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Asymmetric generalized impulse responses with an application in finance ☆

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ABSTRACT

Since the seminal work by Sims (1980), the impulse response functions are regularly applied to capture the propagation mechanism of a shock across time. This paper suggests a new approach for allowing asymmetry in the impulse response functions. This is an issue that has been neglected in the existing literature on the estimation of impulses. In the current paper 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 an asymmetric impulse operates.

1. Introduction

Since the pioneer work by Sims (1980), the impulse response functions are regularly used to capture the dynamic interaction between the variables of interest that are quantified across time. 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 shocks. However, this approach is sensitive to the order in which the variables enter the model. Koop et al. (1996) and Pesaran and Shin (1998) have introduced generalized impulse response functions, which are not sensitive to the way the variables are ordered in the model. An issue within this context that needs to be raised is that in all previous approaches on estimating impulses it has been assumed that the response to a negative shock is the same as the response to a positive shock in the absolute terms. There are a number of 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 underlying shocks is of the same magnitude. It is a well-established fact in the literature that economic actors respond differently to bad news compared to good news. For example, if the profit of a company increases by 5% it will lead to different consequences in terms of absolute magnitude 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 with potential layoffs. It is naturally easier to hire people than firing them for legal, moral 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), Spence (1973) and Stiglitz (1974). If asymmetric information exists then asymmetric impulses must exist. There are also natural constraints that can result in an asymmetric structure. For example, there is no limit on the amount that a stock price can increase theoretically speaking. However, there is a natural limit on how low the stock price can decrease. In the end, the price cannot decrease to less than zero in the reality. Thus, a price increase must have different consequences, in the absolute terms, than a price decrease of the same magnitude. By relying on these facts, we conclude that allowing for potential asymmetry in estimating the impulse responses is an important issue. Thus, the aim of this paper is to introduce asymmetric generalized impulse response (AGIR) functions. We demonstrate how the underlying variables can be fragmented into positive and negative components in order to generate the AGIR functions. An application is provided to evaluate the impact of a shock in the world stock market price on the UAE stock market price.

The rest of the article is organized as follows. Section 2 introduces the AGIR functions. Section 3 provides an application. The last section offers the ending remarks. In Appendix A presented at the end, it is shown how the integrated variables up to two degrees with deterministic trend parts can be decomposed into positive and negative components.

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2. The asymmetric generalized 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. 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 generalized to higher dimensions.[1] By using the recursive method, we can express each variable as

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

and

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

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

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

and

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

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 that 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:

$$X_t^{-} = B_0 + B_1 X_{t-1}^{-} + \ldots + B_k X_{t-k}^{-} + u_t^{-}, \tag{5}$$

where B_0 is 2×1 vector, B_s ($s = 1, \ldots, k$.) is a 2×2 matrix, and u_t^{-} is a 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.[2] This VAR model can be used to trace out the effect of a shock in any variable within the system on other variables or itself. To estimate the impulses we present the VAR model (Eq. (5)) in the moving average representation form as follows:

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

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

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

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 jth equation at time t on X_{t+n}^{-} is defined as:

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

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 jth element equal to one and zero for all other elements.[3] The impulses can be presented with a given confidence interval in order to see whether or not the estimated impulse is statistically significant at that corresponding significance level. These confidence intervals can be generated based on the standard errors that are generated via the Monte Carlo simulations.

An algorithm written in Gauss is used to obtain the cumulative positive and negative changes for each variable based on Eqs. (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 as presented by Eq. (8) 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 the UAE stock market price index (denoted by UAEP) and the world stock market price index (denoted by WP) on daily basis. The period covers 29/11/2002–04/06/2012. The Morgan Stanley Capital International (MSCI) price index is used in both cases. The results for asymmetric impulses combined with the corresponding 95% confidence intervals that are generated via the Monte Carlo simulations are presented in Figs. 1–3.

Fig. 1 presents the standard impulses for the original data combined with the 95% confidence interval. As it is shown, the response of the UAE stock market to a symmetric shock in the world stock market is not statistically significant for a time horizon of twenty four periods.

Next we produce the asymmetric impulses. Fig. 2 demonstrates the response for the variables represented in cumulative positive changes together with the 95% confidence. As can be seen, the cumulative positive changes in the world stock market do not have any significant impact on the UAE stock market.

Fig. 3 illustrates the response for the variables in the cumulative negative format jointly with the 95% confidence. It is evident from these estimations that the cumulative negative changes of the UAE stock market significantly react to an impulse in the cumulative negative changes of the world stock market index. Thus, a negative change in the world stock market will result in a significant negative change in the UAE stock market. It should be noted that in none of the cases does the world market index react to a shock in the UAE stock market as is expected. This in fact can indicate the robustness of the results based on the asymmetric impulses.

[1] See Appendix A for the decomposition of the variables with higher integration orders and with deterministic trend parts.

[2] 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 improve 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.

[3] It should be mentioned that the asymmetric forecast error variance decomposition, denoted by $AVD_{ij}(n)$, can be calculated as $AVD_{ij}(n) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{n} (e_i' A_l \Omega e_j)^2}{\sum_{l=0}^{n} e_i' A_l \Omega A_l' e_i}$, $ij = 1, 2$.