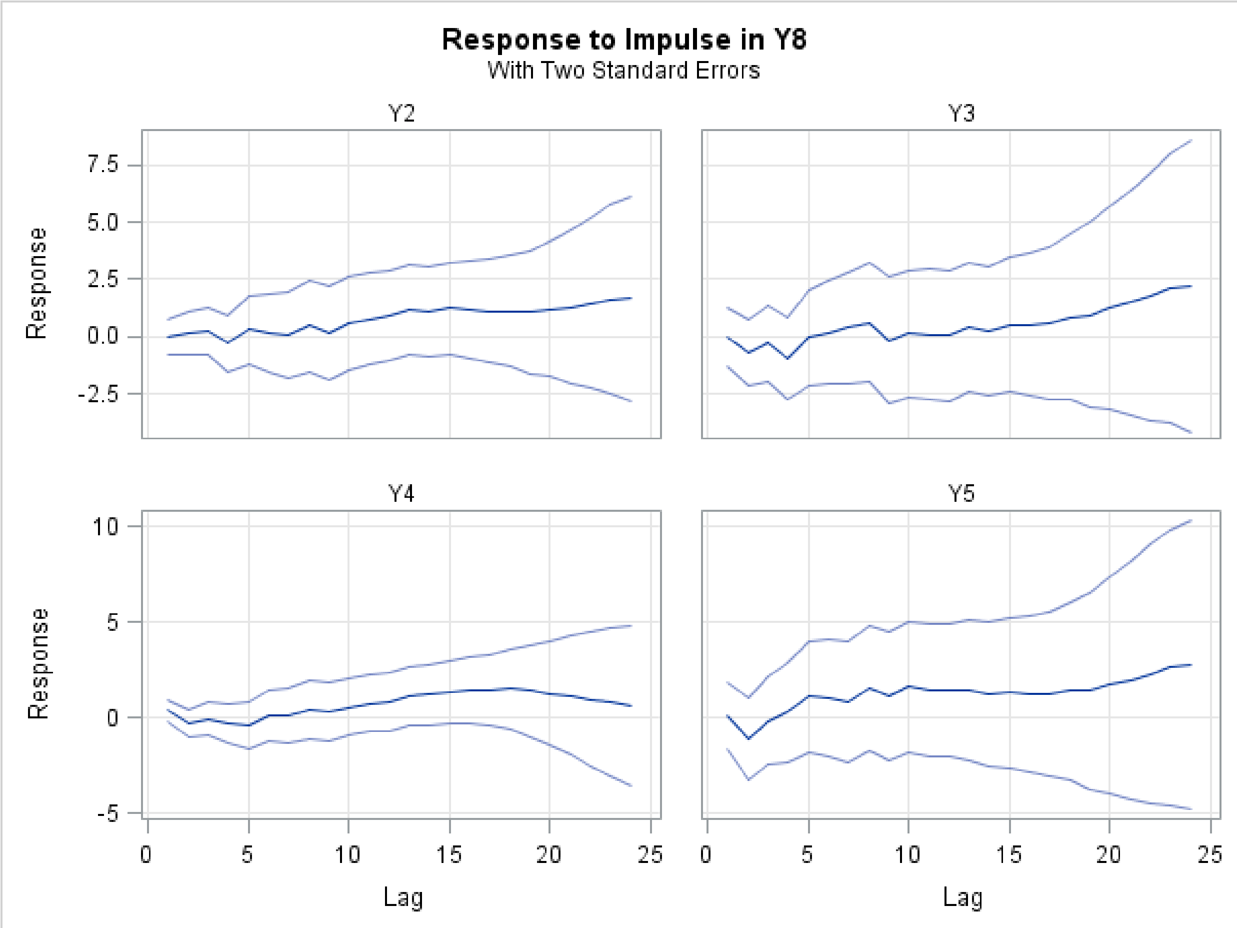
Response to Impulse in Y7
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
20
10
0
-10
-20
-30
10
0
-10
-20
0
5
10
15
20
25

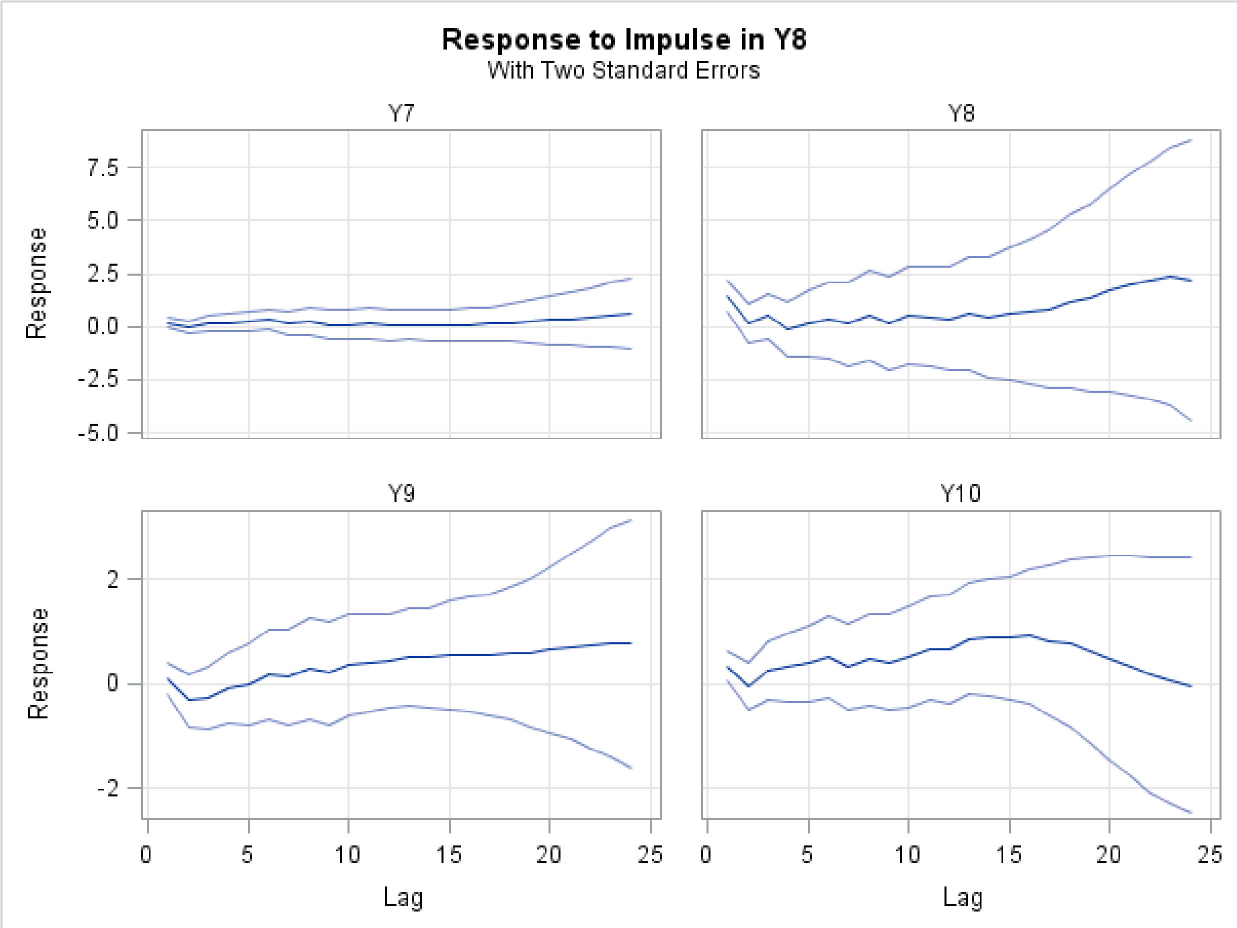


Response to Impulse in Y7
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag

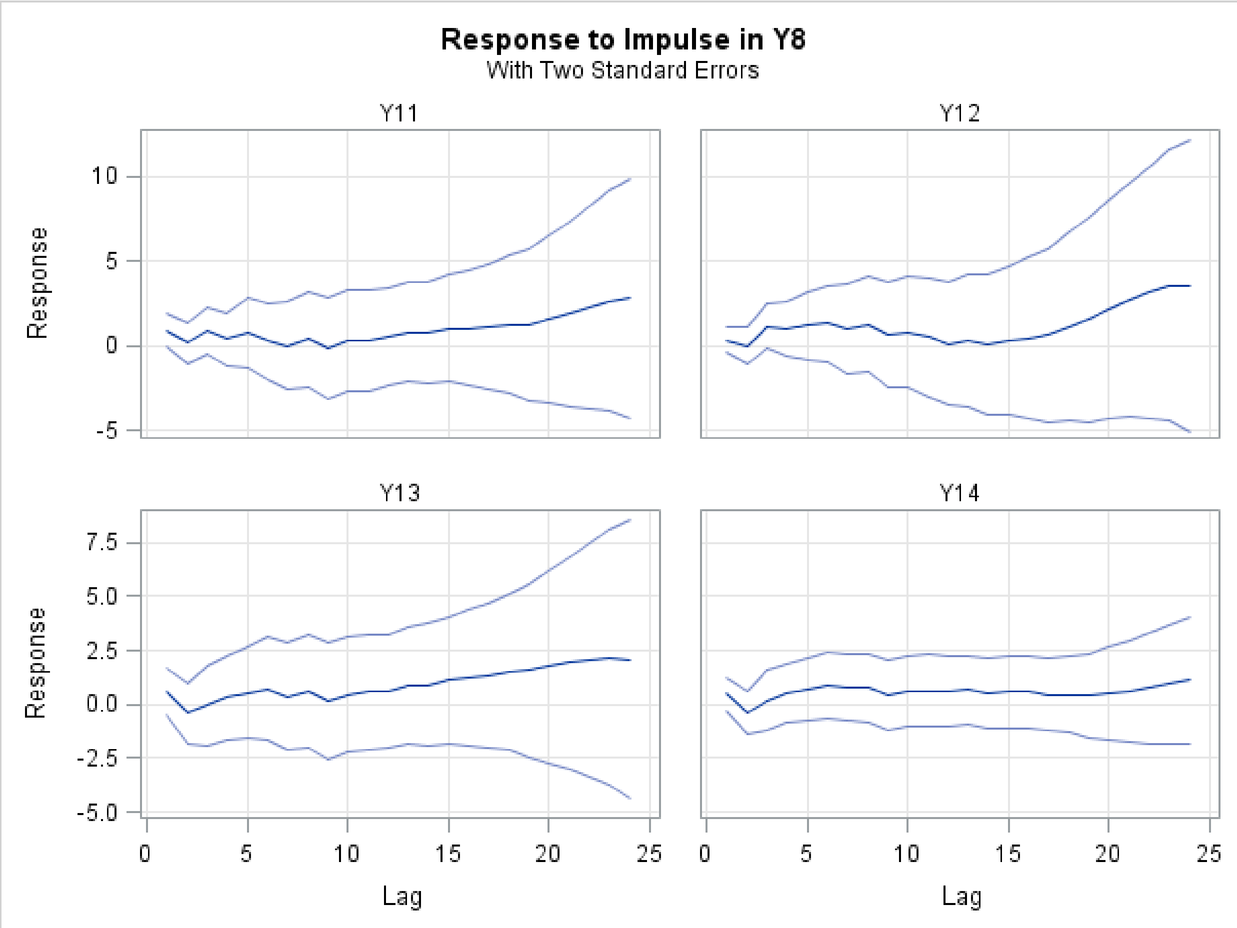

Response to Impulse in Y7
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
10
0
-10
-20
200
0
-200
0
5
10
15
20
25

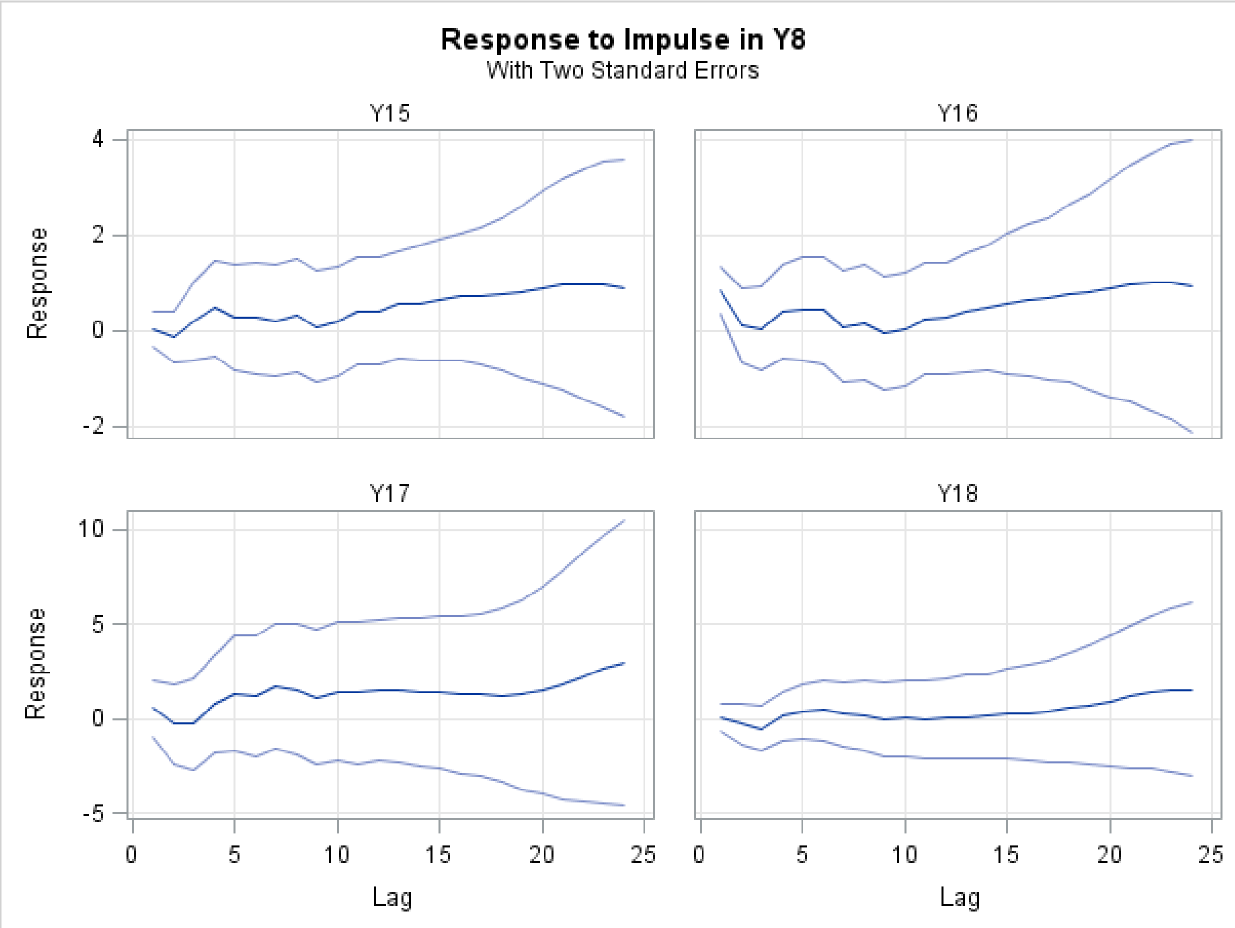

Response to Impulse in Y7
With Two Standard Errors
Int
0.0002
0.0001
0.0000
-0.0001
-0.0002
Response
0
5
10
15
20
25
Lag

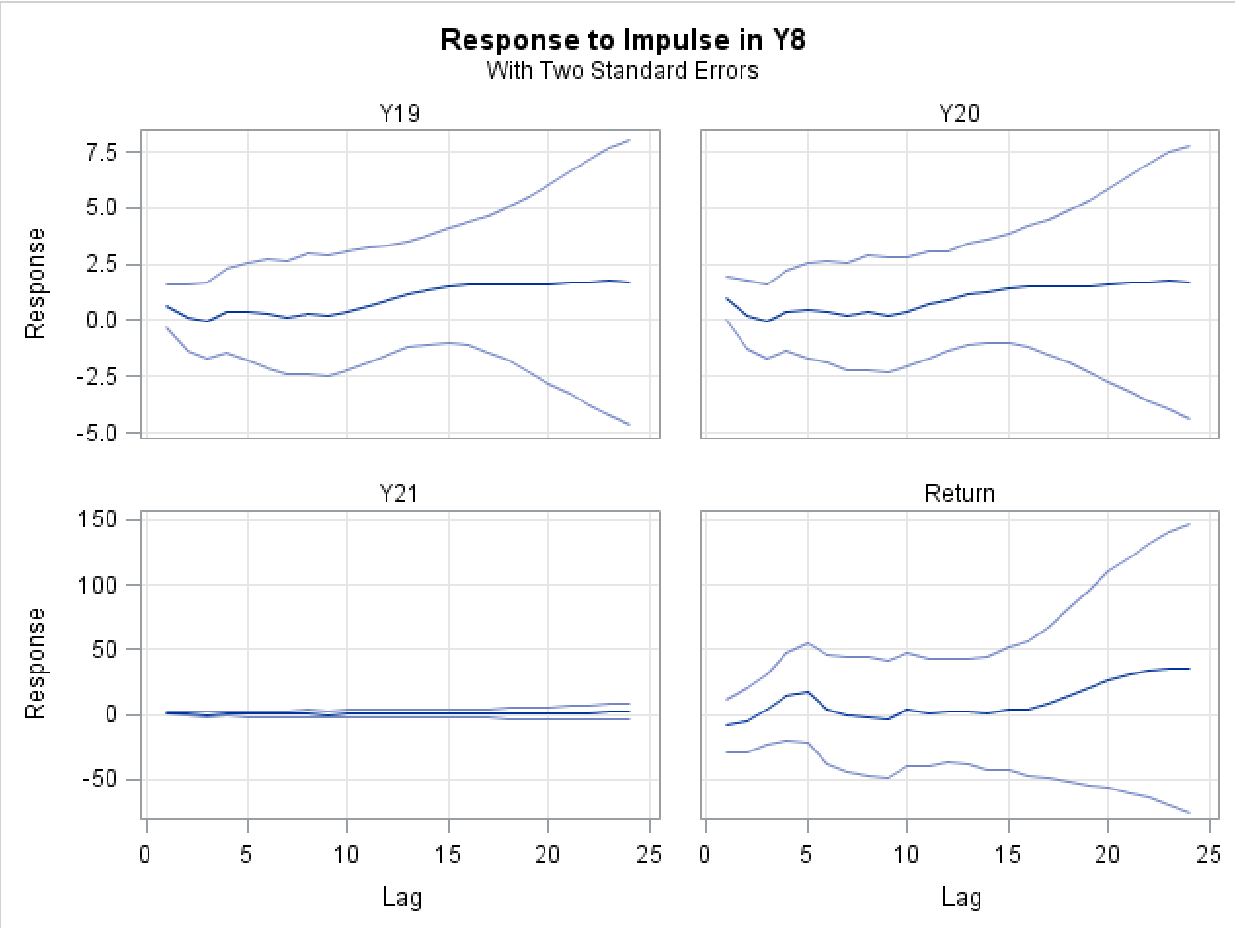

Response to Impulse in Y8
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
7.5
5.0
2.5
0.0
-2.5
10
5
0
-5
0
5
10
15
20
25



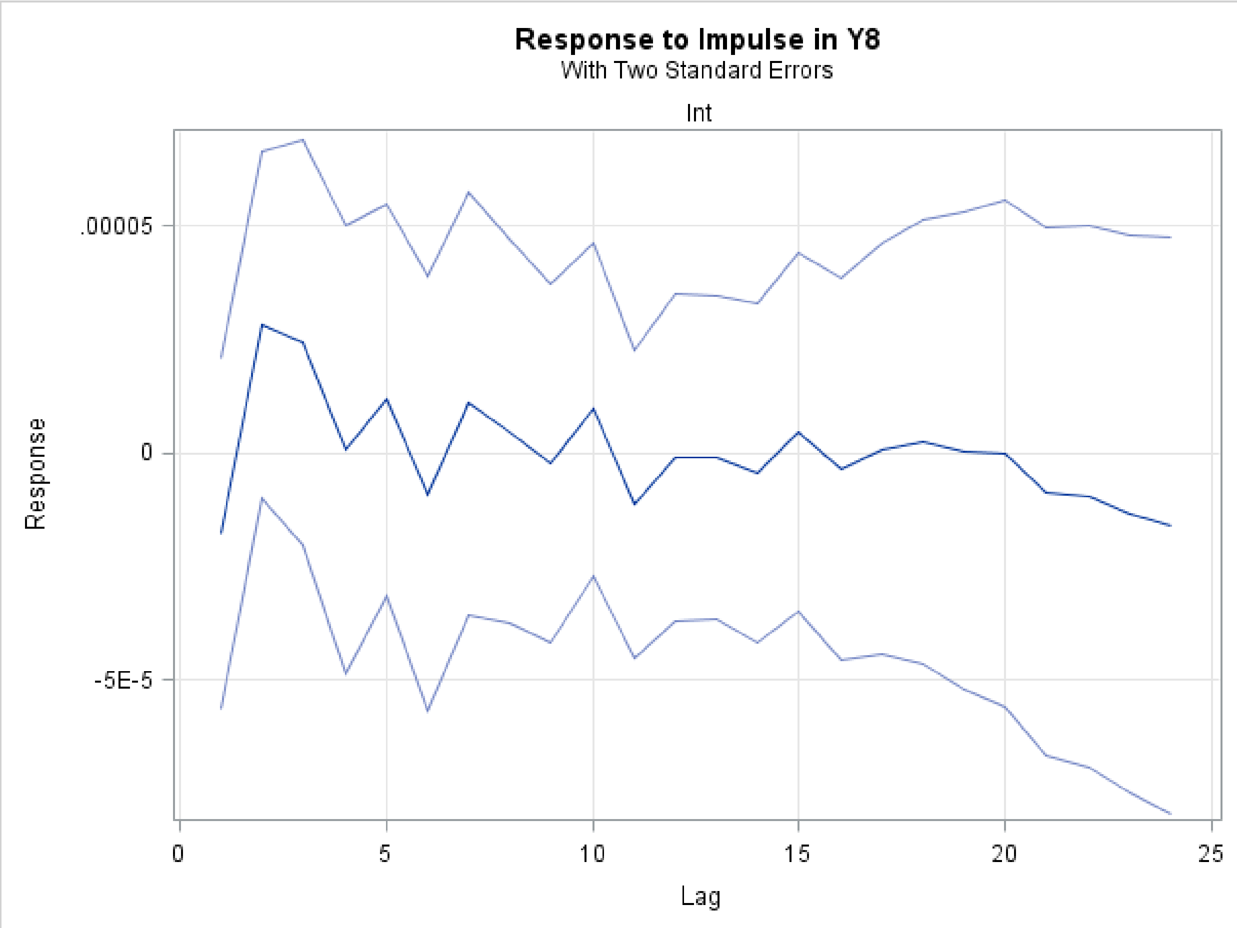
Response to Impulse in Y8
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
7.5
5.0
2.5
0.0
-2.5
-5.0
2
0
-2
0
5
10
15
20
25


Response to Impulse in Y8
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
10
5
0
-5
7.5
5.0
2.5
0.0
-2.5
-5.0
0
5
10
15
20
25

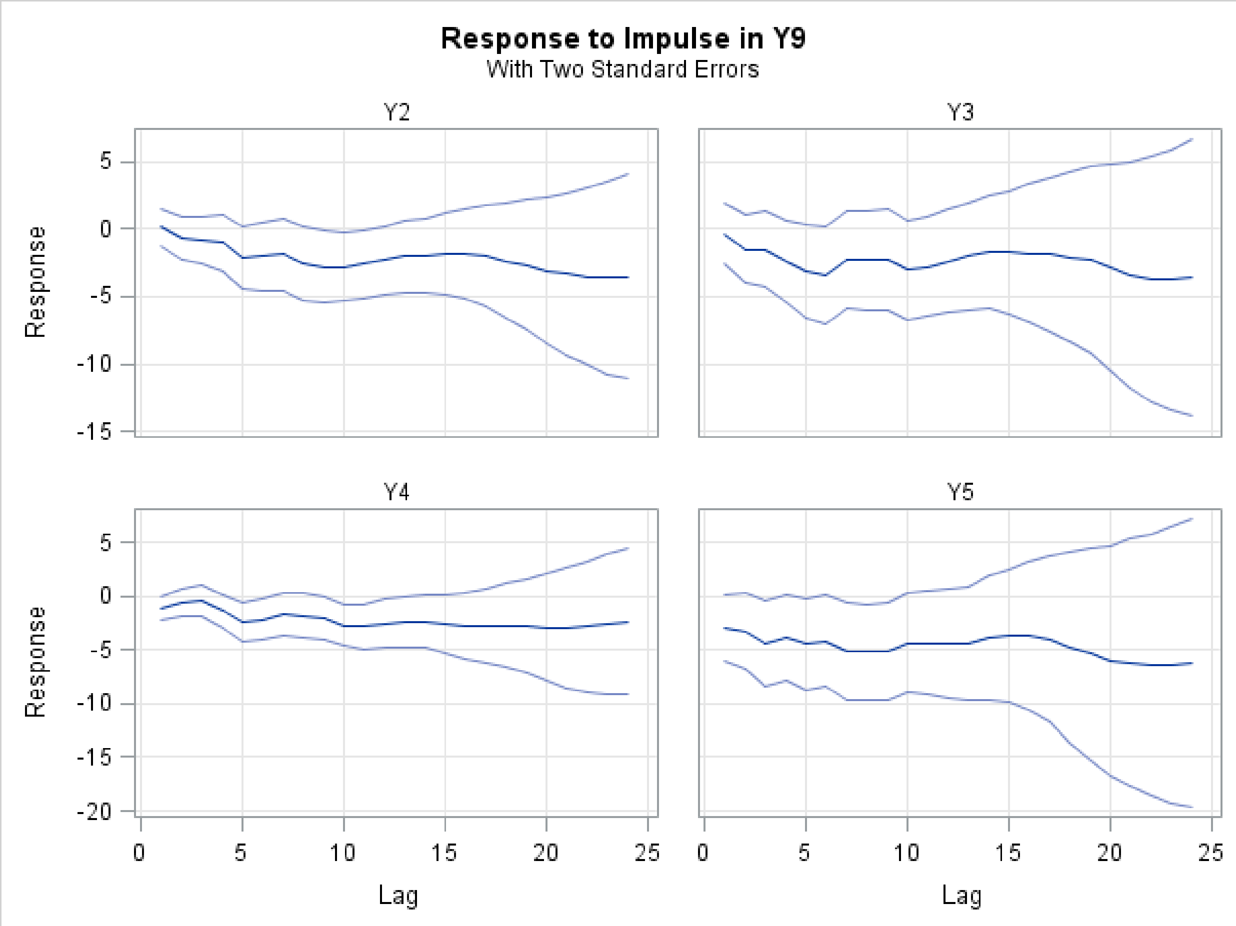

Response to Impulse in Y8
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
4
2
0
-2
10
5
0
-5
0
5
10
15
20
25

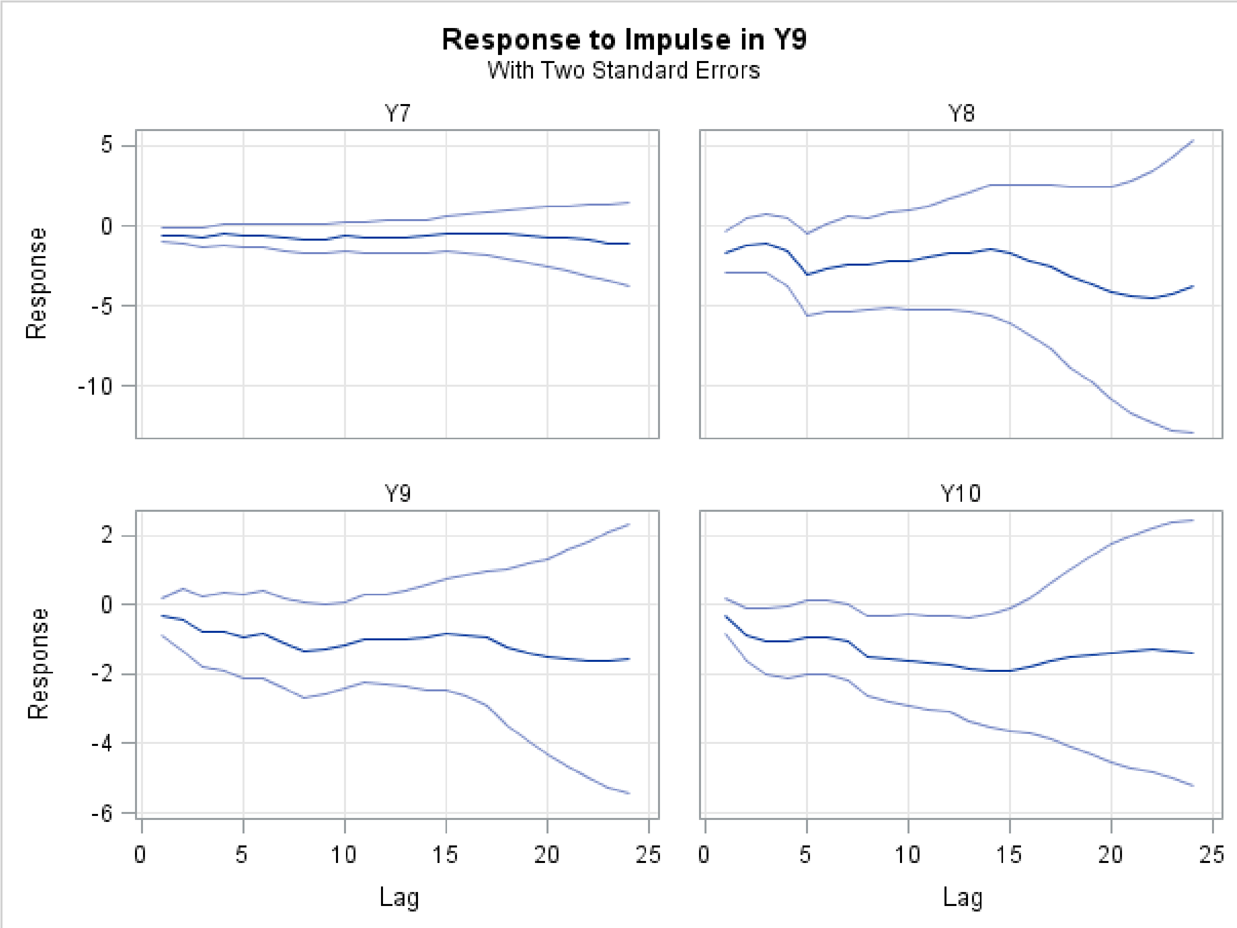


Response to Impulse in Y8
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
7.5
5.0
2.5
0.0
-2.5
-5.0
150
100
50
0
-50
0
5
10
15
20
25

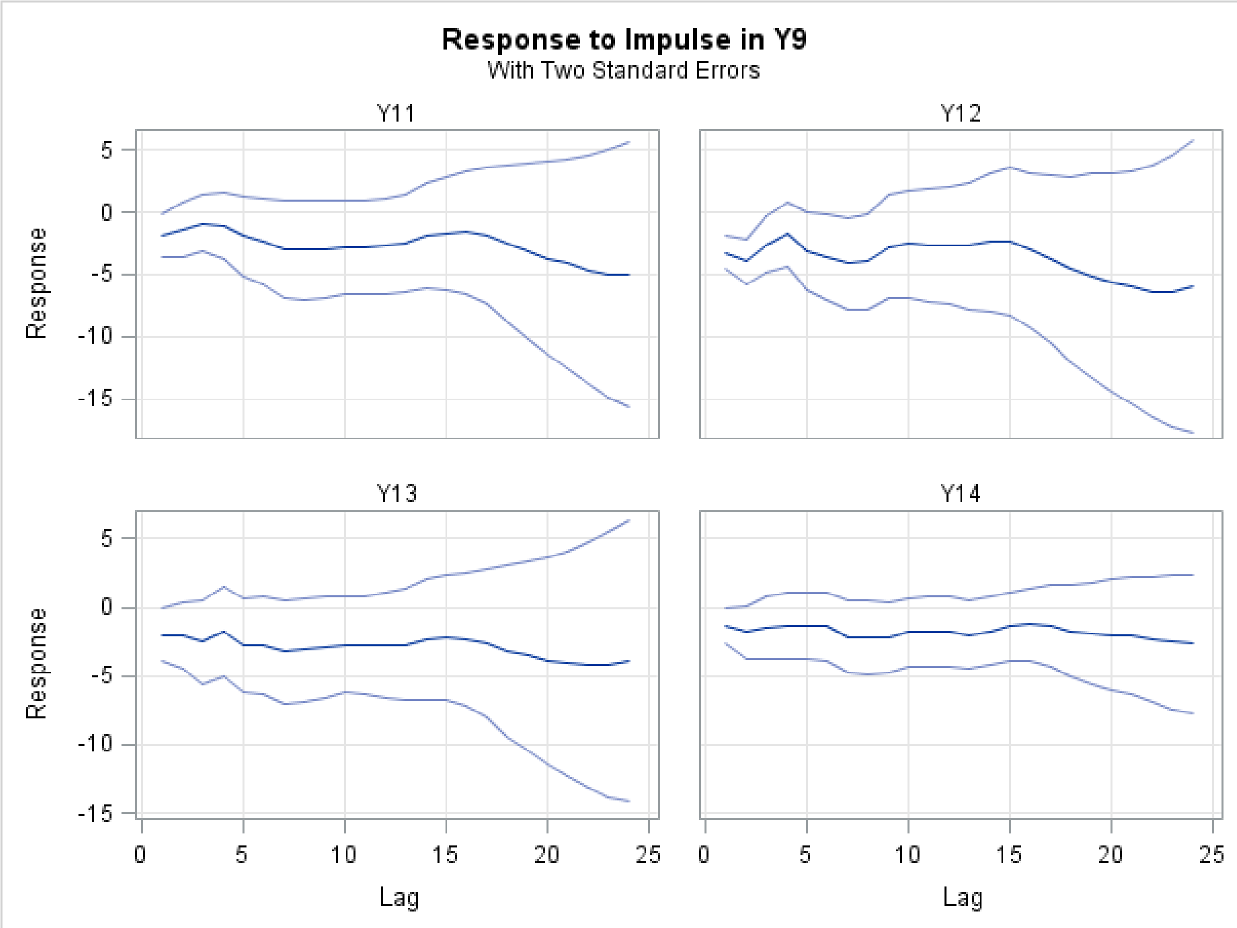


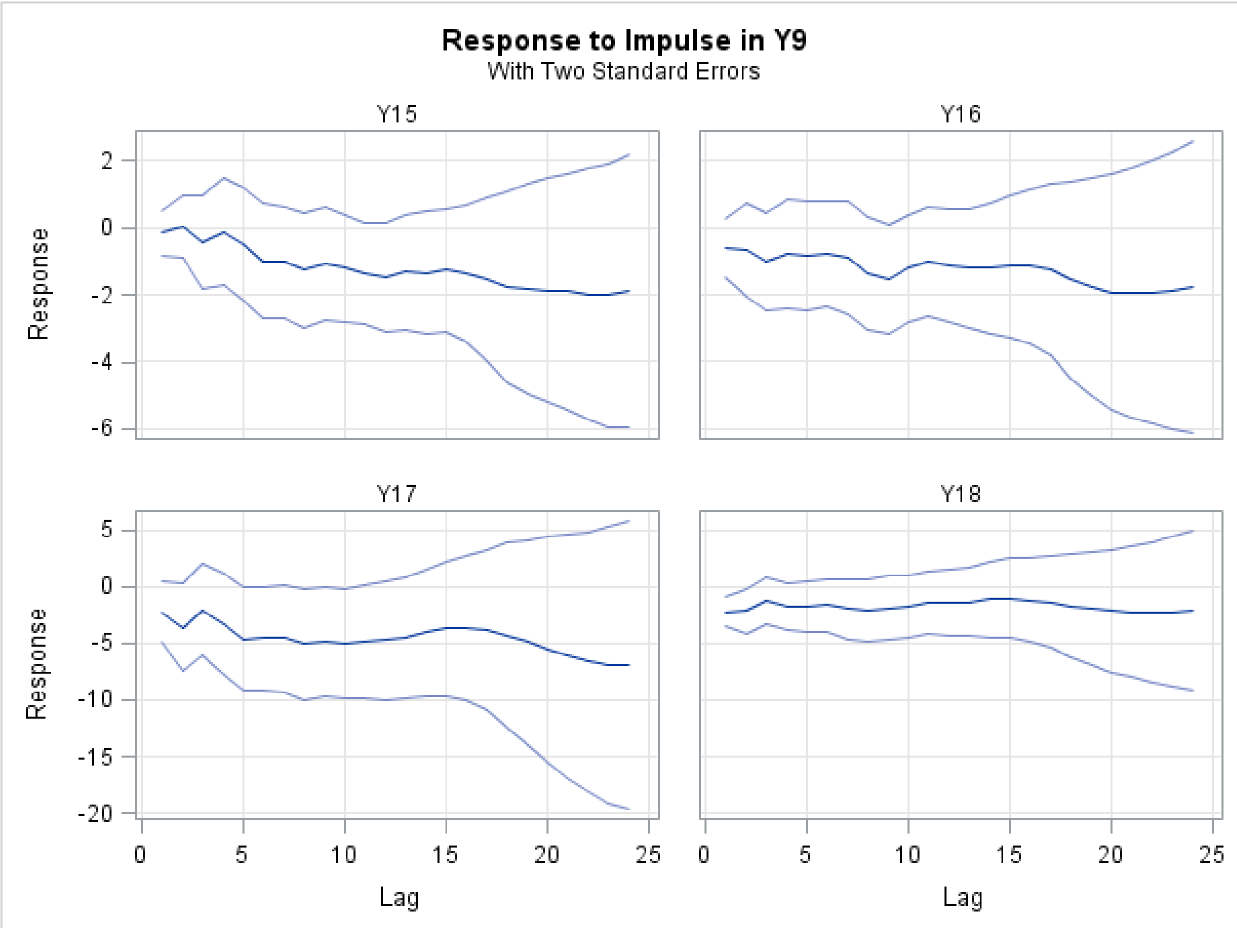
Response to Impulse in Y8
With Two Standard Errors
Int
.00005
0
-5E-5
Response
0
5
10
15
20
25
Lag


Response to Impulse in Y9
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
5
0
-5
-10
-15
-20
0
5
10
15
20
25

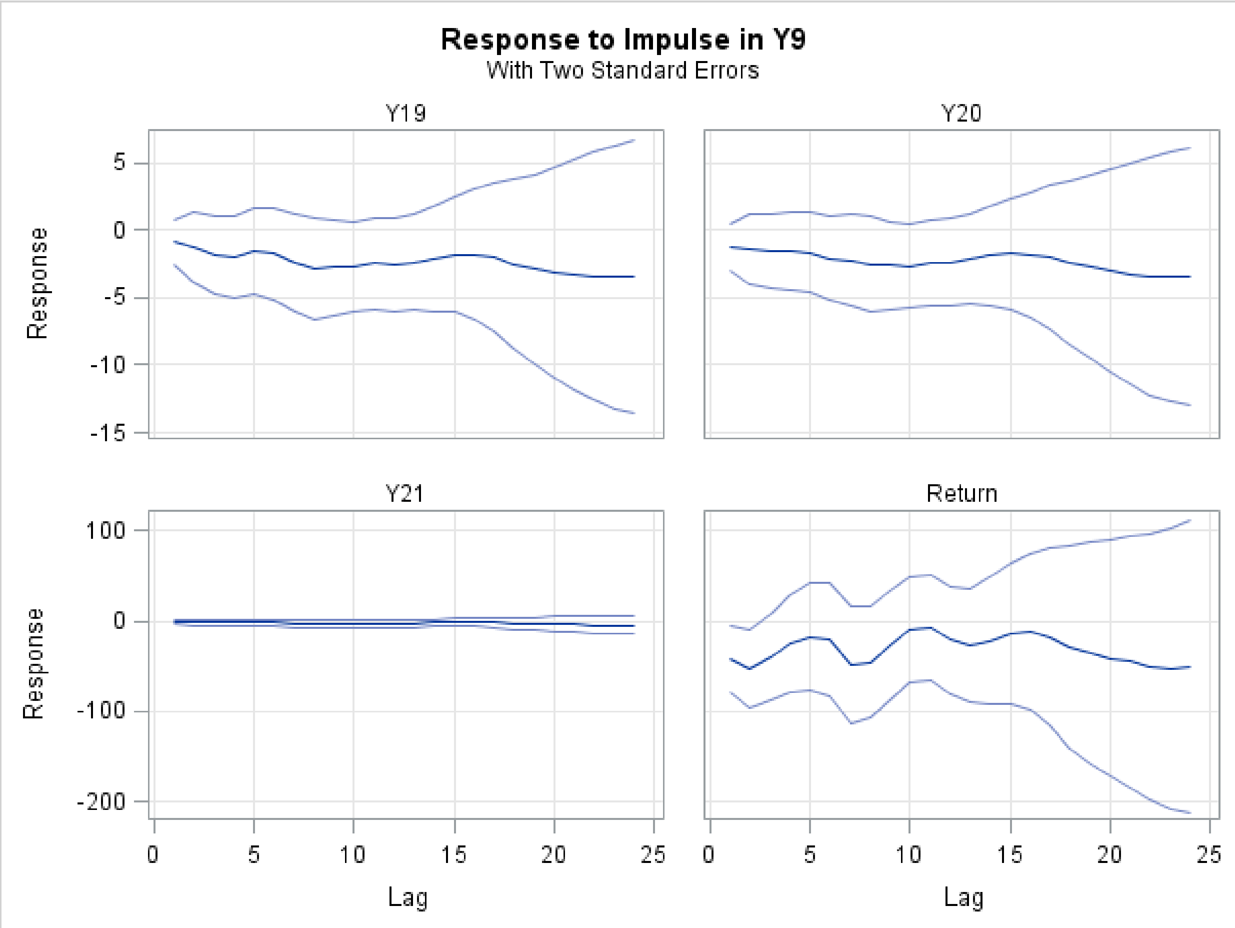


Response to Impulse in Y9
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag

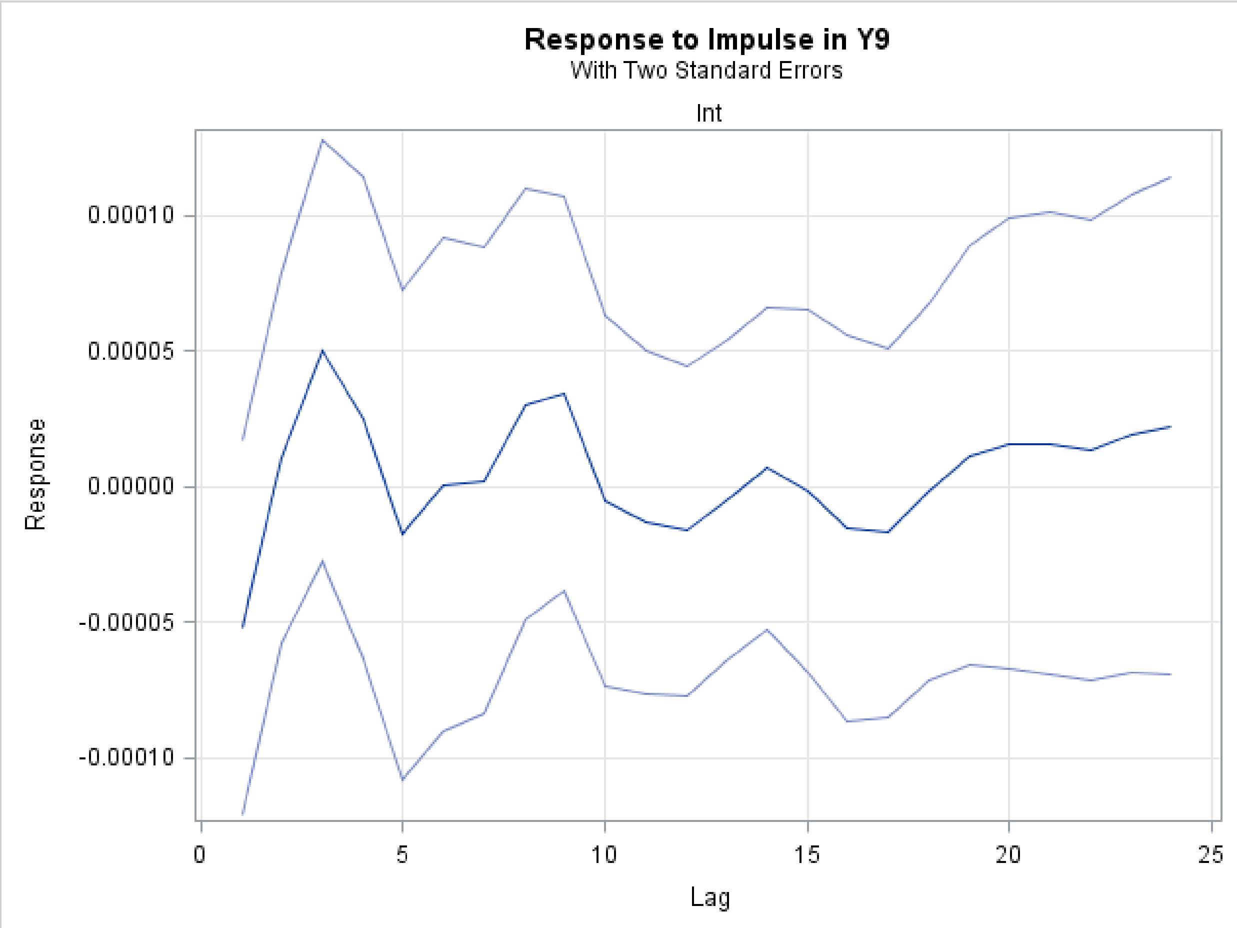

Response to Impulse in Y9
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5
0
-5
-10
-15
0
5
10
15
20
25



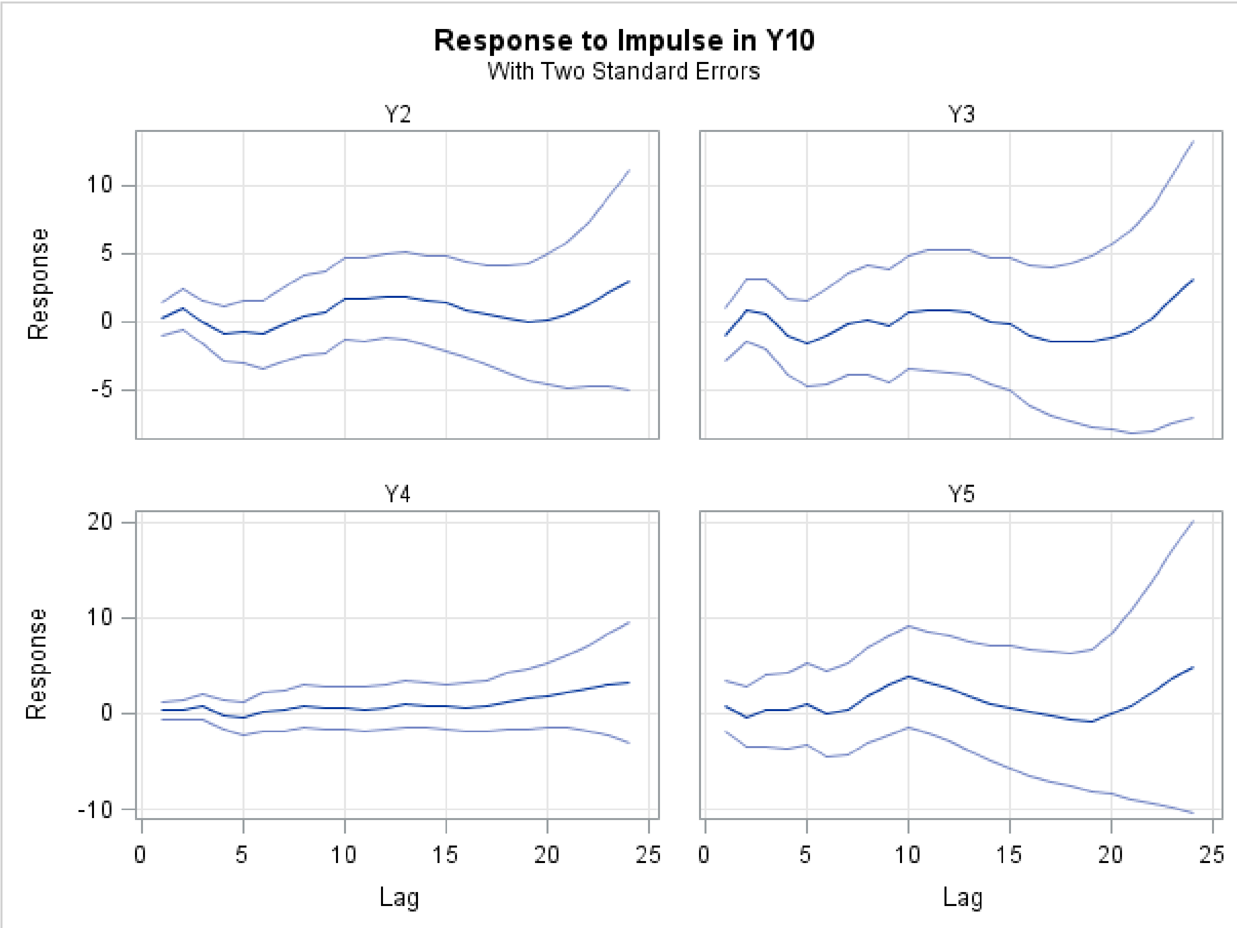
Response to Impulse in Y9
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag

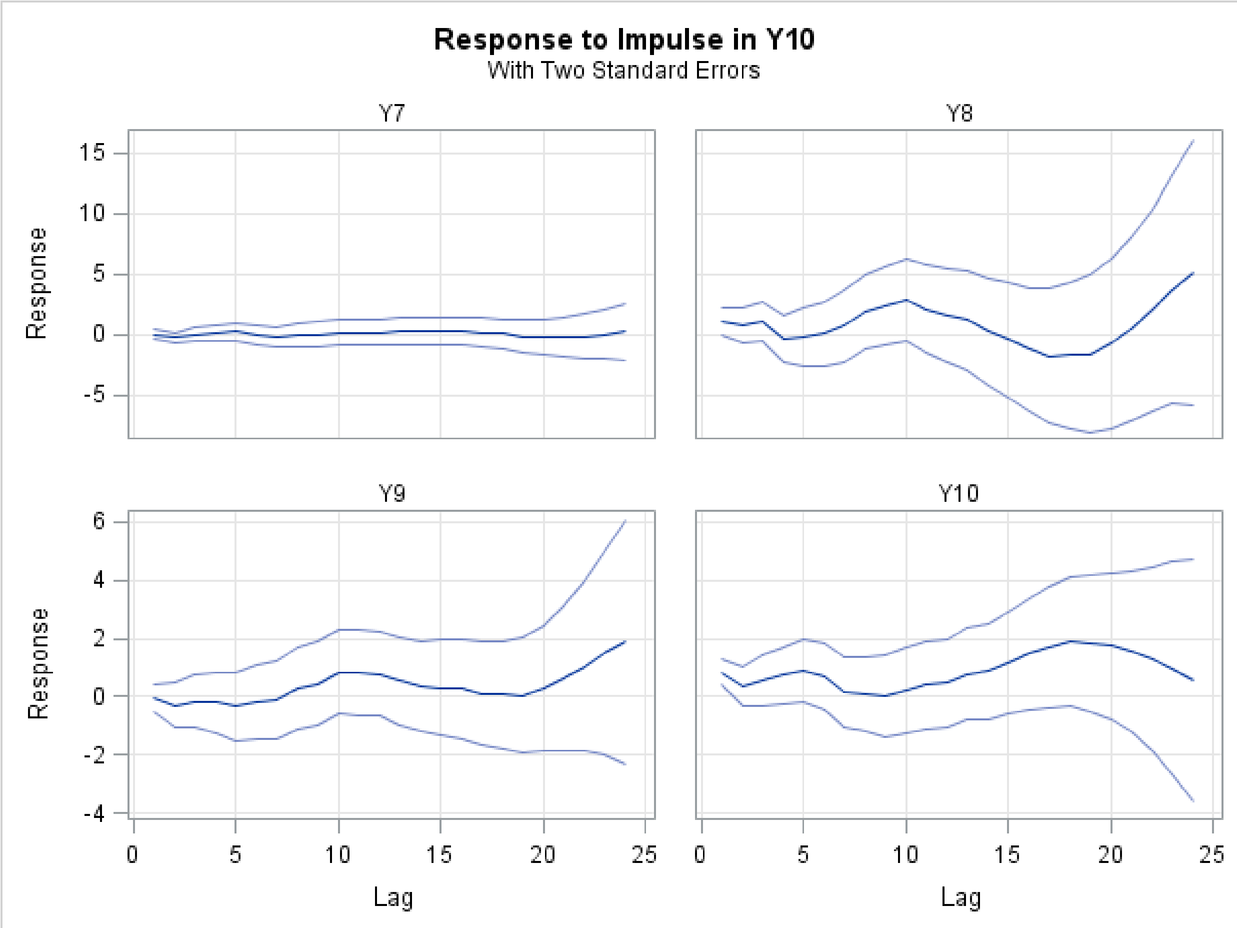


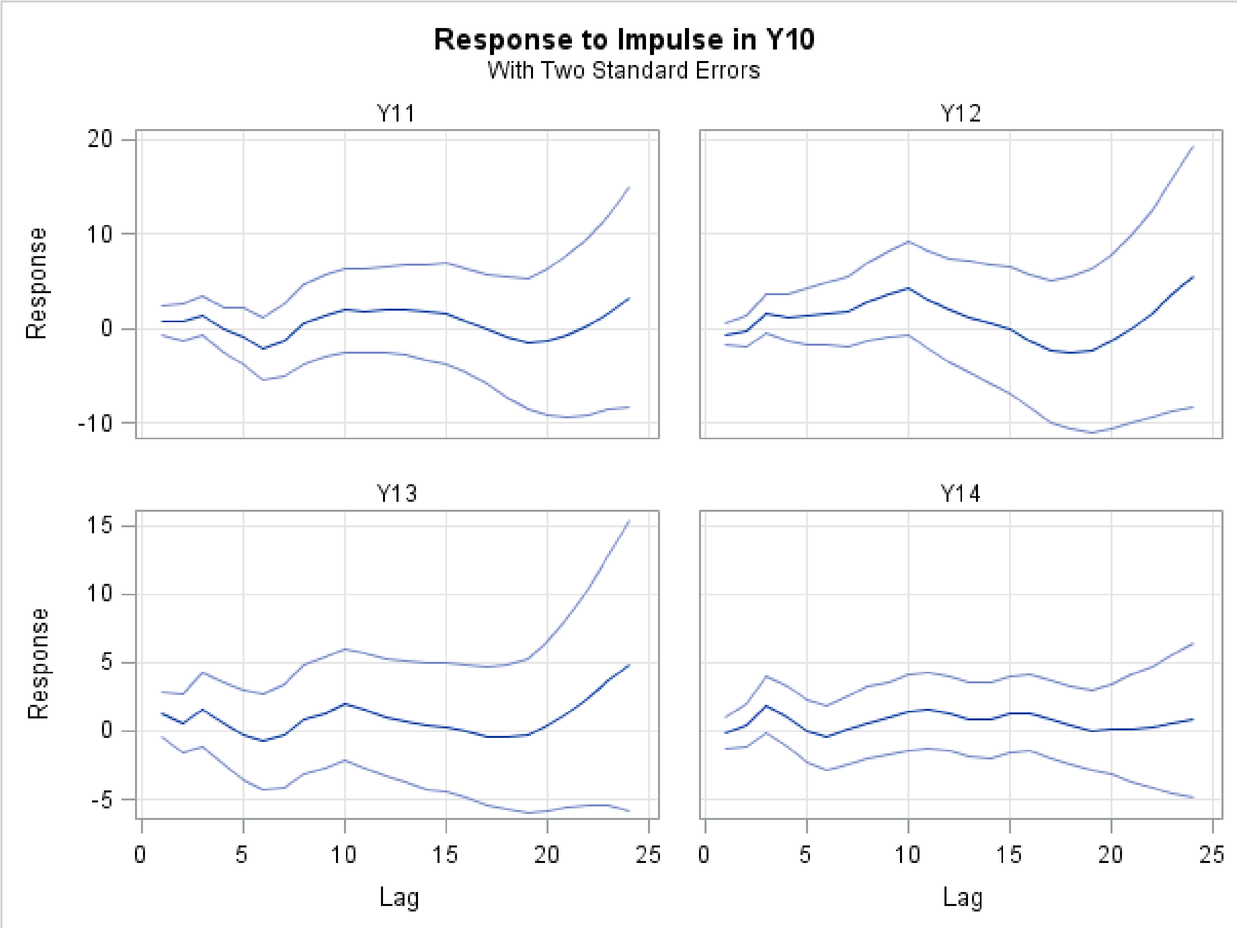
Response to Impulse in Y9
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
5
0
-5
-10
-15
100
0
-100
-200
0
5
10
15
20
25

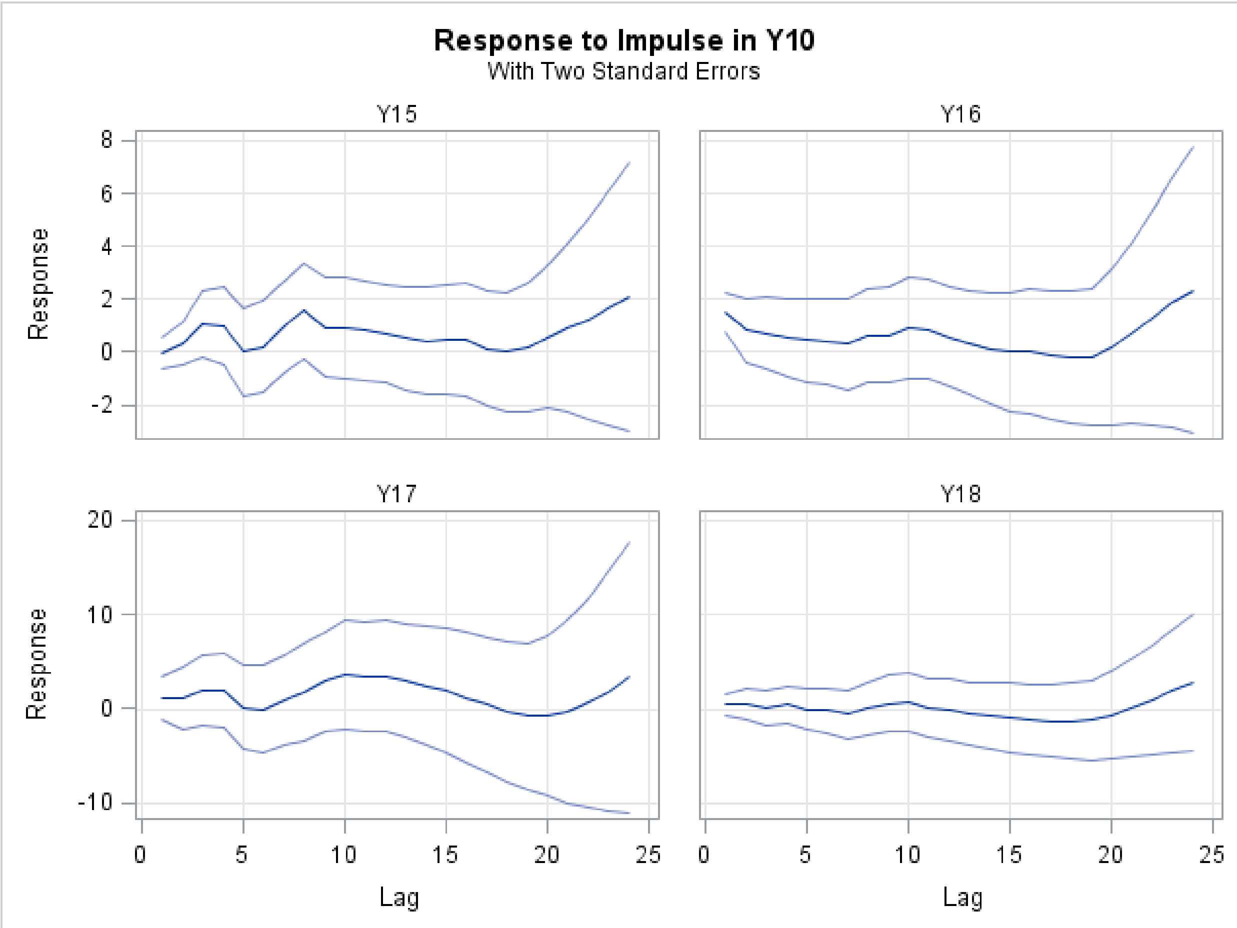


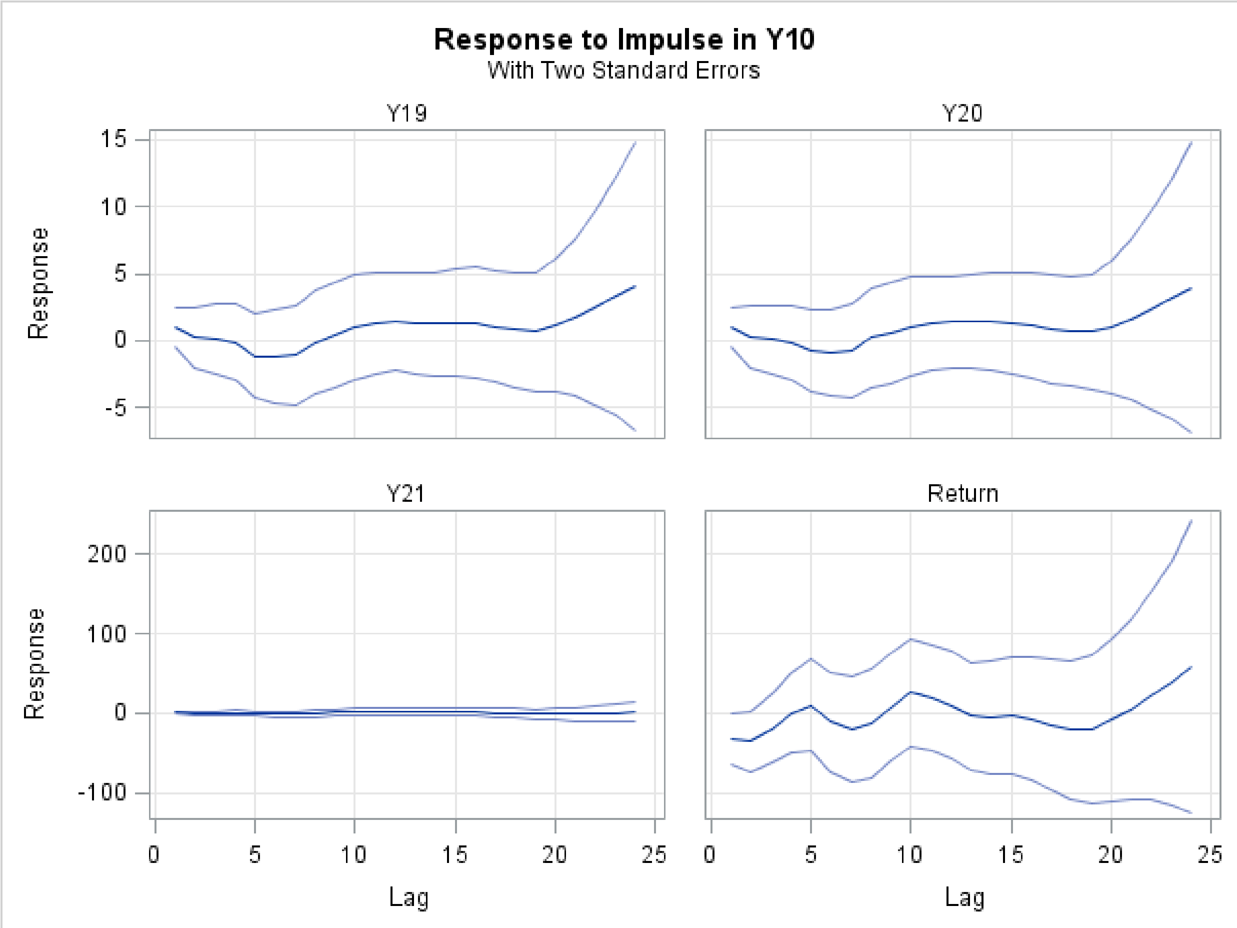
Response to Impulse in Y9
With Two Standard Errors
Int
0.00010
0.00005
0.00000
-0.00005
-0.00010
Response
0
5
10
15
20
25
Lag


Response to Impulse in Y10
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
10
5
0
-5
20
10
0
-10
0
5
10
15
20
25

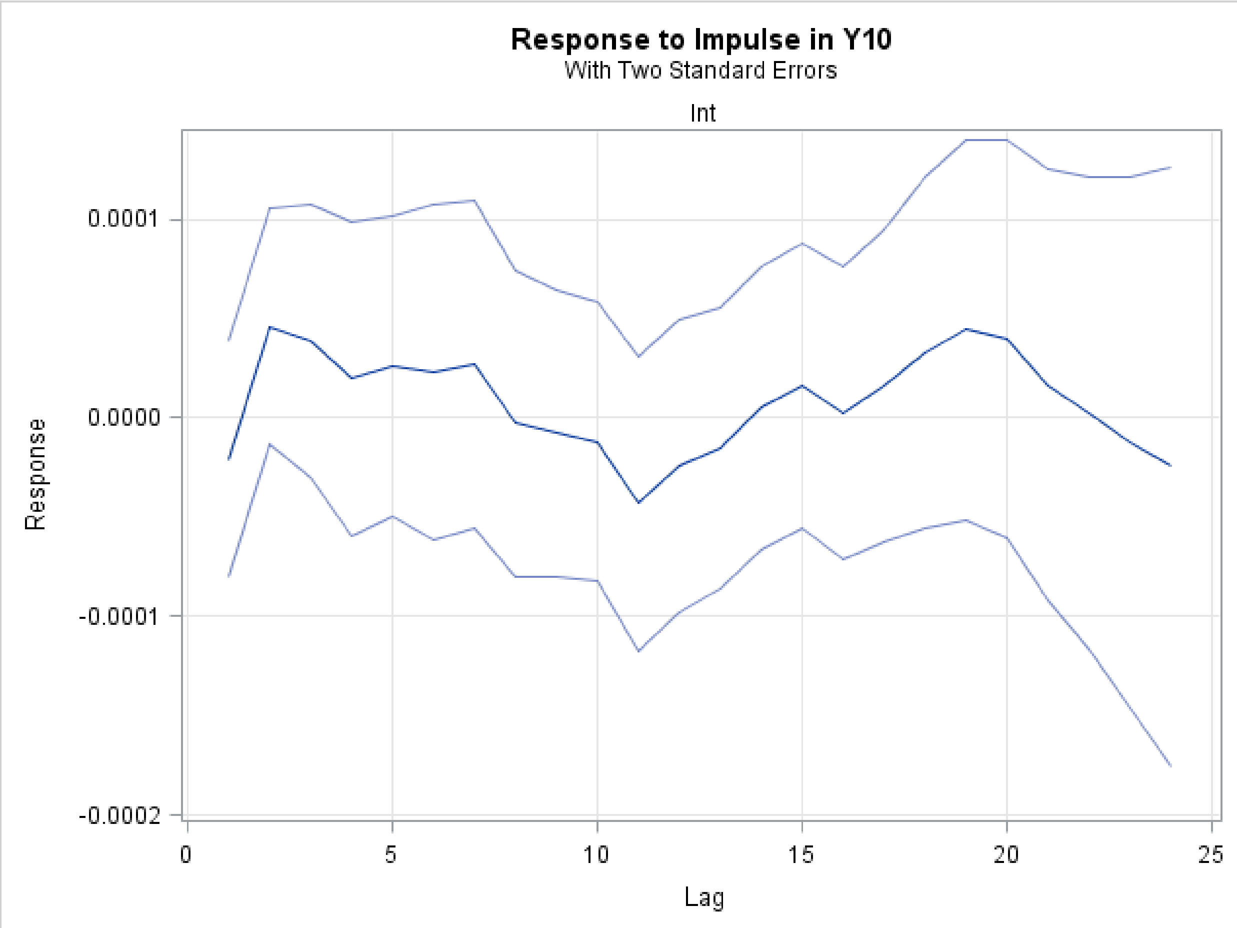

Response to Impulse in Y10
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
15
10
5
0
-5
6
4
2
0
-2
-4
0
5
10
15
20
25

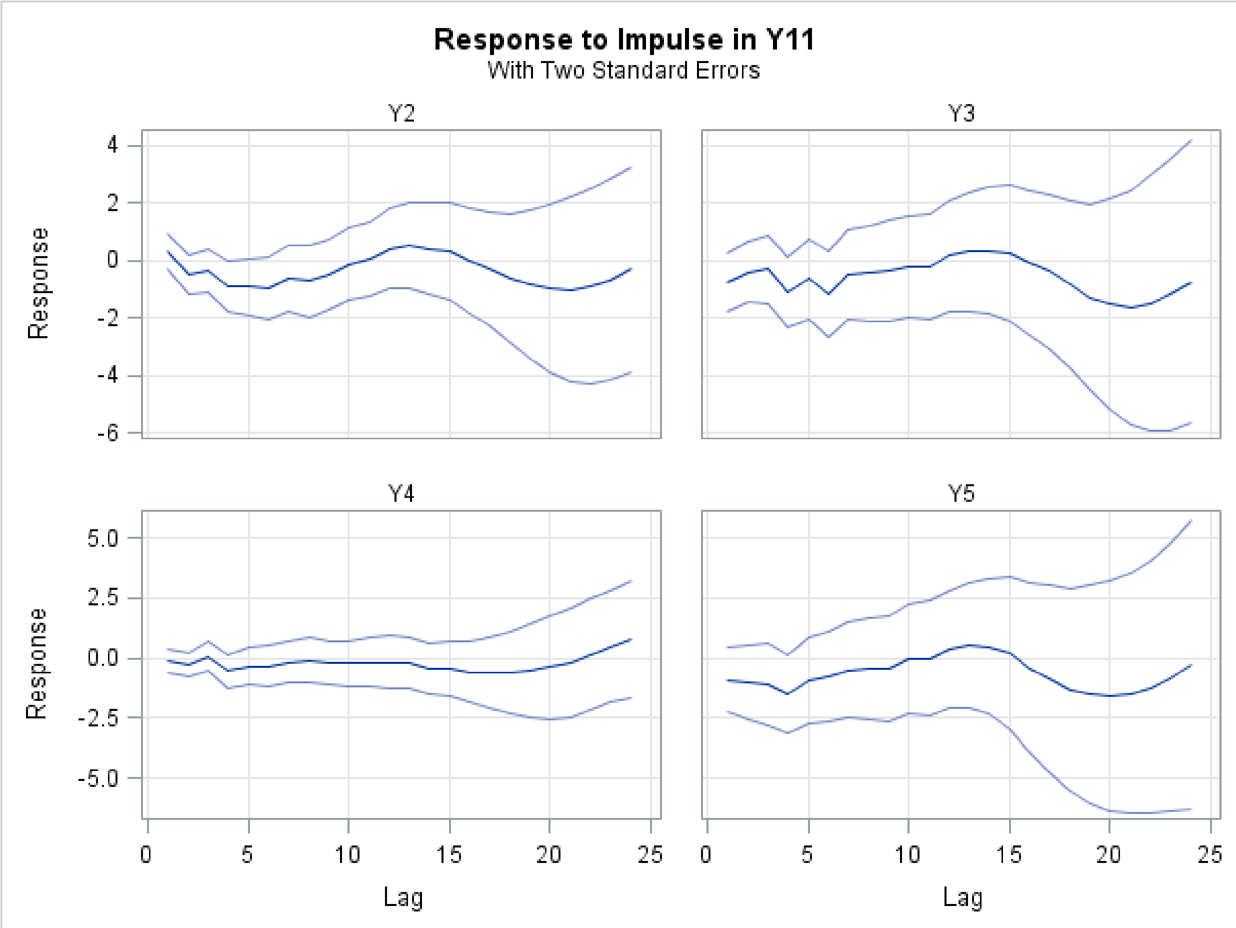

Response to Impulse in Y10
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
20
10
0
-10
15
10
5
0
-5
0
5
10
15
20
25

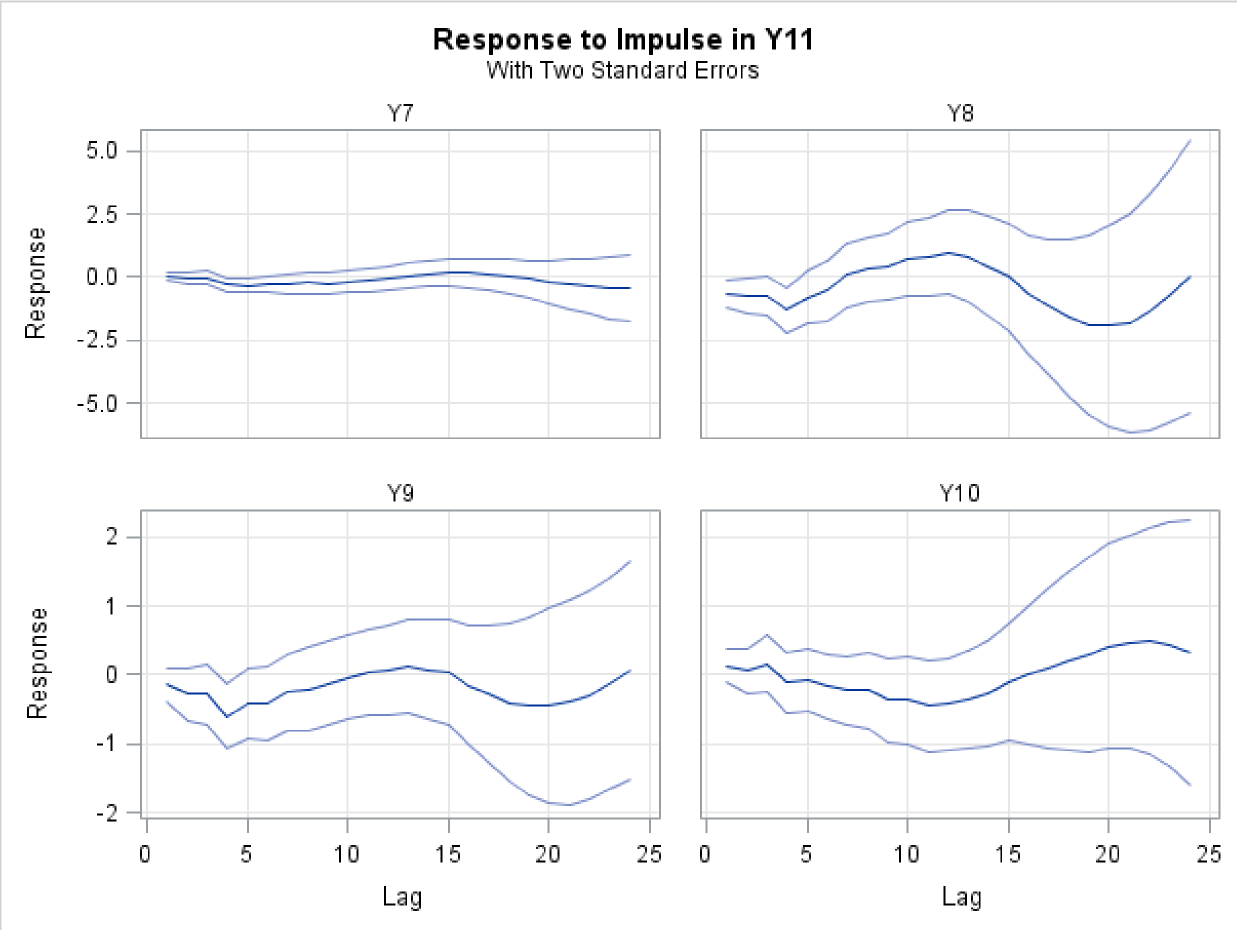

Response to Impulse in Y10
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
8
6
4
2
0
-2
20
10
0
-10
0
5
10
15
20
25

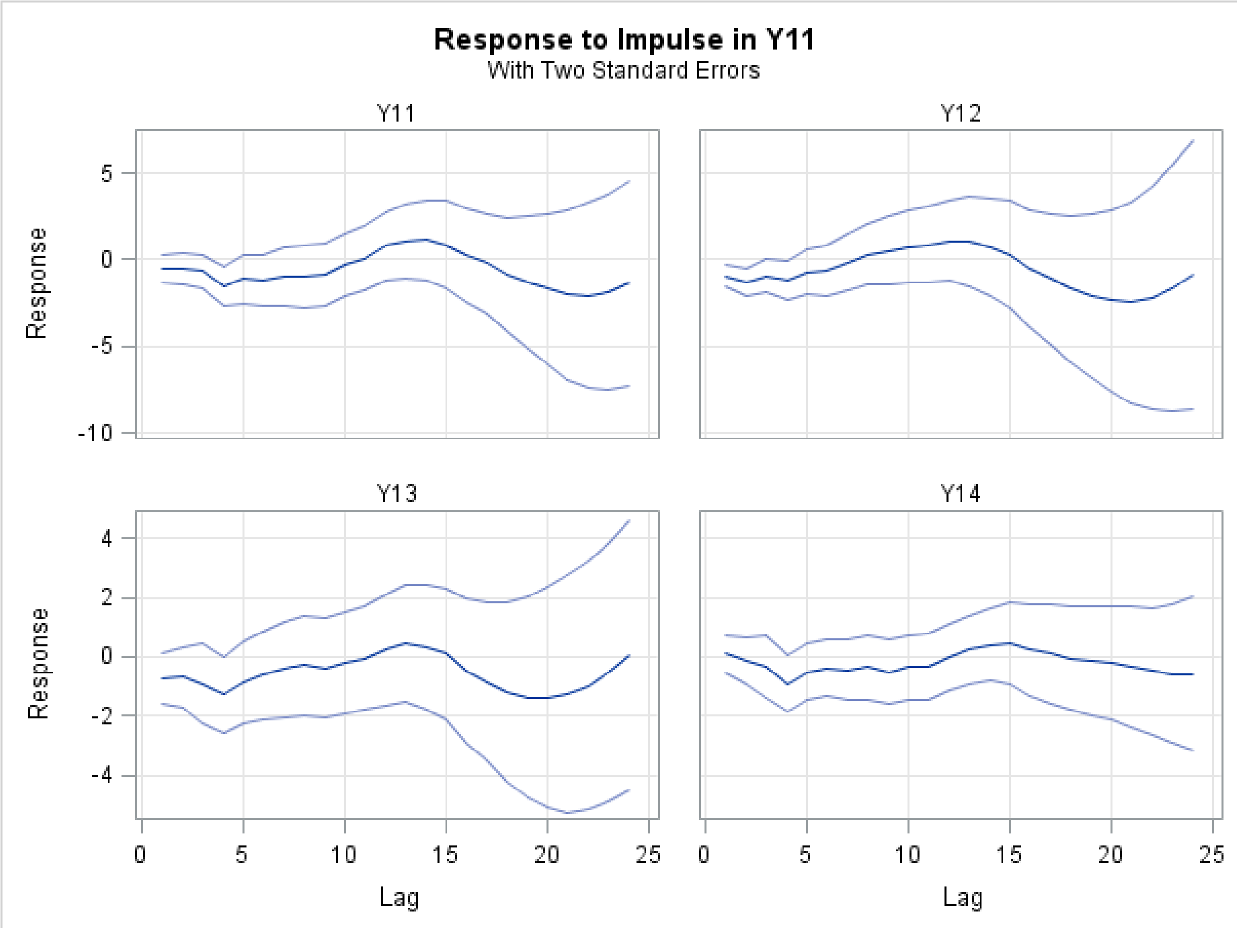


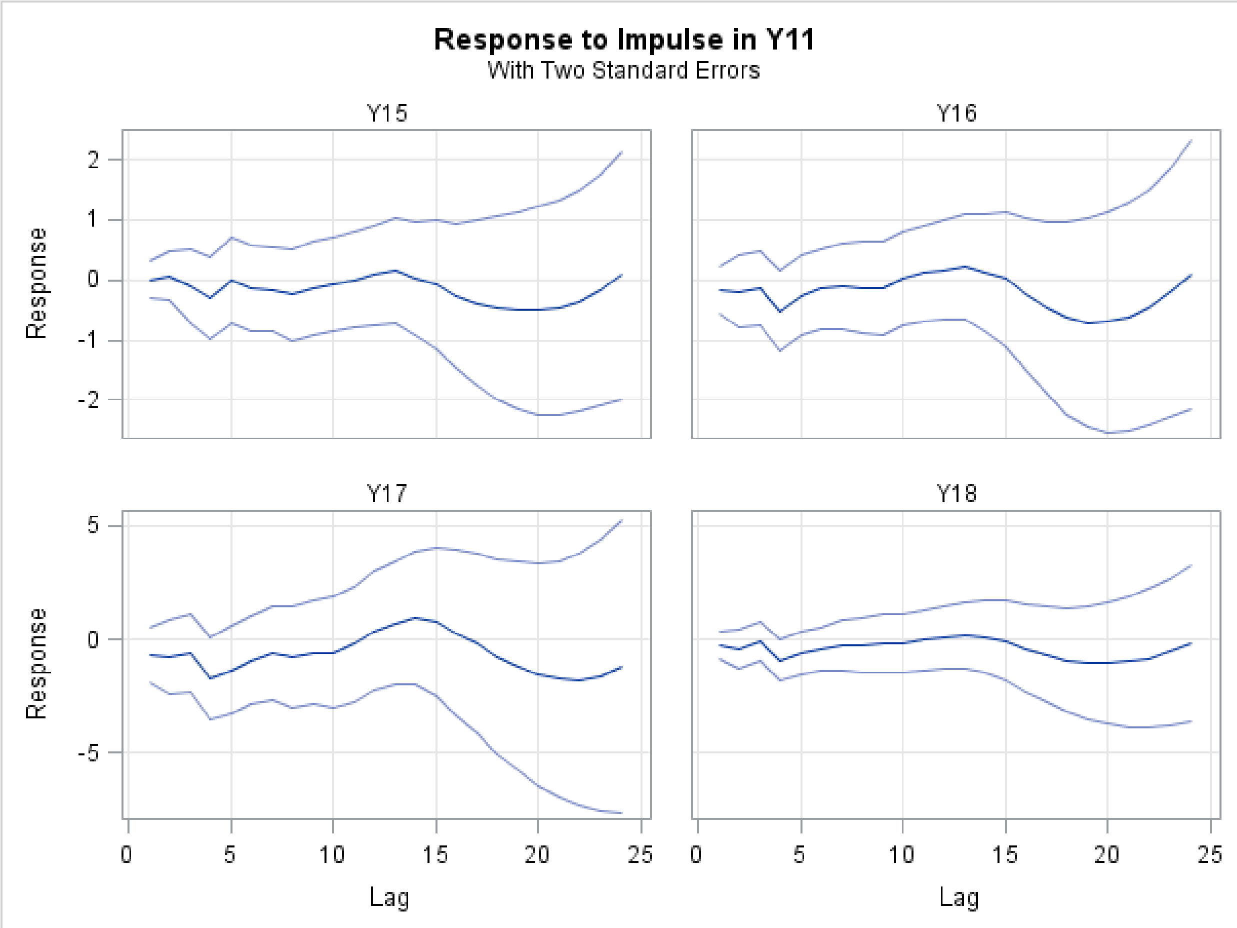
Response to Impulse in Y10
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
15
10
5
0
-5
200
100
0
-100
0
5
10
15
20
25

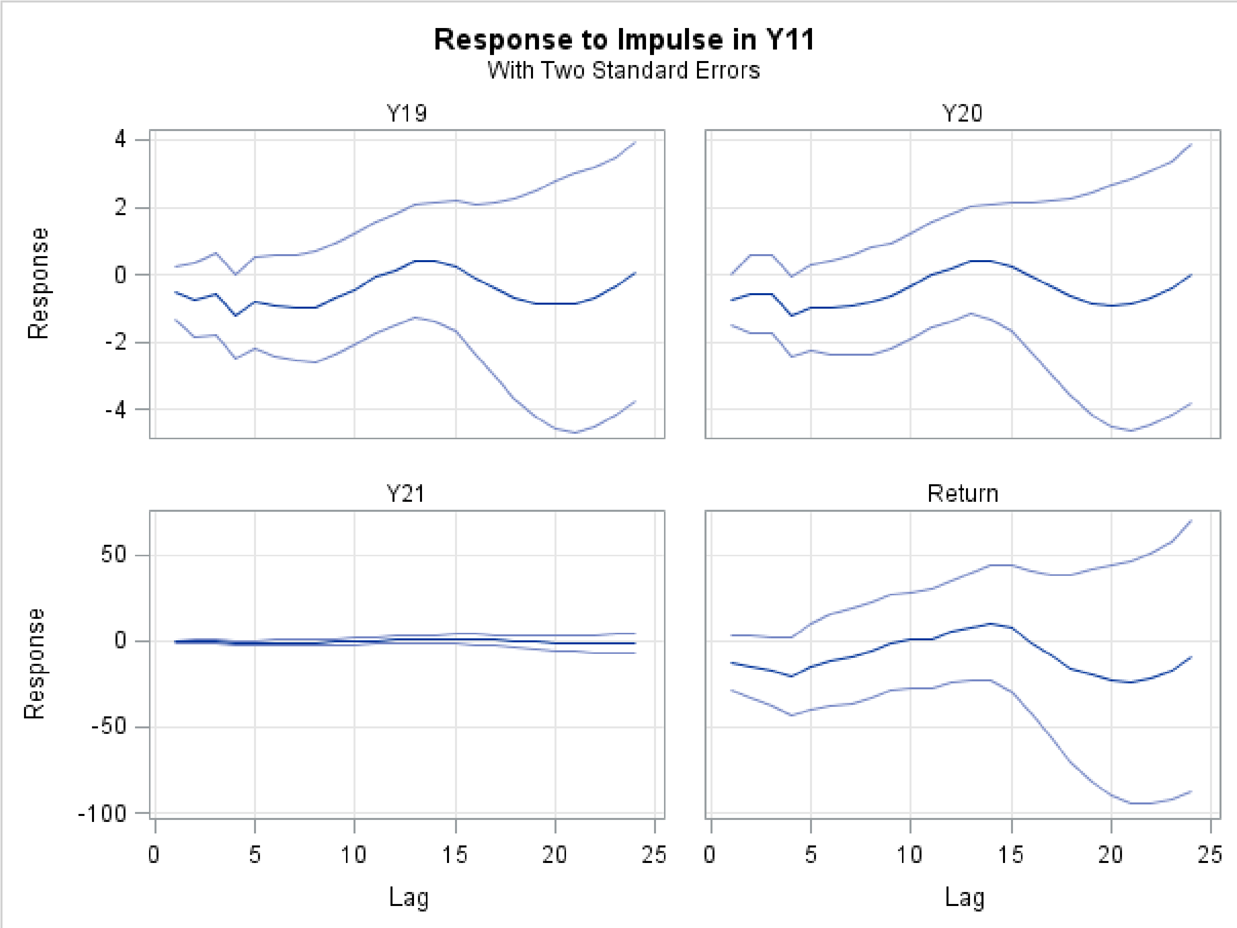

Response to Impulse in Y10
With Two Standard Errors
Int
Response
0.0001
0.0000
-0.0001
-0.0002
0
5
10
15
20
25
Lag

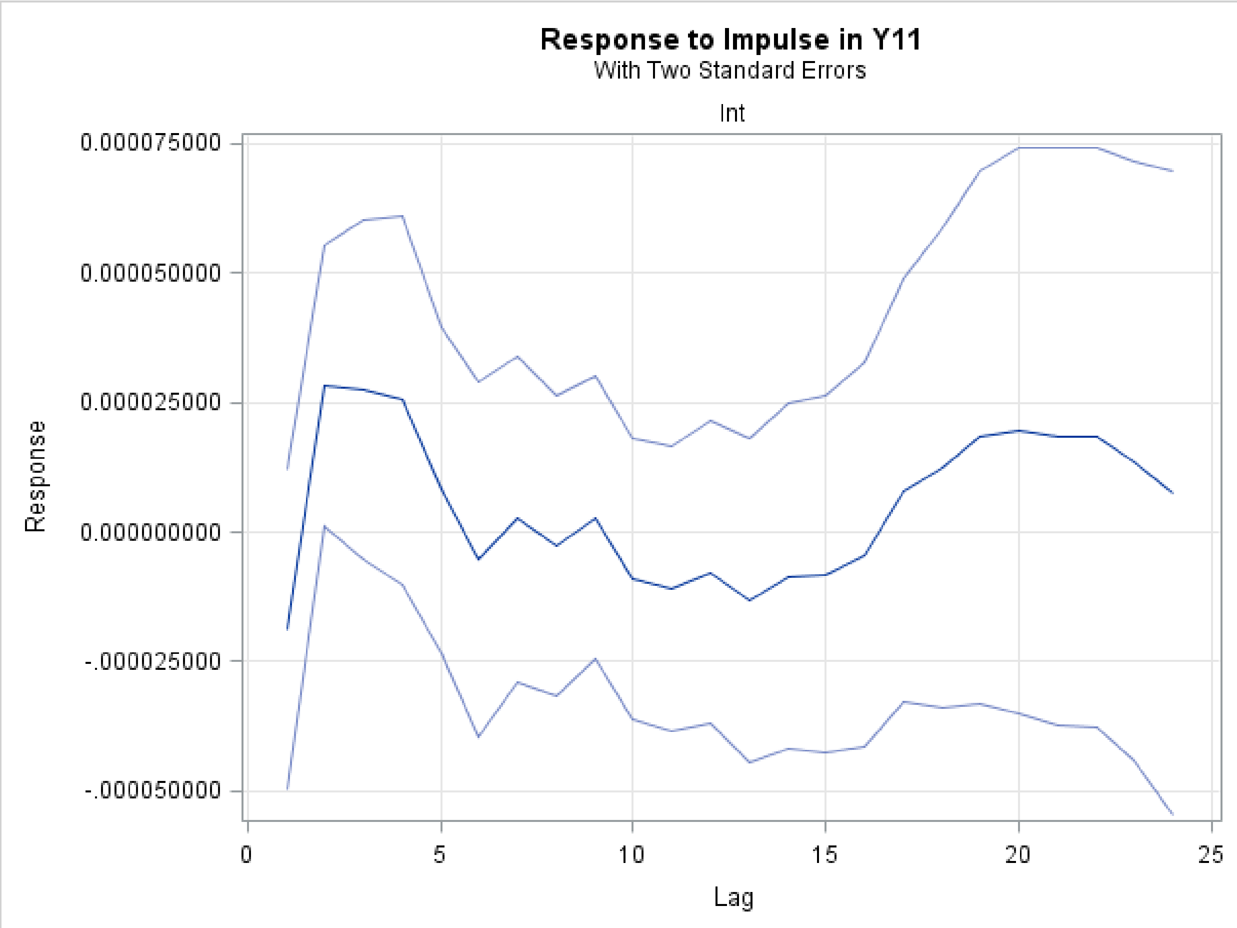

Response to Impulse in Y11
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
4
2
0
-2
-4
-6
5.0
2.5
0.0
-2.5
-5.0
0
5
10
15
20
25

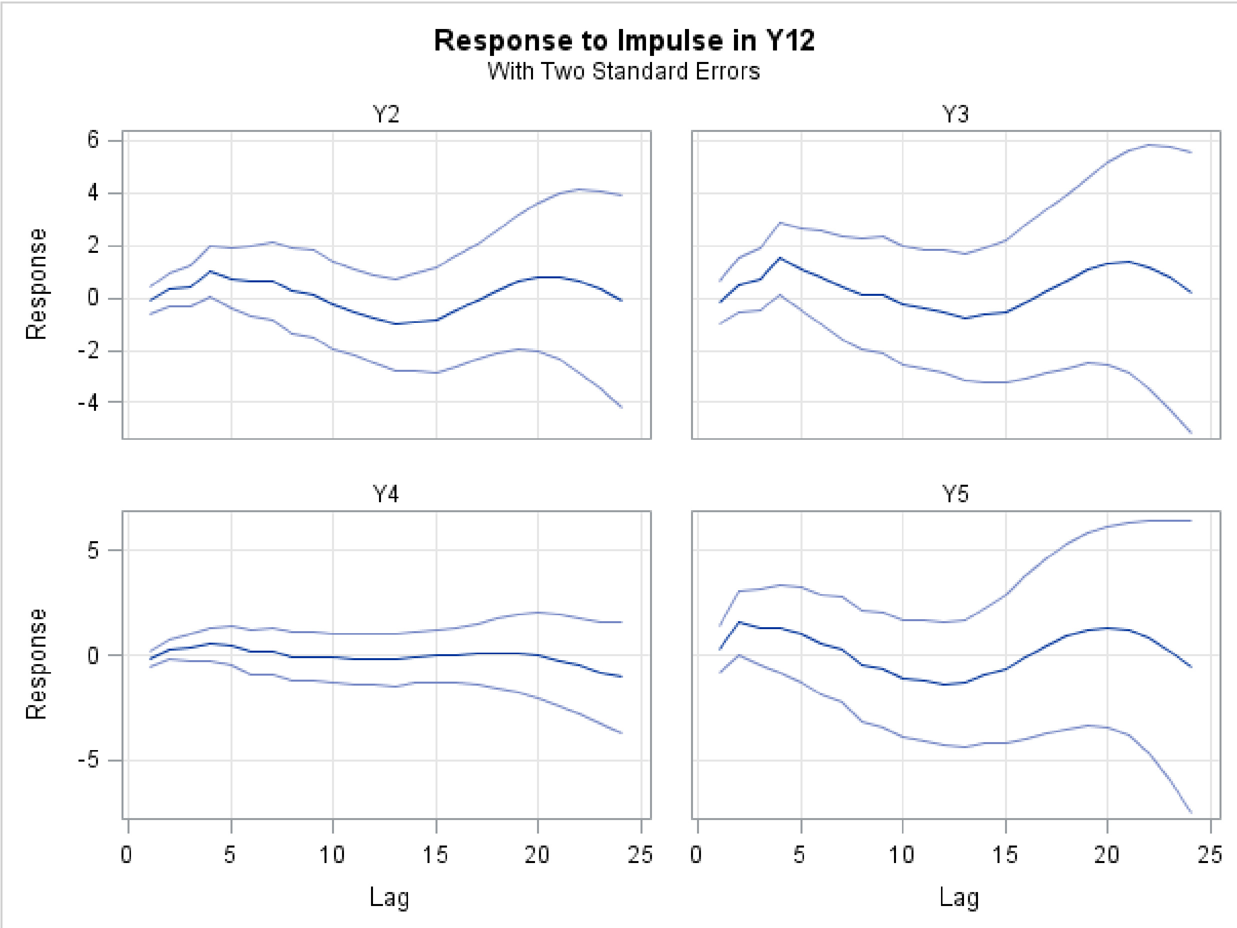

Response to Impulse in Y11
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Lag
5.0
2.5
0.0
-2.5
-5.0
2
1
0
-1
-2
0
5
10
15
20
25


Response to Impulse in Y11
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5
0
-5
-10
4
2
0
-2
-4
0
5
10
15
20
25

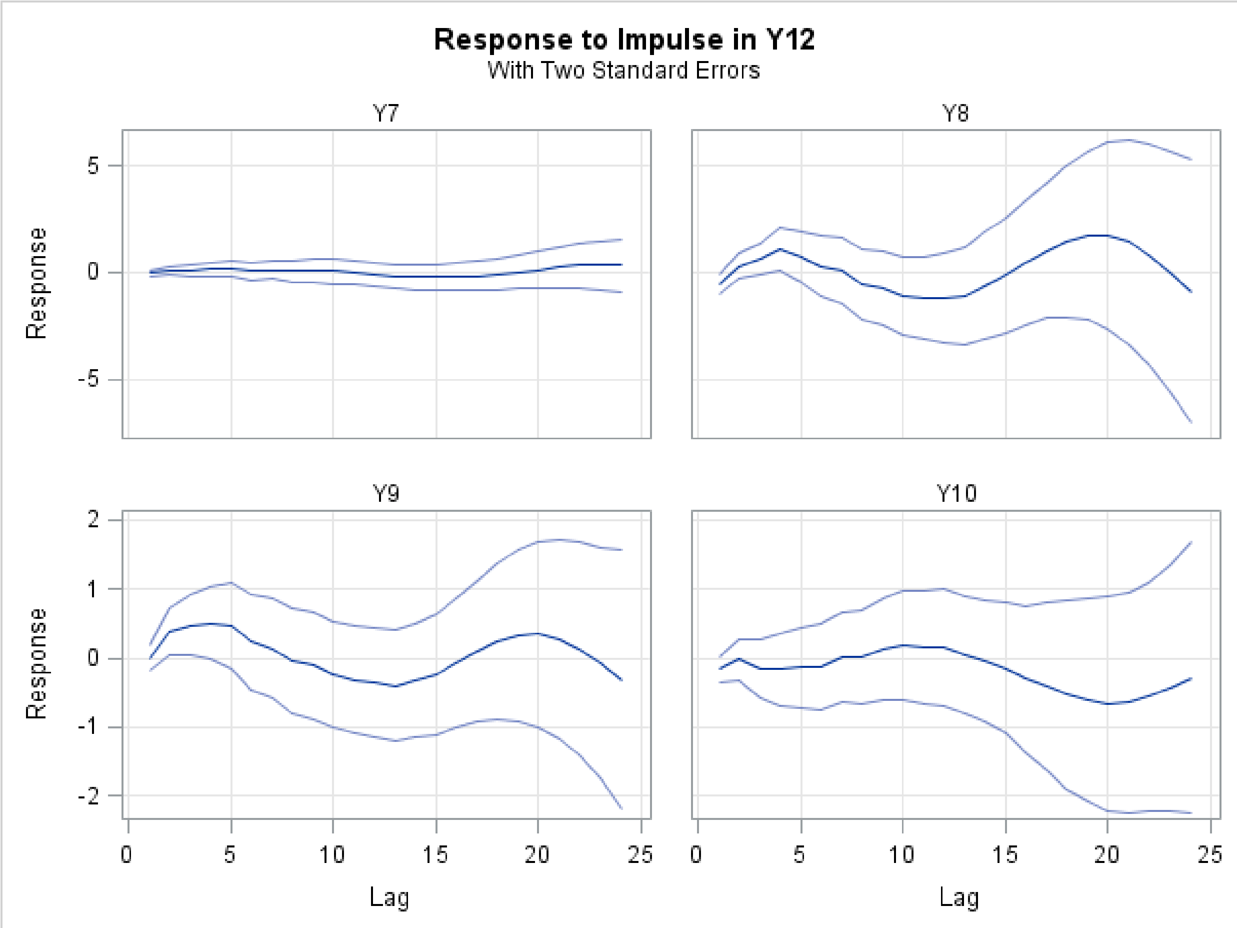

Response to Impulse in Y11
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
2
1
0
-1
-2
5
0
-5
0 5 10 15 20 25
Lag
Lag

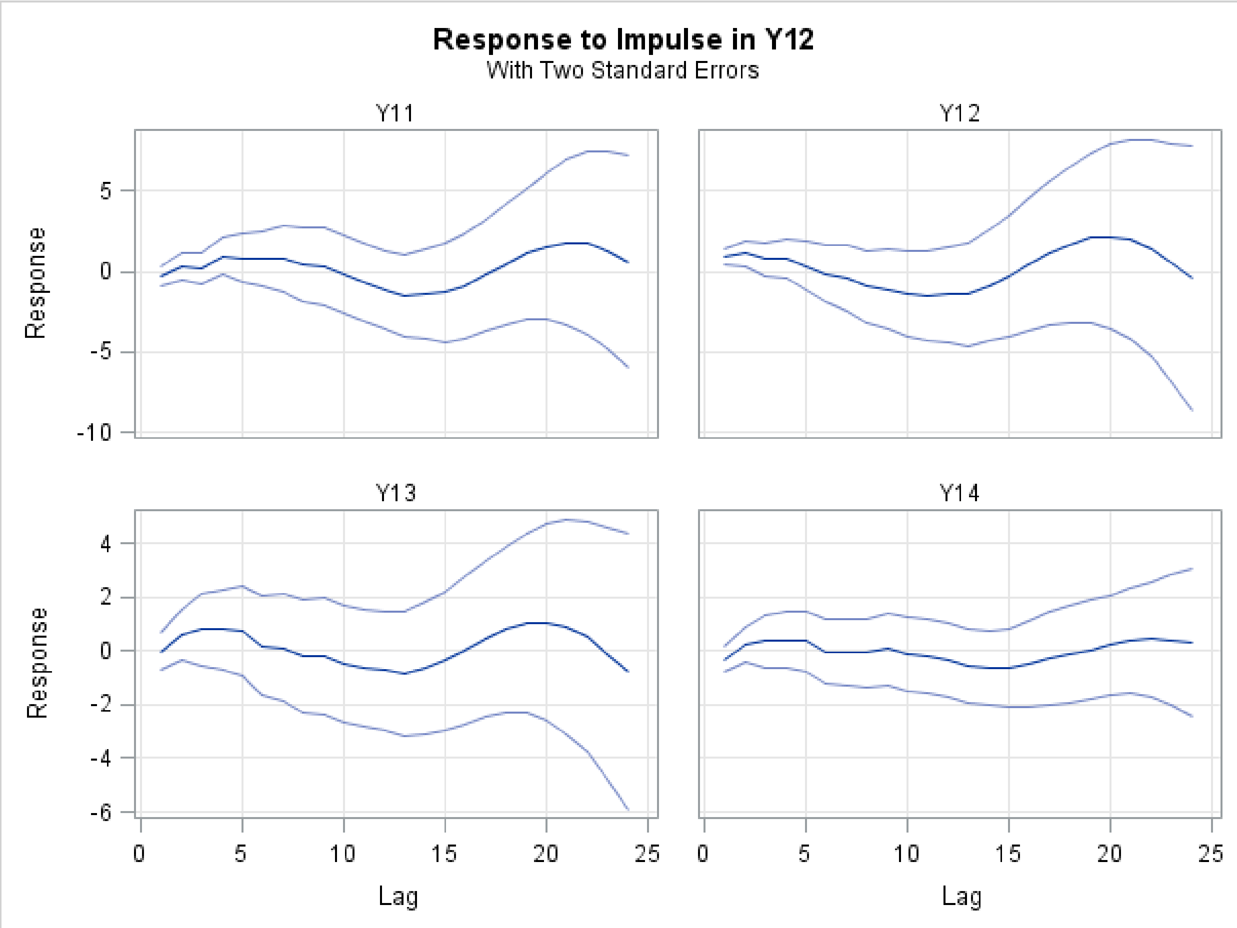

Response to Impulse in Y11
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
4
2
0
-2
-4
50
0
-50
-100
0
5
10
15
20
25

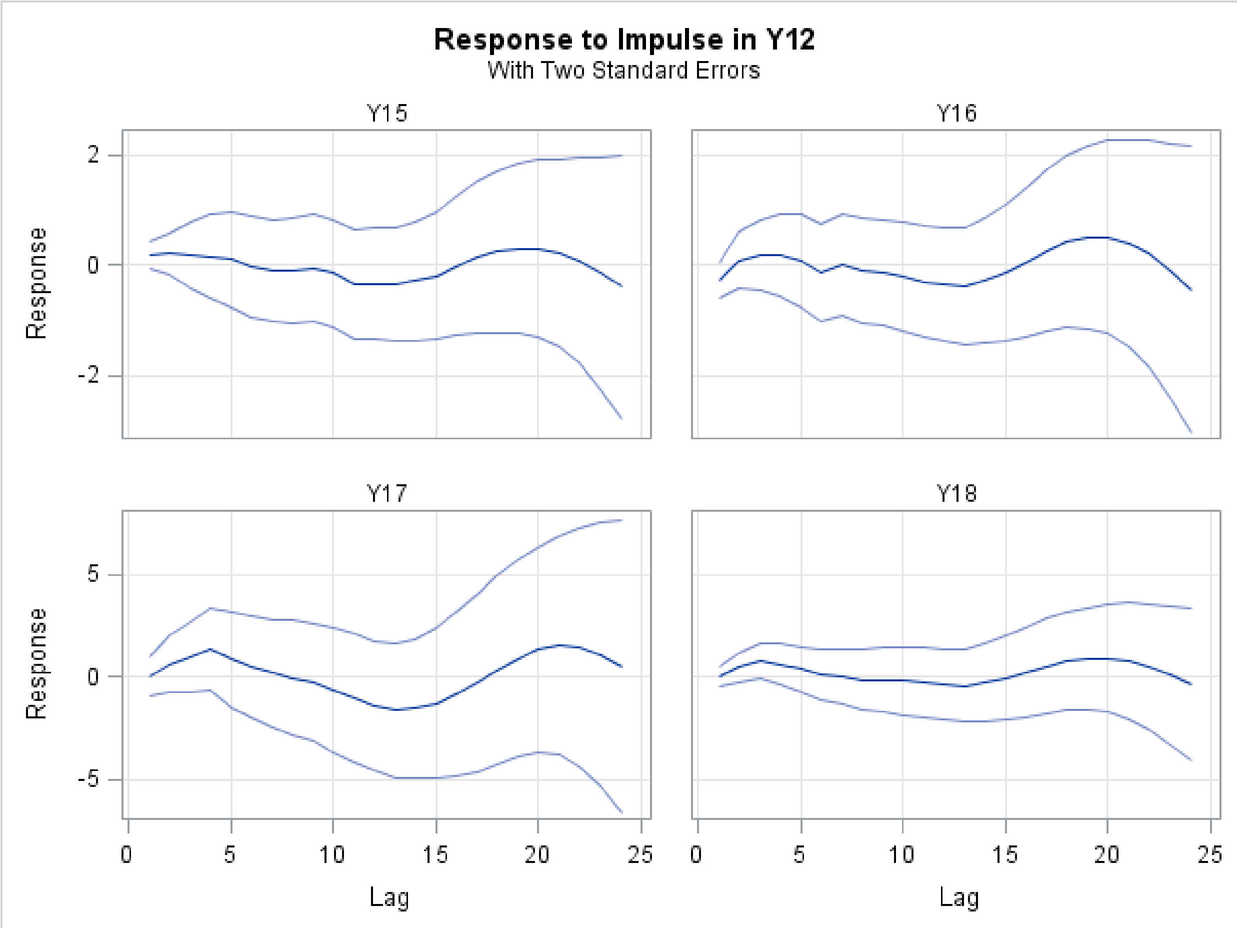

Response to Impulse in Y11
With Two Standard Errors
Int
0.000075000
0.000050000
0.000025000
0.000000000
-.000025000
-.000050000
Response
0
5
10
15
20
25
Lag



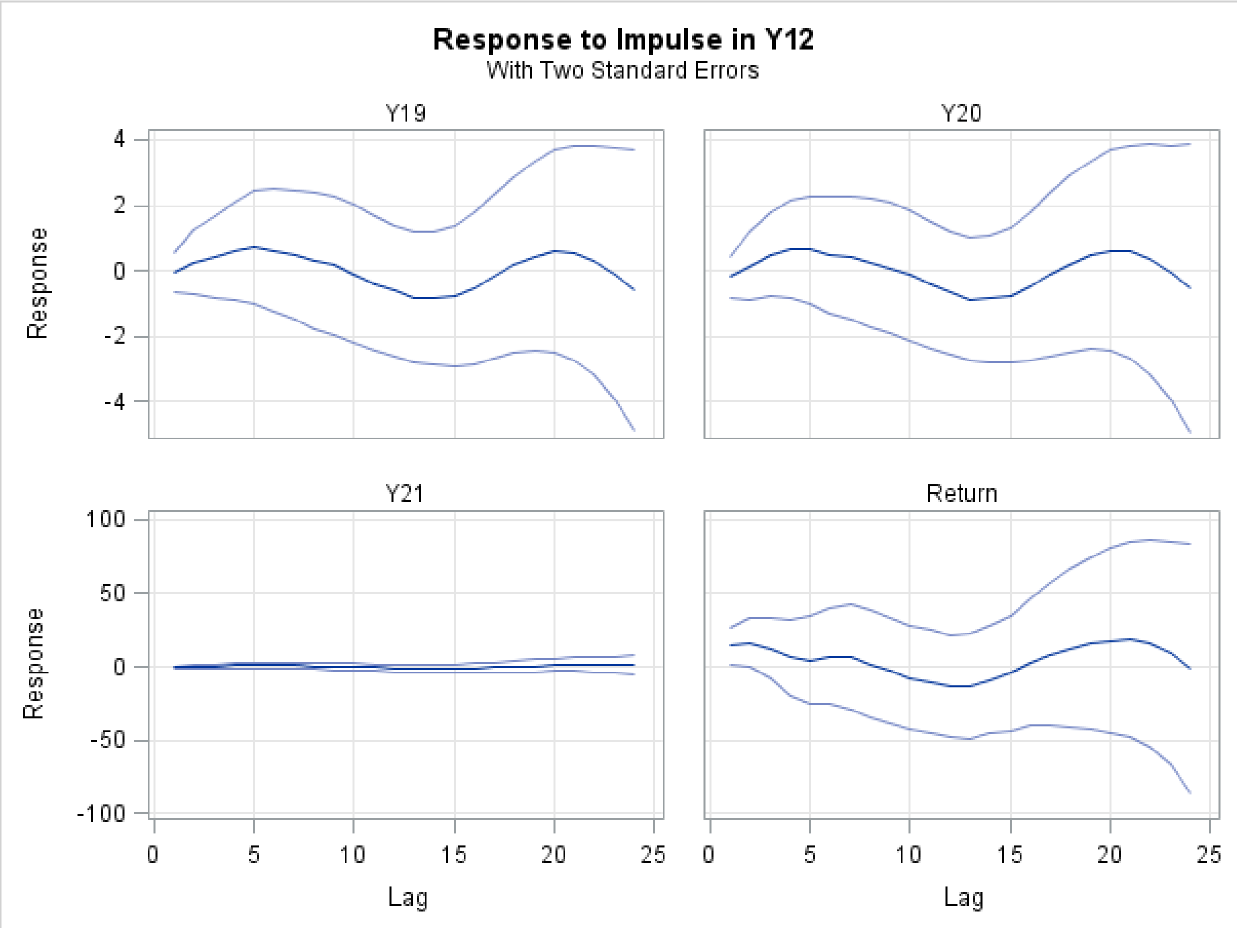
Response to Impulse in Y12
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
6
4
2
0
-2
-4
5
0
-5
0
5
10
15
20
25

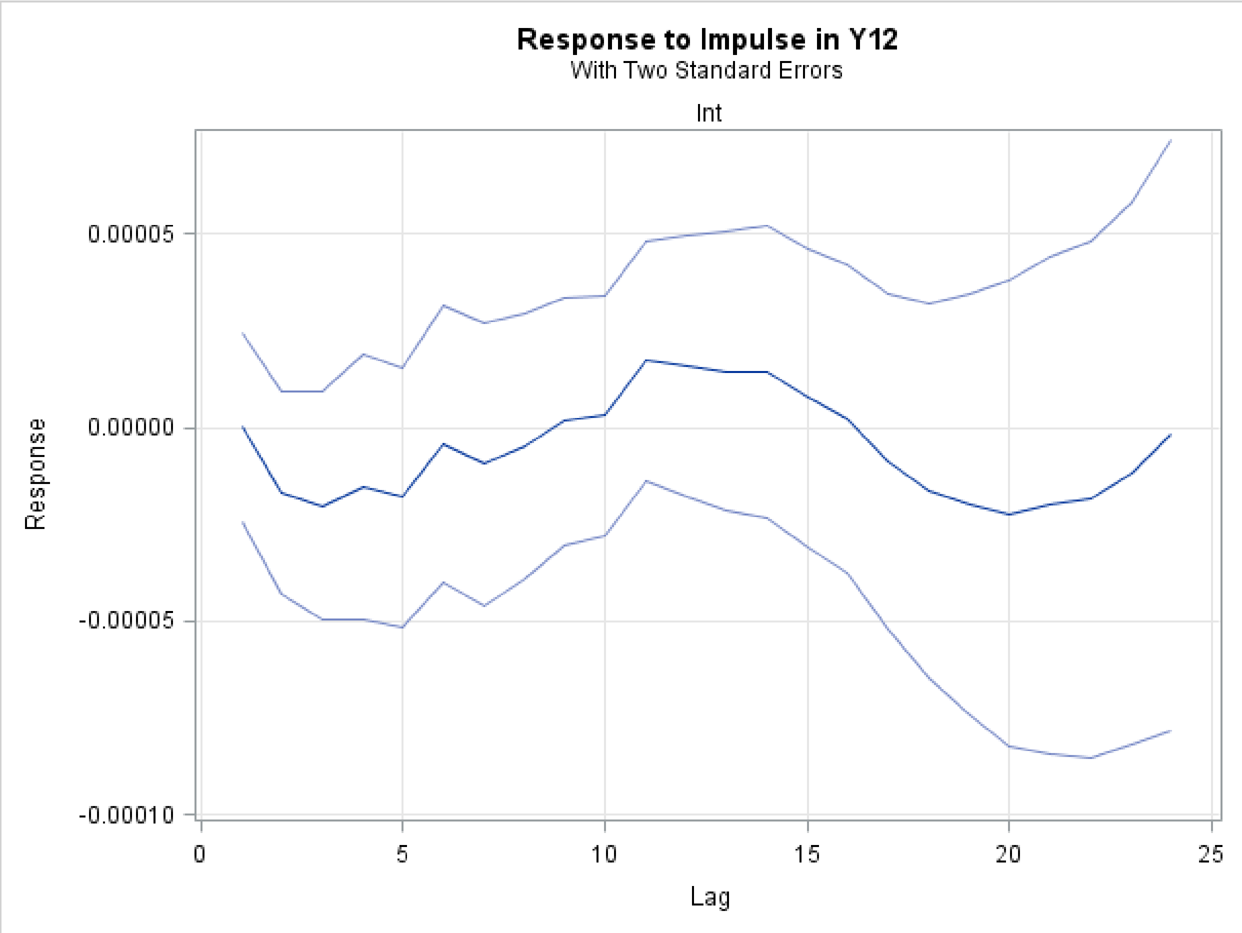

Response to Impulse in Y12
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
5
0
-5
2
1
0
-1
-2
0
5
10
15
20
25

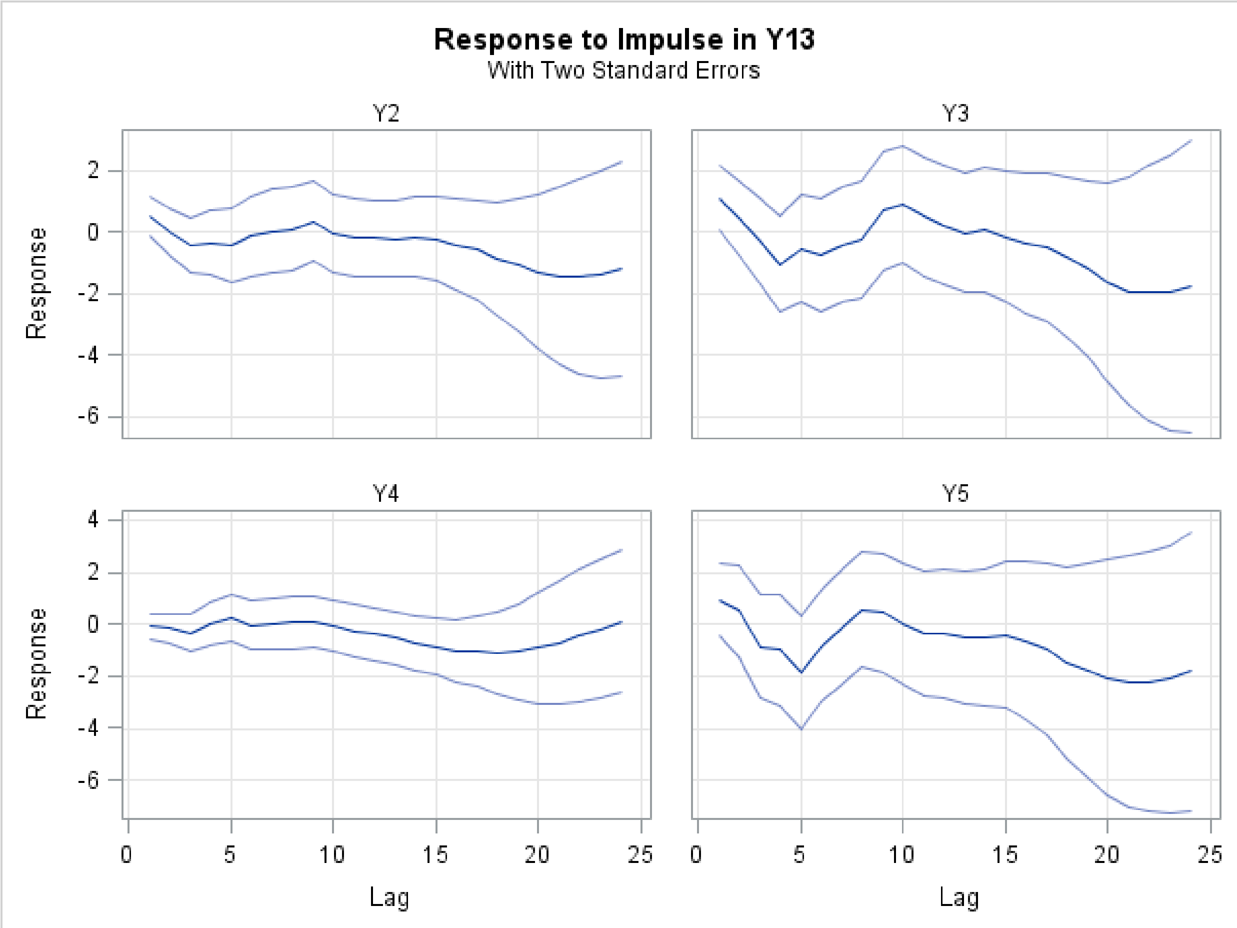

Response to Impulse in Y12
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5
0
-5
-10
4
2
0
-2
-4
-6
0
5
10
15
20
25



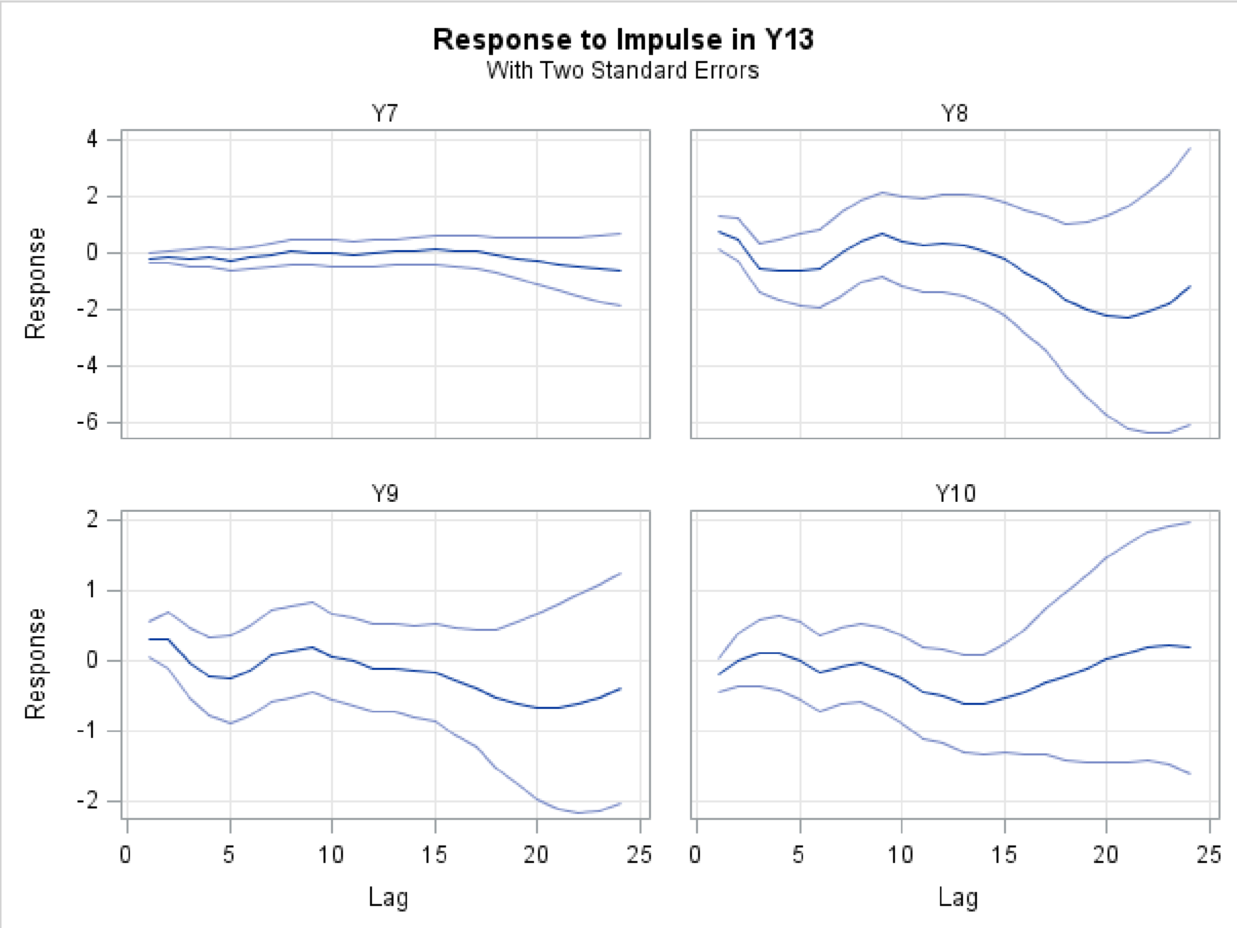
Response to Impulse in Y12
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
2
0
-2
5
0
-5
0
5
10
15
20
25

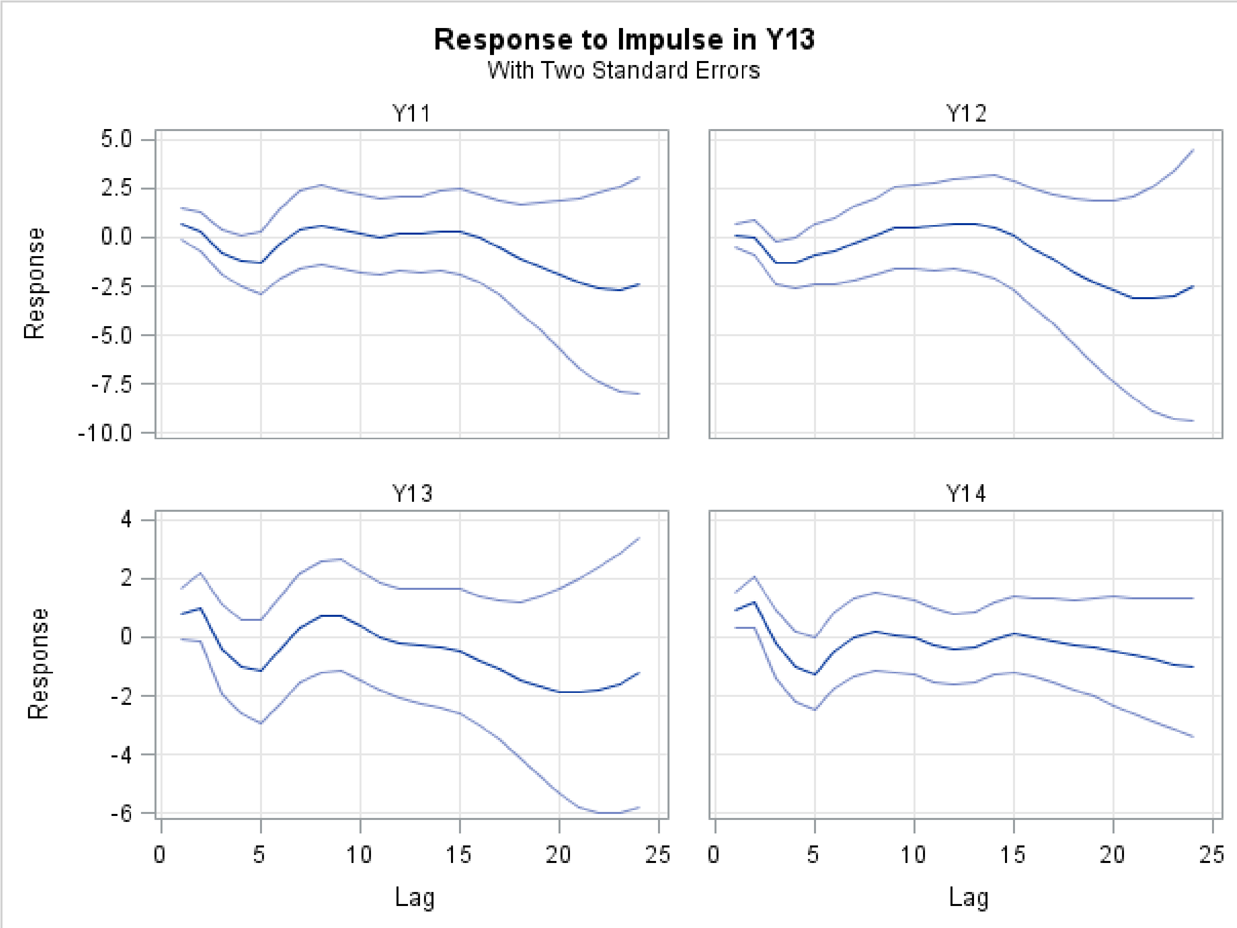

Response to Impulse in Y12
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag

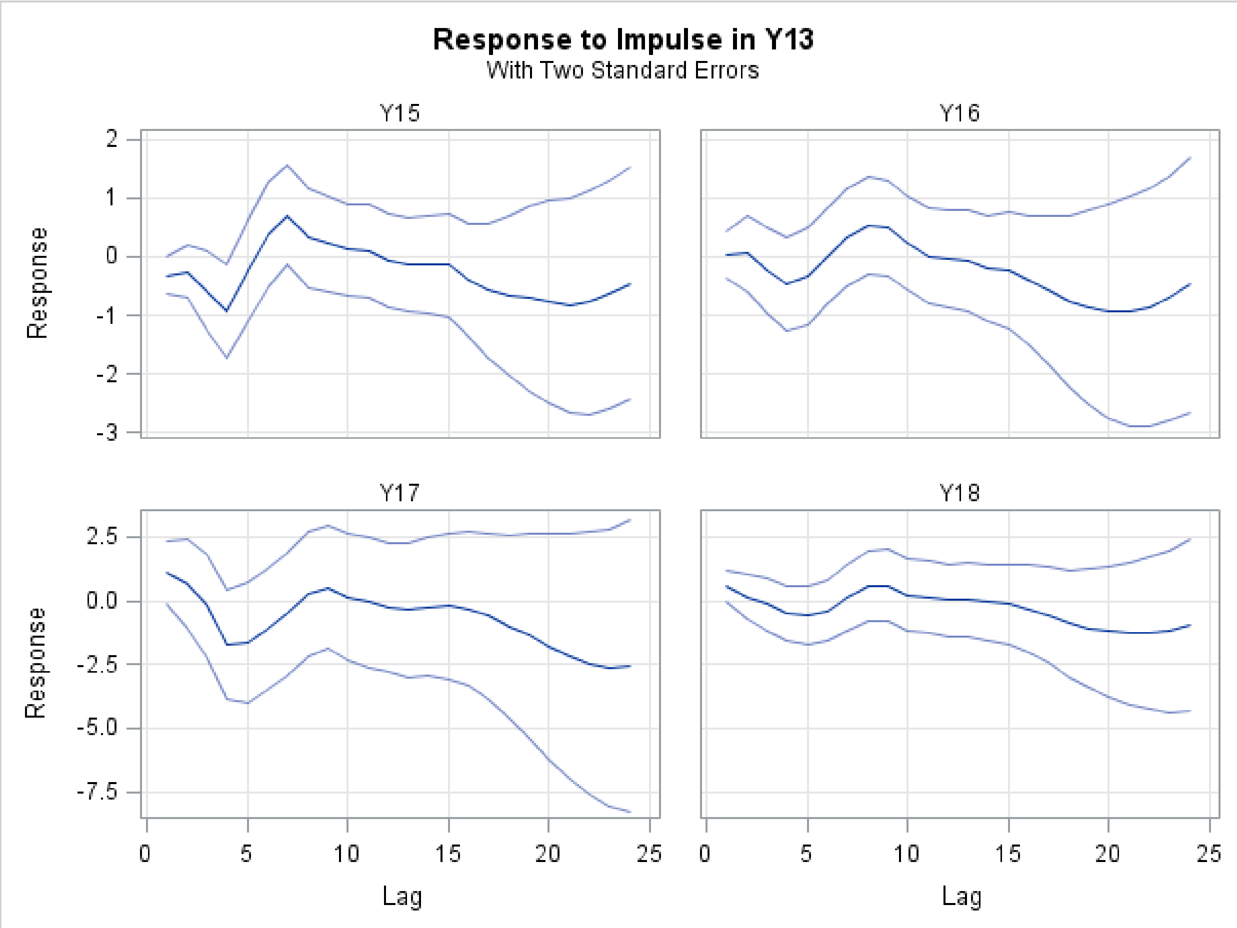

Response to Impulse in Y12
With Two Standard Errors
Int
0.00005
0.00000
-0.00005
-0.00010
Response
0
5
10
15
20
25
Lag



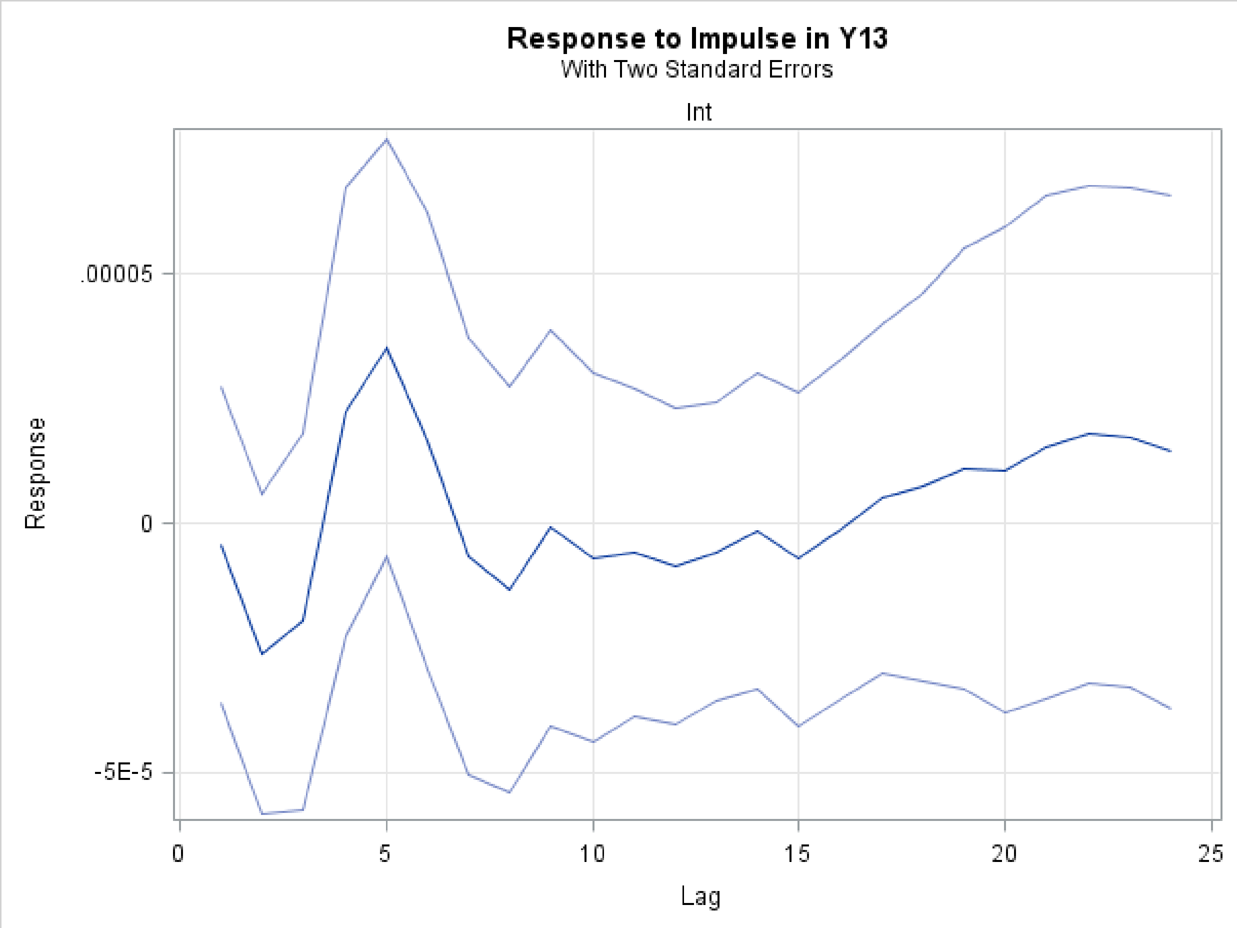
Response to Impulse in Y13
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag

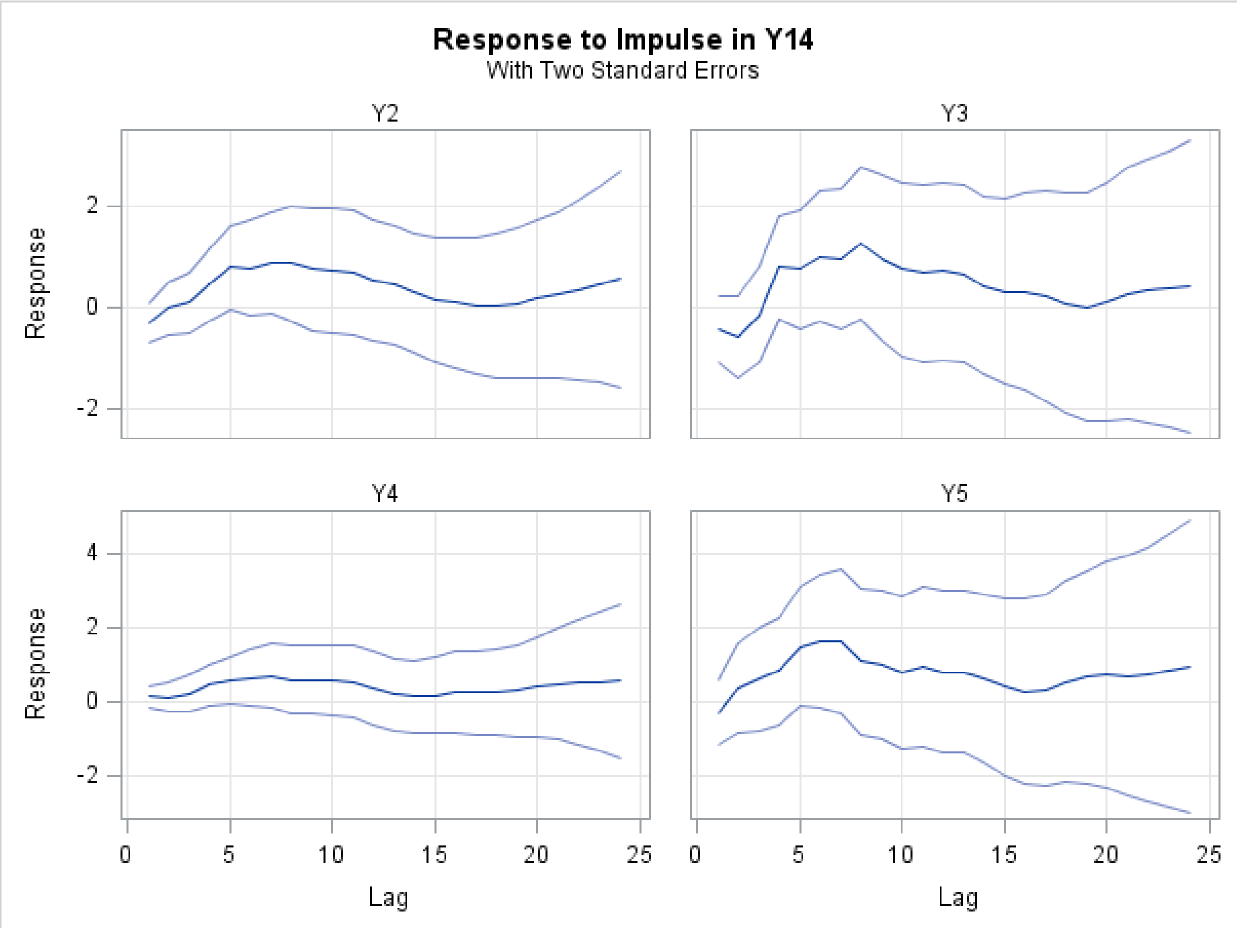

Response to Impulse in Y13
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
4
2
0
-2
-4
-6
2
1
0
-1
-2
0
5
10
15
20
25

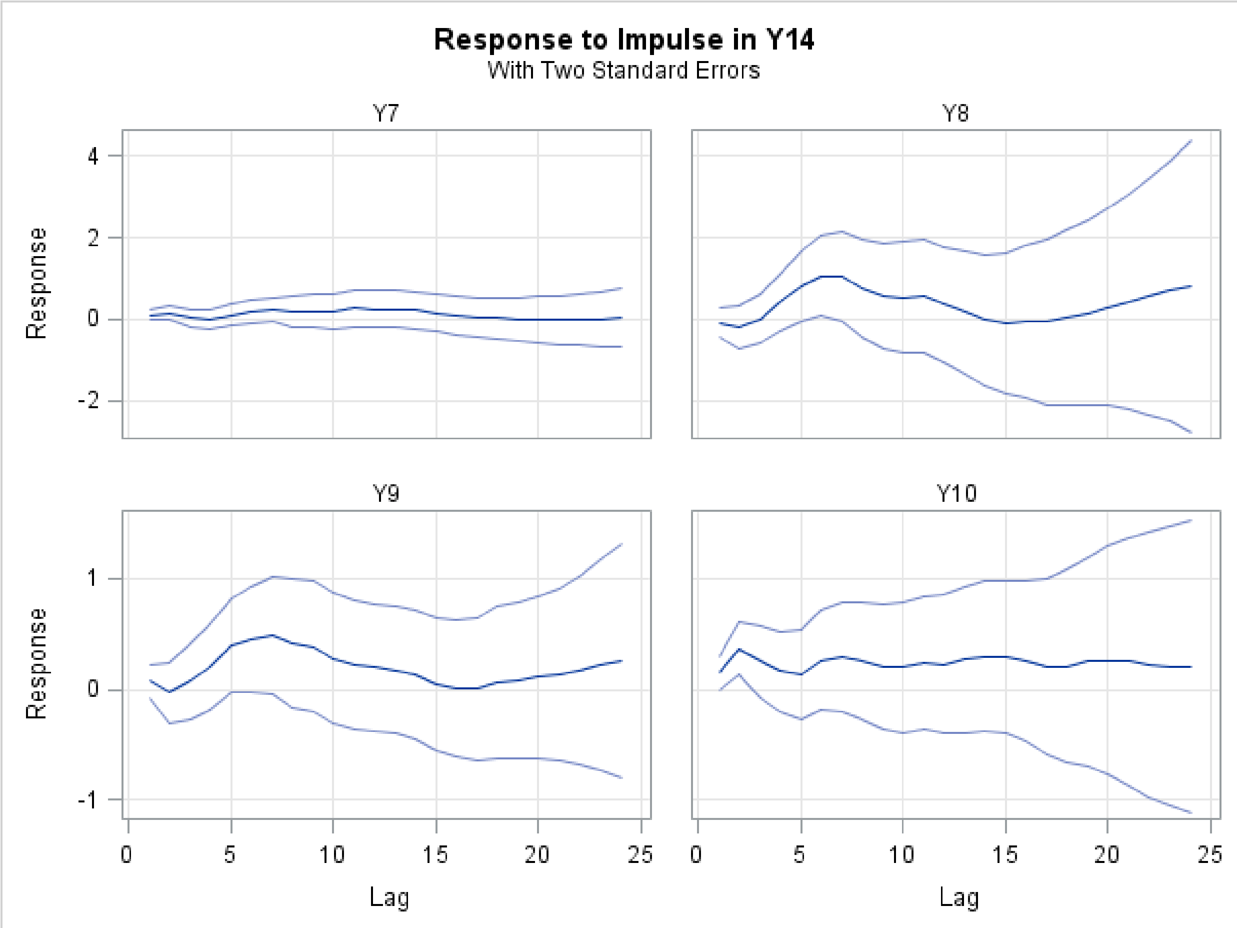

Response to Impulse in Y13
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5.0
2.5
0.0
-2.5
-5.0
-7.5
-10.0
4
2
0
-2
-4
-6
0
5
10
15
20
25


Response to Impulse in Y13
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
2
1
0
-1
-2
-3
2.5
0.0
-2.5
-5.0
-7.5
0
5
10
15
20
25

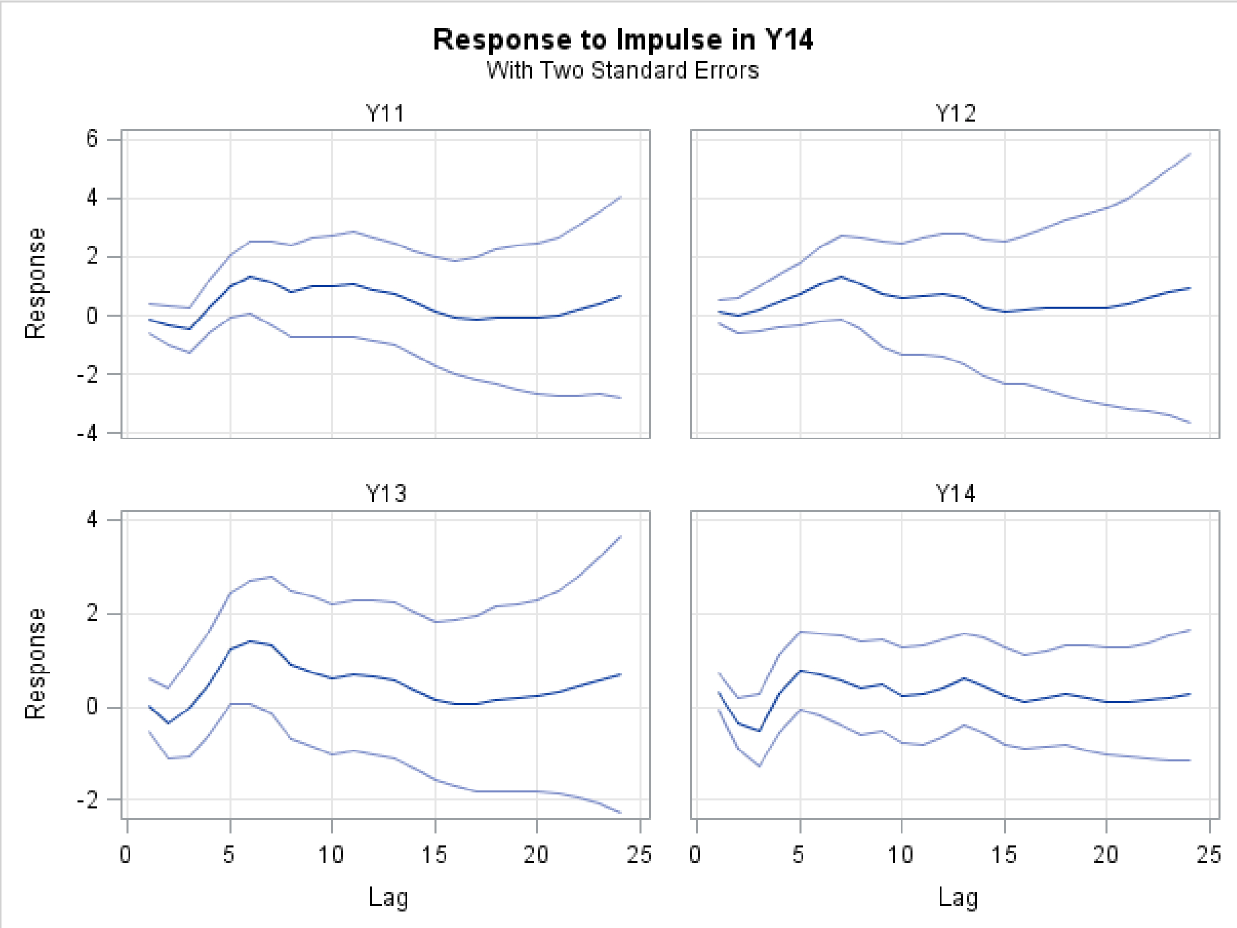

Response to Impulse in Y13
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
4
2
0
-2
-4
-6
50
-50
-100
5
10
15
20
25

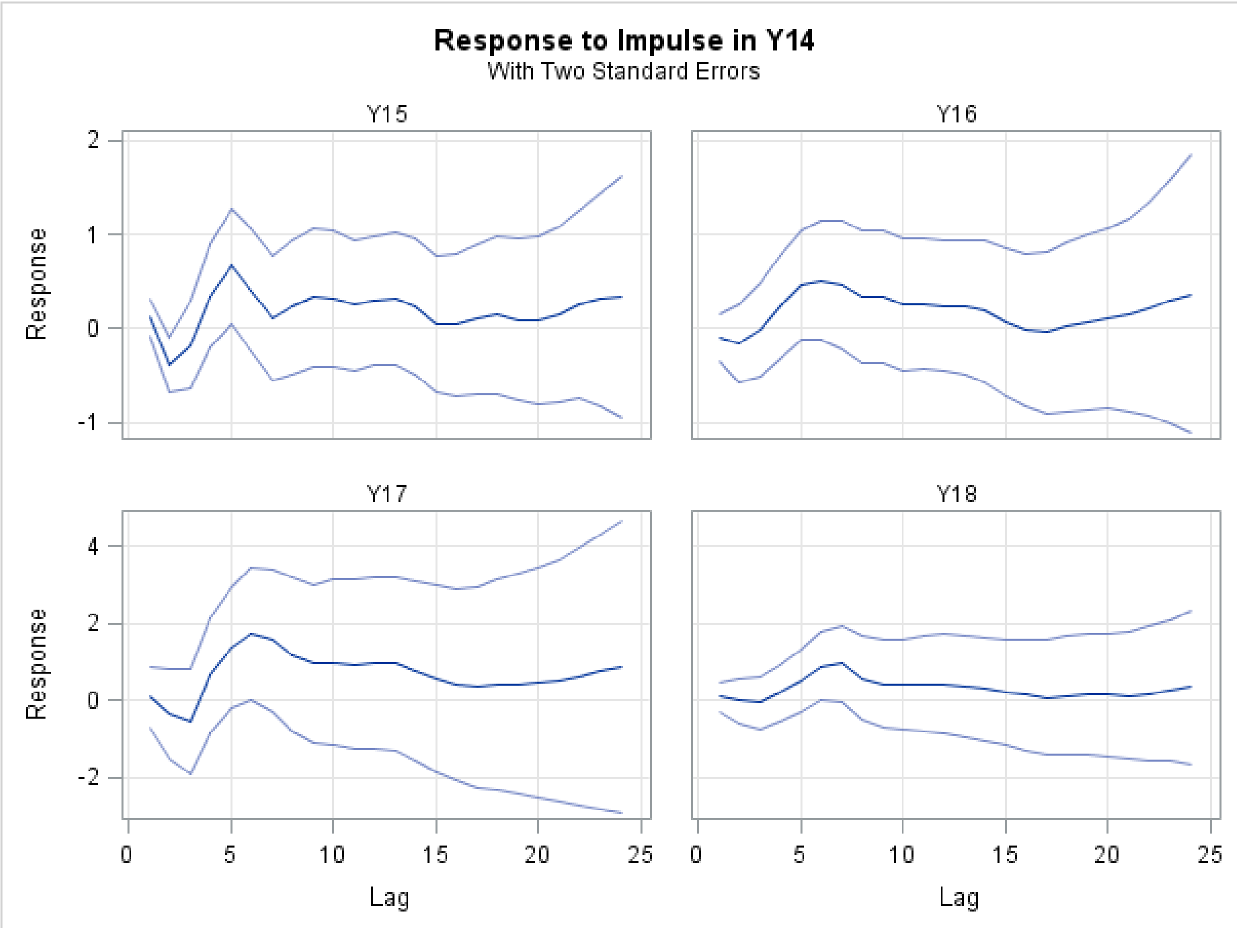

Response to Impulse in Y13
With Two Standard Errors
Int
.00005
0
-5E-5
Response
0
5
10
15
20
25
Lag

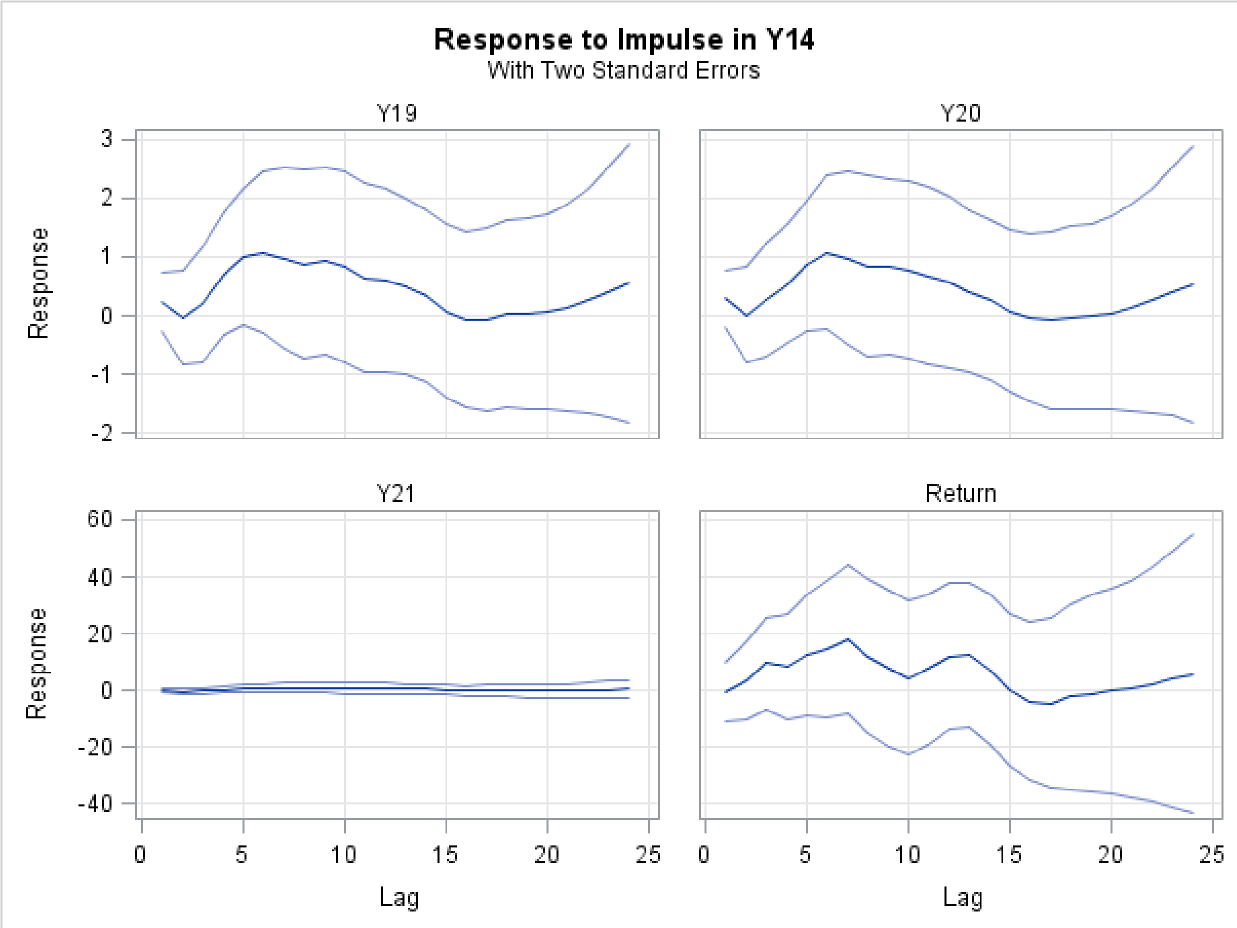

Response to Impulse in Y14
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag

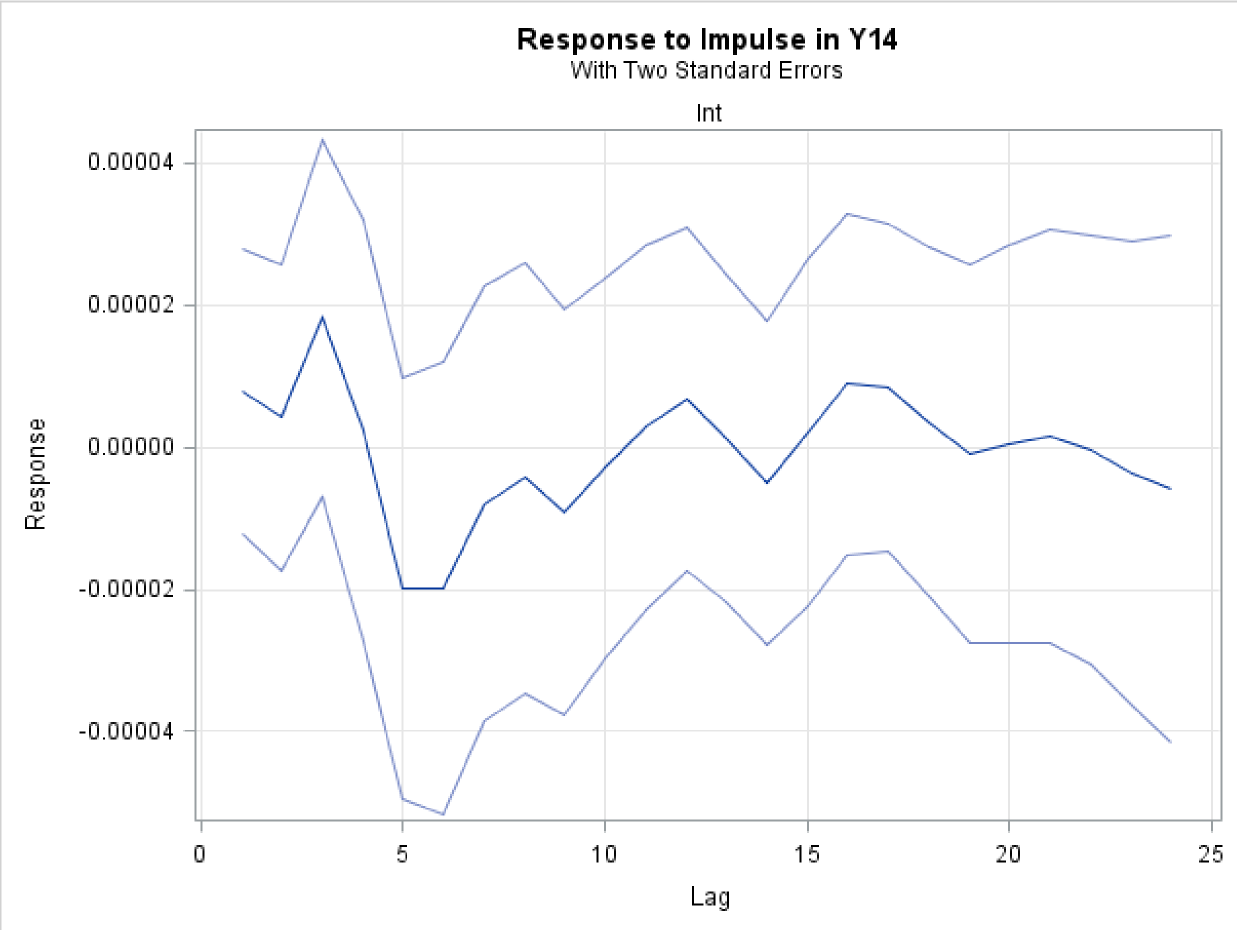


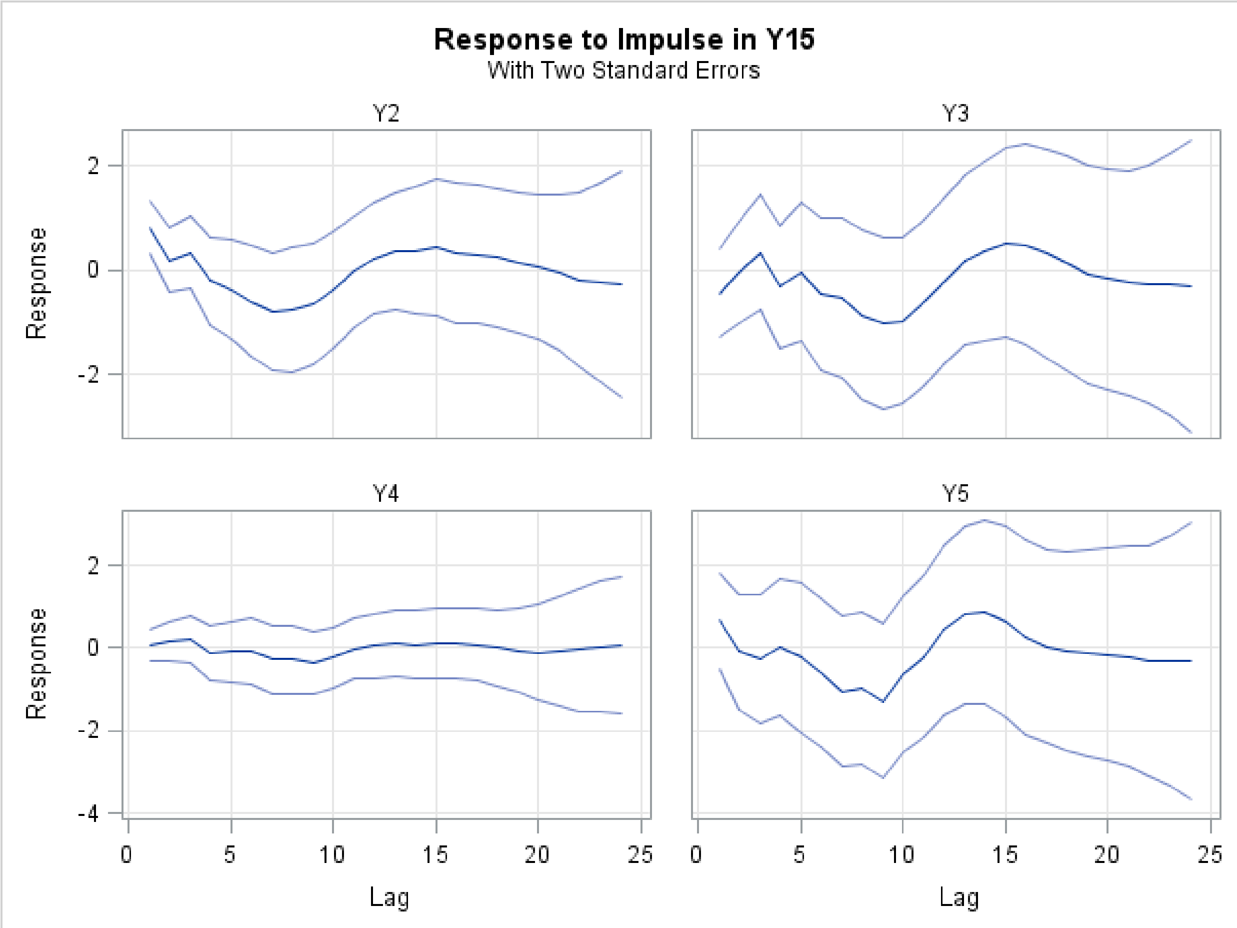
Response to Impulse in Y14
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
4
2
0
-2
1
0
-1
0
5
10
15
20
25


Response to Impulse in Y14
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
6
4
2
0
-2
-4
4
2
0
-2
0
5
10
15
20
25

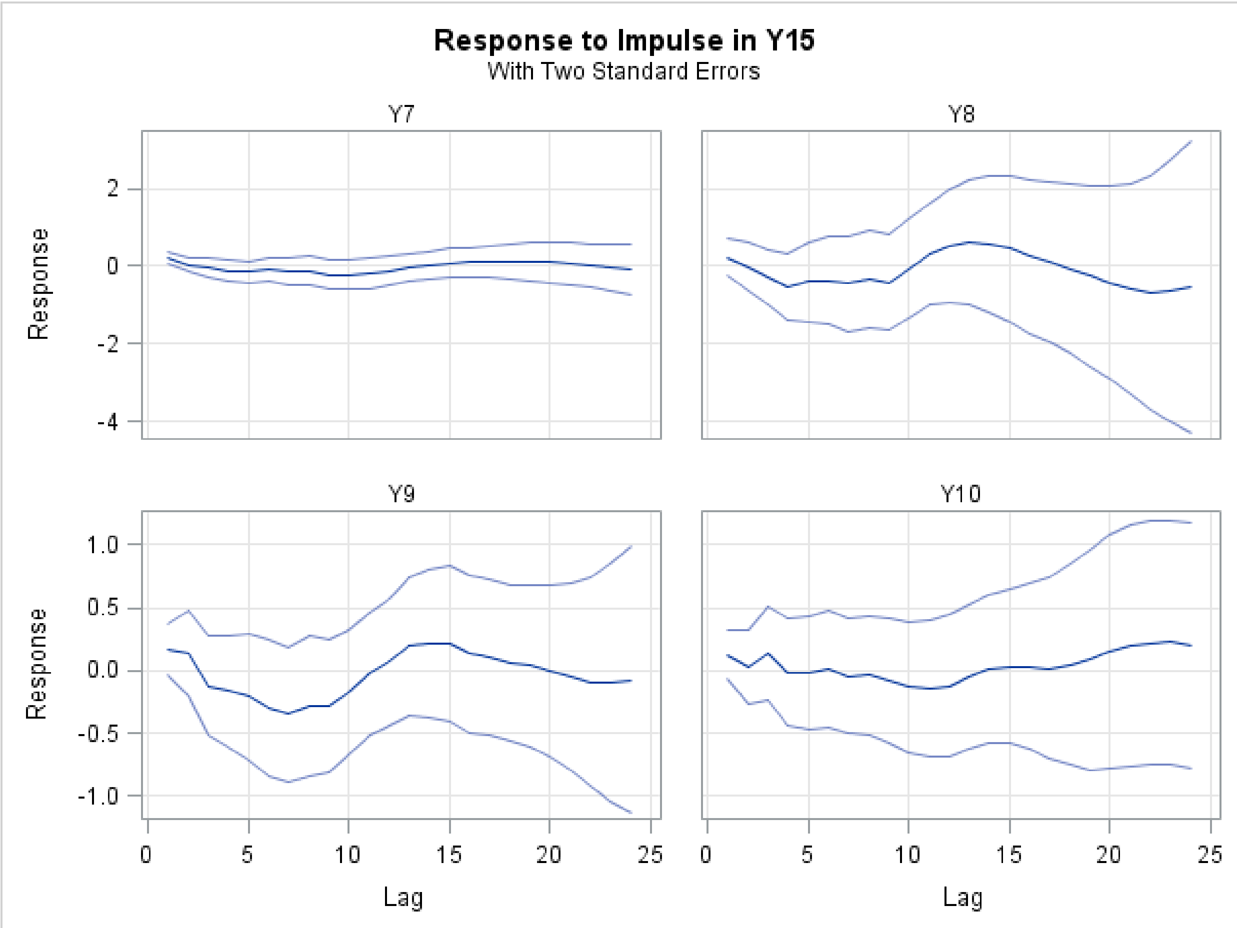

Response to Impulse in Y14
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
2
1
0
-1
4
2
0
-2
0
5
10
15
20
25


Response to Impulse in Y14
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
3
2
1
0
-1
-2
60
40
20
0
-20
-40
0
5
10
15
20
25

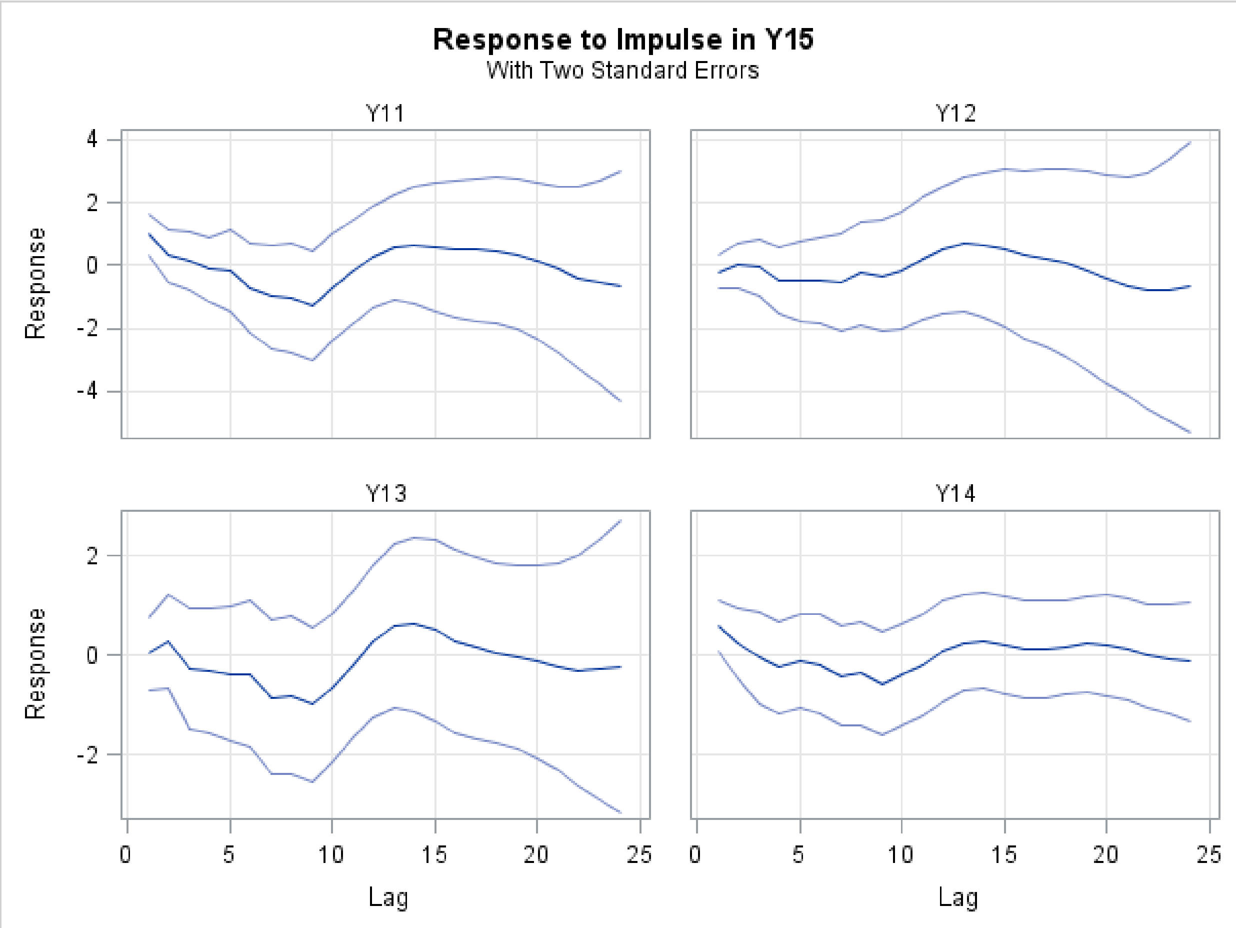

Response to Impulse in Y14
With Two Standard Errors
Int
0.00004
0.00002
0.00000
-0.00002
-0.00004
Response
0
5
10
15
20
25
Lag

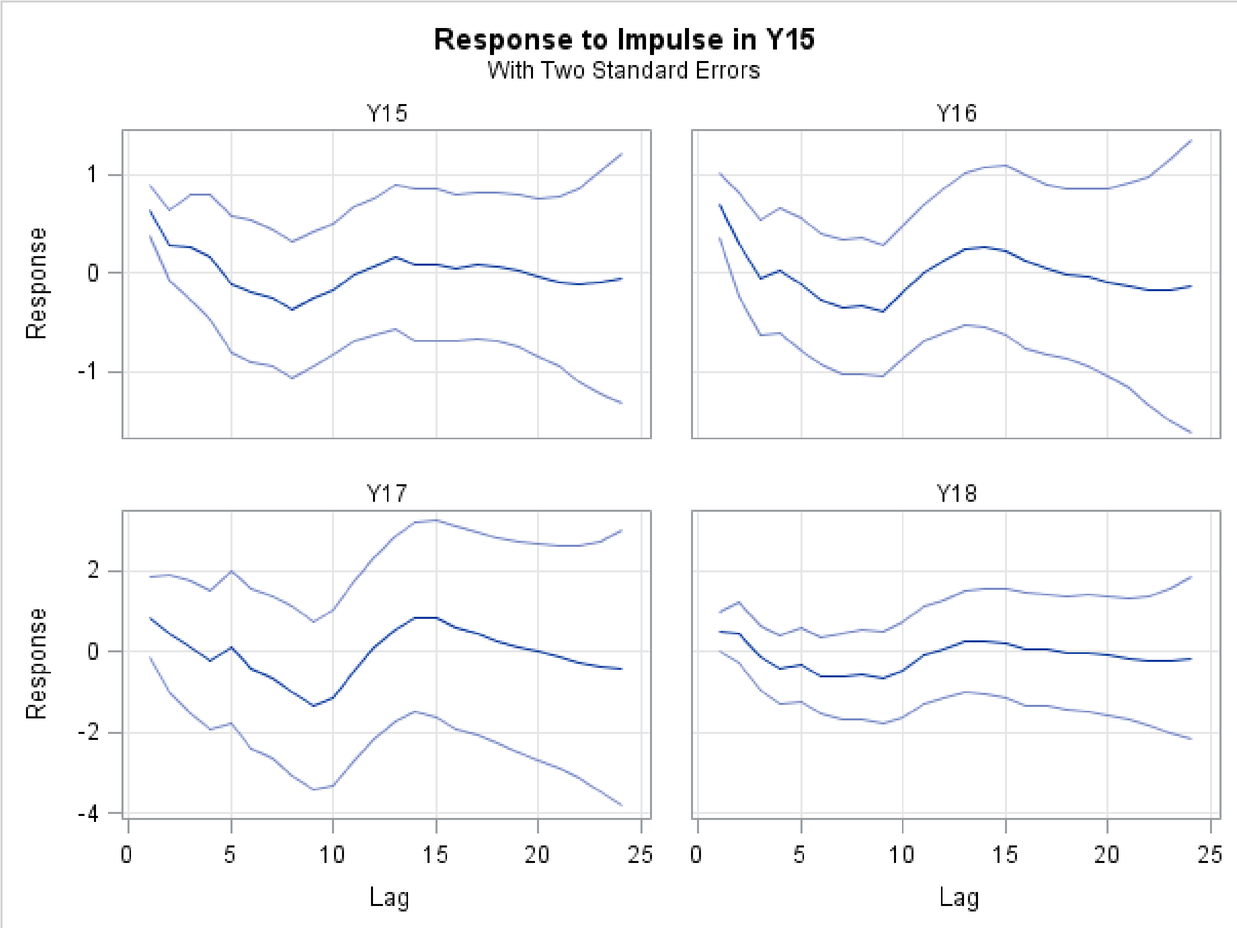


Response to Impulse in Y15
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
2
0
-2
-4
0
5
10
15
20
25

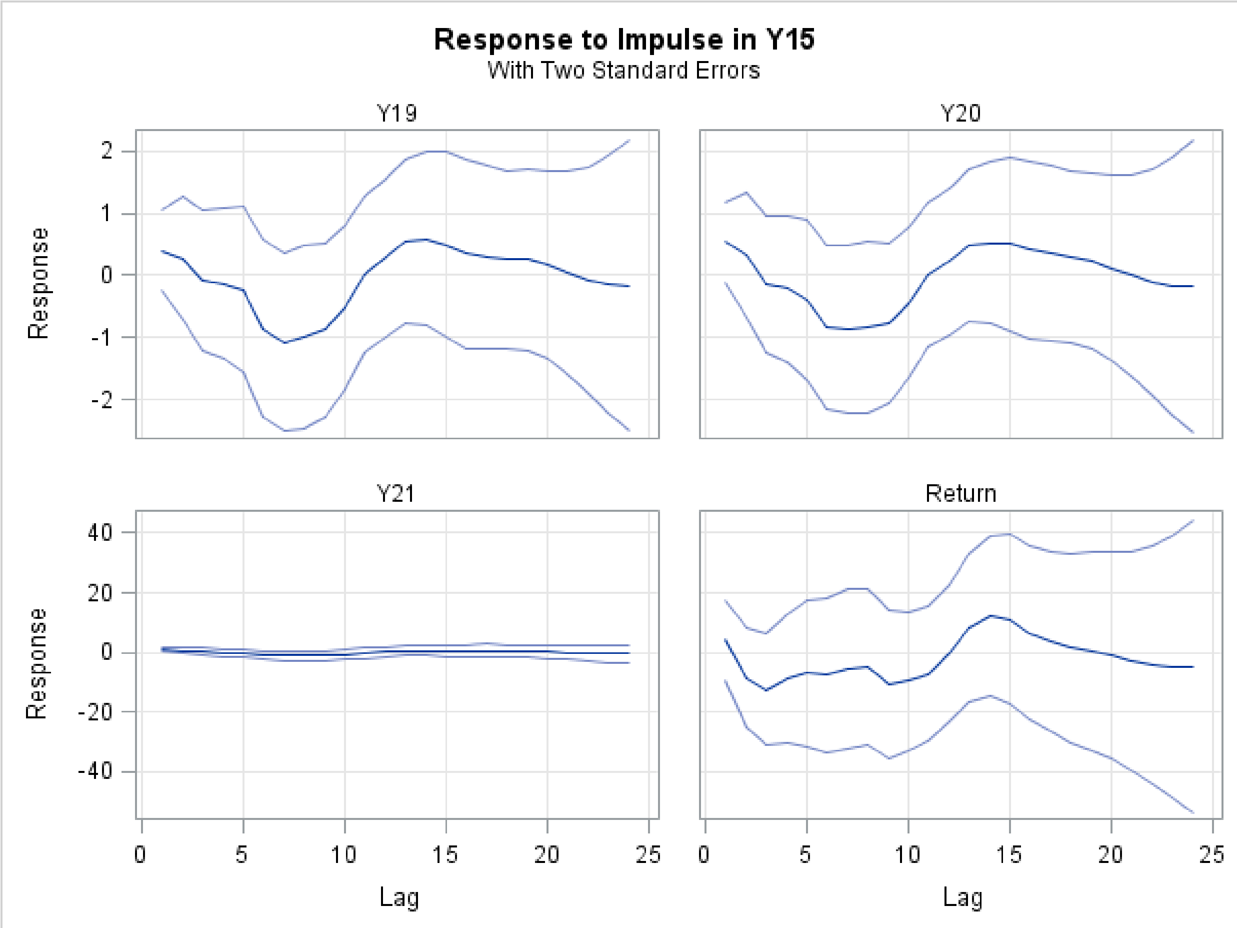


Response to Impulse in Y15
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag

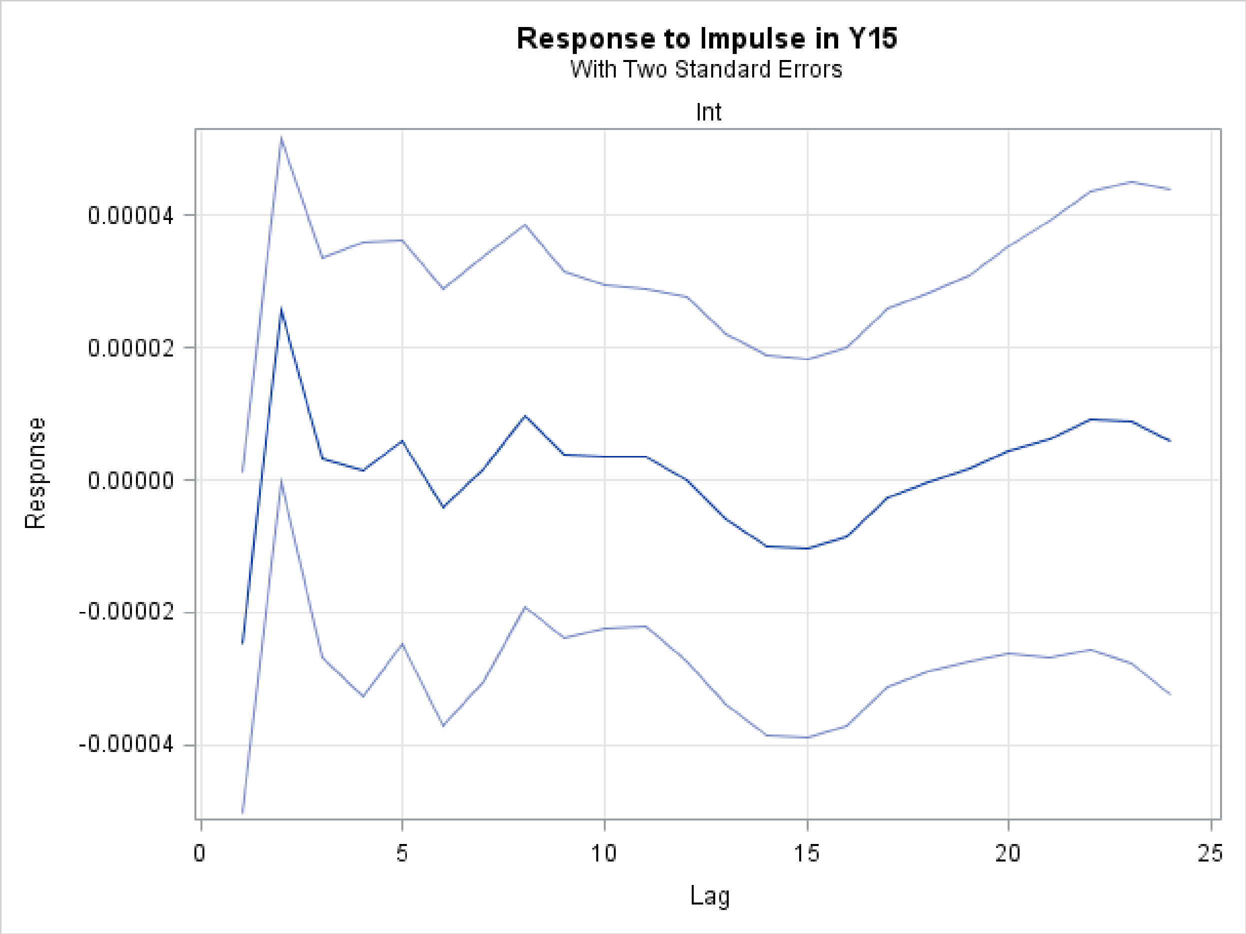

Response to Impulse in Y15
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
4
2
0
-2
-4
2
0
-2
0
5
10
15
20
25



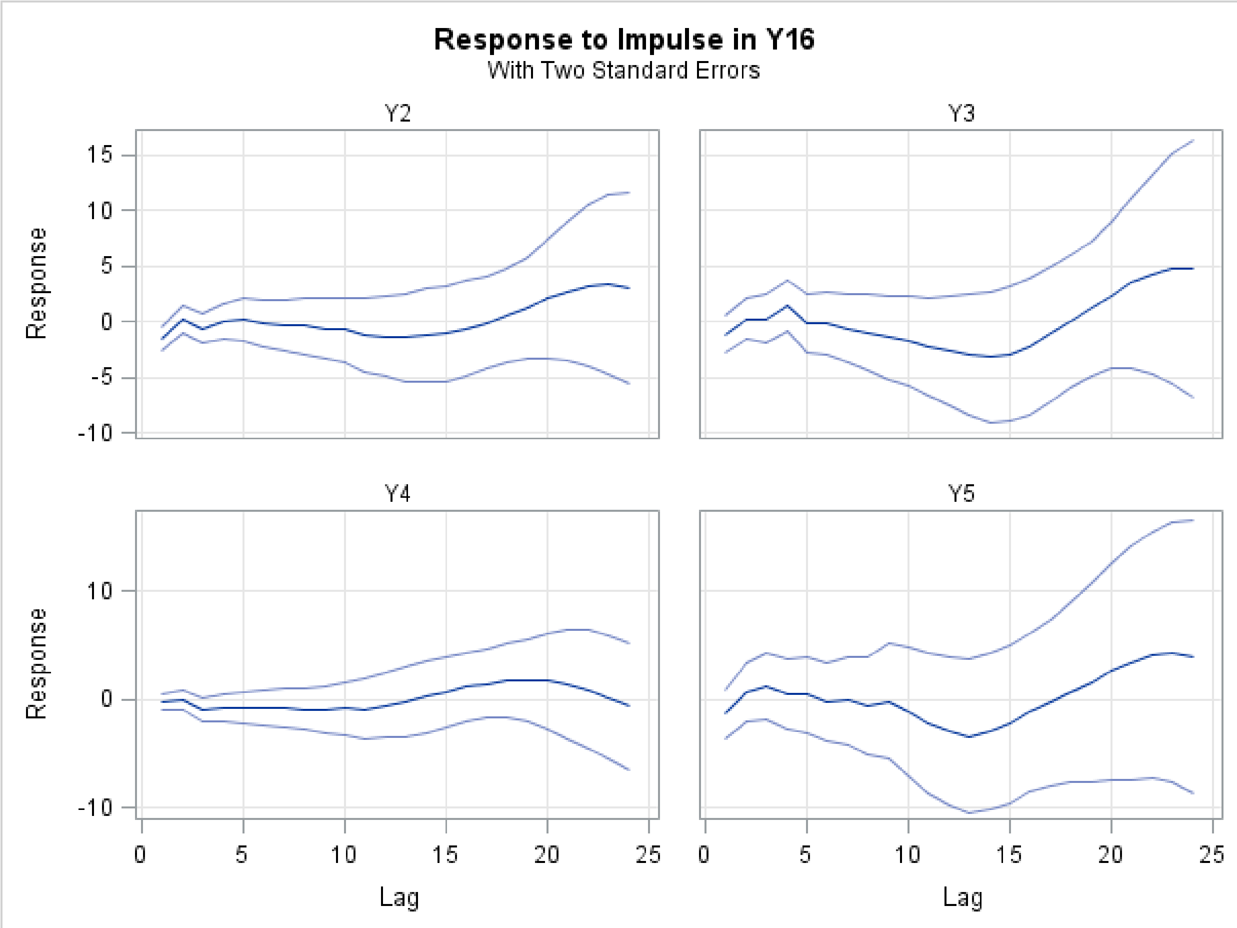
Response to Impulse in Y15
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Lag

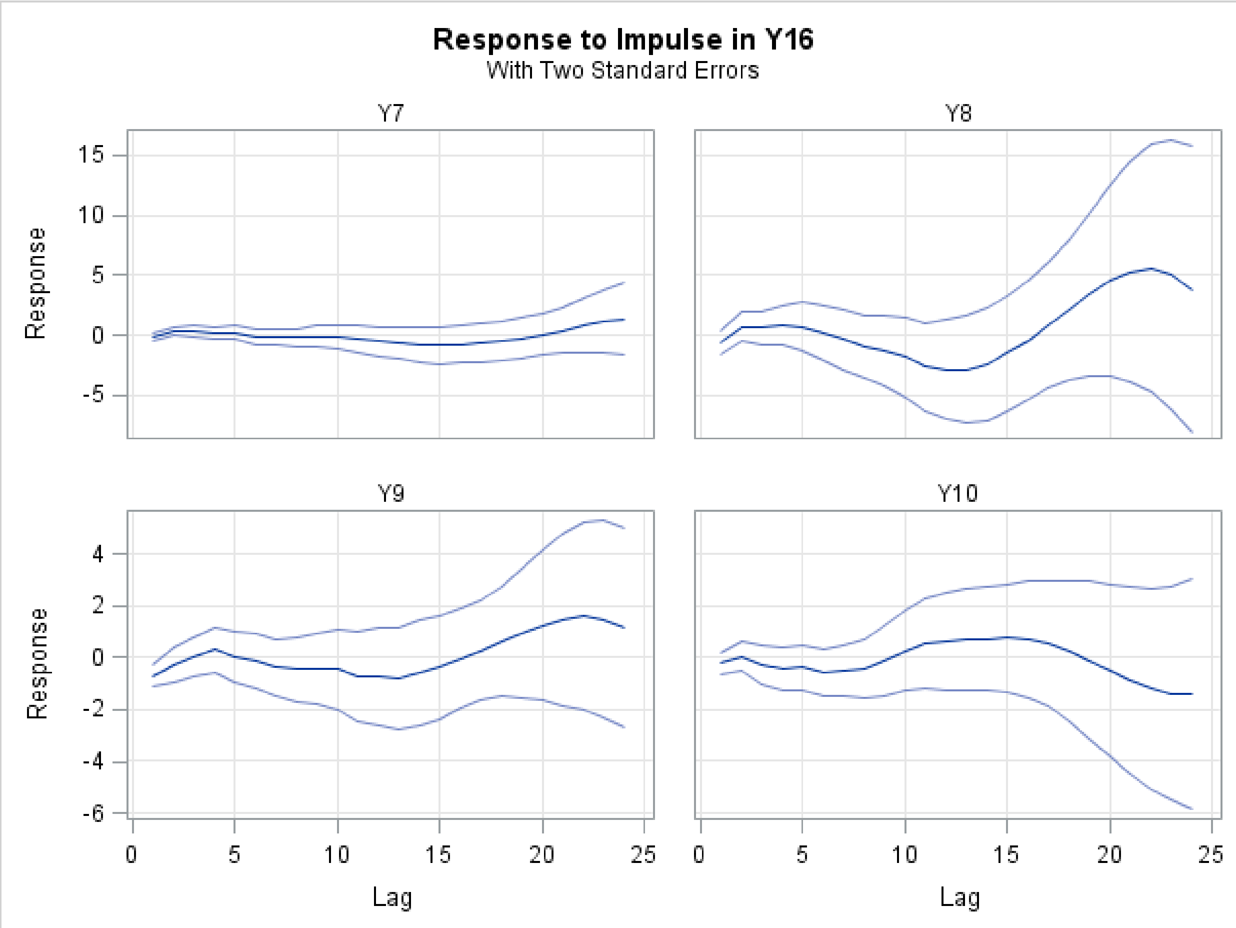


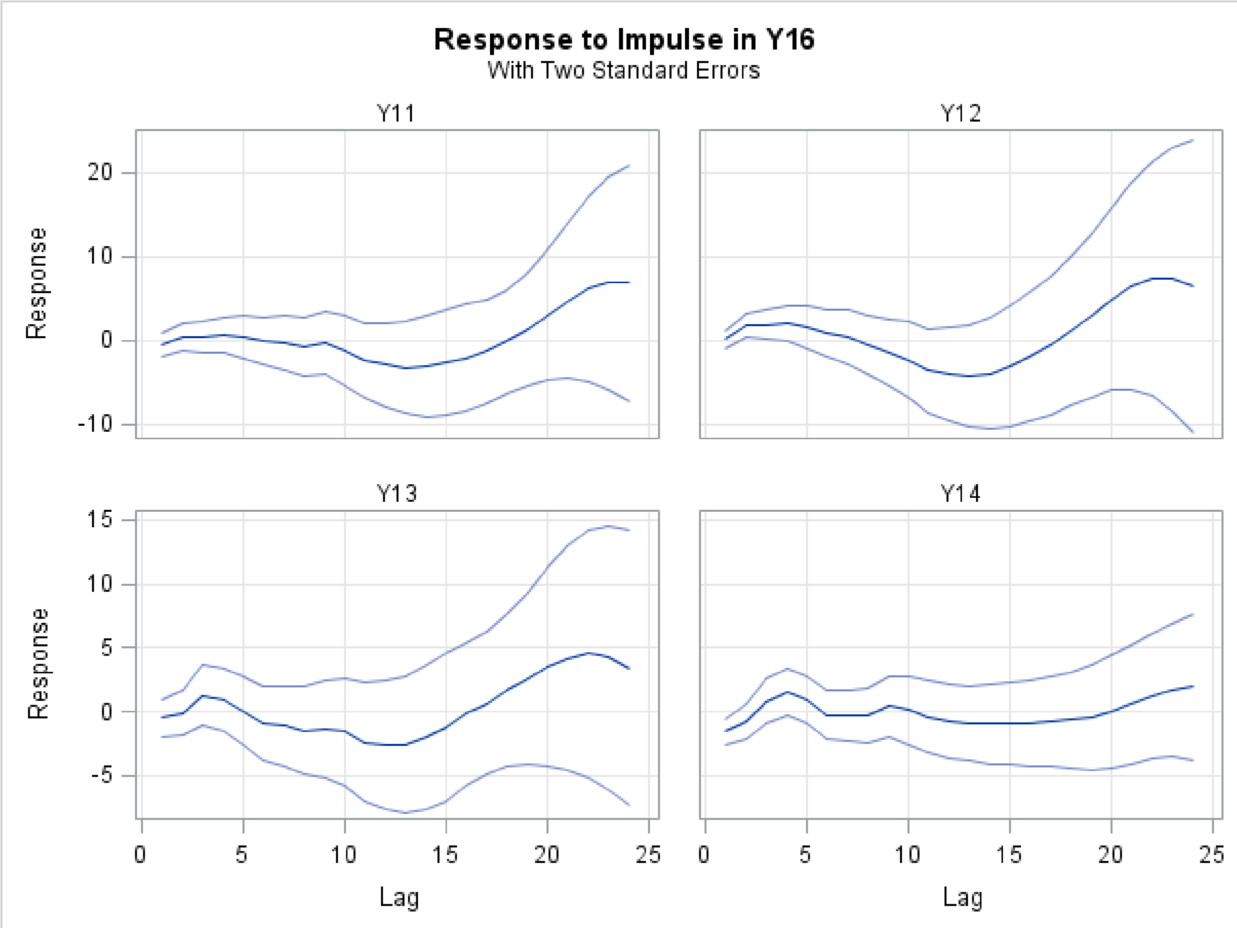
Response to Impulse in Y15
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
2
1
0
-1
-2
40
20
0
-20
-40
0
5
10
15
20
25



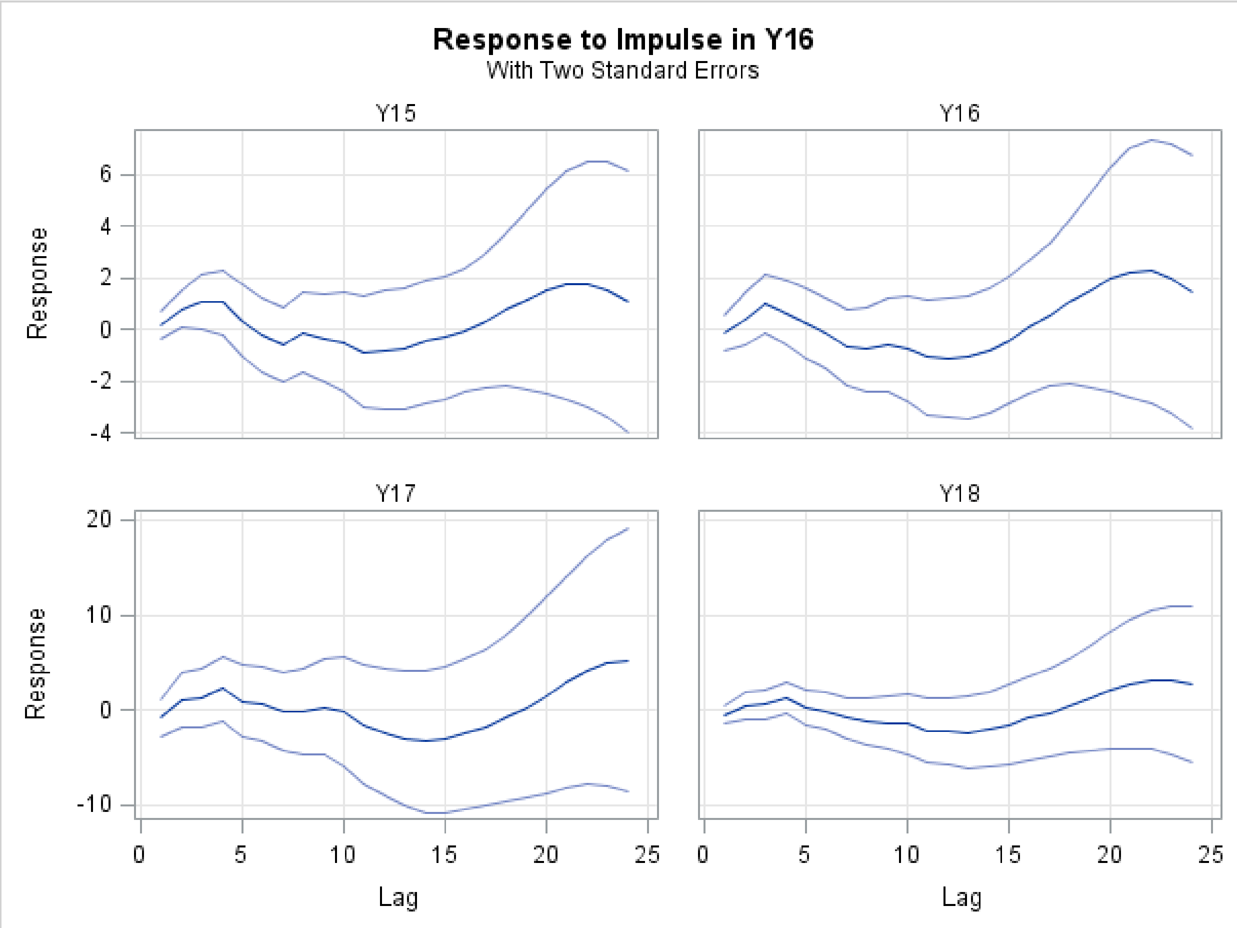
Response to Impulse in Y15
With Two Standard Errors
Int
0.00004
0.00002
0.00000
-0.00002
-0.00004
Response
0
5
10
15
20
25
Lag

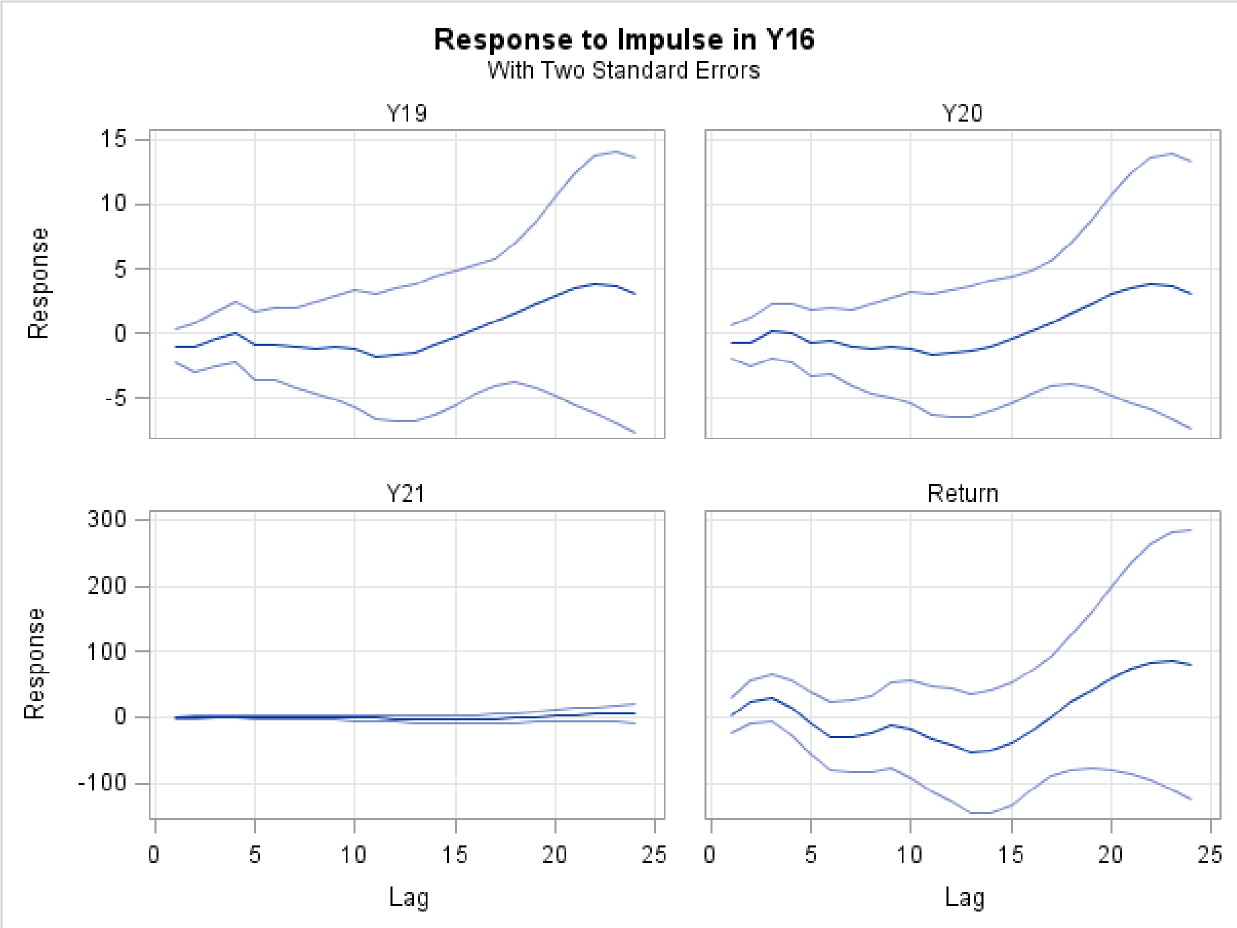

Response to Impulse in Y16
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Lag

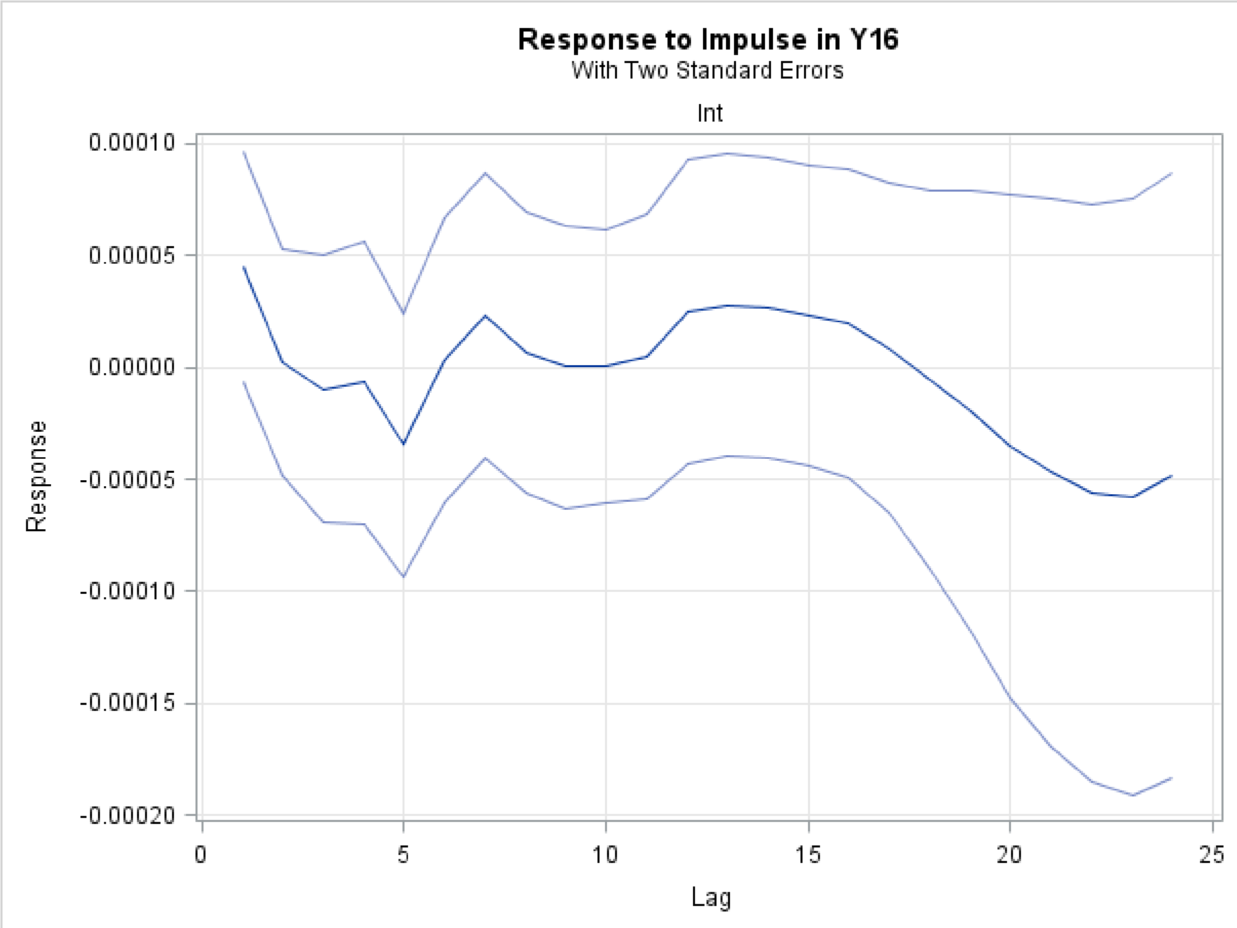

Response to Impulse in Y16
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Lag
15
10
5
0
-5
4
2
-2
-4
-6
20
25

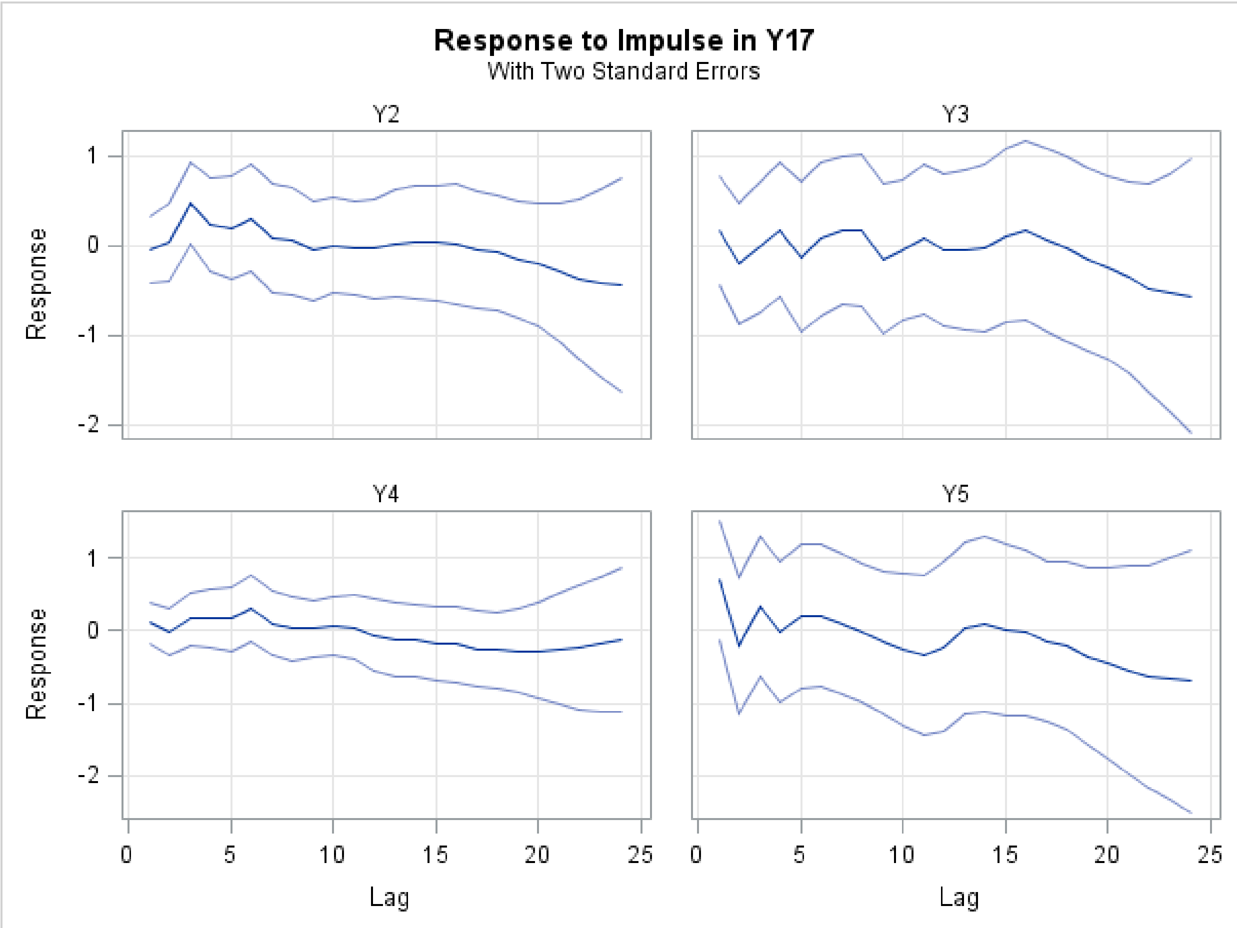


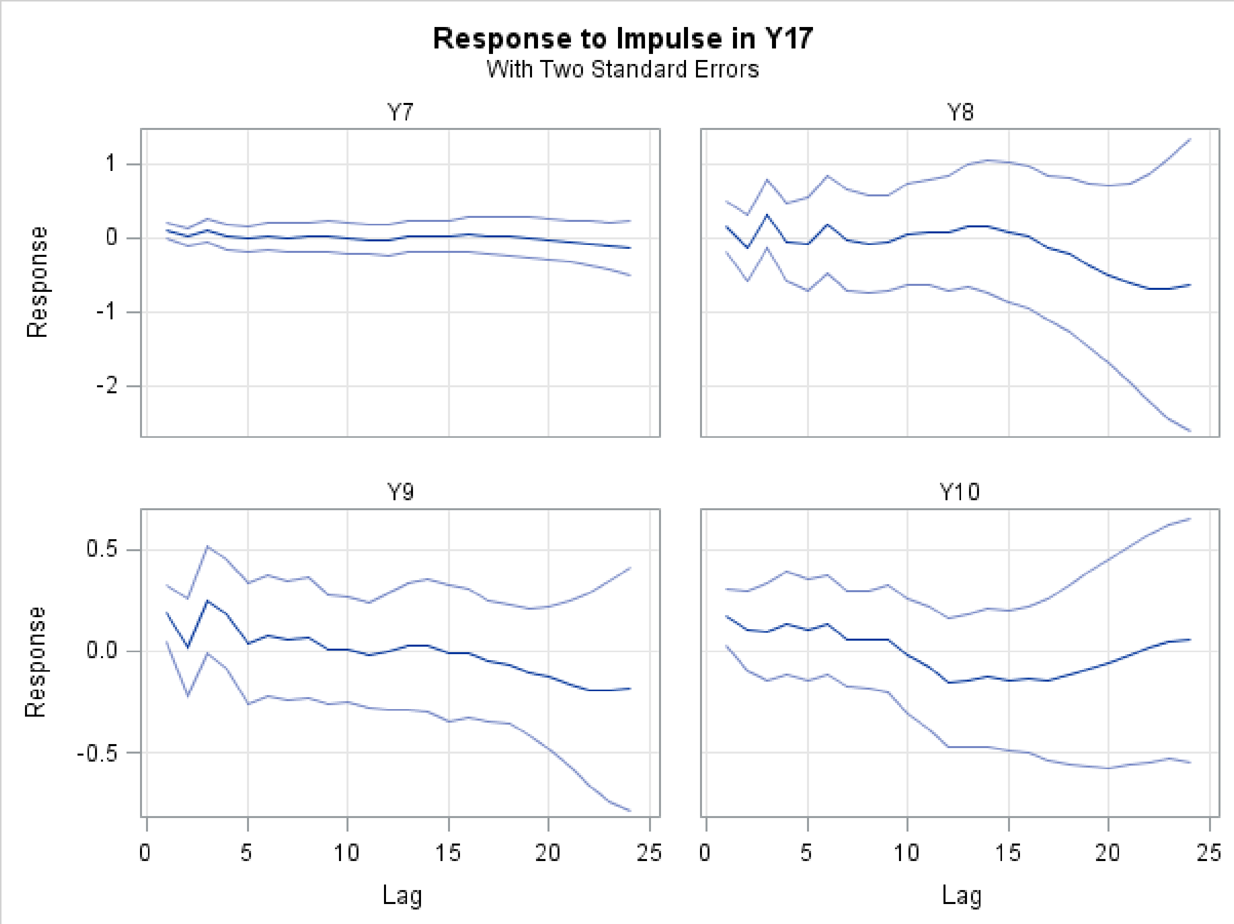
Response to Impulse in Y16
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
20
10
0
-10
15
10
5
0
-5
0
5
10
15
20
25

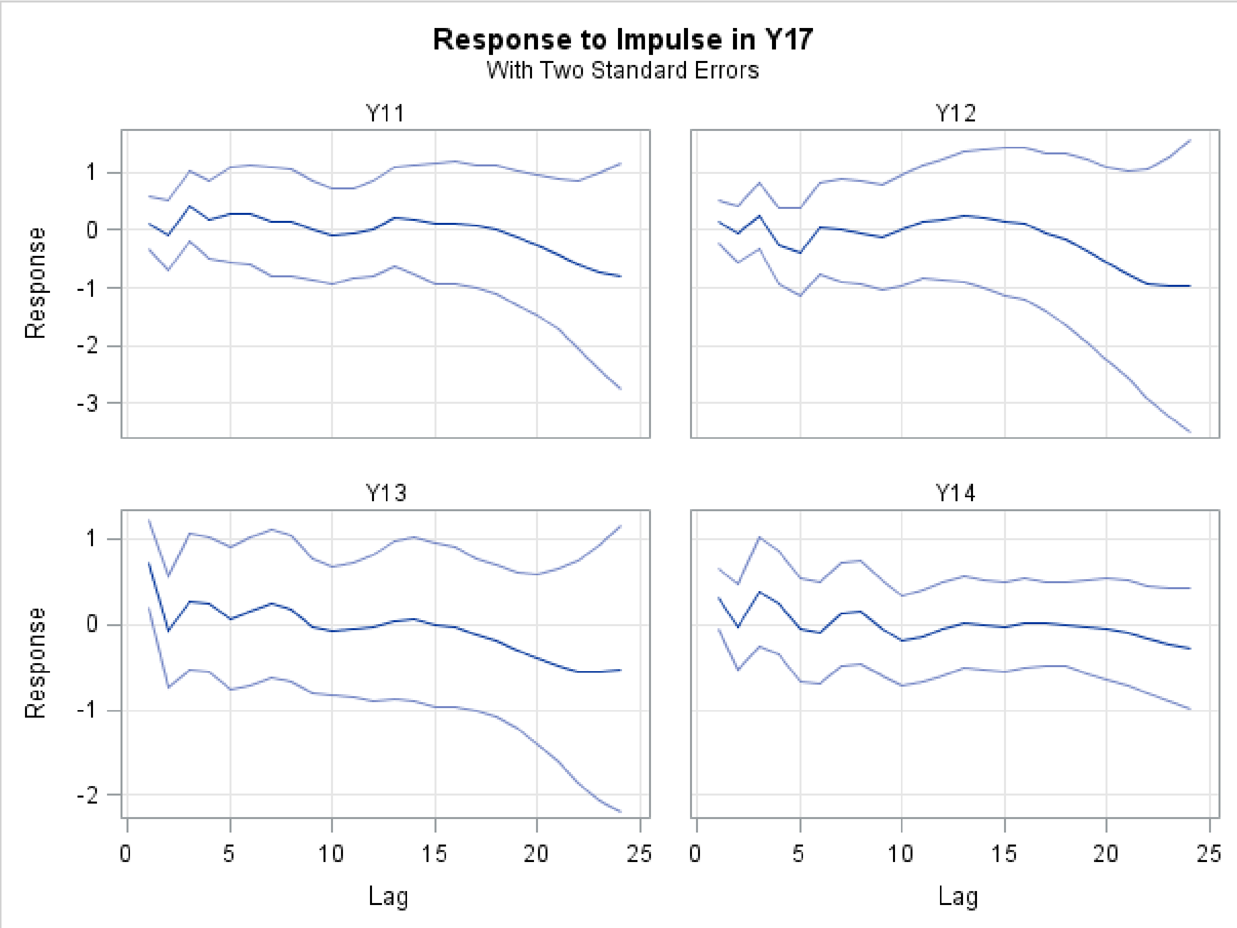

Response to Impulse in Y16
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
6
4
2
0
-2
-4
20
10
0
-10
0
5
10
15
20
25

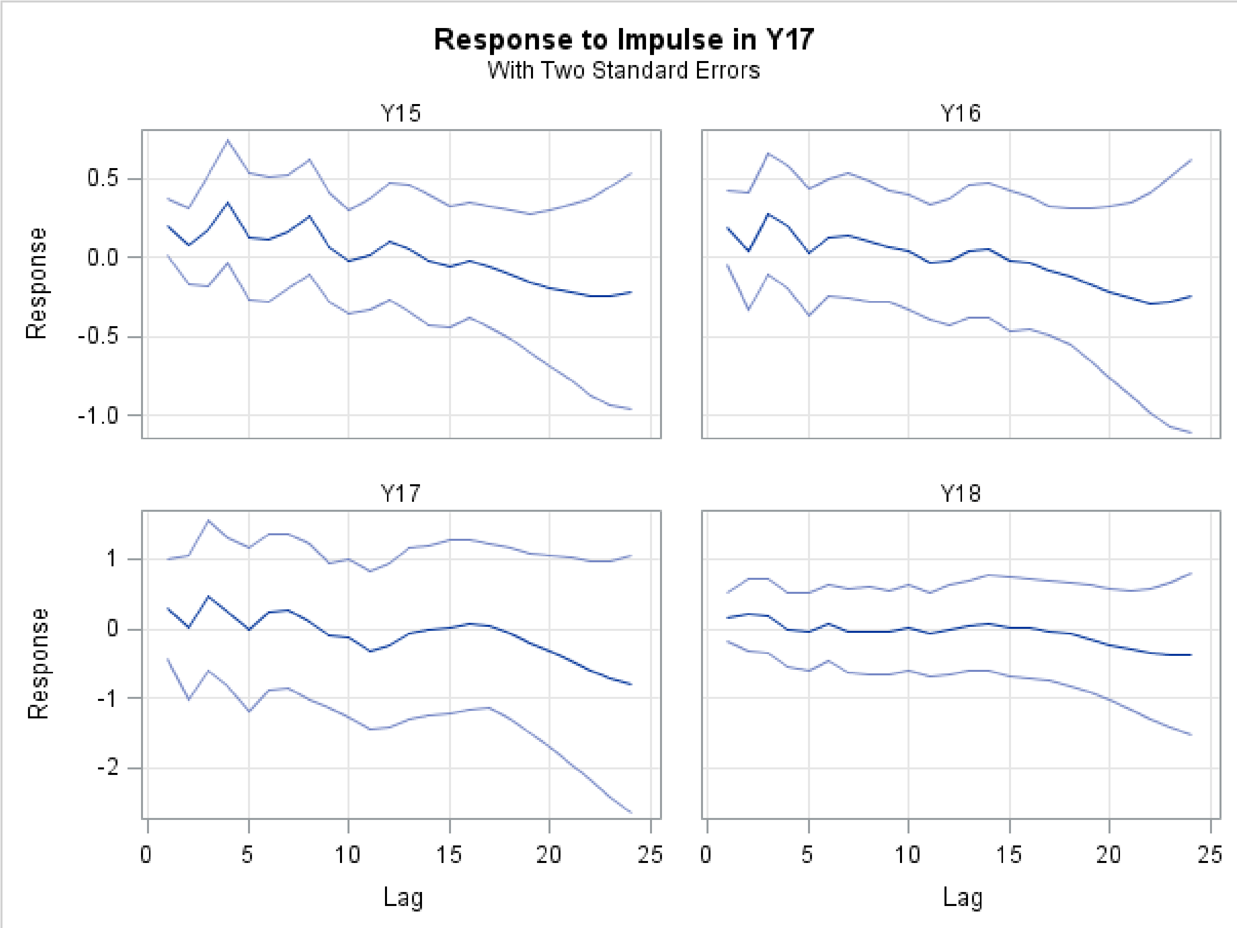

Response to Impulse in Y16
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
15
10
5
0
-5
300
200
100
-100
20
25


Response to Impulse in Y16
With Two Standard Errors
Int
0.00010
0.00005
0.00000
-0.00005
-0.00010
-0.00015
-0.00020
Response
0
5
10
15
20
25
Lag

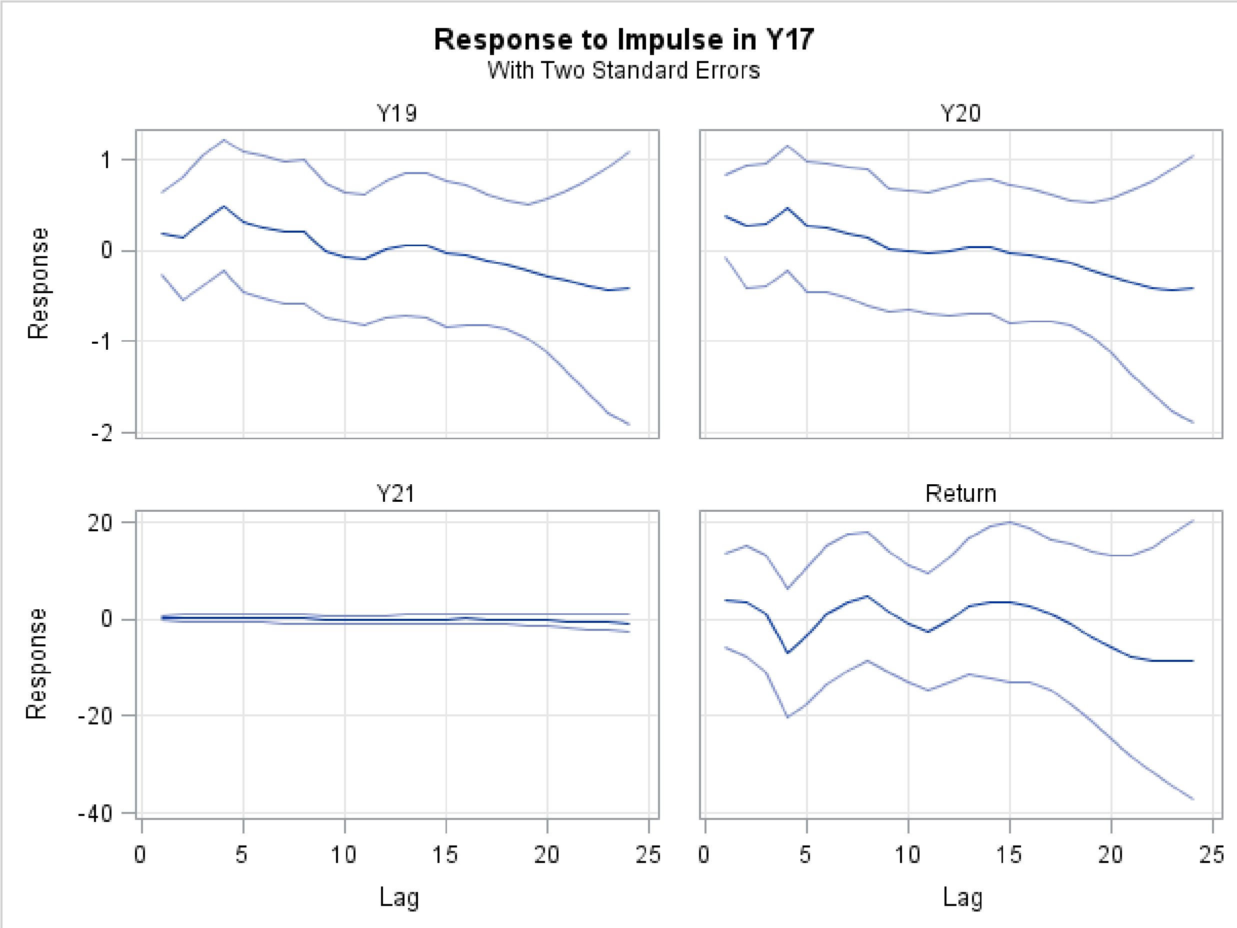

Response to Impulse in Y17
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Lag
1
0
-1
-2
0
5
10
15
20
25


Response to Impulse in Y17
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
1
0
-1
-2
0.5
0.0
-0.5
0
5
10
15
20
25

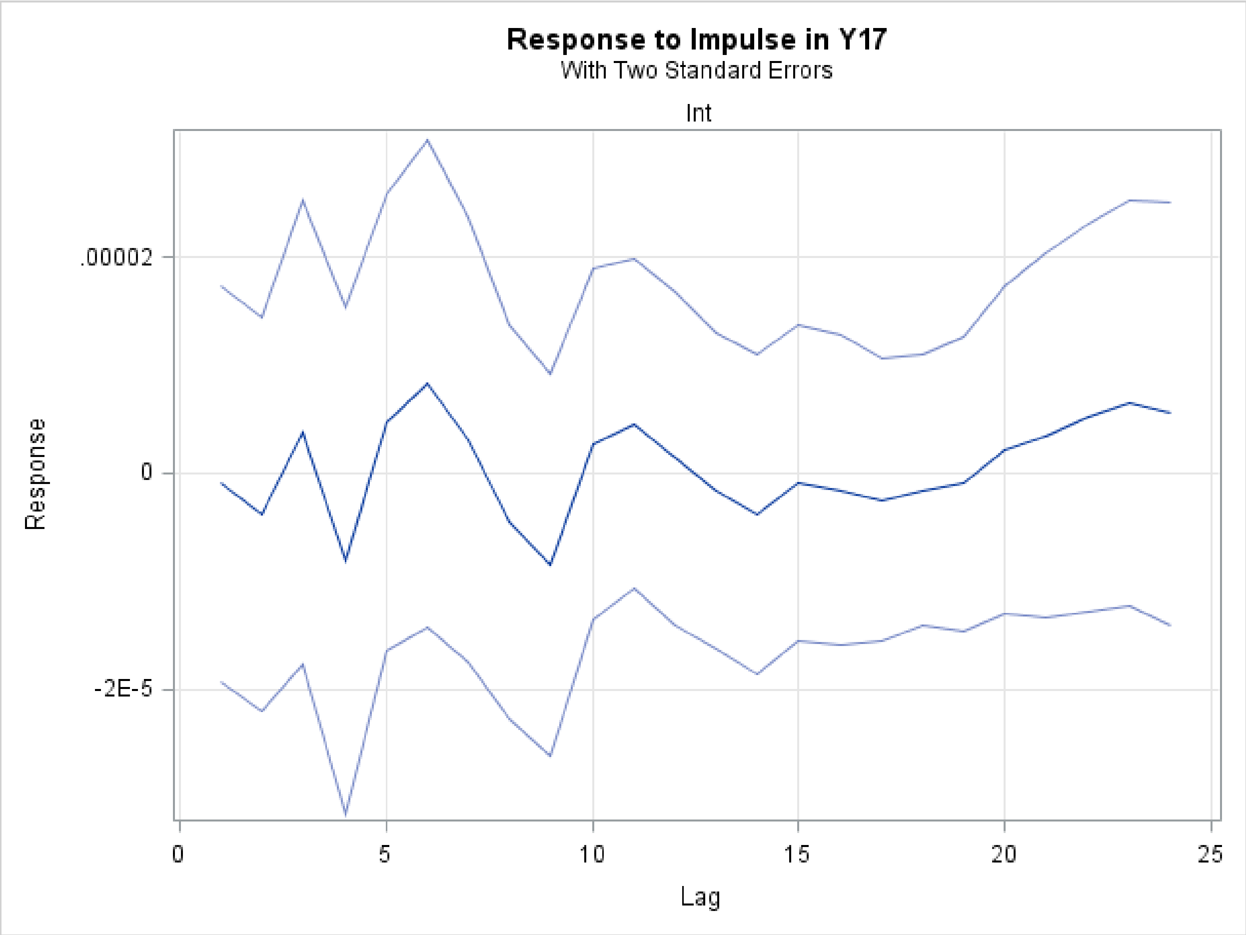

Response to Impulse in Y17
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag

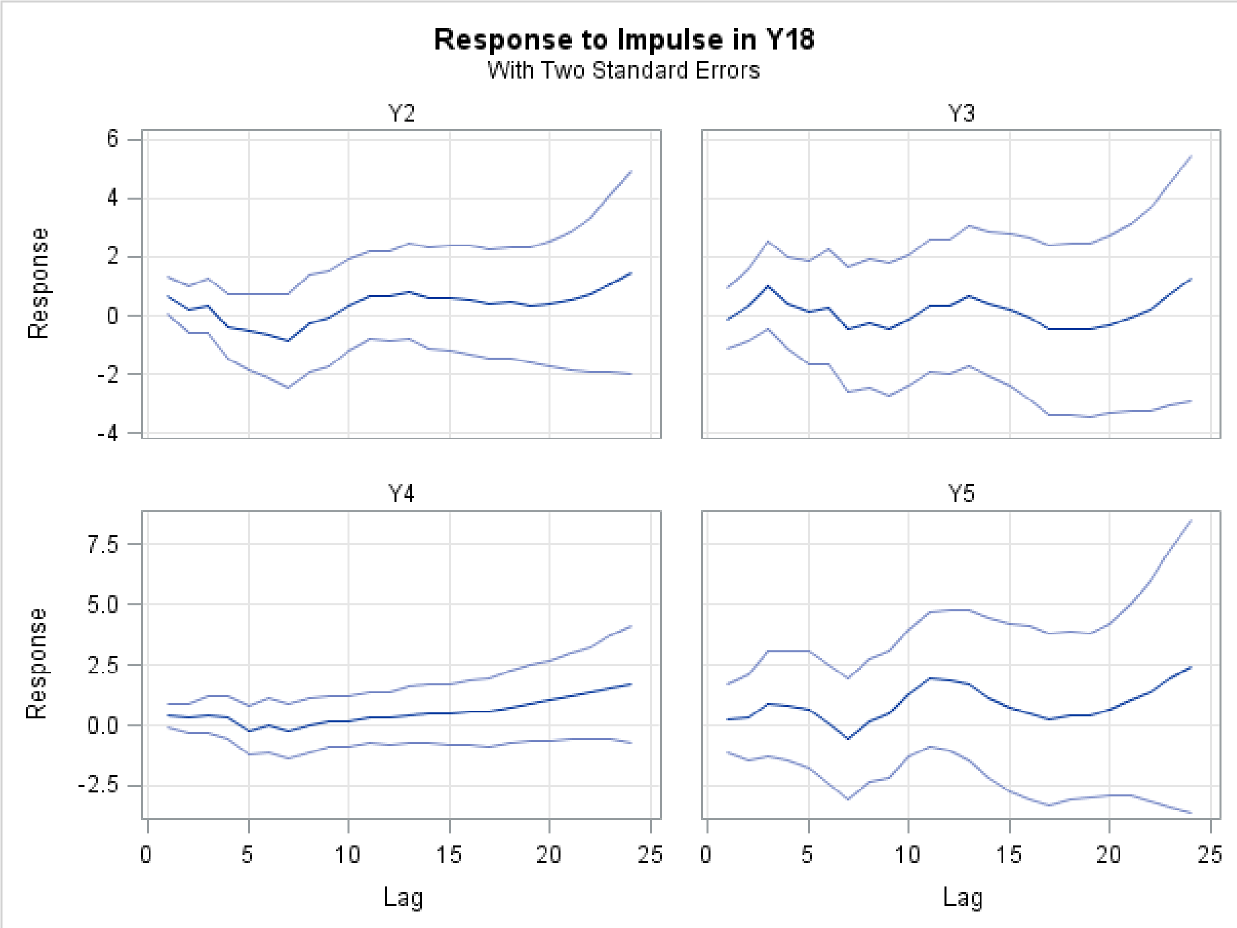


Response to Impulse in Y17
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
0.5
0.0
-0.5
-1.0
1
0
-1
-2
0
5
10
15
20
25
Lag
Lag

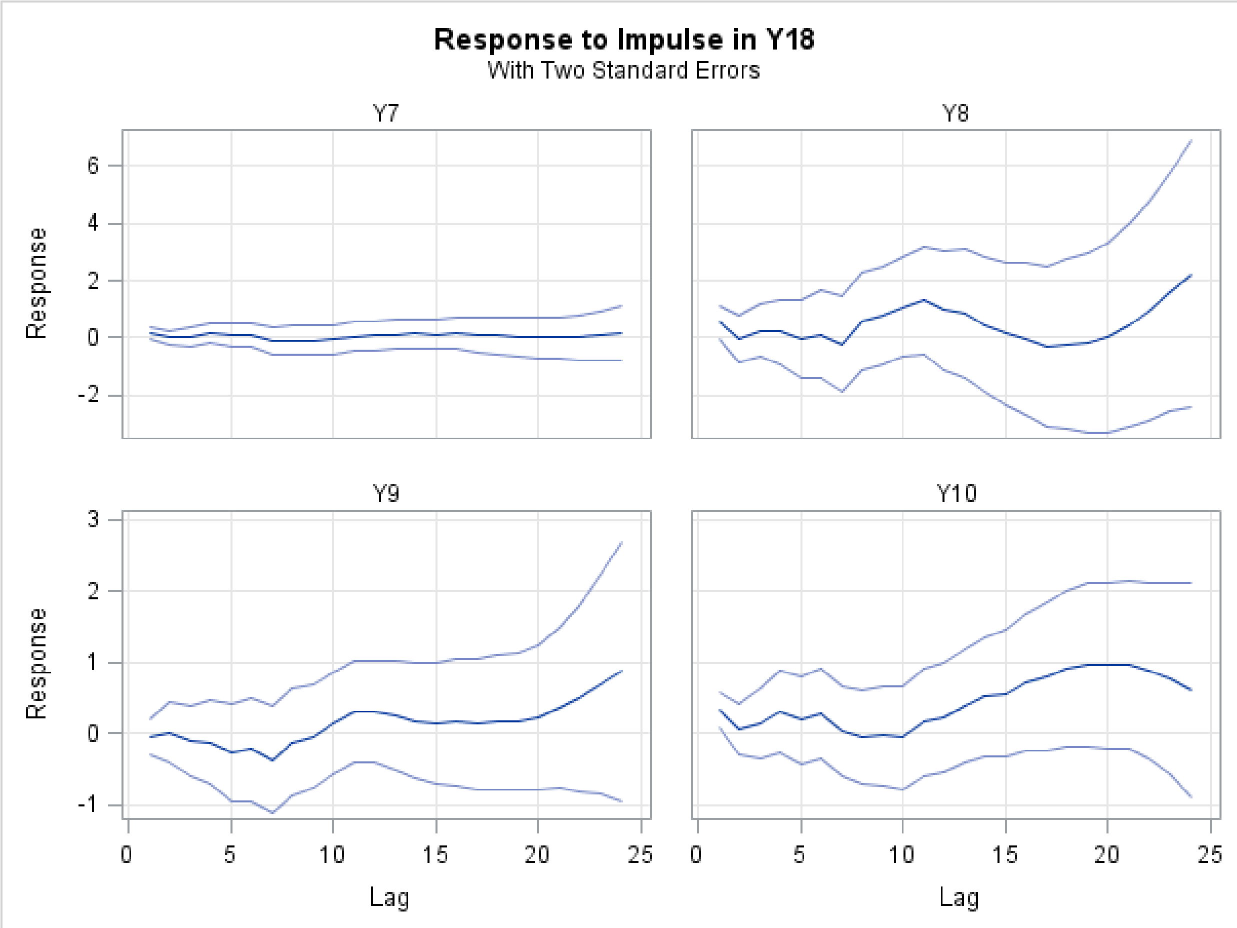


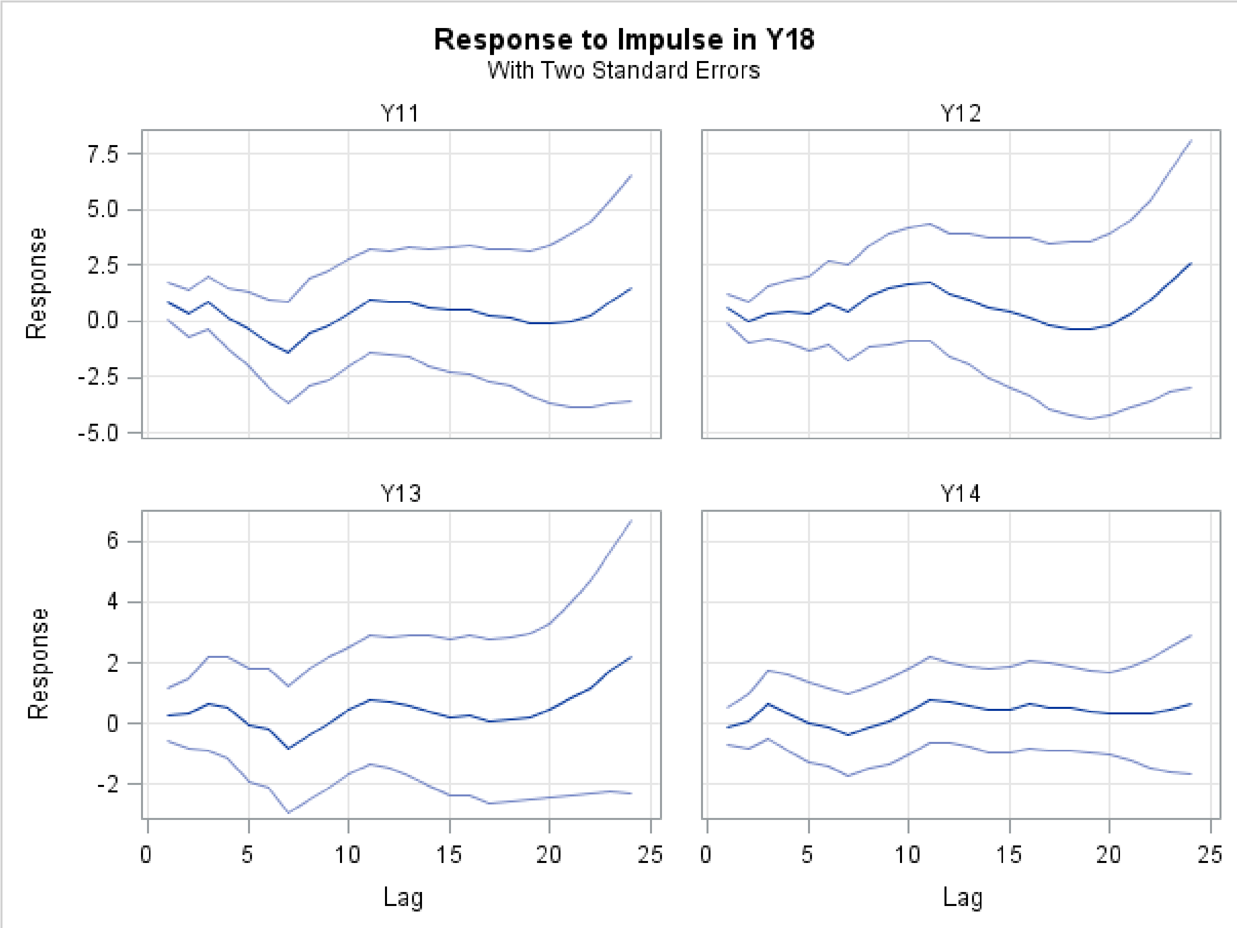
Response to Impulse in Y17
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag

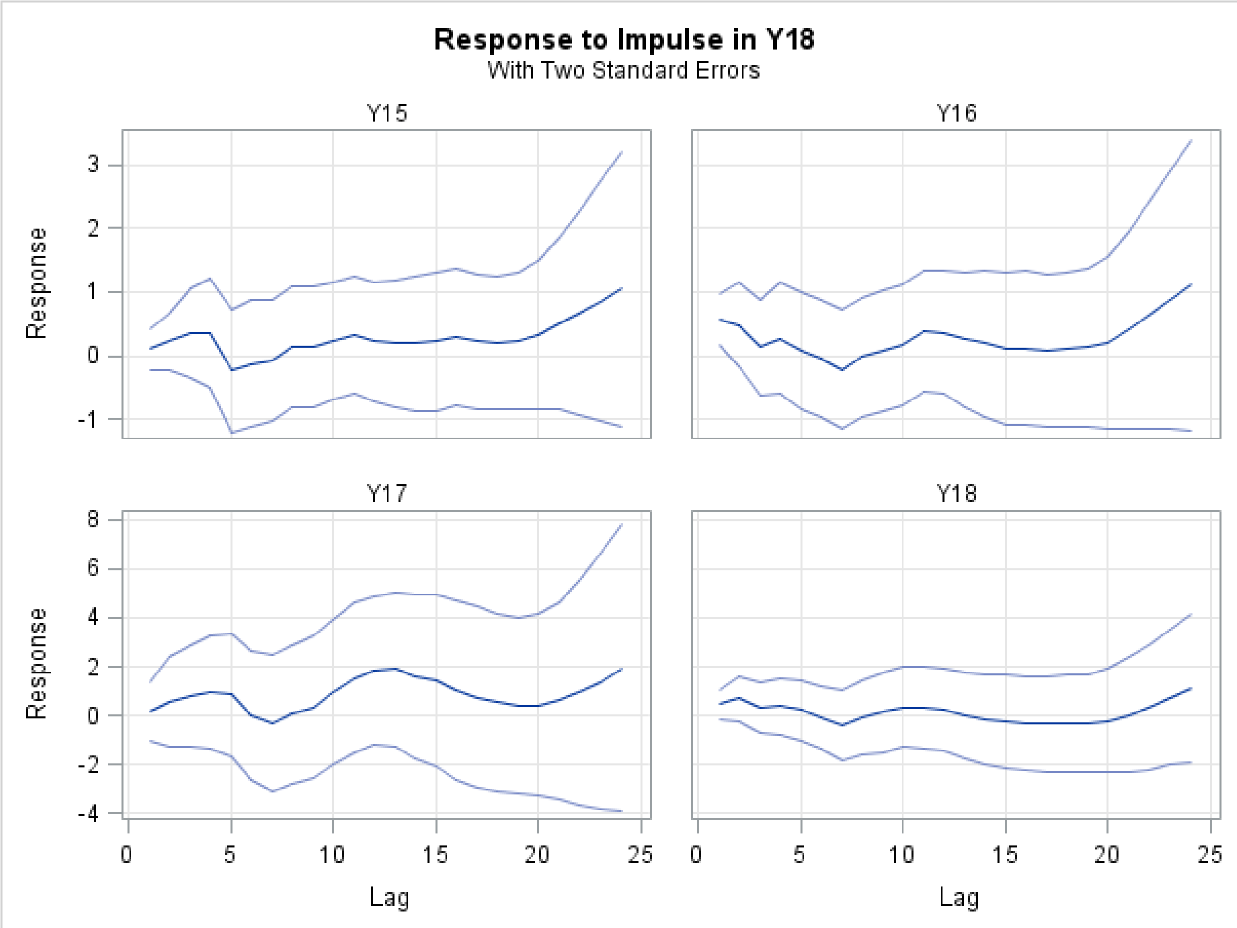

Response to Impulse in Y17
With Two Standard Errors
Int
.00002
0
-2E-5
Response
0
5
10
15
20
25
Lag



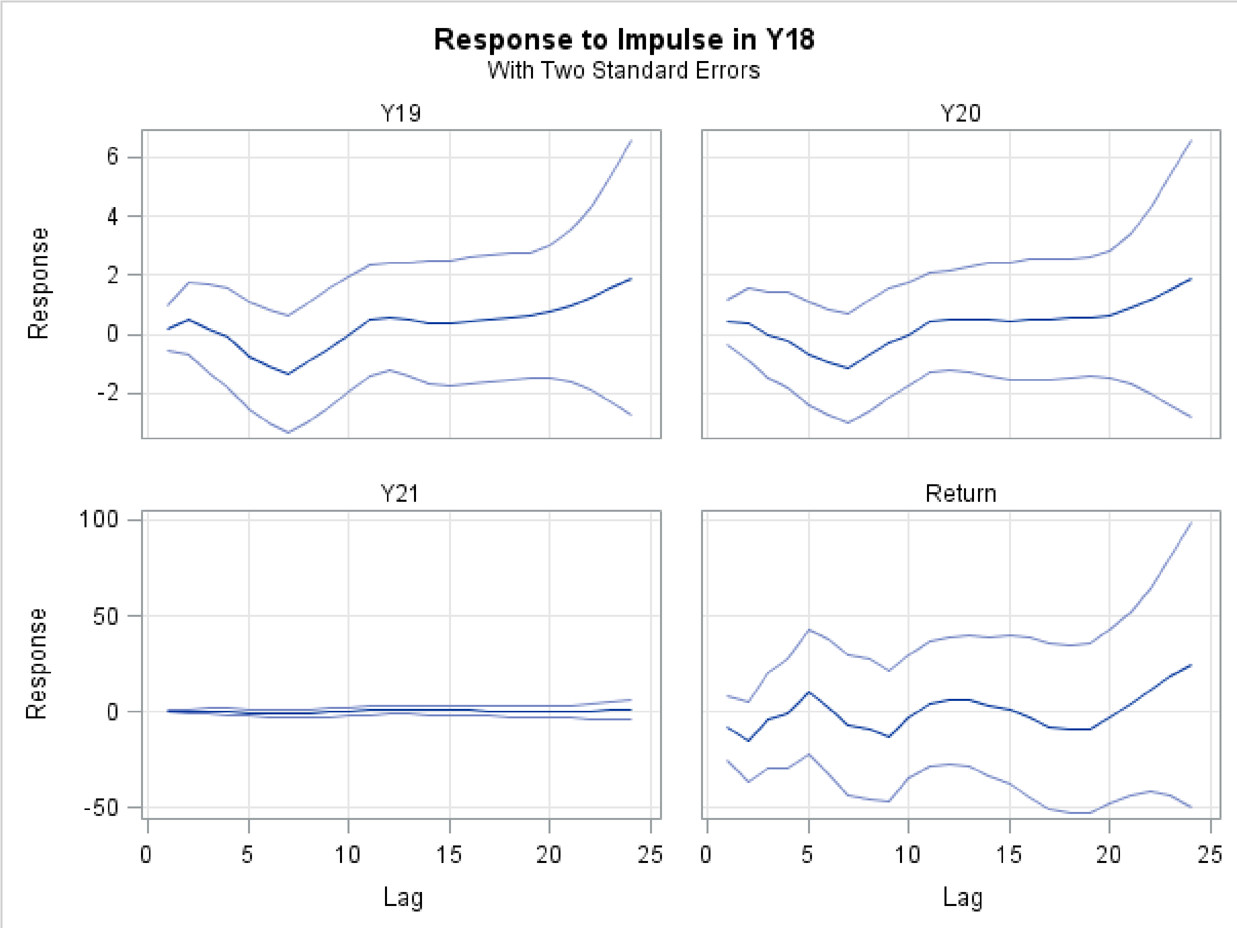
Response to Impulse in Y18
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag

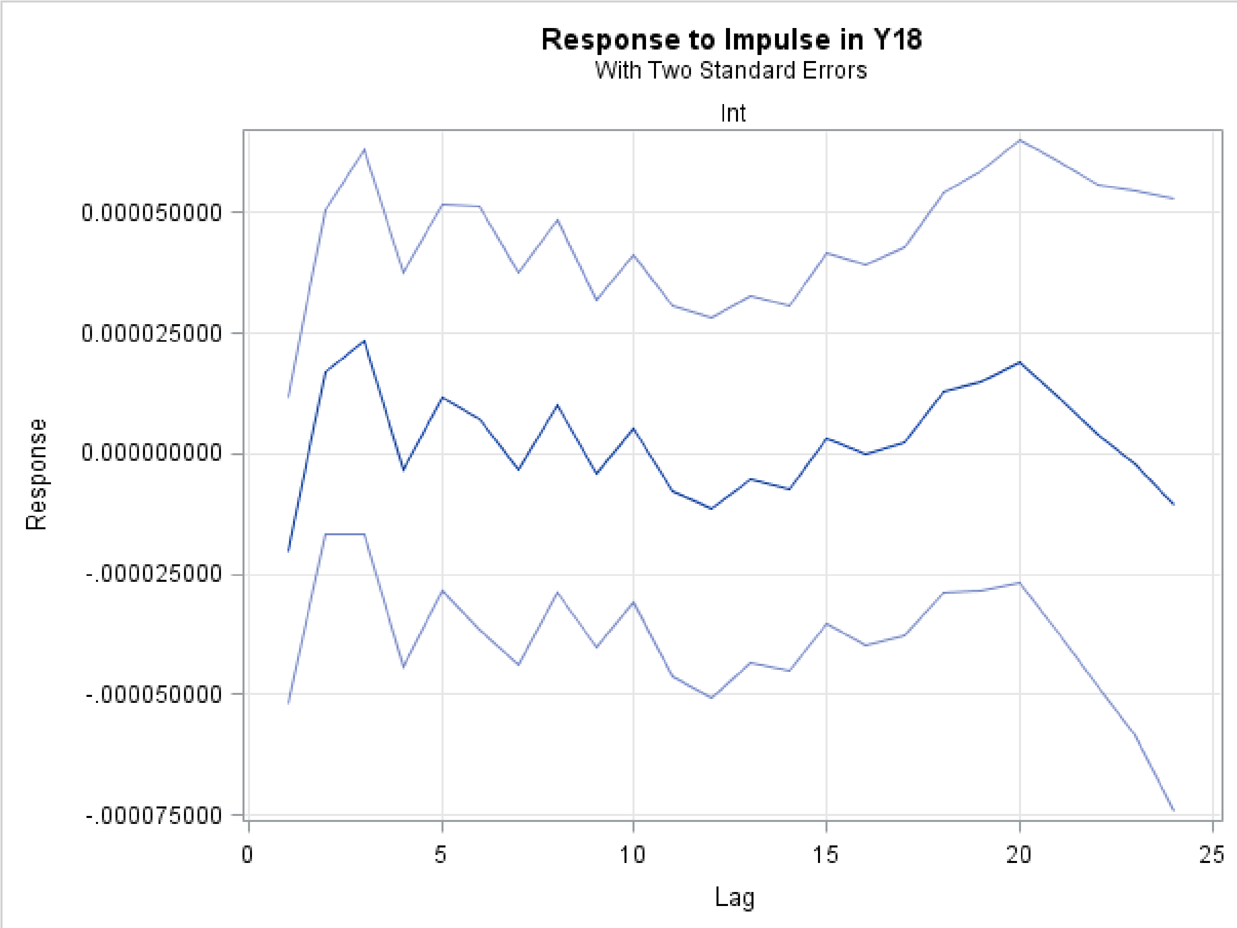

Response to Impulse in Y18
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag

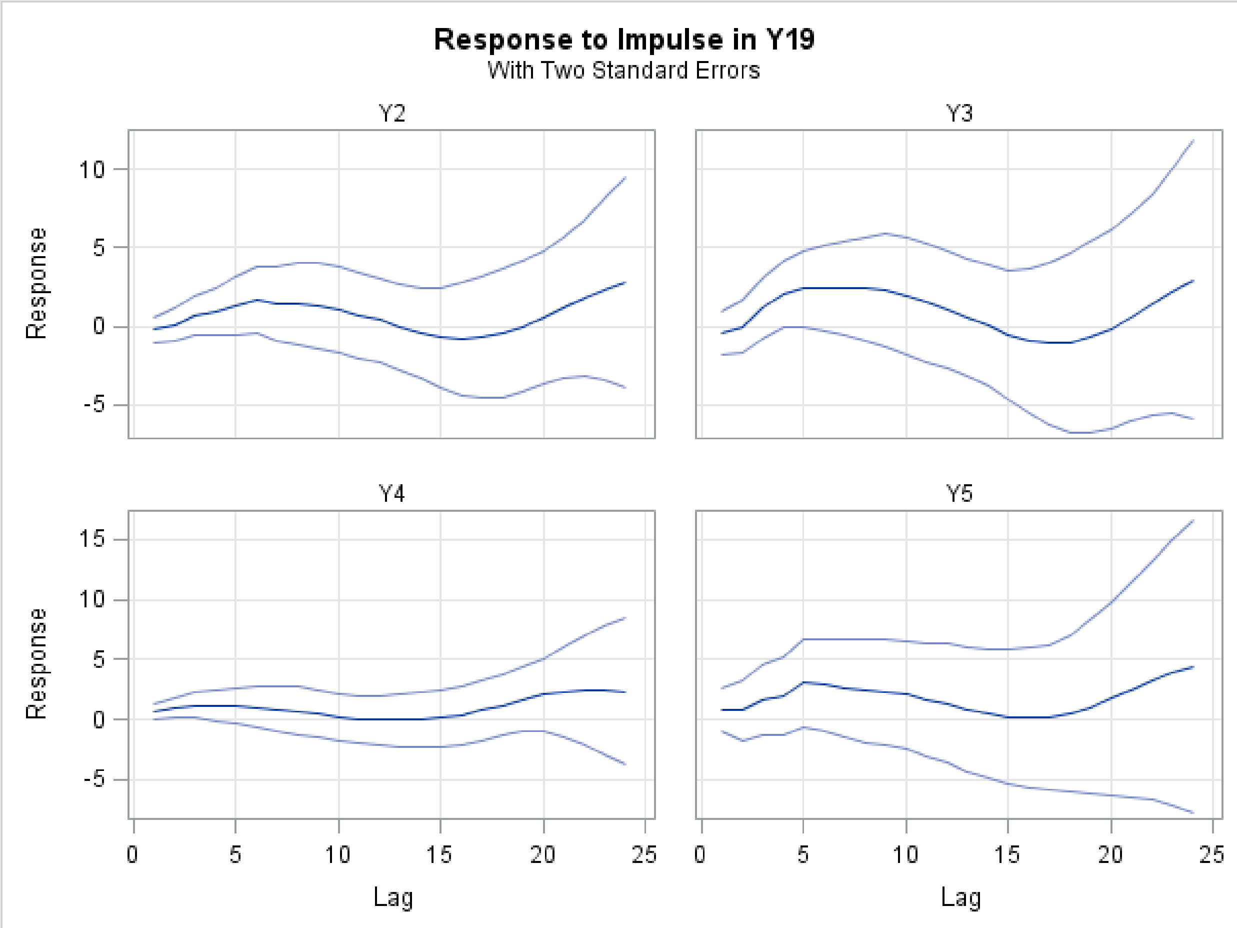

Response to Impulse in Y18
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
7.5
5.0
2.5
0.0
-2.5
-5.0
6
4
2
0
-2
0
5
10
15
20
25

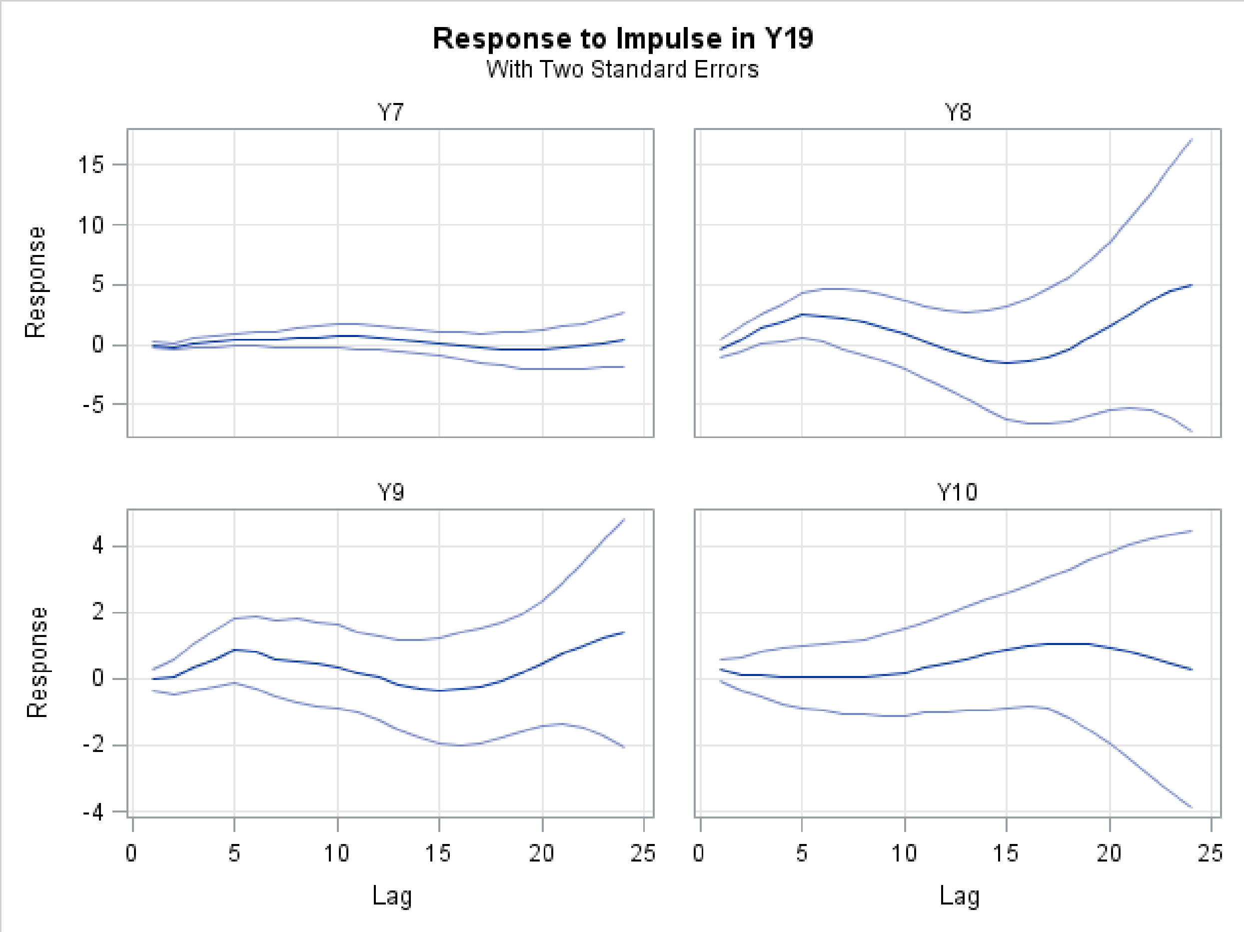


Response to Impulse in Y18
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag

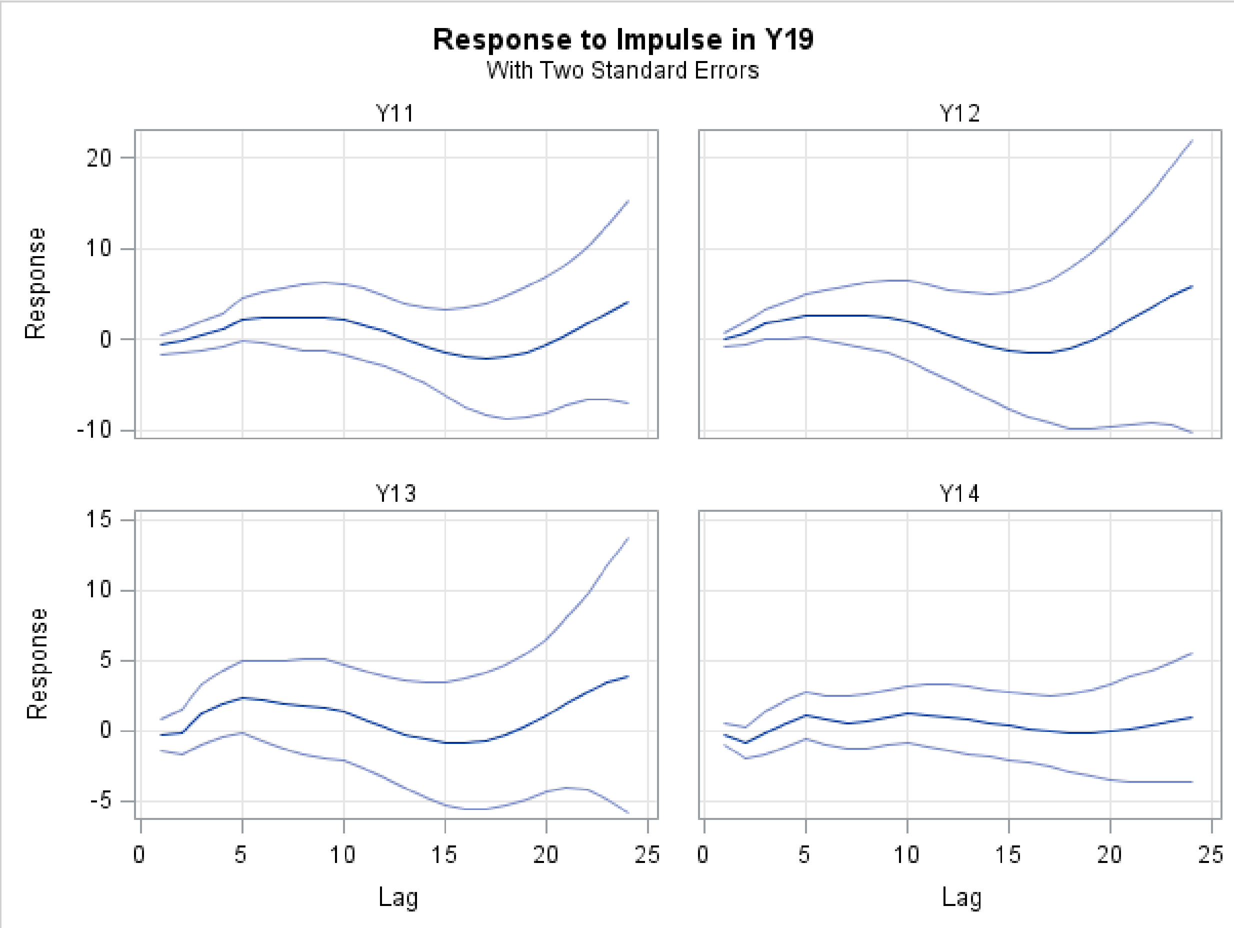

Response to Impulse in Y18
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
6
4
2
0
-2
100
50
0
-50
0
5
10
15
20
25

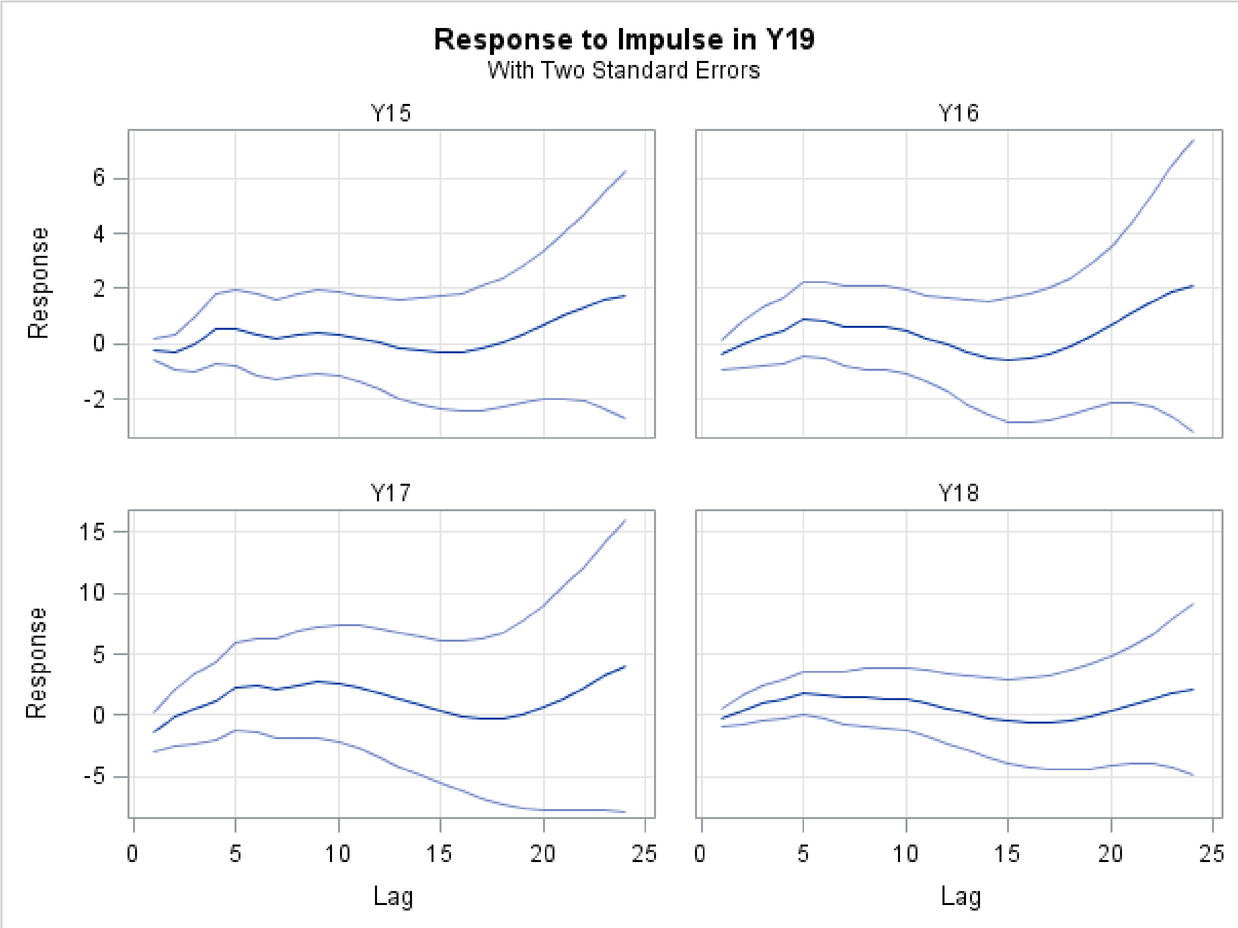

Response to Impulse in Y18
With Two Standard Errors
Int
0.000050000
0.000025000
0.000000000
-.000025000
-.000050000
-.000075000
Response
0
5
10
15
20
25
Lag

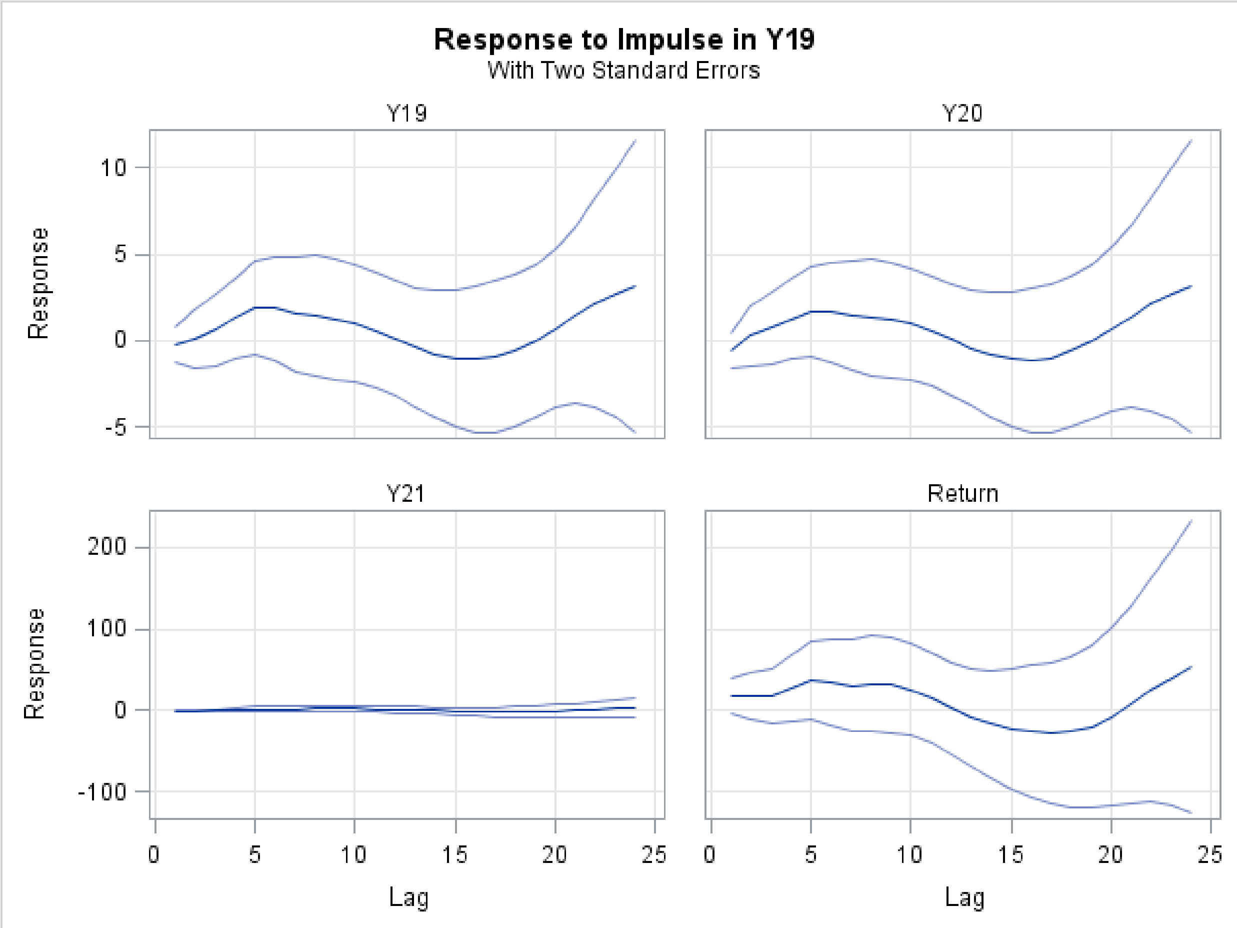

Response to Impulse in Y19
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag
10
5
0
-5
15
10
5
0
-5
0
5
10
15
20
25



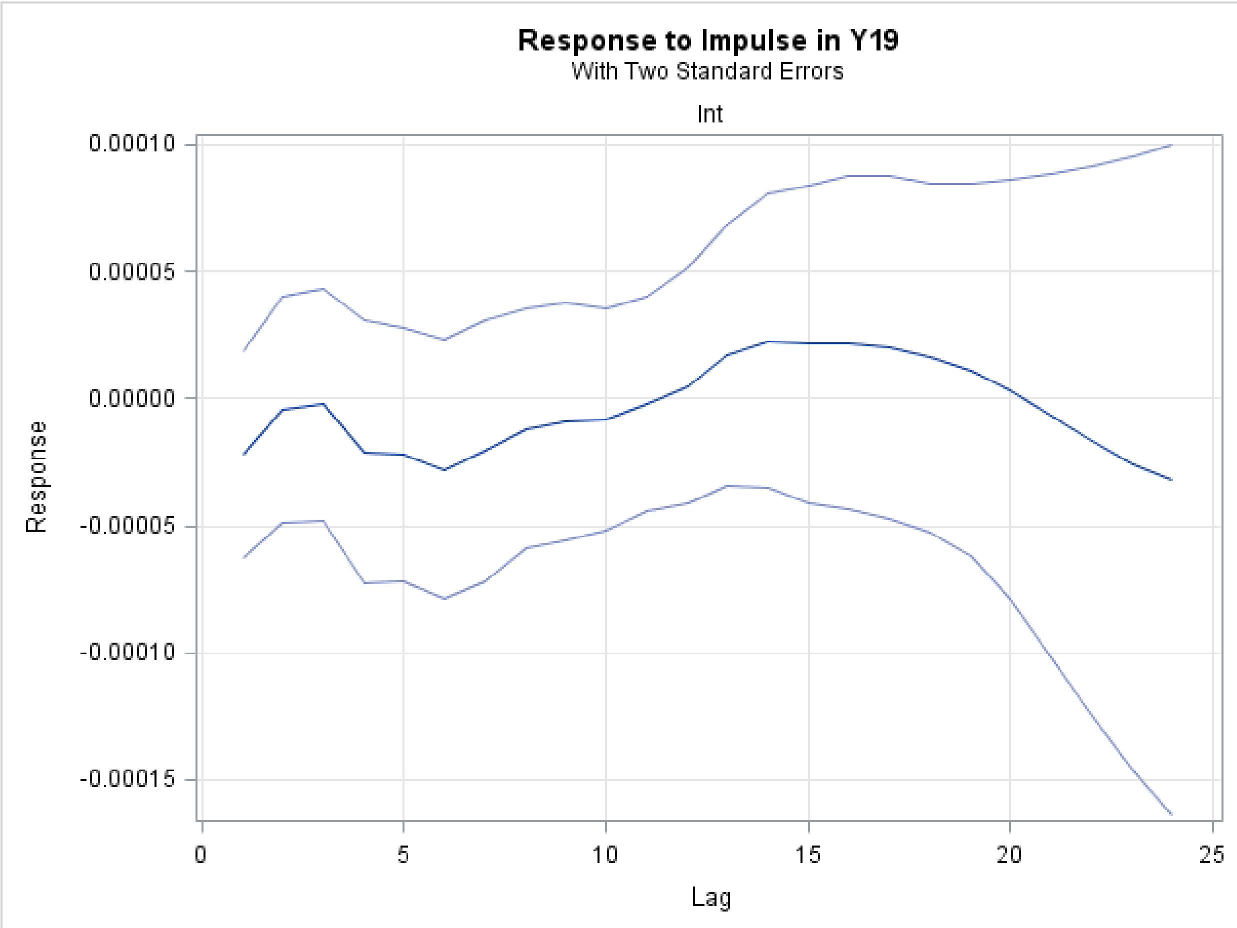
Response to Impulse in Y19
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
15
10
5
0
-5
4
2
0
-2
-4
0
5
10
15
20
25

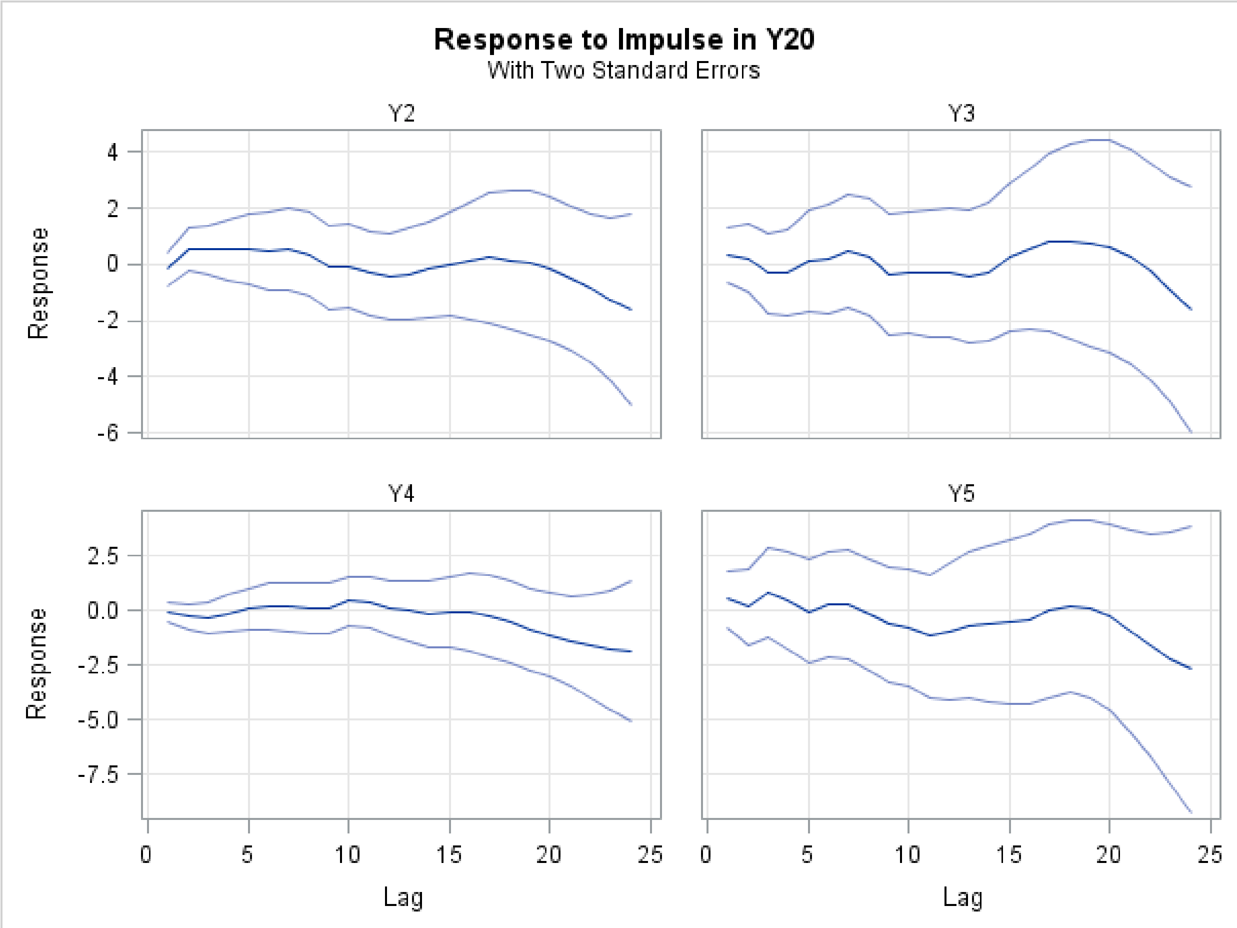

Response to Impulse in Y19
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
20
10
0
-10
15
10
5
0
-5
0
5
10
15
20
25

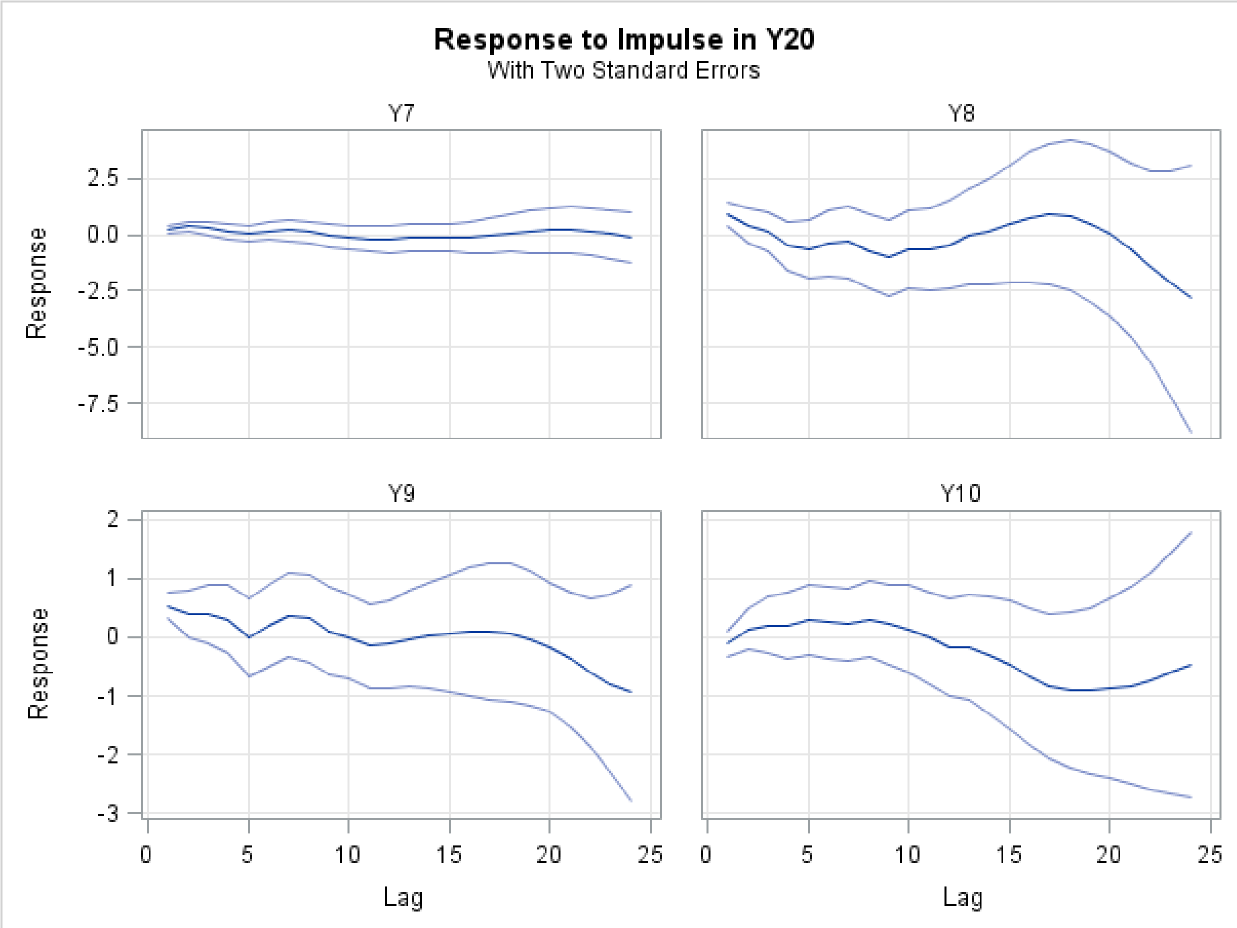

Response to Impulse in Y19
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
6
4
2
0
-2
15
10
5
0
-5
0
5
10
15
20
25



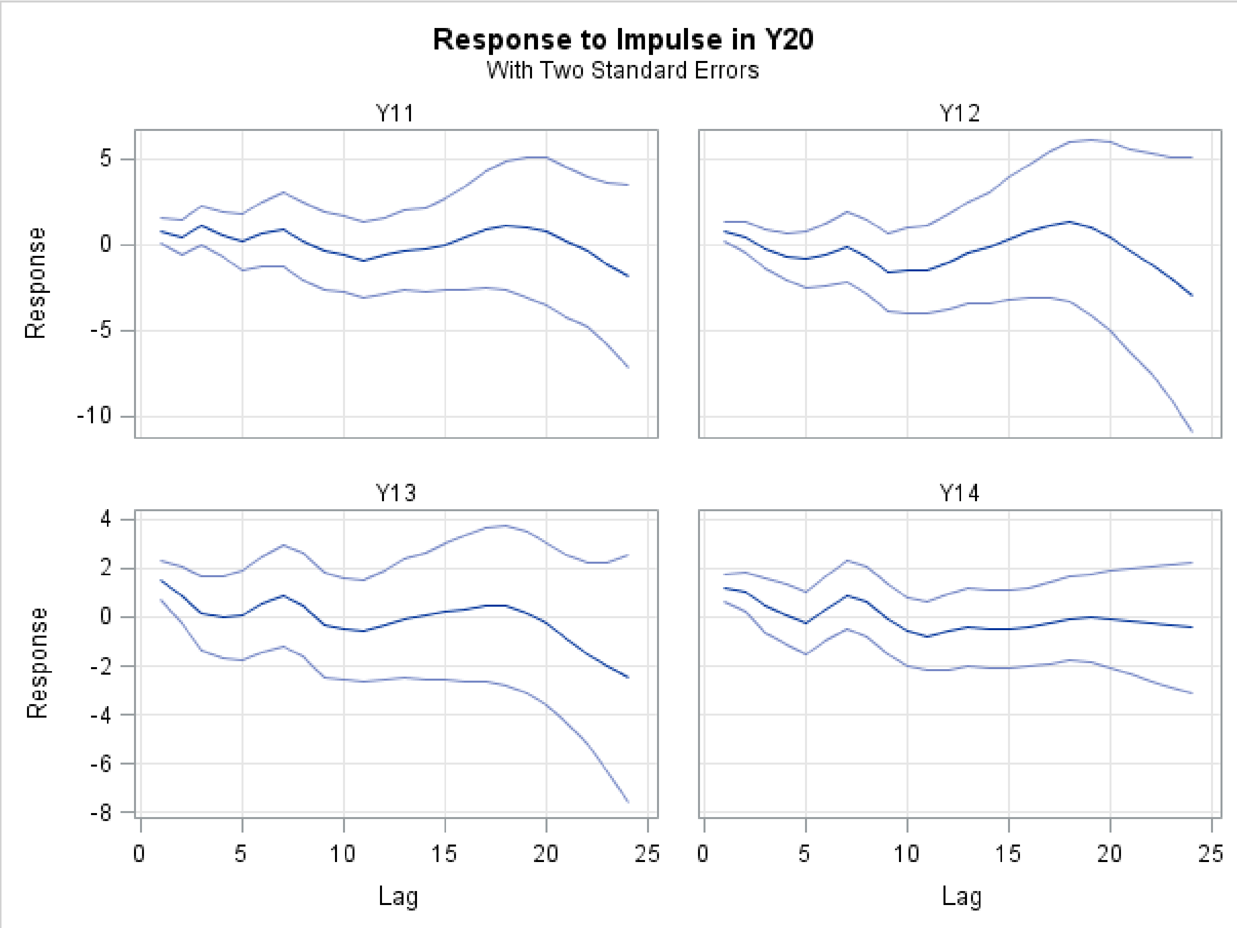
Response to Impulse in Y19
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag
10
5
0
-5
200
100
0
-100
0
5
10
15
20
25

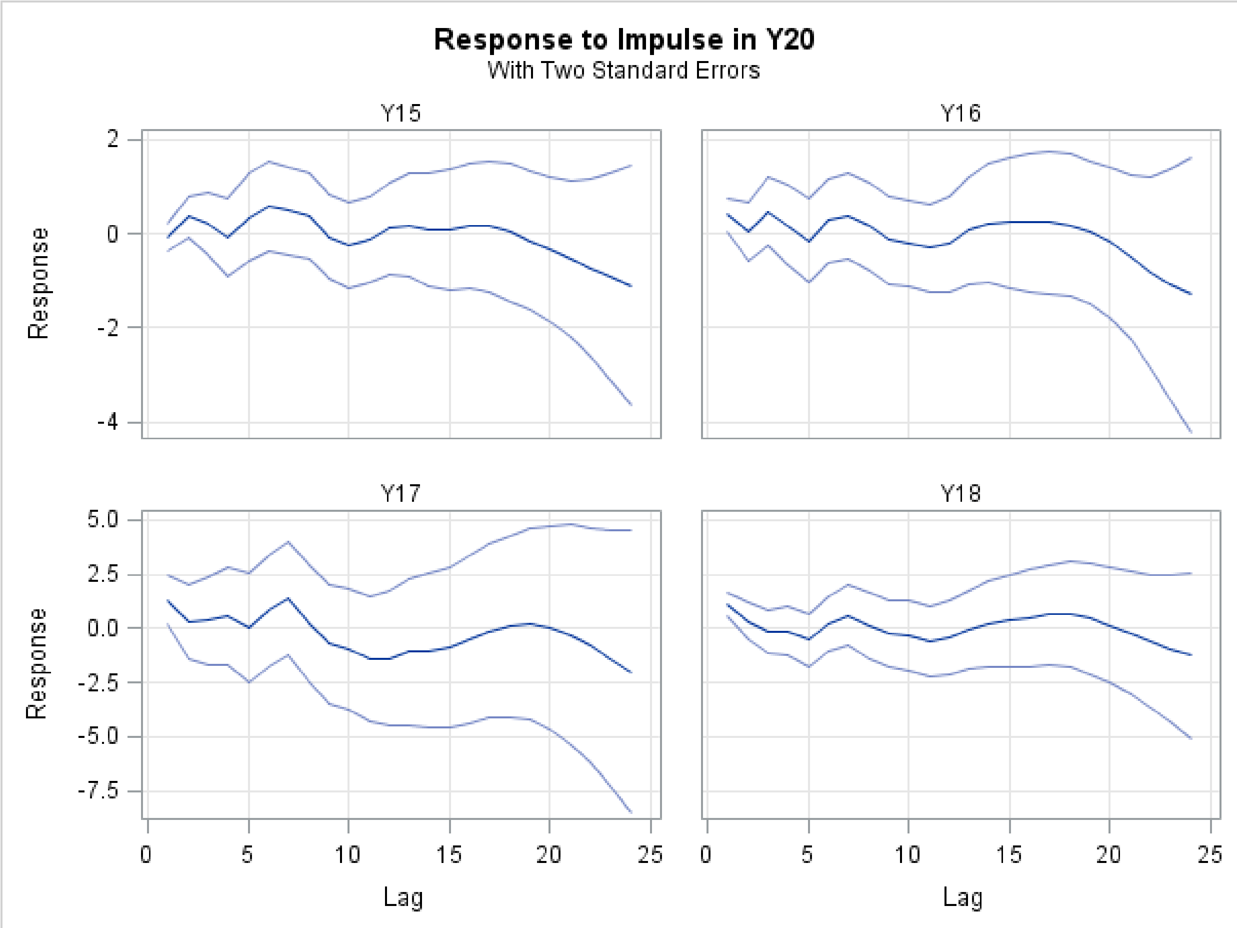

Response to Impulse in Y19
With Two Standard Errors
Int
0.00010
0.00005
0.00000
-0.00005
-0.00010
-0.00015
Response
0
5
10
15
20
25
Lag


Response to Impulse in Y20
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
4
2
0
-2
-4
-6
2.5
0.0
-2.5
-5.0
-7.5
0
5
10
15
20
25
Lag
Lag

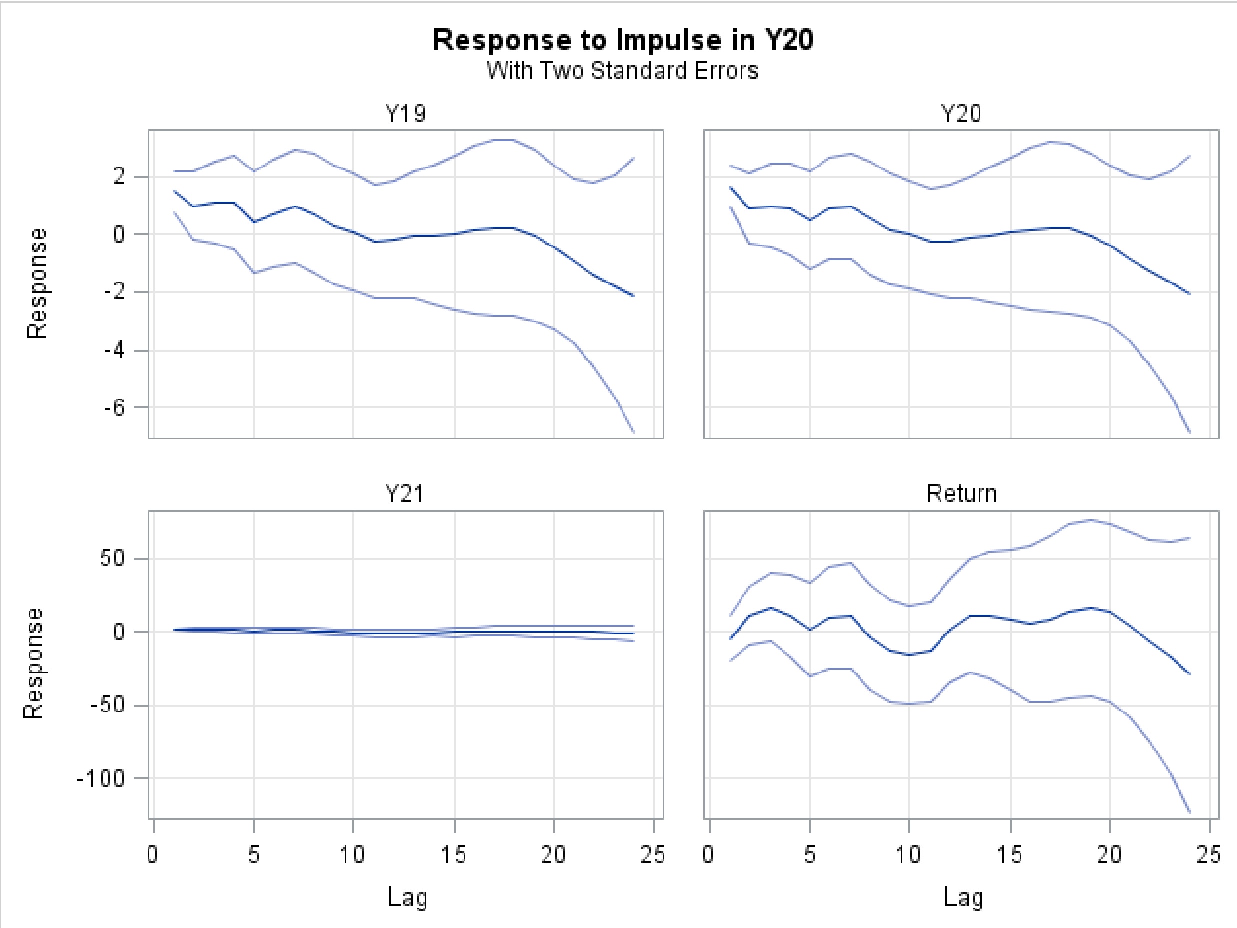


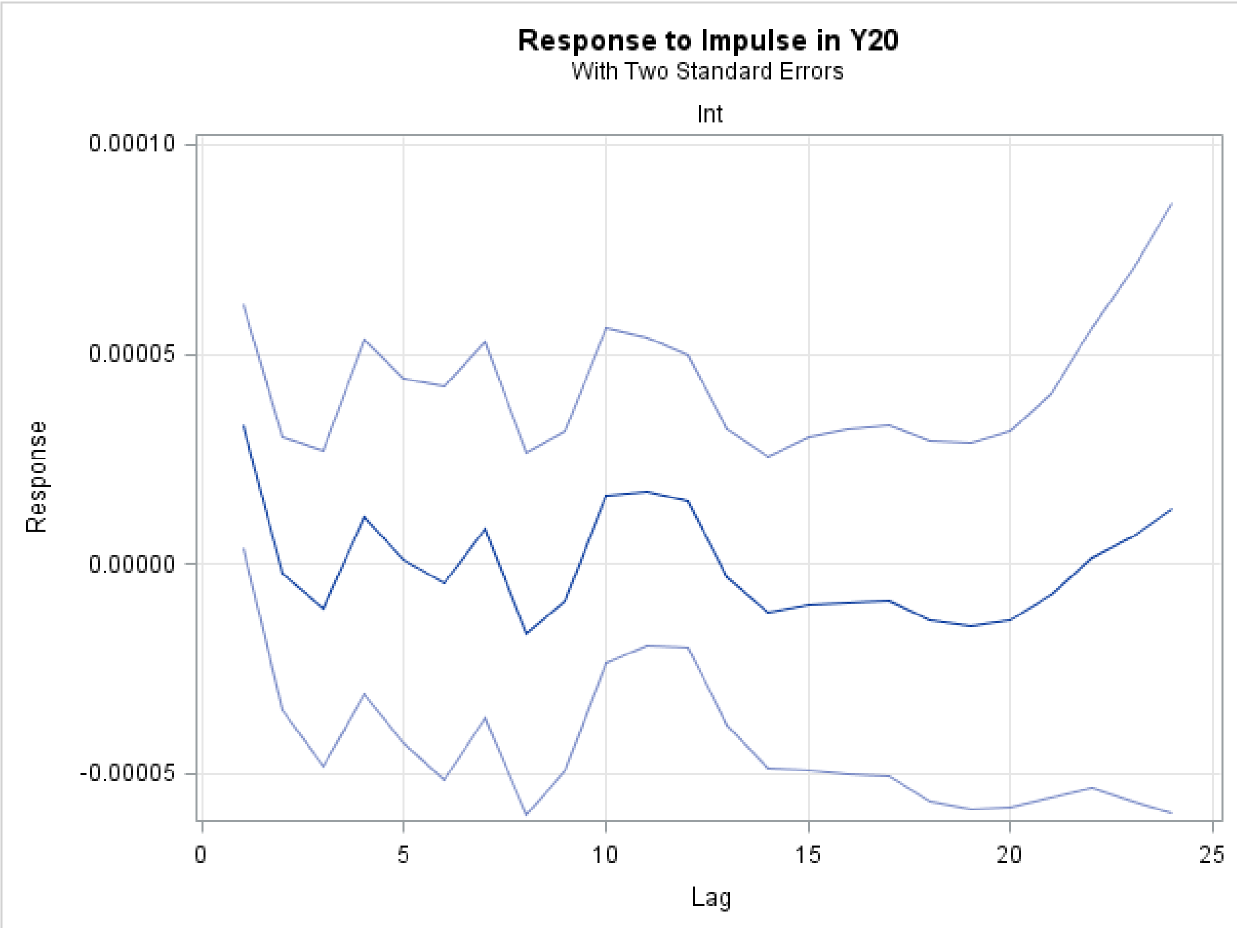
Response to Impulse in Y20
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
2.5
0.0
-2.5
-5.0
-7.5
2
1
0
-1
-2
-3
0
5
10
15
20
25
Lag
Lag


Response to Impulse in Y20
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Lag

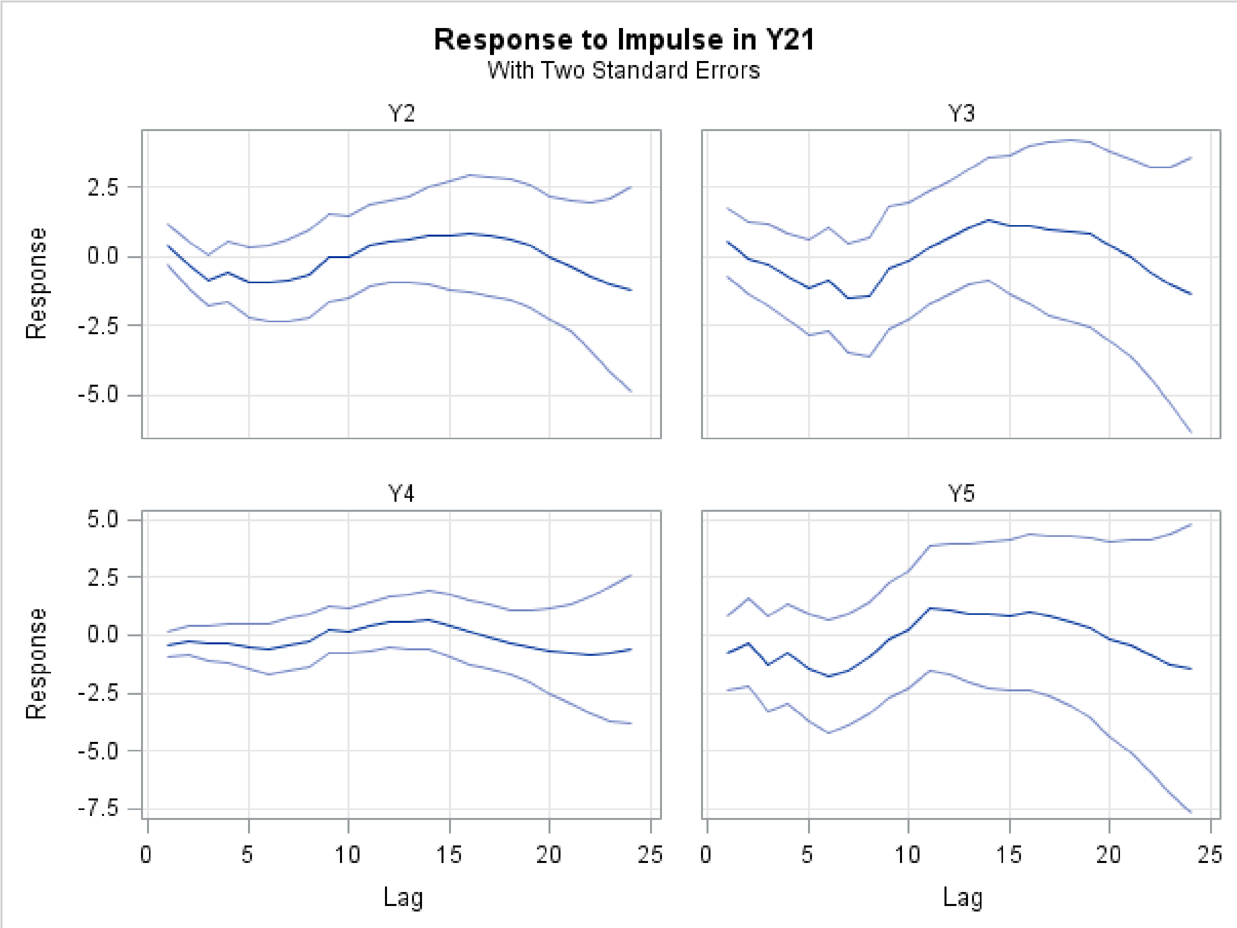


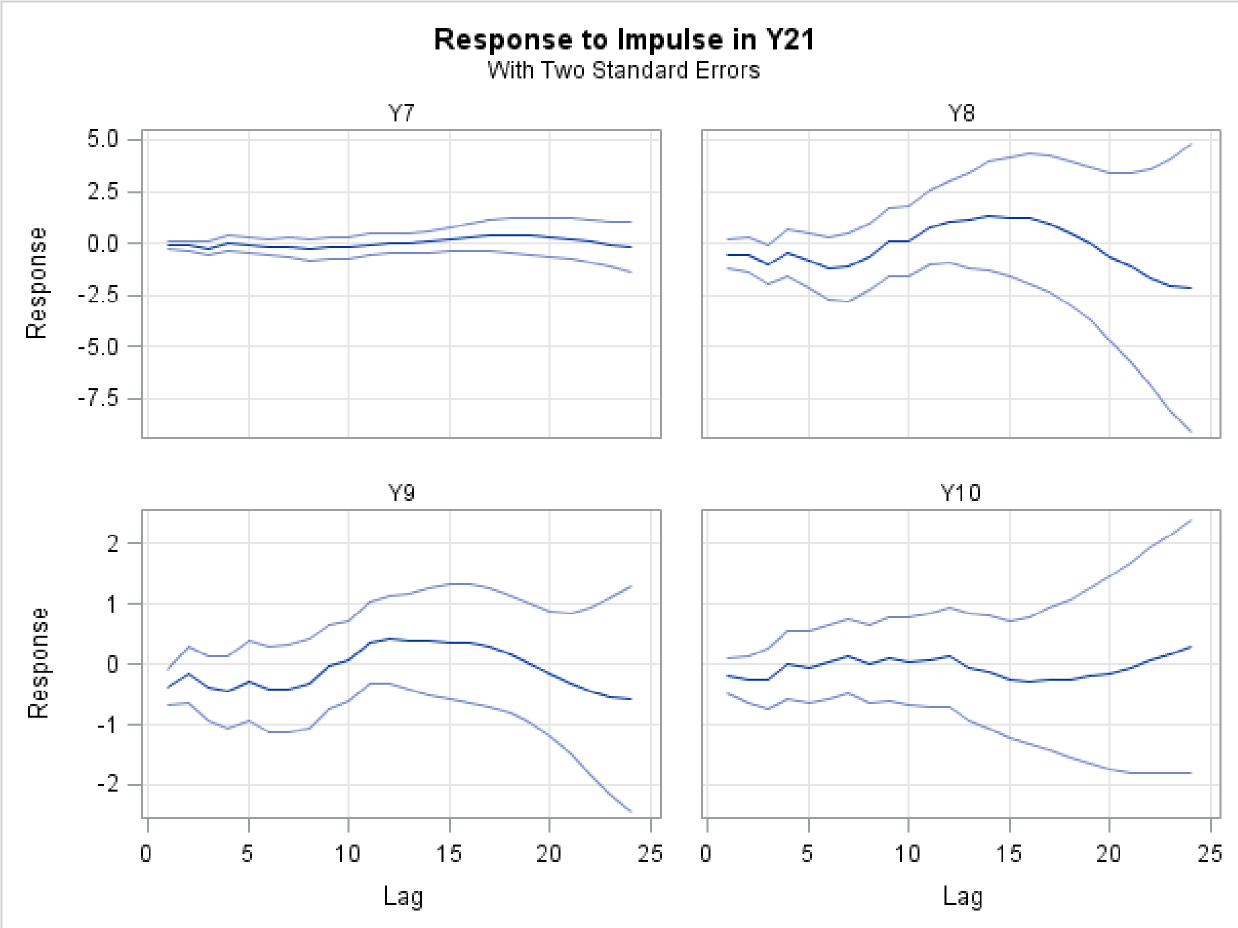
Response to Impulse in Y20
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Lag

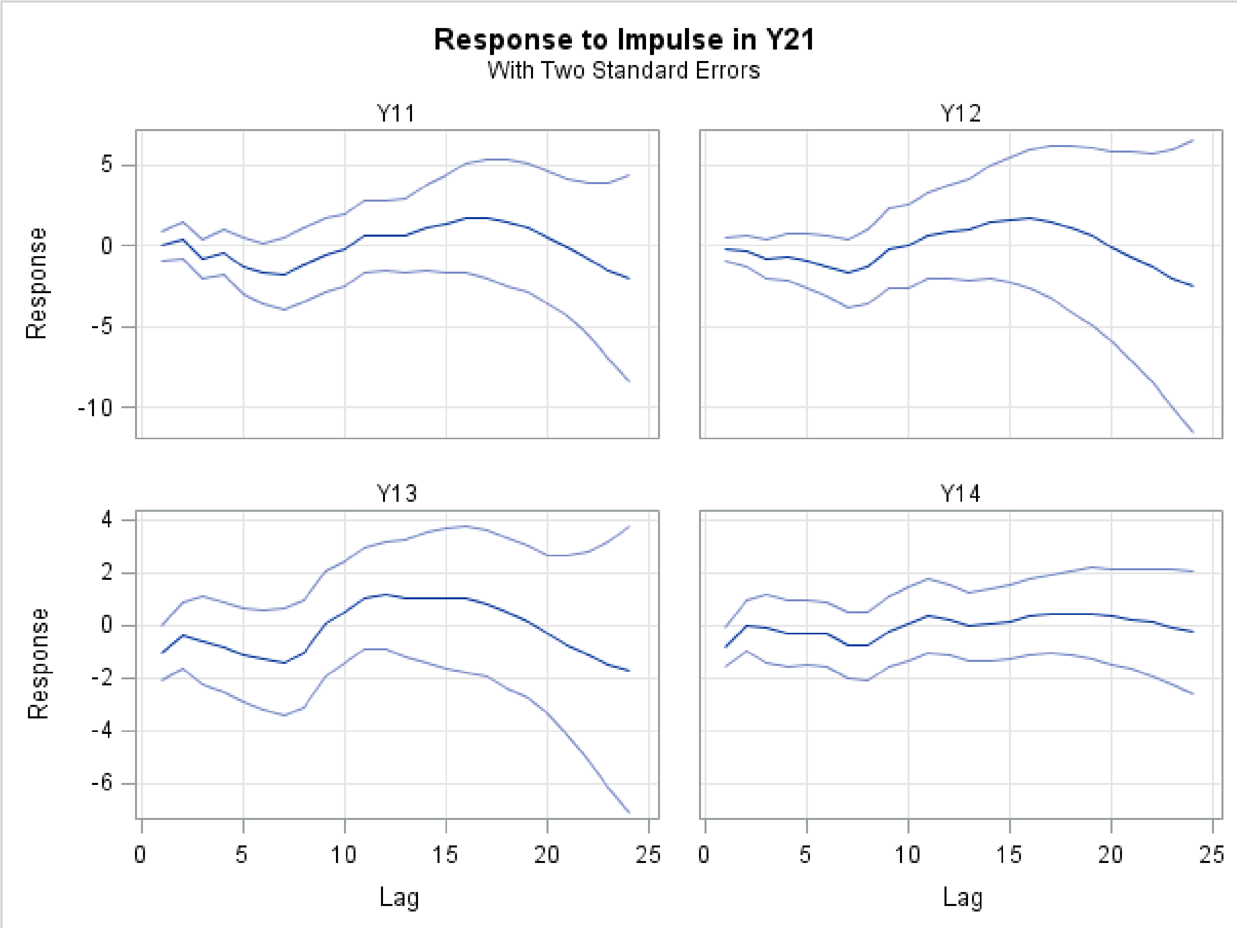

Response to Impulse in Y20
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Lag

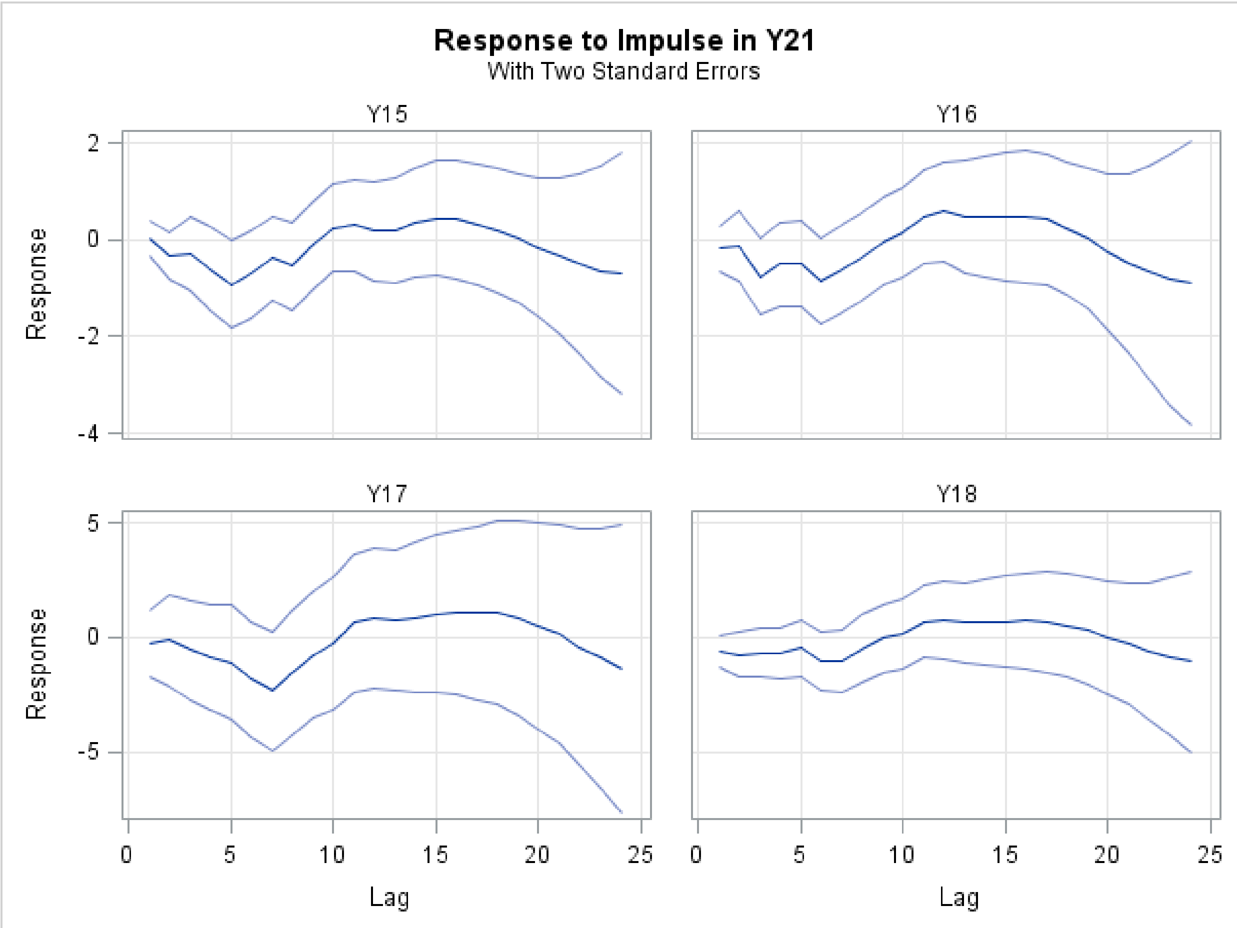


Response to Impulse in Y20
With Two Standard Errors
Int
0.00010
0.00005
0.00000
-0.00005
Response
0
5
10
15
20
25
Lag

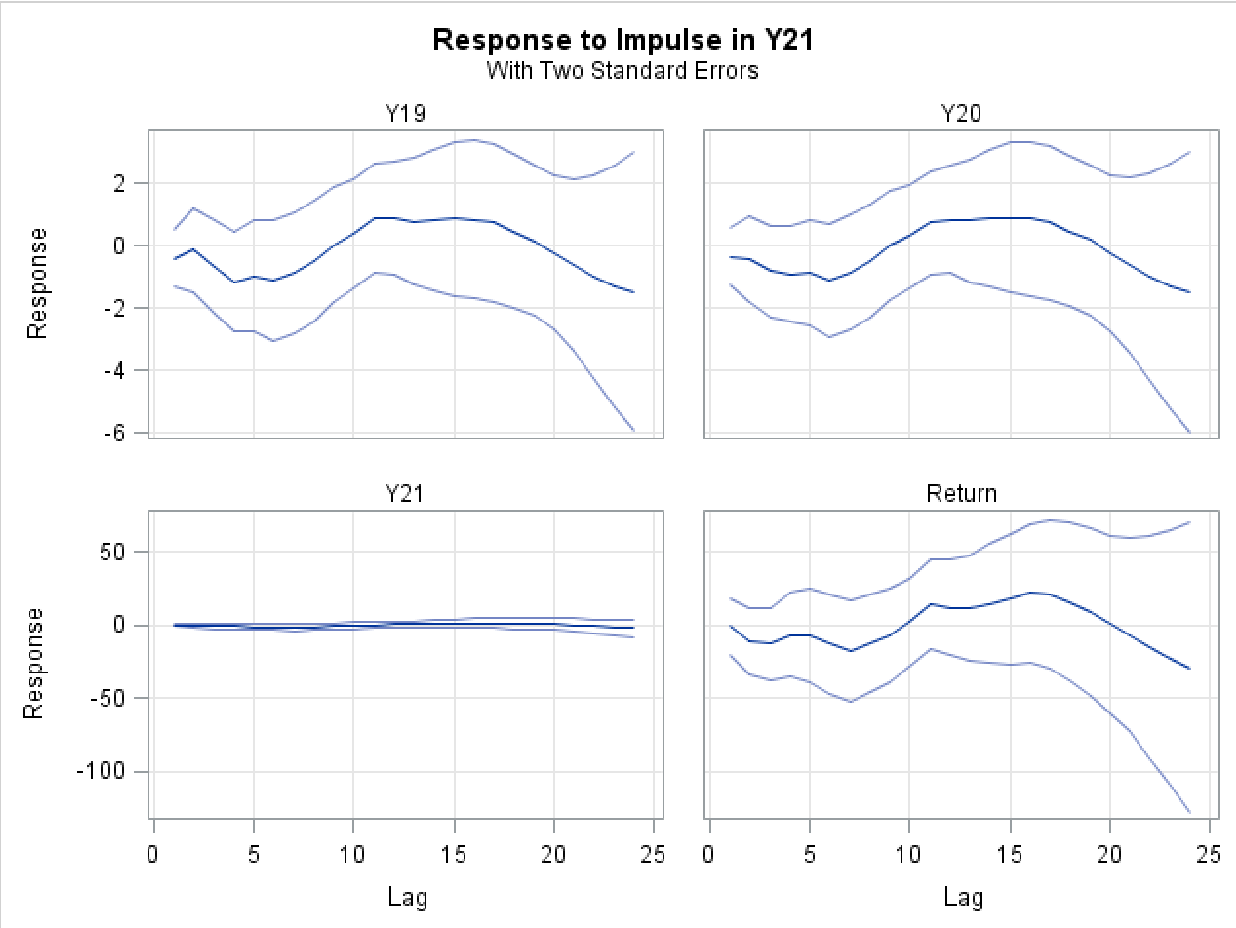

Response to Impulse in Y21
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
Lag
Lag


Response to Impulse in Y21
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
5.0
2.5
0.0
-2.5
-5.0
-7.5
2
1
0
-1
-2
0
5
10
15
20
25
Lag

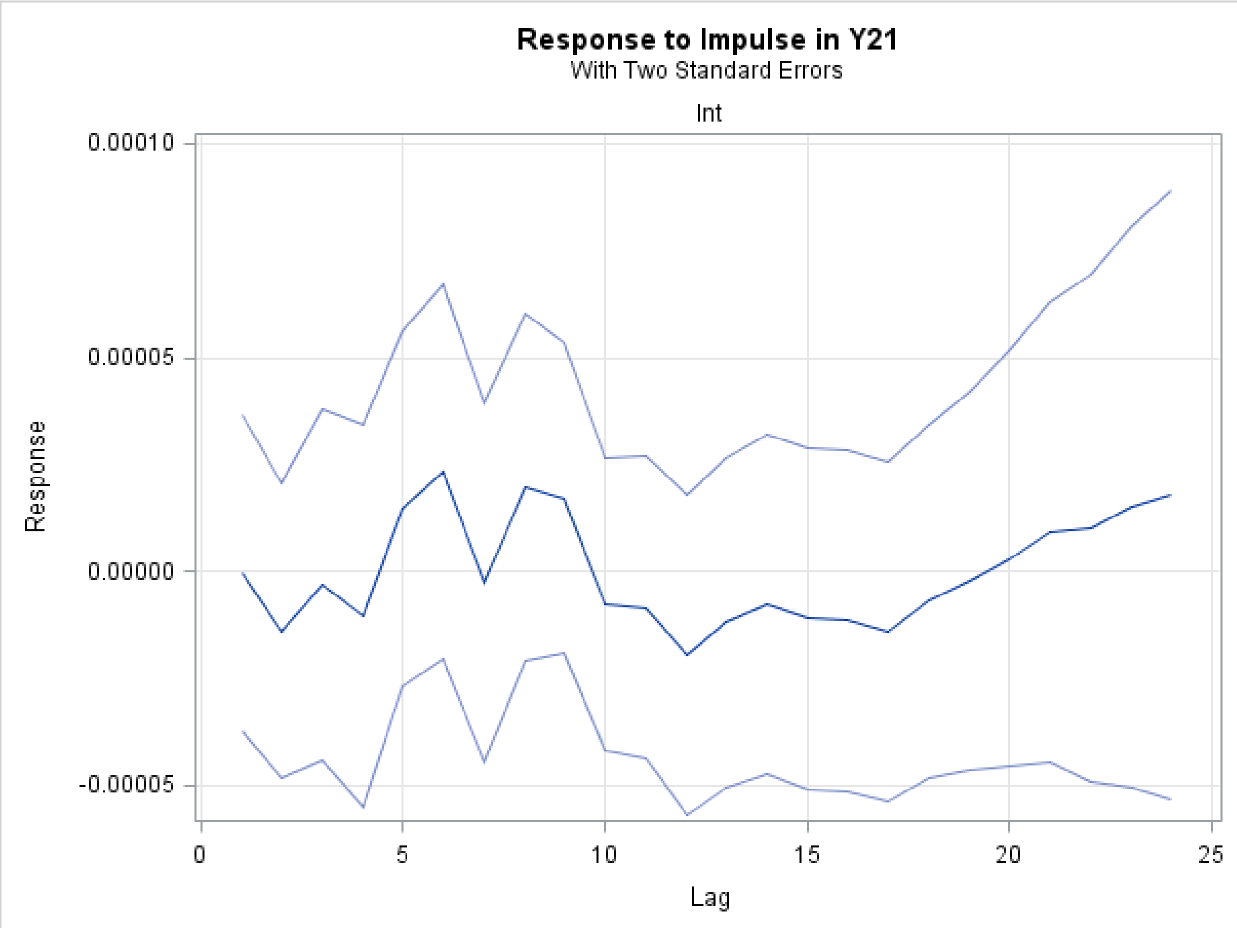

Response to Impulse in Y21
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
Lag
Lag
5
0
-5
-10
4
2
0
-2
-4
-6
0
5
10
15
20
25

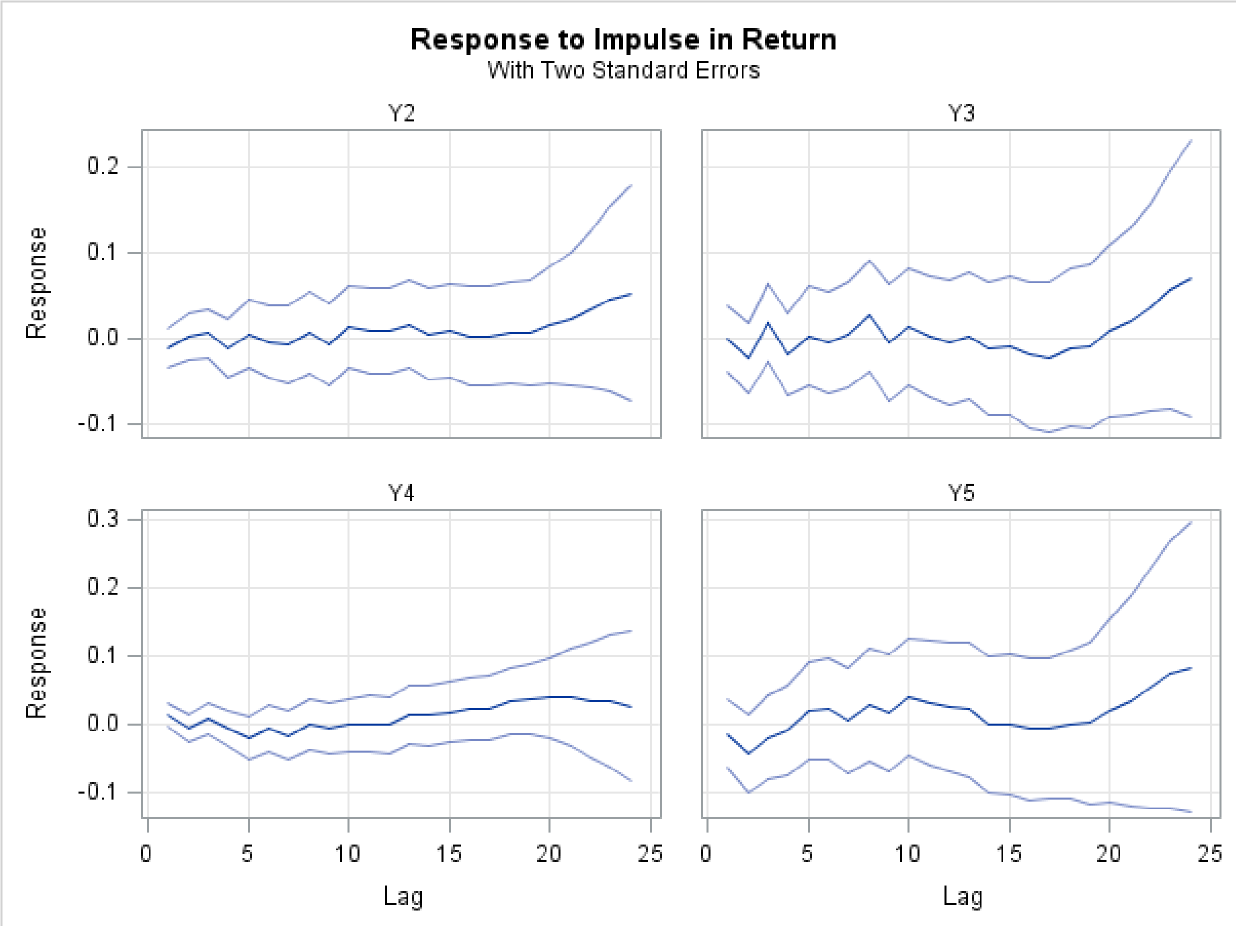


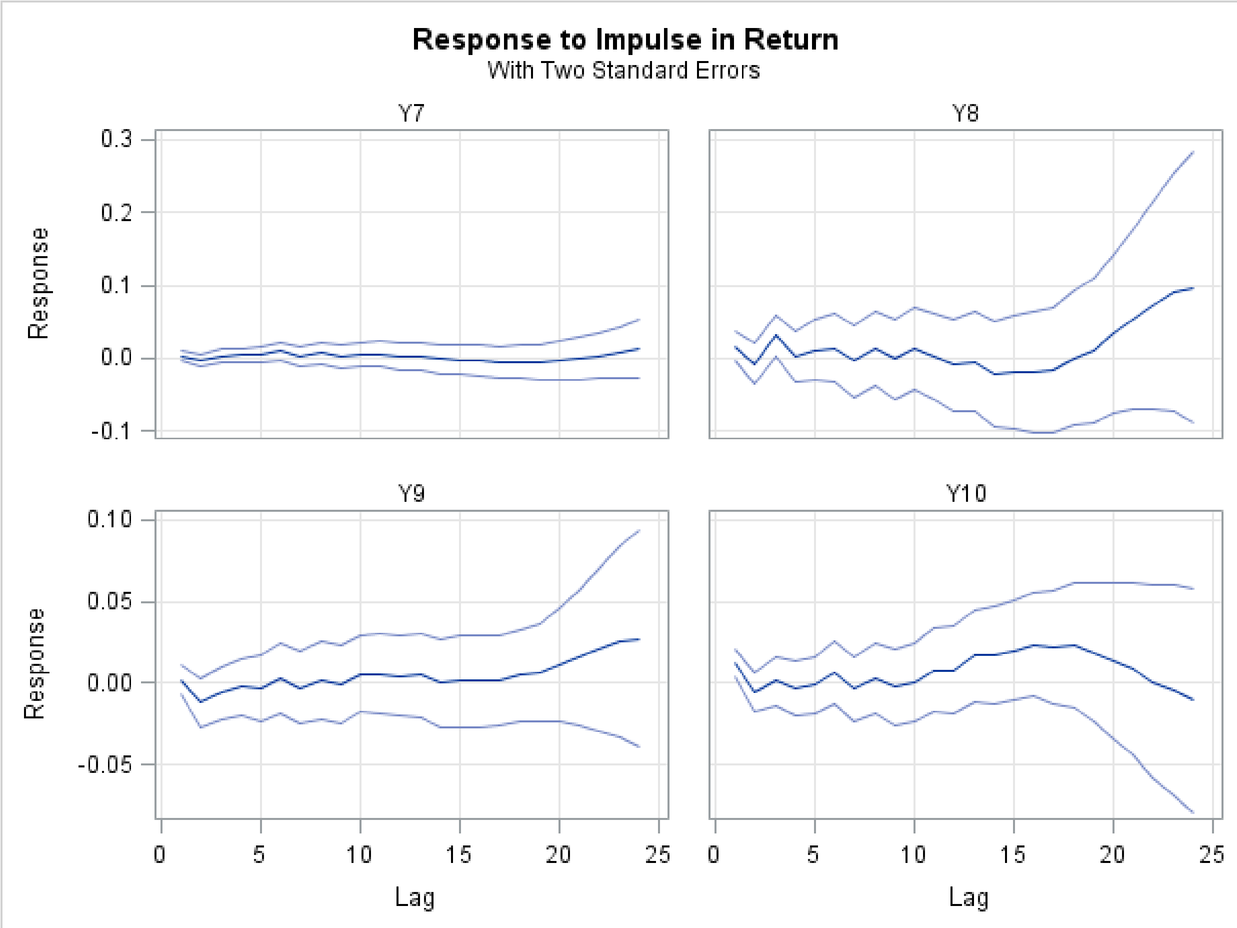
Response to Impulse in Y21
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag

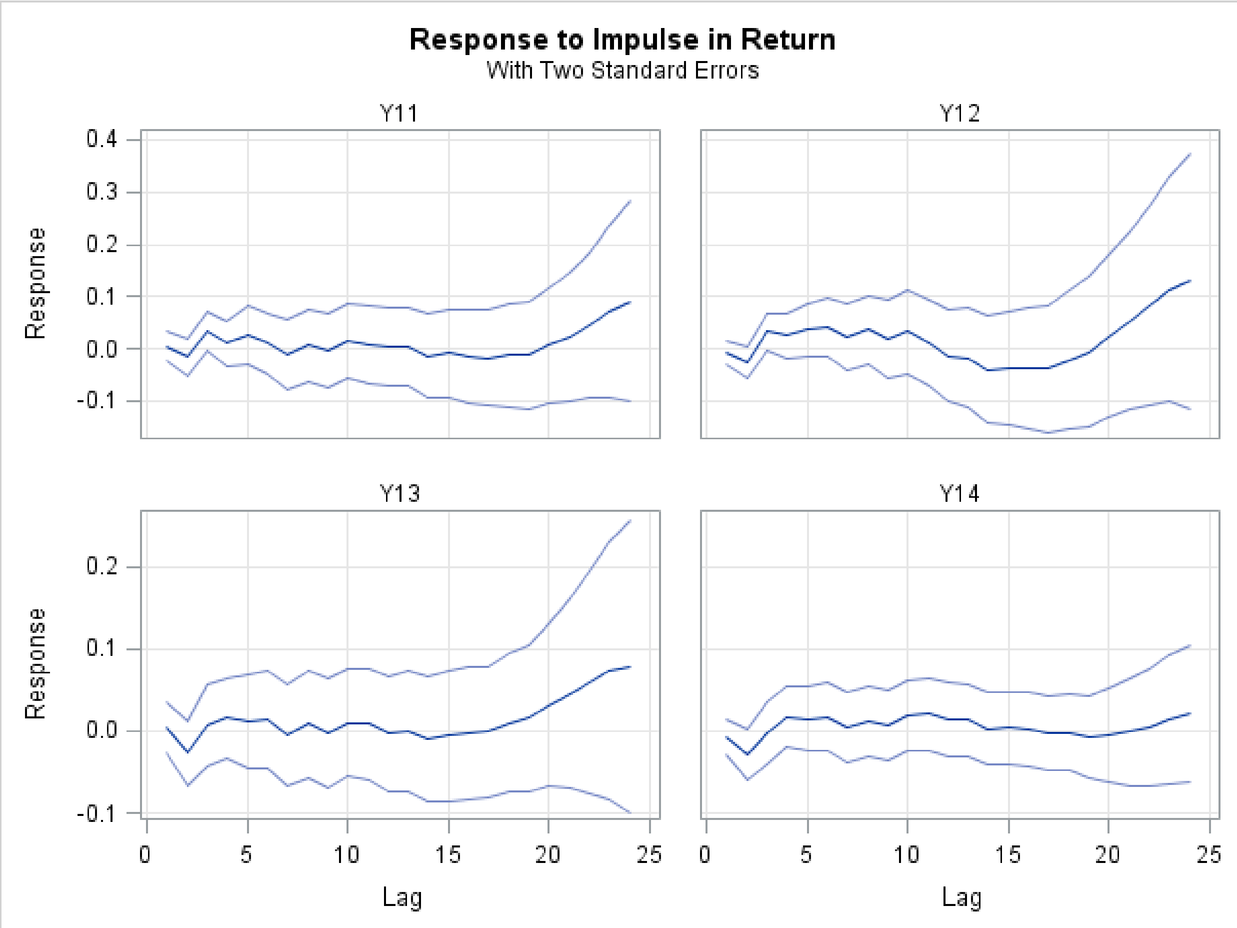


Response to Impulse in Y21
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
2
0
-2
-4
-6
50
0
-50
-100
0
5
10
15
20
25


Response to Impulse in Y21
With Two Standard Errors
Int
0.00010
0.00005
0.00000
-0.00005
Response
0
5
10
15
20
25
Lag


Response to Impulse in Return
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Response
0.2
0.1
0.0
-0.1
0.3
0.2
0.1
0.0
-0.1
0
5
10
15
20
25
Lag
Lag

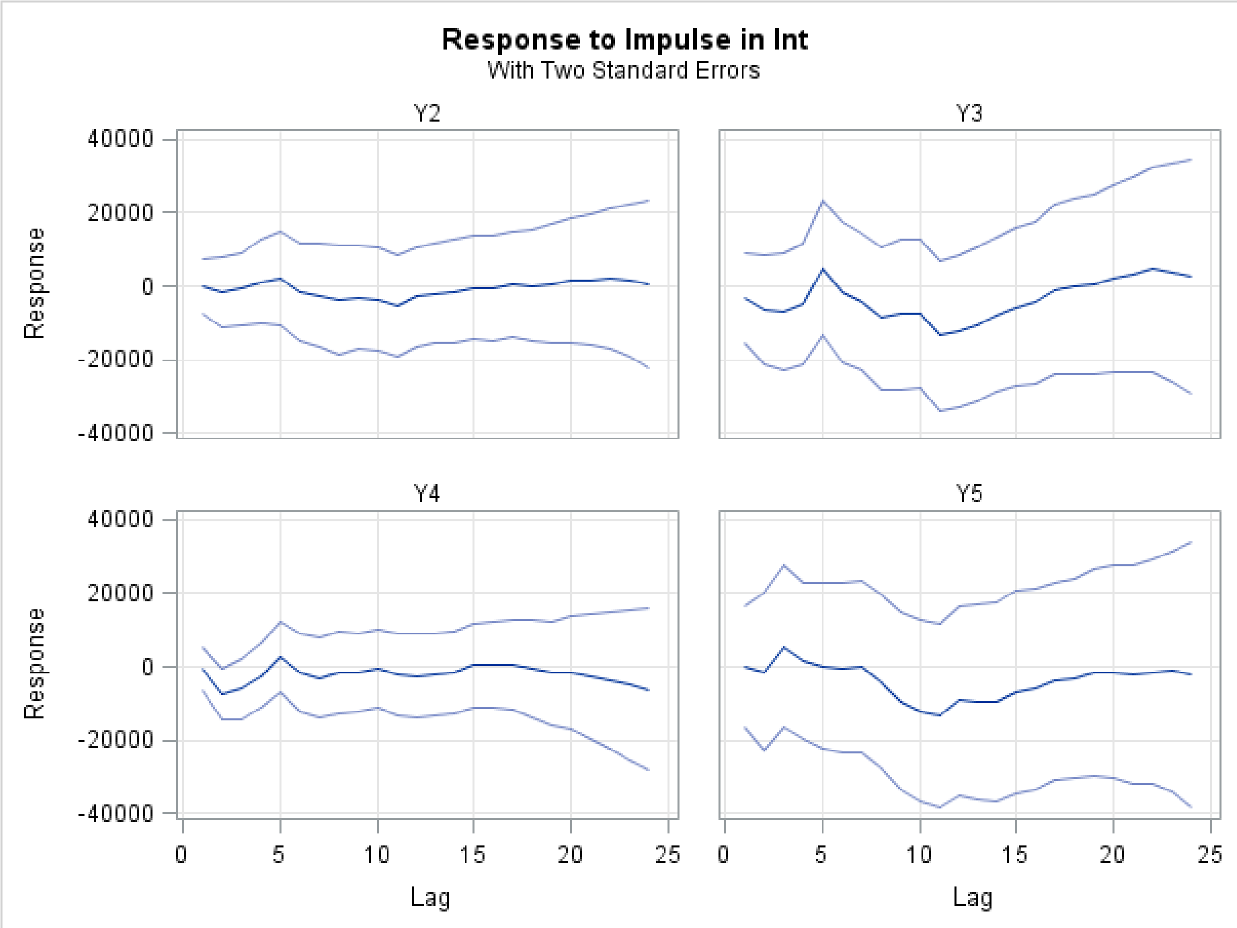

Response to Impulse in Return
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
0.3
0.2
0.1
0.0
-0.1
0.10
0.05
0.00
-0.05
0
5
10
15
20
25

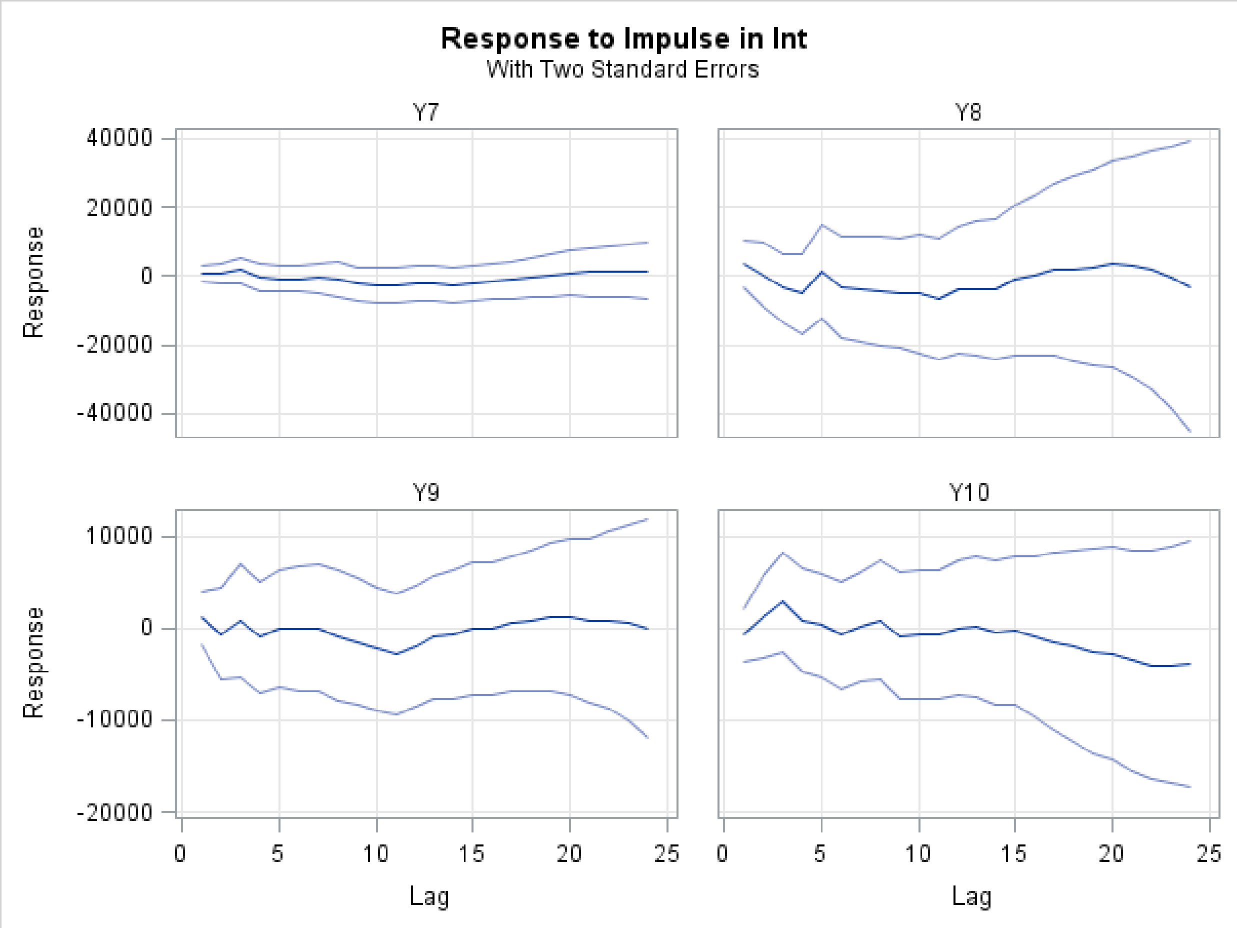

Response to Impulse in Return
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Lag
0.4
0.3
0.2
0.1
0.0
-0.1
0
5
10
15
20
25

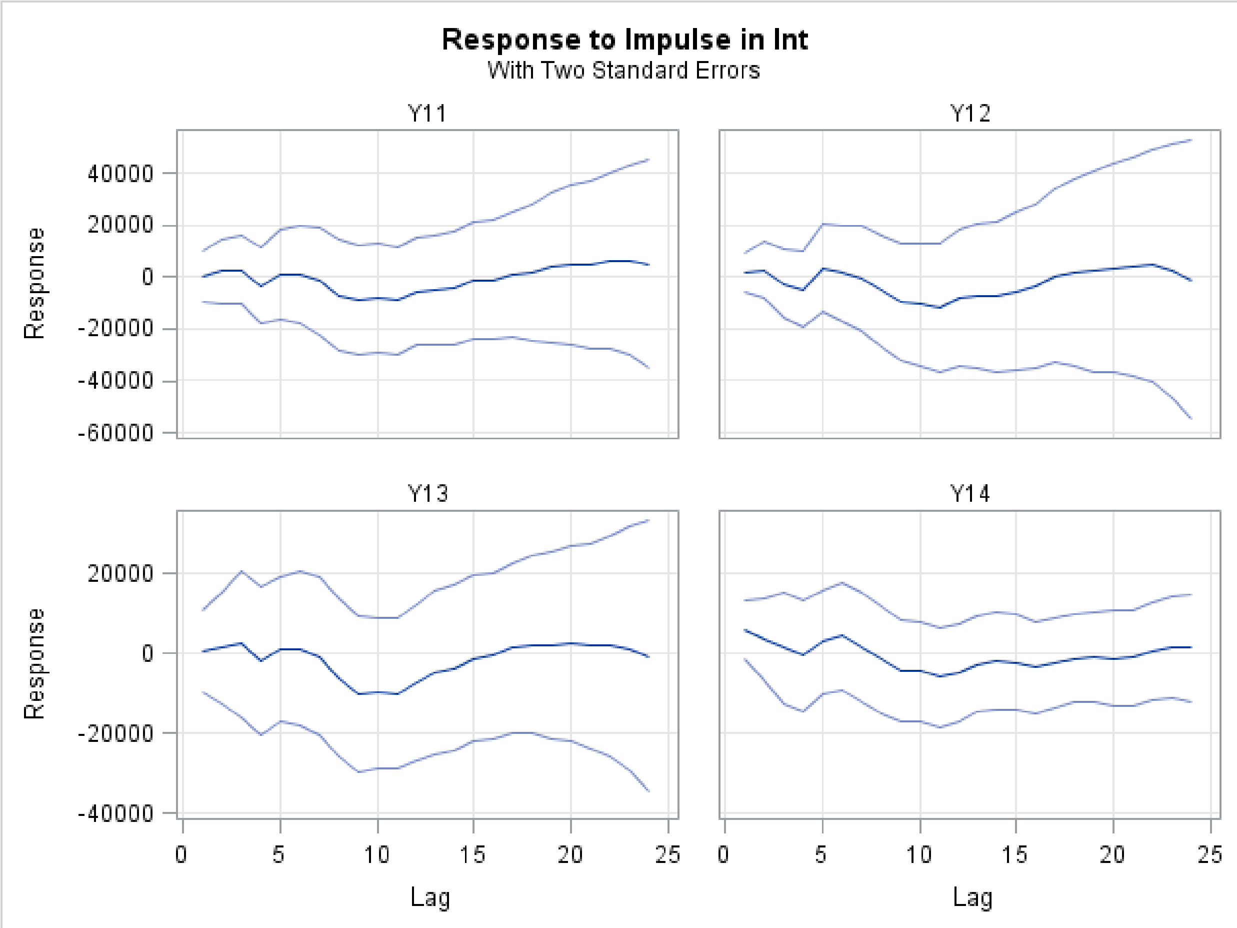

Response to Impulse in Return
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
0.10
0.05
0.00
-0.05
0.3
0.2
0.1
0.0
-0.1
0
5
10
15
20
25
Lag
Lag

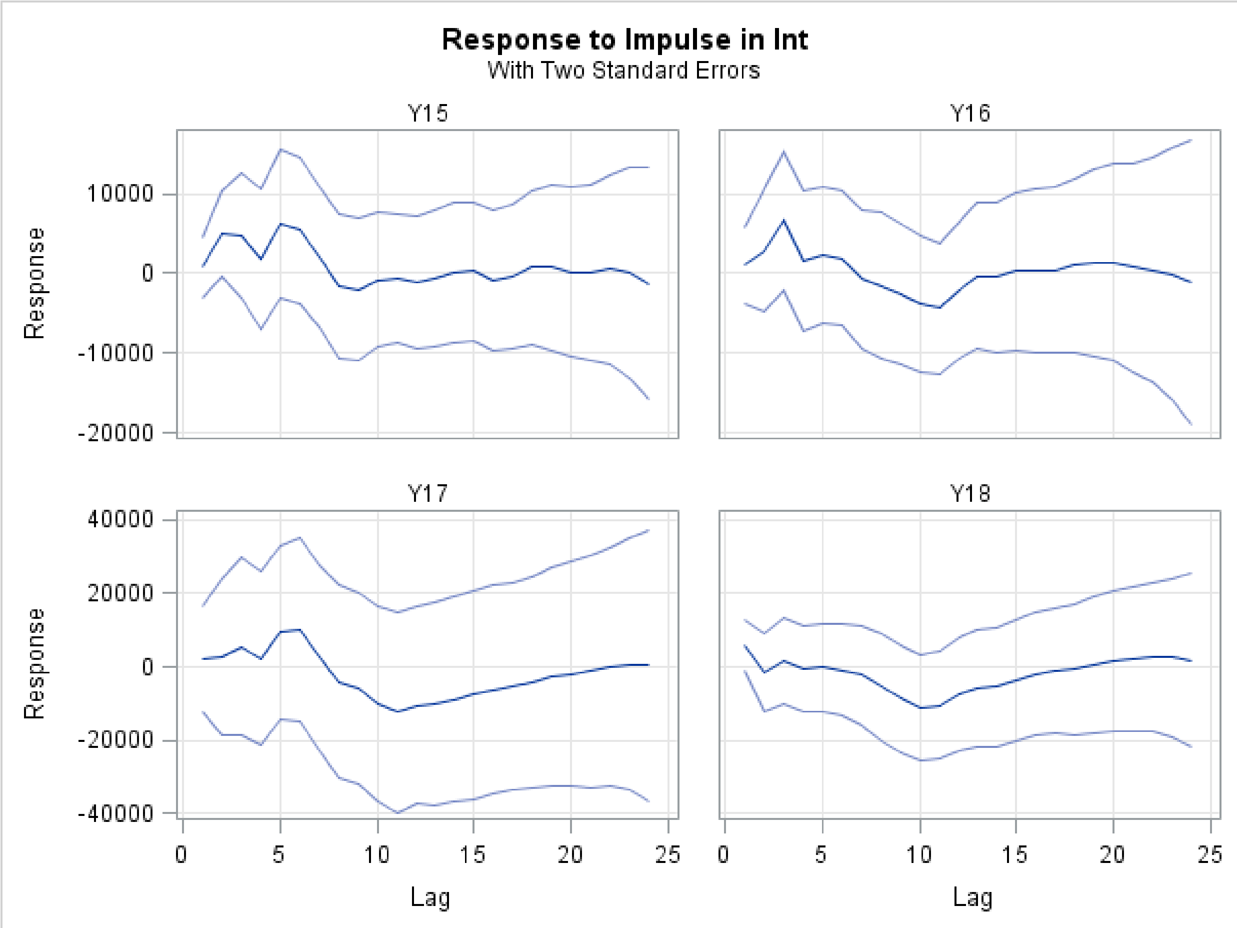

Response to Impulse in Return
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
Lag
Lag
0.2
0.1
0.0
-0.1
4
2
0
-2
0
5
10
15
20
25


Response to Impulse in Return
With Two Standard Errors
Int
0
0
0
-0
-0
-0
Response
0
5
10
15
20
25
Lag

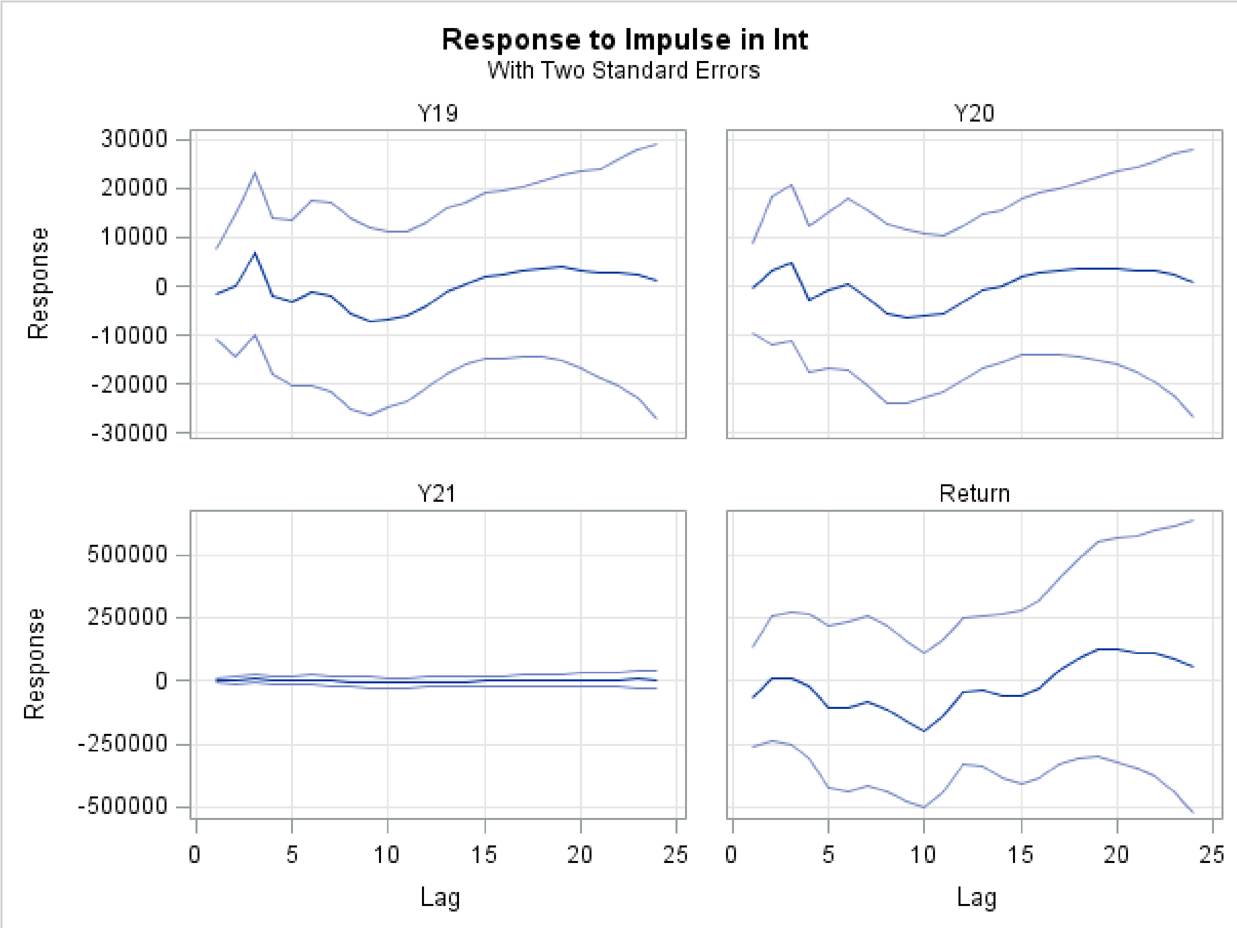

Response to Impulse in Int
With Two Standard Errors
Y2
Y3
Y4
Y5
Response
Lag
40000
20000
0
-20000
-40000
0
5
10
15
20
25

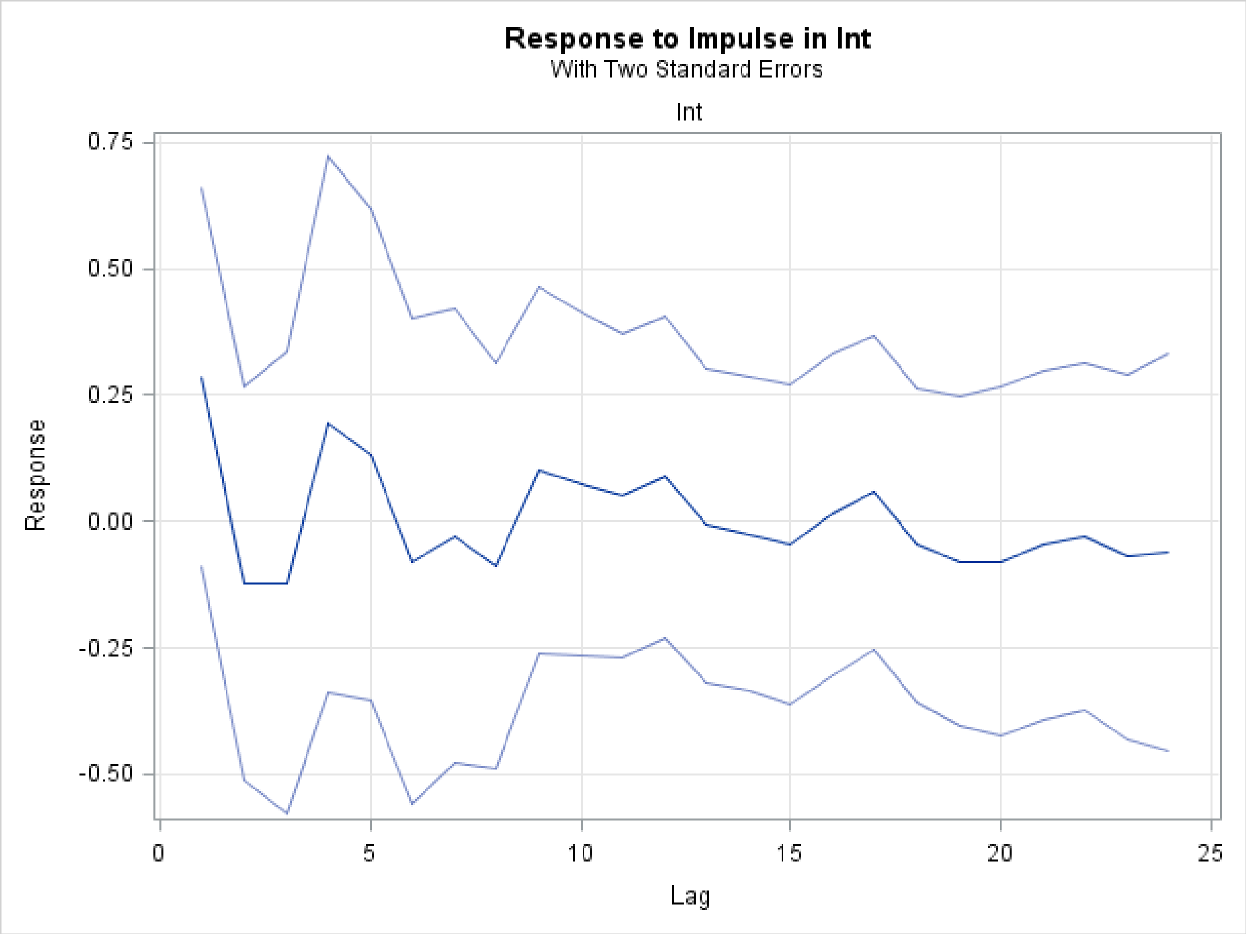

Response to Impulse in Int
With Two Standard Errors
Y7
Y8
Y9
Y10
Response
Response
Lag
Lag
40000
20000
0
-20000
-40000
10000
0
-10000
-20000
0
5
10
15
20
25


Response to Impulse in Int
With Two Standard Errors
Y11
Y12
Y13
Y14
Response
Response
40000
20000
0
-20000
-40000
-60000
20000
0
-20000
-40000
0
5
10
15
20
25
Lag
Lag



Response to Impulse in Int
With Two Standard Errors
Y15
Y16
Y17
Y18
Response
Response
Lag
Lag
10000
0
-10000
-20000
40000
20000
0
-20000
-40000
0
5
10
15
20
25


Response to Impulse in Int
With Two Standard Errors
Y19
Y20
Y21
Return
Response
Response
30000
20000
10000
0
-10000
-20000
-30000
500000
250000
0
-250000
-500000
0
5
10
15
20
25
Lag
Lag


Response to Impulse in Int
With Two Standard Errors
Int
0.75
0.50
0.25
0.00
-0.25
-0.50
Response
0
5
10
15
20
25
Lag