

**Combining Input-Output (IO) analysis with Global Vector
Autoregressive (GVAR) modeling: Evidence for the USA (1992-2006)**

Konstantinos N. Konstantakis *and* Panayotis G. Michaelides*

National Technical University of Athens, Greece

Abstract: The purpose of this paper is to assess the interdependencies among the eight (8) main sectors of economic activity in the US economy, using quarterly data on output and labor for a period of fifteen years (1992-2006), just before the first signs of the global recession made their appearance. In this context, we set up a novel methodological framework which combines Input-Output (IO) analysis with state of the art Global Vector Autoregressive (GVAR) modeling. In addition, we use the IO matrices to provide a procedure in order to test for the existence of dominant sector(s) in the USA and estimate a GVAR model with dominant sector(s) and the exogenous variables of Global Credit and Global Trade acting as the transmission channels. Our results seem to suggest that the US economy has relatively limited connectivity, in terms of sectoral output and labor, among the various sectors.

Keywords: GVAR, Input Output, US sectors, Weight Matrix

*The authors would like to thank Theodore Mariolis for a fruitful discussion. Corresponding author: Panayotis G. Michaelides, Assistant Professor of *Economics*, Laboratory of Theoretical and Applied Economics, School of Applied Mathematics and Physics, National Technical University of Athens, Greece, Heroon Polytechniou 9, 157.80, Zografou Campus, tel: 302107721624, fax: +302107721618, e-mail: pmichael@central.ntua.gr.

1. Introduction

The VAR approach and especially the Global VAR (GVAR) model, provide nowadays a very useful framework for assessing the transmission of shocks among economic entities.¹ The GVAR framework was introduced by Pesaran *et al.* (2004) and developed through several quality theoretical contributions such as Pesaran and Smith (2006), Déés *et al.* (2007b) Chudik and Pesaran (2011a), (2011b) as well as empirical ones such as Déés *et al.* (2005), (2007a), Pesaran *et al.* (2006), Pesaran *et al.* (2007), Bussière *et al.* (2012), Konstantakis and Michaelides (2014).

The GVAR model is suitable for assessing relationships between economic entities while its methodology provides a general, yet practical, modeling framework for the quantitative analysis of the relative importance of different shocks and channels of transmission. In fact, it consists of a compact econometric model of the economic entities involved which is specifically designed to model the economic interdependencies among economic entities, e.g. at both the national and international level.

The GVAR framework is structured upon observables, which typically include economic aggregates, trade and financial variables, with other unit-specific variables serving as proxies for common unobserved factors. It is exactly this characteristic that constitutes an important input in the so-called “decoupling” of the US sectoral economy.

The purpose of this paper is to assess the interdependencies among the eight (8) main sectors of economic activity in the US economy, using quarterly data on output and labor for a period of fifteen years (1992-2006), just before the first signs of the global recession made their appearance.

¹ The so-called factor augmented vector autoregressions (FAVAR) are often viewed as an alternative approach to GVAR (see e.g. Bernanke *et al.* 2005; Korobilis 2013). However, the number of estimated factors used in FAVAR is different for different countries and it is not clear how they relate to each other globally (Dees *et al.* 2007a). In fact, Kapetanios and Pesaran (2011) argue that GVAR estimators perform better than the corresponding ones based on principal components.

We have chosen the variables of output and labor because they are probably the major economic variables at the sectoral level which are able to express, in a nutshell, the economic conditions of each sector. More precisely, we take into consideration the production of each sector through the variable of output as well as the main factor of production (i.e. input) through the variable of labor. Additionally, we have chosen to use the variables of Global Trade and Global Credit instead of their domestic counterparts i.e. US Credit and US Trade, due to the high degree of openness of the US economy.

The present paper is the first, to the best of our knowledge, which provides a simple and practical framework for applying the GVAR approach at the sectoral level. In this framework, we propose combining the traditional Input Output (IO) Leontief methodology with the state of the art GVAR approach. To this end, we set out a detailed methodological framework for constructing the sectoral weight matrix of the GVAR model, which builds on the IO technical coefficients matrix. Next, we provide a procedure in order to test for the existence of dominant entities and we implement the proposed novel sectoral methodology to the US economy.

The proposed framework which combines the traditional IO methodology with the state of the art GVAR modeling has considerable advantages with respect to either of the two approaches upon which it builds. With respect to the GVAR approach, the weight matrix constructed in this work, which is derived based on Leontief's IO matrix, is perfectly capable of capturing the linkages between the various sectors of the economy. Hence, the modeling of the economy is complete since there are no missing relationships due to the fact that all sectors are explicitly included in the GVAR model. With respect to the IO approach, our proposed framework acts as a state of the art econometric technique which is capable of producing robust statistical estimates based on real-world data on economic aggregates instead of mere point calculations, while incorporating the full information set of the IO tables.

The remainder of the paper is structured as follows: section 2 sets out the proposed methodology, section 3 presents the data and the variables; section 4 describes the empirical analysis; section 5 presents the estimation results; section 6 offers a brief discussion; finally, section 7 concludes.

2. Methodology

2.1 GVAR Analysis

The Global VAR model consists of eight (8) major economic entities, namely the eight economic sectors of the US economy. Each sector i , $i = 1, 2, \dots, 8$ follows a VAR model, augmented by the so-called exogenous variables of global trade (T) and credit (D), expressing the transmission channels through which the various economic transactions and shocks take place. The endogenous variables x_{it} denote a 8×2 vector of macroeconomic variables belonging to each sector i , consisting of the sectoral Output (Y) and Labor (L).

We use the variables of output and labor as the model's endogenous variables because they are probably the major economic variables at the sectoral level which are able to express, in a nutshell, the economic conditions of each sector. In fact, we take into consideration the production of each sector through the variable of output as well as the main factor of production (i.e. input) of each sector through the variable of labor.

The foreign variables $x^*_{i,t}$ represent a weighted average of the other sectors' variables that are regarded to be weakly exogenous in each sector's model, whose weights are pre-determined. Mathematically, the VAR model for each sector is:

$$\Phi_i(L, p_i)x_{it} = a_{i0} + \Lambda_i(L, q_i)x^*_{it} + a_{i1}G_t + u_{it}[\mathbf{1}]$$

For $i = 1, 2, \dots, 8$ and $t = 1 \dots T$ where x_{it} is the set of sectoral domestic variables and $\Phi_i(L, p_i)$ is the matrix of lag polynomial of the associated coefficients;

a_{i0} is a vector of fixed intercept; G_t is a set of the Global Variables and a_{i1} is a vector of their respective coefficients $x^*_{it} = Wx_{it}$ is the set of weighted foreign variables and $\Lambda_i(L, q_i)$ is the matrix of lag polynomial of the associated coefficients. Matrix W_i is a 8×8 dimensional matrix of weights and $u_{it} \sim i.i.d(0, \sigma^2)$ with mean zero and the variance-covariance matrix Σ_i .

The implementation of the GVAR methodology has two steps. Firstly, each sector's VARX model is constructed treating the variables of global Trade and global Credit as exogenous. After the construction of each VARX model we relate their corresponding estimates through link matrices by stacking them together to obtain our GVAR model. In particular, we consider the following model for country i :

$$x_{it} = a_{i0} + \Phi_{ip}x_{it-p} + \Lambda_{i0}x^*_{it} + \Lambda_{iq}x^*_{it-q} + a_{i1}G_t + u_{it} \quad [2]$$

To begin with, we group all foreign and domestic variables together as:

$$z_{it} = \begin{pmatrix} x_{it} \\ x^*_{it} \end{pmatrix}$$

Therefore, for each sector i the respective model becomes:

$$A_i z_{it} = a_{i0} + B_{i, \max\{p,q\}} z_{it} + a_{i1} G_t + u_{it}$$

where: $A_i = (I, -\Lambda_{i0})$ and $B_{i, \max\{p,q\}} = (\Phi_{ip}, \Lambda_{iq})$.

By gathering all the domestic endogenous variables together, we define the following global vector $x_t = \begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix}$ and we obtain the identity: $z_{it} = Wx_t, \forall i = 1, \dots, 8$ where W is the weight matrix. Thus, by using the former identity in the i -th sector-specific model, we get:

$$A_i W_i z_{it} = a_{i0} + B_{i, \max\{p,q\}} W_i z_{it - \max\{q,p\}} + a_{i1} G_t + u_{it}$$

By combining each sector model with the later equation we obtain the GVAR:

$$Mx_t = a_{i0} + H_{i, \max\{p,q\}} x_{t - \max\{t,q\}} + a_{i1} G_t + u_{it}$$

where $M = (A_i W_i)$ and $H_i = (B_{i, \max\{p,q\}} W_i)$.

If the M matrix is non-singular, then we obtain the reduced form of the GVAR model:

$$x_t = b_0 + F_{\max\{p,q\}}x_{t-\max\{p,q\}} + b_1G_t + v_t$$

where: $b_i = M^{-1}a_i$. $F_i = M^{-1}H_i$ and $v_t = M^{-1}u_t$

Furthermore, following Chudik and Smith (2013), in the potential presence of a dominant entity we transform each i -th VARX model of the GVAR to account for this dominant sector as follows²:

$$x_{it} = a_{i0} + \Phi_{ip}x_{it-p} + N_{i0}x_{0,t} + N_{i0,k}x_{0,t-k} + \Lambda_{i0}x_{*i,t} + \Lambda_{i,q}x_{*i,t-q} + a_{i1}G_t + u_{it} \quad [3]$$

where $x_{0,t} = \{Y_{0,t}, L_{0,t}\}$ is a 2x1 vector of variables of the dominant sector and $i_0 \neq i = \{1, \dots, 7\}$.

We examine the dynamic characteristic of our GVAR model through the so-called Generalized Impulse Response Functions (GIRFs) following Koop *et al.* (1996) and Pesaran and Shin (1998). Analytically, a positive standard error (σ) unit shock is examined on every variable in the universe of our model aiming at determining the extent to which each economic sector, responds to a shock. Also, we study the extent to which these shocks have persistent effects. The (Generalized) Impulse Response Function (GIRF) is as follows:

$$I_j(n) = \sigma_{jj}^{-1/2} + B_n \Sigma e_j \forall n = 1, 2, \dots \quad [4]$$

where $I_j(n)$ is the Impulse Response Function n periods after a positive standard error unit shock; σ_{jj} is the j th row and j th column element of the variance-covariance matrix Σ of the lower Cholesky decomposition matrix of the error term which is assumed to be

² Note that despite the insightful suggestion by Chudik and Smith (2013) to use a dominant entity, they do not provide a procedure for selecting the number of dominant entities to be used.

normally distributed; B is the coefficients' matrix when inversely expressing the VAR model as an equivalent MA process and e_j is the column vector of a unity matrix. See further Koop *et al.* (1996) and Pesaran and Shin (1998).

2.2 Input Output Analysis

(A) *Constructing the sectoral weight matrix in an IO framework*

In the core of the GVAR methodology at the international level is the so-called trade weight matrix (see e.g. the seminal work by Pesaran *et al.* 2004). To this end, we use the IO matrix³ of the US economy to serve as the means to create the sectoral weight matrix⁴.

As is well known, the IO model is based on the following equation for the various (n) economic sectors:

$$X_i = x_{i1} + x_{i2} + \dots + x_{in} + y_i, \quad i = 1, 2, \dots, n \quad [5]$$

where: $X_i \geq 0$ is the output of sector i , y_i is the final demand for the product of sector i , x_{ij} is the product of sector i used by sector j .

Equation (5) can be written as follows, in matrix form:

$$X = AX + Y \quad [6]$$

where: X is the vector of outputs, Y is the vector of final demand, and A is the so-called input or technical coefficients matrix whose typical element is equal to:

$$(a_{ij})_{n \times n} = \frac{x_{ij}}{X_j} \quad [7]$$

where: $a_{ij} \geq 0$ is interpreted as the quantity of output from sector i required to produce one unit of output in sector j .

Solving the balance equation [6] for X, we obtain:

³ Instead of the standard technical coefficients matrix A, we could also use the tailored hybrid technology-based product IO tables constructed in the spirit of Rueda-Cantuche and ten Raa (2013).

⁴ For an eigenvector method measuring the 'keyness' of inter-sector linkages in a related context, see the works by Dietzenbacher (1992) and, very recently, by Jianxi (2013). In a similar vein, Los (2004) proposed using a dynamic input-output growth model to identify strategic industries.

$$X = (I_n - A)^{-1}Y[8]$$

in which I_n is the $n \times n$ identity matrix, $(I_n - A)^{-1}$ is the so-called Leontief inverse and Y is the column vector of final demand.

As we know, in the IO approach, the main tools of analysis are the technical coefficients matrix A and the Leontief inverse matrix $(I_n - A)^{-1}$, namely the matrix of input-output multipliers of changes in final demand into levels of outputs.

Now, based on the fundamental IO matrix of technical coefficients A , we construct matrix Q , which has the following form:

$$Q \equiv \begin{pmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{nn} \end{pmatrix}$$

where each element of Q is given by the expression:

$$x_{ij} \equiv a_{ij}X_j[9]$$

and the x_{ij} element of matrix Q expresses the product of sector i that is used from sector j , X_j is the total output of the j -th sector and a_{ij} is interpreted as the quantity of output from sector i required to produce one unit of output in sector j , as we have seen earlier. Notice that, in general, $x_{ij} \neq x_{ji}, \forall i, j \in \{1, \dots, n\}$.

In the IO matrix Q , the row elements express the quantities of goods and services, in value terms, supplied by one sector to itself and all others. Similarly, column elements express quantities obtained by a sector from itself and all others. In general, matrix Q expresses an (intermediate) intra-sectoral flow matrix.

Next, we construct the transpose of matrix Q , i.e. Q^T . In matrix Q^T , the row elements express quantities obtained by a sector from itself and all other sectors, whereas the column elements express quantities supplied by a sector to itself and all others.

Now, let matrix P be defined as the difference between matrix Q and its transpose, Q^T , or in matrix notation:

$$P \equiv Q - Q^T$$

Thus, the typical element, p_{ij} , of matrix P is equal to :

$$p_{ij} \equiv x_{ij} - x_{ji}$$

Each element, p_{ij} , measures the net amount of goods and services of a sector, in value terms, that flows between itself and each other sector, in a respective year.

Obviously, P is a matrix with zeros in the main diagonal. In matrix form:

$$P \equiv \begin{pmatrix} 0 & \dots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{1n} & \dots & 0 \end{pmatrix}$$

since, by definition, every element of its main diagonal indicates the quantities that each sector obtains and supplies to itself, which, in a general equilibrium framework, are equal to each other. Hence, $p_{ii} = 0$, and $p_{ij} = -p_{ji}, \forall i, j \in \{1, \dots, n\}$. Apparently, P represents a net (intermediate) intra-sectoral flow matrix.

Since we are interested in constructing the so-called weight matrix, close to the spirit of the GVAR model at the international level (Pesaran et al.2004), we proceed as follows: Let NQ , be the IO matrix whose typical element, nq_{ij} , is given by the following expression:

$$nq_{ij} \equiv |p_{ij}| = |x_{ij} - x_{ji}| \quad [10]$$

A net intra-sectoral flow weight is defined as the ratio of flows of goods and services between sector i and sector j , over the total absolute flows of goods and services realized by sector i . Or in mathematical terms:

$$w_{ij} \equiv \frac{nq_{ij}}{\sum_{i=1}^n nq_{ij}} [11]$$

Obviously, W is a matrix with zeros in the main diagonal. Or, in matrix form:

$$W \equiv \begin{pmatrix} 0 & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \dots & 0 \end{pmatrix}$$

since $nq_{ii} = 0$ as discussed above, and, in general, $w_{ij} \neq w_{ji}, \forall i \neq j$.

For instance, the element w_{12} indicates the flows of goods and services, between sector 1 and sector 2 as a proportion of the total flows of sector 1.

Apparently, W represents an intermediate net intra-sectoral flow weight matrix.

If the net intra-sectoral flow weights of a sector tend to remain stable over time this would imply a situation of structural stability. On the other hand, if the weights were found to be unstable over time, an instability situation might be indicated.

The proposed weights can be computed from the data contained in IO Tables and National Accounts and the derived net intra-sectoral flow weight matrix W is directly analogous to the typical weight matrix of the GVAR model at the international level.

(B) Testing for Dominant Sector(s) in an IO framework

In order to test for the number of dominant sectors, we calculate the eigenvalues of Input Output matrix A^f . However, in what follows, we focus on matrix Q (instead of A), since its eigenvalue distribution expresses the dynamic behavior of any given economy in terms of net intermediate intra-sectoral flows, which is the focus of our analysis.⁶ The eigenvalues $\lambda(i)$, $i=1,\dots,8$ of matrix Q are such that $|Q - \lambda(i)I_n| = 0$ where I_n is the $n \times n$ identity matrix and each eigenvalue is considered to have multiplicity equal to 1. In general: $\lambda(i) = a \pm bj$, where $j^2 = -1$, $a, b \in R$, and the modulus of $\lambda(i)$ is equal to: $|\lambda(i)| = \sqrt{a^2 + b^2} \geq 0$, $i=1,\dots,8$. Now, let $\lambda(pf) = \lambda(1)$ denote the Perron–Frobenius (P–F) eigenvalue of the $n \times n$ matrix Q . We divide each eigenvalue’s modulus with the P–F eigenvalue’s modulus to get the normalized eigenvalue: $\rho(i) = |\lambda(i)| \cdot |\lambda(pf)|^{-1}$, $i=1,\dots,8$. The normalized eigenvalues: $\rho(i)$, $i=2,\dots,8$ are the so-called *non-dominant* eigenvalues, since $\rho(pf) = \rho(1) = 1$.

Following common practice, the number of dominant sectors implied by the economy’s structure is equal to i^* , for which $\rho(i^*) > 0.4$ – 0.3 approximately, since values of $\rho(i^*)$ less than 0.40 – 0.30 might be considered negligible from a practical point of view (Mariolis and Tsoulfidis, 2014).

3. Data and Variables

We have chosen to apply the proposed methodology to the US economy because: (i) it is the largest economy in the world in terms of output produced and, probably, (ii) the world’s dominant economy in terms of power and influence. Also, the US economy

⁵ An interesting approach would also be the investigation of a dominant region in the Input-Output multiregional analysis concept proposed by Canning (2013).

⁶ Of course, the same procedure could alternatively be applied to the technical coefficients matrix A .

presents (iii) interesting connectivity among its economic sectors (e.g. Acemoglu et al.2012), as well as (iv) very good data availability.

We use an eight-sector classification of the US economy because: (i) it avoids large data requirements, a characteristic which is highly desirable for the expository nature of our work, (ii) it avoids large computational complexity related to the already heavy structure of the econometric representation of the GVAR model, (iii) it provides a compact and practical representation of the country's economy, and, (iv) it is consistent with the findings by other researchers highlighting the need for compact classification formats of the US economy (see e.g. Mariolis and Tsoulfidis, 2014). Our classification builds on the respective compact US classification by the Bureau of Labor Statistics (BLS) (2014) and the Canadian classification by the Canadian Industry Statistics (2012). For the detailed industry classification, see Table A1 (Appendix).

The data are quarterly and stop in 2006, just before the first signs of the US recession made their appearance. The model incorporates two (2) sector-specific variables: Output (Y) and Labor (L) that were obtained from the Bureau of Economic Activity (BEA) and the Bureau of Labor Statistics (BLS), respectively. Regarding the global variables, we use the aggregate values of (i) Global Trade and also (ii) Global Credit, both in millions of dollars, which were obtained in constant prices from the World Data Bank.

We have chosen to use the variables of Global Trade and Global Credit instead of their domestic counterparts i.e. US Credit and US Trade, due to the fact that: (a) the US economy is free of trade barriers and, consequently, it has a very high degree of openness (Cooper, 1986) which in turn implies that the use of Global Trade is preferable since, as Romer (1992), Grossman and Helpman (1991) and Edwards (1998) argue, countries that are more open to the rest of the world have a greater ability to absorb shocks (e.g. technological advancements) generated in other nations; (b) the US economy

is considered to be the main locomotive of global demand of goods and services which in turn dictates the use of Global Trade; (c) an increasing percentage of US firms operate at a multinational level and thus they have access to financial markets around the globe and not only to the US market, which in turn implies that the use of Global Credit is preferable. Due to the openness of the US economy, we used IO matrices which contain information on both domestically produced as well as imported inputs, which is consistent with the spirit of the original GVAR model.⁷The Leontief Inverse matrices for the USA are those of years 1995, 2000 and 2005 and come from the OECD (STAN) database. For the Leontief Inverse matrices in the adopted industry classification, see Tables A2-A4. All variables are expressed in constant prices.

The weights are computed using the detailed methodology set out earlier where - for the calculation of the weights - the time span is split into three sub-periods (1992–1997, 1998–2002 and 2003–2007) and for each sub-period we use a representative domestic IO table, assuming that the production technology for the US remains constant during the sub-periods.

4. Empirical Analysis

4.1 GVAR Empirical Analysis

Stationarity

A number of relevant econometric tests need to be carried out first. We start by testing for stationarity based on the ADF methodology following Pesaran *et al.* (2004). In case the time series employed are not stationary, we induce stationarity following, among others, Koop (2013). As we know, there are several ways to test for the existence of a unit root. In this paper, we use the popular Augmented Dickey-Fuller (ADF)

⁷Despite the fact that we could subtract the absolute values of the imports column proportionally from the intermediate cells in the (intermediate) flow matrix (Q), we worked using total IO matrices, because of the openness of the US economy, as discussed earlier.

methodology (Dickey and Fuller. 1979) following Pesaran et al. (2004). The ADF test is based on the following regression:

$$\Delta Y_t = \alpha + bt + \rho Y_{t-1} + \sum_{i=1}^m \gamma_i \Delta Y_{t-1} + \varepsilon_t \quad [12]$$

where Δ is the first difference operator, t the time and ε the error term:

The original time series were found to be non-stationary. In fact, all the variables were $I(1)$. Thus, stationarity was induced by means of first differencing (Tables A5-A11).

Asymptotic Properties

For the purpose of estimation and inference in stationary models, Chudik and Pesaran (2011a) showed that the relevant asymptotics are: $\frac{T}{N} \rightarrow k < \infty$ [13]

where T denotes the time dimension and N is the number of endogenous variables in the model. Our model clearly complies with this asymptotic condition $T/N < \infty$.

Cointegration

Also, we have to check for cointegration between the different variables that enter the model. We employ the popular Johansen (1988) methodology that allows for more than one cointegrating relationship, in contrast to other tests. The methodology is based on the following equation: $\Delta y_t = m + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + e_p$ [14]

where: $\Pi = \sum_{i=1}^p A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^p A_j$ [15]

The existence of cointegration depends upon the rank of the coefficient matrix Π which is tested through the likelihood ratio, namely the trace test described by the following formulas: $J_{trace} = -T \sum_{i=r+1}^k \log(1 - \lambda_i)$ [16]

where: T is the sample size and λ_i is the largest canonical correlation.

The trace test tests the null hypothesis of $r < n$ cointegrating vectors and the critical values are found in Johansen and Juselius (1990).

The results of testing for cointegration, which are available upon request by the authors, suggest that no cointegration is present in any of the US economic sectors leading us to apply the GVAR methodology using a VARX model for each sector with stationary variables, i.e. the first differences⁸ enter the VARX model of each sector.

4.2 Input Output Empirical Analysis

Testing for Dominant Sector(s)

Close to the spirit of Chudik and Smith (2013), we proceed by investigating the existence of dominant sector(s) in the GVAR model. In this context, we divide each eigenvalue's modulus with the P-F eigenvalue's modulus to get the normalized eigenvalue: $\rho(i) = |\lambda(i)| \cdot |\lambda(pf)|^{-1}$, $i=1,\dots,8$. The normalized eigenvalues: $\rho(i)$, $i=2,\dots,8$ are the so-called *non-dominant* eigenvalues, since $\rho(pf)=\rho(1)=1$.

Tables 1,3 and 5 present the eigenvalues of the US matrix Q for the years 1995,2000 and 2005⁹ respectively, whereas Tables 2,4 and 6 present the normalized eigenvalues for the respective years.

Table 1: Eigenvalues of Q (1995)		Table 2: Normalized Eigenvalues of Q (1995)	
Eigenvalue	λ_i	Eigenvalue	ρ_i
1	21817,28	1	1
2	4206,5	2	0,19
3	117,09	3	0,01
4	701,88	4	0,03
5	359,64	5	0,02
6	1637,76	6	0,08
7	2441,33	7	0,11
8	2295,43	8	0,11

⁸Of course, for the variables that were found to be I(2) we used second differences so as to ensure that all the variables in the model are stationary.

⁹The same procedure was applied to the technical coefficients matrix A for years 1995, 2000 and 2005, and yielded similar results which are available upon request by the authors.

Table 3: Eigenvalues of Q (2000)		Table 4: Normalized Eigenvalues of Q (2000)	
Eigenvalue	λ_i	Eigenvalue	ρ_i
1	39285,19	1	1
2	6546,66	2	0,17
3	102,08	3	0
4	495,38	4	0,01
5	1218,1	5	0,03
6	3623,88	6	0,09
7	2262,32	7	0,06
8	2687,03	8	0,07

Table 5: Eigenvalues of Q (2005)		Table 6: Normalized Eigenvalues of Q (2005)	
Eigenvalue	λ_i	Eigenvalue	ρ_i
1	7313.01	1	1
2	9930.26	2	0.14
3	9081.20	3	0.13
4	5932.55	4	0.08
5	184.24	5	0.02
6	3182.29	6	0.04
7	2102.92	7	0.03
8	741.30	8	0.01

Following common practice, the number of dominant sectors implied by the economy's structure is equal to i^* , for which $\rho(i^*) > 0.4 - 0.3$ approximately, since values of $\rho(i^*)$ less than $0.40 - 0.30$ might be considered negligible from a practical point of view, as we have seen earlier. Hence, the results of Tables 2, 4 and 6 suggest the existence of one dominant sector in the US economy, throughout the period of our investigation.

Constructing the sectoral weight matrix

Next, we proceed by constructing the weight matrix of our GVAR model using the methodology described earlier. As we have seen, a net intra-sectoral flow weight matrix

W has the form:
$$W = \begin{pmatrix} 0 & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \dots & 0 \end{pmatrix}$$

since $w_{ii} = 0$ as explained earlier and, in general, $w_{ij} \neq w_{ji}, \forall i \neq j$. The typical element w_{ij} is defined as the ratio of flows of goods and services between sector i and sector j , over the total flows of goods and services realized by sector i : $w_{ij} = \frac{nq_{ij}}{\sum_{i=1}^n nq_{ij}}$

In our investigation, we construct three weight matrices for the years 1995, 2000 and 2005, respectively(see Tables 7-9), based on the IO inverse matrices for the US economy (see Tables A2-A4, Appendix) and the respective flow matrices Q (see Tables A12-A14, Appendix)

Table 7: Weight Matrix (1995)

Sector	1	2	3	4	5	6	7	8
1	0.00	0.02	0.05	0.03	0.53	0.20	0.16	0.00
2	0.02	0.00	0.16	0.02	0.20	0.34	0.18	0.07
3	0.01	0.03	0.00	0.02	0.03	0.05	0.83	0.03
4	0.03	0.01	0.08	0.00	0.02	0.08	0.71	0.07
5	0.23	0.07	0.07	0.01	0.00	0.35	0.25	0.02
6	0.04	0.05	0.04	0.02	0.14	0.00	0.67	0.05
7	0.02	0.01	0.40	0.09	0.06	0.37	0.00	0.05
8	0.00	0.05	0.13	0.08	0.03	0.23	0.47	0.00

Table 8: Weight Matrix (2000)

Sector	1	2	3	4	5	6	7	8
1	0.00	0.02	0.07	0.04	0.65	0.17	0.05	0.01
2	0.02	0.00	0.17	0.03	0.12	0.26	0.32	0.07
3	0.06	0.14	0.00	0.02	0.08	0.12	0.56	0.02
4	0.06	0.05	0.04	0.00	0.09	0.36	0.37	0.02
5	0.38	0.08	0.06	0.04	0.00	0.33	0.09	0.03
6	0.05	0.08	0.04	0.07	0.17	0.00	0.57	0.02
7	0.01	0.08	0.16	0.06	0.04	0.44	0.00	0.22
8	0.01	0.06	0.02	0.01	0.05	0.05	0.80	0.00

Table 9: Weight Matrix (2005)

Sector	1	2	3	4	5	6	7	8
1	0.00	0.02	0.06	0.04	0.58	0.23	0.05	0.02
2	0.01	0.00	0.16	0.03	0.10	0.28	0.37	0.05
3	0.04	0.14	0.00	0.01	0.05	0.09	0.65	0.01
4	0.05	0.05	0.01	0.00	0.09	0.31	0.48	0.01
5	0.30	0.06	0.04	0.04	0.00	0.28	0.26	0.01
6	0.05	0.07	0.03	0.05	0.11	0.00	0.65	0.03
7	0.01	0.07	0.14	0.05	0.07	0.45	0.00	0.21
8	0.01	0.04	0.01	0.00	0.01	0.09	0.83	0.00

As we have seen, if the net intra-sectoral flow weights of a sector tend to remain stable over time this would imply a situation of structural stability. On the other hand, if the weights were found to be unstable over time, an instability situation might be indicated. Based on the calculated weight matrices, we find evidence of increased structural stability over time, with very few exceptions.

By means of the matrices W we proceed with estimating the GVAR model, using sector 7 (information technology, finance and communications), as the dominant sector in the US economy because: (a) it is the largest sector in terms of output produced, as well as the (b) the largest sector in terms of the output exchanged.

5. Estimation Results and Stability

Next, for the implementation of our model we have to determine the optimum lag length for each sector's variables.

Optimum Lag Length of the GVAR model

We make use of the so-called Schwartz-Bayes Information criterion (SBIC) introduced by Schwartz (1978), where the optimum lag length is given by the objective function:

$$\hat{k} = \operatorname{argmin}_{k \leq n} \left\{ -2 \frac{\ln(LL(k))}{n} + k \frac{\ln(n)}{n} \right\} \quad [17]$$

where $LL(k)$ is the log-likelihood function of a VAR(k) model, n is the number of observations and k is the number of lags and \hat{k} is the optimum lag length selected. As the works of Breiman and Freedman (1983) and Speed and Yu (1992) have shown, SBIC is an optimal selection criterion when used in finite samples.

The optimum lag length for each sector was equal to two (2) quarters (Pesaran et al. 2005). Therefore, the VARX model for each sector $i, i \neq 7$ is as follows:

$$\begin{pmatrix} \Delta Y_{i,t} \\ \Delta L_{i,t} \end{pmatrix} = a_{i,0} + \Phi_{i,p} \begin{pmatrix} \Delta Y_{i,t} \\ \Delta L_{i,t} \end{pmatrix} + N_{i,0} \begin{pmatrix} \Delta Y_{7,t} \\ \Delta L_{7,t} \end{pmatrix} + N_{i,p} \begin{pmatrix} \Delta Y_{7,t} \\ \Delta L_{7,t} \end{pmatrix} + \sum_{i=1, i \neq 7}^8 \Lambda_{i,0} \begin{pmatrix} \Delta Y_{i,t}^* \\ \Delta L_{i,t}^* \end{pmatrix} + \Lambda_{i,p} \begin{pmatrix} \Delta Y_{i,t}^* \\ \Delta L_{i,t}^* \end{pmatrix} + A_i \begin{pmatrix} \Delta TRADE_t \\ CREDIT_t \end{pmatrix} + u_i \quad [18]$$

while, for the dominant sector, $i=7$, its VARX model is the following:

$$\begin{pmatrix} \Delta Y_{i,t} \\ \Delta L_{i,t} \end{pmatrix} = a_{i,0} + \Phi_{i,p} \begin{pmatrix} \Delta Y_{i,t} \\ \Delta L_{i,t} \end{pmatrix} + \sum_{i=1, i \neq 7}^8 \Lambda_{i,0} \begin{pmatrix} \Delta Y_{i,t}^* \\ \Delta L_{i,t}^* \end{pmatrix} + \Lambda_{i,p} \begin{pmatrix} \Delta Y_{i,t}^* \\ \Delta L_{i,t}^* \end{pmatrix} + A_i \begin{pmatrix} \Delta TRADE_t \\ CREDIT_t \end{pmatrix} + u_i$$

where Δ is the first differencing operator, $\{Y_{i,t}, L_{i,t}\}$ is the 1×2 vector representing output and labor, respectively, for all sectors $i = 1, \dots, 8$, p is the lag length that is $p=2$, $\{\Delta TRADE_t, CREDIT_t\}$ are the exogenous variables of global Trade and global Credit with A_i the respective coefficients, $\Phi_{i,p}$, $N_{i,p}$ and $\Lambda_{i,p}$ are the matrices of lagged polynomials, $N_{i,0}$ and $\Lambda_{i,0}$ are the coefficient matrices of the dominant sector and the other sectors respectively and $a_{i,0}$ is the intercept, while u_{it} is a vector of idiosyncratic, serially uncorrelated sector-specific shocks with mean zero and the variance-covariance matrix Σ_i , $u_{it} \sim i.i.d(0, \sigma^2)$.

The effect of the foreign variables on their sector-specific counterpart is presented in Table A16, Appendix. The results suggest that in all sectors labor seems to be significantly affected by output and *vice versa*. In this context, it is worth noticing that

the dominant sector 7, as expected, appears to have the most significant interconnections with the rest of the sectors, a fact that seems to be consistent with our choice of the dominant sector. Additionally, we witness relatively limited interconnectivity among the various sectors mainly with respect to their output, a fact which is consistent with the findings by other researches (e.g. Mariolis and Tsoulfidis, 2014).

GVAR Stability Conditions

Also, in order to determine whether the model is stable, we have to check the stability of the sector-by-sector models, separately. However, following Pesaran et al. (2004) and Mutl (2009) it is not sufficient to examine the sector-by-sector stability, ignoring the endogeneity of the other variables $x^*_{i,t}$. Hence, it does not suffice to require that $\rho(\Phi_i) < 1$ for stability, where $\rho(\Phi_i)$ is the spectral radius of the matrix $\Phi_i, i = 1, \dots, 8$. Instead, Mutl (2009, p. 9) derived a sufficient condition for the model to be stable, namely that the maximum absolute row sums of W are less or equal to k_w , that is:

$$\|W\|_1 \leq k_w [19]$$

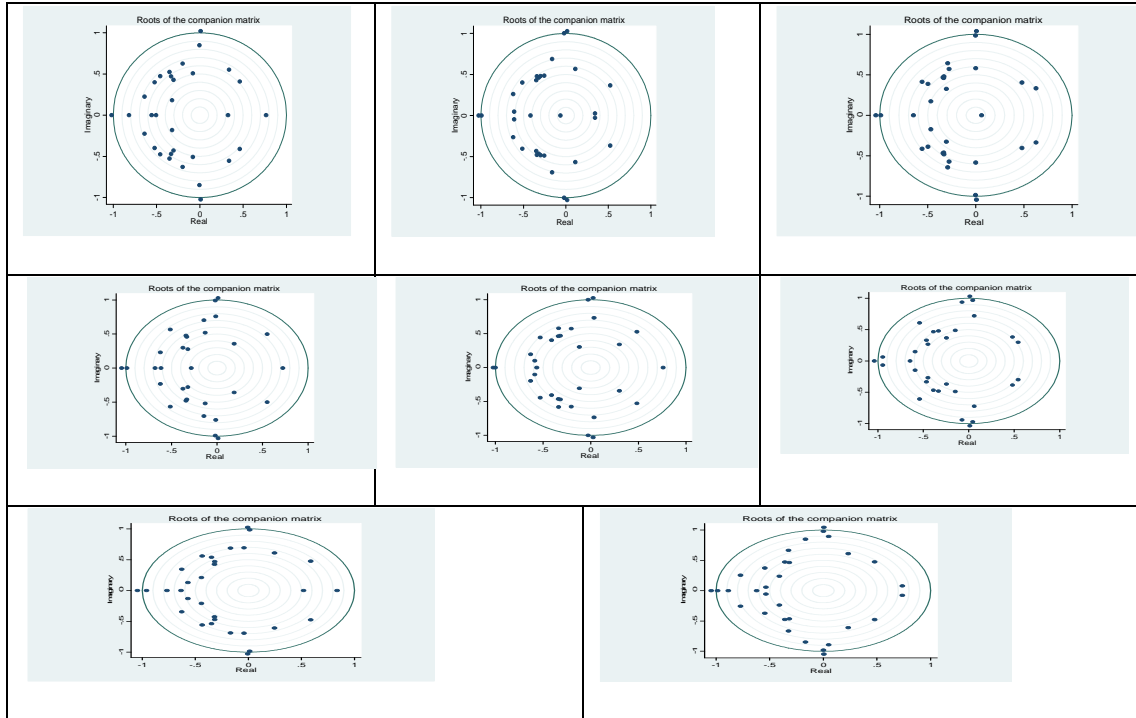
where k_w is the uniform bound of absolute row and column sums of the weight matrix

$$W: \sum_{j=1}^1 \sum_{m=1}^k |w_{ij,qm}|_1 \leq k_w < \infty [20]$$

where k_w does not depend on T or N and the choice of indexes i and q , but can potentially depend on other parameters of the model; and $w_{ij,qm}$ denotes the (q, m) -th element of W_{ij} . Finally, note that if r is the maximum number of eigenvalues of Φ , then according to the fundamental algebraic theorem, $r \leq \text{rank}(\Phi)$.

The results of our analysis are consistent with the stability of each sector's VARX model (see Figure 1), based on the eigenvalues lying on or inside the unit circle, and imply stability of the estimated model and of the various sectors of the US economy.

Figure 1: Stability of the VARX models



6. Discussion

It should be noted that the aim of the empirical analysis is not to provide a deep and sophisticated analysis of the US sectoral economy, but rather to provide an illustration of the methodology proposed in this paper including a brief discussion of its main results.

In this framework, we base our detailed analysis on Generalized Impulse Response Function (GIRFs) and, more precisely, on the robust Confidence Intervals (C.I.) (bootstrapped, 10.000 iterations) rather than the point estimates in order to avoid any possible structural instability. Each GIRF shows the dynamic response of the variable of each sector to unit shocks to: (i) Output and (ii) Labor on each one of the rest of the sectors, for up to 8 periods, i.e. 2 years.

In the exposition of the results, the reader can focus on the first two years following the shock, which is a reasonable time horizon over which the model presents credible results (Dees *et al.* 2007a). Figure A1 (Appendix) shows the estimates of the GIRFs and their associated 90% C.I. For instance, a positive shock of one standard deviation on the output of sector 2 (Y2*) affects positively the output of sector 1 (Y1), in the short run i.e. 2-3 quarters. This effect, after approximately 4 quarters, becomes negative and it dies out at the end of the period investigated, i.e. after eight quarters. The effect is not persistent since the output of sector 1 (Y1) returns back to its initial equilibrium position.

In general, the GIRFs suggest relatively limited interconnectivity, in terms of both sectoral output and labor, between the various sectors of the US economy, a finding which is consistent with previous findings based on the results of Table A.2. All the effects seem to have a temporary character since they die out rather quickly, in less than eight (8) quarters. It is worth noticing that we do not witness any persistent effect, since in all cases all variables return back to their initial equilibrium position, implying relatively increased stability of the US sectoral economy.

In detail, the GIRFs suggest that sectors 1,3,4,5 and 7 that account for the primary production of goods (sector 1), primary production of energy (sector 3), constructions (sector 4), final products (sector 5) and information technology, finance and communications (sector 7), are the sectors with the highest connectivity, in terms of output, with the rest of the sectors. This could be attributed to the nature of these specific sectors since they act either as the main supplier for the production of other goods e.g. sector 1 and 3, or as leading demand sectors for goods e.g. sectors 3, 5 and 7. Either way, most of the above sectors exhibit relatively significant connectivity with at least three other sectors. Our findings are, in general terms, also consistent with the

findings of Jianxi (2013), regarding the influence of these sectors on the economy of the US, as a whole.

Moreover, sectors 3, 5, 6 and 8 that account for the production of energy (sector 3), final products (sector 5), trade (sector 6) and education and health services (sector 8), are the sectors with the highest connectivity, in terms of labor, with the rest of the sectors in the economy. This, in turn, could be attributed to the fact that employees in these sectors exhibit increased diversification in terms of skills and specialization, in the sense that all other sectors could easily act as employee suppliers for these specific sectors. It is worth noticing that each of the aforementioned sectors exhibits considerable connectivity with over four sectors.

Of course, using one of the most important tools of IO analysis, i.e. the matrix of technical coefficients A , we can easily observe that, in general, the leading sectors in terms of connectivity are sectors 3, 6, and 7 that account for primary production of energy (sector 3), trade (sector 6) and information technology, finance and communications (sector 7). These sectors are consistent with the findings of our GVAR model.

7. Conclusion

In this paper we have assessed the interdependencies among the eight (8) main sectors of economic activity in the US economy, using quarterly data on output and labor for the time period 1992-2006, just before the first signs of the global recession made their appearance. In this context, we set up a novel methodological framework which combined Input-Output (IO) analysis with state of the art Global Vector Autoregressive (GVAR) model. The purpose of our paper was not to provide a deep and sophisticated

analysis of the US sectoral economy, but rather to provide an illustration of the methodology proposed including a brief discussion of its main results.

In a novel approach, we used the GVAR methodology at the sectoral level and suggested using the IO matrices of the economy to serve as the means to construct the GVAR weight matrix. To this end, we proposed and derived a simple yet practical framework for constructing the weight matrix based on the technical coefficients matrix, for the years 1995, 2000 and 2005, respectively.

In addition, we used the IO matrices and offered a procedure to examine for the existence of dominant sector(s) in the US sectoral economy. The empirical analysis suggested the existence of one dominant sector in our dataset. Hence, we employed the model using a dominant sector and the results of our econometric investigation suggested that the US economy has relatively limited connectivity among its sectors, in terms of both sectoral output and labor. Additionally, it is worth noticing that we did not witness any persistent effect since, in finite time, all the variables returned back to their *initial* equilibrium positions. This finding could be viewed as an expression of the increased stability of the US economy.

Our combined GVAR-IO findings are, in general terms, consistent with the connectivity links pictured through the IO technical coefficients matrix of the US economy. In this context, our results clearly imply that a combination of IO and GVAR is highly desirable because it is capable of providing very useful insights, since it is able of decomposing the connection between the various sectors in terms of all the variables that enter the model. A good example for future research, besides widening the database and accounting for additional variables, would be the construction of a GVAR model at the international level based on relevant global IO matrices.

References

- Acemoglu, D., V.M. Carvalho, A. Ozdaglar and A. Tahbaz-Salehi (2012), "The Network Origins of Aggregate Fluctuations", *Econometrica*, 80, 1977–2016.
- Bernanke, B., Boivin, J., and Eliasziw, P. (2005), "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach", *Quarterly Journal of Economics*, 120(1):387
- Breiman, L. A. and Freedman, D. F. (1983), "How many variables should be entered in a regression equation?" *Journal of American Statistics Association*, 78: 131-136.
- Bussière M. and A. Chudik and G. Sestieri(2012), "Modelling global trade flows: results from a GVAR model," *Globalization and Monetary Policy Institute Working Paper* 119, Federal Reserve Bank of Dallas.
- Canning P. (2013), "Maximum Likelihood Estimates of a US Multiregional Household Expenditure System", *Economic Systems Research*, 25(2):245-264.
- Chudik A. & Vanessa Smith, (2013). "The GVAR approach and the dominance of the U.S. economy," *Globalization and Monetary Policy Institute Working Paper* 136, Federal Reserve Bank of Dallas.
- Chudik, A. and Fratzscher, M. (2011a), "Identifying the global transmission of the 2007-2009 financial crisis in a GVAR model", *European Economic Review*, 55:325-339.
- Chudik, A. and M. H. Pesaran (2011b), "Infinite dimensional VARs and factor models", *Journal of Econometrics*, 163: 4-22.
- Dées, S. di Mauro, F., Pesaran, H. and Smith, V. (2005), Exploring the International Linkages of the Euro Area: A Global VAR Analysis, *Working Paper Series, No 56 European Central Bank* December.
- Dées, S., F. di Mauro, M. H. Pesaran, and L. V. Smith (2007b), " Exploring the international linkages of the euro area: a Global VAR analysis", *Journal of Applied Econometrics* 22: 1-38.
- Dees, S., Pesaran, M., Smith, L., and Smith, R. (2010), "Supply, demand and monetary policy shocks in a multi-country New Keynesian model", *European Central Bank Working Paper*, 1239.
- Dées, S., S. Holly, M. H. Pesaran, and L. V. Smith (2007a), "Long-run macroeconomic relations in the global economy", *Economics, the Open Access, Open Assessment E-Journal*, Kiel Institute for the World Economy.
- Dickey, D.A. and W.A. Fuller (1979), "Distribution of the estimators for autoregressive time series with a unit root" *Journal of the American Statistical Association*, 74: 427-431.
- Dietzenbacher, E. (1992) The Measurement of Interindustry Linkages: Key Sectors in the Netherlands, *Economic Modeling*, 9, 419–437.
- Edwards, S. (1998), "Openness, productivity and growth: What do we really know?", *Economic Journal*, 108, 383-398.
- Grossman, G. M. & Helpman, E., (1991), "Trade, knowledge spillovers, and growth," *European Economic Review*, vol. 35(2-3), pages 517-526, April.
- Jianxi L. (2013), "Which industries to bail out first in economic recessions: Ranking US sectors by the Power-of-Pull", *Economic Systems Research*, 25:2, 157-169.
- Johansen, S. (1995), *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*, New York: Oxford University Press.

Johansen, S. and Juselius, K. (1990), "Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, 52(2):169–210.

Kapetanios, G., Pesaran, M. Hashem and Yamagata, T. (2011), "Panels with non-stationary multifactor error structures," *Journal of Econometrics*, 160(2): 326-348.

Kim K.Y. (2013), "Household Debt, Financialization, and Macroeconomic Performance in the U.S., 1951-2009", *Journal of Post Keynesian Economics*, 35(4):675-694.

Konstantakis, K. and Michaelides, P. (2014), Transmission of the Debt Crisis: From US to Eu-15 or vice versa?, A GVAR approach, *Journal of Economics and Business (forthcoming)* doi: <http://dx.doi.org/10.1016/j.jeconbus.2014.04.001>.

Koop, G. (2013), "Forecasting with Medium and Large Bayesian VARs", *Journal of Applied Econometrics*, 28: 177–203.

Koop, G., M. H. Pesaran and S. M. Potter.(1996), "Impulse Response Analysis in Nonlinear Multivariate Models," *Journal of Econometrics*, 74: 119–147.

Korobilis D. (2013), "Bayesian forecasting with highly correlated predictors," *Economics Letters*, 118(1):148-150.

Kose, M., C. Otrok, and C. Whiteman (2003), "International Business Cycles: World, Region, and Country-Specific Factors", *American Economic Review*, 93(4): 1216-1239.

Los, B. (2004), "Identification of Strategic Industries: A Dynamic Perspective", *Papers in Regional Science*, 83:669–698.

Mariolis T, and Tsoulfids L. (2014), "On Brody's Conjecture: Theory, Facts and Figures about instability of the US economy", *Economic Systems Research*, 26(2):209-223.

Mutl, J. (2009), "Consistent Estimation of Global VAR Models," Economics Series 234, Institute for Advanced Studies.

Pesaran M.H. and R. Smith, (2006), "Macroeconometric Modelling With A Global Perspective," Manchester School, University of Manchester, Vol. 74(s1):24-49.

Pesaran M.H and Y. Shin (1998), "Generalized impulse response analysis in linear multivariate models", *Economics Letters*, 58:17.

Pesaran, M. H., L. V. Smith, and R. P. Smith (2007), "What if the UK or Sweden had joined the Euro in 1999? an empirical evaluation using a Global VAR.", *International Journal of Finance and Economics* 12:55-87.

Pesaran, M. H., Schuermann, T. & Weiner, S. M. (2004), "Modelling Regional Interdependencies using a Global Error-Correcting macro-econometric model", *Journal of Business and Economic Statistics*, 22(2):129–162.

Pesaran, M. H., T. Schuermann, B.J.Treutler, and S. M. Weiner (2006), "Macroeconomic dynamics and credit risk: A global perspective", *Journal of Money Credit and Banking* 38 (5): 211-262.

Pesaran, M.H., Shin, Y. and Smith, R. (2000), "Structural Analysis of Vector Error Correction Models with Exogenous I(1) Variables", *Journal of Econometrics*, 97:293-343.

Romer P.M.(1992), "Increasing Returns and New Developments in the Theory of Growth," NBER Working Papers 3098, National Bureau of Economic Research, Inc.

Rueda-Cantuche J. and ten Raa T. (2013), "Testing Assumption made in the Construction of Input Output Tables", *Economics Systems Research*, 25(2):170-181.

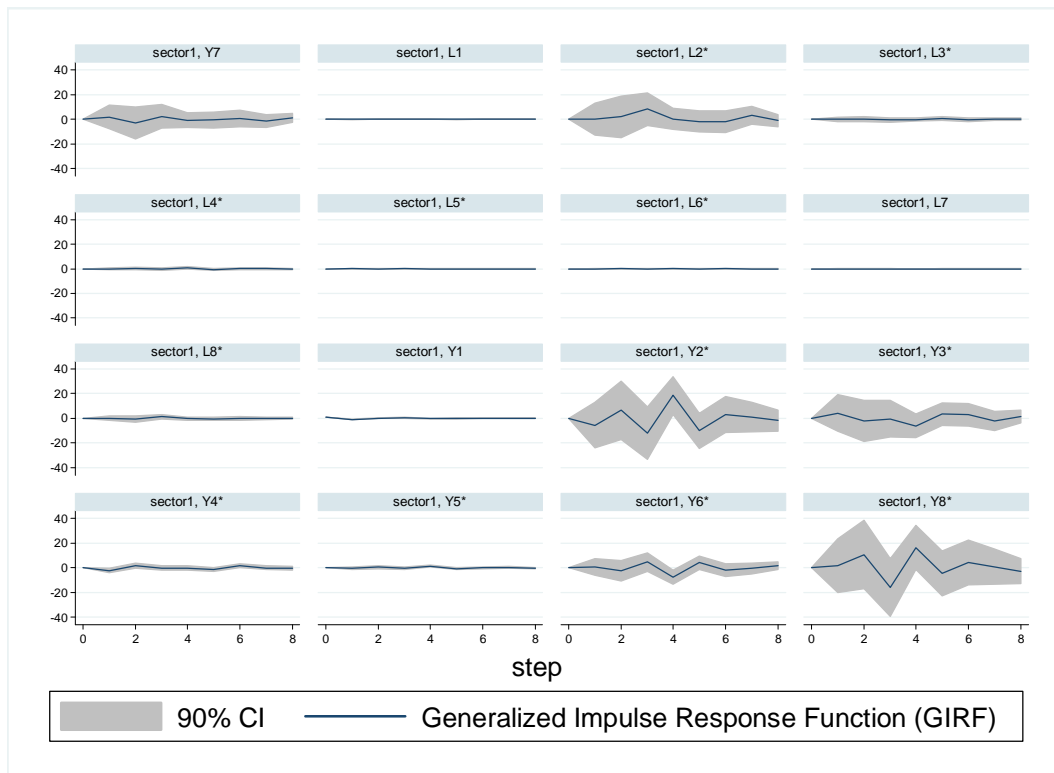
Schwarz, G. E. (1978), "Estimating the dimension of a model", *Annals of Statistics*, 6 (2): 461-464.

Speed T.P and Yu Bin (1992), "Model selection and Prediction: Normal Regression", *Annals of the Institute of Statistical Mathematics*, 45:35-54.

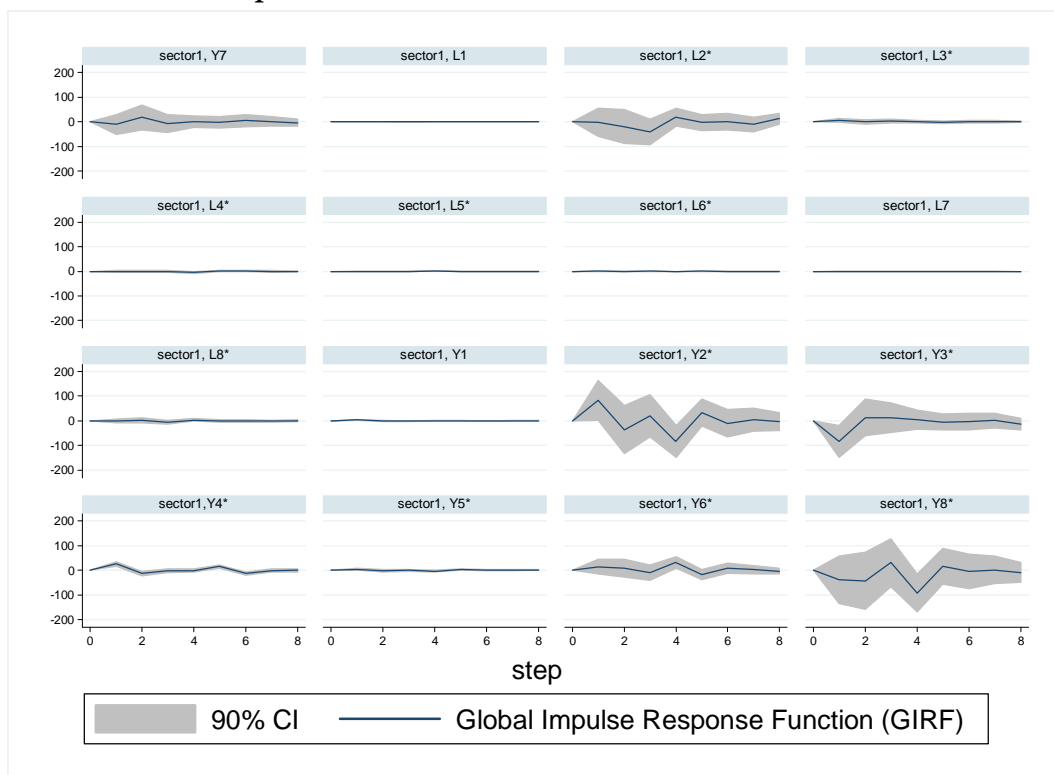
Valcarcel, J.V. (2012), "The dynamic adjustments of stock prices to inflation disturbances", *Journal of Economics and Business*, 64(2):117-144.

Appendix: Figure A1

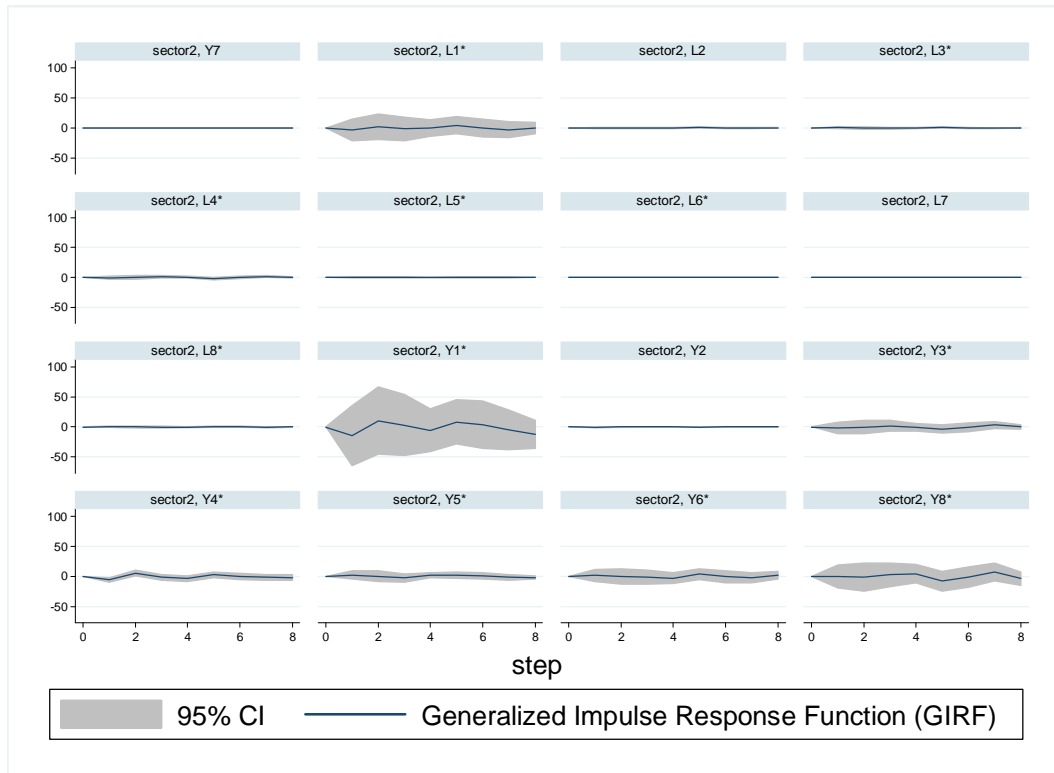
GIRF sector 1: Response of Y1



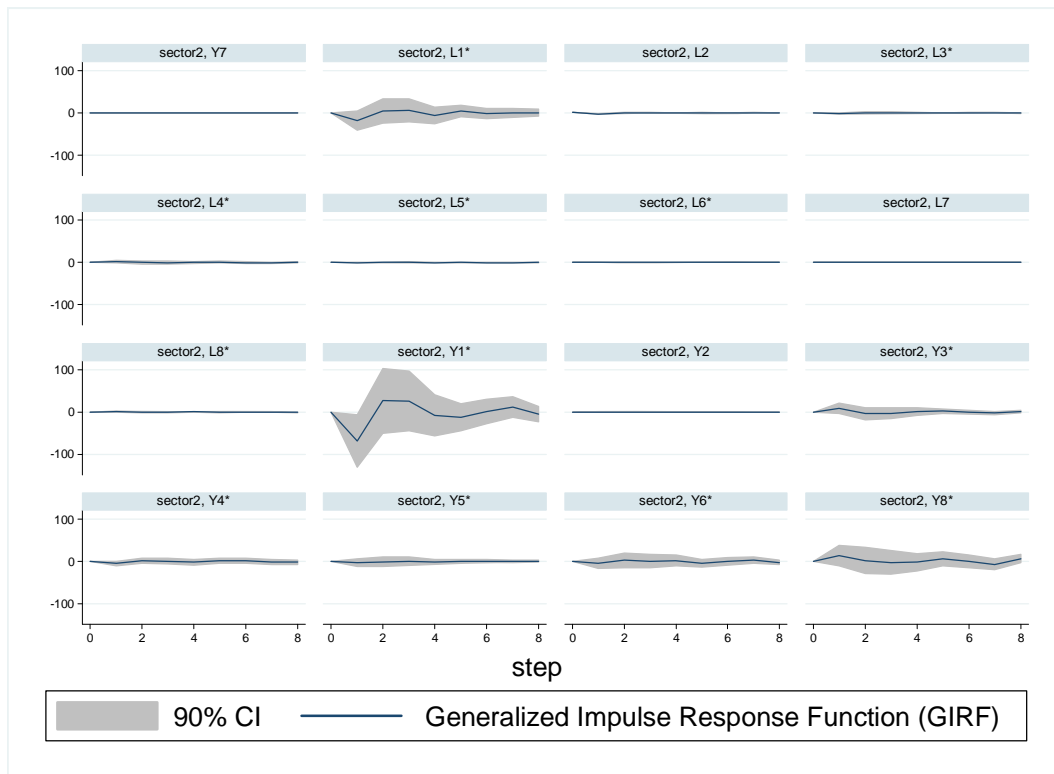
GIRF sector 1: Response of L1



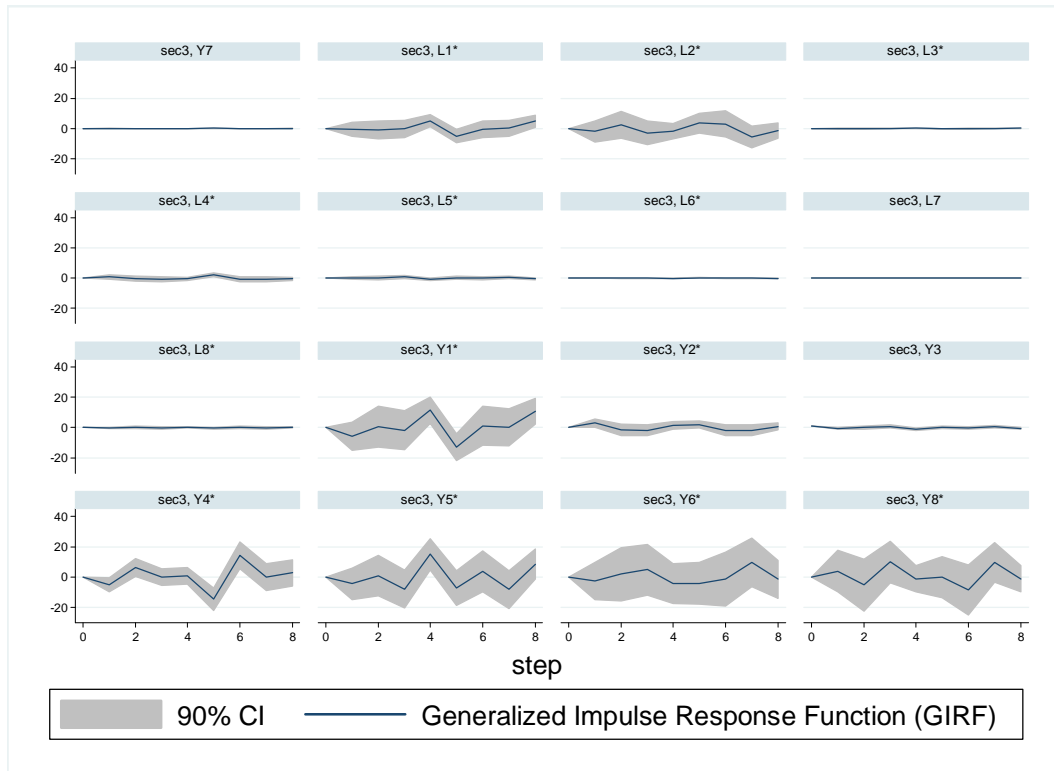
GIRF sector 2: Response of Y1



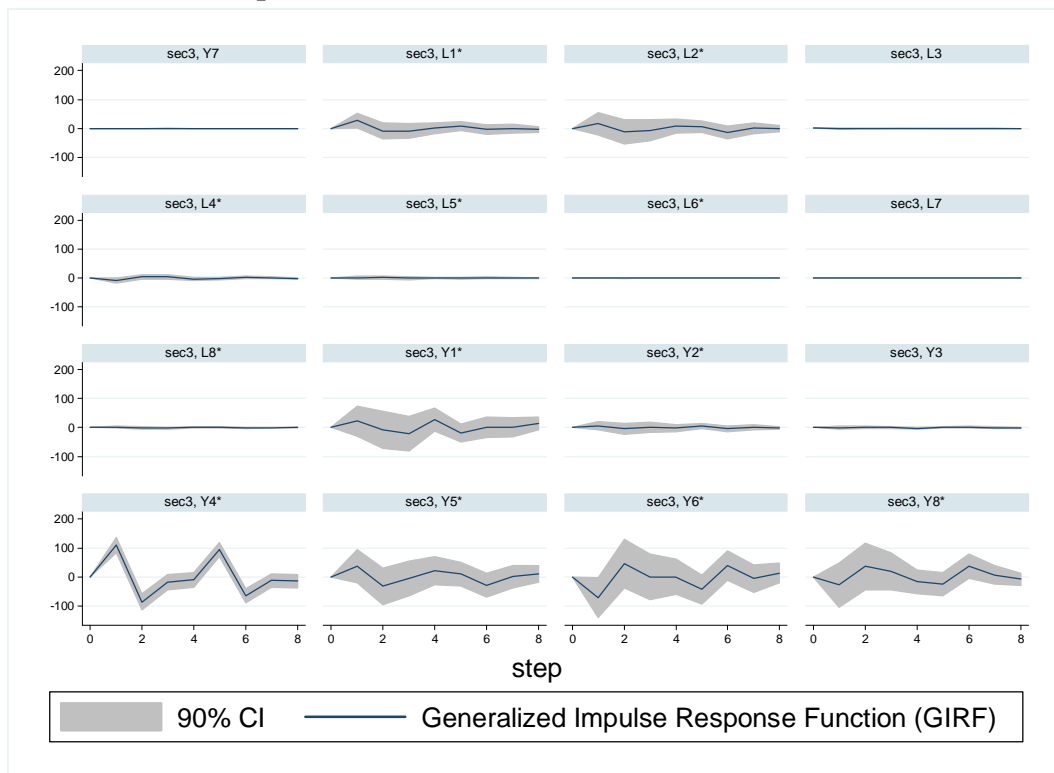
GIRF sector 2: Response of L2



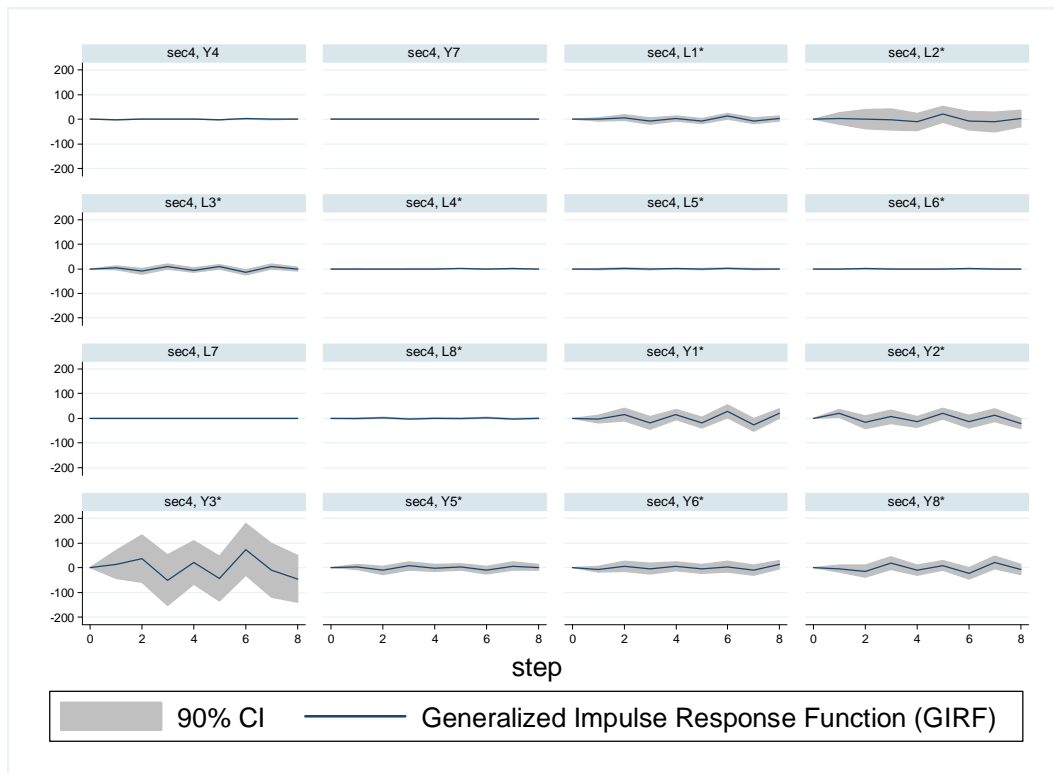
GIRF sector 3: Response of Y3



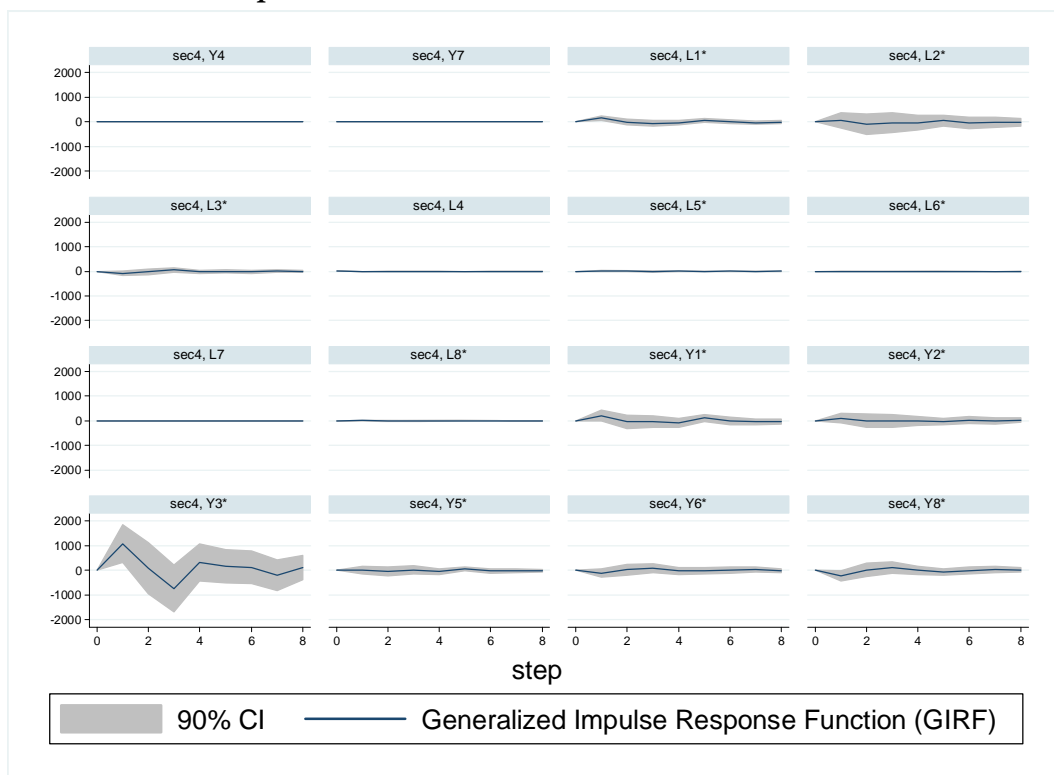
GIRF sector 3: Response of L3



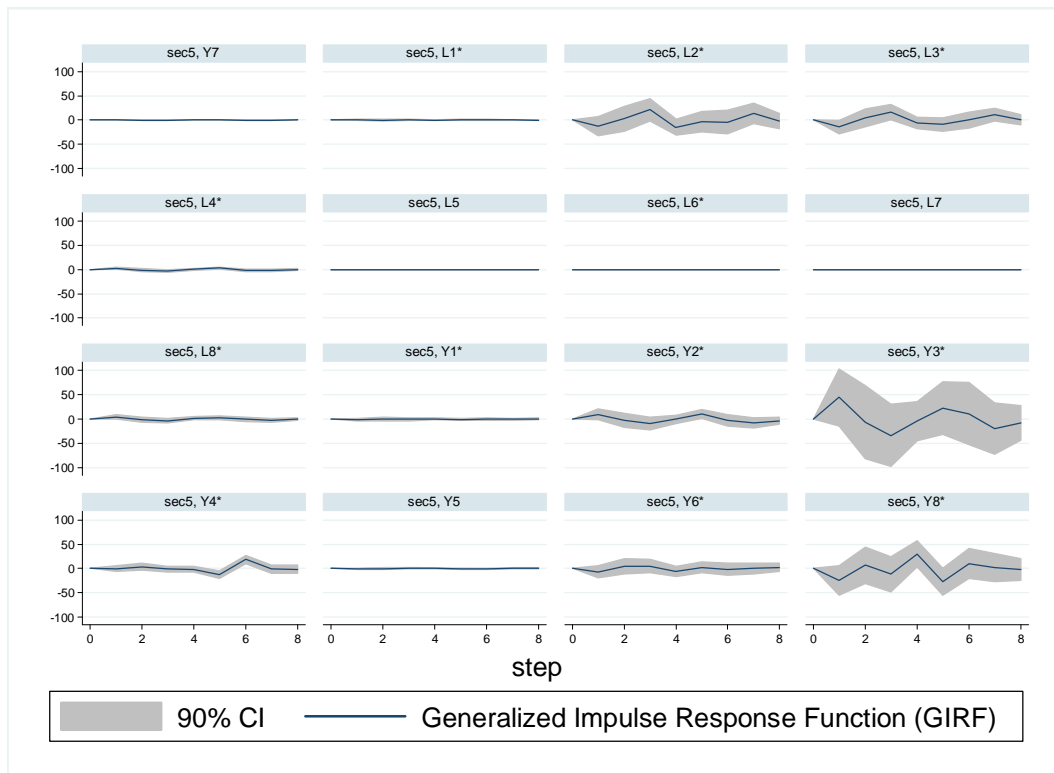
GIRF sector 4: Response of Y4



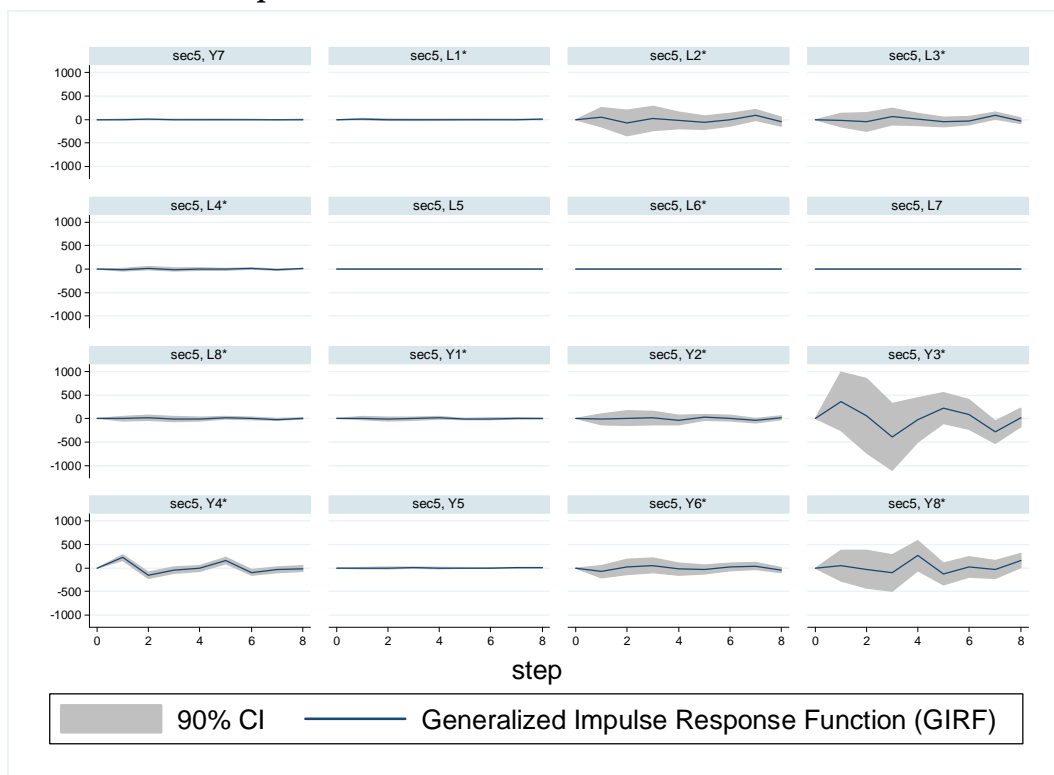
GIRF sector 4: Response of L4



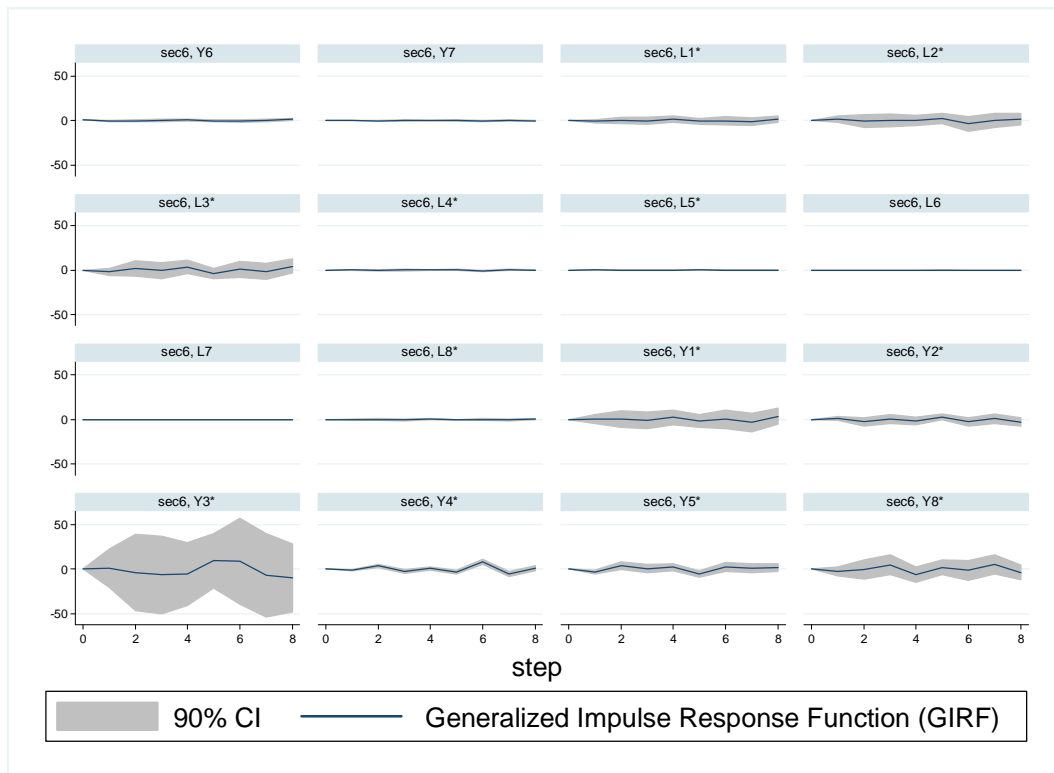
GIRF sector 5: Response of Y5



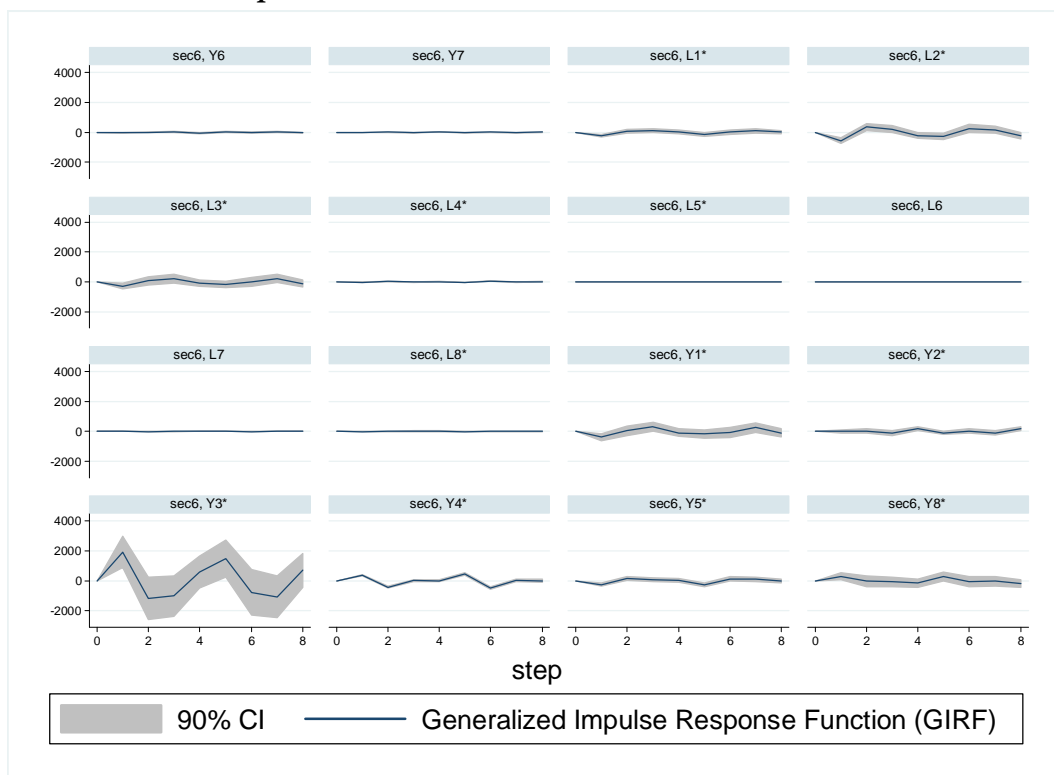
GIRF sector 5: Response of L5



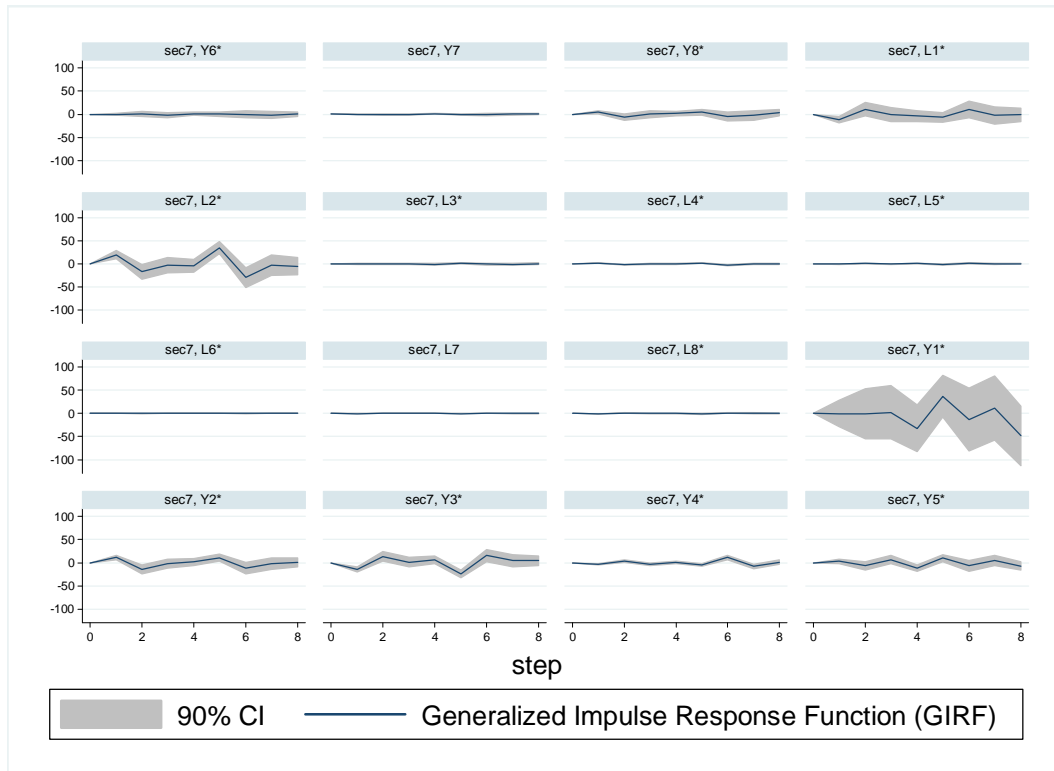
GIRF sector 6: Response of Y6



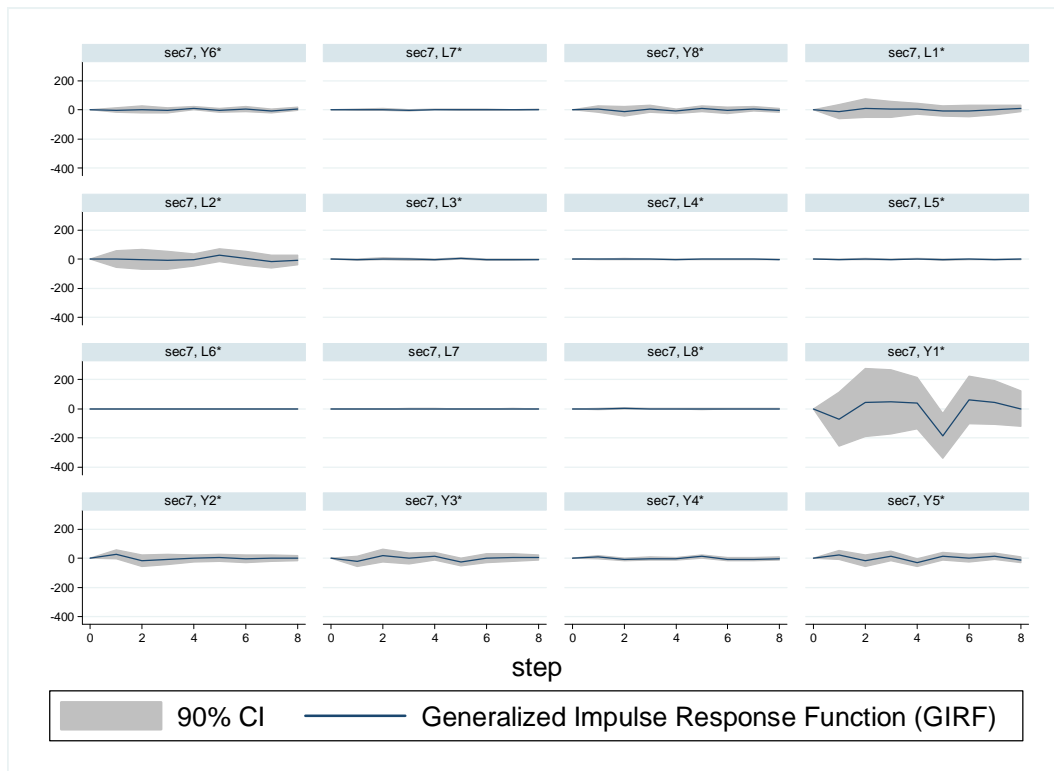
GIRF sector 6: Response of L6



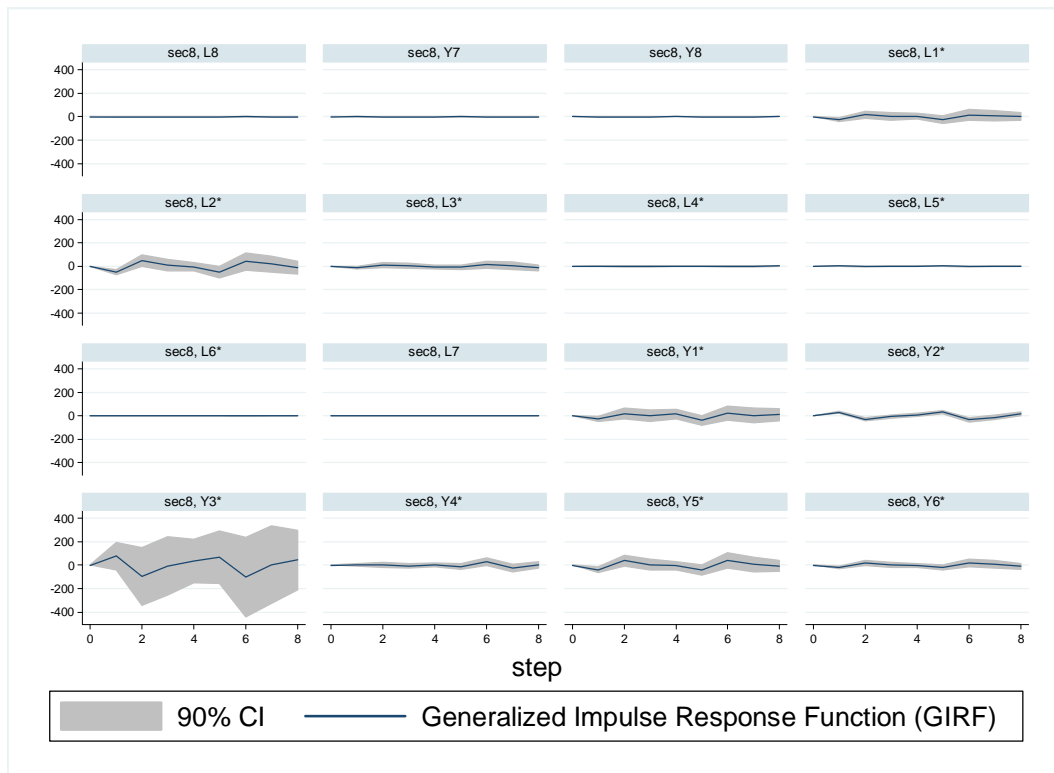
GIRF sector 7: Response of Y7



GIRF sector 7: Response of Y7



GIRF sector 8: Response of Y8



GIRF sector 8: Response of L8

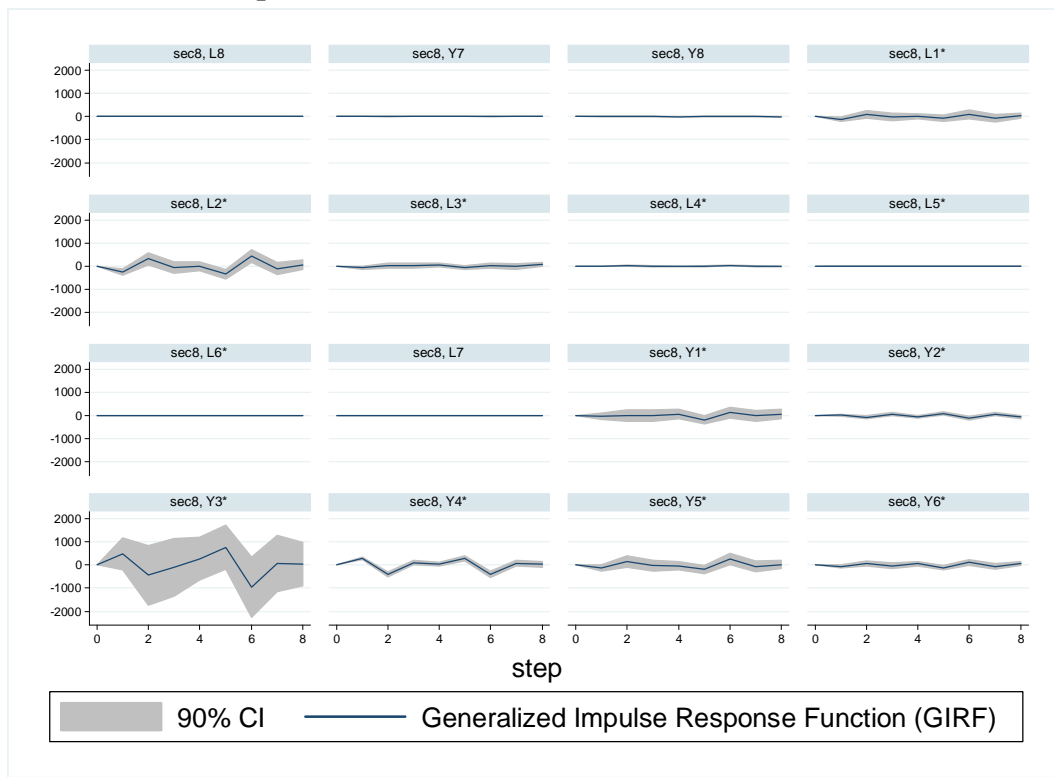


Table A1: Industry Classification		
INDUSTRIAL SECTORS (U.S. ECONOMY)		
SECTORS	DESCRIPTION	NACE CLASSIFICATION
1	AGRICULTURE, FORESTRY AND FISHING	A01,A02,A03
2	MINING, PETROLEUM AND COAL PRODUCTS	B, C10-C12, C13-C15, C16, C17, C18, C19, C20, C21,C22, C23, C24, C25, C26, C27, C28, C29, C30, C31-C32, C33
3	ELECTRICITY, GAS, WATER, TRANSPORT AND STORAGE	D, E36, E37-E39, H49, H50, H51, H52, H53
4	CONSTRUCTION	F
5	FOOD & BEVERAGES, WOOD PRODUCTS AND FURNITURE, METAL PRODUCTS	I
6	WHOLESALE & RETAIL TRADE	G45, G46, G47
7	INFORMATION, TECHNOLOGY REAL ESTATE, FINANCE AND INSURANCE, COMMUNICATION AND PERSONAL SERVICES	J58, J59-J60, J61, J62-J63, S95, K64, K65, K66, L, L68A, M71, M72, N77, M73, M74-M75, N79, N80-N82, O, Q87-Q88, R90-R92, R93, S94, S96, T, U, M69-M70, N78
8	EDUCATIONAL ORGANIZATIONS & HEALTH SERVICES	P, Q86

Table A2: Leontief Inverse matrix of the US economy for the year 1995

Sector	1	2	3	4	5	6	7	8
1	1.36	0.05	0.05	0.02	0.53	0.09	0.16	0.04
2	0.18	6.19	1.04	0.25	0.97	0.92	0.57	0.35
3	0.12	0.69	7.89	0.32	0.98	5.46	1.48	0.61
4	0.05	0.27	0.52	2.24	0.35	0.38	0.57	0.24
5	0.19	0.49	1.42	0.71	8.86	1.17	1.41	0.57
6	0.14	0.45	0.86	0.29	0.90	2.29	0.81	0.37
7	0.22	0.94	1.30	0.41	1.17	1.11	14.28	2.19
8	0.01	0.07	0.19	0.04	0.11	0.17	0.32	5.29

Table A3: Leontief Inverse matrix of the US economy for the year 2000

Sector	1	2	3	4	5	6	7	8
1	1.32	0.03	0.04	0.02	0.62	0.07	0.11	0.02
2	0.22	6.14	1.06	0.23	0.84	0.84	0.47	0.21
3	0.12	0.45	7.49	0.27	0.85	5.31	0.64	0.23
4	0.03	0.10	0.19	2.13	0.13	0.16	0.15	0.06
5	0.17	0.43	1.29	0.60	8.31	1.01	0.87	0.30
6	0.10	0.37	0.65	0.25	0.67	1.97	0.46	0.15
7	0.28	1.22	1.79	0.56	1.80	1.63	12.87	1.53
8	0.05	0.31	0.44	0.17	0.45	0.40	0.82	4.36

Table A4: Leontief Inverse matrix of the US economy for the year 2005

Sector	1	2	3	4	5	6	7	8
1	1.32	0.03	0.04	0.02	0.62	0.08	0.11	0.03
2	0.23	6.37	1.30	0.27	0.95	1.04	0.69	0.33
3	0.10	0.39	7.34	0.25	0.86	5.21	0.72	0.30
4	0.03	0.09	0.20	2.13	0.12	0.17	0.19	0.08
5	0.15	0.37	1.26	0.58	8.07	1.01	1.01	0.43
6	0.08	0.36	0.66	0.26	0.68	1.89	0.59	0.27
7	0.26	1.13	1.61	0.53	1.68	1.46	14.55	2.07
8	0.05	0.34	0.55	0.19	0.50	0.51	1.11	5.58

Table A5: ADF test Sector 1 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1	0.78	No	0	Yes
Y2*	0.86	No	0	Yes
Y3*	0.8	No	0.01	Yes
Y4*	0.83	No	0.02	Yes
Y5*	0.92	No	0.02	Yes
Y6*	0.98	No	0.1	Yes
Y7**	0.86	No	0	Yes
Y8*	0.98	No	0.05	Yes
L1	0.91	No	0	Yes
L2*	0.43	No	0	Yes
L3*	0.84	No	0	Yes
L4*	0.83	No	0	Yes
L5*	0.92	No	0	Yes
L6*	0.96	No	0	Yes
L7*	0.99	No	0.03	Yes
L8*	0.67	No	0	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A6: ADF test Sector 2 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.7	No	0	Yes
Y2	0.99	No	0.04	Yes
Y3*	0.63	No	0	Yes
Y4*	0.68	No	0	Yes
Y5*	0.99	No	0.02	Yes
Y6*	0.85	No	0	Yes
Y7**	0.99	No	0.02	Yes
Y8*	0.91	No	0	Yes
L1*	0.92	No	0	Yes
L2	0.78	No	0	Yes
L3*	0.74	No	0	Yes
L4*	0.67	No	0	Yes
L5*	0.89	No	0.02	Yes
L6*	0.97	No	0.04	Yes
L7*	0.99	No	0.03	Yes
L8*	0.7	No	0	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A7: ADF test Sector 3 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.7	No	0	Yes
Y2*	0.99	No	0	Yes
Y3	0.99	No	0.07	Yes
Y4*	0.27	No	0.01	Yes
Y5*	0.91	No	0.05	Yes
Y6*	0.85	No	0	Yes
Y7**	0.99	No	0	Yes
Y8*	0.67	No	0	Yes
L1*	0.87	No	0.01	Yes
L2*	0.89	No	0.04	Yes
L3	0.99	No	0	Yes
L4*	0.26	No	0.02	Yes
L5*	0.48	No	0.01	Yes
L6*	0.93	No	0.02	Yes
L7*	0.99	No	0.03	Yes
L8*	0.6	No	0	Yes

Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A8: ADF test Sector 4 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.57	No	0	Yes
Y2*	0.99	No	0	Yes
Y3*	0.6	No	0.01	Yes
Y4 ⁺	0.99	No	0.01	Yes
Y5*	0.59	No	0.01	Yes
Y6*	0.81	No	0.01	Yes
Y7 ⁺⁺	0.99	No	0	Yes
Y8*	0.52	No	0	Yes
L1*	0.88	No	0	Yes
L2*	0.93	No	0.01	Yes
L3*	0.58	No	0	Yes
L4	0.98	No	0.04	Yes
L5*	0.82	No	0	Yes
L6*	0.97	No	0.03	Yes
L7*	0.99	No	0.03	Yes
L8*	0.55	No	0	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A9: ADF test Sector 5 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.64	No	0	Yes
Y2*	0.99	No	0	Yes
Y3*	0.84	No	0.01	Yes
Y4 ⁺⁺	0.61	No	0.01	Yes
Y5*	0.99	No	0.02	Yes
Y6*	0.85	No	0.02	Yes
Y7 ⁺⁺	0.99	No	0	Yes
Y8*	0.78	No	0	Yes
L1*	0.88	No	0	Yes
L2*	0.68	No	0.01	Yes
L3*	0.86	No	0	Yes
L4*	0.65	No	0	Yes

L5*	0.95	No	0.04	Yes
L6*	0.85	No	0	Yes
L7*	0.99	No	0.03	Yes
L8*	0.75	No	0	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A10: ADF test Sector 6 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.95	No	0	Yes
Y2*	0.99	No	0.02	Yes
Y3*	0.83	No	0.02	Yes
Y4*	0.74	No	0	Yes
Y5*	0.99	No	0.02	Yes
Y6 ⁺	0.99	No	0.02	Yes
Y7 ⁺⁺	0.99	No	0	Yes
Y8*	0.99	No	0.03	Yes
L1*	0.99	No	0.01	Yes
L2*	0.86	No	0	Yes
L3*	0.95	No	0.01	Yes
L4*	0.85	No	0	Yes
L5*	0.78	No	0	Yes
L6	0.74	No	0	Yes
L7*	0.99	No	0.03	Yes
L8*	0.86	No	0.01	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A11: ADF test Sector 7 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.82	No	0	Yes
Y2*	0.97	No	0	Yes
Y3*	0.99	No	0,09	Yes
Y4*	0.99	No	0,05	Yes
Y5*	0.97	No	0,02	Yes
Y6 ⁺⁺	0.99	No	0	Yes
Y7 ⁺	0.99	No	0	Yes
Y8 ⁺⁺	0.99	No	0	Yes
L1*	0.79	No	0	Yes

L2*	0.67	No	0	Yes
L3*	0.94	No	0,01	Yes
L4*	0.92	No	0,01	Yes
L5*	0.82	No	0	Yes
L6*	0.99	No	0,01	Yes
L7	0.99	No	0,03	Yes
L8*	0.29	No	0,01	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A12: ADF test Sector 8 (Note: + denotes second difference)

Original Variables			First Differenced Variables	
Variables	p-value	Stationarity	p-value	Stationarity
Y1*	0.73	No	0	Yes
Y2*	0.99	No	0	Yes
Y3*	0.56	No	0.01	Yes
Y4*	0.26	No	0	Yes
Y5*	0.82	No	0.01	Yes
Y6*	0.98	No	0.03	Yes
Y7**	0.99	No	0	Yes
Y8**	0.99	No	0	Yes
L1*	0.54	No	0	Yes
L2*	0.23	No	0	Yes
L3*	0.31	No	0	Yes
L4*	0.3	No	0	Yes
L5*	0.84	No	0	Yes
L6*	0.56	No	0.04	Yes
L7*	0.99	No	0.03	Yes
L8**	0.99	No	0.01	Yes
Credit	0.1	Yes		
Trade	0.89	No	0	Yes

Table A13: Matrix Q for US economy for the year 1995

Sector s	1	2	3	4	5	6	7	8
1	119.14	0.57	-14.71	-8.81	208.63	107.03	71.75	1.89
2	8.10	361.77	61.34	12.97	65.26	125.08	70.09	23.10
3	5.57	11.94	2283.96	36.87	107.24	124.43	1660.22	76.99
4	4.02	5.64	78.71	710.01	50.34	63.89	391.24	36.29
5	5.38	1.96	49.69	42.92	4201.09	31.22	323.00	24.60
6	29.11	20.27	210.50	103.96	336.25	1694.70	1789.44	121.36
7	11.43	12.67	99.72	41.08	100.82	343.09	21769.84	429.05
8	0.02	0.66	20.40	3.39	9.96	21.76	227.25	2436.41

Table A14: Matrix Q for US economy for the year 2000

Sector s	1	2	3	4	5	6	7	8
1	141.85	0.04	-35.90	-22.26	426.81	137.01	47.84	-2.11
2	14.20	498.28	124.65	23.80	87.58	204.53	249.20	50.48
3	10.32	8.94	3601.53	61.45	158.50	179.77	758.83	64.46
4	4.92	3.36	45.71	1223.40	29.96	29.65	273.54	23.39
5	6.85	3.16	96.31	69.36	6539.99	56.71	458.88	35.48
6	28.68	25.63	273.95	182.63	427.18	2321.09	2035.91	125.59
7	17.14	28.98	308.70	115.12	353.68	806.56	39202.54	695.52
8	2.43	5.55	46.91	32.42	69.69	163.60	1304.63	2691.96

Table A15: Matrix Q for US economy for the year 2005

Sector s	1	2	3	4	5	6	7	8
1	187.10	0.51	-63.43	-39.46	674.51	296.24	-37.25	-25.71
2	18.76	748.28	251.14	46.89	146.51	442.32	580.00	83.78
3	10.29	11.42	5905.73	92.61	252.55	310.14	1393.11	131.49
4	5.41	4.01	80.68	2116.26	38.70	48.22	558.65	58.66
5	8.17	4.08	161.22	122.39	9904.94	78.39	966.18	90.77
6	29.24	36.79	467.39	328.61	691.09	3296.05	4550.47	450.53
7	20.77	34.37	265.89	128.83	385.76	990.89	72175.80	1248.84
8	2.64	9.24	110.81	64.00	120.21	262.94	2908.37	9133.89

Table A16: GVAR Estimation Effects of Foreign Variables on their sector-specific counterparts

	Y1	L1	Y2	L2	Y3	L3	Y4	L4	Y5	L5	Y6	L6	Y7	L7	Y8	L8
Y1*			-14.59	-68.02	-5.86	22.21	38.17	263.71	-1.34	10.49	-3.68	-453.7	23.8	-70.17	-50.77	-14.47
t-stat			-0.57	-2.14*	-1.03	0.7	3.64*	1.89*	-0.75	0.55	-1.4	-3.57*	1.2	-0.62	-1.27	-0.17
L1*			-3.4	-18.5	0.92	27.43	22.9	162.55	0.54	8	-1.77	-241.07	-11.59	25.57	-41.51	-115.45
t-stat			-0.36	-1.58	0.23	1.78*	5.11*	2.72*	0.69	1.07	-1.74*	-4.92*	-2.59*	0.75	-1.51	-2.09*
Y2*	7.84	83.5			3.01	6.32	21.48	112.63	9.86	-14.59	1.11	88.42	11.85	25.17	116.59	27.23
t-stat	0.7	1.71*			1.87*	0.71	2.28*	0.9	-1.45	-0.2	0.89	1.48	4.07*	1.34	9.45*	1.1
L2*	3.2	4.83			-1.9	20.72	21.63	117.7	-12.74	54.57	4.56	-560.17	20.03	-13.84	-126.65	-260.9
t-stat	0.4	0.14			-0.46	0.98	1.34	0.54	-1.09	0.44	2.34*	-5.06*	3.71*	-0.43	-2.99*	-3.05*
Y3*	4.12	-83.78	-2.95	8.93			65.14	1080.94	49.15	480.62	5.34	1933.26	-14.68	-20.03	386.1	404.18
t-stat	0.37	-2.13*	-0.64	1.47			1.77*	2.33*	1.48	1.36	0.46	3.05*	-4.46*	-0.94	1.84*	1.24
L3*	-0.42	6.84	0.71	-1.31			-4.67	-110.98	-14.67	-57.05	-2.68	-342.28	0.11	-3.14	-25.68	-75.82
t-stat	-0.36	1.33	0.79	-1.41			-0.97	-1.73*	-1.74*	-0.57	-1.17	-3.09*	0.22	-0.97	-1.58	-2.32*
Y4*	-2.35	25.33	-6.04	-4.67	-5.17	109.75			21.17	222.44	-1.46	375.77	-2.75	7.35	48.64	287.05
t-stat	-2.11*	5.24*	-2.87*	-1.78*	-1.79*	6.8			1.33	6.16*	-2.76*	14.78*	-3.04*	1.25	2.44*	7.14*
L4*	0.45	-4.33	-0.61	2.32	0.81	-8.32			2.69	-12.12	0.24	-33.5	1.61	-1.26	11.54	-7.02
t-stat	0.66	-1.44	-0.49	1.49	0.91	-1.68*			1.91*	-0.81	1.38	-3.89*	5.58*	-0.52	2.76*	-1.09
Y5*	-0.42	4.07	2.17	-2.73	-10.66	38.03	13.42	-13.09			-5.2	-262.43	3.38	23.95	-123.88	-131.49
t-stat	-0.38	1.74*	0.6	-0.6	-1.47	1.09	1.91*	-0.14			-4.05*	-3.98*	1.17	1.28	-3.04*	-1.6
L5*	0.03	-0.36	-0.39	-0.45	0.74	2.65	-1.22	23.77			0.5	9.97	-0.58	-1.62	7.77	6.92
t-stat	0.48	-1.22	-0.73	-0.9	1.29	0.82	-1.38	2.13*			3.69*	1.51	-2.11*	-0.9	3.5*	1.51
Y6*	0.09	50.1	1.47	-9.85	3.3	-71.82	-8.09	-115.04	-7.18	-76.66			0.92	-1.27	-66.83	-57.98
t-stat	1.12	1.76*	0.29	-1.27	0.35	-1.73*	-1.2	-1.14	-0.95	-0.95			2.17*	-0.46	-3.82*	-1.64*
L6*	0.09	-0.77	-0.71	0.17	0.15	0.14	-0.79	0.53	0.11	0.91			0.17	0.27	3.02	-0.98
t-stat	1.03	-2.1*	-0.73	1.74*	1.8*	0.33	-1.98*	1.01	1.27	0.85			4.49*	1.07	8.02*	-1.3

Y8*	26.4	-217.92	2.48	27.1	3.78	-27.71	-26.44	-255.7	-39.06	47.87	4.29	306.78	4.45	-8.84		
t-stat	1.36	-2.59*	0.29	1.65*	0.45	-0.59	-3.13*	-2.27*	-1.83*	0.24	1.32	2.01*	2.17*	-4.71*		
L8*	-1.48	11.27	0.17	-0.6	-0.22	1.43	1.67	21.1	4.68	8.94	-0.42	-30.5	-0.92	-1.65		
t-stat	-1.22	2.13*	0.29	-0.66	-0.62	0.7	2.22*	2.09*	1.8*	0.31	-1.5	-2.22*	-3.27*	-0.91		
Trade	0	-0.01	0.01	0.01	0	0	0	-0.01	0	0	-0.01	0.01	-0.01	0	-0.01	0
t-stat	0.48	-4.05*	1.55	2.35*	0.2	-1.12	-1.32	-1.67*	0.45	0.04	-2.77*	2.56*	-5.01*	-0.08	-3.36*	0.12
Credit	0	0	0	-0.01	0.01	0.01	0	0.01	0	0	0.01	-0.01	0.01	0	0.01	0
t-stat	0.1	0.42	0.36	-2.83*	2.16*	2.16*	-0.28	3.22*	0.45	-0.32	4.28*	-3.39*	4.22*	0.55	5.01*	0.41

*: denotes statistical significance at the 10% or higher

