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Asymmetric Generalized Impulse Responses and Variance Decompositions with an Application

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Abstract

This paper introduces asymmetric impulse response functions and asymmetric variance decompositions. It is shown how the underlying variables can be transformed into cumulative positive and negative changes in order to estimate the impulses to an asymmetric innovation. An application is provided to demonstrate how the propagation mechanism of these asymmetric impulses and responses operates.

Running title: Asymmetric Generalized Impulses

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1. Introduction

Since the pioneer work by Sims (1980), the impulse response functions and variance decompositions are regularly used to capture the dynamic interaction between the variables of interest. These calculations are produced by transforming the vector autoregressive (VAR) model into its vector moving average representation. Sims suggested using the Cholesky decomposition in order to identify the underlying chocks. However, this approach is sensitive to the order in which the variables enter the model. Koop et. al., (1996) and Pesaran and Shin (2008) have introduced generalized impulse response functions, which are not sensitive to the way the variables are ordered in the model. Nonetheless, in all previous approaches on generating impulses it has been assumed that the response to a negative shock is similar as the response to a positive shock in absolute terms. There are logical reasons to believe that this might not be the case and in reality it matters, in terms of the absolute size of the response, whether the shock is positive or negative. This is likely to be the case even in situations in which the absolute size of the shocks is the same. It is a well-established fact that economic actors respond differently to a bad news compared to a good news. For example, if the profit of a company increases by 5% it will lead to different consequences compared to the case in which when the profit decreases by 5%. It is surely much easier in a boom market to expand and employ more people compared to a bust market potential layoffs. It is easier to hire people than firing them for legal and other pertinent reasons. However, the standard impulse response analyses do not account for this potential asymmetric effect. Another reason for the existence of asymmetric effects is the fact that imperfect information prevails in many circumstances as is indicated by the seminal contributions of Akerlof (1970), Spense (1973) and Stiglitz (1974). By relying on these facts, we conclude that allowing for potential asymmetry in estimating the impulse responses and variance decompositions is important. Thus, the aim of this paper is to introduce asymmetric generalized impulse response (AGIR) functions and asymmetric variance decompositions (AVD). We demonstrate how the underlying variables can be fragmented into positive and negative components in order to generate the AGIR functions as well as the AVD. An application is provided to evaluate the impact of contractionary as well as expansionary fiscal policy on economic performance in Sweden.

The rest of the article is organised as follows. Section 2 introduces the AGIR functions and the AVD. Section 3 provides an application. The last section offers ending remarks.

2. Asymmetric Generalised Impulses

One operational approach to construct the positive shocks as well as negative shocks of the underlying variables is provided by Granger and Yoon (2002), which was used for conducting hidden cointegration analysis. Based on their idea we suggest the calculation of asymmetric impulse responses and variance decompositions. For simplicity, assume that we are interested in the dynamic interaction between two integrated variables X_{1t} and X_{2t}. However, the results can be generalised to higher dimensions. By using the recursive method, we can express each variable as

$$X_{1t} = X_{1t-1} + \varepsilon_{1t} = X_{1,0} + \sum_{r=1}^{t} \varepsilon_{1r}, \qquad (1)$$

and

$$X_{2t} = X_{2t-1} + \varepsilon_{2t} = X_{2,0} + \sum_{r=1}^{t} \varepsilon_{2r}, \qquad (2)$$

for $t = 1,2,\ldots T$. The values $X_{1,0}$ and $X_{2,0}$ represent initial values. The denotations ε_{1r} and ε_{2r} signify the error terms. The underlying shocks can be defined as $\varepsilon_{1r}^{+} := \max(\varepsilon_{1r}, 0)$,

$\varepsilon_{2r}^{+} := \max(\varepsilon_{2r}, 0)$, $\varepsilon_{1r}^{-} := \min(\varepsilon_{1r}, 0)$ and $\varepsilon_{2r}^{-} := \min(\varepsilon_{2r}, 0)$. These results lead to having $\varepsilon_{1r} = \varepsilon_{1r}^{+} + \varepsilon_{1r}^{-}$ and $\varepsilon_{2r} = \varepsilon_{2r}^{+} + \varepsilon_{2r}^{-}$. This in turn means

$$X_{1t} = X_{1t-1} + \varepsilon_{1t} = X_{1,0} + \sum_{r=1}^{t} \varepsilon_{1r}^{+} + \sum_{r=1}^{t} \varepsilon_{1r}^{-}, \qquad (3)$$

and

$$X_{2t} = X_{2t-1} + \varepsilon_{2t} = X_{2,0} + \sum_{r=1}^{t} \varepsilon_{2r}^{+} + \sum_{r=1}^{t} \varepsilon_{2r}^{-}. \qquad (4)$$

These results can be used to obtain the cumulative representation of the positive and negative shocks of each variable in the form of $X_{1t}^{+} := \sum_{r=1}^{t} \varepsilon_{1r}^{+}$, $X_{1t}^{-} := \sum_{r=1}^{t} \varepsilon_{1r}^{-}$, $X_{2t}^{+} := \sum_{r=1}^{t} \varepsilon_{2r}^{+}$ and $X_{2t}^{-} := \sum_{r=1}^{t} \varepsilon_{2r}^{-}$. These values can be utilized to estimate the asymmetric impulses and variance decompositions. Since truly exogenous variables are rare in reality, the VAR model that treats all variables in the model endogenously can be used. Assume the we are interested in capturing the dynamic interaction between cumulative negative and positive shocks, i.e., the vector $X_t^{-} = (X_{1t}^{-}, X_{2t}^{-})$. Then, the following VAR(k) model can be estimated:

$$X_t^{-} = B_0 + B_1 X_{t-1}^{-} + \ldots + B_k X_{t-k}^{-} + u_t^{-} \qquad (5)$$

Where B_0 is 2×1 vector, B_s (s=1, …, k.) is an 2×2 matrix, and u_t^{-} is an 2×1 vector of error terms. The exogeneity problem is resolved since past values of X_t^{-} are exogenous in determining X_t^{-}. The optimal lag order, k, can be chosen by minimizing an information criterion. The forecasting performance in this model is strong since past values of X_t^{-} are expected to be the best information set in determining X_t^{-} itself.[1] This VAR model can be used to trace out the effect of a shock in any variable within the system on other variables or

[1] A VAR system allows testing of economic relationship by testing whether variables within X_t^{-} are methodically linked so they do not wander too far from each other (cointegration testing) and by testing whether past values of one variable improves the forecasting capability of another variable after that other variable's past values have already been taken into account (Granger causality testing). However, conducting this kind of analysis is beyond the scope of this paper. The interested reader is referred to Granger and Yoo (2002) and Hatemi-J (2010, 2011).

itself. To estimate the impulses we present the VAR model (eq. 5) in the moving average representation form as follows:

$$X_t^- = \sum_{i=0}^{\infty} C_i + \sum_{i=0}^{\infty} A_i u_{t-i}^-, \qquad \text{for } t = 1, \cdots, T. \tag{6}$$

where the *2×2* coefficient matrixes (A_i) are obtained recursively as the following:

$$A_i = B_1 A_{i-1} + B_2 A_{i-2} + \cdots + B_k A_{i-k}, \quad \text{for } i = 1,\ 2, \cdots, \tag{7}$$

with $A_0 = I_2$ and $A_i = 0, \forall i < 0$, and $C_i = A_i B_0$. The asymmetric generalized impulse response of the effect of a standard error shock in the *j*th equation at time *t* on X_{t+n}^- is defined as:

$$AGIR(n) = \sigma_{jj}^{-0.5} A_n \Omega e_j, \text{ for } n = 0,1,2, \cdots, \tag{8}$$

where Ω is the variance-covariance matrix in the VAR model ($\Omega = \{\sigma_{ij}, i, j = 1, 2.\}$) and e_j is a *2*×1 selection vector with its *j*th element equal to one and zero for all other elements. The asymmetric forecast error variance decomposition, denoted by $AVD_{ij}(n)$, can be calculated as

$$AVD_{ij}(n) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{n} \left(e_i' A_l \Omega e_j\right)^2}{\sum_{l=0}^{n} e_i' A_l \Omega A_l' e_i}, \ ij = 1, 2. \tag{9}$$

An algorithm written in Gauss is used to obtain the cumulative positive and negative changes for each variable based on equations (3) and (4). The algorithm is available on request. After creating the cumulative positive and negative changes for each variable, it is straight forward to estimate the asymmetric impulses and variance decompositions as presented by equations (8) and (9) via a number of well-known econometric packages that are available on the market. It should be mentioned that these estimations can also be conducted by transforming the VAR model into its vector error correction representation first.

3. An Application

The procedure suggested in this paper is applied to investigate the potentially asymmetric relationship between government spending and GDP in Sweden during the period 1993-2010 on quarterly basis. The variables are used at constant prices. The source of the data is the Swedish statistical bureau. The results for asymmetric impulses combined with the 95% confidence intervals are presented in Figures 1-3.

Figure 1. The asymmetric Generalised Responses for Original Data.

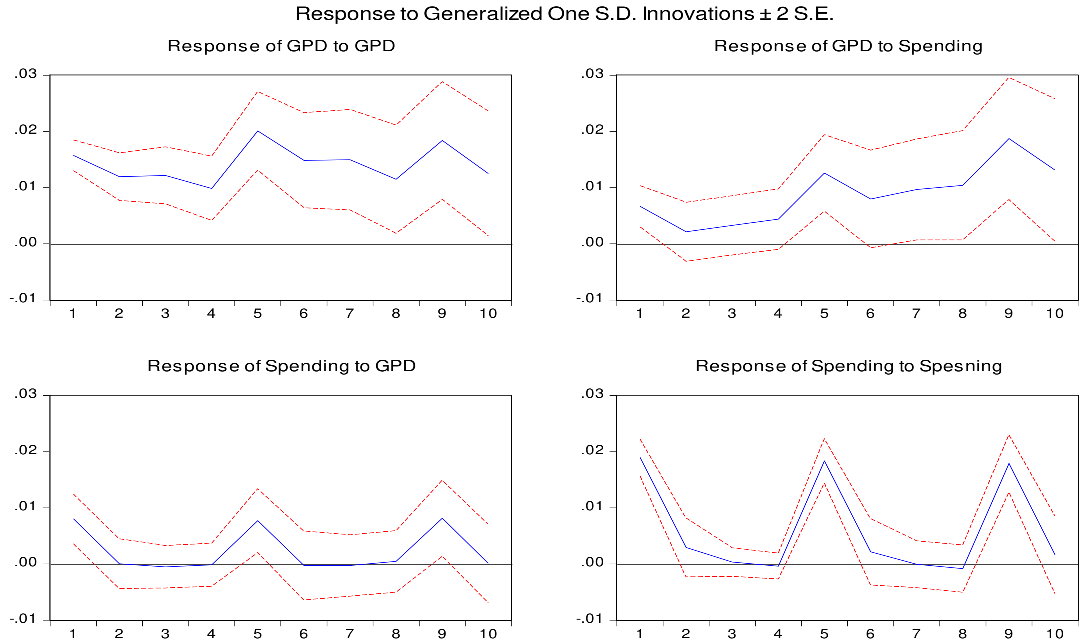


Figure 1 presents the impulses for the original data. As is shown, government spending has a positive impact on economic performance. However, it is statistically significant for short period of time only. The response of spending to economic output is not significant. These results are also supported by the asymmetric variance decompositions to some extent. Because more than 87% of variation in the forecast error in GDP is explained by itself and only less than 13% is explained by the forecast error in government spending (S) after 10 questers,. The corresponding values for S are 81.5% by itself and 18.55% by GDP.

Next we produce the asymmetric impulses. Figure 2 demonstrates the response for the variables represented in cumulative positive changes. As can be clearly seen the cumulative positive changes of spending significantly react to an impulse in neither cumulative positive changes of GDP nor the revers. The estimated asymmetric variance decompositions for this particular case revealed the following. Around 93% of variation in the forecast error in GDP^{+}

is explained by itself and while around 7% is explained by the forecast error in S^{+}. The comparable values for S^{+} are 89% by itself and 11% by GDP^{+}.

Figure 2. The Asymmetric Generalised Responses for Cumulative Positive Shocks.

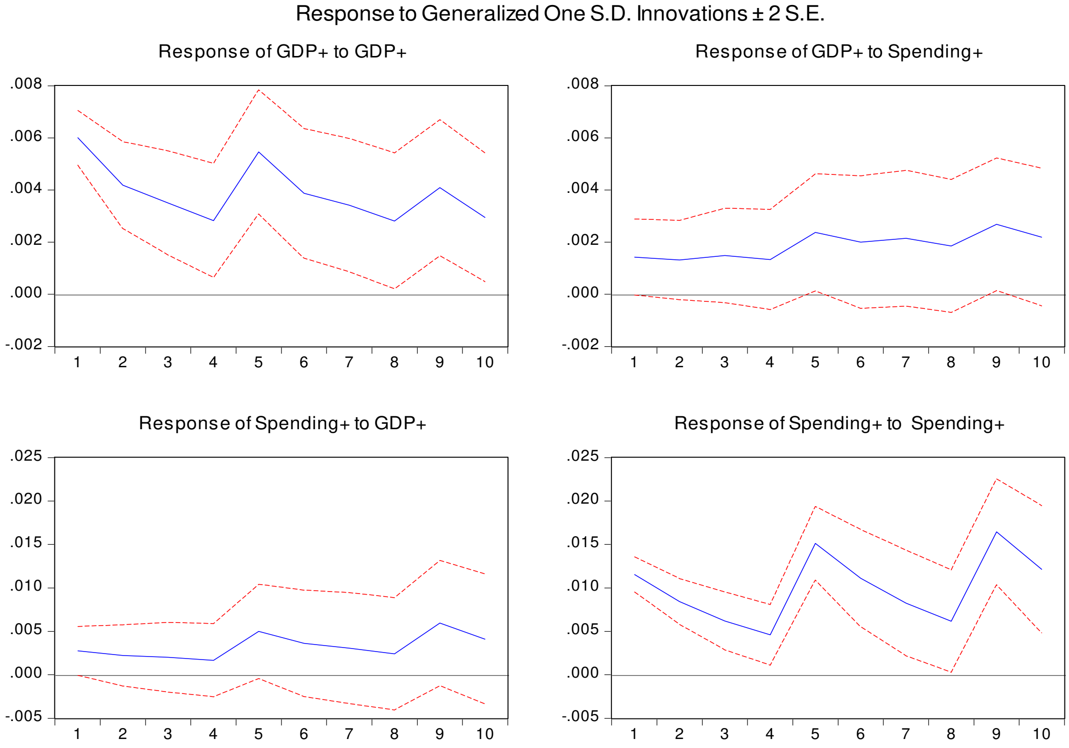
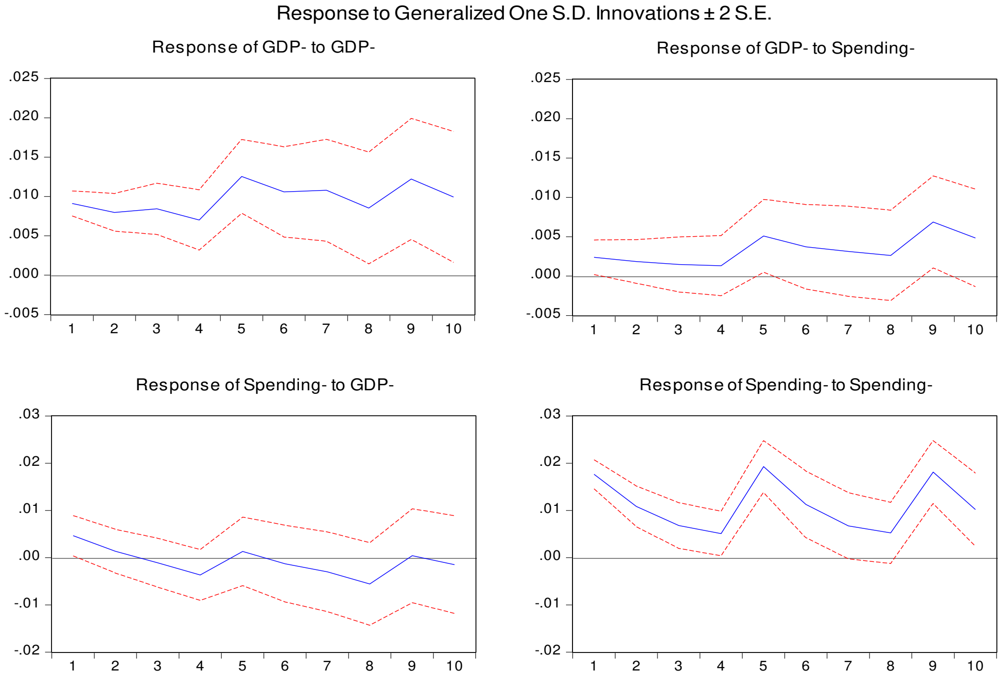


Figure 3 illustrates the response for the variables in the cumulative negative format. It is evident from these estimations that the cumulative negative changes of spending significantly react to an impulse in neither the cumulative negative changes of GDP nor the reverse. This conclusion is also confirmed by the asymmetric variance decompositions. More than 97% of variation in the forecast error in GDP^{-} is explained by an innovation in itself and only less than 3% is explained by an innovation in the forecast error in S^{-}. The analogous values for S^{-} are 95% by itself and 5% by GDP^{-}.

Figure 3. The Asymmetric Generalised Responses for Cumulative Negative Shocks.



4. Concluding Remarks

This article introduces a procedure for calculating the asymmetric impulse response functions and asymmetric variance decompositions. Allowing for asymmetry in these estimates might be important in order to figure out whether positive shocks have the same absolute impact as the negative shocks or not. This can be achieved by estimating the impulses and responses to innovations based on the cumulative values of the positive and negative changes of the underlying variables.

An application is provided to investigate the dynamic relationship between government spending and GDP in Sweden. The estimations indicate that an innovation in the government spending does not lead to a significant response in the GDP. This seems to be the case regardless if the asymmetric property is taken into account in estimating the impulses or not. The asymmetric variance decompositions also provide support for this conclusion to an extent. These results can be interpreted as empirical evidence that the conducted fiscal policy, regardless if it is contractionary or expansionary, is not a major factor behind the successful economic performance in Sweden.

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