GVAR Toolbox 2.0

User Guide

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PREFACE

The GVAR Toolbox 2.0 represents a considerable advance over the earlier versions of this package. It contains a number of new features for the purpose of global VAR modelling, comprising a set of Matlab procedures executed via an Excel-based interface. This document describes how to run and use the GVAR Toolbox 2.0, with the aim of building a global VAR model that allows for global interlinkages. In addition, it contains details of the underlying econometric and computing methods.

This document consists of two parts:

Part I takes the user through the processes involved in building a GVAR model using this software. The GVAR methodology is demonstrated using the recently updated version of the GVAR database covering the period 1979Q1-2013Q1.

Part II (Technical appendices) provides a review of the underlying econometric techniques used in the development and analysis of a GVAR model. It also provides a detailed outline of the data sources and methods used in the compilation, revision and updating of the GVAR database to its most recent version.

In developing the GVAR Toolbox 2.0 we have benefited greatly from comments, suggestions and input by M. Hashem Pesaran as well as from feedback by many GVAR Toolbox users, including participants of the GVAR modelling course organised by the Global Economic Modelling Network (Ecomod). We are especially grateful to the beta tester of the toolbox Kamiar Mohaddes for his helpful feedback on preliminary versions of the package.

Our special thanks goes to the Inter-American Development Bank, and in particular Rodrigo Mariscal, Ambrogio Cesa Bianchi and Alessandro Rebucci for providing us with the updated 1979Q1-2013Q1 GVAR database. It can be downloaded either as part of the toolbox or separately in source form at: https://sites.google.com/site/gvarmodelling/data. The updated GVAR data are included in the variable worksheets of the demo interface files of the toolbox with all transformations performed as described in Dees, di Mauro, Pesaran and Smith (2007). Transformations for all commodity price indices follow those of the oil price.

Finally, we would like to thank Meiling He for her assistance during the early stages of preparing this version of the toolbox. L. Vanessa Smith acknowledges financial support from the ESRC Grant No. ES/I031626/1.

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Part I

Global VAR Modelling using the GVAR Toolbox

1. INTRODUCTION

1.1 What is a GVAR model?

The GVAR (Global Vector AutoRegressive) methodology is a relatively novel approach to global macroeconomic modelling that combines time series, panel data, and factor analysis techniques to address a wide set of economic and financial issues ranging from policy analysis to risk management.

The associated GVAR model is a global model combining individual country vector error-correcting models, in which domestic variables are related to country-specific foreign variables in a consistent manner. The latter are constructed from the domestic variables so as to match the international trade, financial or other desired pattern of the country under consideration, and serve as a proxy for common unobserved factors. This compact model of the world economy relies exclusively on observables, which typically include macroeconomic aggregates and financial variables.

Some key advantages of the GVAR modelling approach are that it:

- Allows for interdependence at a variety of levels (national and international) in a transparent way that can be empirically evaluated
- Allows for long-run relationships consistent with the theory and short-run relationships that are consistent with the data
- Provides a coherent, theory-consistent solution to the curse of dimensionality in global modelling.

The GVAR methodology provides a general yet practical global modelling framework for the quantitative analysis of the relative importance of different shocks and channels of transmission mechanisms. This makes it a suitable tool for policy analysis. Its use, however, is much broader.

The GVAR model has been used to analyse credit risk in Pesaran, Schuermann, Treutler and Weiner (2006) and Pesaran, Schuermann and Treutler (2007). An extended and updated version of the GVAR by Dees, di Mauro, Pesaran and Smith (2007) (hereafter, DdPS), which treats the euro area as a single economic area, was used by Pesaran, Smith and Smith (2007) to evaluate the UK entry into the euro. Pesaran, Schuermann and Smith (2009a, 2009b) evaluate the forecasting performance of the GVAR model. Further developments of a global modelling approach are provided in Dees, Pesaran, Smith and Smith (2013). The GVAR Handbook edited by di Mauro and Pesaran (2013) provides a review of many other applications of the GVAR approach. See also Chudik and Pesaran (2014) for a survey of the latest developments in GVAR modelling, including both the theoretical foundations of the approach and its numerous empirical applications.

The GVAR Toolbox can be used either with the existing DdPS-GVAR structure or variants of it, or as a very general modelling framework for any large system where components are driven by weighted averages of other components - whatever the data. In principle, it can be used with as many or as few countries (greater than two) as desired, so long as the weak exogeneity assumptions required are satisfied. The approach can be equally applied to regions, states, firms or regional housing markets to name a few possibilities.

1.2 What is the GVAR Toolbox 2.0?

The GVAR Toolbox 2.0 is the third release of a collection of Matlab procedures designed for the purpose of GVAR modelling. The procedures operate by processing information inputted by the user throughout the course of the program via an Excel-based interface. Using an Excel-based platform makes this tool easy to use, with no knowledge of programming required. This document aims to guide the user in developing, estimating and analysing GVAR models using the GVAR Toolbox 2.0.

The GVAR Toolbox is available to download, free of charge, from the website (https://sites.google.com/site/gvarmodelling/gvar-toolbox). Please acknowledge any use of the GVAR Toolbox by citing it as: Smith, L.V. and A. Galesi (2014), GVAR Toolbox 2.0, https://sites.google.com/site/gvarmodelling/gvar-toolbox.

1.3 New Features of the GVAR Toolbox 2.0

The GVAR Toolbox 2.0 represents a considerable advance over the earlier versions of this package. The new options and changes in the GVAR Toolbox 2.0 include the following:

- Different weights (e.g. trade, financial, and so on) can be used for different variables when computing the country-specific foreign variables
- Instead of inputting the maximum order of the GVAR model (p), the user is now required to input the maximum lag order of the domestic (p_i) and foreign variables (q_i) of the individual country models, from which the maximum order of the GVAR is then computed. The conditions that $q_i \leq p-1$ and $q_i \leq p_i$ for each country (for $p > 1$) during the lag order selection of the individual models have been removed.
- Specification of the weak exogeneity regressions based on model selection criteria
- A shrinkage estimator applied to the correlation matrix of the GVAR model residuals with the associated shrinkage parameter computed internally by the program†
- Orthogonalised impulse responses
- GVAR model (ex-ante and conditional) forecasts†
- Trend/Cycle decomposition of the GVAR
- Including a dominant unit in the GVAR model

†A shrinkage estimator and ex-ante forecasts were also included in version 1.1 of the GVAR Toolbox. The former can still be implemented in this version of the toolbox. The latter have been updated allowing the forecasts to be subjected to lower bounds, most notably for any interest rate variables included in the GVAR model.

1.4 System requirements for the GVAR Toolbox 2.0

The GVAR program works under the operating system of Microsoft Windows. It features an interface based on Microsoft Excel, and it relies on a set of Matlab routines for execution. Thus, in order to use it, both Microsoft Excel and Matlab have to be installed on the user's computer. No specific Matlab toolboxes are required for running the program.

The GVAR program has been tested using several versions of Microsoft Excel and Matlab, the oldest being the 2003 and 7.1 releases, respectively. The program is designed in such a way that the user is not required to have specific background knowledge of these two programs.

2. INSTALLING THE FILES

Download the **GVAR_Toolbox2.0_August2014.zip** file from https://sites.google.com/site/gvarmodelling/gvar-toolbox and unzip it in a directory of your choice. The chosen directory will then become your 'working directory' where the unzipped folder **GVAR_Toolbox2.0_August2014** can now be found. Note that if the chosen directory path name is too long or complex, an error message is likely to occur.

Within the unzipped **GVAR_Toolbox2.0_August2014** folder, you will find a subfolder named **GVAR_Toolbox2.0** and a text file named **License.txt**. All users should read the **License.txt** file and ensure they agree to the Terms and Conditions contained within before using the software.

The **GVAR_Toolbox2.0** folder contains four files and six subfolders. The four files comprise one Matlab script file and three Excel files. Each Excel file serves as an interface for the program. (An interface file is where most of the data are stored, and where the settings and specifications are defined throughout the GVAR analysis.) The files are:

- **gvar.m:** a Matlab script file which contains all the functions needed for performing the GVAR analysis.
- **gvarBriefDemo.xls:** contains the data, and includes a minimal number of predefined settings and specifications available, associated with DdPS. No pauses will be made by the program when using this interface file, nor will the user be requested to intervene at any stage to check intermediate results and/or provide any input. It is recommended that the brief demo be used for the first trial run of the program. The output produced can be found in the Output Brief Demo folder.
- **gvarFullDemo.xls:** contains the data, and includes the full set of predefined settings and specifications available. A number of pauses will be made by the program when using this interface file and the user will be required to intervene at certain instances to provide input and/or check intermediate results, guided by the information displayed in the Matlab command window. Working with this interface file will take the program longer to run compared to gvarBriefDemo.xls. It is recommended that the user works with the full demo, in order to gain a better understanding of the program and its full potential, having first used the brief demo. The output produced can be found in the Output Full Demo folder. This interface file is used as an illustration in this guide.
- **gvarExperiment.xls:** contains the data and the defined countries, regions and variables, associated with DdPS, but with no predefined settings or specifications. This interface file allows the user to experiment with defining the settings and specifications. When running this file for the *first* time, the user must enable the 'Run the program with pauses' function, found under the first set of settings in the MAIN worksheet. (This is to enable the user to enter the required specifications.) Details on the individual settings/functions can be found in Chapter 5. If you wish to only use a subset of the included countries in your analysis, please read Chapter 4, and make sure that the provided databases are adjusted accordingly.

The six subfolders within the Toolbox are:

- **Codes**: contains all Matlab routines (m-files) required by the **gvar.m** script. Unless you wish to modify the functioning of the program, you are not required to work with files contained in this folder.

- **Flows**: contains a **flows.xls** file which includes the annual flows data (1980-2013). It serves as a database for the computation of the weight matrices, used in turn for constructing the foreign variables and putting together the GVAR model.[1]
- **Output of Demos**: contains two further subfolders **Output Brief Demo** and **Output Full Demo** that contain the output results from using the demo interface files. Specifically:
  - **Output Brief Demo:** contains all the output produced when using the gvarBriefDemo.xls interface file. See Chapter 6 for an explanation of how the output is presented.
  - **Output Full Demo:** contains all the output produced when using the gvarFullDemo.xls interface file. A description of this is provided in Chapter 6.
- **Samples**: contains copies of the sample files for the GVAR analysis. The sample files, **gvarBriefDemo.xls, gvarFullDemo, gvarExperiment.xls** and **flows.xls,** are contained within the subfolder **DdPS**. These files include the specifications and updated data (1979Q1-2013Q1) for the GVAR model estimated in DdPS.[2]
- **Tech**: contains technical files required for the functioning of the program. Specifically, **coint_critvalues.xls** contains the critical values used for the cointegration tests (taken from MacKinnon, Haug and Michelis, 1999), and **girfs_graphs.xls** and **girfs_graphs_bs.xls** are used for plotting the impulse responses. The user is not required to modify files contained in this folder.
- **Template**: contains blank templates of the interface **gvar.xls** and **flows.xls** file for those wishing to build a GVAR model from scratch.

To run the program, there must be an **Excel interface** file and a **flows.xls** file in the **GVAR_Toolbox2.0** folder and the **Flows** subfolder, respectively.[3] Thus, the toolbox contains precompleted files in the correct folders, so that users can immediately start familiarising themselves with the program.

The country and variable specification in the demo interface files is taken largely from the GVAR model in DdPS, using the (1979Q1-2013Q1) GVAR dataset. The DdPS model features 33 countries with eight of them modelled as a single region (the euro area), a set of country-specific variables (real GDP, CPI inflation, real equity price, real exchange rate, the short-term interest rate and the long-term interest rate), and a global variable (the oil price). Two additional global variables (agricultural raw material and metals price indices) are included in the demo interface files.

It is recommended that all users read Chapter 3. Thereafter:

- To run the program using a demo interface file:
  - Double click on the gvar.m file. The Matlab command window and the editor window will open. You can close the editor as you are not required to modify the **gvar.m** script in order to run the program.

[1]The flows for 2013 were not yet available when the flows file was updated. Thus, these were completed by the flows of 2012.

[2]The exception is that the oil price is no longer included in the US model as in DdPS, but rather enters the ‘dominant unit’ model along with additional global variables. This is for demonstration purposes of the new features.

[3]While the Excel interface file can have any name, this is not the case for the flows.xls file. Whether the existing flows data or an alternative dataset is used, this file should always have the name flows.xls.

  - Click by the prompt in the Matlab command window, type **gvar** and press enter.
  - Follow the instructions in the command window.

- To run the program using gvarExperiment.xls or any other interface file, go to Chapter 5.
- To build a GVAR model from scratch, i.e. importing the data and initial inputs required *before* running the program, go to Chapter 4.

3. RULES, LIMITATIONS AND OTHER ESSENTIAL INFORMATION

Before going through the individual steps involved in using the program, it is useful to summarise some notational rules and other practices, which must be followed at all times.

3.1 Labelling rules

There is a set of conventions for the labels entered in any interface file that should be followed throughout. For example, names should always be in upper case (capitals) and short names in lower case. The rules for label names are listed in Table 3.1 below for easy reference.

Table 3.1 Labelling rules and conventions

Field Name	**Format**	**Example**	**Notes**
country name region name variable name	upper case	CANADA EURO INFLATION	can contain spaces but must not start with a number or contain symbols
country short name region short name variable short name	lower case	can euro[a] dp[b]	must not contain spaces, symbols or numbers
country code	integer only	112	
dates	yyyyMmm yyyyQq yyyy	2001M11 2001Q4 2001	for monthly data for quarterly data for annual data

Notes: [a] The country name and country short name can be the same, as long as they are in upper case and lower case, respectively. [b] The variable short names could also be in upper case format, for example DP, or in a combination of upper and lower case, for example Dp, however lower case is recommended.

3.2 Size limitations

Table 3.2 summarises the maximum number of individual models, as well as the maximum number of domestic, foreign and global variables, permitted in the current version of the program.

Table 3.2 Size limitations

	Max. no. can input into the interface file	**Max. no. can use in the modelling stage**
Individual models	N-1[c]	N-1
Country-specific variables	20[d]	any 12 domestic[e,g] any 8 weakly exogenous[f,g]
Global variables	10[d]	Subject to the above constraints on domestic and weakly exogenous variables

Notes: [c] N denotes the number of columns per worksheet permitted by your version of Excel. In each worksheet for the variables, one column is required for the date field. Thus, you can only have up to N-1 individuals models. [d] These are capped based on the design of the interface file. [e] This includes any global variable(s) treated as domestic. [f] This includes all foreign-specific and any global variable(s) treated as weakly exogenous. Note that all foreign-specific variables included in the invidivual models at the estimation stage are treated as weakly exogenous. For details of the individual model structure and weakly exogenous variables see the Appendix to this user guide. [g] The critical values provided for the cointegration tests only cover a matrix of 12 domestic by 8 weakly exogenous variables. Users are not, therefore, limited here by the capability of the program per se, and could expand the critical values matrix currently available, if required. These can be generated by using the Fortran program provided by Mackinnon, Haug and Michelis (1999). However, one should consider the degrees of freedom available when choosing to increase the number of variables included in the individual models.

3.2.1 Other information

- Interface files corresponding to previous releases of the toolbox are not compatible with this release and should not be used.
- The interface files included in the toolbox contain a number of values hidden within the cells of the white coloured columns that separate the different input panels. These serve as links to the Matlab code and their deletion will result in program errors. Caution is therefore required when deleting input from the interface files so that this does not extend to the white coloured columns.
- All excel files (with the exception of the interface file) used within the toolbox should have the extension .xls. Therefore any .xlsx files should be converted to .xls. While the program can handle .xlsx interface files it is recommended that these be converted to .xls files too because they reduce the computational speed of the program considerably.
- Up to ten sets of different weights can be used for computing the foreign variables, and six for computing the feedback variables that enter the dominant unit model. These numbers can be further extended. Please contact the gvar helpdesk for this purpose.
- You cannot run the Matlab script if the relevant Excel files are open. Thus, you must get into the habit of saving and closing the files before running the Matlab script. In fact, it is recommended that Excel is completely closed before doing so.

- When defining the *settings* for the program, white cells within the interface file and flows.xls file require you to fill in data, and blue cells contain information for you generated by the program. However, there are points, typically within the specification phases, where it is essential that you do not enter data into blank (empty) cells, so please read the instructions for each stage carefully.

- Dropdown menus are found in many of the fields in the interface file where you define the program settings.

  – The dropdown menus are not apparent until you click within the field.

  – These fields are compulsory, and not completing them will result in an error message and cause the program to terminate.

  – You can type entries in these fields rather than selecting an option from the menu, if you prefer. The program will inform you if you have made an invalid entry.

  – For dropdown menus with the options 1 or 0: 1 means yes, enable that function, and 0 means no or disable that function.

- Flows data can only be used at the annual frequency, while data for the variables of the individual models can be used at the annual, quartely or monthly frequency. Furthermore, it is not required that data be available for all variables in the individual models.

- If you select one type of weights, it doesn't matter whether you leave the fields related to alternative choices blank, as the program will ignore them by default. This feature generally holds for all the settings in the interface file.

- Similarly, if you put a zero in a field indicating that you do not wish to carry out a particular function, the program will ignore any other information relating to that function that you may have entered, meaning you can temporarily disable functions as you please. For example, you can define the settings for a test you wish to ultimately run, but switch it off temporarily. Thus, your settings will be there ready for future use but your analysis will run more rapidly in the meantime.

- As an indication of the time it takes to carry out a GVAR analysis using this program: working on a machine of the following specification: Intel Core i7-2620M CPU at 2.70 GHz with 6 GB of RAM memory, it takes on average 60-90 minutes to obtain estimates and confidence bands for two or three shocks using 2000 bootstrap replications. If bootstrapped critical values for structural stability test statistics are also computed, then the process will take a couple of hours.

4. BUILDING A GVAR MODEL FROM SCRATCH: INITIAL INPUTS AND DATA

To build a GVAR model from scratch copy the template interface file **gvar.xls** and cross-country flows file **flows.xls** from the **Template** folder, and paste them into **GVAR_Toolbox2.0**\ and **GVAR_Toolbox2.0****Flows**\ respectively. Your next steps are to input the necessary labels and to import the data.

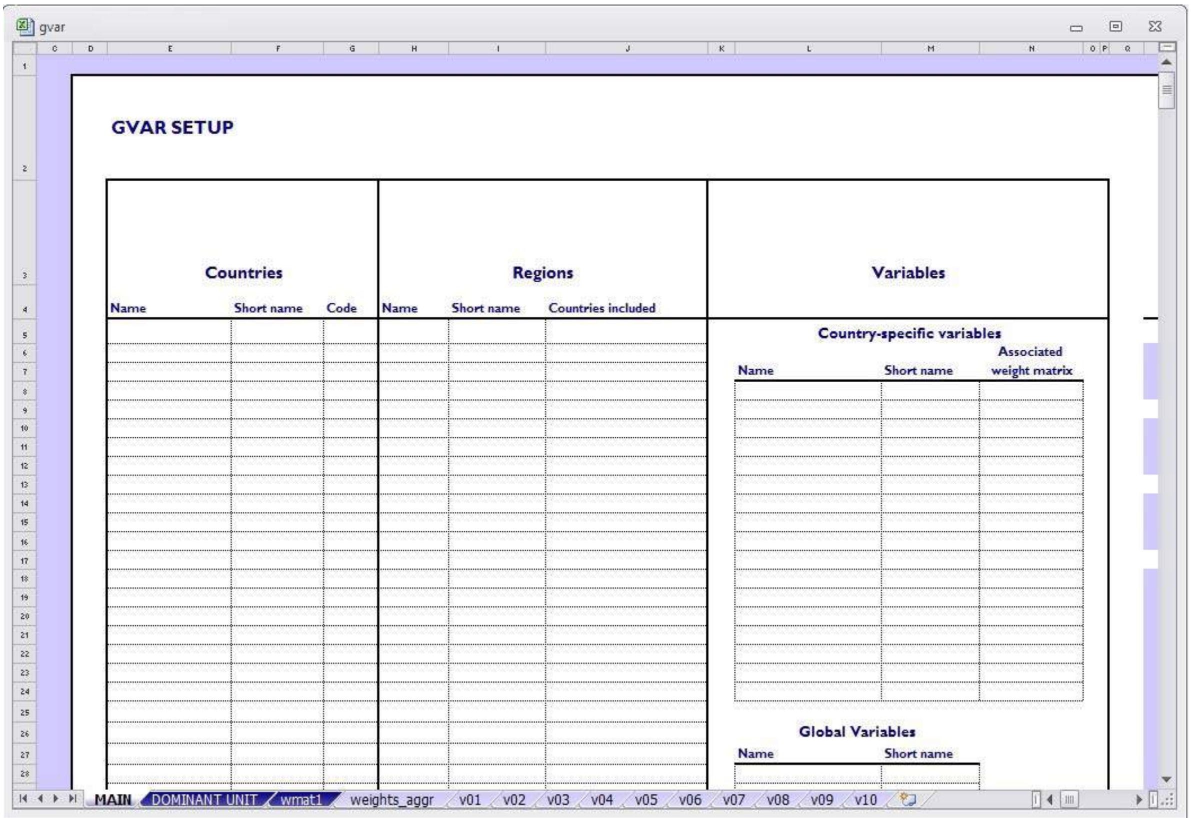
4.1 Defining the countries, regions and variables

In defining the countries, regions and variables, you will need to follow the labelling rules as provided in Table 3.1 of the previous section. Please refer to Table 3.2 for details of the maximum number of countries and variables.

1. Open **GVAR_Toolbox2.0****gvar.xls**. It includes three worksheets with dark blue tabs (called **MAIN**, **DOMINANT UNIT**, **wmat1**) as shown in Figure 4.1. The distinct tab colouring of these worksheets indicates that they are essential to the running of the program and should never be deleted. There are also several empty worksheets with light blue tabs for storing the data used in the analysis.

2. Go to the **MAIN** interface worksheet.

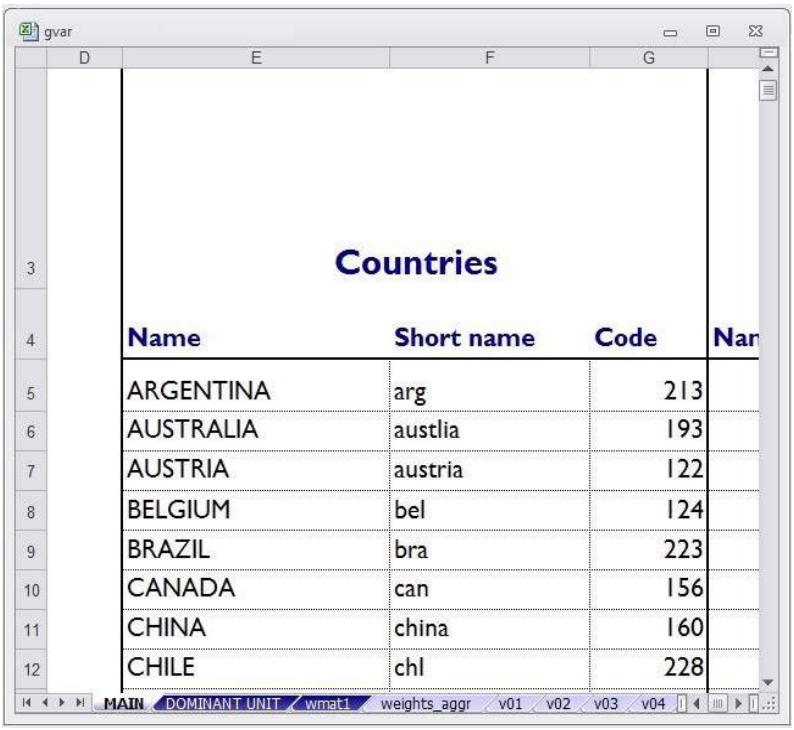
Figure 4.1 The MAIN interface worksheet



3. **Define the list of countries to be used in the GVAR analysis:** Columns E-G correspond to the list of countries in the GVAR model. Fill column E with the **country names**. Column F is for **country short names**. The country ordering provided here will generally be maintained for conducting the GVAR analysis and arranging the output (except in the case where regions are constructed, to be discussed next). If the main weight matrix, which corresponds to worksheet wmat1, is to be constructed from within the program (either using the existing flows database or a database inputted by the user), then column G should be filled with integers which will be referred to as **country codes**. Country codes are used for extracting the flows data used for computing the weight matrices. If you wish to import your own weight matrix, the country codes column can be left blank.

   Figure 4.2 provides an example, showing the country names (upper case) and the country short names (lower case). As the main weight matrix will be constructed by the program, the country codes have also been inserted.[1]

Figure 4.2 Defining the list of countries



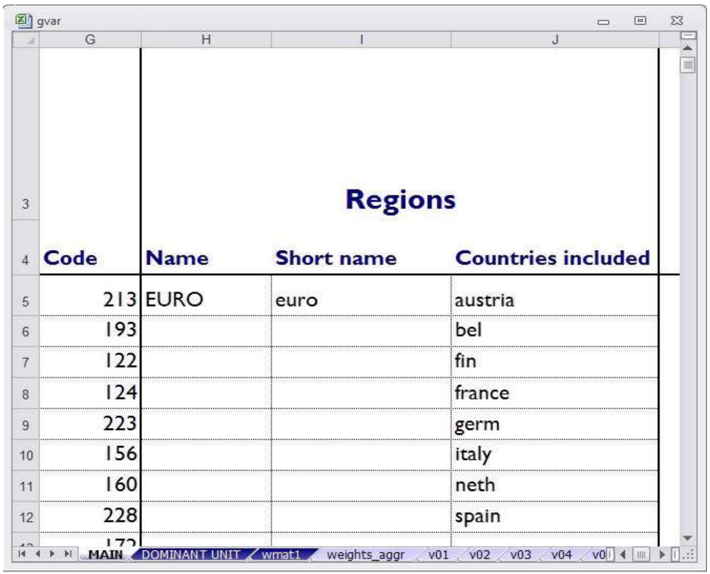
Name	Short name	Code
ARGENTINA	arg	213
AUSTRALIA	austlia	193
AUSTRIA	austria	122
BELGIUM	bel	124
BRAZIL	bra	223
CANADA	can	156
CHINA	china	160
CHILE	chl	228

4. **Define the list of regions for the GVAR analysis:** This step is optional. If you want to aggregate several countries into regions at the outset of the analysis, complete columns H-J, otherwise leave these columns blank. For illustration, we follow DdPS and aggregate eight euro area countries into a single euro region (see Figure 4.3). Column H is filled with a name for the region, referred to as **region name**. Fill column I with the **region short name**. In column J, list the countries you want to aggregate, one per row. Start the list in the same row as the region name (here, cell J5) using the **country short names** as previously defined in column F. Ensure that the list of country short names that comprise each region is in alphabetical order. The region names in column H or I need not be in alphabetical order. Note that you only need to enter the region once, in the first row. In the case where regions

[1]Here, the IFS country codes have generally been used but this is not a requirement.

are defined, the program will use the alphabetical order of the country and region short names for conducting the GVAR analysis and arranging the output.

Figure 4.3 Defining a region

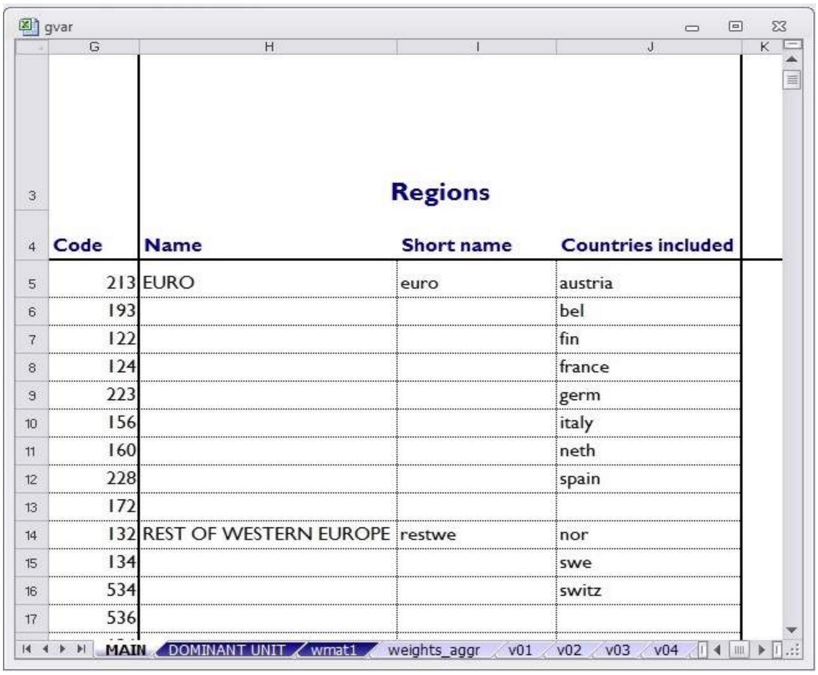


Regions

Code	Name	Short name	Countries included
213	EURO	euro	austria
193			bel
122			fin
124			france
223			germ
156			italy
160			neth
228			spain

If you want to create a second region, leave a blank row after the last filled cell in column J before starting again. You must leave a blank row to separate the regions lists. If there is no blank cell in column J, the program will consider these countries as belonging to the same region. There is no limit to the number of regions you can construct. Figure 4.4 shows an example of two regions being defined.

Figure 4.4 Defining multiple regions



Regions

Code	Name	Short name	Countries included
213	EURO	euro	austria
193			bel
122			fin
124			france
223			germ
156			italy
160			neth
228			spain
172			
132	REST OF WESTERN EUROPE	restwe	nor
134			swe
534			switz
536			

5. **Define the list of variables included in the GVAR analysis:** Columns L-M are for the country-specific and global variables. Column L is for the **variable names** and column M for the **variable short names**. Discussion of column N and the required input will be deferred to Section 5.1. Figure 4.5 shows how this would look following our example.

Figure 4.5 Defining country-specific and global variables

Variables

Country-specific variables

Name	Short name	Associated weight matrix
REAL GDP	y	
INFLATION	Dp	
REAL EQUITY PRICES	eq	
REAL EXCHANGE RATE	ep	
NOMINAL S RATE	r	
NOMINAL L RATE	lr	

Global Variables

Name	Short name
OIL PRICE	poil
RAW MATERIAL PRICE	pmat
METAL PRICE	pmetal

4.2 Importing the data

The next step is to import the data. The following data should be imported into the gvar.xls file:

- The data for all the variables, with all required transformations (e.g. taking logs, converting per annum interest rates to quarterly ones and so on) already performed.[2]

- The data used to construct the weights for aggregating the variables of the countries comprising a region (in order to compute the regional variables), and for aggregation of the country-specific impulse responses and variance decomposition results.

  For the weights used to construct the foreign variables and solve the GVAR model, you can use a program built matrix constructed from the flows data, or a user-provided matrix:

- For the program built option, if you only wish to use the existing cross-country flows database throughout the analysis, no further action is required. If you wish to import your own cross-country flows database for this purpose, you need to input the data into the flows.xls file. If you would like to use additional weight matrices for constructing the foreign variables these have to be provided by the user.

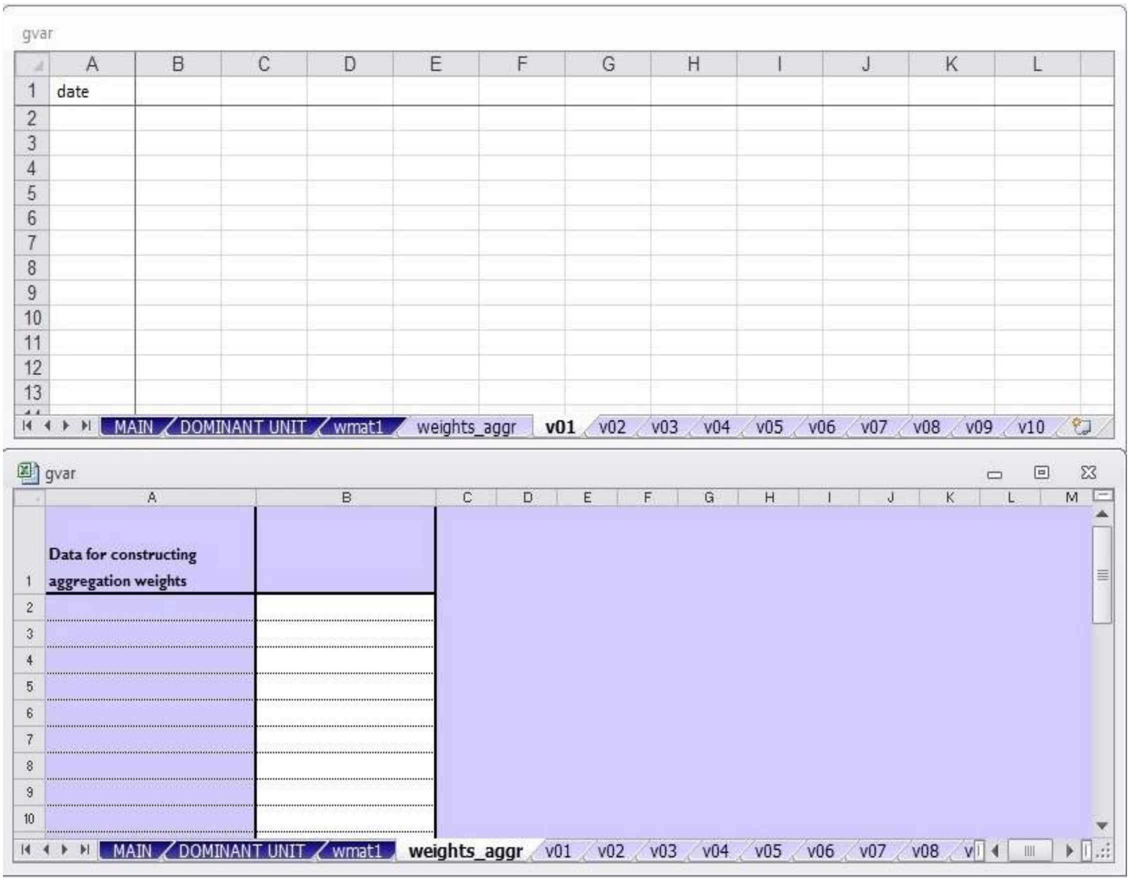
- If you wish to utilise one or more user-provided weight matrices, these need to be imported into the gvar.xls file.

[2] These must be performed before importing the data, and can be done either in extra worksheets created within gvar.xls, or in a separate file. Appendix B describes procedures for the interpolation of data and assessment of seasonal components, should these be required.

4.2.1 Importing variables and aggregation weights data

1. In gvar.xls, you will see eleven worksheets with light-blue tabs as shown in Figure 4.6. Ten are labelled **v01**, **v02**,...,**v10**. These are referred to as **variable worksheets**, as each stores data for one variable. The eleventh worksheet (labelled **weights_aggr**) is the **aggregation weights worksheet**. It stores data (e.g. Purchasing Power Parity (PPP) GDP of each country) used to construct the weights for aggregating the country variables into regional ones, and the country-specific impulse responses and forecast error variance decompositions into their regional counterparts (see Section A.4 for the construction of these weights).[3]

Figure 4.6 Variable and aggregation weights worksheets

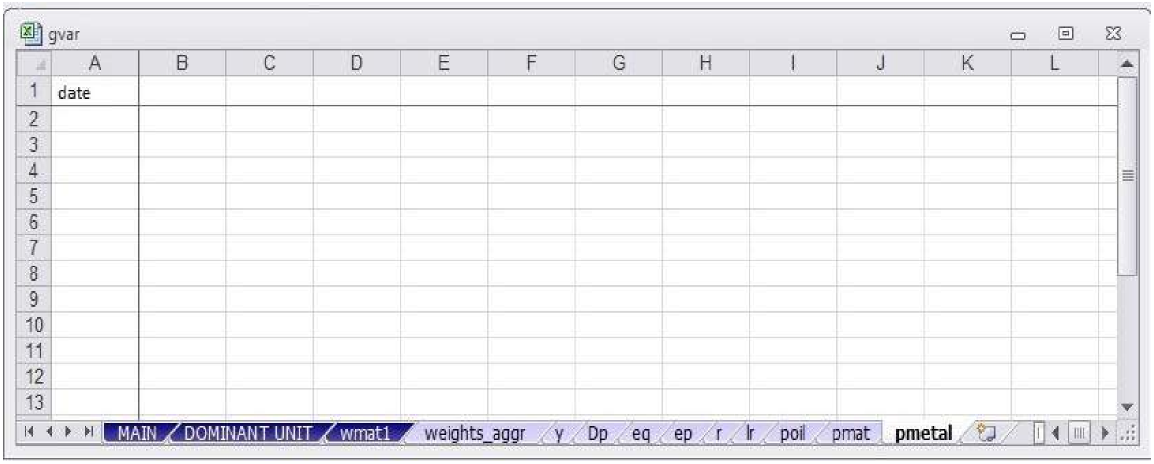


2. **Rename the variable worksheets** according to the **variable short names** defined earlier. Each variable worksheet will contain a particular variable, be it a country-specific or global one. If you have fewer than ten variables, you can ignore or delete the unused variable worksheets. If you have more than ten variables, add new worksheets by copying the existing ones, up to a total of 30 (the sum of country-specific (domestic) and global variables imported cannot exceed 30). It is essential that the *names* of the worksheets exactly match the variable short names listed in the MAIN worksheet. However, the order in which the worksheets appear does not have to match the order in which the variables were previously defined, although it is recommended that you maintain consistency throughout.

[3] Note that the weights used for computing the regional variables, here the PPP-GDP weights are not the same as the weights (constructed from the flows data) used for computation of the country-specific foreign variables.

In our example, we have six country-specific variables and three global variables. Thus, nine variable worksheets have been renamed with their variable short names, and the remaining one has been deleted (Figure 4.7).

Figure 4.7 Renaming variable worksheets

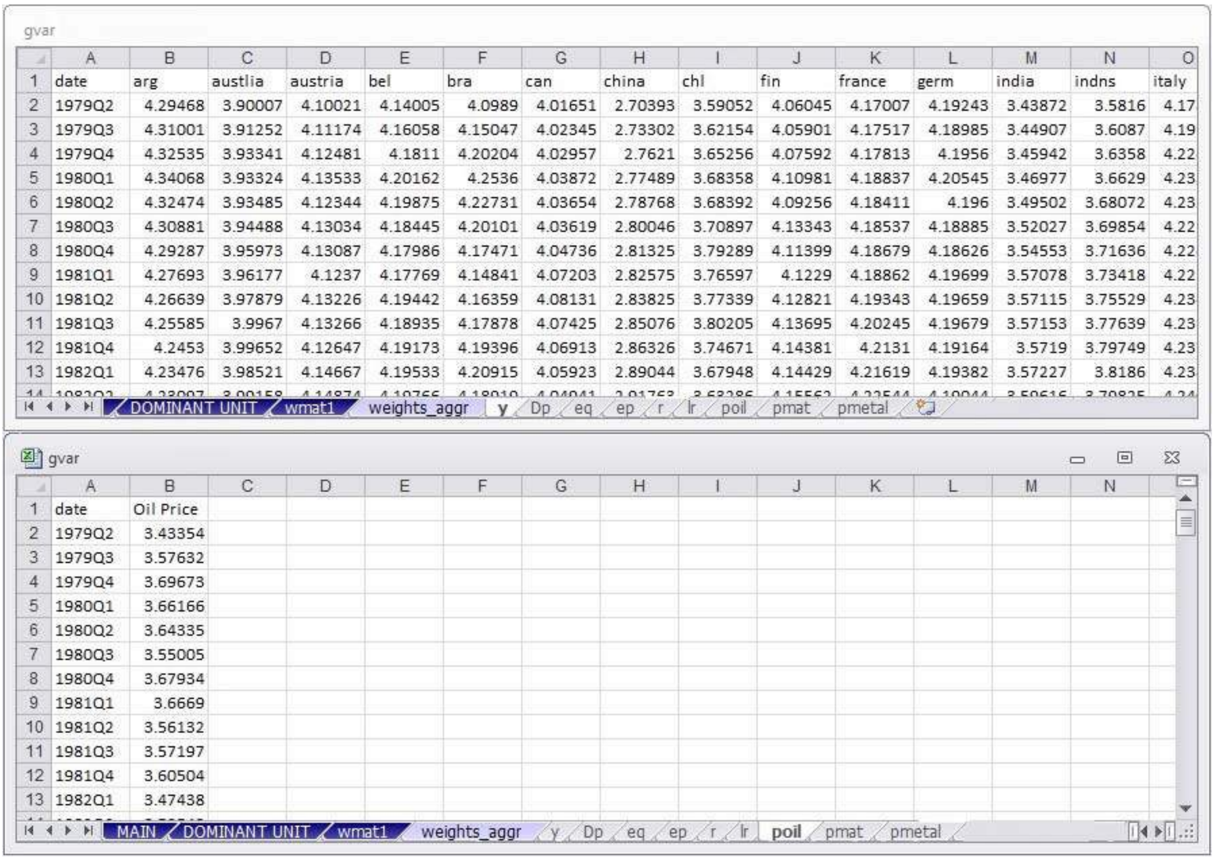


3. **Insert data into the variable worksheets:** Assuming you have performed all the relevant transformations of the raw data, you can now insert your data into the interface file. For each country-specific variable worksheet, enter labels for the observation dates in column A, using the format **yyyyMmm** for monthly data, **yyyyQq** for quarterly data, and **yyyy** for annual data. The country short names will be the column headings (in **row 1**), entered in exactly the same order and format as in the MAIN worksheet. We strongly recommend you copy and paste[4] the country short names to avoid errors occuring.[5] Finally, add the data, starting in cell B2. *If one or more observations is not available for a particular country variable, then the entire series has to be replaced with the missing data code* **123456789**. *The program cannot deal with data series that contain the missing data code for a subset of observations.* For global variable worksheets, add the dates to column A, label column B with the variable short name, and insert the global variable data series starting in cell B2. If you have multiple global variables to enter, you must use a separate worksheet for each one. Figure 4.8 shows an example of data imported for a country-specific variable and then a global variable.

[4]Copy the country short names from column F of the MAIN worksheet, and paste them into your variable sheet, starting in cell B1 and using the 'paste transpose' option.

[5]MatLab assumes that the order of the countries is exactly the same as previously set in the MAIN worksheet. If you change the order, the program will assign data to the wrong country. In case of a misnamed country, the program will consider the data of the given variable for the given country as missing, and an error message will be generated.

Figure 4.8 Inserting data for country-specific and global variables

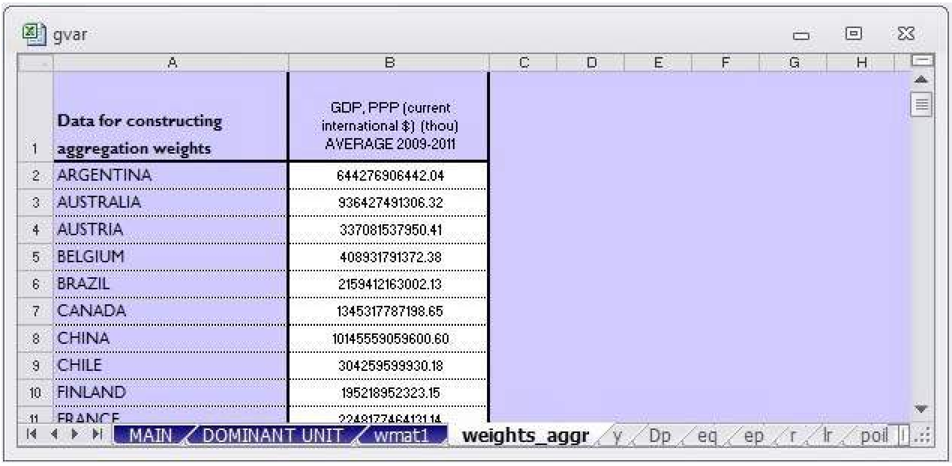


	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	date	arg	austlia	austria	bel	bra	can	china	chl	fin	france	germ	india	indns	italy
2	1979Q2	4.29468	3.90007	4.10021	4.14005	4.0989	4.01651	2.70393	3.59052	4.06045	4.17007	4.19243	3.43872	3.5816	4.17
3	1979Q3	4.31001	3.91252	4.11174	4.16058	4.15047	4.02345	2.73302	3.62154	4.05901	4.17517	4.18985	3.44907	3.6087	4.19
4	1979Q4	4.32535	3.93341	4.12481	4.1811	4.20204	4.02957	2.7621	3.65256	4.07592	4.17813	4.1956	3.45942	3.6358	4.22
5	1980Q1	4.34068	3.93324	4.13533	4.20162	4.2536	4.03872	2.77489	3.68358	4.10981	4.18837	4.20545	3.46977	3.6629	4.23
6	1980Q2	4.32474	3.93485	4.12344	4.19875	4.22731	4.03654	2.78768	3.68392	4.09256	4.18411	4.196	3.49502	3.68072	4.23
7	1980Q3	4.30881	3.94488	4.13034	4.18445	4.20101	4.03619	2.80046	3.70897	4.13343	4.18537	4.18885	3.52027	3.69854	4.22
8	1980Q4	4.29287	3.95973	4.13087	4.17986	4.17471	4.04736	2.81325	3.79289	4.11399	4.18679	4.18626	3.54553	3.71636	4.22
9	1981Q1	4.27693	3.96177	4.1237	4.17769	4.14841	4.07203	2.82575	3.76597	4.1229	4.18862	4.19699	3.57078	3.73418	4.22
10	1981Q2	4.26639	3.97879	4.13226	4.19442	4.16359	4.08131	2.83825	3.77339	4.12821	4.19343	4.19659	3.57115	3.75529	4.23
11	1981Q3	4.25585	3.9967	4.13266	4.18935	4.17878	4.07425	2.85076	3.80205	4.13695	4.20245	4.19679	3.57153	3.77639	4.23
12	1981Q4	4.2453	3.99652	4.12647	4.19173	4.19396	4.06913	2.86326	3.74671	4.14381	4.2131	4.19164	3.5719	3.79749	4.23
13	1982Q1	4.23476	3.98521	4.14667	4.19533	4.20915	4.05923	2.89044	3.67948	4.14429	4.21619	4.19382	3.57227	3.8186	4.23

	A	B
1	date	Oil Price
2	1979Q2	3.43354
3	1979Q3	3.57632
4	1979Q4	3.69673
5	1980Q1	3.66166
6	1980Q2	3.64335
7	1980Q3	3.55005
8	1980Q4	3.67934
9	1981Q1	3.6669
10	1981Q2	3.56132
11	1981Q3	3.57197
12	1981Q4	3.60504
13	1982Q1	3.47438

4. **Insert data into the aggregation weights worksheet:** Go to the **aggregation weights worksheet** (**weights_aggr**) and insert the country data in column B starting from cell B2. You can add a description label of the series in cell B1 if you wish. You may also wish to insert the country names in column A. (This is not required but can be useful when checking your data). Note that you must follow the country name order and format as defined in the MAIN worksheet. Following DdPS, here we use PPP-GDP data (averaged over 2009-2011) for computation of the weights used for aggregation (see Figure 4.9).

Figure 4.9 Inserting data for aggregation weights



	A	B
1	**Data for constructing aggregation weights**	GDP, PPP (current international $) (thou) AVERAGE 2009-2011
2	ARGENTINA	644276906442.04
3	AUSTRALIA	936427491306.32
4	AUSTRIA	337081537950.41
5	BELGIUM	408931791372.38
6	BRAZIL	2159412163002.13
7	CANADA	1345317787198.65
8	CHINA	10145559059600.60
9	CHILE	304259599930.18
10	FINLAND	195218952323.15

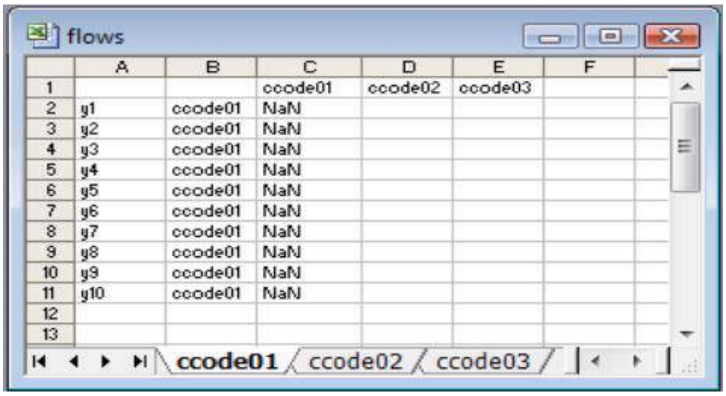
4.2.2 Importing cross-country flows data

If you wish to use the program-built weight matrix option with the flows database provided and no other weight matrices, please move on to Chapter 5. If you wish to use the program-built weight matrix option but provide your own cross-country flows data, you need to import these here. If you are constructing your own weight matrix and importing it from outside the program (this is mandatory if you wish to use more than one set of weights for constructing the foreign variables), please refer to Section 4.2.3.

1. Open **Flows\flows.xls**.

2. **Create data worksheets for each country:** You have three worksheets (**ccode01**, **ccode02** and **ccode03**) to start you off as shown in Figure 4.10. These are templates to help you understand how to organise the cross-country flows data. You need one worksheet per country in the GVAR, so add further worksheets if required. Each worksheet should be labelled with the corresponding **country code** as defined in the MAIN worksheet of **gvar.xls**. The ordering of the country codes within each flows worksheet as well as that of the flows worksheets themselves, does not necessarily have to follow the ordering of the country codes as defined in the MAIN worksheet of gvar.xls.

Figure 4.10 Flows worksheet


flows

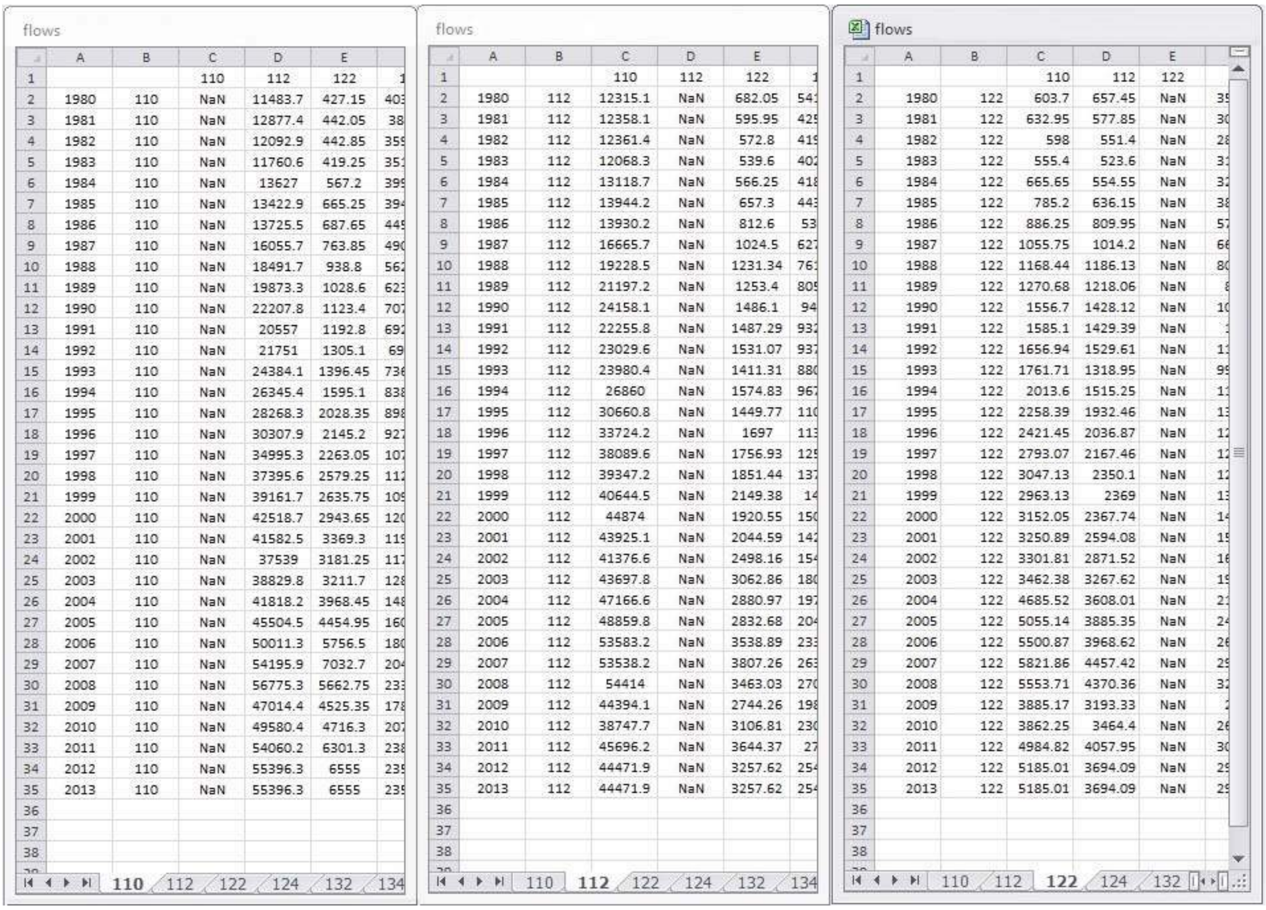
	A	B	C	D	E	F
1			ccode01	ccode02	ccode03	
2	y1	ccode01	NaN			
3	y2	ccode01	NaN			
4	y3	ccode01	NaN			
5	y4	ccode01	NaN			
6	y5	ccode01	NaN			
7	y6	ccode01	NaN			
8	y7	ccode01	NaN			
9	y8	ccode01	NaN			
10	y9	ccode01	NaN			
11	y10	ccode01	NaN			
12						
13						

ccode01 / ccode02 / ccode03

3. **Import the flows data:** Column A contains the date sequence (start in cell A2). Dates should be integers only. In the current version, only annual dates are supported. For convenience, in column B (starting in cell B2) you can list the country code that corresponds to the name of the worksheet that you are working in. Row 1 (starting from cell C1) is for your full list of country codes.[6] Finally, import the cross-country flows data, starting from cell C2. Note that in cells related to flows of a country with itself, you should put **NaN**. Save and close the files. Following our example of DdPS, 33 flow worksheets are created, labelled using the corresponding country codes, and the trade flows data are then imported (see Figure 4.11).

[6]You could copy these from the MAIN worksheet in gvar.xls and paste using the ‘transpose’ option, to minimise the chance of making an error. In any case, make sure that the data for each country goes in the correct column.

Figure 4.11 Inserting flows data



4.2.3 User-provided weight matrix

If you are providing your own weight matrix and no regions are defined in columns H-J[7], you must construct it with the countries listed in exactly the same order as in the MAIN worksheet, using the country short names. If you have defined one or more regions in columns H-J, the *regional* weight matrix and not the country level weight matrix needs to be provided, constructed as described in Section A.3. In this case, the country and region names need to be placed in alphabetical order according to the short names.

Further you need to ensure that the values of your weight matrix sum to one down the columns, i.e. you may need to transpose your weight matrix. For a time-varying weight matrix you must ensure that this is the case for every year included in the matrix.

To import your own weight matrix (fixed or time-varying) in the gvar interface file:

1. Open **gvar.xls.**
2. Select the worksheet **wmat1.**

[7]In the case where you are working with regions from the outset and no further regions are defined in columns H-J, list the region short names (along with any country short names) in column E of the MAIN worksheet, leave columns C-J blank, construct the associated regional variables externally and import them as described in Section 4.2 (see Section A.5 for the construction of regional variables).

3. Insert the weight matrix starting from cell B2 (fixed weights) or cell C2 (time-varying weights), making sure that it has zeros on the main diagonal (for each year in the case of time-varying weights). Further ensure that you use the country/region short names (in *alphabetical order* when at least one region is defined in columns H-J, otherwise in the order specified in column F) both in column A (starting from cell A2) and row 1 (starting from cell B1) for fixed weights, and column B (repeatably, starting from cell B2) and row 1 (starting from cell C1) for time-varying weights. In addition, for time-varying weights only, in column A (starting from cell A2) repeat the associated year of each weight matrix. It is important to ensure that the years that appear in column A cover exactly the time span of the sample used for estimation in the GVAR analysis. If this is not the case the program will not be able to compute the foreign specific variables and an error will occur.

4. Save and close the files.

Figure 4.12 shows an example where a fixed weight matrix has been imported into worksheet wmat1 assuming that a euro region has been specified in columns H-J.

Figure 4.12 User-provided fixed weight matrix

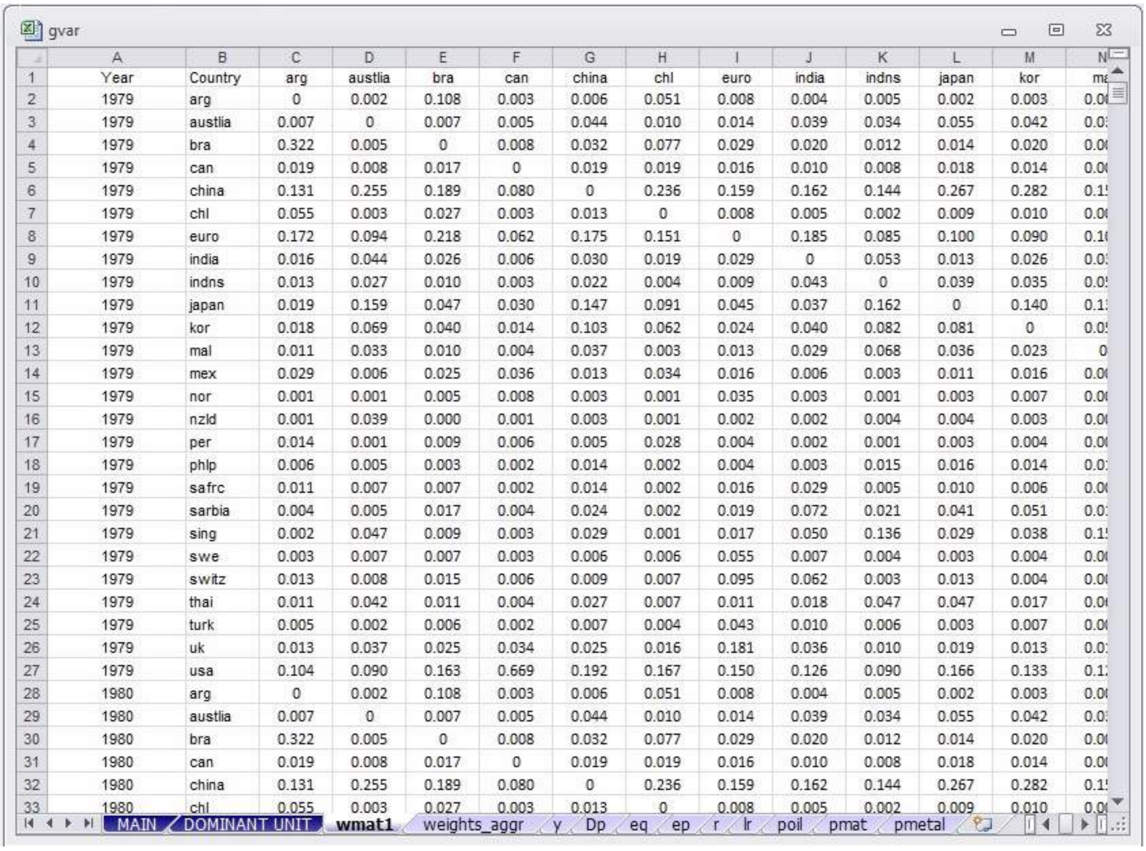
gvar

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Countries	arg	austlia	bra	can	china	chl	euro	india	indns	japan	kor	mal	mex
2	arg	0	0.002	0.108	0.003	0.006	0.051	0.008	0.004	0.005	0.002	0.003	0.004	0.005
3	austlia	0.007	0	0.007	0.005	0.044	0.010	0.014	0.039	0.034	0.055	0.042	0.036	0.003
4	bra	0.322	0.005	0	0.008	0.032	0.077	0.029	0.020	0.012	0.014	0.020	0.008	0.014
5	can	0.019	0.008	0.017	0	0.019	0.019	0.016	0.010	0.008	0.018	0.014	0.006	0.033
6	china	0.131	0.255	0.189	0.080	0	0.236	0.159	0.162	0.144	0.267	0.282	0.157	0.090
7	chl	0.055	0.003	0.027	0.003	0.013	0	0.008	0.005	0.002	0.009	0.010	0.001	0.006
8	euro	0.172	0.094	0.218	0.062	0.175	0.151	0	0.185	0.085	0.100	0.090	0.100	0.067
9	india	0.016	0.044	0.026	0.006	0.030	0.019	0.029	0	0.053	0.013	0.026	0.033	0.006
10	indns	0.013	0.027	0.010	0.003	0.022	0.004	0.009	0.043	0	0.039	0.035	0.051	0.002
11	japan	0.019	0.159	0.047	0.030	0.147	0.091	0.045	0.037	0.162	0	0.140	0.138	0.031
12	kor	0.018	0.069	0.040	0.014	0.103	0.062	0.024	0.040	0.082	0.081	0	0.051	0.025
13	mal	0.011	0.033	0.010	0.004	0.037	0.003	0.013	0.029	0.068	0.036	0.023	0	0.010
14	mex	0.029	0.006	0.025	0.036	0.013	0.034	0.016	0.006	0.003	0.011	0.016	0.006	0
15	nor	0.001	0.001	0.005	0.008	0.003	0.001	0.035	0.003	0.001	0.003	0.007	0.001	0.000
16	nzld	0.001	0.039	0.000	0.001	0.003	0.001	0.002	0.002	0.004	0.004	0.003	0.005	0.001
17	per	0.014	0.001	0.009	0.006	0.005	0.028	0.004	0.002	0.001	0.003	0.004	0.000	0.002
18	phlp	0.006	0.005	0.003	0.002	0.014	0.002	0.004	0.003	0.015	0.016	0.014	0.017	0.003
19	safrc	0.011	0.007	0.007	0.002	0.014	0.002	0.016	0.029	0.005	0.010	0.006	0.006	0.000

MAIN DOMINANT UNIT wmat1 weights_aggr y Dp eq ep r lr poil pmat pmetal

Under the same specification of a euro region defined in columns H-J, Figure 4.13 shows an example where a time-varying weight matrix has been imported into worksheet wmat1 that contains the same weights for all years.

Figure 4.13 User-provided time-varying weight matrix



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Year	Country	arg	austlia	bra	can	china	chl	euro	india	indns	japan	kor	ma
2	1979	arg	0	0.002	0.108	0.003	0.006	0.051	0.008	0.004	0.005	0.002	0.003	0.0
3	1979	austlia	0.007	0	0.007	0.005	0.044	0.010	0.014	0.039	0.034	0.055	0.042	0.0
4	1979	bra	0.322	0.005	0	0.008	0.032	0.077	0.029	0.020	0.012	0.014	0.020	0.0
5	1979	can	0.019	0.008	0.017	0	0.019	0.019	0.016	0.010	0.008	0.018	0.014	0.0
6	1979	china	0.131	0.255	0.189	0.080	0	0.236	0.159	0.162	0.144	0.267	0.282	0.1
7	1979	chl	0.055	0.003	0.027	0.003	0.013	0	0.008	0.005	0.002	0.009	0.010	0.0
8	1979	euro	0.172	0.094	0.218	0.062	0.175	0.151	0	0.185	0.085	0.100	0.090	0.1
9	1979	india	0.016	0.044	0.026	0.006	0.030	0.019	0.029	0	0.053	0.013	0.026	0.0
10	1979	indns	0.013	0.027	0.010	0.003	0.022	0.004	0.009	0.043	0	0.039	0.035	0.0
11	1979	japan	0.019	0.159	0.047	0.030	0.147	0.091	0.045	0.037	0.162	0	0.140	0.1
12	1979	kor	0.018	0.069	0.040	0.014	0.103	0.062	0.024	0.040	0.082	0.081	0	0.0
13	1979	mal	0.011	0.033	0.010	0.004	0.037	0.003	0.013	0.029	0.068	0.036	0.023	0
14	1979	mex	0.029	0.006	0.025	0.036	0.013	0.034	0.016	0.006	0.003	0.011	0.016	0.0
15	1979	nor	0.001	0.001	0.005	0.008	0.003	0.001	0.035	0.003	0.001	0.003	0.007	0.0
16	1979	nzld	0.001	0.039	0.000	0.001	0.003	0.001	0.002	0.002	0.004	0.004	0.003	0.0
17	1979	per	0.014	0.001	0.009	0.006	0.005	0.028	0.004	0.002	0.001	0.003	0.004	0.0
18	1979	phlp	0.006	0.005	0.003	0.002	0.014	0.002	0.004	0.003	0.015	0.016	0.014	0.0
19	1979	safrc	0.011	0.007	0.007	0.002	0.014	0.002	0.016	0.029	0.005	0.010	0.006	0.0
20	1979	sarbia	0.004	0.005	0.017	0.004	0.024	0.002	0.019	0.072	0.021	0.041	0.051	0.0
21	1979	sing	0.002	0.047	0.009	0.003	0.029	0.001	0.017	0.050	0.136	0.029	0.038	0.1
22	1979	swe	0.003	0.007	0.007	0.003	0.006	0.006	0.055	0.007	0.004	0.003	0.004	0.0
23	1979	switz	0.013	0.008	0.015	0.006	0.009	0.007	0.095	0.062	0.003	0.013	0.004	0.0
24	1979	thai	0.011	0.042	0.011	0.004	0.027	0.007	0.011	0.018	0.047	0.047	0.017	0.0
25	1979	turk	0.005	0.002	0.006	0.002	0.007	0.004	0.043	0.010	0.006	0.003	0.007	0.0
26	1979	uk	0.013	0.037	0.025	0.034	0.025	0.016	0.181	0.036	0.010	0.019	0.013	0.0
27	1979	usa	0.104	0.090	0.163	0.669	0.192	0.167	0.150	0.126	0.090	0.166	0.133	0.1
28	1980	arg	0	0.002	0.108	0.003	0.006	0.051	0.008	0.004	0.005	0.002	0.003	0.0
29	1980	austlia	0.007	0	0.007	0.005	0.044	0.010	0.014	0.039	0.034	0.055	0.042	0.0
30	1980	bra	0.322	0.005	0	0.008	0.032	0.077	0.029	0.020	0.012	0.014	0.020	0.0
31	1980	can	0.019	0.008	0.017	0	0.019	0.019	0.016	0.010	0.008	0.018	0.014	0.0
32	1980	china	0.131	0.255	0.189	0.080	0	0.236	0.159	0.162	0.144	0.267	0.282	0.1
33	1980	chl	0.055	0.003	0.027	0.003	0.013	0	0.008	0.005	0.002	0.009	0.010	0.0

Importing additional user-provided weight matrices

Worksheet **wmat1,** being associated with the main weight matrix of the program, is the only worksheet directly linked to the settings of the interface file (Section 5.1.2) whether it contains data or not. It can contain user-provided weights (as seen in Section 4.2.3) or it can be left blank if the corresponding weight matrix will be constructed by the program through the existing or provided flows. In the latter case any data included in this worksheeet will be ignored, though the worksheet itself should never be deleted or renamed.

The main weight matrix contains one set of weights, for example trade weights, used to construct the foreign variables. You may wish to use additional weight matrices throughout the GVAR analysis. For example you may want to use trade weights to construct the foreign counterparts of certain variables and financial weights for others. The financial weights should then be provided by the user and imported into the gvar interface file as follows:

1. Open **gvar.xls.**

2. Create an additional worksheet for the financial weights named **wmat2** (adjacent to the existing worksheet wmat1), a worksheet named **wmat3** if a third set of weights is required, and so on up to **wmat10** (the maximum number of weight matrices permitted, see Section 3.2.1). Under no circumstances should any of these additional weight matrices be imported into **wmat1,** even in the case where this worksheet happens to be blank for the reason mentioned earlier. The new worksheets should appear in consecutive order (i.e. wmat2, wmat3 and so on) as shown in Figure 4.14 below and should not be given different names other than those mentioned here.

Figure 4.14 Inserting wmat worksheets into the interface file

3. For each new worksheet insert the corresponding weight matrix (fixed or time-varying) as discussed in Section 4.2.3.

4. Save and close the files.

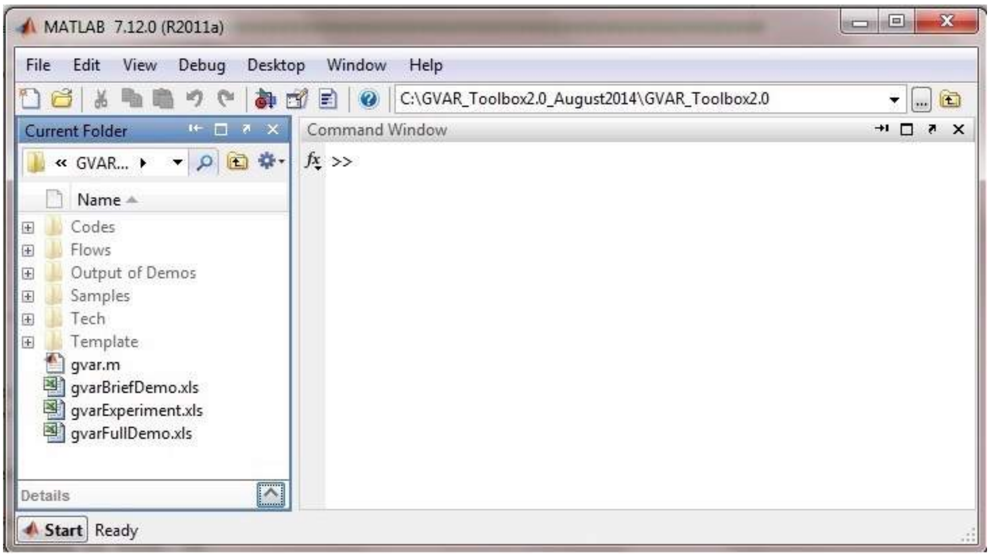
5. PERFORMING THE GVAR ANALYSIS

You are now ready to run the GVAR program and start performing the analysis:

1. Double-click on **GVAR_Toolbox2.0\gvar.m**. Matlab will open and two windows will appear: the main Matlab command window and the editor window. You can close the editor as you are not required to modify the **gvar.m** script in order to run the program.

2. Your working directory path should now be displayed in the current directory field above the command window (see Figure 5.1).[1]

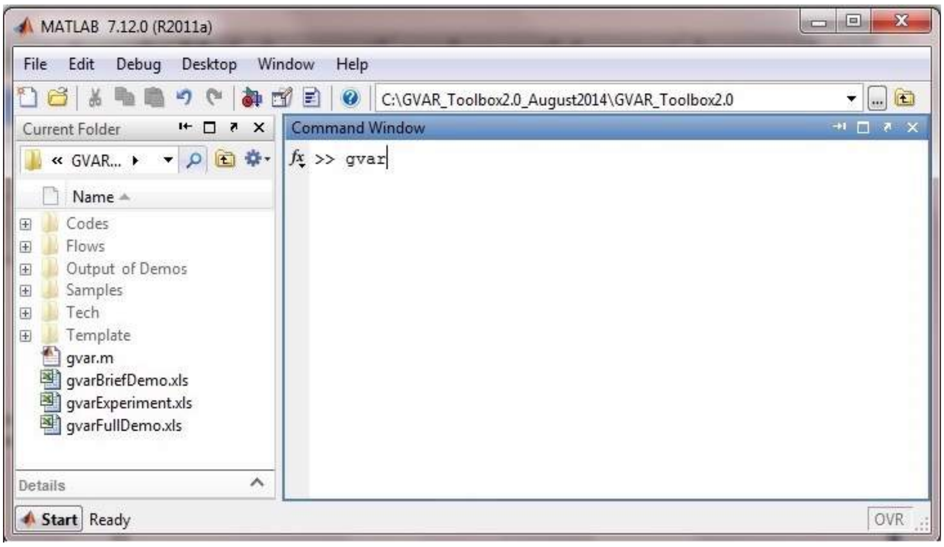
Figure 5.1 Checking the working directory path



3. In the Matlab command window, click by the prompt, type **gvar** (set by default as the program name and not to be changed) and press enter (see Figure 5.2). This will launch the GVAR program.

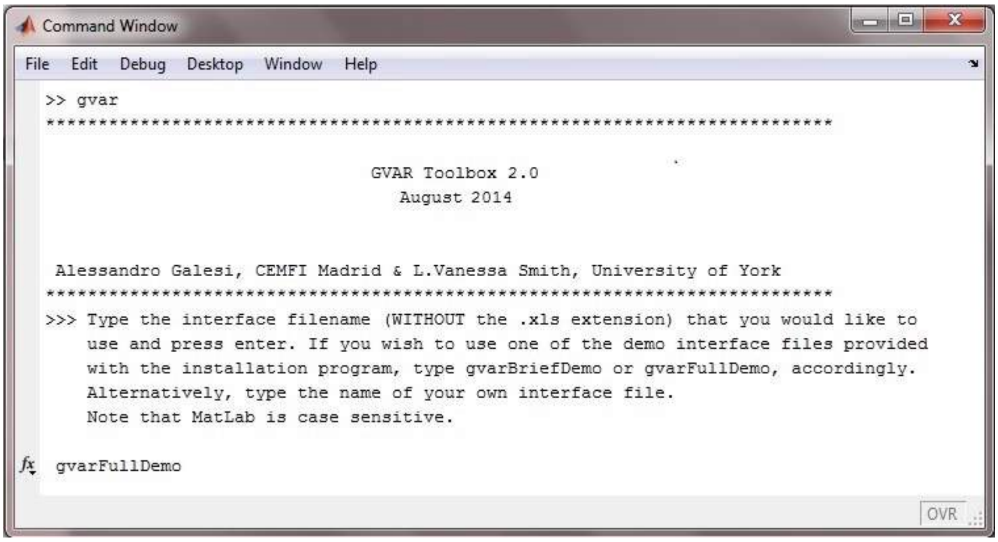
[1] If this is not the case, or if you get the error message: 'Windows cannot find C:\..my path..\gvar.m. Please check that the name is correct and retry', click on the dotted button in the top righthand corner, locate the GVAR_Toolbox1.1 folder, click on it and select OK.

Figure 5.2 Launching the GVAR program from the MatLab prompt



4. Next you have to type the name of the interface Excel file which will interact with the GVAR program. Type the filename *without* the extension '.xls'. As the full demo is used for illustration, we need to type here 'gvarFullDemo' (see Figure 5.3).[2] The interface filename is user-specific and can have any arbitrary name. You can, therefore, have several GVAR interface files, each with a different name, which you can use independently by typing the required name as shown below. Remember all interface files need to be placed in the same folder as the gvar.m file.

Figure 5.3 Typing the interface filename



After typing the interface filename, the program will start running and a link between Matlab and Excel will be established through which information will be shared. The program will

[2]Recall that MatLab is case-sensitive, so you have to be careful when typing in the filename here. It has to match the format of your Excel filename exactly.

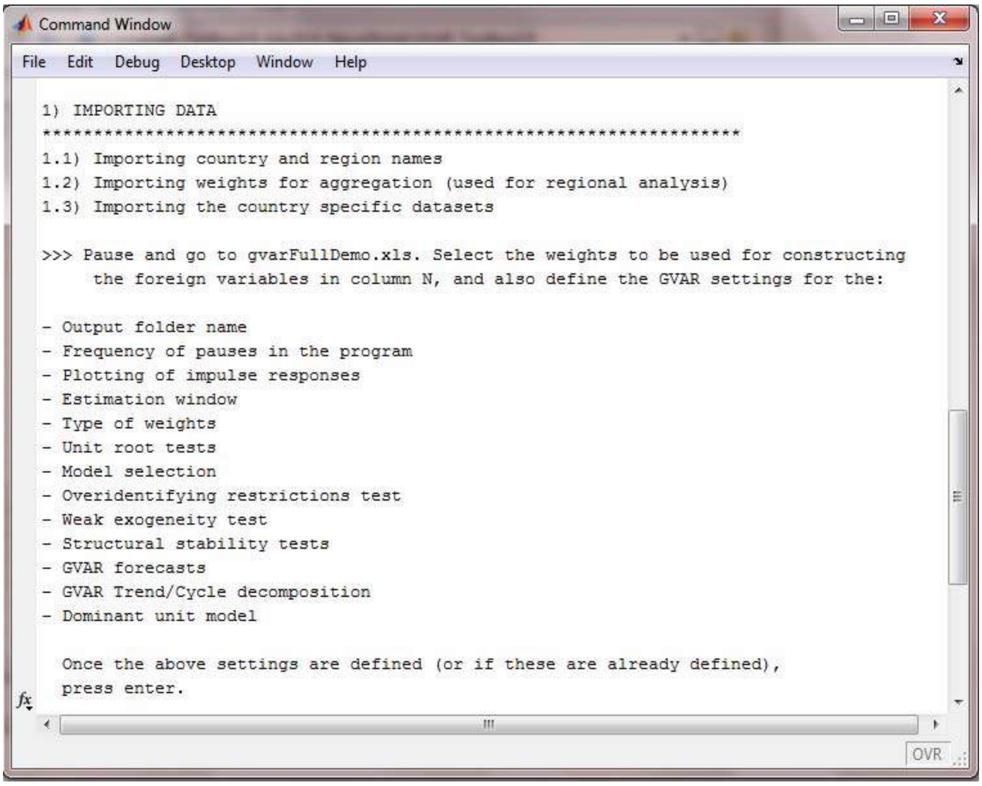
typically[3] perform numerous **pauses** during the process of the specification of the country-specific models, their estimation and the construction and analysis of the GVAR model. During these stages, the user is called upon to supply settings and/or check intermediate results in the MAIN and DOMINANT UNIT worksheets of the interface file (the latter assuming the dominant unit model function is enabled) that will open automatically each time. Once this file has opened, always refer back to the Matlab command window for instructions and information. Additional guidance is also available by clicking on many of the headings and field names within the MAIN and DOMINANT UNIT worksheets.

After every pause, once the required settings have been supplied and/or the intermediate results have been checked **you must save and close the interface file**.[4]

5.1 Defining the preliminary settings and selecting the weights for construction of the foreign variables

After a few seconds/minutes (depending on the speed of your computer), the program will pause for the first time, and a message will appear in the Matlab command window, as shown in Figure 5.4.

Figure 5.4 Pause message: Define the GVAR settings and select the weights for construction of the foreign variables



[3]This will be the case for all interface files where the 'Run the program with pauses' function is enabled (see Section 5.1.2).

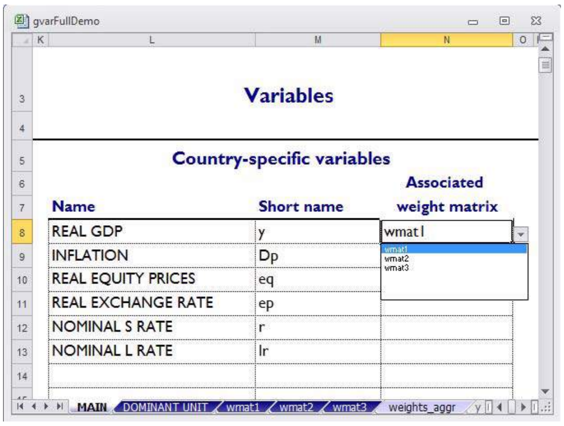
[4]As the program runs, it reads from and writes to the interface file. The writing action has to be carried out with this file closed, otherwise the interface file will be considered as read-only by Excel and thus, MatLab will not have permission to write to it.

The program requires you to select the weights for constructing each of the foreign variables and also to define the settings in the **MAIN** worksheet of the **gvarFullDemo.xls** file which has been automatically reopened. Selection of the weights will be discussed first followed by how to define the settings.

5.1.1 Selecting the weights for constructing the foreign variables

Column N in the MAIN worksheet contains a dropdown list for each domestic variable defined in column M. To access this, click in each of the corresponding cells in column N. Each dropdown list includes the names of all worksheets with the prefix wmat that appear in the interface file (wmat1, wmat2 and wmat3 in the case of the **gvarFullDemo.xls**), containing the available weights for construction of the foreign variables**.** For each domestic variable, select the name of the weight matrix that you would like to use to contruct the associated foreign variable as shown in Figure 5.5 below. See Section 5.1.2 for more details on the content of these weight matrices.

Figure 5.5 Selecting the associated weight matrix for the domestic variables in the MAIN sheet



Because **wmat1** is the only weight matrix directly linked to the interface file settings as already mentioned, it has to be selected for *at least* one of the variables. For the same reason, if the dropdown list contains a number of weight matrices but you only wish to use one of these for all variables, you *must* select **wmat1.** If you would like to use only two of the available set of weights then you must select **wmat1** for one or more variables**,** and you can select *any* other weight matrix of your choice for the remaining variables. Some examples are provided in Figure 5.6 below.

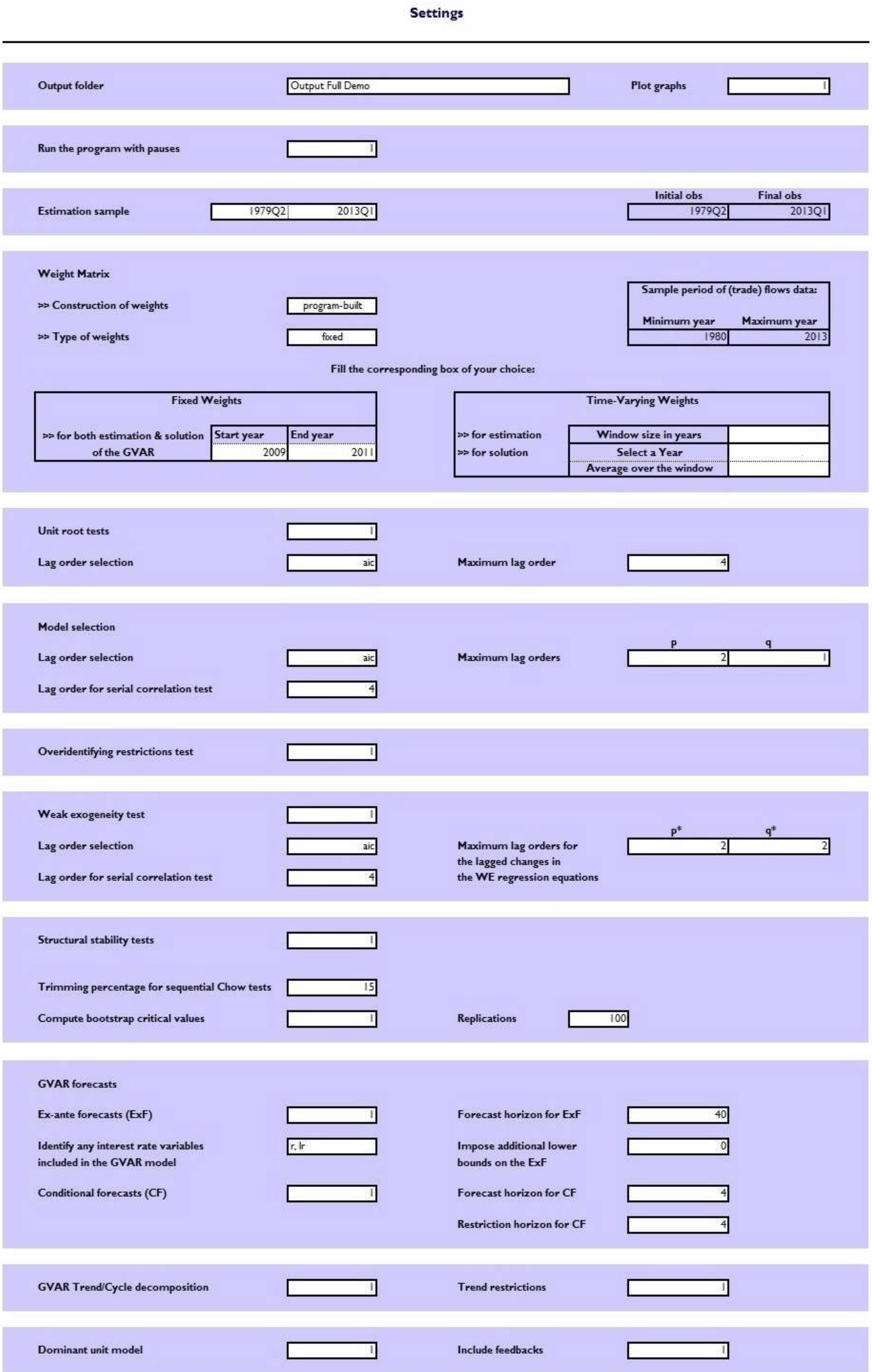
Figure 5.6 Examples of selected weight matrices associated with the domestic variables

	Associated weight matrix		
Short name	**Example 1**	**Example 2**	**Example 3**
y	wmat1	wmat1	wmat3
Dp	wmat1	wmat1	wmat1
eq	wmat1	wmat2	wmat3
ep	wmat1	wmat2	wmat1
r	wmat1	wmat3	wmat3
lr	wmat1	wmat2	wmat3

5.1.2 Defining the preliminary settings

Figure 5.7 shows the inputs you have to define next in the MAIN worksheet of the Excel interface file, each of which is described separately below.

Figure 5.7 Defining the GVAR settings in the MAIN worksheet



Settings

Output folder	Output Full Demo	Plot graphs	1
Run the program with pauses	1		
Estimation sample	1979Q2 2013Q1	Initial obs / Final obs	1979Q2 / 2013Q1

Weight Matrix

>> Construction of weights	program-built	Sample period of (trade) flows data: Minimum year / Maximum year	1980 / 2013
>> Type of weights	fixed		

Fill the corresponding box of your choice:

Fixed Weights	Start year	End year
>> for both estimation & solution of the GVAR	2009	2011

Time-Varying Weights		
>> for estimation	Window size in years	
>> for solution	Select a Year	
	Average over the window	

Unit root tests	1		
Lag order selection	aic	Maximum lag order	4

Model selection

			p	q
Lag order selection	aic	Maximum lag orders	2	1
Lag order for serial correlation test	4			

Overidentifying restrictions test	1

			p*	q*
Weak exogeneity test	1			
Lag order selection	aic	Maximum lag orders for the lagged changes in the WE regression equations	2	2
Lag order for serial correlation test	4			

Structural stability tests	1		
Trimming percentage for sequential Chow tests	15		
Compute bootstrap critical values	1	Replications	100

GVAR forecasts

Ex-ante forecasts (ExF)	1	Forecast horizon for ExF	40
Identify any interest rate variables included in the GVAR model	r, lr	Impose additional lower bounds on the ExF	0
Conditional forecasts (CF)	1	Forecast horizon for CF	4
		Restriction horizon for CF	4

GVAR Trend/Cycle decomposition	1	Trend restrictions	1
Dominant unit model	1	Include feedbacks	1

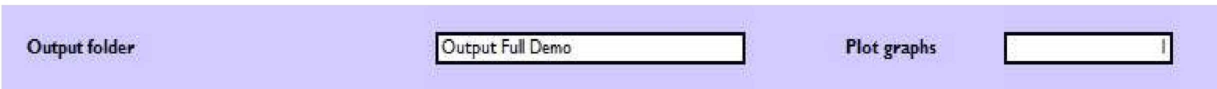
Output folder and plotting of graphs

By design, the program will produce the following main output:

- The **output.xls** file, containing all diagnostic and estimation results related to the individual VARX* models and the GVAR model
- The **countrydata.xls** file, containing separate Excel worksheets with data for the domestic, foreign and global variables included in the individual country models
- A folder automatically named according to the specified shock for each simulation performed, which stores the results of the dynamic analysis (impulse responses and forecast decompositions).

This output will be located in a program-generated folder named **Output** under **GVAR_Toolbox2.0**\. You can, however, choose to create a further folder under **Output**\ by typing your desired folder name in cell U7. There are no restrictions on the name you can choose (it can contain spaces, numbers and symbols). Furthermore, you can select whether to produce graphs of the impulse responses that follow at a later stage. If you wish to do so, select **1** in cell Z7, otherwise select **0**. See Figure 5.8.

Figure 5.8 Output settings



Frequency of pauses

The program requires a completed interface file to run the full analysis, and the pauses in the program allow the user to define and modify settings and specifications during the intermediate steps of the analysis. Thus, it is both useful and necessary[5] to run the program *with* the full set of pauses at least for the initial run(s), to input the information.

Thereafter, you can run the program without most pauses[6], as the program will retain and use the settings and specifications from your last run (including any modifications you have made just before any rerun). In this case, the program will estimate the individual models, and it will not show the intermediate results, such as the lag orders, the ranks and so on. Whilst this feature can be especially useful when *refining* your GVAR specification during subsequent runs of the program, three things are important to note when you are running the program with the function **Run the program with pauses** disabled (i.e. set to 0):

i. To retain the lag orders for the VARX* models and the weak exogeneity regressions if these were previously computed based on a lag order selection criterion, select **no** in the **Lag order selection** field in cells U43 and U55, respectively at the initial settings stage (this is also the case when running the program with the **Run the program with pauses** function enabled, i.e. set to 1).

[5]Strictly speaking, the user could input all the necessary information into the interface file before running the program. However, this is not recommended.

[6]There are certain functions, for example the ‘Overidentifying restrictions test’ function, that when enabled a pause will be made (in this case for the user to insert the overidentifying restrictions in a separate excel file that will open for this purpose), irrespective of whether the program is being run with the ‘Run the program with pauses’ function enabled or not.

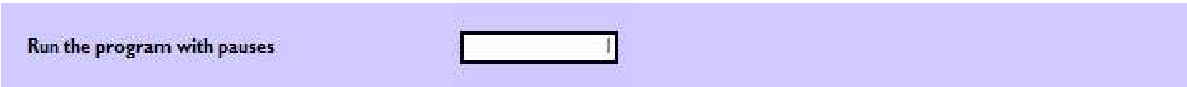
ii. If you change the lag orders or the nature of the deterministics selected for the VARX* estimation, the number of cointegrating relations will not be recomputed to reflect these changes. (This will only be done when running the program with the **Run the program with pauses** function enabled). The program will simply use all the existing information provided in the MAIN worksheet to solve the GVAR model.

iii. If you would like to obtain bootstrapped critical values for the structural stability tests but do not wish to proceed with the dynamic analysis of the GVAR, ensure you have provided the information for the covariance matrix required for bootstrapping. See Section 5.12.

To run the program with all possible pauses, select **1** in cell U11, otherwise choose **0** (see Figure 5.9).

Also note that each time you run the program with the **Run the program with pauses** function enabled, certain fields will be automatically filled with their default values. Thus, any changes you make to these default values will be overwritten during every rerun when this function is enabled, and will need to be re-entered. These fields are the specification of the individual models (both for estimation of the VARX* models and for conducting the weak exogeneity tests) including any dominant unit model; the deterministics for the VECMX* estimation; and the shocks for the dynamic analysis.

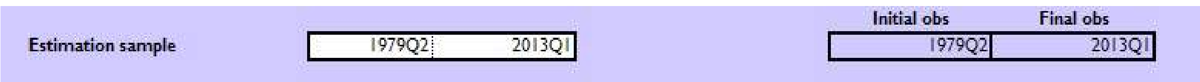
Figure 5.9 Frequency of pauses



Estimation sample

At this stage you are required to select the estimation sample for the estimation of the individual country models. Type the first and last observation dates in cells T15 and U15 (as in Figure 5.10). The format of the dates should be consistent with that of the previous data inputting phase. The dates in the shaded fields on the right (Y15 and Z15) are pre-generated by the program and give the first and last feasible observation dates that can be chosen.

Figure 5.10 Setting the estimation sample

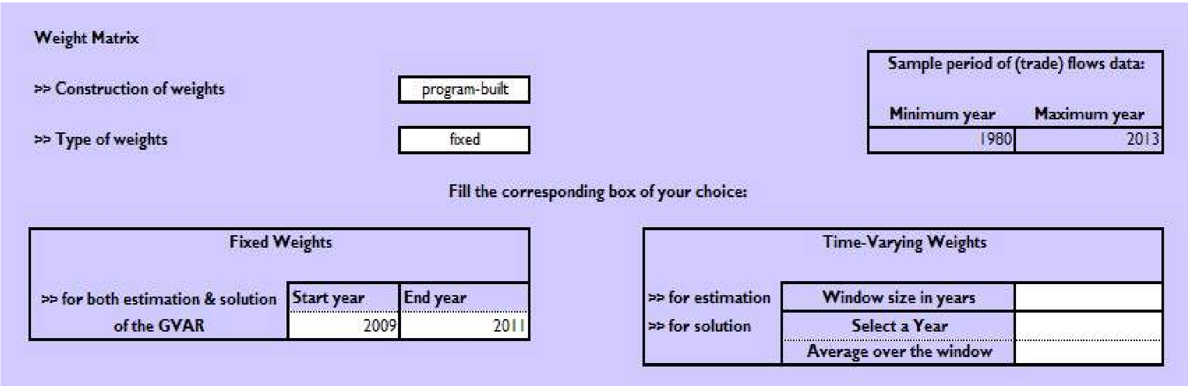


The weight matrix panel in the case of a single weight matrix

We first consider the case where the weight matrix **wmat1** is selected in column N for computing the foreign counterparts of all domestic variables and putting the GVAR together. The weights associated with **wmat1** can either be constructed from within the program using the existing trade flows database or the flows database imported earlier by the user, or it can be constructed outside and imported into the program as described in Section 4.2.3. In the former case you should select **program-built**, while in the latter case you should select **user-provided** (in cell U21). In either case you have two options for construction of the weights: fixed weights or time-varying weights.

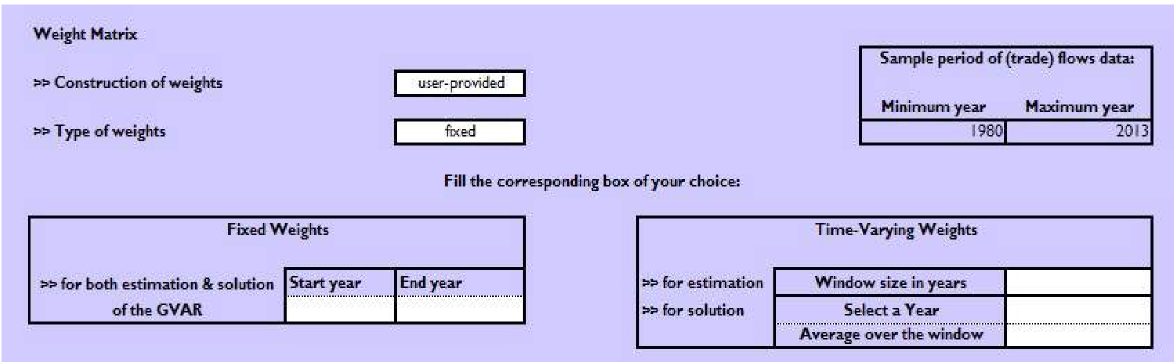
With fixed weights under the program-built option, you have to specify the annual range of cross-country flows data to be used. More precisely, you have to specify the first and last years of the range in cells T30 and U30, respectively. To assist you, cells Y23 and Z23 state the feasible range according to the cross-country flows data previously imported (i.e. the minimum and the maximum available years). The program will average the flows data over the selected period, and create a weight matrix to be used both for estimation (i.e. for computing the foreign-specific variables) and for the solution of the GVAR (i.e. for building the 'link' matrices for each model). As an example, see Figure 5.11.

Figure 5.11 Type of weights: Program-built weight matrix using fixed weights



If you opt for the user-provided weight matrix under fixed weights, you only need to complete cells U21 and U23. You can leave all subsequent fields in this part blank (see Figure 5.12 for clarification).

Figure 5.12 Type of weights: User-provided weight matrix



With time-varying weights, the weight matrix used for computing the foreign-specific variables, used subsequently in the estimation of the country specific models, is allowed to vary over time. The foreign-specific variables are, therefore, constructed using weight matrices to match the year of the associated domestic variable observations.

Under the program-built option, initially the user is required to specify a window size (cell Z29) for averaging across the cross-country flows data in order for the sequence of weight matrices to be constructed. This works exactly like a moving average filter. For example, suppose you have data for your variables ranging from 2000 to 2009, and cross-country flows data for the period

1980-2009, and you select a three-year window. The program will build one weight matrix for each sample year (so in this case, given the sample ranges from 2000 to 2009, there will be ten matrices), where each matrix corresponds to a given year, and is constructed using the current and past two years of the cross-country flows data. Thus, the matrix related to the year 2009 is constructed using an average of flows over the period 2007-2009, the matrix of 2008 is constructed using the average over the period 2006-2008, and so on. The data for the foreign-specific variables will then be constructed taking into account the observational year that the associated domestic variable data belongs to, by using the sequence of yearly-specific weight matrices.

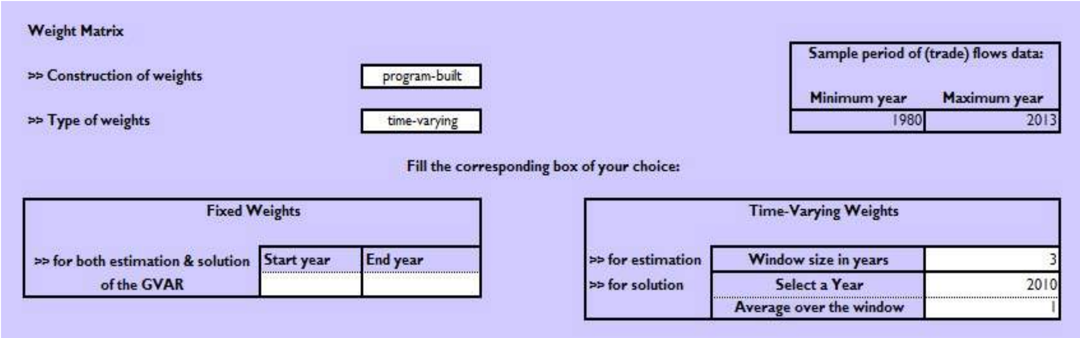
Note that if the cross-country database does not cover all dates within the estimation sample (e.g. the sample spans the period 1970 to 2009 but the cross-country flows data only covers the period 1970 to 2006), then the time-varying weights cannot be used, and an error message will appear in the Matlab command window. However, even if the estimation sample begins from a date for which cross-country flows data are not available, time-varying weights are still permitted. This is because the observations of the foreign-specific variables for which the flows data are not available will be constructed using the earliest available weight matrix. For example, if the sample ranges from 1970 to 2009, while the cross-country flows data spans from 1980 to 2009, the data for the period 1970-1980 will be constructed using the matrix based on 1980 data (if the window size in years is equal to 1), or the matrix based on 1980-1981 data (if the window size is equal to 2), and so on.

Next, in order to solve the GVAR under time-varying weights, a particular year from the sequence of weight matrices needs to be chosen (cell Z30). Along with this, the user has to specify whether the chosen weight matrix should contain an average over the window size selected for estimation, constructed as described above, or a single year (cell Z31). The weight matrix corresponding to this particular year will then be extracted from the sequence of annual weight matrices previously constructed, and will be used to solve the GVAR model. For example, working with a **Window size in years** of **3** and with 2008 as your year (**Select a Year**): if you select **1** as the **Average over the window**, the weight matrix used for the solution of the GVAR will be the one corresponding to the cross-country flows data over the period 2006-2008. If instead you set the **Average over the window** to **0** , the matrix used for solution of the GVAR model will be based on 2008 data only (see Section A.27 for further clarification on the construction of time-varying weights and the associated solution of the GVAR).

If the options **user-provided** and **time-varying** are selected then the **Window size in years** and **Average over the window** are no longer relevant. The only information required by the user is the year to solve the GVAR (cell Z30) associated with **Select a Year.** Remember to ensure that the years spanning the user-provided weight matrix match those selected in the estimation sample.

An example of how to fill in the fields under the program-built option with time-varying weights is given in Figure 5.13.

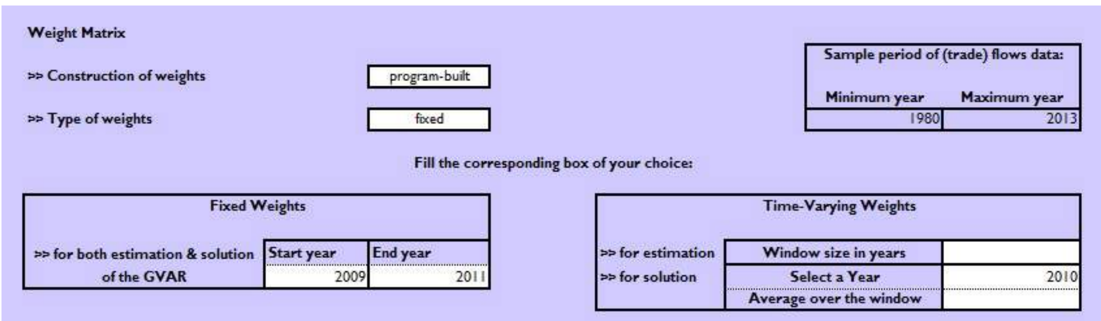
Figure 5.13 Type of weights: Program-built weight matrix using time-varying weights



The weight matrix panel in the case of multiple weight matrices Here we consider the case where multiple weight matrices, **wmat1, wmat2**, **wmat3** are selected in column N for computing the foreign counterparts of the domestic variables. Recall **wmat1** is the *only* worksheet directly associated with the options provided in the settings of the interface file, while the other worksheets, **wmat2**, **wmat3** can *only* contain user-provided weights. This means that if **program-built** is selected (cell U21), only the weights associated with the **wmat1** worksheet will be built by the program (these can be viewed in the first sheet of the output file at the end of the program). In this case, as already mentioned, the **wmat1** worksheet can be left blank or any content will be ignored. Only under the **user-provided** option will any weights that appear in the **wmat1** worksheet be used.

If **fixed** weights are selected (cell U23) this means that under the **program-built** option the weights associated with **wmat1** will be constructed as fixed based on the window specified by cells T30 and U30. Under the **user-provided** option the weights provided in the worksheet **wmat1** should be fixed. These weights together with those of the other selected weight matrices, **wmat2**, **wmat3**, assuming they are all fixed, will be used for creating the link matrices used to solve the GVAR (as shown in Section A.16 for a single set of weights). However, if at least one of the selected weight matrices, **wmat2**, **wmat3**, contains time varying weights, then the GVAR will be solved under time-varying weights and the user is required to input the selected year in cell Z30 as shown in Figure 5.14. The specified year will apply to all such worksheets that contain time-varying weights. Input related to **Window size in years** and **Average over the window** in this case is not relevant and can be ignored.

Figure 5.14 Multiple weight matrices: Program-built fixed weight matrix for wmat1, time-varying weight matrix for either wmat2 and/or wmat3

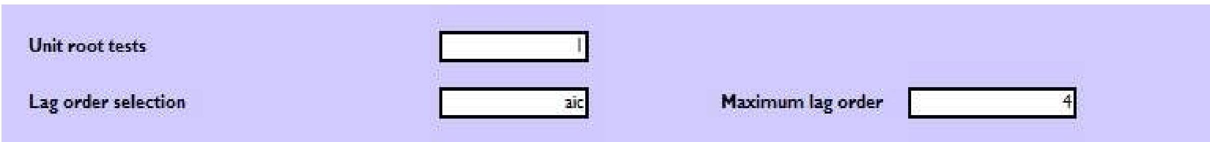


Similarly, if **time-varying** weights are selected (cell U23) this means that under the **program-built** option the weights associated with **wmat1** will be constructed as time-varying based on the information provided in the panel **Time-Varying Weights.** Under the **user-provided** option the weights in the **wmat1** worksheet have to be time-varying and only information in cell Z30 is required. In either case, if any of the selected weight matrices, **wmat2**, **wmat3**, contains time varying weights, then the year specified in cell Z30 will also be applied to these when solving the GVAR. The solution in this case follows the same procedure as described in Section A.27 for a single weight matrix.

Unit root tests

If you select **1** for **Unit root tests** (cell U35), the program will perform unit root tests (Augmented Dickey-Fuller and Weighted-Symmetric Dickey Fuller type tests) for all domestic, foreign-specific and global variables entering the individual models of the GVAR. In practice, the program runs a set of unit root test regressions for each variable of each country, with the *number of lagged changes* ranging from zero to the specified maximum number, defined as the **Maximum lag order** (cell Y37). The program then produces the unit root test statistics associated with a specific regression selected according to a lag order selection criterion (cell U37) specified by the user. You can choose between the Akaike, denoted by **aic**, and the Schwartz Bayesian, denoted by **sbc**. See Figure 5.15 for an example.

Figure 5.15 Unit root tests: Lag order selection and maximum lag order



There is no need to specify the deterministic components for each unit root test regression. For each variable tested in levels, the program runs two regressions: one including an intercept and a trend, and another including an intercept only. Regressions performed using first and second differences of the variables as regressands are carried out including an intercept only.

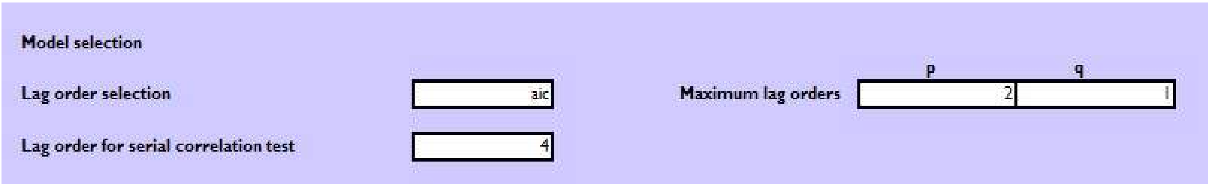
Model selection

Here one needs to specify the information criterion for selecting the lag orders for the domestic (endogenous) and foreign (weakly exogenous) variables that enter the country-specific VARX* models. The lag orders of the domestic and foreign variables that enter as regressors in the individual country models are denoted by p_i and q_i, respectively. The program will select the appropriate lag orders according to a lag order selection criterion (cell U43): select **aic** for the Akaike criterion or **sbc** for the Schwartz Bayesian criterion. The selected orderings can be changed if desired at a later stage of the program. To complete the lag order selection options you also have to specify the maximum lag orders for p_i and q_i (cells Y43 and Z43).

It is possible to skip the lag order selection and directly input arbitrarily chosen lag orders by selecting **no** for the **Lag order selection** and leaving the **Maximum lag orders** blank. If you do this, you will need to input the lag orders at the second pause of the program, which is dedicated to model specification. However, we recommend choosing a lag order selection criterion at this stage, as this procedure is relatively fast in computational terms and it is possible to change the lag orders that will be generated at a later stage.

The lag order for performing the F-version of the familiar Lagrange Multiplier serial correlation test on the residuals of the individual country models also needs to be specified here (cell U45). For quarterly data the recommended value is 4. The lag order defined here will be used for computing the residual serial correlation F-statistics, for both the VARX* model residuals (at the VARX* order selection stage) and for the VECMX* model residuals (based on the final selected model). See Figure 5.16 for an example.

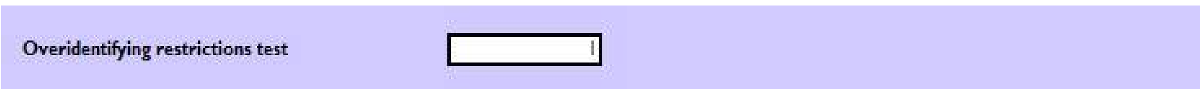
Figure 5.16 Model selection settings



Overidentifying restrictions test

Select **1** (cell U49) to test for overidentifying restrictions on the coefficients of the cointegrating relations (e.g. testing economic long-run relationships), otherwise select **0** (see Figure 5.17). If you choose to carry out this test, the likelihood ratio statistics will be computed (see Section A.11 for details). The associated bootstrap critical values will be computed during the dynamic analysis of the GVAR. Thus, after the program solves the GVAR model, the user will need to proceed with the dynamic analysis and enable the bootstrap function in the dynamic analysis settings in order to obtain the bootstrap critical values for this test. The likelihood ratio statistics will only be exported together with the corresponding critical values, so proceeding with the dynamic analysis and the bootstrap is required for the output of this test.

Figure 5.17 Overidentifying restrictions test setting



Weak exogeneity test

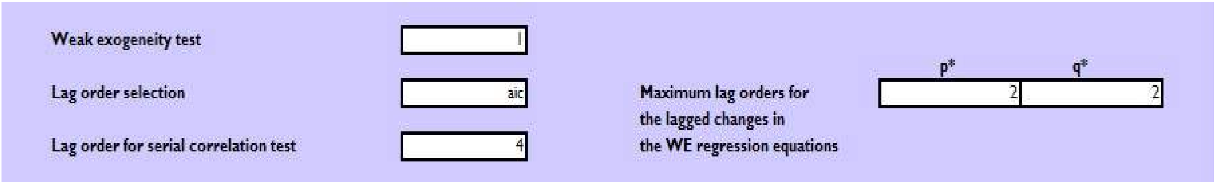
To perform the weak exogeneity test on the foreign variables of the country-specific models, select **1** for this option (cell U53), otherwise select **0**. In addition, one needs to specify the maximum lag orders of the usual domestic (cell Y55) and foreign variables (cell Z55) that will enter as regressors in the weak exogeneity regressions, which are denoted by p_i^* and q_i^* respectively. The program will select the appropriate lag orders according to a lag order selection criterion (cell U55): select aic for the Akaike criterion or sbc for the Schwartz Bayesian criterion. The selected orderings can be changed if desired, at a later stage of the program.

It is possible to skip the lag order selection by selecting **no** in the **Lag order selection** field and leaving the cells corresponding to the maximum lag orders p^* and q^* blank. If you do this, the program will automatically set the lag orders of the weak exogeneity regressions to those previously used at the estimation stage of the individual country models. In any case, it is possible to change the lag orders that will be generated at a later stage.

The lag order for performing the F-version of the familiar Lagrange Multiplier serial correlation test on the residuals of the weak exogeneity regressions also needs to be specified here (cell U57). For quarterly data the recommended value is 4. Residual serial correlation F-statistics will be computed for the weak exogeneity regression residuals at the lag order selection stage, as well as for the final selected model.

If you have chosen to carry out the test and are running the program with the **Run the program with pauses** function enabled, then you will be able to specify the country-specific regressors (for the foreign variables) associated with this test at a later stage. All domestic variables that were previously used at the estimation stage of the individual country models will enter these regressions by default. See Figure 5.18 for an example.

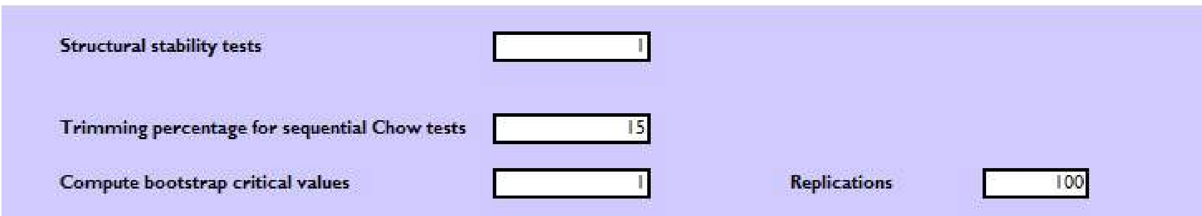
Figure 5.18 Weak exogeneity test settings



Structural stability tests

Next you have to define the settings for the structural stability tests.[7] You can turn these on and off by selecting **1** or **0** in the first field (cell U61). You also need to define the trimming percentage of the sample required for the sequential Chow tests, i.e. a value between **0** and **100** (cell U64). This will determine the first and last two subsamples used to conduct the sequential Chow tests. It should be defined such that it yields a reasonable number of observations in the smallest of the two subsamples. Given the size of the available GVAR dataset, trimming is set to 15% in our example. To specify whether to compute the bootstrap critical values of the tests: select **1** (cell U66) and state the number of replications in the adjacent field (cell X66), otherwise select **0** and ignore the replications field (see Figure 5.19). For demonstration purposes, only 100 replications will be specified here, though this can be changed by the user.

Figure 5.19 Structural stability tests settings



GVAR forecasts

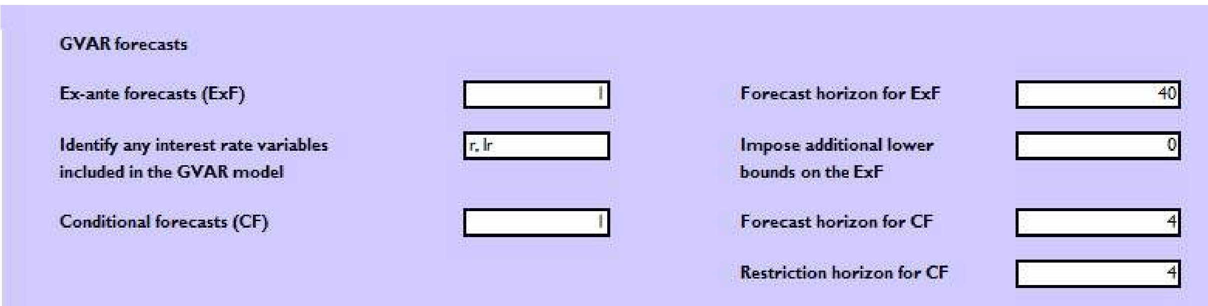
To obtain point forecasts of the variables in the GVAR (these are referred to as ex-ante forecasts to distinguish them from the conditional forecasts), select **1** in the corresponding field (cell U72), otherwise select **0**, then specify the forecast horizon (cell Y72) (see Figure 5.20). Details of the

[7] These tests are the ones carried out in DdPS, a description of which can be found in Section A.15 of this user guide.

ex-ante forecast computations can be found in Section A.25.1. To avoid negative forecasts of any interest rate variables included in the GVAR model particularly with the use of the most recent GVAR database, the toolbox offers the option of subjecting the forecasts of such variables in all countries to an internally specified lower bound (see Section A.25.1 for more details). The user is encouraged to make use of this feature by defining the short names of any interest rate variables included in the GVAR in cell U74. These should be separated by a comma, as shown in Figure 5.20, with or without a space between them. If this cell is left blank then the interest rates of all countries will not be subjected to a lower bound. If you wish to impose further lower bound restrictions on any additional variables within the GVAR model this can be done by selecting **1** in cell Y74, otherwise select **0.**[8]

To compute conditional forecasts, conditional on predefined values (restrictions) imposed on selected variables over the forecast horizon and beyond (see Section A.25.2), select **1** in the corresponding field (cell U77), otherwise select **0**, then specify the corresponding forecast horizon (cell Y77) (see Figure 5.20). For conditional forecasts you also have to specify the restriction horizon, that is the horizon over which the restrictions will be imposed (cell Y79). In our example the restriction horizon has been set equal to the forecast horizon at four quarters, though this need not necessarily be the case. The restriction horizon should be greater or equal to the forecast horizon.

Figure 5.20 GVAR forecasts settings



Trend/cycle decomposition of the GVAR

To perform the trend/cycle decomposition, select **1** in the corresponding field (cell U83), otherwise select **0**. You also need to define whether you wish to impose trend restrictions on selected country variables of the GVAR model during the trend/cycle decomposition, i.e. select **1** in cell Y83 if trend restricitons are to be imposed, otherwise select **0** (see Figure 5.21). See Section A.26 for details of this function.

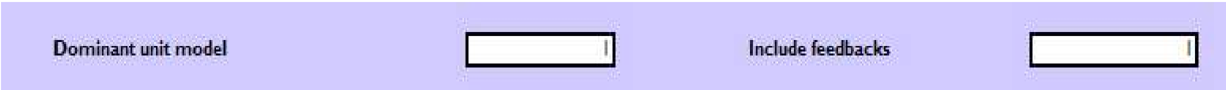
Figure 5.21 GVAR Trend/Cycle decomposition settings

[8]Lower bound restrictions for any interest rate variables can alternatively be imposed through this option by explicitly defining the lower bound at a later stage (assuming that cell U74 is left empty). However, it is recommened that this option only be used for lower bound restrictions on any additional variables.

Dominant unit

Select **1** (cell U87) if a dominant unit will be included in the GVAR model, otherwise select **0.** You also need to define whether you wish to include feedback variables in the dominant unit model, i.e. select **1** in cell Y87 if feedback variables are to be included, otherwise select **0** (see Figure 5.22). More information related to this function can be found in Section A.24.

Figure 5.22 Dominant unit setting

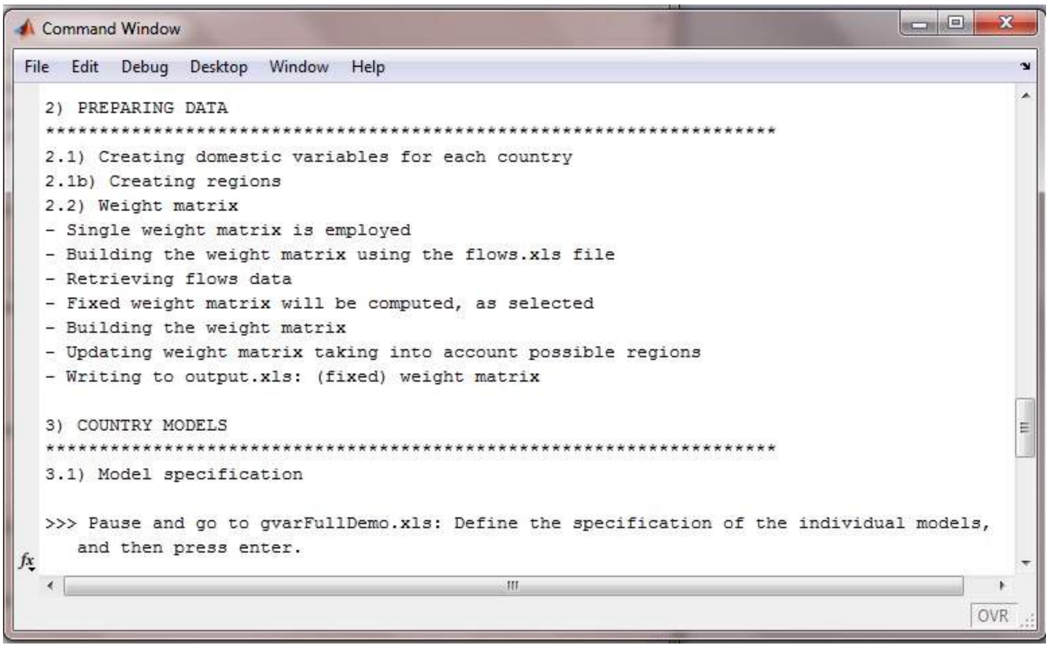


This is the end of the first pause. All settings have now been defined and so the program will continue processing the imported data, computing descriptive statistics of the variables, and performing the corresponding unit root tests, if selected.

5.2 Specification of the individual VARX* models

A message will appear in the Matlab command window stating that you have to select the individual model specification, as shown in Figure 5.23. This is the second pause.

Figure 5.23 Pause message: Individual model specification



GvarFullDemo.xls will open automatically. In the MAIN worksheet (unless otherwise specified), the program will have inserted the labelling for the countries and the variables. If you have defined regions, you will see (in columns AE-AF) that the lists of country names and country short names have changed, and are in alphabetical order according to the country and region short names. In our example, because we aggregate eight countries into a single region, our list has shortened (the eight country models ‘do not exist anymore’ for the program), whilst a new country/region appears, representing the euro area.

To the right of these lists you will see three panels corresponding to the domestic, foreign-specific and global variables (columns AH-CG). These serve to define the specification of each country/regional model, and are discussed below (see Figure 5.24). Having defined your specifications it is important to consult Table 3.2 to ensure that all restrictions on the number of domestic, foreign-specific and global variables permitted at the modelling stage are adhered to for all countries.

5.2.1 Domestic variables

The panel for the domestic variables features cells which either contain ones or are empty. The program reads the imported data for each country, inserting a one when it finds data for a given variable for a given country, and leaving the cell empty when no data are available. Replace the **1** with a **0** wherever you do not wish to include that variable in that country as a domestic (endogenous) variable. Remember not to fill any empty cells. An empty cell means that the data are not available for that particular variable in that country. Forcing the program to include a variable for which data are not available will result in an error.

5.2.2 Foreign-specific variables

The panel for the foreign-specific variables features no empty cells. In fact, it is not necessary to have data for a variable for a particular country in order to construct its foreign-specific counterpart. The idea is as before: for a given variable, replace the **1** with a **0** if you do not wish to include the particular variable in the specific country as a foreign-specific (weakly exogenous) variable.

5.2.3 Global variables

The panel for the global variables features no empty cells. For a given country, retain the value of **1** if you want to include the given global variable as a weakly exogenous variable; replace the **1** with a **2** if you want to include it as an endogenous variable; or replace the **1** with a **0** if you don't wish to include that global variable at all. Note that you can only include a global variable as endogenous in one country (so there cannot be more than one value of **2** in the column of integers for a particular global variable). If the function **Dominant unit model** was previously enabled, any global variable(s) that are not included as endogenous in any country model will by default be modelled as part of the dominant unit model (to be specified later). Thus, if you would like all global variables to be included in the dominant unit model none of these should enter as endogenous in any country model at this stage.

5.2.4 User-defined lag order selection

If you have previously chosen to use an information criterion to select the lag orders for the country-specific models, then the model specification phase is now completed. However, if you have chosen to input them manually, you need to do so here. In columns CJ-CK, insert lag orders in the corresponding fields for each country-specific VARX* model. In this case, the program will determine the lag order of the GVAR as the maximum value between those inputted in cells Y43 and Z43. Once all the lag orders have been entered, the model selection phase is complete.

5.2.5 Saving the specification of the individual models

After having defined the individual model specifications following largely DdPS (except for the oil price variable which is not included as endogenous in the US model), the MAIN worksheet will look like the example given in Figure 5.24 below.[9]

Figure 5.24 Selected individual model specifications in the MAIN worksheet

gvarFullDemo

SPECIFICATION & ESTIMATION OF INDIVIDUAL MODELS

		Domestic Variables						Foreign Variables						Global Variables		
		REAL GDP	INFLATION	REAL EQUITY PRICES	REAL EXCHANGE RATE	NOMINAL S RATE	NOMINAL L RATE	REAL GDP	INFLATION	REAL EQUITY PRICES	REAL EXCHANGE RATE	NOMINAL S RATE	NOMINAL L RATE	OIL PRICE	RAW MATERIAL PRICE	METAL PRICE
Models		y	Dp	eq	ep	r	lr	ys	Dps	eqs	eps	rs	lrs	poil	pmat	pmetal
ARGENTINA	arg	1	1	1	1	1		1	1	1	0	1	1	1	1	1
AUSTRALIA	austlia	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
BRAZIL	bra	1	1		1	1		1	1	1	0	1	1	1	1	1
CANADA	can	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
CHINA	china	1	1		1	1		1	1	1	0	1	1	1	1	1
CHILE	chl	1	1	1	1	1		1	1	1	0	1	1	1	1	1
EURO	euro	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
INDIA	india	1	1	1	1	1		1	1	1	0	1	1	1	1	1
INDONESIA	indns	1	1		1	1		1	1	1	0	1	1	1	1	1
JAPAN	japan	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
KOREA	kor	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
MALAYSIA	mal	1	1	1	1	1		1	1	1	0	1	1	1	1	1
MEXICO	mex	1	1		1	1		1	1	1	0	1	1	1	1	1
NORWAY	nor	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
NEW ZEALAND	nzld	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
PERU	per	1	1		1	1		1	1	1	0	1	1	1	1	1
PHILIPPINES	phlp	1	1	1	1	1		1	1	1	0	1	1	1	1	1
SOUTH AFRICA	safrc	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
SAUDI ARABIA	sarbia	1	1		1			1	1	1	0	1	1	1	1	1
SINGAPORE	sing	1	1	1	1	1		1	1	1	0	1	1	1	1	1
SWEDEN	swe	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
SWITZERLAND	switz	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
THAILAND	thai	1	1	1	1	1		1	1	1	0	1	1	1	1	1
TURKEY	turk	1	1		1	1		1	1	1	0	1	1	1	1	1
UNITED KINGDOM	uk	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
USA	usa	1	1	1	0	1	1	1	1	0	1	0	0	1	1	1

MAIN / DOMINANT UNIT / wmat1 / wmat2 / wmat3 / weights_aggr / y / Dp / eq / ep / r / lr / poil / pmat / pmetal

1. Save and close gvarFullDemo.xls.
2. Go to the Matlab command window prompt and press enter.
3. A message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.[10]

The program will start running again.

As previously stated, you will need to change the default values for the specification of the individual VARX* models to your preferred ones *each time you run the program with the **Run the program with pauses** function enabled*, as yours will have been automatically overwritten by the program.

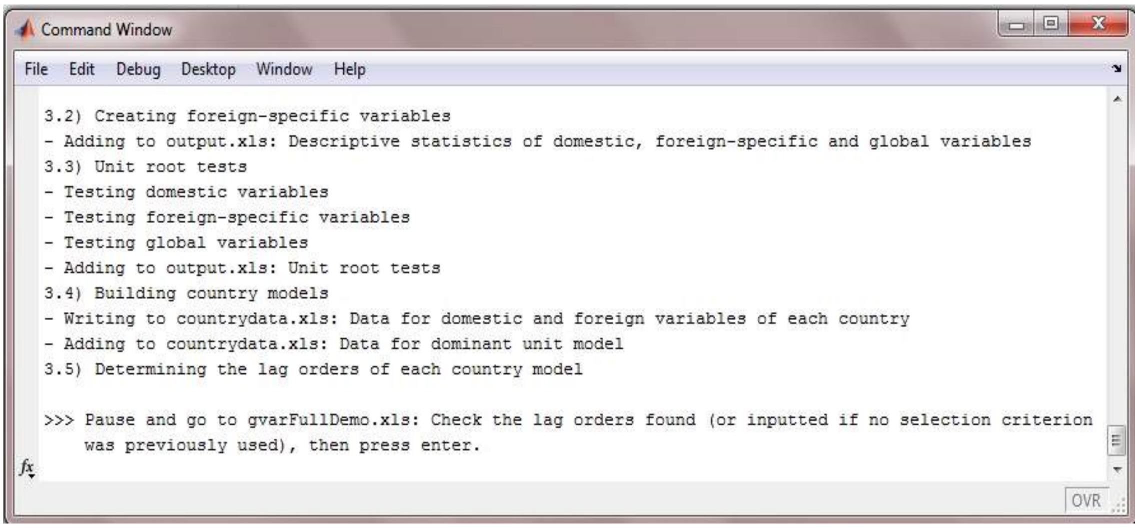
[9]See Pesaran, Schuermann and Weiner (2004) for a discussion on the exclusion of the foreign exchange rate from the individual country models.

[10]These three steps need to be repeated after each pause, i.e. save and close the Excel file you are working in, and press enter twice in MatLab.

5.2.6 Checking the lag orders

The program will make a third pause to show you the lag orders found, based on the selected lag order criterion. These will simply be your inputted lag orders if you chose not to use an information criterion. If you have chosen a lag order selection criterion during your initial run, to retain any changes you may have made to the lag orders during a second or subsequent run, select **no** in the **Lag order selection** field (cell U43). This way your lag orders will not be overwritten each time you run the program. The following pause message will appear in the Matlab command window (Figure 5.25):

Figure 5.25 Pause message: Check the lag orders for the individual country models

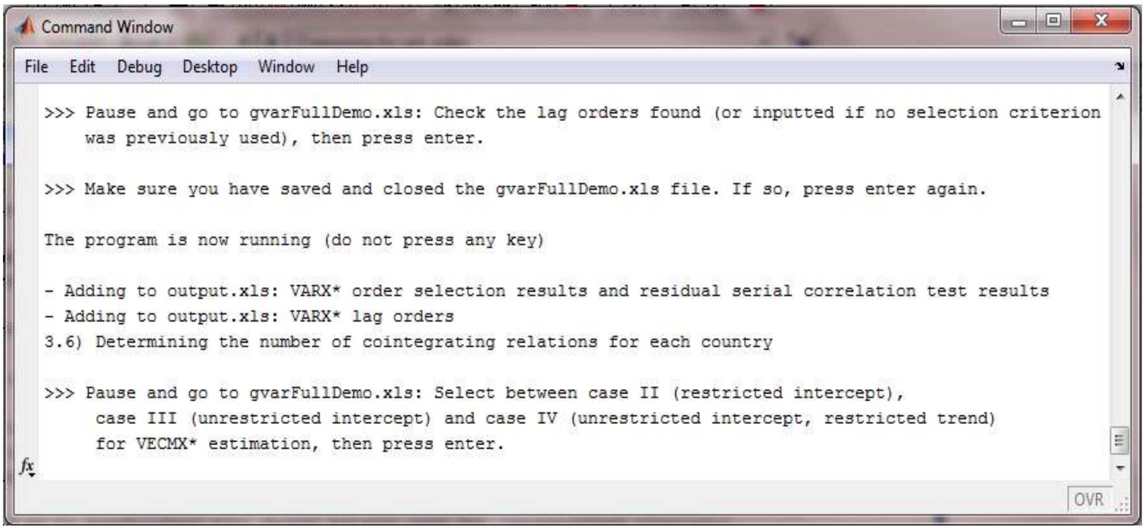


The gvarFullDemo.xls file will automatically open. You can now check the lag orders in columns CJ-CK. If you wish, you can change the lag orders found by simply replacing the existing lag order you want to modify with the new one. Then, as usual, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

5.3 Determining the rank orders

The fourth pause displays the following message in Matlab (Figure 5.26):

Figure 5.26 Pause message: Treatment of the deterministic components in the VECMX* estimation



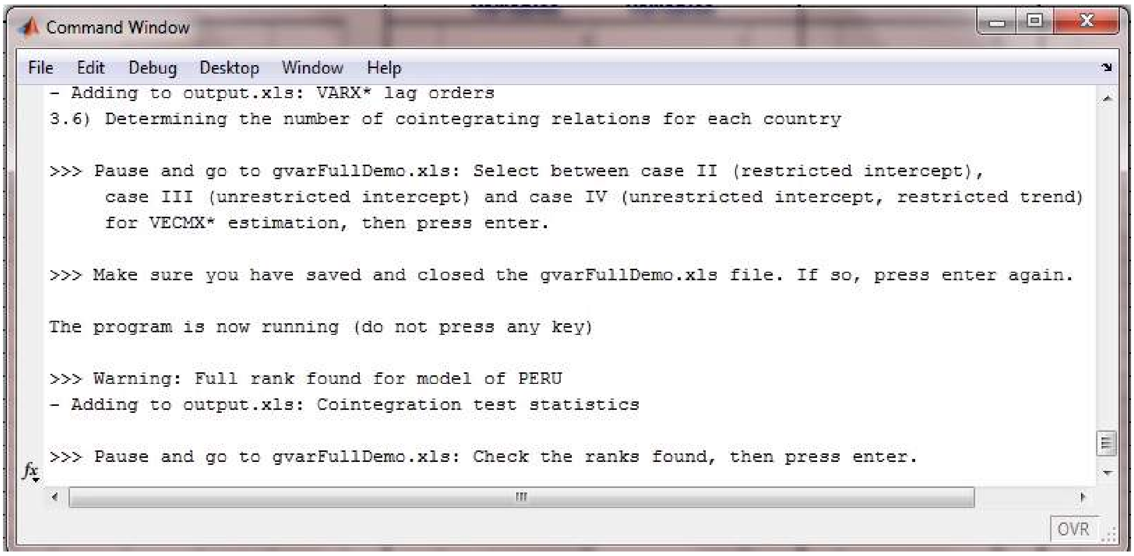
The program requires you to decide how to treat the deterministic components (the intercept and the linear trend) in the VECMX* estimation. You can choose between case II (restricted intercepts and no trends), case III (unrestricted intercepts and no trends) and case IV (unrestricted intercepts and restricted trends), where the trends are restricted to lie in the cointegration space. (see Section A.8.1 for further details). You have to define your choice in column CN of the open gvarFullDemo.xls file. By default, case IV (denoted by the integer **4**) is set for all individual models, but you can replace it by typing **3** for case III or **2** for case II, for some or all models. A formal test of case IV versus case III can be carried out by testing for co-trending restrictions (see Section A.10 for details). When you are satisfied with your choice, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

Note that should you wish to set the deterministics for any country in the VECMX* estimation to case II or case III, you will need to alter the default values to your preferred ones *each time you run the program with the* ***Run the program with pauses*** *function enabled*, as yours will have been automatically overwritten by the program.

5.3.1 Checking the rank orders

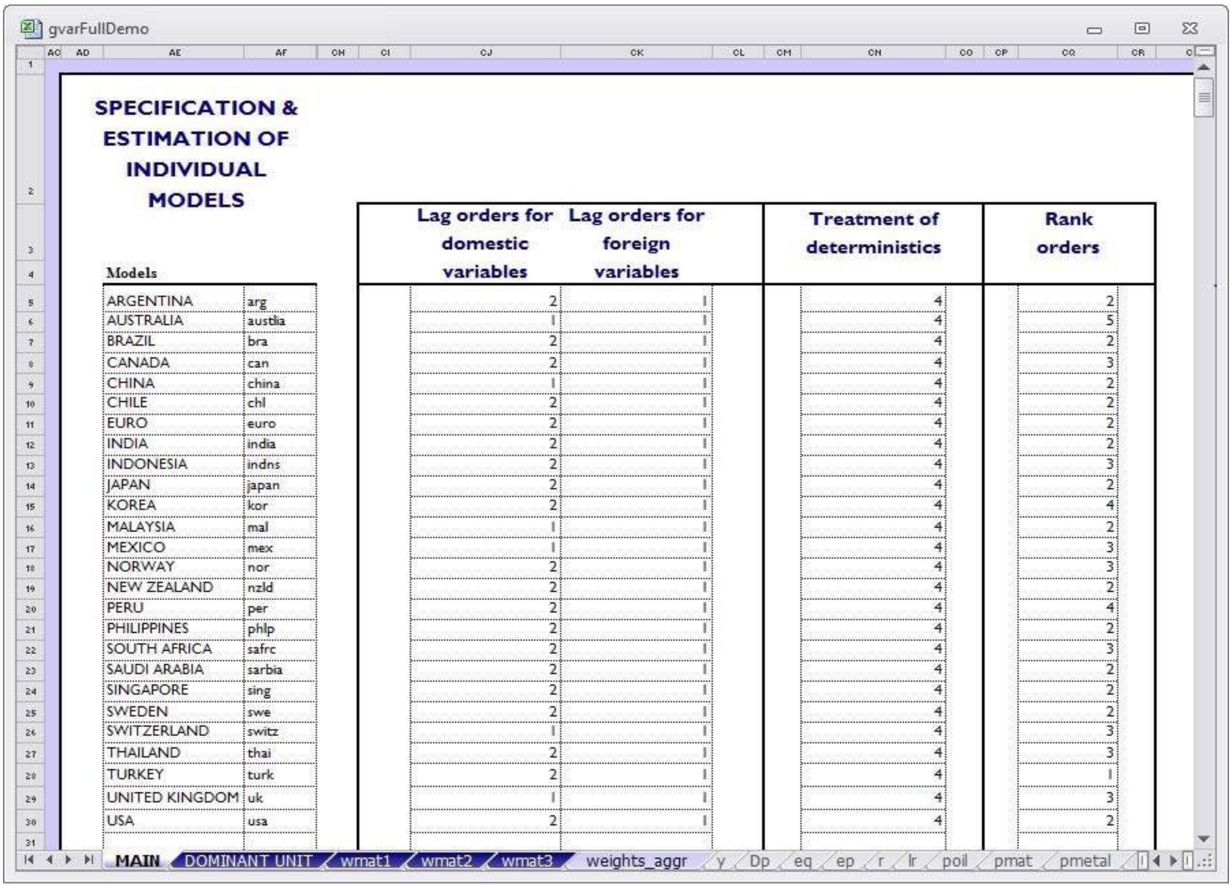
The fifth pause allows you to check the rank orders found from applying the cointegration trace statistic using the 95% critical value. You will see the following message in the Matlab command window (Figure 5.27):

Figure 5.27 Pause message: Check the rank orders for the individual country models



The gvarFullDemo.xls file will automatically open. You can check the rank orders in column CQ. If you want, you can also modify them by replacing the original values with your desired ones. Note that if, for example, a country includes five domestic variables and cointegration is rejected for all rank orders: $0, 1, ..., 4$ then a rank order of 5 will be set for that country. A warning of full rank will be generated in the Matlab command window and the user can then change the rank order if desired. In fact, one can spot these cases by simply checking the number of domestic (endogenous) variables for the individual models in columns AH-AM, together with the associated rank orders in column CQ. Once you have completed checking the rank orders, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again. Figure 5.28 shows the model specification (selected lag orders, deterministics and rank orders) in our example.

Figure 5.28 Lag orders, treatment of deterministics in the VECMX* and rank orders



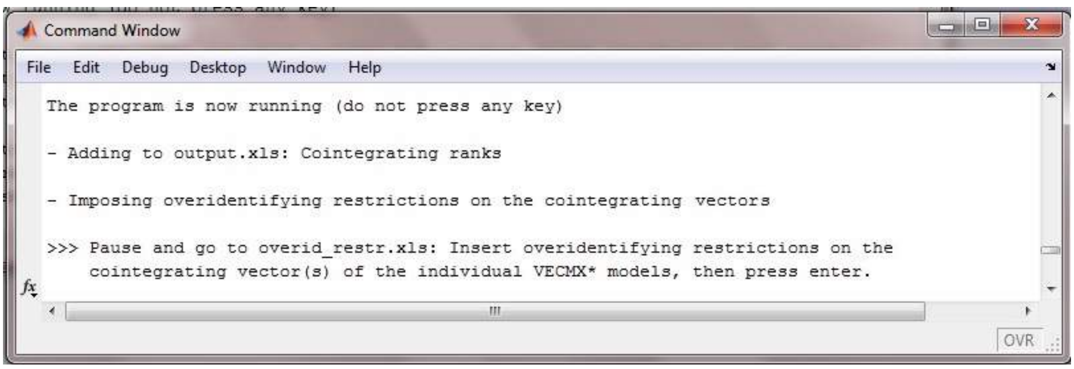
SPECIFICATION & ESTIMATION OF INDIVIDUAL MODELS

Models		Lag orders for domestic variables	Lag orders for foreign variables	Treatment of deterministics	Rank orders
ARGENTINA	arg	2	1	4	2
AUSTRALIA	austlia	1	1	4	5
BRAZIL	bra	2	1	4	2
CANADA	can	2	1	4	3
CHINA	china	1	1	4	2
CHILE	chl	2	1	4	2
EURO	euro	2	1	4	2
INDIA	india	2	1	4	2
INDONESIA	indns	2	1	4	3
JAPAN	japan	2	1	4	2
KOREA	kor	2	1	4	4
MALAYSIA	mal	1	1	4	2
MEXICO	mex	1	1	4	3
NORWAY	nor	2	1	4	3
NEW ZEALAND	nzld	2	1	4	2
PERU	per	2	1	4	4
PHILIPPINES	phlp	2	1	4	2
SOUTH AFRICA	safrc	2	1	4	3
SAUDI ARABIA	sarbia	2	1	4	2
SINGAPORE	sing	2	1	4	2
SWEDEN	swe	2	1	4	2
SWITZERLAND	switz	1	1	4	3
THAILAND	thai	2	1	4	3
TURKEY	turk	2	1	4	1
UNITED KINGDOM	uk	1	1	4	3
USA	usa	2	1	4	2

5.4 Imposing overidentifying restrictions on the cointegrating vectors

The sixth pause occurs if you have chosen to impose and test for overidentifying restrictions on the coefficients of the cointegrating relations. This pause will occur whether you are running the program with the **Run the program with pauses** function enabled or not. The same is true for all such functions where information is required to be inputted outside the interface file. In this case, the Matlab command window will read as follows (Figure 5.29):

Figure 5.29 Pause message: Impose overidentifying restrictions on the cointegrating vectors

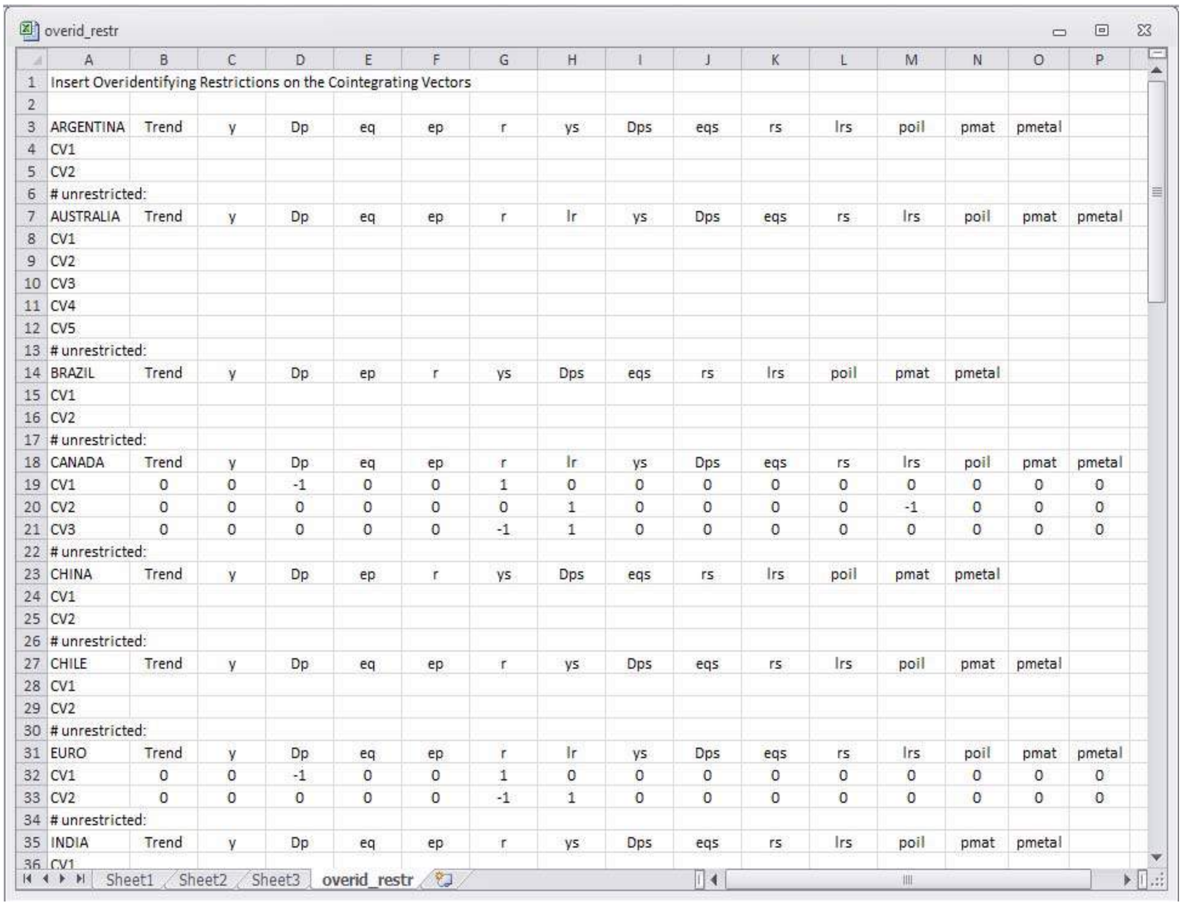


The worksheet **overid_restr** will automatically open. You only need to fill the cells corresponding to the coefficients of the cointegrating relations of those countries (or country) for which you wish to impose restrictions. The cointegrating relations associated with empty cells will be estimated by default under exact identification, using the identity matrix normalisation scheme. Overidentifying restrictions should be imposed on the coefficients of *all* cointegrating relations of a particular country, and on *all* elements of any cointegrating vector.

If you wish to allow for some elements to be left unrestricted, these have to be estimated outside the program and subsequently imposed here (see Section A.11 for further details). In addition, the total number of unrestricted elements across all cointegrating vectors for a particular country should be imposed in the cell adjacent to # unrestricted, otherwise this cell should be left empty.

Figure 5.30 is an example in which long-run restrictions have been imposed on Canada and the euro area (with no elements of the cointegrating vectors estimated 'unrestrictedly' outside the program). Specifically, the Fisher equation, the term structure condition that the vertical spread in the yield curve is stationary, and the uncovered interest parity in terms of the long rates are imposed for Canada and the former two for the euro area.

Figure 5.30 Overidentifying restrictions



overid_restr

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Insert Overidentifying Restrictions on the Cointegrating Vectors															
2																
3	ARGENTINA	Trend	y	Dp	eq	ep	r	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal	
4	CV1															
5	CV2															
6	# unrestricted:															
7	AUSTRALIA	Trend	y	Dp	eq	ep	r	lr	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal
8	CV1															
9	CV2															
10	CV3															
11	CV4															
12	CV5															
13	# unrestricted:															
14	BRAZIL	Trend	y	Dp	ep	r	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal		
15	CV1															
16	CV2															
17	# unrestricted:															
18	CANADA	Trend	y	Dp	eq	ep	r	lr	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal
19	CV1	0	0	-1	0	0	1	0	0	0	0	0	0	0	0	0
20	CV2	0	0	0	0	0	0	1	0	0	0	0	-1	0	0	0
21	CV3	0	0	0	0	0	-1	1	0	0	0	0	0	0	0	0
22	# unrestricted:															
23	CHINA	Trend	y	Dp	ep	r	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal		
24	CV1															
25	CV2															
26	# unrestricted:															
27	CHILE	Trend	y	Dp	eq	ep	r	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal	
28	CV1															
29	CV2															
30	# unrestricted:															
31	EURO	Trend	y	Dp	eq	ep	r	lr	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal
32	CV1	0	0	-1	0	0	1	0	0	0	0	0	0	0	0	0
33	CV2	0	0	0	0	0	-1	1	0	0	0	0	0	0	0	0
34	# unrestricted:															
35	INDIA	Trend	y	Dp	eq	ep	r	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal	
36	CV1															

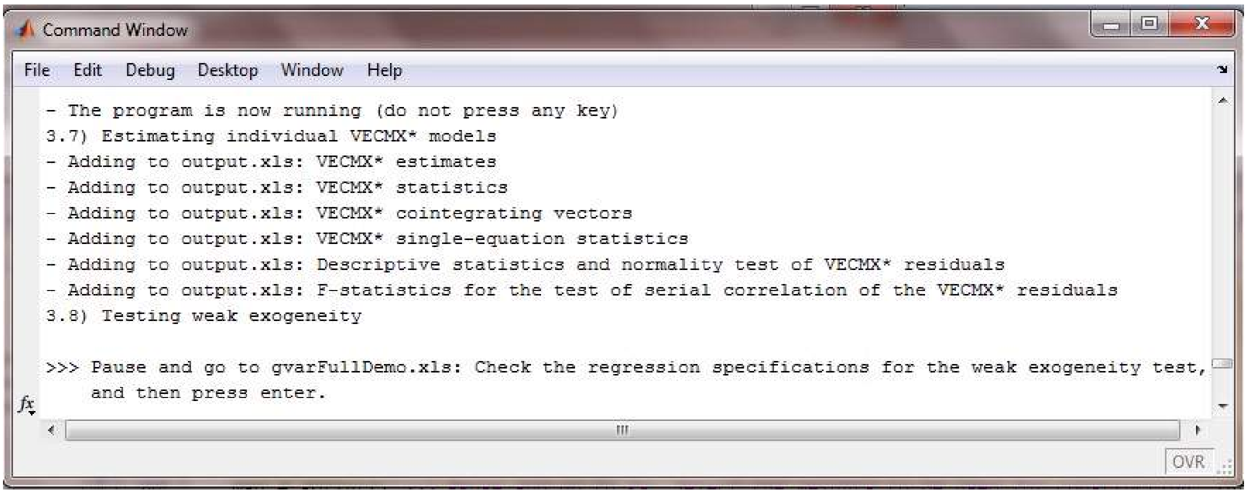
Sheet1 Sheet2 Sheet3 overid_restr

When you have finished, save and close overid_restr.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close overid_restr.xls: if overid_restr.xls is closed, then press enter again.

5.5 Regression specification for the weak exogeneity test

The seventh pause relates to the specification of the regressors and lag orders for the weak exogeneity test. The message shown in Figure 5.31 will be displayed in the Matlab command window.

Figure 5.31 Pause message: Check the regression specifications for the weak exogeneity test



The gvarFullDemo.xls file will automatically open. By default, the program will set the same specification for the domestic, foreign and global variables as used at the estimation stage of the country-specific models. The specification of the foreign and global variables, can be further modified (see Section A.12 for further details on the weak exogeneity test).[11] For a given variable, starting from column CT replace the **1** with a **0** if you do not wish to include the particular variable in the specific country as a foreign-specific (weakly exogenous) variable.

Note that any global variable previously included as domestic in the estimation stage of a particular country model will automatically be excluded (set to 0) from that model's specification when testing for weak exogeneity. This should not be changed because for each country the domestic variables are included in the weak exogeneity test regressions by default. Including it in the regressions (by setting its value to 1) will lead to perfect multicollinearity and cause the program to produce an error.

5.5.1 User-defined lag order selection

If you have previously chosen to use an information criterion to select the lag orders for the weak exogeneity regressions, then the specification phase is now completed. However, if you have chosen **no** in the **Lag order selection** field (cell U55), by default the program will set the same lag orders for the domestic and foreign variables as used at the estimation stage of the country-specific models. These will apply to all equations of the country-specific weak exogeneity regressions. You can modify the lag orders by replacing the generated values with your desired ones, as these

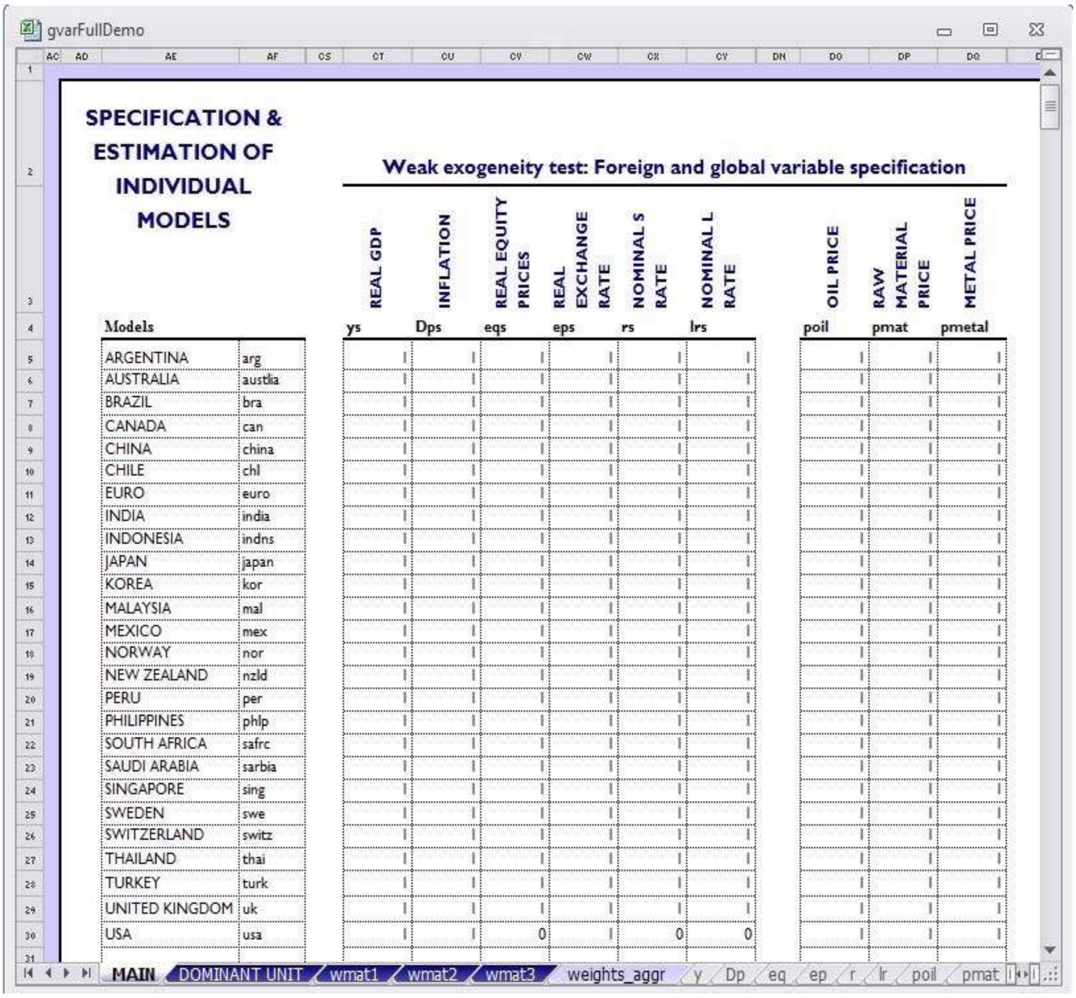
[11]The specification of the domestic variables in the weak exogeneity regressions will remain the same as in the VARX* models, and cannot be modified.

do not necessarily have to be equal to the lag orders of the individual VARX* models. In columns DZ-EA, change the lag orders for each country in the corresponding cells as appropriate. The model selection phase is then complete.

5.5.2 Saving the specification of the weak exogeneity regressions

After having defined the specification of the weak exogeneity regressions, the MAIN worksheet will look like the example given in Figure 5.32 below. Following DdPS, the foreign real exchange rate is included as a regressor in the weak exogeneity test regressions for all countries, not only the US.

Figure 5.32 Checking the regression specifications for the weak exogeneity test


gvarFullDemo

SPECIFICATION & ESTIMATION OF INDIVIDUAL MODELS

Weak exogeneity test: Foreign and global variable specification

		REAL GDP	INFLATION	REAL EQUITY PRICES	REAL EXCHANGE RATE	NOMINAL S RATE	NOMINAL L RATE	OIL PRICE	RAW MATERIAL PRICE	METAL PRICE
Models		ys	Dps	eqs	eps	rs	lrs	poil	pmat	pmetal
ARGENTINA	arg	1	1	1	1	1	1	1	1	1
AUSTRALIA	austlia	1	1	1	1	1	1	1	1	1
BRAZIL	bra	1	1	1	1	1	1	1	1	1
CANADA	can	1	1	1	1	1	1	1	1	1
CHINA	china	1	1	1	1	1	1	1	1	1
CHILE	chl	1	1	1	1	1	1	1	1	1
EURO	euro	1	1	1	1	1	1	1	1	1
INDIA	india	1	1	1	1	1	1	1	1	1
INDONESIA	indns	1	1	1	1	1	1	1	1	1
JAPAN	japan	1	1	1	1	1	1	1	1	1
KOREA	kor	1	1	1	1	1	1	1	1	1
MALAYSIA	mal	1	1	1	1	1	1	1	1	1
MEXICO	mex	1	1	1	1	1	1	1	1	1
NORWAY	nor	1	1	1	1	1	1	1	1	1
NEW ZEALAND	nzld	1	1	1	1	1	1	1	1	1
PERU	per	1	1	1	1	1	1	1	1	1
PHILIPPINES	phlp	1	1	1	1	1	1	1	1	1
SOUTH AFRICA	safrc	1	1	1	1	1	1	1	1	1
SAUDI ARABIA	sarbia	1	1	1	1	1	1	1	1	1
SINGAPORE	sing	1	1	1	1	1	1	1	1	1
SWEDEN	swe	1	1	1	1	1	1	1	1	1
SWITZERLAND	switz	1	1	1	1	1	1	1	1	1
THAILAND	thai	1	1	1	1	1	1	1	1	1
TURKEY	turk	1	1	1	1	1	1	1	1	1
UNITED KINGDOM	uk	1	1	1	1	1	1	1	1	1
USA	usa	1	1	0	1	0	0	1	1	1

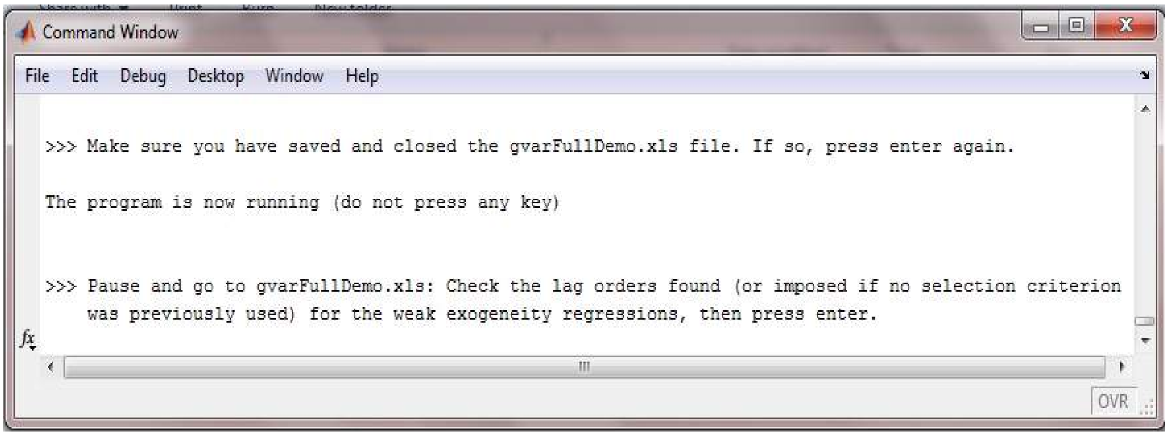
When you have finished, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

You will need to change the default values for the specification of the weak exogeneity test regressions, i.e. for the regressors (foreign and global), to your preferred ones *each time you run the program with the **Run the program with pauses** function enabled*, as yours will have been automatically overwritten by the program.

5.5.3 Checking the lag orders

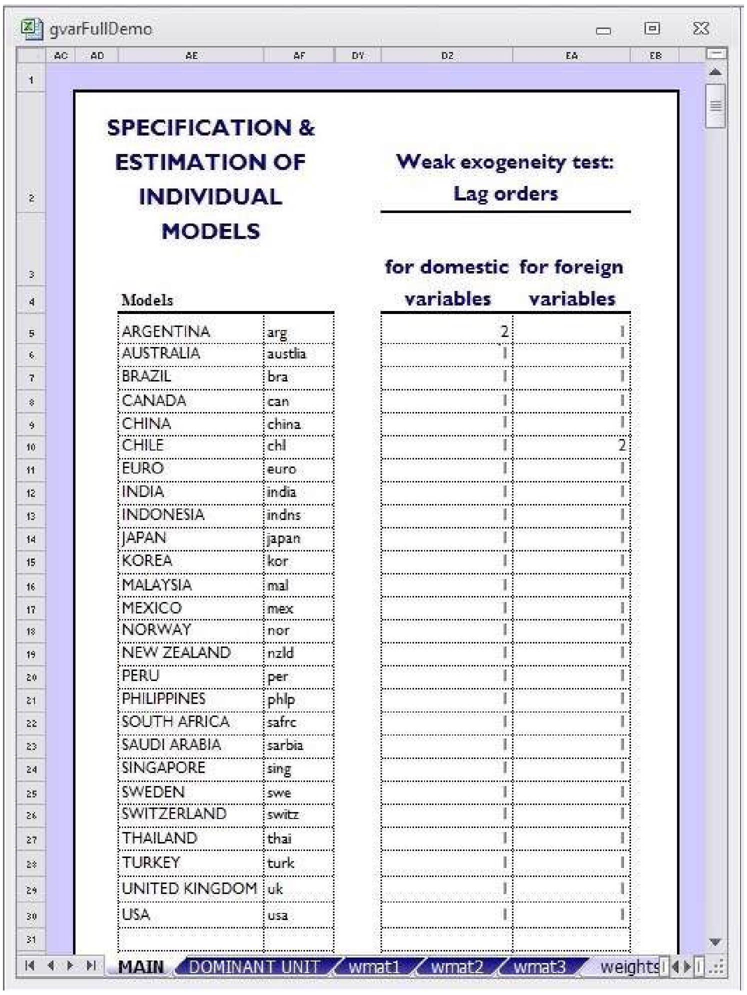
The program will make an eighth pause to show you the lag orders found, based on the selected lag order criterion. If you chose not to use an information criterion, these will simply be your inputted lag orders (based on your adjustments to the automatically generated ones as mentioned earlier). If you have chosen a lag order selection criterion during your initial run, to retain any changes you may have made to the lag orders during a second or subsequent run, select **no** in the **Lag order selection** field (cell U55). This way your lag orders will not be overwritten each time you run the program. The following pause message will appear in the Matlab command window (Figure 5.33):

Figure 5.33 Pause message: Check the lag orders for the weak exogeneity regressions



The gvarFullDemo.xls file will automatically open. You can now check the lag orders in columns DZ-EA as shown in Figure 5.34. If you wish, you can change the lag orders found by simply replacing the existing lag order you want to modify with the new one. Then, as usual, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

Figure 5.34 Checking the lag orders for the weak exogeneity regressions



gvarFullDemo

SPECIFICATION & ESTIMATION OF INDIVIDUAL MODELS

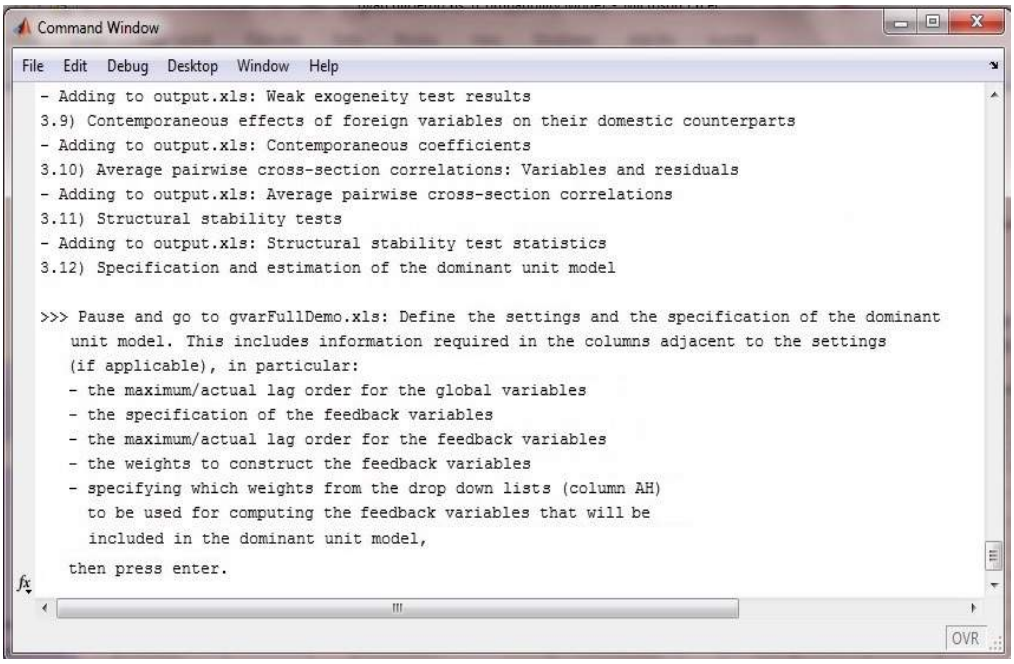
Weak exogeneity test: Lag orders

Models		for domestic variables	for foreign variables
ARGENTINA	arg	2	1
AUSTRALIA	austlia	1	1
BRAZIL	bra	1	1
CANADA	can	1	1
CHINA	china	1	1
CHILE	chl	1	2
EURO	euro	1	1
INDIA	india	1	1
INDONESIA	indns	1	1
JAPAN	japan	1	1
KOREA	kor	1	1
MALAYSIA	mal	1	1
MEXICO	mex	1	1
NORWAY	nor	1	1
NEW ZEALAND	nzld	1	1
PERU	per	1	1
PHILIPPINES	phlp	1	1
SOUTH AFRICA	safrc	1	1
SAUDI ARABIA	sarbia	1	1
SINGAPORE	sing	1	1
SWEDEN	swe	1	1
SWITZERLAND	switz	1	1
THAILAND	thai	1	1
TURKEY	turk	1	1
UNITED KINGDOM	uk	1	1
USA	usa	1	1

5.6 Defining the dominant unit settings and specification

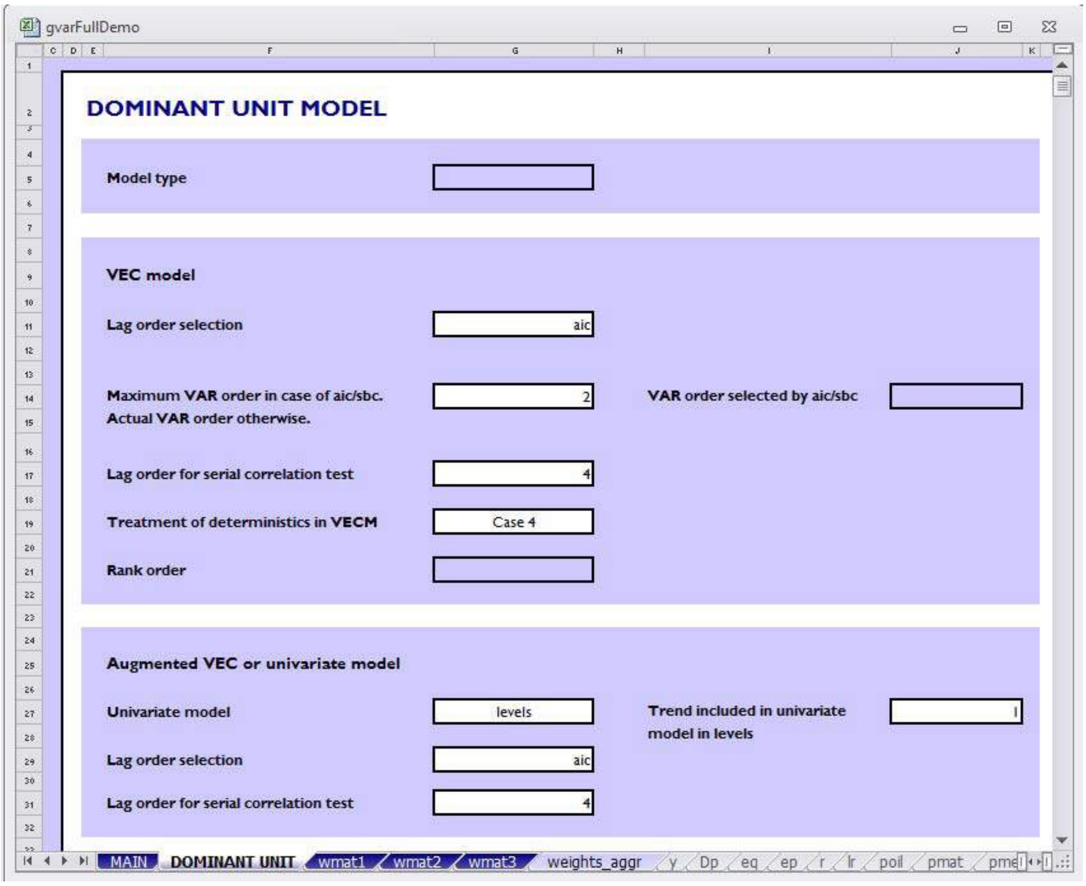
If the dominant unit function has been enabled the program will pause and the following message will be displayed in the Matlab command window (Figure 5.35). The short name reserved by the program for the dominant unit model used in the analysis is ‘du_model’.

Figure 5.35 Pause message: Define the dominant unit settings and specification



You are required to define the settings and specification of the dominant unit model in the DOMINANT UNIT worksheet of the gvarFullDemo.xls file which has been automatically reopened. This requires a set of inputs as shown in Figure 5.36 together with additional information supplied adjacent to this panel (if applicable). Each of these inputs are described separately below, together with all other required information.

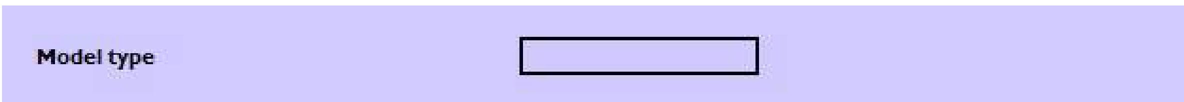
Figure 5.36 Defining the dominant unit settings and specification in the DOMINANT UNIT worksheet



5.6.1 Model type

Cell G5 displayed in Figure 5.37 will provide information on the type of dominant unit model included in the GVAR, that is whether it is univariate or multivariate. It does not require any input from the user, and will be filled by the program with the relevant information when it continues to run.

Figure 5.37 Model type



5.6.2 VEC model

Here one needs to specify the information related to the vector error correction (VEC) model used in the first stage of modelling the dominant unit (see Section A.24.1 for further details). *This panel only requires to be filled if the dominant unit model is multivariate*. If it is not, go directly to Section 5.6.3. Any information provided in this panel will be ignored by the program.

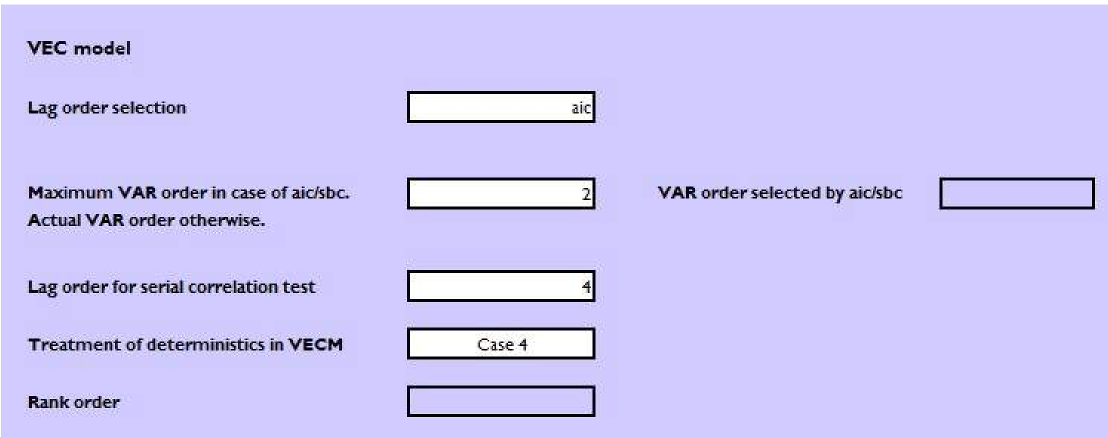
Initially one needs to specify the information criterion for selecting the lag order for the global variables included in the corresponding first stage VAR model of the dominant unit analysis (recall these are the global variables that have not been specified earlier as endogenous in any of the individual country models). The program will select the appropriate lag orders according to a lag order selection criterion (cell G11): select **aic** for the Akaike criterion or **sbc** for the Schwartz Bayesian criterion. To complete the lag order selection options, you also have to specify the maximum lag order of the VAR (cell G14). The VAR order selected by the chosen information criterion will appear in cell J14 when the program continues to run, and therefore this cell is not required to be filled by the user. This lag order can be changed if desired at a later stage of the program.

It is possible to skip the lag order selection by selecting **no** for the **Lag order selection** function and directly inputting an arbitrarily chosen lag order in cell G14 directly below this function. This inputted value will then be the order of the VAR used when estimating the corresponding VEC model.

The lag order for performing the F-version of the familiar Lagrange Multiplier serial correlation test on the residuals of the first stage VEC model also needs to be specified here (cell G17). For quarterly data the recommended value is 4. The lag order defined here will be used for computing the residual serial correlation F-statistics, for both the VAR model residuals (at the VAR order selection stage) and for the VEC model residuals (based on the final selected model).

Next the nature of the deterministics included in the VECM has to be selected (cell G19). The user can choose between Case II, Case III, and Case IV (see Section A.8.1 for details of these cases). Cell G21 is reserved for the rank order of the VEC dominant unit model. This will be filled by the program as it continues to run and therefore it is not required to be filled by the user. This rank can be changed if desired at a later stage of the program. See Figure 5.38 for an example.

Figure 5.38 Dominant unit VEC model settings



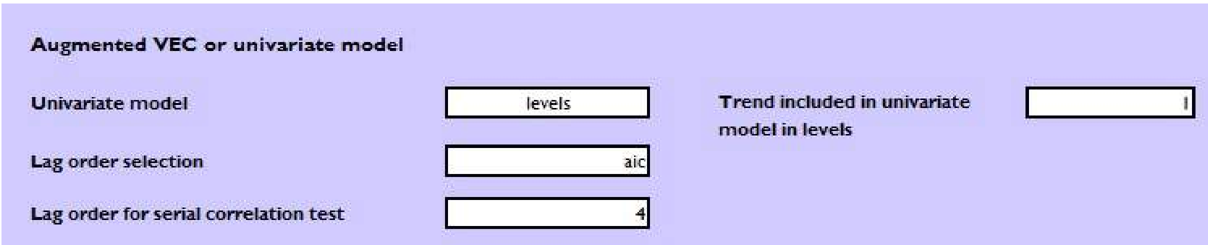
If **Include feedbacks** was set to **0** at the initial settings stage of the GVAR analysis in the MAIN worksheet of the interface file, go to Section 5.6.4 as no further settings are required to be filled.

5.6.3 Augmented regression

At this stage the user has to define the settings for the augmented VEC dominant unit model, assuming that **Include feedbacks** was previously set to 1. *This is also the panel that needs to be filled if the dominant unit model is univariate, whether augmentation is required or not (i.e. whether **Include feedbacks** was previously set to 1 or not).* If the dominant unit model is univariate, in cell G27 select **levels** to estimate the model in levels or **first differences** to estimate the model in first differences. If you have chosen to estimate a univariate model in levels then you also have to select whether you would like to include a trend in the regression by selecting **1** in cell J27, **0** otherwise. If the dominant unit model is multivariate then cells G27 and J27 can be ignored.

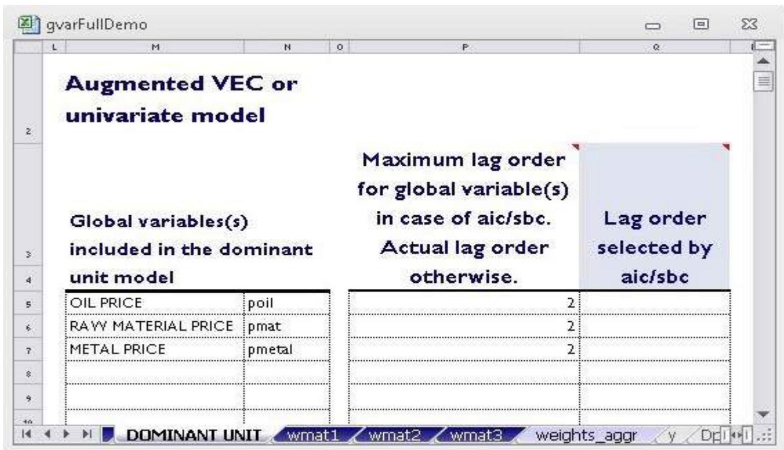
Next one needs to specify the information criterion for selecting the lag orders for the augmented VEC or the univariate dominant unit model. Augmenting the VECM with additional variables is likely to alter the lag order found for this model in the first stage regression, which is the reason why it is selected again. Note that the lag orders for both the global and feedback variables in the augmented VEC model are equation specific (see Section A.24.1). The program will once again select the appropriate lag orders according to a lag order selection criterion (cell G29): select **aic** for the Akaike criterion or **sbc** for the Schwartz Bayesian criterion. The lag order for performing the F-version of the familiar Lagrange Multiplier serial correlation test on the residuals of the augmented VEC or univariate dominant unit model also needs to be specified here (cell G31). See Figure 5.39 for an example.

Figure 5.39 Dominant unit augmented VEC or univariate model settings



To complete the lag order selection, in the columns adjacent to the settings you also have to specify the maximum lag order for the global and feedback variable(s). Both of these should be greater than zero. The maximum lag order for the global variables of the dominant unit model should be inputted in column P. See Figure 5.40 where a maximum lag order of 2 has been specified for all global variables included in the dominant unit model.

Figure 5.40 Specifying the (maximum) lag order for the domestic variables in the augmented VEC or univariate model



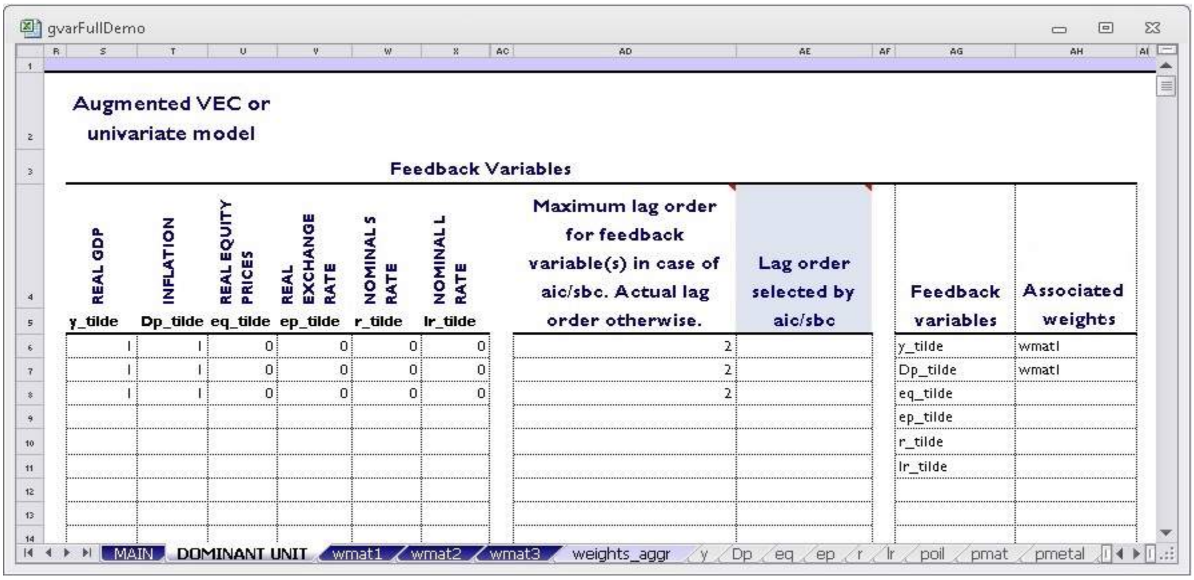
Before specifying the maximum lag order for the feedback variable(s) (characterised by the suffix tilde) in column AD (see Figure 5.41), you first have to specify which of these will be included in the dominant unit model. The default value of **1** should be retained for those feedback variables that you wish to include in the augmented model. To exclude a particular feedback variable, change the value of **1** to **0**. The feedback variable(s) included in the various equations need not be the same. In the multivariate case, assuming that the **Include feedbacks** function was previously enabled (i.e. set to 1), it is possible to exclude all feedback variables from one or more, though not all, equations (at least one feedback variable has to be included in at least one equation of the augmented model). For any such equation, the cell corresponding to the maximum lag order for the feedback variables can be left blank. Any specified value will be ignored by the program. It is important to note that when running the program with the **Run the program with pauses** function enabled, selection of the feedback variables to enter the augmented dominant unit model equation(s) can only be performed under the first pause of the dominant unit model as seen in Figure 5.35. Any change to the inclusion or exclusion of feedback variables beyond this pause will result in a program error.

Columns Q and AE are not required to be filled by the user. These columns will be filled by the program with the lag order(s) selected by the chosen information criterion as the program continues to run. These lag orders can be changed if desired at a later stage of the program. In our example, y_tilde (real GDP) and Dp_tilde (inflation) are the two feedback variables that have been selected to enter the augmented VEC, while the rest of the variables will not be included.

As before it is possible to skip the lag order selection by selecting **no** for the **Lag order selection** and directly inputting arbitrarily chosen lag orders in columns P and AD. These inputted lag orders will then be the ones used when estimating the augmented dominant unit model.

Information required for the feedback variables is not yet complete. A list of the short names of all feedback variables appears in column AG (Figure 5.41). In the adjacent column AH you are required to select the set of weights used to construct each of the feedback variables included in the overall equations of the augmented dominant unit model. A dropdown list of the available weights can be accessed by clicking in each of the corresponding cells in column AH. (The available weights need to be provided by the user and will be discussed next). Weights need to be selected only for the variables that are included in the dominant unit model (i.e. those that appear with the value of 1 in columns S-X). For the feedback variables excluded from the dominant unit model (i.e. that have a value of 0 specified in columns S-X), any set of weights selected, including the empty cell, will be ignored by the program. Since only the feedback variables associated with real GDP and inflation will be included in the augmented VEC model in our example, an associated weight matrix has been selected only for these two variables (see Figure 5.41).

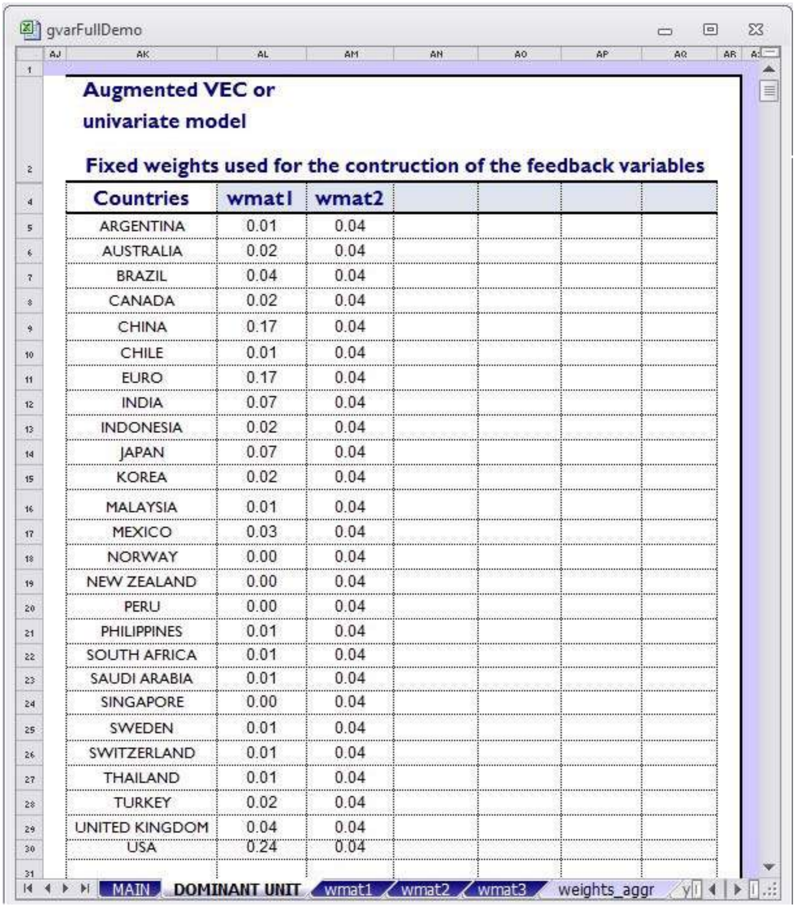
Figure 5.41 Specifiying the feedback variables to be included in the augmented VEC or univariate model, their corresponding (maximum) lag order, and the associated weights used for their construction



Finally, the fixed weights required to construct the feedback variables should be inputted in columns AL to AQ. Column AK contains the variable long names and will be provided by the program. These will match the list of country long names that appears in column AE of the MAIN worksheet. The corresponding weights for this country list should be provided in the adjacent columns. Note that in our example, weights are required for the euro as a single country, given that a euro region was selected at the beginning of the analysis. You can provide up to six sets of different weights making sure that each of them adds up to one across the (non-dominant unit) countries included in the GVAR model. The first set of weights should always be inputted in column AL under the heading wmat1, the second set in column AM under the heading wmat2, and so on, and should not be given any other names. All name headings for the weights provided in cells AL4:AQ4 will appear in the dropdown lists of column AH mentioned earlier (whether they contain data or not) at the first pause of the dominant unit specification stage. It is therefore advisable to include at least as many name headings for the weights that you wish to use before you start running the program. Then once you input the relevant data for the weights at the appropriate pause, if you wish you can delete the remaining headings. The weights only need to be inputted once and can then be used for any subsequent runs whether the **Run the program with pauses** function is enabled or not (providing of course the countries under column AK remain the same).

Figure 5.42 shows an example where two sets of weights have been inputted in the dominant unit sheet: wmat1 in column AL contains PPP-GDP weights based on the three year average 2009-2011 (constructed from the data provided in the weights_aggr worksheet) and wmat2 in column AM contains equal weights. Only the former will be used for the construction of the feedback variables in our example, as shown in column AH of Figure 5.41.

Figure 5.42 Inserting the weights used to construct the feedback variables included in the augmented VEC or univariate model


gvarFullDemo

Augmented VEC or univariate model

Fixed weights used for the contruction of the feedback variables

Countries	wmat1	wmat2
ARGENTINA	0.01	0.04
AUSTRALIA	0.02	0.04
BRAZIL	0.04	0.04
CANADA	0.02	0.04
CHINA	0.17	0.04
CHILE	0.01	0.04
EURO	0.17	0.04
INDIA	0.07	0.04
INDONESIA	0.02	0.04
JAPAN	0.07	0.04
KOREA	0.02	0.04
MALAYSIA	0.01	0.04
MEXICO	0.03	0.04
NORWAY	0.00	0.04
NEW ZEALAND	0.00	0.04
PERU	0.00	0.04
PHILIPPINES	0.01	0.04
SOUTH AFRICA	0.01	0.04
SAUDI ARABIA	0.01	0.04
SINGAPORE	0.00	0.04
SWEDEN	0.01	0.04
SWITZERLAND	0.01	0.04
THAILAND	0.01	0.04
TURKEY	0.02	0.04
UNITED KINGDOM	0.04	0.04
USA	0.24	0.04

MAIN DOMINANT UNIT wmat1 wmat2 wmat3 weights_aggr

If the dominant unit model is univariate and the function **Include feedbacks** in the settings of the MAIN worksheet is set to **0**, then no information related to the feedback variables is required.

5.6.4 Saving the settings

Having defined the settings and specification for the dominant unit model:

1. Save and close the gvarFullDemo.xls file.
2. Go to the Matlab command window prompt and press enter.
3. A message will remind you to save and close the gvarFullDemo.xls file: if gvarFullDemo.xls is closed, then press enter again.

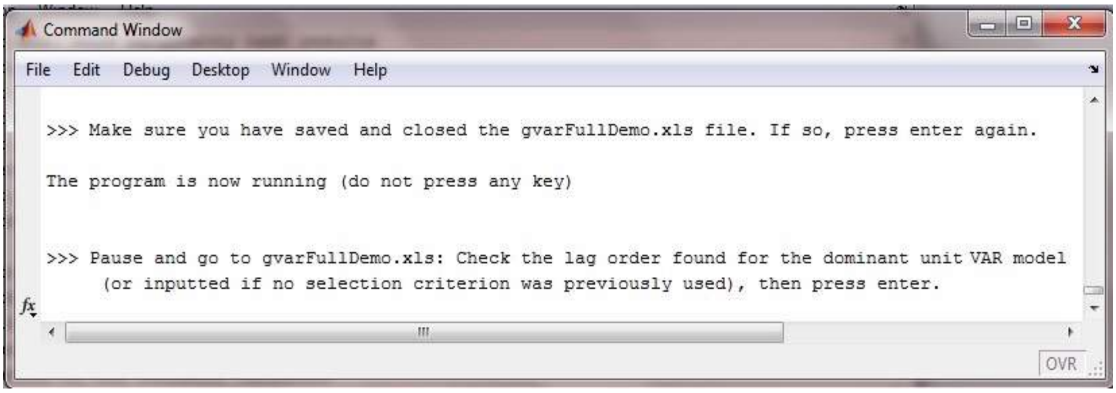
All settings and information for the dominant unit model have now been defined and so the program will continue processing it all and then carry on with the estimation.

5.7 Estimation of the dominant unit model

5.7.1 Checking the lag order for the first stage VAR model

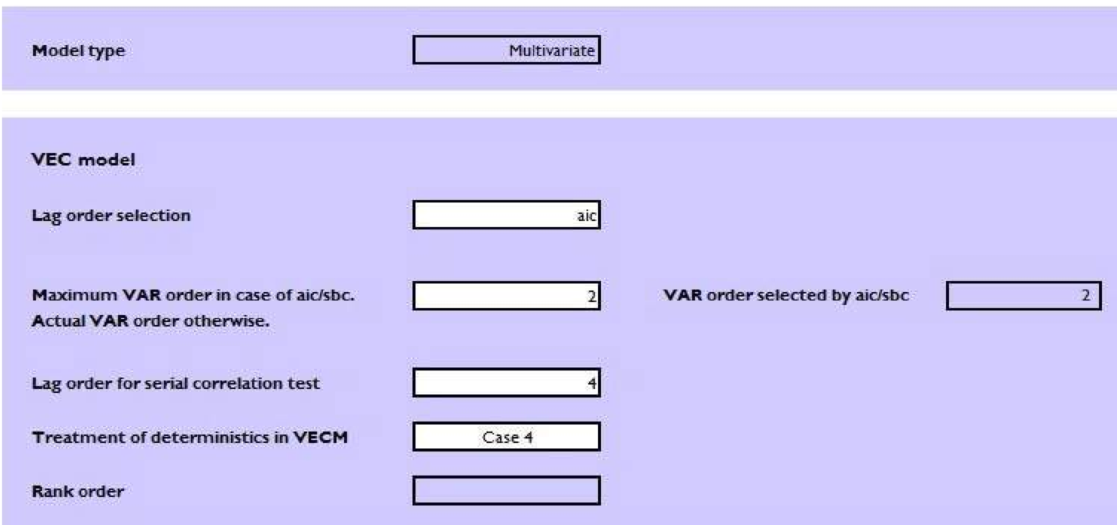
The first pause made by the program during the estimation phase of the dominant unit model, assuming it is multivariate, is to show you the lag order found for the VAR model of the first stage based on the selected lag order criterion. If you chose not to use an information criterion (i.e. **no** was previously selected in cell G11) the program will not perform this pause and the lag order of the VAR will be taken as that inputted earlier at the settings stage of the dominant unit worksheet in cell G14. The following pause message will appear in the Matlab command window (Figure 5.43):

Figure 5.43 Pause message: Check the lag order for the dominant unit VAR model



The gvarFullDemo.xls file will automatically open. You can now check the lag order in cell J14 adjacent to the field **VAR order selected by aic/sbc**. If you wish, you can change the lag order found by simply replacing the existing lag order with the new one. You will also notice that **Multivariate** has now appeared in the **Model type** field indicating that the dominant unit model is multivariate. Figure 5.44 shows the lag order found in our example.

Figure 5.44 Checking the lag order for the dominant unit VEC model

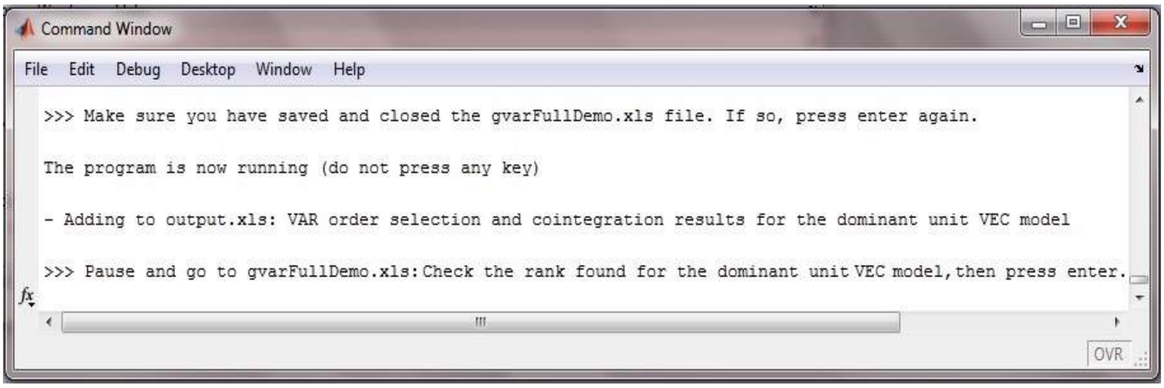


Then, as usual, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

5.7.2 Checking the rank order for the first stage VEC model

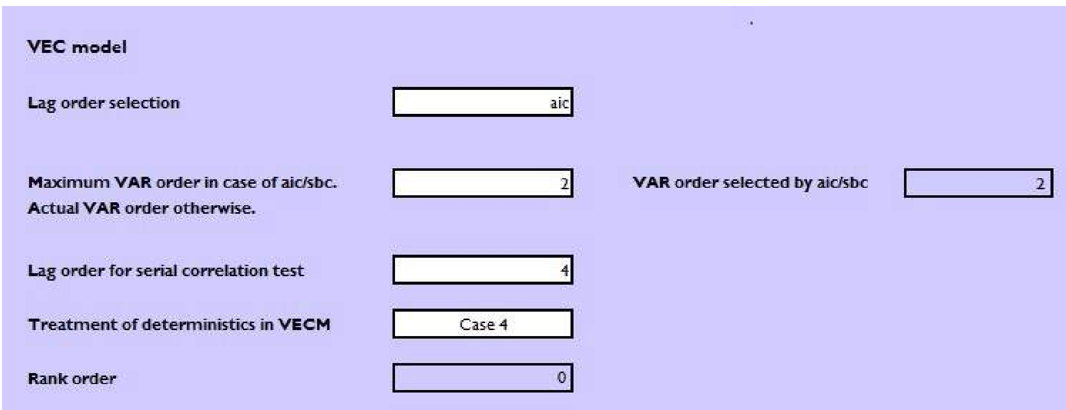
The next pause allows you to check the rank order found from applying the cointegration trace statistic. This is applied using the 95% critical value based on the choice regarding the treatment of the deterministic components of the corresponding VEC model made earlier. You will see the following message in the Matlab command window (Figure 5.45):

Figure 5.45 Pause message: Check the rank order for the dominant unit VEC model



The gvarFullDemo.xls file will automatically open. You can check the rank order in cell G21 adjacent to the field **Rank order**. If you want, you can also modify this by replacing the original value with your desired one. As with the country-specific models, a warning of full rank will be generated in the Matlab command window should this be the case, and the user can then change the rank order if desired. Once you have completed the check, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again. Figure 5.46 shows the rank order found in our example.

Figure 5.46 Checking the rank order for the dominant unit VEC model



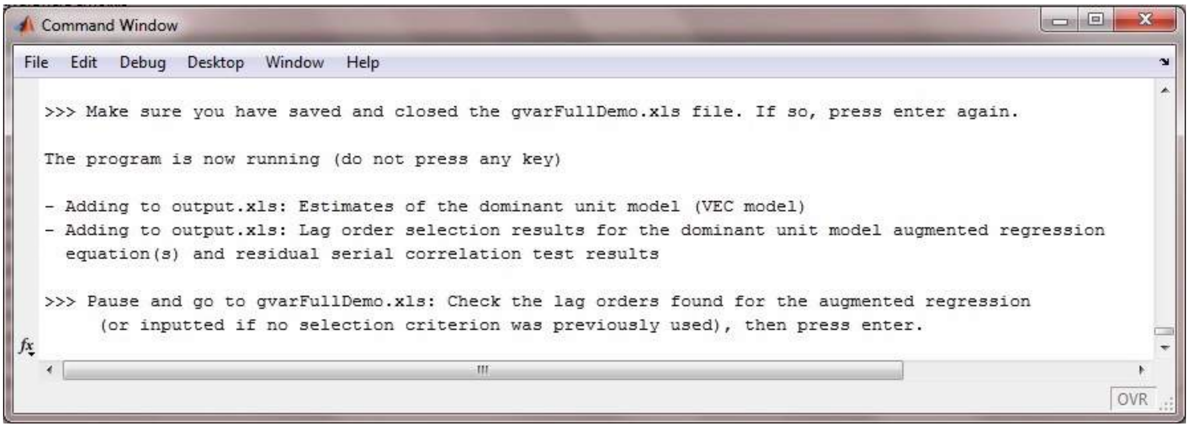
Note that if the dominant unit model is univariate then the above two pauses will not occur. Similarly, if no augmentation has been previously selected in the case of a multivariate model, no further pauses related to the dominant unit model will be made.

5.7.3 Checking the lag orders for the augmented model

Assuming that augmentation has been previously selected (i.e. **Include feedbacks** was set to 1), the following pause is to show you the lag orders found for the domestic and feedback variables of the augmented VEC model based on the selected lag order criterion. These will be the lags for the augmented univariate model if only one global variable is included in the dominant unit. In particular, they will be the lag orders for the univariate model in levels if **levels** was specified at the dominant unit settings stage, or the lag orders for the univariate model in first differences if **first differences** was specified.

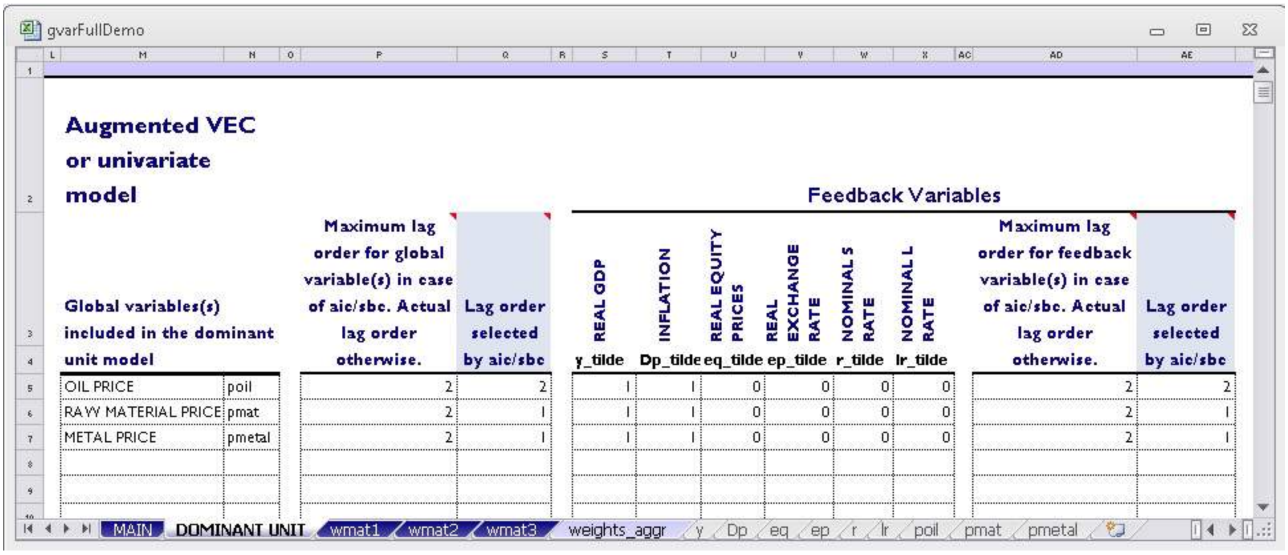
You will see the following message in the Matlab command window (Figure 5.47):

Figure 5.47 Pause message: Check the lag orders for the augmented VEC or univariate model



The gvarFullDemo.xls file will automatically open. You can now check the lag orders in columns Q and AE for the domestic and feedback variables of the dominant unit, respectively. If you wish, you can change the lags orders found by simply replacing the existing lag orders you want to modify with the new ones. If the dominant unit model is univariate and no feedback variables were previously selected at the settings stage, only the lag order in column Q is relevant and needs to be checked. Once again if you chose not to use an information criterion (i.e. **no** was previously selected in cell G29) the program will not perform this pause and the lag orders for the augmented VEC model will be taken as those inputted earlier at the settings stage of the dominant unit model in columns P and AD. Similar for the case of a univariate model. Figure 5.48 shows the lag orders found in our example.

Figure 5.48 Checking the lag orders for the augmented VEC or univariate model



Then, as usual, save and close gvarFullDemo.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close gvarFullDemo.xls: if gvarFullDemo.xls is closed, then press enter again.

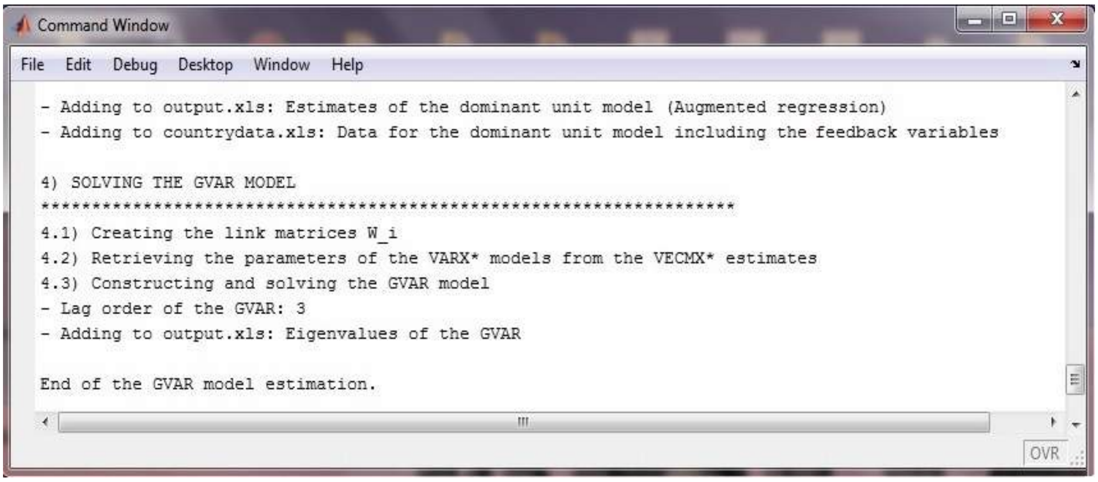
In the case where the function **Run the program with pauses** is disabled (i.e. set to 0) all inputted information (including any changes) under the dominant unit settings will be retained. Specifically, if the field **Lag order selection** is set to an information criterion, **aic** or **sbc**, the lag order(s) under the column heading **Lag order selected by aic/sbc** are used by the program (columns Q and AE), while if it is set to **no** the lag order(s) under columns P and AD are used.

You will need to change the default values for the specification of any feedback variables in the dominant unit model to your preferred ones *each time you run the program with the* ***Run the program with pauses*** *function is enabled*, as yours will have been automatically overwritten by the program. This is also the case if you change the lag orders selected by an information criterion.

5.8 Solving the GVAR model

Once the specification and estimation of the individual country models is complete, the program will construct and solve the GVAR model. The Matlab command window will read as shown in Figure 5.49 below:

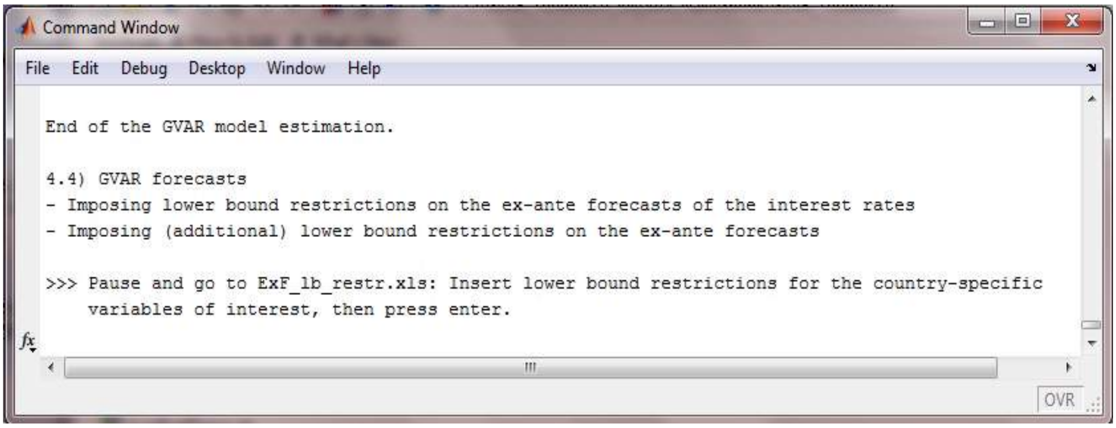
Figure 5.49 Solving the GVAR model



5.9 GVAR forecasts

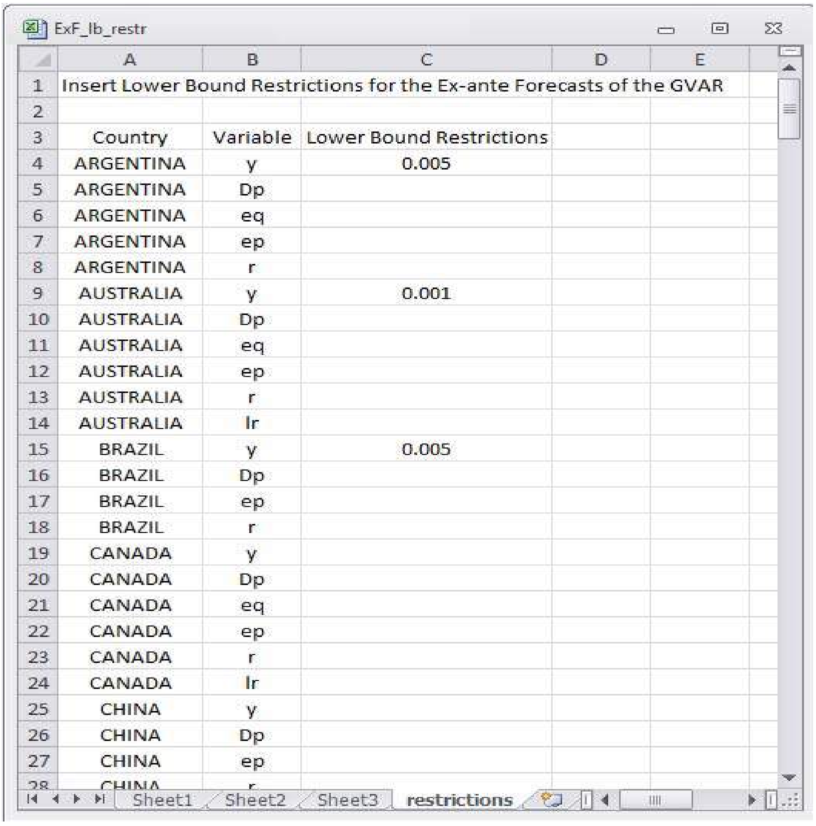
If you have chosen to generate ex-ante forecasts of the GVAR model, the program will then compute these over the specified horizon. The ex-ante forecasts of any interest rate variables defined in cell U74 will be subjected to a lower bound as mentioned earlier. Further, if the function **Impose additional lower bounds** has been enabled (i.e. set to 1) then the program will pause. In this case, the Matlab command window will read as follows (Figure 5.50):

Figure 5.50 Pause message: Impose (additional) lower bound restrictions on the ex-ante forecasts



The worksheet **ExF_lb_restr** will automatically open. You are required to fill the cells in column C with the value(s) of the desired lower bound for the country variables of interest leaving the remaining cells empty. *The value(s) of the imposed lower bound should be compatible with any a priori transformations made to the associated country variable source data.* The forecasts for the country variables corresponding to empty cells will not be subjected to any lower bound. For demonstration purposes this function is turned off (set to 0) in the gvarFullDemo interface file. This means that only the interest rate forecasts in the associated output.xls file will be subjected to the internally specified lower bound, given that the interest rate variables are specified in cell U74 of the MAIN worksheet of the gvarFullDemo interface file. Figure 5.51 shows an example where the function **Impose additional lower bounds** has been enabled and lower bounds have been imposed on real GDP in Argentina, Australia and Brazil as prompted by the pause message shown in Figure 5.50.

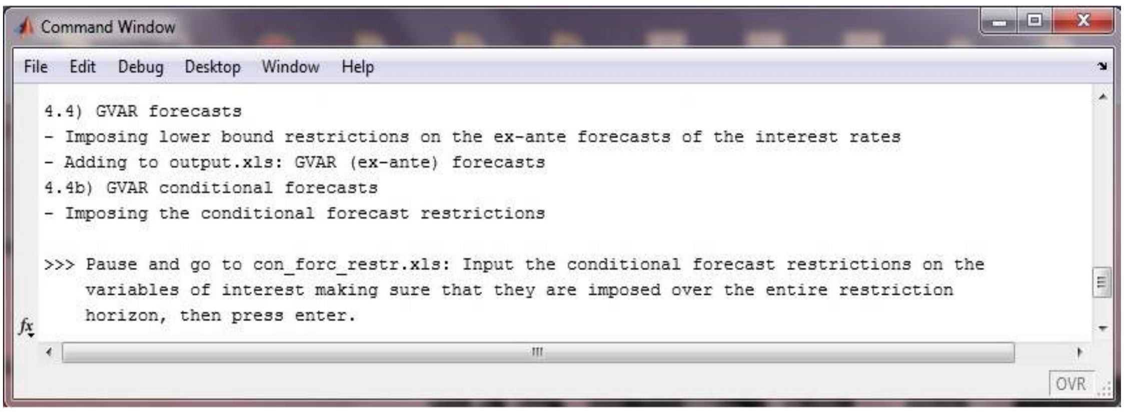
Figure 5.51 Lower bound (additional) restrictions imposed on the variables of the GVAR



	A	B	C	D	E
1	Insert Lower Bound Restrictions for the Ex-ante Forecasts of the GVAR				
2					
3	Country	Variable	Lower Bound Restrictions		
4	ARGENTINA	y	0.005		
5	ARGENTINA	Dp			
6	ARGENTINA	eq			
7	ARGENTINA	ep			
8	ARGENTINA	r			
9	AUSTRALIA	y	0.001		
10	AUSTRALIA	Dp			
11	AUSTRALIA	eq			
12	AUSTRALIA	ep			
13	AUSTRALIA	r			
14	AUSTRALIA	lr			
15	BRAZIL	y	0.005		
16	BRAZIL	Dp			
17	BRAZIL	ep			
18	BRAZIL	r			
19	CANADA	y			
20	CANADA	Dp			
21	CANADA	eq			
22	CANADA	ep			
23	CANADA	r			
24	CANADA	lr			
25	CHINA	y			
26	CHINA	Dp			
27	CHINA	ep			
28	CHINA	r			

If conditional forecasts have previously been selected then the program will make another pause. In this case, the Matlab command window will read as follows (Figure 5.52):

Figure 5.52 Pause message: Impose the conditional forecast restrictions



The worksheet **con_fore_restrict** will automatically open. For the country variables of interest, fill *all cells starting from column C until the end of the restriction horizon* with the desired values. Once again these values should be compatible with any a priori transformations made to the associated country variable source data. Figure 5.53 shows an example where the short and long-term interest rates in the USA are restricted to 0.01 and 0.02 respectively over the period 2013Q2-2014Q1 (the restrictions horizon), which coincides with the associated forecast horizon defined earlier. Forecasts over this horizon will be computed conditional on these restrictions.

Figure 5.53 Conditional forecast restrictions

con_forc_restr

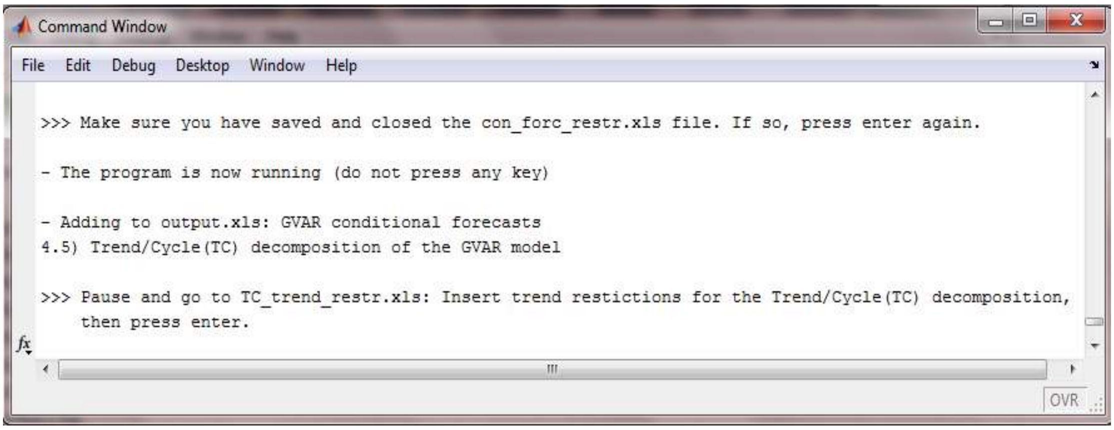
	A	B	C	D	E	F	G
1	Country	Variable	2013Q2	2013Q3	2013Q4	2014Q1	
2	arg	y					
3	arg	Dp					
4	arg	eq					
5	arg	ep					
6	arg	r					
7	austlia	y					
8	austlia	Dp					
9	austlia	eq					
10	austlia	ep					
11	austlia	r					
12	austlia	lr					
13	bra	y					
14	bra	Dp					
15	bra	ep					
16	bra	r					
124	⋮	⋮					
125	uk	y					
126	uk	Dp					
127	uk	eq					
128	uk	ep					
129	uk	r					
130	uk	lr					
131	usa	y					
132	usa	Dp					
133	usa	eq					
134	usa	r	0.01	0.01	0.01	0.01	
135	usa	lr	0.02	0.02	0.02	0.02	
136	du_model	poil					
137	du_model	pmat					
138	du_model	pmetal					

Sheet1 Sheet2 Sheet3 restrictions

5.10 Trend/Cycle decomposition

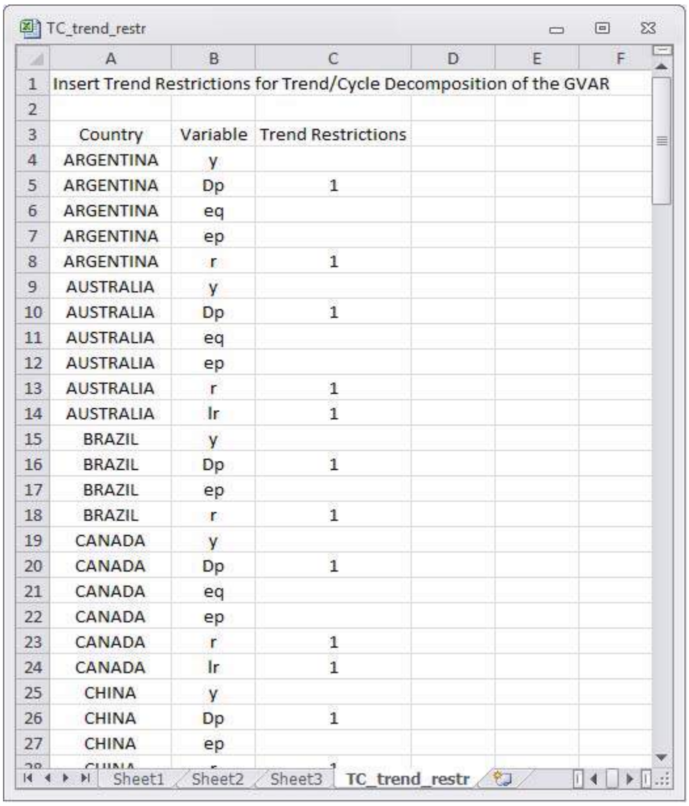
Further, if you have chosen to perform the Trend/Cycle decomposition of the GVAR model, the program will also compute these. The next pause occurs if you have chosen to impose trend restrictions on the country variables of the GVAR model. In this case, the Matlab command window will read as follows (Figure 5.54):

Figure 5.54 Pause message: Impose trend restrictions for the Trend/Cycle decomposition



The worksheet **TC_trend_restr** will automatically open. You need to fill the cells with the value of **1** only for those country variable(s) that you wish to impose a zero trend restriction in the associated regression equation. No trend restrictions will be imposed on the country variables corresponding to empty cells. Figure 5.55 is an example in which trend restrictions have been imposed on inflation and the short and long-term interest rates of all countries.

Figure 5.55 Trend/Cycle decomposition trend restrictions



	A	B	C	D	E	F
1	Insert Trend Restrictions for Trend/Cycle Decomposition of the GVAR					
2						
3	Country	Variable	Trend Restrictions			
4	ARGENTINA	y				
5	ARGENTINA	Dp	1			
6	ARGENTINA	eq				
7	ARGENTINA	ep				
8	ARGENTINA	r	1			
9	AUSTRALIA	y				
10	AUSTRALIA	Dp	1			
11	AUSTRALIA	eq				
12	AUSTRALIA	ep				
13	AUSTRALIA	r	1			
14	AUSTRALIA	lr	1			
15	BRAZIL	y				
16	BRAZIL	Dp	1			
17	BRAZIL	ep				
18	BRAZIL	r	1			
19	CANADA	y				
20	CANADA	Dp	1			
21	CANADA	eq				
22	CANADA	ep				
23	CANADA	r	1			
24	CANADA	lr	1			
25	CHINA	y				
26	CHINA	Dp	1			
27	CHINA	ep				

When you have finished, save and close TC_trend_restr.xls; go to the Matlab command window prompt and press enter; a message will remind you to save and close TC_trend_restr.xls: if TC_trend_restr.xls is closed, then press enter again.

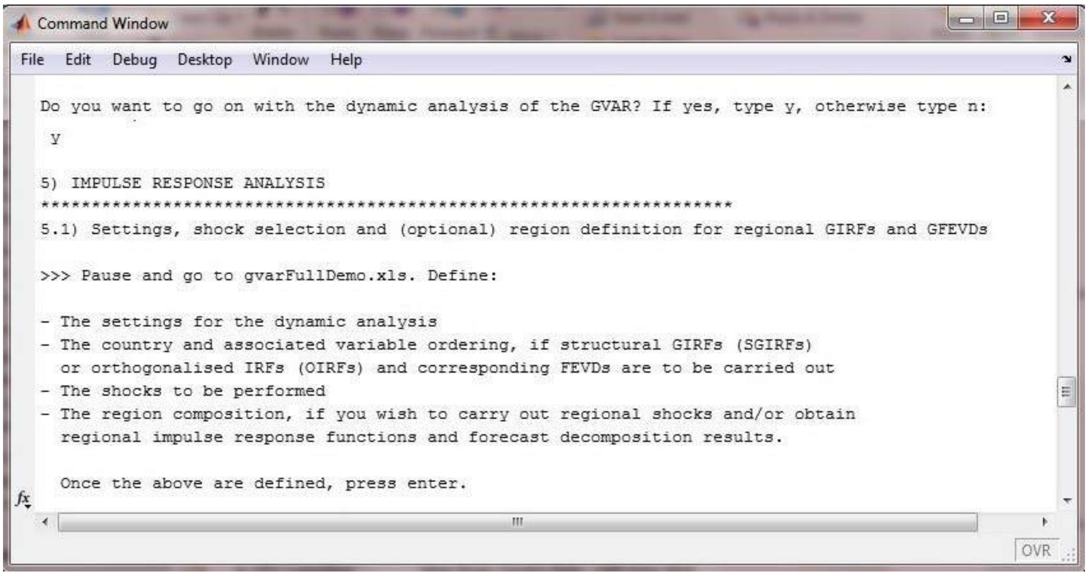
5.11 Dynamic analysis

The following pause refers to the dynamic analysis of the specified GVAR model (which includes the dominant unit model if previously selected). In particular, persistence profiles (PPs), impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) can be obtained. Matlab will first ask you whether you wish to proceed with the dynamic analysis of the GVAR.

If you do not wish to proceed with the dynamic analysis at this stage, type **n** and press enter. If you have not previously opted to compute bootstrap critical values for the structural stability tests, you can now go straight to Chapter 6 related to the retrieval of the output. If you have, the bootstrap critical values for these tests will be computed at this stage, and the program will conduct its final related pause(s) before ending (see Section 5.12). Information in this section then becomes relevant.

If you do wish to conduct the dynamic analysis, type **y** and press enter as shown in Figure 5.56. You are now required to define the settings for the dynamic analysis, the shocks you wish to entertain and also in the case of regional shocks and/or regional level IRF and FEVD results, the region composition of the countries entering the GVAR analysis.

Figure 5.56 Pause message: Dynamic analysis of the GVAR



The gvarFullDemo.xls file will automatically open. Figures 5.57 and 5.58 are a (completed) example of what you will see in the MAIN worksheet. The dynamic analysis input will be explained below.

Figure 5.57 Dynamic analysis in the MAIN worksheet: Settings

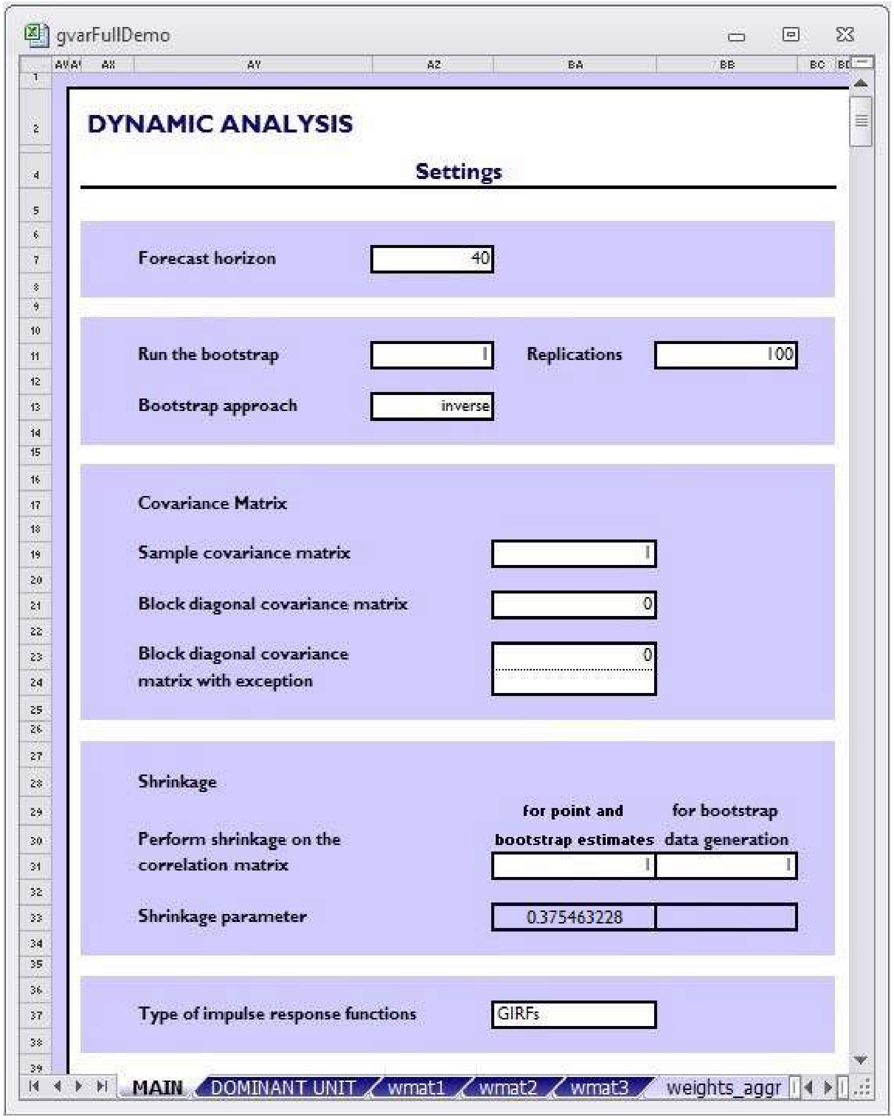
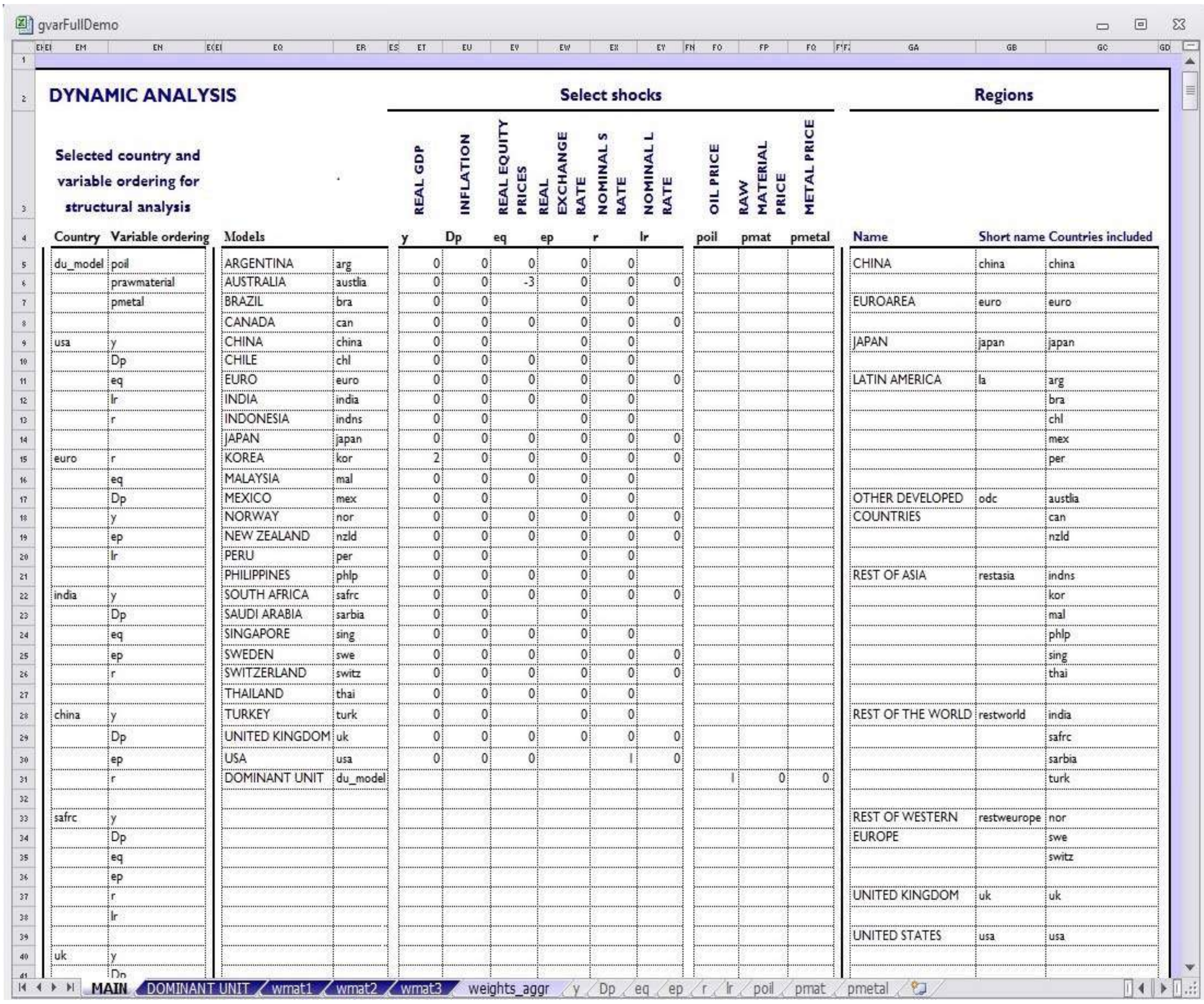


Figure 5.58 Dynamic analysis in the MAIN worksheet: Additional input



5.11.1 Forecast horizon

You have to define the forecast horizon for the persistence profiles, impulse responses and forecast error variance decompositions, in cell EG7. The recommended forecast horizon is 40 periods (see Figure 5.59), which is a reasonable choice to assess the model's convergence properties. However, you need to bear in mind that setting a large forecast horizon will increase the computational time of the program, especially if bootstrapping is performed.

Figure 5.59 Forecast horizon

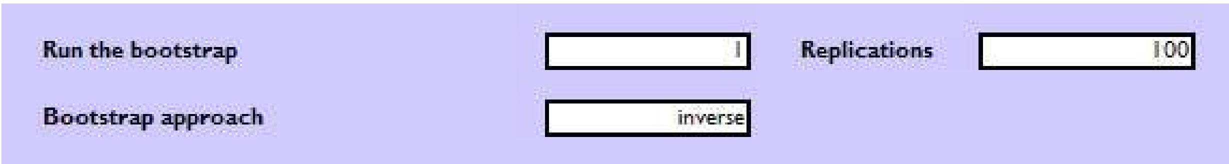
5.11.2 Bootstrapping

Next you can select whether or not to run the boostrap. If yes, then the program will deliver the point estimates of all dynamic analysis results, together with their corresponding bootstrap median estimates and 90% bootstrap confidence bands. If you want to perform the bootstrap, select **1** and specify the number of replications in the adjacent cell, otherwise select **0** (see Figure 5.60). You also need to select which bootstrap approach you would like to use, **inverse** or **shuffle** (see Section A.22.1 for details of these approaches).

The bootstrap is a long process which can take a number of hours, depending on how many bootstrap replications are performed and how long the forecast horizon is. You may wish to initially run a bootstrap with few replications (no more than a hundred), and if the results are of some interest, you can then start the 'actual' boostrapping with a few thousand replications.

As earlier, for demonstration purposes, only 100 replications will be specified here and the bootstrap approach selected will be the inverse approach.[12]

Figure 5.60 Bootstrap and number of replications



5.11.3 Selecting the covariance matrix

Now you need to select the covariance matrix to be used in the dynamic analysis of the GVAR model. The example below works through the settings (column EH). The procedure is as follows:

Choose one of the three types of covariance matrix:

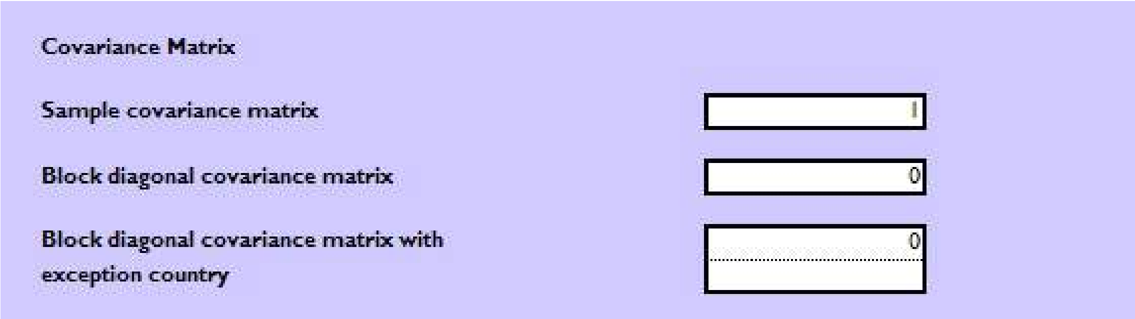
- **Sample covariance matrix:** this is the standard variance-covariance matrix computed from the estimated residuals of the country-specific models.
- **Block-diagonal matrix:** this is a transformation of the sample covariance matrix. Specifically, cross-country correlations are all set to zero whilst allowing for intra-country correlations across variables. Thus, the obtained matrix is a block-diagonal matrix.
- **Block-diagonal matrix with exception country:** this is the block diagonal matrix described above but allows for cross-country correlations of a given **exception country** with the other countries to be non-zero. The exception country is entered in the cell below (cell EH24). Note that the country short name is used.

Select **1** in the field of the matrix of your choice, making sure that the other fields are set to **0**.

Figure 5.61 shows the sample covariance matrix selected for computing the point and bootstrap estimates (assuming the bootstrap option has been previously enabled) and for generating the bootstrap data.

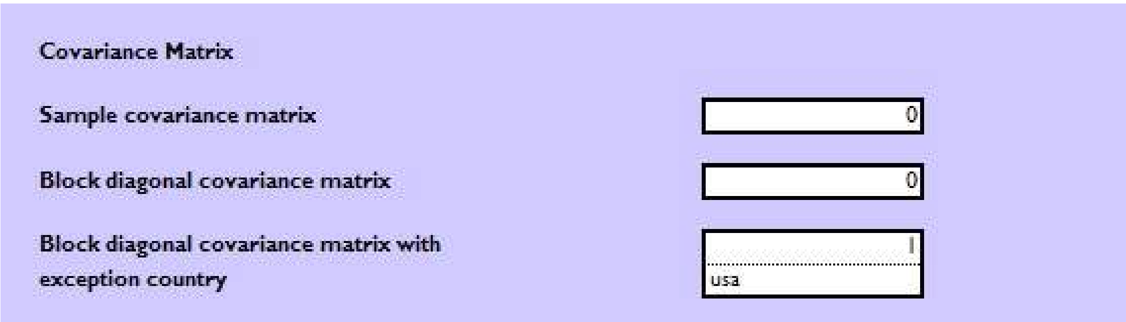
[12]The specified number of bootstrap replications has to be at least 20. If not the program will pause, the interface file will open, and the user will be requested to change this setting as appropriate.

Figure 5.61 Selecting the covariance matrix: Example 1



Another example is provided in Figure 5.62. This shows a block diagonal covariance matrix with an exception country. You can select the country short name for your exception country from the dropdown menu (click in the cell and scroll up to view the menu).

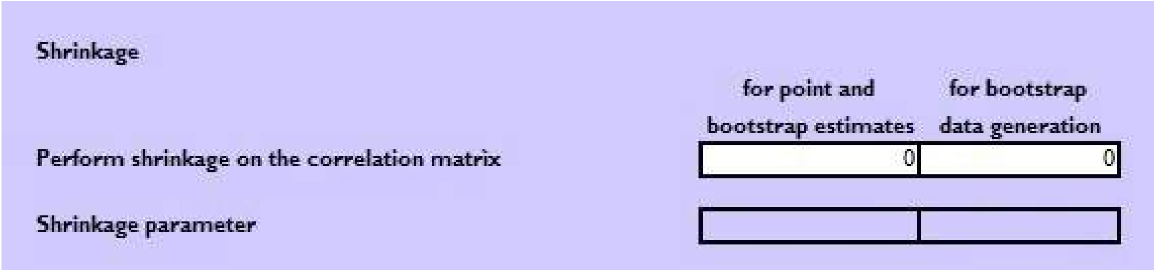
Figure 5.62 Selecting the covariance matrix: Example 2



Performing shrinkage on the correlation matrix

Select whether to perform shrinkage on the corresponding correlation matrix of the chosen covariance matrix when computing the point and bootstrap estimates, and when generating the bootstrap data (the latter is applicable only if the bootstrap option is enabled). These selections also apply to the computation of the persistence profiles and related bootstrap bounds. To perform shrinkage, select **1** otherwise select **0**. The shrinkage parameter field (cell EH33) does not require any input from the user. The program will compute internally the associated shrinkage parameter and export its value (between 0 and 1) here, when appropriate. No value should be entered in cell **EH33** by the user (see Figure 5.63). The default shrinkage approach implemented in the current version of the toolbox is the Ledoit and Wolf (2004, LW) type shrinkage estimator performed on the correlation matrix as proposed in Bailey, Pesaran and Smith (2014). For more details see Section A.21.2.

Figure 5.63 Selecting whether to perform shrinkage on the correlation matrix: Example 1



There are certain instances under which performing shrinkage on the correlation matrix will not be an option but a requirement. However, you need to select whether to perform shrinkage on the correlation matrix without prior knowledge of these cases. You should therefore begin by making your initial selections as shown, for example, in Figure 5.63. The program will then pause where appropriate (depending on your full set of dynamic analysis settings selections), and inform you through the Matlab command window whether a particular selection is required. You will then have the opportunity to make changes to your initial selections or simply retain the existing ones. The program will pause for this purpose whether the **Run the program with pauses** function is enabled (i.e. set to 1) or not (i.e. set to 0). This is to ensure that the 'appropriate' selections are made in the case where the selected covariance matrix is not positive definite (not known to the user in advance). It is therefore importnat to follow the instructions given in the Matlab command window carefully throughout the running of the program. See Section A.23.1 for details of the workings of the program in relation to shrinkage and associated pauses.

Given the bootstrap approach and type of impulse responses selected as shown in Figure 5.57 together with the initial shrinkage performance selections shown in Figure 5.63, the program will pause and the Matlab command window will read as follows (Figure 5.64):

Figure 5.64 Pause message: Ensure that any appropriate changes are made to the original selections

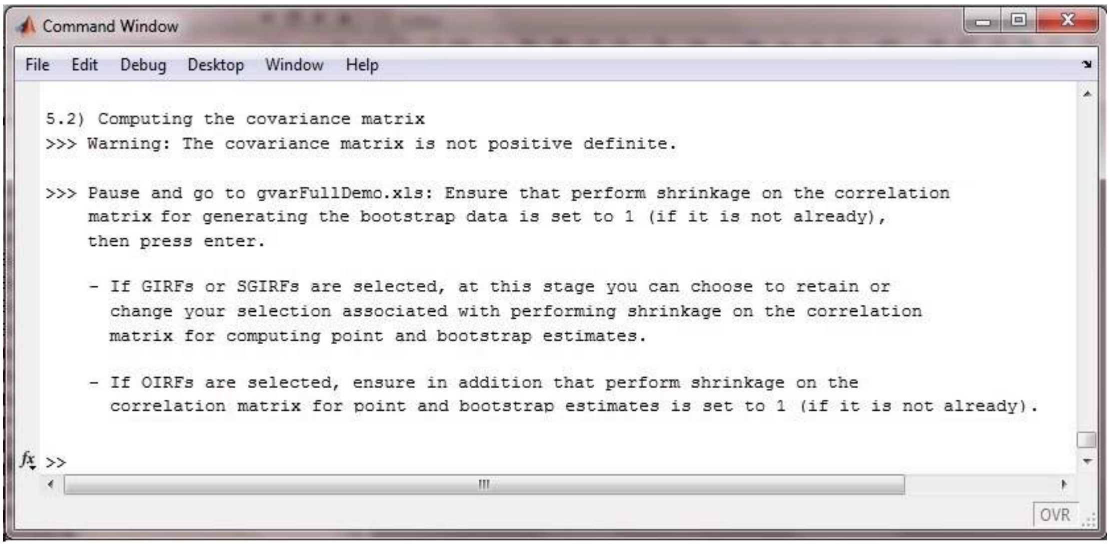


Figure 5.65 shows a completed example of the shrinkage panel, where the shrinkage selection fields have been appropriately (re)defined following the above instructions in the command window, and the shrinkage parameter has been exported to cell EH33.

Figure 5.65 Selecting whether to perform shrinkage on the correlation matrix: Example 2

Naive shrinkage In addition to the default LW type shrinkage on the correlation matrix provided by the toolbox, there is also the possibility of performing the shrinkage approach that featured in previous versions. We will call this the 'naive' shrinkage approach (to distinguish it from the main LW type shrinkage approach) as it requires the shrinkage parameter to be provided by the user. In particular, to perform naive shrinkage the user is required to input the desired shrinkage parameter value in cell **EI33** adjacent to the cell where the same parameter is exported for the main shrinkage approach.

The option of naive shrinkage is of limited functionality in that it can only be implemented with the **Run the program with pauses** function disabled (i.e. set to 0). For this reason it is required that all necessary information be provided in the interface file beforehand. Under this condition and in accordance with the **Perform shrinkage on the correlation matrix** selections, naive shrinkage will be implemented by default if a value between 0 and 1 is provided in cell **EI33**, overriding the main shrinkage approach. The program will follow the chosen shrinkage selections, and despite the requirement that the function **Run the program with pauses** be disabled, pauses will be made by the program when necessary. Once again, this is to ensure that the 'appropriate' selections are made in the case where the selected covariance matrix is not positive definite (not known to the user in advance). It is therefore importnat to follow the instructions given in the Matlab command window carefully throughout the running of the program.

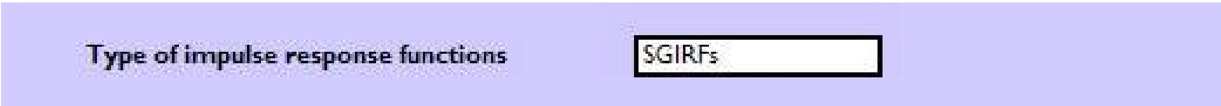
Providing **Run the program with pauses** is set to **0** and an appropriate value is given in cell **EI33**, the program works in a very similar way to the main shrinkage approach (see Section A.23.2 for more details). Figure 5.66 gives an example of the completed shrinkage selections in the case where naive shrinkage is implemented, having initially run the program using the main shrinkage approach.

Figure 5.66 Selecting whether to perform shrinkage on the correlation matrix: Example 3

5.11.4 Structural GIRFs and GFEVD

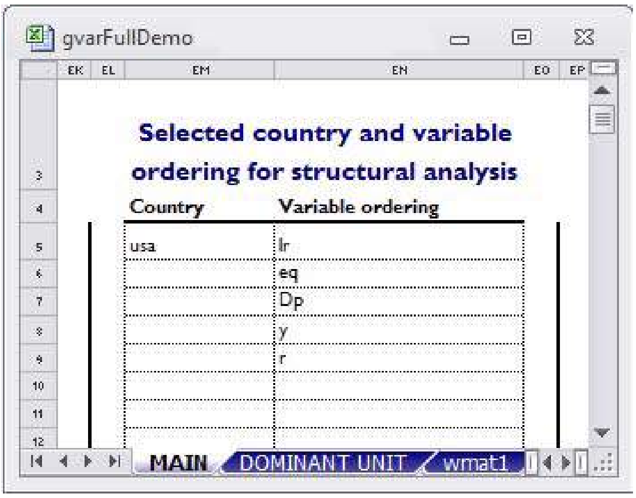
To carry out the structural GIRFs and GFEVD, select **SGIRFs** in the relevant field (see Figure 5.67). This will allow you to focus on identification of shocks to a particular country, which needs to be defined next. You can then consider alternative orderings for the variables within that country model.

Figure 5.67 Structural analysis setting: SGIRFs



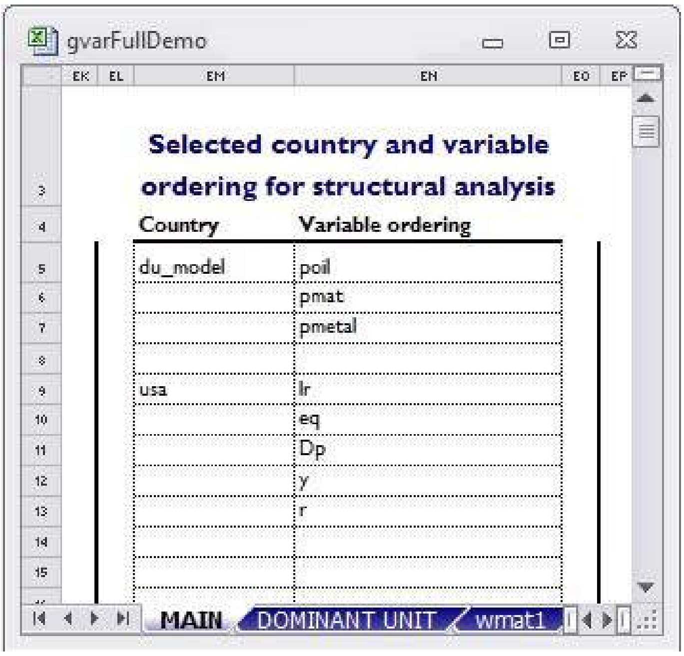
To define the country of interest, type the country short name in cell EM5. This country will be placed first within the given country ordering (if this is not already the case from the outset). You can change the ordering of variables for this particular country by listing the corresponding variable short names starting from cell EN5. It is important to ensure that the list of variables corresponds to the endogenous variables included in the country of interest at the specification stage of the individual models. See Figure 5.68 for an example where the country model placed first is the USA, assuming that it comprises the following endogenous variables: real GDP (y), inflation (Dp), real equity prices (eq), nominal short-term interest rate (r) and nominal long-term interest rate (lr). In Figure 5.68 these variables are reshuffled as follows: lr, eq, Dp, y, r. The results will depend on this ordering (see Section A.19.2 for further details).

Figure 5.68 Variable ordering for structural GIRFs in the case of no dominant unit model



The SGIRFs option allows to conduct structural analysis only for a single country, i.e. only one country should appear in column EM. The only exception is when a dominant unit model is included in the GVAR. In this case, the dominant unit should be placed first (using the short name ‘du_model’) followed by the country of interest, say USA, with the variables in each model ordered as desired by the user. These two countries will then be treated as a single block for purposes of structural identification (see Section A.24.2). Following our previous example and earlier specifications, Figure 5.69 below illustrates this case.

Figure 5.69 Variable ordering for structural GIRFs in the case of a dominant unit model



If the dominant unit model is univariate including for example only oil prices, then rows 6 and 7 in Figure 5.69 would need to be deleted.

Enabling the SGIRFs option will result in computation of the structural GIRFs and corresponding structural GFEVD, based on the formulas given in Sections A.19 and A.20 respectively. For demonstration purposes, this option will not be selected so as to focus on the standard GIRFs and GFEVD under the option GIRFs. Selecting SGIRFs will only change the numerical content of the corresponding 'SGIRFs' and 'SGFEVDs' folders produced in the program output.

5.11.5 Orthogonalised IRFs and FEVD

To compute the orthogonalised IRFs and FEVD, select **OIRFs** in the relevant field (see Figure 5.70). This will allow you to focus on identification of shocks to all countries, under a selected country and variable ordering to be defined next.

Figure 5.70 Structural analysis setting: OIRFs

For the orthogonalised IRFs and FEVD, contrary to the structural GIRFs and GFEVD, *all* countries and endogenous variables entering the GVAR model (as defined at the specification stage) have to be ordered. Specifically, enter the short name of each country starting from cell EM5 and the corresponding endogenous variables (short name) starting from cell EN5, leaving a blank row to separate the lists as shown in Figure 5.71. In this example, the country model placed first is the USA, the second is the euro area and so on. The results will depend on the defined country and variable orderings (see Section A.19.2).

Figure 5.71 Variable ordering for orthogonalised IRFs in the case of no dominant unit model

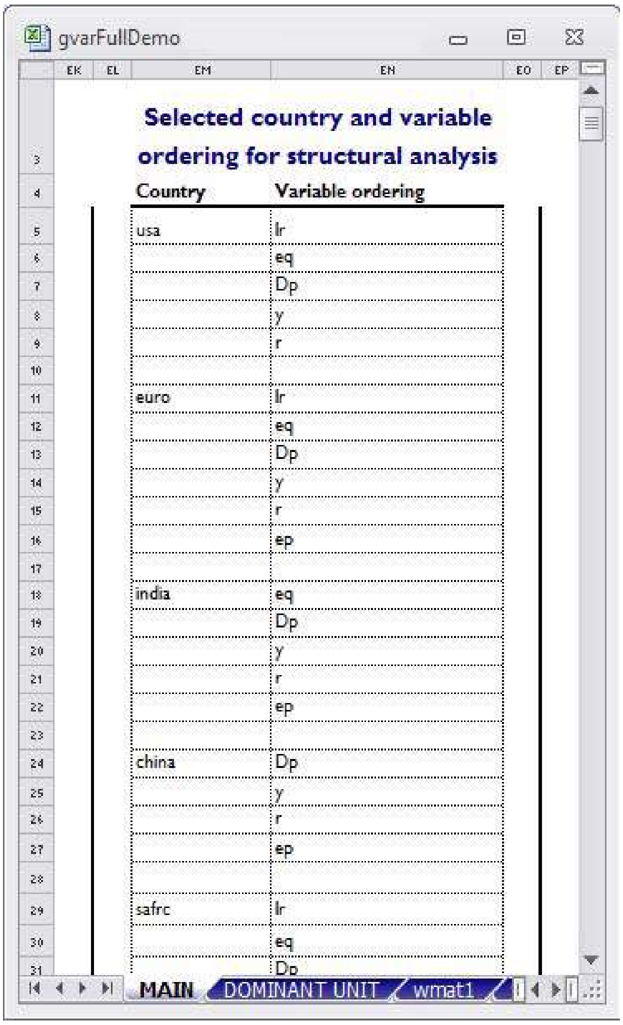
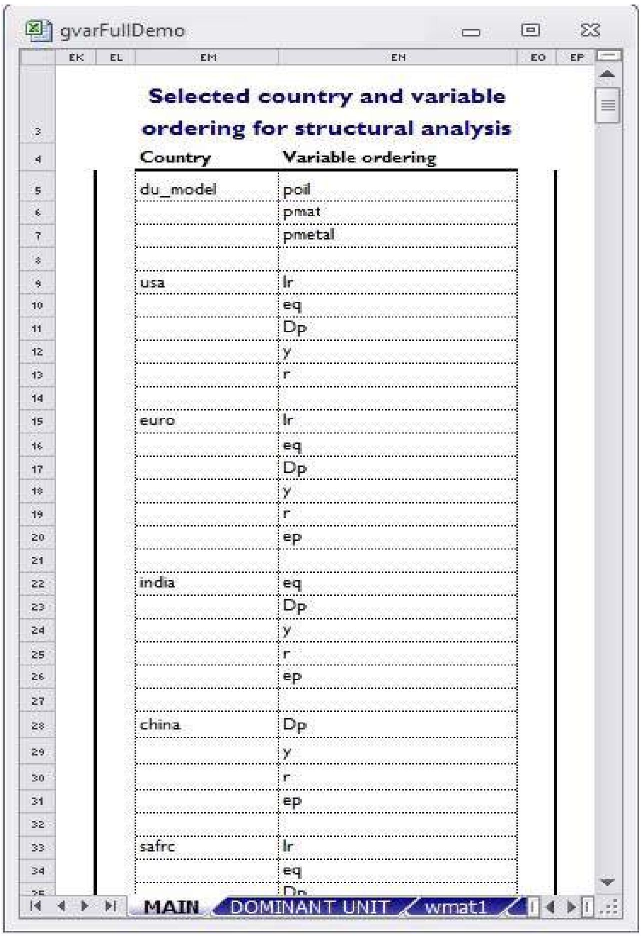


Figure 5.72 illustrates the case where a dominant unit model is included in the GVAR (see Section A.24.2). As earlier when the dominant unit model is multivariate rows 6 and 7 in Figure 5.72 would need to be deleted.

Figure 5.72 Variable ordering for orthogonalised IRFs in the case of a dominant unit model



Selecting the OIRFs option will result in computation of the orthogonalised IRFs and corresponding FEVD, based on the formulas given in Sections A.19 and A.20 respectively. For demonstration purposes, this option will not be selected so as to focus on the standard GIRFs and GFEVD. Selecting OIRFs will only change the numerical content of the corresponding ‘OIRFs’ and ‘OFEVDs’ folders produced in the program output.

Any reordering of the countries and variables for the purpose of computing the SGIRFs and OIRFs will only be reflected in the output associated with these functions. For all other output the original ordering will be maintained.

5.11.6 Regional aggregation

Before examining the shocks selection panel, we will discuss the choice of whether to perform regional aggregation or not. You would want to group countries into regions at this stage for two purposes:

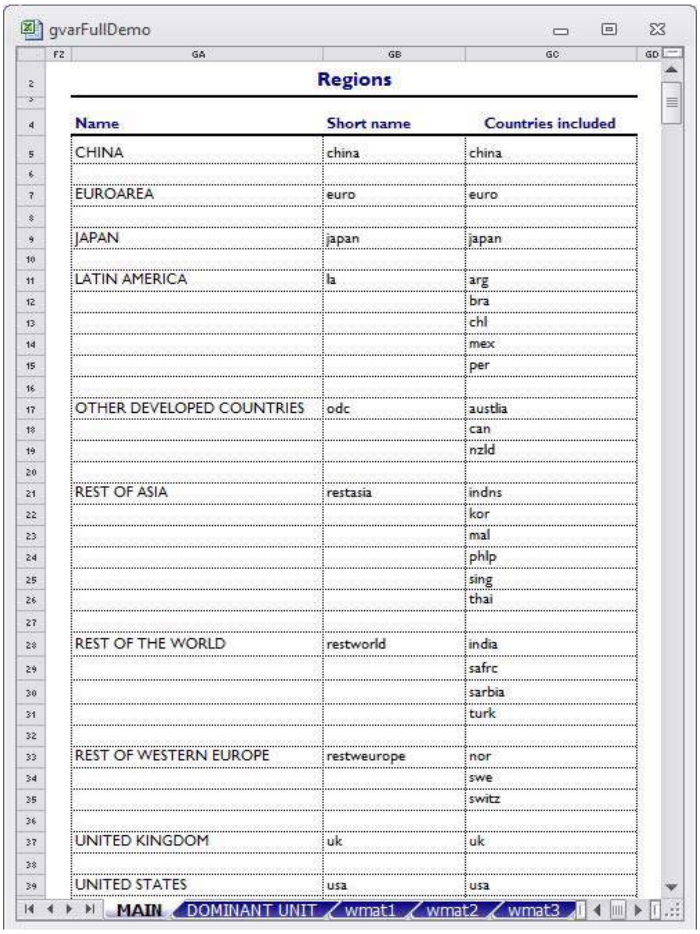
- **To aggregate the results:** if you would like to have synthetic measures of impulse responses and forecast error variance decompositions, you can aggregate the country-specific results into regional ones.

- **To simulate regional shocks:** if you would like to simulate a shock that originates in a specific region rather than a specific country (for example, a shock that originates in Latin

America rather than in, say, Brazil or Argentina), then you must first determine the countries that comprise each region.

To define the regions, follow the scheme in Figure 5.73: column GA contains the **region names**, column GB refers to the **region short names**, and column GC contains the **corresponding groups of countries for each region**. The procedure is similar to that used when aggregating countries into regions at the outset, making sure that you adhere to the naming conventions for names and short names. The difference here is that *all* countries listed at the individual model specification and estimation stage have to be grouped into regions.[13] Once again ensure that the list of country short names that comprise each region is in alphabetical order. The region names in column GA and GB need not be in alphabetical order. The country level GIRF and GFEVD results of all countries belonging to a particular region are then aggregated to produce the associated regional level results. A region can comprise a single country if desired, in which case the aggregated GIRF and GFEVD results will coincide with the corresponding country level results. Note that if in our example individual country models were estimated for all 33 countries separately, then at this stage a euro region could be defined comprising any set of European countries. Any dominant unit model should not appear in the regions list, as is the case in our example figure given below.

Figure 5.73 Defining regions for aggregation of results and for computing regional shocks



[13]Any previously created regions (e.g. euro) can be combined with additional countries to form a new region, or can be left as is.

5.11.7 Shock selection

Shock simulations are chosen in columns ET-FX. You will see that some cells are empty, whilst others contain a zero. As before, the empty cells imply that there are no data available for that particular variable in the specific country, and therefore it cannot be shocked. **Remember not to enter any data into empty cells here.** The shocks defined here apply both to the impulse response analysis and the forecast error variance decompositions.

You can simulate three types of shocks:

- **country-specific shocks:** shocks that originate in a given country. To simulate a positive (one standard error) shock to a particular variable in a given country, type **1** in the corresponding cell. To simulate a negative shock, type **-1**.

- **region-specific shocks:** shocks that originate in a given region. This is a shock to **a variable in all countries that belong to a specific region**. To simulate a positive (one standard error) shock to a particular variable in a given region, type **2** in the corresponding cell of any country that belongs to the given region as defined in Section 5.11.6, provided that cell is not blank. To simulate a negative shock, you should type **-2**.

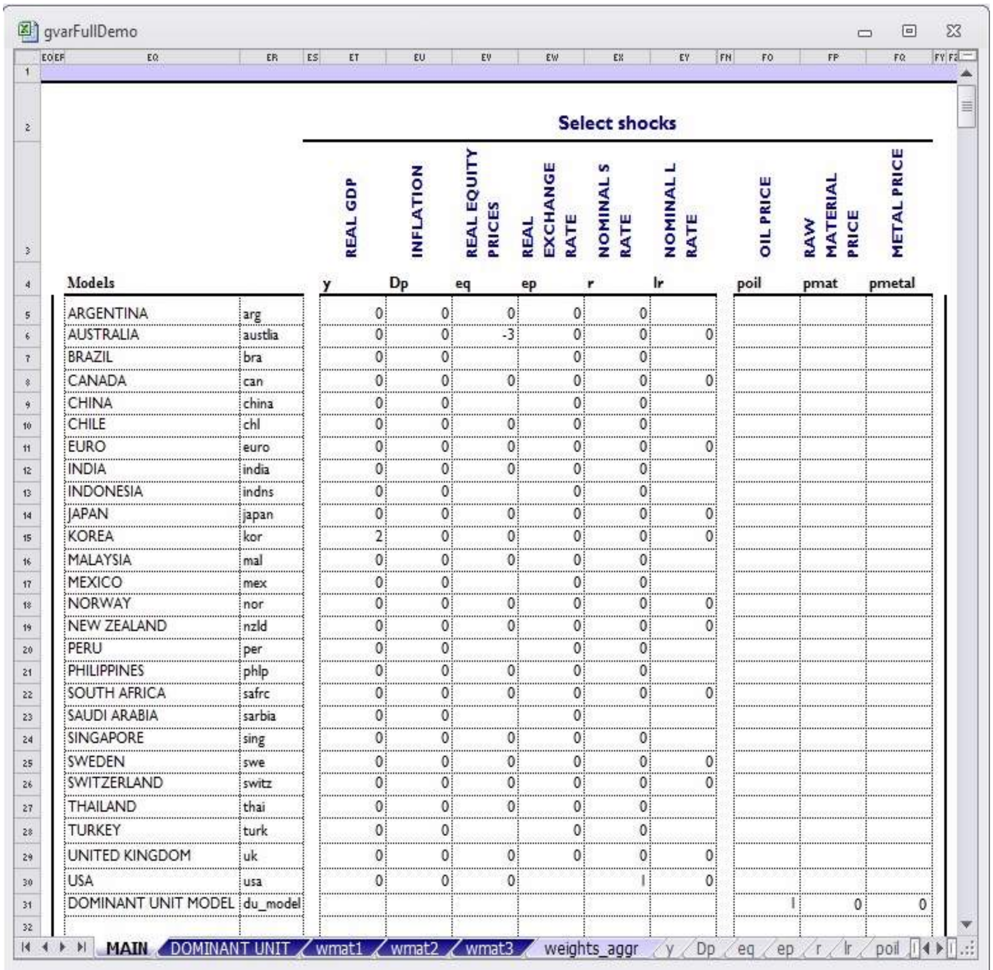
- **global shocks:** there are two different types of global shocks. The first one is a **shock to a global variable**. To simulate a positive (one standard error) shock to a particular global variable, type **1** in the corresponding cell of the country which contains that global variable as endogenous or of the dominant unit model. To simulate a negative shock, you type **-1**. The second type of global shock is one to **a variable in all countries**. To simulate a positive (one standard error) shock to a particular variable in all countries for which that variable exists as endogenous, type **3** in the corresponding cell of any of those countries (i.e. where the cell is not blank). To simulate a negative shock, you should type **-3**.

The regional and global shocks are defined in terms of the regional and country PPP-GDP weights respectively (see Section A.19 for further details).

In our example (Figure 5.74), four shocks have been selected: a country-specific positive shock to the USA short-term interest rate (1 in the short-term interest rate cell of the USA) a regional positive shock to real GDP in region ‘REST OF ASIA’ (2 in the real GDP cell of Korea, a country which belongs to that defined region); a global negative shock to real equity prices (-3 in the equity cell of Australia); and a positive shock to the global variable oil price (1 in the oil price cell of the DOMINANT UNIT model).

For the above defined shocks, by default individual country GIRFs and GFEVDs will be computed for all variables in the GVAR model. In addition, if regions are defined as shown in Section 5.11.6, regional level GIRFs and GFEVDs will be provided, using PPP-GDP weights to aggregate the individual country results.

Figure 5.74 Selection of shocks example



gvarFullDemo

Select shocks

Models		REAL GDP y	INFLATION Dp	REAL EQUITY PRICES eq	REAL EXCHANGE RATE ep	NOMINAL S RATE r	NOMINAL L RATE lr	OIL PRICE poil	RAW MATERIAL PRICE pmat	METAL PRICE pmetal
ARGENTINA	arg	0	0	0	0	0				
AUSTRALIA	austlia	0	0	-3	0	0	0			
BRAZIL	bra	0	0		0	0				
CANADA	can	0	0	0	0	0	0			
CHINA	china	0	0		0	0				
CHILE	chl	0	0	0	0	0				
EURO	euro	0	0	0	0	0	0			
INDIA	india	0	0	0	0	0				
INDONESIA	indns	0	0		0	0				
JAPAN	japan	0	0	0	0	0	0			
KOREA	kor	2	0	0	0	0	0			
MALAYSIA	mal	0	0	0	0	0				
MEXICO	mex	0	0		0	0				
NORWAY	nor	0	0	0	0	0	0			
NEW ZEALAND	nzld	0	0	0	0	0	0			
PERU	per	0	0		0	0				
PHILIPPINES	phlp	0	0	0	0	0				
SOUTH AFRICA	safrc	0	0	0	0	0	0			
SAUDI ARABIA	sarbia	0	0		0					
SINGAPORE	sing	0	0	0	0	0				
SWEDEN	swe	0	0	0	0	0	0			
SWITZERLAND	switz	0	0	0	0	0	0			
THAILAND	thai	0	0	0	0	0				
TURKEY	turk	0	0		0	0				
UNITED KINGDOM	uk	0	0	0	0	0	0			
USA	usa	0	0	0		1	0			
DOMINANT UNIT MODEL	du_model							1	0	0

Having defined all dynamic analysis input, save and close gvarFullDemo.xls, go to the Matlab command window prompt and press enter. A message will remind you to save and close gvarFullDemo.xls. If gvarFullDemo.xls is closed, then press enter again.

When running the program with pauses, for every run you will need to redefine any shocks you wish to carry out, as by default all shocks are set to zero.

5.12 Covariance matrix for bootstrapping the structrual stability tests

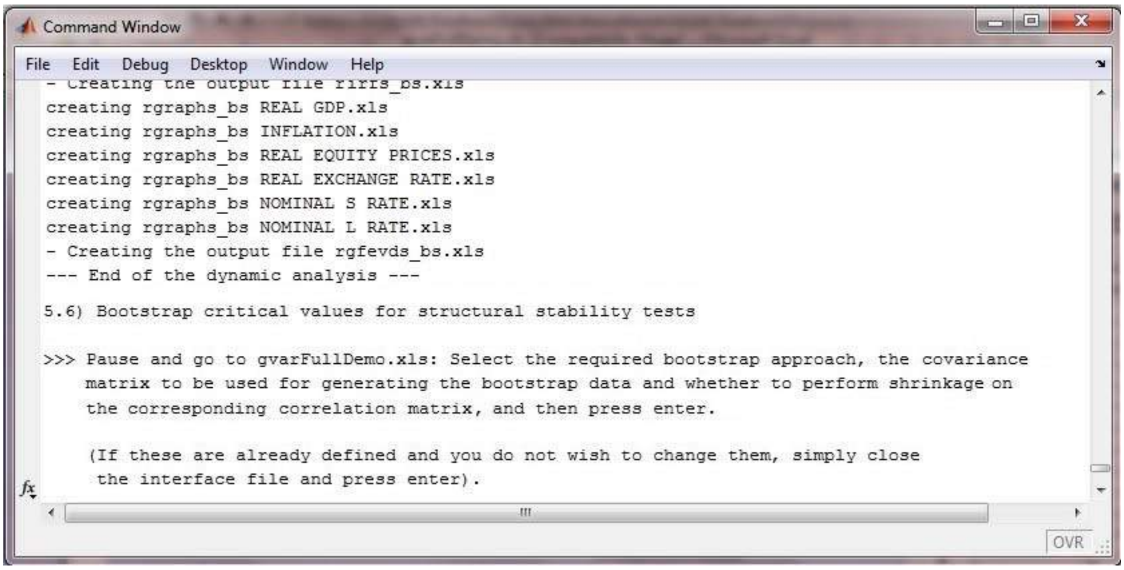
The final set of pauses refers to selecting the covariance matrix for computing the bootstrap critical values of the structrual stability tests, provided this function was previously enabled (see Figure 5.75). In this case, after the dynamic analysis of the GVAR model (or the solution of the GVAR model, if dynamic analysis is not pursued), the gvarFullDemo.xls file will automatically open. Within the dynamic analysis settings panel shown in Figure 5.57, you are required to select the desired bootstrap approach and covariance matrix, and only under the inverse bootstrap approach whether to perform or not shrinkage of the selected covariance matrix for generating the bootstrap data.

If you have previously chosen to carry out the bootstrap for the dynamic analysis, these settings will already be filled. You can then either use the same options for obtaining the bootstrap critical values of the stuctural stability tests (and therefore simply close the interface file that has opened), or make changes to the existing selections (and then save and close the interface file as usual). If you previously did not choose to carry out the bootstrap for the dynamic analysis, or the dynamic analysis at all, you are now required to input the required selections.

The field related to shrinkage performance for the point and bootstrap estimates is not applicable when bootstraping to obtain the critical values for the structural stability tests. Similarly under the bootstrap approach **shuffle**, information in the shrinkage panel is not applicable as mentioned earlier. Any selected options associated with these fields will be ignored.

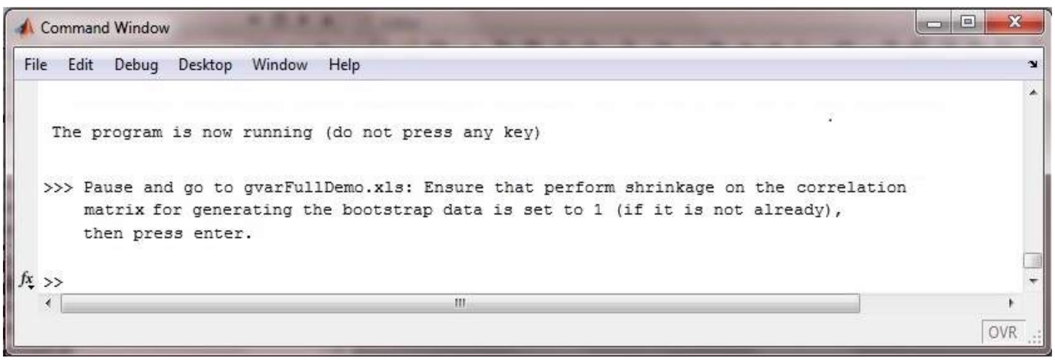
The first message that will appear in the Matlab command window is shown in Figure 5.75.

Figure 5.75 Pause message: Select the covariance matrix for bootstrapping the structural stability tests



Then, depending on your choice of bootstrap approach, an additional pause will be made. Figure 5.76 displays the pause message in the case where the bootstrap approach **inverse** has been selected. This pause requests you to ensure that your previous selections are in line with the required ones.

Figure 5.76 Pause message: Ensure that any appropriate changes are made to the original selections



6. OUTPUT FROM THE GVAR ANALYSIS

A message in the Matlab command window will inform you when all the above computations are complete and the program has ended.

6.1 Description of the output

You will now find a new output folder under the path: **GVAR_Toolbox2.0****Output****'Output Folder name chosen'**\\, which contains all the output from the program. In particular, in this folder you will find two Excel files, **output.xls** and **countrydata.xls**, and two folders, **GIRFs** and **GFEVDs**. Additional Excel files: **overid_restr.xls** (if you chose to perform the overidentifying restrictions test), **ExF_lb_restr.xls** (if you chose to impose additional lower bound restrictions on the ex-ante forecasts), **con_forc_restr.xls** (if you chose to compute conditional forecasts) and **TCdecomposition.xls** and **TC_trend_restr.xls** (if you chose to perform the Trend/Cycle decomposition and impose trend restrictions), will also be included. Output.xls contains all the results of the analysis which relates to the estimated GVAR model, whilst the two folders contain results specific to the chosen shocks carried out at the dynamic analysis stage. Described below is the output produced from using the full demo interface file. Output obtained from using the brief demo, or any other interface file, is presented in a similar format.

6.1.1 The output.xls file

In **output.xls** you will find all the results associated with the constructed GVAR model computed prior to the GIRFs and GFEVDs. The output is organised in the following Excel worksheets:

- **The weight matrix**

  The **weightmatrix** worksheet will be created first. It contains the matrix of weights (either built by the program or user-provided) used for both constructing the foreign-specific variables and for solving the GVAR model. Note that the weights (shares) add up to one by column, not by row. It is, therefore, simply the transposed weight matrix in DdPS. See Figure 6.1 for an example of a fixed weight matrix.

Figure 6.1 Weight Matrix

Weight Matrix (based on fixed weights)

Country	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO	INDIA	INDONESIA	JAPAN	KO
ARGENTINA	0	0.001904	0.108362	0.002621	0.006035	0.051491	0.007624	0.003592	0.005202	0.001565	0.00
AUSTRALIA	0.006877	0	0.006916	0.004651	0.044492	0.009840	0.014148	0.038750	0.033641	0.055311	0.04
BRAZIL	0.322290	0.005346	0	0.007625	0.032211	0.076699	0.028805	0.019554	0.011543	0.013810	0.02
CANADA	0.018747	0.008327	0.017065	0	0.019286	0.019456	0.016293	0.010391	0.008242	0.017884	0.01
CHINA	0.130908	0.254827	0.189320	0.079665	0	0.235825	0.159299	0.161630	0.144419	0.266836	0.28
CHILE	0.055301	0.003171	0.026533	0.003450	0.012698	0	0.007608	0.005303	0.001882	0.008868	0.01
EURO	0.172226	0.094425	0.217700	0.062083	0.174748	0.150598	0	0.184844	0.084600	0.099749	0.08
INDIA	0.015639	0.044279	0.025620	0.006030	0.030443	0.018550	0.029025	0	0.052815	0.012925	0.02
INDONESIA	0.013025	0.026513	0.010150	0.003312	0.022375	0.004307	0.009471	0.043052	0	0.038513	0.03
JAPAN	0.019246	0.159434	0.046595	0.030149	0.147459	0.090564	0.044895	0.037088	0.162079	0	0.13
KOREA	0.018003	0.069362	0.039519	0.014033	0.103307	0.061666	0.024270	0.039811	0.081555	0.080557	0
MALAYSIA	0.011473	0.032744	0.010153	0.004137	0.036722	0.002964	0.012855	0.029064	0.067680	0.036093	0.02
MEXICO	0.029058	0.006366	0.025076	0.036330	0.012613	0.033603	0.016068	0.006358	0.003351	0.011175	0.01
NORWAY	0.000820	0.001493	0.004822	0.008084	0.003256	0.001275	0.035151	0.003274	0.001053	0.002872	0.00
NEW ZEALAND	0.000767	0.039398	0.000357	0.001109	0.003368	0.000702	0.002046	0.002314	0.004081	0.004017	0.00
PERU	0.013814	0.000625	0.009470	0.005749	0.004839	0.027826	0.003543	0.001798	0.000556	0.002624	0.00
PHILIPPINES	0.005933	0.004570	0.002533	0.001949	0.013694	0.002170	0.003801	0.003446	0.014847	0.016297	0.01
SOUTH AFRICA	0.010540	0.006752	0.007081	0.001752	0.014233	0.001525	0.015741	0.029113	0.005442	0.009537	0.00
SAUDI ARABIA	0.004442	0.005218	0.016986	0.004237	0.023837	0.001646	0.019254	0.072443	0.021482	0.040581	0.05

- **Descriptive statistics of the variables**

  By default, **dstats_domestic** (see Figure 6.2), **dstats_foreign** and **dstats_global** (see Figure 6.3) will be created. They contain the basic statistics for the domestic, foreign-specific and global variables used in the analysis. The following statistics are computed for each variable: the mean, the median, the maximum, the minimum, the standard deviation, the skewness and kurtosis coefficients, and finally the Jarque-Bera statistic with its corresponding p-value. All the statistics are computed according to the estimation sample chosen.

Figure 6.2 Descriptive statistics: Domestic variables

Descriptive Statistics of Domestic Variables

REAL GDP	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
*******************									
ARGENTINA	4.535710	4.490830	5.179011	4.160843	0.277229	0.720126	2.468149	13.406976	0.001227
AUSTRALIA	4.444337	4.431644	4.981684	3.900074	0.328110	0.009437	1.678703	9.524805	0.008545
BRAZIL	4.537376	4.519545	5.016420	4.098902	0.255994	0.269499	2.060597	6.362937	0.041525
CANADA	4.449339	4.409102	4.845561	4.016507	0.262579	-0.047555	1.647276	10.049510	0.006573
CHINA	4.291992	4.255651	6.009943	2.703928	0.968918	0.130963	1.880105	7.154000	0.027959
CHILE	4.348968	4.454854	5.156874	3.572243	0.503006	-0.089623	1.564893	11.481418	0.003212
EURO	4.478381	4.487521	4.741040	4.149594	0.192735	-0.270869	1.686096	11.113119	0.003862
INDIA	4.399039	4.360808	5.477034	3.438718	0.593771	0.192042	1.858474	7.885607	0.019394
INDONESIA	4.457083	4.551983	5.271323	3.581601	0.461237	-0.139440	1.907468	6.867833	0.032260
JAPAN	4.508033	4.576509	4.718801	4.094173	0.183483	-0.898013	2.404261	20.465224	0.000036
KOREA	4.269549	4.422274	5.075056	3.155213	0.599117	-0.425424	1.878086	10.976090	0.004136
MALAYSIA	4.280286	4.444218	5.162907	3.260733	0.577500	-0.203672	1.643389	11.017872	0.004050
MEXICO	4.440182	4.408685	4.869788	3.986222	0.255898	0.095791	1.591898	11.073646	0.003939
NORWAY	4.351362	4.387144	4.719060	3.815306	0.275483	-0.252995	1.655218	11.359431	0.003415
NEW ZEALAND	4.788742	4.780486	5.158919	4.441161	0.222065	0.164566	1.601056	11.343276	0.003442
PERU	4.587075	4.519256	5.314947	4.107444	0.317989	0.777334	2.494696	15.245154	0.000489

Figure 6.3 Descriptive statistics: Foreign-specific and global variables

output

	A	B	C	D	E	F	G	H	I	J
1	Descriptive Statistics of Foreign-Specific Variables									
2										
3	REAL GDP	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
4	*******************									
5	ARGENTINA	4.453451	4.454029	5.081689	3.828288	0.371390	0.045235	1.798135	7.872654	0.019520
6	AUSTRALIA	4.402591	4.441130	5.215374	3.536288	0.500176	-0.078536	1.811184	7.792790	0.020315
7	BRAZIL	4.424383	4.431330	5.121992	3.747577	0.414740	0.020760	1.772533	8.185089	0.016697
8	CANADA	4.421956	4.426893	4.922102	3.865599	0.330935	-0.138495	1.711663	9.482150	0.008729
9	CHINA	4.434310	4.478565	4.914385	3.865688	0.322407	-0.219653	1.756096	9.521851	0.008558
10	CHILE	4.420936	4.424741	5.159349	3.682284	0.440504	0.006292	1.807260	7.703312	0.021245
11	EURO	4.429166	4.431143	5.076433	3.773493	0.394883	-0.012005	1.774182	8.155675	0.016944
12	INDIA	4.425545	4.443287	5.106188	3.732163	0.412863	-0.016794	1.769779	8.219724	0.016410
13	INDONESIA	4.381756	4.439693	5.137229	3.544754	0.476739	-0.128167	1.784801	8.387170	0.015092
14	JAPAN	4.385907	4.412509	5.253839	3.506675	0.523074	-0.019013	1.783949	8.026529	0.018074
15	KOREA	4.408571	4.420737	5.238824	3.578862	0.491198	0.012474	1.806311	7.718724	0.021081
16	MALAYSIA	4.389461	4.446234	5.140047	3.558258	0.471332	-0.126425	1.797477	8.204535	0.016535
17	MEXICO	4.416745	4.426185	4.938554	3.835102	0.345184	-0.148006	1.723979	9.367283	0.009245
18	NORWAY	4.459054	4.461401	4.848893	4.015985	0.269571	-0.133497	1.710126	9.472978	0.008769
19	NEW ZEALAND	4.409485	4.431508	5.109296	3.671809	0.432059	-0.061303	1.767567	8.330943	0.015522
20	PERU	4.417048	4.424792	5.088369	3.725802	0.412431	0.037141	1.761377	8.361914	0.015284

Sheet1 / Sheet2 / Sheet3 / weightmatrix / dstats_domestic / **dstats_foreign** / dstats_global / urt_domestic / urt_f

output

	A	B	C	D	E	F	G	H	I	J
1	Descriptive Statistics of Global Variables									
2										
3	Statistics	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
4	*******************									
5	OIL PRICE	3.423208	3.317834	4.811408	2.406514	0.633329	0.667823	2.429125	11.955829	0.002534
6	RAW MATERIAL PRICE	4.548989	4.587188	5.103502	4.055756	0.234834	-0.344649	2.602033	3.484131	0.175158
7	METAL PRICE	4.368300	4.196889	5.516015	3.807911	0.471344	1.046141	2.764243	25.576707	0.000003

Sheet1 / Sheet2 / Sheet3 / weightmatrix / dstats_domestic / dstats_foreign / **dstats_global**

- **Unit root tests**

  If you have opted to carry out the unit root tests, **urt_domestic**, **urt_foreign** (see Figure 6.4) and **urt_global (**see Figure 6.5**)** will be created: they contain the Augmented Dickey-Fuller (**ADF**) and Weighted-Symmetric augmented Dickey-Fuller (**WS**) tests for all domestic, foreign-specific and global variables included in the GVAR. All variables are tested for unit roots in their levels, and in their first and second differences. When testing the levels, two type of regressions are computed: one including both an intercept and a trend, and another including an intercept only. When testing first and second differences, only the intercept is included. Asymptotic 5% critical values are used for both tests.

Figure 6.4 Unit root test results for the domestic and foreign variables

output

	A	B	C	D	E	F	G	H	I	J
1	Unit Root Tests for the Domestic Variables at the 5% Significance Level									
2										
3	Domestic Variables	Statistic	Critical Value	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO
4	y (with trend)	ADF	-3.45	-2.087383	-3.123300	-2.330659	-2.308313	-2.221038	-2.878856	-0.458748
5	y (with trend)	WS	-3.24	-1.628138	-3.038478	-2.305316	-2.505373	-2.285587	-2.583553	-0.880745
6	y (no trend)	ADF	-2.89	0.666479	-0.207085	1.049939	-0.662644	0.444432	0.080130	-1.553504
7	y (no trend)	WS	-2.55	0.383326	2.003156	1.669339	1.154938	0.268837	1.430857	0.886491
8	Dy	ADF	-2.89	-5.184875	-6.746209	-6.911173	-5.124731	-3.619916	-4.976038	-4.179254
9	Dy	WS	-2.55	-5.314596	-6.696966	-6.572337	-5.306462	-3.793466	-4.918721	-4.376228
10	DDy	ADF	-2.89	-7.624866	-9.324870	-9.127714	-8.162353	-11.673888	-10.169627	-9.042369
11	DDy	WS	-2.55	-7.740484	-9.519906	-8.195779	-8.332563	-11.736151	-10.268202	-9.052660
12	Dp (with trend)	ADF	-3.45	-3.733665	-3.872703	-2.831972	-2.608278	-3.127163	-5.331489	-3.053567
13	Dp (with trend)	WS	-3.24	-3.840500	-3.882052	-2.832547	-2.509551	-3.155687	-5.004044	-2.025626
14	Dp (no trend)	ADF	-2.89	-2.471695	-3.097434	-2.248240	-2.306743	-2.958213	-3.395876	-3.323640
15	Dp (no trend)	WS	-2.55	-2.694361	-2.563416	-2.507009	-1.266976	-3.112284	-2.006396	-0.691155
16	DDp	ADF	-2.89	-12.821583	-10.272176	-6.428918	-7.992644	-7.191622	-7.450204	-6.994868
17	DDp	WS	-2.55	-13.003781	-10.473432	-6.632939	-8.034568	-7.398911	-7.419781	-7.072209
18	DDDp	ADF	-2.89	-15.433882	-10.760278	-9.106720	-11.259151	-9.212236	-11.525845	-10.150556
19	DDDp	WS	-2.55	-15.707141	-10.950064	-9.341463	-11.367783	-9.453914	-11.734005	-9.994391
20	eq (with trend)	ADF	-3.45	-3.969603	-3.470727		-3.141468		-2.137810	-1.876191
21	eq (with trend)	WS	-3.24	-3.639584	-3.644367		-2.956829		-2.379132	-2.085656
22	eq (no trend)	ADF	-2.89	-3.161510	-1.518364		-0.861606		-0.806896	-1.775570
23	eq (no trend)	WS	-2.55	-3.281466	-0.795400		-0.786045		-0.178909	-0.983278
24	Deq	ADF	-2.89	-7.131113	-6.514622		-6.358527		-5.751319	-7.209359
25	Deq	WS	-2.55	-6.801952	-6.180034		-6.559727		-5.207357	-7.343496

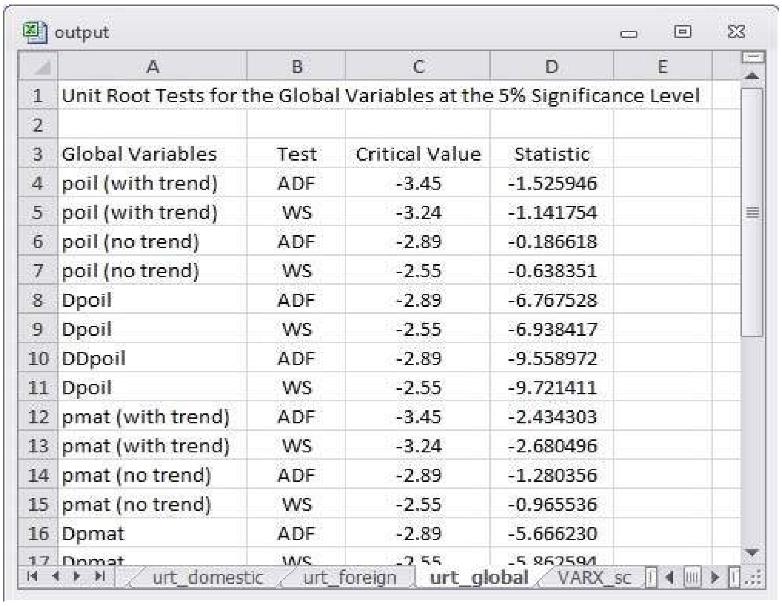
urt_domestic / urt_foreign / urt_global / VARX_sc / VARXorder / coint_max&traceVARX / ncntVARX / ECMS_VARX

output

	A	B	C	D	E	F	G	H	I	J
1	Unit Root Tests for the Foreign Variables at the 5% Significance Level									
2										
3	Foreign Variables	Statistic	Critical Value	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO
4	ys (with trend)	ADF	-3.45	-3.511976	-1.749309	-4.226589	-1.426891	-0.774403	-3.482429	-3.533809
5	ys (with trend)	WS	-3.24	-3.146766	-1.997722	-3.558831	-1.697348	-1.132542	-3.359239	-3.363156
6	ys (no trend)	ADF	-2.89	0.685301	-1.091416	0.125697	-0.980161	-1.637206	-0.113734	-0.403662
7	ys (no trend)	WS	-2.55	1.474715	0.788778	1.224839	1.351823	1.034709	1.355869	1.213520
8	Dys	ADF	-2.89	-6.041712	-5.650062	-4.788840	-4.886513	-5.381109	-4.673539	-5.074101
9	Dys	WS	-2.55	-6.083517	-5.827021	-4.895753	-4.740684	-5.498834	-4.823549	-5.068945
10	DDy	ADF	-2.89	-8.536517	-9.754912	-9.350221	-7.720589	-7.910934	-10.148097	-7.446606
11	DDy	WS	-2.55	-7.912767	-9.838117	-9.188060	-7.792964	-8.109031	-9.888373	-7.715749
12	Dps (with trend)	ADF	-3.45	-2.780255	-2.821206	-3.477916	-2.958904	-3.223554	-2.810216	-2.898215
13	Dps (with trend)	WS	-3.24	-2.805891	-2.876953	-3.635081	-2.637888	-3.409845	-2.808927	-3.095099
14	Dps (no trend)	ADF	-2.89	-2.143550	-2.351923	-2.541789	-2.354918	-2.278428	-2.003814	-1.931007
15	Dps (no trend)	WS	-2.55	-2.412080	-1.646551	-2.711855	-0.719456	-2.093587	-2.260660	-1.809397
16	DDps	ADF	-2.89	-6.338221	-8.074969	-12.886458	-8.958906	-8.015489	-7.796499	-7.739290
17	DDps	WS	-2.55	-6.540471	-8.229486	-13.069678	-9.133792	-8.111694	-7.946072	-7.718506
18	DDDp	ADF	-2.89	-9.034594	-10.448324	-10.837162	-12.004434	-9.750968	-8.451014	-10.582625
19	DDDp	WS	-2.55	-9.248849	-10.667460	-11.085687	-11.827082	-9.589776	-8.611328	-10.143705
20	eqs (with trend)	ADF	-3.45	-1.984905	-2.486343	-2.650819	-1.794809	-2.363178	-2.414461	-2.212308
21	eqs (with trend)	WS	-3.24	-2.227377	-2.556497	-2.863291	-2.074151	-2.543843	-2.640908	-2.427696
22	eqs (no trend)	ADF	-2.89	-1.409851	-1.885740	-1.431505	-1.294526	-1.604149	-1.653340	-1.448429
23	eqs (no trend)	WS	-2.55	-0.321979	-0.847691	-0.709646	-0.375501	-0.673672	-0.758803	-0.360815
24	Deqs	ADF	-2.89	-7.232505	-7.400999	-6.213659	-6.917597	-7.353124	-7.587492	-7.411975
25	Deqs	WS	-2.55	-7.380208	-7.519736	-6.393901	-7.030415	-7.488095	-7.732169	-7.518637

urt_domestic / urt_foreign / urt_global / VARX_sc / VARXorder / coint_max&traceVARX / ncntVARX / ECMS_VARX

Figure 6.5 Unit root test results for the global variables



	A	B	C	D	E
1	Unit Root Tests for the Global Variables at the 5% Significance Level				
2					
3	Global Variables	Test	Critical Value	Statistic	
4	poil (with trend)	ADF	-3.45	-1.525946	
5	poil (with trend)	WS	-3.24	-1.141754	
6	poil (no trend)	ADF	-2.89	-0.186618	
7	poil (no trend)	WS	-2.55	-0.638351	
8	Dpoil	ADF	-2.89	-6.767528	
9	Dpoil	WS	-2.55	-6.938417	
10	DDpoil	ADF	-2.89	-9.558972	
11	Dpoil	WS	-2.55	-9.721411	
12	pmat (with trend)	ADF	-3.45	-2.434303	
13	pmat (with trend)	WS	-3.24	-2.680496	
14	pmat (no trend)	ADF	-2.89	-1.280356	
15	pmat (no trend)	WS	-2.55	-0.965536	
16	Dpmat	ADF	-2.89	-5.666230	
17	Dpmat	WS	-2.55	-5.862594	

- **Lag orders and statistics of individual VARX* models**

  If you chose to perform the information criterion based lag order selection for the individual country models two worksheets will be created. The first one, labelled **VARX_sc**, contains the Akaike (**AIC**), the Schwartz Bayesian (**SBC**) and the log-likelihood (**logLik**) statistics for the individual VARX* models (see Figure 6.6). These are computed for all possible lag order specifications (see Section A.7), where the maximum lag orders are defined in the initial settings of the interface file MAIN worksheet. In addition, the F-statistics for testing the residual serial correlation of the individual VARX* model equations are computed (column J onwards) with the corresponding 95% critical values (column I) and degrees of freedom (column H). If **no** is selected in the **Lag order selection** field in the **Model selection** display of the MAIN worksheet, the VARX_sc sheet will not be created. The same is true if the function **Run the program with pauses** is disabled.

Figure 6.6 Choice criteria for the VARX* order and serial correlation results

output

Choice Criteria for Selecting the Order of the VARX* Models Together With Corresponding Residual Serial Correlation F-Statistics

	p	q	AIC	SBC	logLik			Fcrit_0.05	y	Dp	eq	ep
ARGENTINA	1	1	679.2536	512.6278	794.2536		F(4,107)	2.4566	10.7389	0.9634	1.0736	0.6433
ARGENTINA	2	1	730.1963	527.3475	870.1963		F(4,102)	2.4608	1.0956	0.7879	2.4164	1.2990
AUSTRALIA	1	1	2822.4201	2613.7756	2966.4201		F(4,106)	2.4574	3.1481	0.0628	0.3985	2.0269
AUSTRALIA	2	1	2819.2607	2558.4551	2999.2607		F(4,100)	2.4626	4.9405	1.2095	0.7174	2.0659
BRAZIL	1	1	868.7685	741.2636	956.7685		F(4,108)	2.4558	1.4355	1.5071		2.0806
BRAZIL	2	1	874.4569	723.7693	978.4569		F(4,104)	2.4591	1.6662	0.9724		1.7690
CANADA	1	1	3134.1990	2925.5546	3278.1990		F(4,106)	2.4574	2.3029	1.5121	1.7967	6.7974
CANADA	2	1	3137.2230	2876.4174	3317.2230		F(4,100)	2.4626	4.7081	1.0324	1.2453	6.3012
CHINA	1	1	1811.0763	1683.5713	1899.0763		F(4,108)	2.4558	1.6889	3.4780		1.3244
CHINA	2	1	1810.8684	1660.1807	1914.8684		F(4,104)	2.4591	3.2288	2.6410		0.7149
CHILE	1	1	1513.5480	1346.9222	1628.5480		F(4,107)	2.4566	2.4101	2.4877	2.1236	1.8504
CHILE	2	1	1520.8365	1317.9877	1660.8365		F(4,102)	2.4608	2.5179	1.4460	0.8775	1.3367
EURO	1	1	3270.8695	3062.2250	3414.8695		F(4,106)	2.4574	1.2757	2.3929	2.2071	2.9315
EURO	2	1	3280.9582	3020.1526	3460.9582		F(4,100)	2.4626	1.9503	2.6791	0.5007	0.5360
INDIA	1	1	1871.5137	1704.8879	1986.5137		F(4,107)	2.4566	3.4396	4.2408	4.7240	2.3214
INDIA	2	1	1880.0841	1677.2353	2020.0841		F(4,102)	2.4608	1.9507	3.1657	3.2341	1.4581
INDONESIA	1	1	1268.9143	1141.4094	1356.9143		F(4,108)	2.4558	0.7637	1.4803		3.1383
INDONESIA	2	1	1283.6729	1132.9852	1387.6729		F(4,104)	2.4591	1.5913	3.1082		1.9563
JAPAN	1	1	2896.3624	2687.7179	3040.3624		F(4,106)	2.4574	1.9217	0.4299	2.1673	4.4287
JAPAN	2	1	2905.9830	2645.1774	3085.9830		F(4,100)	2.4626	4.3281	0.4796	1.7736	4.5374
KOREA	1	1	2445.5331	2236.8887	2589.5331		F(4,106)	2.4574	1.0829	5.0583	1.0093	3.9818
KOREA	2	1	2473.7808	2212.9753	2653.7808		F(4,100)	2.4626	4.0972	5.6180	1.5408	1.6542
MALAYSIA	1	1	2010.9697	1844.3439	2125.9697		F(4,107)	2.4566	0.8320	1.0653	0.4333	3.5876
MALAYSIA	2	1	2006.3658	1803.5171	2146.3658		F(4,102)	2.4608	0.6488	1.3890	0.2460	2.2475
MEXICO	1	1	1343.7454	1216.2404	1431.7454		F(4,108)	2.4558	1.9310	0.9566		1.0726
MEXICO	2	1	1335.6583	1184.9707	1439.6583		F(4,104)	2.4591	3.0816	1.8548		0.5830
NORWAY	1	1	2708.1813	2499.5368	2852.1813		F(4,106)	2.4574	2.4712	2.8015	1.3804	2.2558

urt_foreign urt_global VARX_sc VARXorder coint_max&traceVARX ncntVARX ECMS_VARX ECMS_stat

The second worksheet, labelled **VARXord**, contains the lag orders of the individual model domestic and foreign variables used in the analysis, selected either according to the chosen information criterion or inputted by the user (see Figure 6.7).

Figure 6.7 Order results for the VARX* models

VARX* Order of Individual Models (p: lag order of domestic variables, q: lag order of foreign variables)

	p	q
ARGENTINA	2	1
AUSTRALIA	1	1
BRAZIL	2	1
CANADA	2	1
CHINA	1	1
CHILE	2	1
EURO	2	1
INDIA	2	1
INDONESIA	2	1
JAPAN	2	1
KOREA	2	1
MALAYSIA	1	1
MEXICO	1	1
NORWAY	2	1
NEW ZEALAND	2	1
PERU	2	1
PHILIPPINES	2	1
SOUTH AFRICA	2	1
SAUDI ARABIA	2	1
SINGAPORE	2	1
SWEDEN	2	1
SWITZERLAND	1	1
THAILAND	2	1
TURKEY	2	1
UNITED KINGDOM	1	1
USA	2	1

urt_foreign | urt_global | VARX_sc | **VARXorder** | coint_max&traceVARX | ncntVARX

- **Cointegration tests**

  By default, the program will create the worksheet **coint_max&traceVARX** (see Figure 6.8). It contains both the trace and maximum eigenvalue statistics used for determining the dimension of the cointegration space of the individual models, as well as the critical values for the trace statistic. Tests are conducted using (by default) the trace statistic at the 5% level of significance. The critical values for models including weakly exogenous variables are obtained from Mackinnon, Haug and Michelis (1999). The **ncntVARX** worksheet (see Figure 6.9) contains the rank orders for each model, implied by the cointegration tests and selected according to the trace statistic. If the function **Run the program with pauses** is disabled whilst running the program, the **coint_max&traceVARX** worksheet will not be included in the output file, as the cointegration statistics will not be computed.

Figure 6.8 Cointegration test results for the individual models

Detailed Cointegration Results for the Maximum Eigenvalue Statistic at the 5% Significance Level

Country	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO	INDIA	INDONESIA
# endogenous variables	5	6	4	6	4	5	6	5	4
# foreign (star) variables	8	8	8	8	8	8	8	8	8
r=0	98.566	116.209	92.373	89.867	99.322	84.679	90.134	63.948	84.868
r=1	68.666	85.851	54.353	69.681	50.781	69.723	55.168	52.575	59.604
r=2	43.301	67.298	29.467	48.566	43.894	32.374	48.817	41.127	49.474
r=3	24.360	50.274	24.178	43.318	19.633	26.435	31.708	27.779	22.009
r=4	17.112	40.846		27.441		23.571	27.780	18.472	
r=5		28.554		21.054			22.800		

Detailed Cointegration Results for the Trace Statistic at the 5% Significance Level

Country	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO	INDIA	INDONESIA
# endogenous variables	5	6	4	6	4	5	6	5	4
# foreign (star) variables	8	8	8	8	8	8	8	8	8
r=0	252.005	389.033	200.372	299.927	213.629	236.782	276.407	203.901	215.955
r=1	153.439	272.824	107.998	210.060	114.307	152.103	186.273	139.953	131.088
r=2	84.773	186.973	53.645	140.379	63.526	82.380	131.105	87.378	71.484
r=3	41.472	119.675	24.178	91.813	19.633	50.006	82.288	46.251	22.009
r=4	17.112	69.400		48.495		23.571	50.580	18.472	
r=5		28.554		21.054			22.800		

Critical Values for Trace Statistic at the 5% Significance Level (MacKinnon, Haug, Michelis, 1999)

Country	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO	INDIA	INDONESIA
# endogenous variables	5	6	4	6	4	5	6	5	4
# foreign (star) variables	8	8	8	8	8	8	8	8	8
r=0	178.460	223.880	136.940	223.880	136.940	178.460	223.880	178.460	136.940
r=1	136.940	178.460	99.120	178.460	99.120	136.940	178.460	136.940	99.120
r=2	99.120	136.940	64.910	136.940	64.910	99.120	136.940	99.120	64.910
r=3	64.910	99.120	33.870	99.120	33.870	64.910	99.120	64.910	33.870
r=4	33.870	64.910		64.910		33.870	64.910	33.870	
r=5		33.870		33.870			33.870		

urt_foreign / urt_global / VARX_sc / VARXorder / coint_max&traceVARX / ncntVARX / ECMS_VARX

Figure 6.9 Cointegrating rank order results for the individual models

Cointegrating Relationships for the Individual VARX* Models

Country	# Cointegrating relations
ARGENTINA	2
AUSTRALIA	5
BRAZIL	2
CANADA	3
CHINA	2
CHILE	2
EURO	2
INDIA	2
INDONESIA	3
JAPAN	2
KOREA	4
MALAYSIA	2
MEXICO	3
NORWAY	3
NEW ZEALAND	2
PERU	4
PHILIPPINES	2
SOUTH AFRICA	3
SAUDI ARABIA	2
SINGAPORE	2
SWEDEN	2
SWITZERLAND	3
THAILAND	3
TURKEY	1
UNITED KINGDOM	3
USA	2

urt_foreign / urt_global / VARX_sc / VARXorder

- **Individual VECMX* model estimation**

  Again, by default, several worksheets related to the estimation of each individual VECMX* model will be created:

- **ECMS_VARX** contains the estimated coefficients of each model (see Figure 6.10). The coefficients are ordered as follows: deterministic component (intercept and trend, or just intercept), lagged levels of domestic (endogenous) and foreign (weakly exogenous) variables, contemporaneous differences of foreign variables, and lagged differences of domestic (if $p_i > 1$) and foreign (if $q_i > 1$) variables, where as noted earlier p_i and q_i are the lag orders of the VARX* models, respectively.

- **ECMS_stats** contains the log-likelihood, the Akaike and the Schwartz Bayesian statistics (see Figure 6.11).

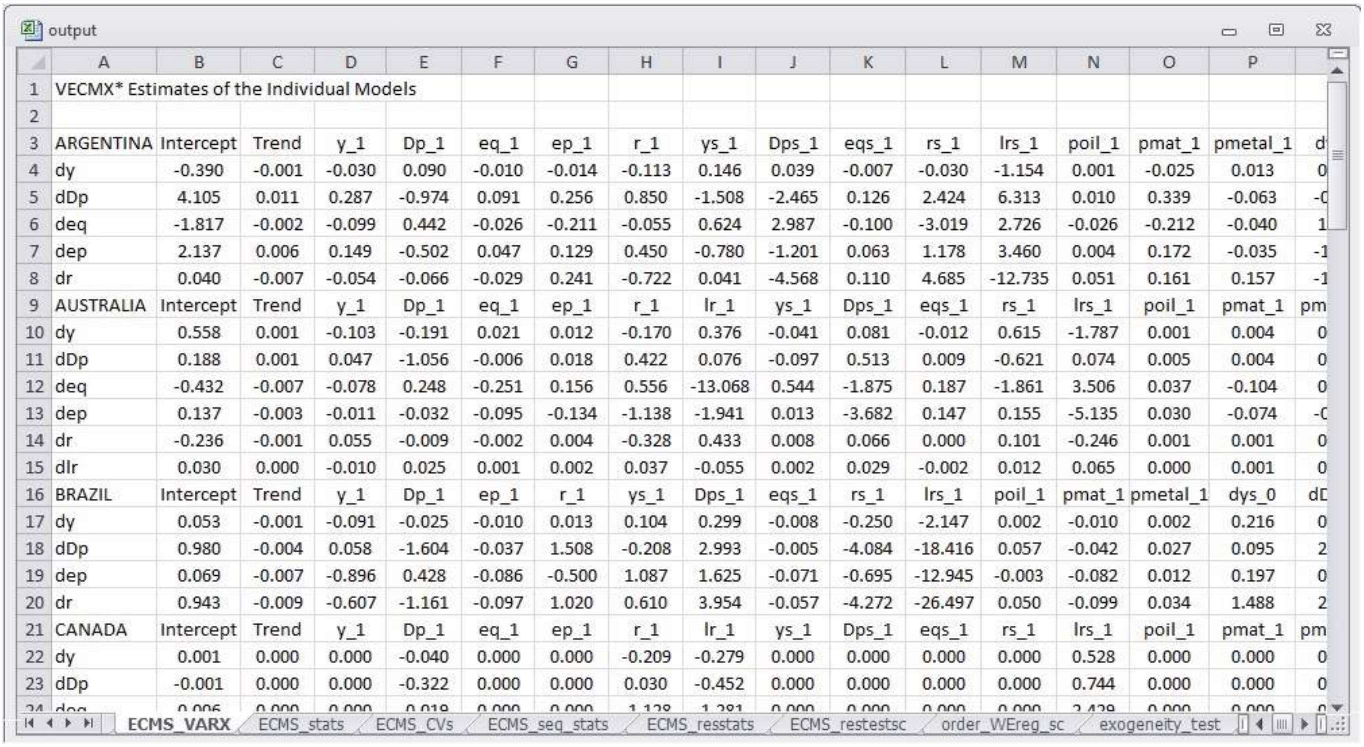
- **ECMS_CVs** contains the cointegrating vectors (the beta vector is arbitrarily normalised using the identity matrix) (see Figure 6.11).

- **ECMS_seq_stats** contains the statistics for each equation of the individual VECMX* models, namely the R^2 (column C), the adjusted R^2 (column D), the Akaike (**AIC**) and the Schwartz Bayesian (**SBC**) statistics (see Figure 6.11).

- **ECMS_resstats** contains descriptive statistics, as well as the Jarque-Bera normality test, for the residuals obtained from the VECMX* estimation (see Figure 6.12).

- **ECMS_restestsc** contains the F-statistics for the serial correlation test of the residuals obtained from the VECMX* estimation (see Figure 6.13).

Figure 6.10 Estimated coefficients of the individual VECMX* models



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	
1	VECMX* Estimates of the Individual Models																
2																	
3	ARGENTINA	Intercept	Trend	y_1	Dp_1	eq_1	ep_1	r_1	ys_1	Dps_1	eqs_1	rs_1	lrs_1	poil_1	pmat_1	pmetal_1	d
4	dy	-0.390	-0.001	-0.030	0.090	-0.010	-0.014	-0.113	0.146	0.039	-0.007	-0.030	-1.154	0.001	-0.025	0.013	0
5	dDp	4.105	0.011	0.287	-0.974	0.091	0.256	0.850	-1.508	-2.465	0.126	2.424	6.313	0.010	0.339	-0.063	-0
6	deq	-1.817	-0.002	-0.099	0.442	-0.026	-0.211	-0.055	0.624	2.987	-0.100	-3.019	2.726	-0.026	-0.212	-0.040	1
7	dep	2.137	0.006	0.149	-0.502	0.047	0.129	0.450	-0.780	-1.201	0.063	1.178	3.460	0.004	0.172	-0.035	-1
8	dr	0.040	-0.007	-0.054	-0.066	-0.029	0.241	-0.722	0.041	-4.568	0.110	4.685	-12.735	0.051	0.161	0.157	-1
9	AUSTRALIA	Intercept	Trend	y_1	Dp_1	eq_1	ep_1	r_1	lr_1	ys_1	Dps_1	eqs_1	rs_1	lrs_1	poil_1	pmat_1	pm
10	dy	0.558	0.001	-0.103	-0.191	0.021	0.012	-0.170	0.376	-0.041	0.081	-0.012	0.615	-1.787	0.001	0.004	0
11	dDp	0.188	0.001	0.047	-1.056	-0.006	0.018	0.422	0.076	-0.097	0.513	0.009	-0.621	0.074	0.005	0.004	0
12	deq	-0.432	-0.007	-0.078	0.248	-0.251	0.156	0.556	-13.068	0.544	-1.875	0.187	-1.861	3.506	0.037	-0.104	0
13	dep	0.137	-0.003	-0.011	-0.032	-0.095	-0.134	-1.138	-1.941	0.013	-3.682	0.147	0.155	-5.135	0.030	-0.074	-0
14	dr	-0.236	-0.001	0.055	-0.009	-0.002	0.004	-0.328	0.433	0.008	0.066	0.000	0.101	-0.246	0.001	0.001	0
15	dlr	0.030	0.000	-0.010	0.025	0.001	0.002	0.037	-0.055	0.002	0.029	-0.002	0.012	0.065	0.000	0.001	0
16	BRAZIL	Intercept	Trend	y_1	Dp_1	ep_1	r_1	ys_1	Dps_1	eqs_1	rs_1	lrs_1	poil_1	pmat_1	pmetal_1	dys_0	dD
17	dy	0.053	-0.001	-0.091	-0.025	-0.010	0.013	0.104	0.299	-0.008	-0.250	-2.147	0.002	-0.010	0.002	0.216	0
18	dDp	0.980	-0.004	0.058	-1.604	-0.037	1.508	-0.208	2.993	-0.005	-4.084	-18.416	0.057	-0.042	0.027	0.095	2
19	dep	0.069	-0.007	-0.896	0.428	-0.086	-0.500	1.087	1.625	-0.071	-0.695	-12.945	-0.003	-0.082	0.012	0.197	0
20	dr	0.943	-0.009	-0.607	-1.161	-0.097	1.020	0.610	3.954	-0.057	-4.272	-26.497	0.050	-0.099	0.034	1.488	2
21	CANADA	Intercept	Trend	y_1	Dp_1	eq_1	ep_1	r_1	lr_1	ys_1	Dps_1	eqs_1	rs_1	lrs_1	poil_1	pmat_1	pm
22	dy	0.001	0.000	0.000	-0.040	0.000	0.000	-0.209	-0.279	0.000	0.000	0.000	0.000	0.528	0.000	0.000	0
23	dDp	-0.001	0.000	0.000	-0.322	0.000	0.000	0.030	-0.452	0.000	0.000	0.000	0.000	0.744	0.000	0.000	0

Figure 6.11 VECMX* statistics, cointegrating vectors and individual equation statistics

VECMX* Estimation: Statistics

Country	logLik	Akaike	Schwartz Bayesian
ARGENTINA	827.810	747.810	631.896
AUSTRALIA	2952.143	2868.143	2746.434
BRAZIL	951.634	891.634	804.699
CANADA	3271.317	3090.353	2933.870
CHINA	1867.313	1823.313	1759.561
CHILE	1619.646	1539.646	1423.733
EURO	3395.406	3239.125	3091.335
INDIA	1976.395	1896.395	1780.481
INDONESIA	1376.668	1312.668	1219.937
JAPAN	3021.625	2919.625	2771.836
KOREA	2622.139	2508.139	2342.963
MALAYSIA	2081.669	2026.669	1946.978
MEXICO	1419.641	1371.641	1302.093
NORWAY	2861.521	2753.521	2597.038
NEW ZEALAND	2717.566	2615.566	2467.776
PERU	935.287	867.287	768.761
PHILIPPINES	1733.638	1653.638	1537.724
SOUTH AFRICA	2805.405	2697.405	2540.921
SAUDI ARABIA	1469.476	1427.476	1366.622
SINGAPORE	2149.347	2069.347	1953.433
SWEDEN	2860.483	2758.483	2610.693
SWITZERLAND	3152.443	3080.443	2976.121
THAILAND	1820.296	1735.296	1612.138
TURKEY	1227.359	1171.359	1090.219
UNITED KINGDOM	3155.263	3083.263	2978.941
USA	2758.259	2688.259	2586.835

VECMX* Estimation: Cointegrating Vectors

ARGENTINA		
***********		
ALPHA	a1	a2
y	-0.0298	0.0904
Dp	0.2866	-0.9741
eq	-0.0990	0.4417
ep	0.1489	-0.5020
r	-0.0537	-0.0657
BETA	CV1	CV2
Trend	0.1043	0.0197
y	1	0
Dp	0	1
eq	0.4844	0.0492
ep	-3.0593	-1.1631
r	10.6756	2.2685
ys	-1.9489	0.9750
Dps	60.3079	20.2747
eqs	-1.3925	-0.5392
rs	-61.9472	-20.7150
lrs	180.3207	46.5748
poil	-0.6948	-0.2144
pmat	-1.8887	-0.9033
pmetal	-2.2106	-0.5858
AUSTRALIA		
***********		

VECMX* Single-Equation Statistics

Country	Variable	R_square	Rbar_square	AIC	SBC
ARGENTINA	y	0.542	0.483	360.119	336.936
ARGENTINA	Dp	0.869	0.853	136.555	113.372
ARGENTINA	eq	0.404	0.328	-14.502	-37.685
ARGENTINA	ep	0.268	0.174	78.262	55.080
ARGENTINA	r	0.676	0.635	100.601	77.418
AUSTRALIA	y	0.420	0.357	485.540	465.255
AUSTRALIA	Dp	0.599	0.556	505.826	485.541
AUSTRALIA	eq	0.650	0.612	199.538	179.254
AUSTRALIA	ep	0.576	0.530	251.637	231.353
AUSTRALIA	r	0.354	0.284	640.823	620.539
AUSTRALIA	lr	0.401	0.337	720.154	699.869
BRAZIL	y	0.412	0.343	369.081	347.347
BRAZIL	Dp	0.495	0.436	109.179	87.445
BRAZIL	ep	0.425	0.357	169.346	147.612
BRAZIL	r	0.349	0.272	54.894	33.160
CANADA	y	0.566	0.502	499.697	473.616
CANADA	Dp	0.455	0.375	527.384	501.303
CANADA	eq	0.804	0.775	246.424	220.343
CANADA	ep	0.583	0.522	320.416	294.335
CANADA	r	0.607	0.550	672.154	646.073
CANADA	lr	0.812	0.784	799.933	773.852
CHINA	y	0.264	0.204	410.378	394.440
CHINA	Dp	0.271	0.212	436.100	420.162
CHINA	ep	0.329	0.275	242.301	226.363
CHINA	r	0.375	0.324	724.360	708.422
CHILE	y	0.526	0.466	367.001	343.819
CHILE	Dp	0.465	0.397	383.902	360.720

Figure 6.12 Descriptive statistics of the VECMX* residuals

Descriptive Statistics of VECMX* Residuals

Stats	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
ARGENTINA									
y	-1E-16	0.001075	0.034787	-0.054578	0.014669	-0.56614	3.977666	13.3331523	0.0012727
Dp	-9.4E-16	-0.00491	0.398737	-0.276885	0.077796	0.7671046	8.499194	190.256774	0
eq	1.29E-16	-0.02199	0.98888	-0.51393	0.240179	0.7855967	4.867242	35.1253127	2.358E-08
ep	3.68E-16	-0.00325	0.644046	-0.284937	0.120195	1.6229999	10.81991	416.002189	0
r	-5.4E-16	0.009548	0.708098	-0.3357	0.101738	2.1661444	19.61531	1703.97799	0
AUSTRALIA									
y	1.7E-16	0.000156	0.015994	-0.015083	0.00584	-0.086931	3.129091	0.34619064	0.8410574
Dp	-3.1E-16	-0.00035	0.0217	-0.014904	0.005019	0.5019335	5.962058	57.7632786	2.863E-13
eq	6.27E-16	0.006033	0.152287	-0.209135	0.049353	-0.82113	5.558701	54.3909789	1.546E-12
ep	3.47E-16	-0.00411	0.117332	-0.072549	0.033455	0.7570135	4.338057	24.0881071	5.879E-06
r	-1.4E-16	5.82E-05	0.006621	-0.006206	0.001833	0.4096752	6.061376	59.334992	1.305E-13
lr	1.91E-17	-0.0001	0.003528	-0.002634	0.001014	0.6766249	4.607587	26.161735	2.085E-06
BRAZIL									
y	1.52E-16	0.002324	0.046679	-0.038835	0.013822	-0.265352	3.538962	3.56753298	0.1680042
Dp	-6.5E-16	0.002159	0.242028	-0.62144	0.096145	-2.212208	16.29299	1135.21748	0
ep	3.03E-15	-0.00113	0.353966	-0.207883	0.061365	1.5372916	11.51262	475.260276	0
r	7.27E-16	0.002393	0.442337	-0.888038	0.144166	-1.92355	15.44556	982.028989	0
CANADA									
y	-8.2E-19	-6.4E-05	0.01794	-0.012808	0.0051	0.268526	3.587569	3.94621068	0.1390245
Dp	-2.9E-18	8.53E-06	0.019726	-0.01208	0.004148	0.4261363	6.03385	58.6698821	1.82E-13
eq	-2E-18	8.99E-05	0.126937	-0.10739	0.033759	0.3477404	4.584168	18.0246287	0.0001219
ep	1.76E-18	0.001838	0.055092	-0.053634	0.019435	-0.253112	3.412123	2.66345434	0.2640209
r	2.92E-20	1.12E-05	0.005645	-0.004948	0.001408	0.5979845	6.261857	71.0652087	3.331E-16
lr	-1.6E-19	-1.8E-05	0.002424	-0.002116	0.000543	0.2018535	6.417495	69.8889191	6.661E-16
CHINA									
y	-3.1E-16	-0.00033	0.031145	-0.027651	0.010464	0.027414	3.715278	3.33919729	0.1883226
Dp	-4.4E-16	-0.00057	0.037022	-0.02145	0.008636	0.6997184	5.306961	42.997301	4.605E-10

Figure 6.13 F-statistics for the serial correlation test of the VECMX* residuals

F- Statistics for the Serial Correlation Test of the VECMX* Residuals

		Fcrit_0.05	y	Dp	eq	ep	r	lr	poil	pmat	pmetal
ARGENTINA	F(4,114)	2.451273	0.767166	0.852500	1.066360	0.624334	0.965415				
AUSTRALIA	F(4,116)	2.449880	2.521034	0.114955	0.426455	1.750201	2.371198	1.127128			
BRAZIL	F(4,115)	2.450571	2.573114	1.802686		1.002749	0.823960				
CANADA	F(4,112)	2.452716	3.547830	4.729207	3.601967	2.241992	1.955837	2.390240			
CHINA	F(4,119)	2.447881	2.069183	4.751777		0.298093	0.185432				
CHILE	F(4,114)	2.451273	1.668042	1.751302	1.139081	2.168908	0.436358				
EURO	F(4,113)	2.451988	3.288706	1.553524	1.461298	2.478595	2.723224	1.418208			
INDIA	F(4,114)	2.451273	1.999251	2.318059	1.112295	1.585290	0.958608				
INDONESIA	F(4,114)	2.451273	1.404640	3.623132		2.497221	2.150758				
JAPAN	F(4,113)	2.451988	1.359692	0.732933	0.983641	4.292512	1.881067	1.056668			
KOREA	F(4,111)	2.453458	3.706619	4.282631	1.549288	2.990890	1.036446	1.233415			
MALAYSIA	F(4,119)	2.447881	0.562975	0.978705	1.595788	3.279198	1.753914				
MEXICO	F(4,118)	2.448536	1.909504	1.058913		0.708263	1.796287				
NORWAY	F(4,112)	2.452716	0.542356	2.773737	1.386352	1.852744	1.211714	2.836856			
NEW ZEALAND	F(4,113)	2.451988	1.012158	2.724125	1.341317	4.139548	2.140069	5.936820			
PERU	F(4,113)	2.451988	2.369607	4.965402		1.831407	5.634111				
PHILIPPINES	F(4,114)	2.451273	2.284755	0.919214	0.209860	0.041892	2.540075				
SOUTH AFRICA	F(4,112)	2.452716	3.028130	3.391934	1.226426	1.024027	0.776723	0.672514			
SAUDI ARABIA	F(4,116)	2.449880	22.477947	2.304449		1.227555					
SINGAPORE	F(4,114)	2.451273	1.898826	2.493785	1.993866	1.258388	3.859625				
SWEDEN	F(4,113)	2.451988	0.792570	4.777189	5.128841	1.899479	1.892276	2.574108			
SWITZERLAND	F(4,118)	2.448536	3.056408	2.808061	2.547311	1.865417	1.776591	2.770806			
THAILAND	F(4,113)	2.451988	0.798312	3.081495	0.770248	2.375017	1.147741				
TURKEY	F(4,116)	2.449880	1.658806	3.136690		0.300174	3.001385				
UNITED KINGDOM	F(4,118)	2.448536	0.919354	2.056851	1.026657	4.626693	1.062185	1.085785			
USA	F(4,116)	2.449880	0.826395	1.964279	1.482912		3.641693	0.185890			

- **Weak exogeneity test**

  If you have chosen to carry out the weak exogeneity test, and have chosen to perform the information criterion based lag order selection for the weak exogeneity regressions two worksheets will be created. The first one, labelled **order_WE_sc**, contains the Akaike (**AIC**), the Schwartz Bayesian (**SBC**) and the log-likelihood (**logLik**) statistics for the individual country models (see Figure 6.14). These are computed for all possible lag order specifications (see Section A.12), where the maximum lag orders are defined in the initial settings of the interface file MAIN worksheet. In addition, the F-statistics for testing the residual serial correlation of the individual regression equations are computed (column J onwards) with the corresponding 95% critical values (column I) and degrees of freedom (column H). If **no** is selected in the **Lag order selection** field in the panel associated with the weak exogeneity test in the MAIN worksheet, the **order_WEreg_sc** worksheet will not be created. The same is true if the program is run with the **Run the program with pauses** function disabled.

Figure 6.14 Choice criteria for selecting the order of the weak exogeneity regressions together with serial correlation results

output.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Choice Criteria for Selecting the Order of the Weak Exogeneity Regressions Together With Corresponding Residual Serial Correlation F-Statistics														
2															
3		p*	q*	AIC	SBC	logLik			Fcrit_0.05	ys	Dps	eqs	eps	rs	lrs
4	ARGENTINA	1	1	2474.303	2277.250	2610.303		F(4,113)	2.451988	1.891900	1.916734	0.486678		0.753580	5.205129
5	ARGENTINA	1	2	2459.807	2159.210	2667.807		F(4,103)	2.459920	1.116151	3.154473	0.637333		1.659989	2.263313
6	ARGENTINA	2	1	2506.929	2252.578	2682.929		F(4,107)	2.456566	0.381467	0.819801	0.696651		0.265260	3.914055
7	ARGENTINA	2	2	2501.844	2143.441	2749.844		F(4,98)	2.464505	0.529885	1.053783	0.565945		1.305510	2.988103
8	AUSTRALIA	1	1	3158.495	2915.076	3326.495		F(4,109)	2.454983	0.766021	3.443245	0.368339		1.120201	2.579670
9	AUSTRALIA	1	2	3142.213	2795.371	3382.213		F(4,99)	2.463550	0.704123	1.634239	0.774111		0.504979	0.660657
10	AUSTRALIA	2	1	3139.482	2827.324	3355.482		F(4,102)	2.460800	0.577891	4.204839	0.627001		1.096804	0.859797
11	AUSTRALIA	2	2	3135.451	2719.241	3423.451		F(4,93)	2.469595	0.563873	2.197605	0.912883		1.111449	0.981518
12	BRAZIL	1	1	2717.101	2531.640	2845.101		F(4,114)	2.451273	0.593345	1.090336	1.975814		0.878412	3.968345
13	BRAZIL	1	2	2711.731	2422.696	2911.731		F(4,104)	2.459057	0.432182	2.947658	1.015661		0.575523	1.642123
14	BRAZIL	2	1	2700.000	2468.773	2860.000		F(4,109)	2.454983	1.392963	1.347428	0.694293		0.984849	3.368590
15	BRAZIL	2	2	2710.994	2375.713	2942.994		F(4,100)	2.462615	0.807602	2.251629	0.709483		0.490835	1.540770
16	CANADA	1	1	3055.465	2835.229	3207.465		F(4,111)	2.453458	1.244746	5.063975	1.896236		2.812995	2.267670
17	CANADA	1	2	3034.671	2710.952	3258.671		F(4,101)	2.461698	0.786641	3.461858	0.506860		0.799375	1.228945
18	CANADA	2	1	3029.227	2740.192	3229.227		F(4,104)	2.459057	1.009493	3.702593	1.322922		1.996878	0.984968
19	CANADA	2	2	3015.189	2622.102	3287.189		F(4,95)	2.467494	0.677777	3.276464	0.657839		0.668709	1.251938
20	CHINA	1	1	3006.655	2821.193	3134.655		F(4,114)	2.451273	0.271274	0.312074	0.609862		1.444864	6.585379
21	CHINA	1	2	2991.606	2702.571	3191.606		F(4,104)	2.459057	0.552207	0.525574	0.467314		1.217885	1.898521
22	CHINA	2	1	2999.508	2768.281	3159.508		F(4,109)	2.454983	0.280299	0.938552	1.142086		2.675415	3.776813
23	CHINA	2	2	3001.163	2665.883	3233.163		F(4,100)	2.462615	0.799017	1.217604	0.584821		2.942335	2.086014
24	CHILE	1	1	2727.574	2530.521	2863.574		F(4,113)	2.451988	0.541467	4.804418	0.687545		1.567733	6.102170
25	CHILE	1	2	2739.564	2438.968	2947.564		F(4,103)	2.459920	0.629007	2.657346	0.818423		2.148081	1.548048
26	CHILE	2	1	2699.042	2444.691	2875.042		F(4,107)	2.456566	0.901413	4.473192	0.666836		2.833453	3.148892
27	CHILE	2	2	2732.496	2374.092	2980.496		F(4,98)	2.464505	0.580947	1.447190	0.586997		1.320483	1.420498
28	EURO	1	1	3003.372	2794.728	3147.372		F(4,112)	2.452716	0.718804	1.678399	0.282730		1.513157	2.348075
29	EURO	1	2	2981.699	2669.542	3197.699		F(4,102)	2.460800	0.260385	1.744667	0.724851		0.480827	0.882791
30	EURO	2	1	2980.655	2703.182	3172.655		F(4,105)	2.458210	0.530760	1.087913	0.036156		0.452615	1.293701
31	EURO	2	2	2973.538	2592.012	3237.538		F(4,96)	2.466476	0.426972	1.343800	0.687468		0.490464	1.083555

order_WEreg_sc | exogeneity_test | contemp_coeff | avgcorr_vall | str_stab_stats | str_stab_breakdates | DUmodel_VAR&coint

The next sheet the program will create is the **exogeneity_test** worksheet, which contains the final lag orders (imposed or selected), and the corresponding F-statistics for testing the weak exogeneity of the foreign variables. The final lag orders are given in the columns B and C, and the F-statistics are generated in column K onwards, with the critical values at the 5% level of significance in column J, and degrees of freedom in column I (see Figure 6.15).

Figure 6.15 F-statistics for the weak exogeneity test together with final selected lag orders

output.xls

Order of Weak Exogeneity Regression Equations
(p*: lag order of domestic variables, q*: lag order of foreign variables)

	p*	q*
ARGENTINA	2	1
AUSTRALIA	1	1
BRAZIL	1	1
CANADA	1	1
CHINA	1	1
CHILE	1	2
EURO	1	1
INDIA	1	1
INDONESIA	1	1
JAPAN	1	1
KOREA	1	1
MALAYSIA	1	1
MEXICO	1	1
NORWAY	1	1
NEW ZEALAND	1	1
PERU	1	1
PHILIPPINES	1	1
SOUTH AFRICA	1	1
SAUDI ARABIA	1	1
SINGAPORE	1	1
SWEDEN	1	1
SWITZERLAND	1	1
THAILAND	1	1
TURKEY	1	1
UNITED KINGDOM	1	1
USA	1	1

Test for Weak Exogeneity at the 5% Significance Level

Country	F test	Fcrit_0.05	ys	Dps	eqs	eps
ARGENTINA	F(2,111)	3.07806	0.95398	0.22851	0.37309	
AUSTRALIA	F(5,113)	2.29463	0.99493	2.34669	0.96332	
BRAZIL	F(2,118)	3.07309	1.19824	0.91783	1.08803	
CANADA	F(3,115)	2.68350	4.86488	1.61739	1.22402	
CHINA	F(2,118)	3.07309	0.26295	0.33458	0.14511	
CHILE	F(2,107)	3.08119	0.16613	0.04811	0.12326	
EURO	F(2,116)	3.07445	3.50559	0.14972	1.23203	
INDIA	F(2,117)	3.07376	3.47605	1.77583	0.31676	
INDONESIA	F(3,117)	2.68213	0.58977	1.10688	1.25209	
JAPAN	F(2,116)	3.07445	1.91979	2.29324	1.21119	
KOREA	F(4,114)	2.45127	0.44153	0.57359	4.01936	
MALAYSIA	F(2,117)	3.07376	3.33052	3.91035	0.43377	
MEXICO	F(3,117)	2.68213	0.08364	3.04711	1.58321	
NORWAY	F(3,115)	2.68350	4.09928	1.87694	1.00352	
NEW ZEALAND	F(2,116)	3.07445	2.23355	0.31487	0.03287	
PERU	F(4,116)	2.44988	0.32156	0.53050	0.53559	
PHILIPPINES	F(2,117)	3.07376	0.06659	1.52683	0.99898	
SOUTH AFRICA	F(3,115)	2.68350	0.07010	0.57700	0.46695	
SAUDI ARABIA	F(2,119)	3.07243	0.46681	1.28099	2.00207	
SINGAPORE	F(2,117)	3.07376	2.32362	0.50785	1.97832	
SWEDEN	F(2,116)	3.07445	0.91666	0.94015	0.02382	
SWITZERLAND	F(3,115)	2.68350	2.00515	2.22981	1.24051	
THAILAND	F(3,116)	2.68281	0.60226	0.49323	0.69146	
TURKEY	F(1,119)	3.92080	0.05700	0.40422	0.09642	
UNITED KINGDOM	F(3,115)	2.68350	2.40319	0.98964	0.20999	
USA	F(2,120)	3.07178	0.23466	5.05593		0.50123

exogeneity_test | contemp_coeff | avgcorr_vall | str_stab_stats | str_stab_breakdates | DUmodel_VAR&coint | DUmodel_VECM_est

- **Contemporaneous effect of foreign variables on domestic counterparts**

  By default, for each country the program generates the estimated contemporaneous coefficients i.e. the contemporaneous effect of the foreign variables on their domestic counterparts. Results are reported in the **contemp_effect** worksheet (see Figure 6.16). In addition to these coefficient estimates, standard errors and t-values are calculated. The program also computes White's heteroskedasticity robust and Newey-West heteroskedasticity and autocorrelation consistent standard errors (SE), as well as the corresponding t-values.

Figure 6.16 Contemporaneous effect of foreign variables on their domestic counterparts

	A	B	C	D	E	F	G	H
1	Contemporaneous Effects of Foreign Variables on Domestic Counterparts							
2								
3			y	Dp	eq	ep	r	lr
4	ARGENTINA	Coefficient	0.070171	-2.072661	1.501261		3.282990	
5	ARGENTINA	Standard error	0.228507	0.496377	0.355689		0.475370	
6	ARGENTINA	t-ratio	0.307084	-4.175580	4.220713		6.906180	
7	ARGENTINA	White's adjusted SE	0.209717	1.375153	0.386458		1.483159	
8	ARGENTINA	t-ratio_White	0.334597	-1.507222	3.884671		2.213512	
9	ARGENTINA	Newey-West's adjusted SE	0.235487	1.387459	0.357135		1.622977	
10	ARGENTINA	t-ratio_NeweyWest	0.297982	-1.493854	4.203629		2.022820	
11	AUSTRALIA	Coefficient	0.261235	0.473237	0.737765		0.373340	0.809830
12	AUSTRALIA	Standard error	0.106697	0.130837	0.071731		0.134495	0.139925
13	AUSTRALIA	t-ratio	2.448379	3.616983	10.285121		2.775864	5.787605
14	AUSTRALIA	White's adjusted SE	0.108133	0.118856	0.137478		0.092634	0.158440
15	AUSTRALIA	t-ratio_White	2.415877	3.981593	5.366434		4.030282	5.111263
16	AUSTRALIA	Newey-West's adjusted SE	0.104974	0.124836	0.142538		0.111294	0.158974
17	AUSTRALIA	t-ratio_NeweyWest	2.488574	3.790861	5.175934		3.354522	5.094089
18	BRAZIL	Coefficient	0.216260	2.197008			0.649831	
19	BRAZIL	Standard error	0.285194	0.535391			0.839691	
20	BRAZIL	t-ratio	0.758290	4.103561			0.773893	
21	BRAZIL	White's adjusted SE	0.298545	0.916801			1.291745	
22	BRAZIL	t-ratio_White	0.724379	2.396386			0.503065	
23	BRAZIL	Newey-West's adjusted SE	0.252505	0.647354			1.036215	
24	BRAZIL	t-ratio_NeweyWest	0.856459	3.393828			0.627120	
25	CANADA	Coefficient	0.506745	0.399709	0.892380		0.369542	0.976616
26	CANADA	Standard error	0.111451	0.104230	0.054228		0.080727	0.058106

contemp_coeff / avgcorr_vall / str_stab_stats / str_stab_breakdates / DUmodel_VAR&coint

- **Average pairwise correlations**

  Also by default, the program computes the average pairwise correlations of the GVAR variables and estimated residuals for each country model, and reports them in **avgcorr_vall** (see Figure 6.17). In particular, correlations are computed for the GVAR variables in levels (column C), in first differences (column D), and for the VECMX* residuals (column E).

Figure 6.17 Average pairwise cross-section correlations

	A	B	C	D	E
1	Average Pairwise Cross-Section Correlations: Variables and Residuals				
2					
3			Levels	First Differences	VECMX* Residuals
4	y	ARGENTINA	0.901040	0.077873	0.005602
5	y	AUSTRALIA	0.973386	0.138374	0.021127
6	y	BRAZIL	0.959768	0.153811	0.027242
7	y	CANADA	0.967501	0.205699	-0.010716
8	y	CHINA	0.972932	0.087703	-0.085201
9	y	CHILE	0.964924	0.146186	0.006893
10	y	EURO	0.960632	0.250698	-0.019241
11	y	INDIA	0.972671	-0.017196	-0.013102
12	y	INDONESIA	0.963910	0.099619	-0.015596
13	y	JAPAN	0.888863	0.152311	-0.018153
14	y	KOREA	0.956038	0.120882	0.004871
15	y	MALAYSIA	0.965637	0.203481	-0.010349
16	y	MEXICO	0.963422	0.163326	0.019709
17	y	NORWAY	0.960908	0.101059	-0.008621
18	y	NEW ZEALAND	0.962564	0.147921	0.039134
19	y	PERU	0.875412	0.058806	0.013087
	⋮	⋮	⋮	⋮	⋮
29	y	USA	0.964157	0.212471	-0.032439
30	Dp	ARGENTINA	0.275350	0.050721	0.044433
31	Dp	AUSTRALIA	0.346790	0.075768	0.010073

avgcorr_vall / str_stab_stats / str_stab_breakdates

- **Structural stability tests**

  If you have chosen to perform structural stability tests, the program will report the corresponding statistics in **str_stab_stats** (see Figure 6.18). These include the Ploberger and Kramer's (1992) CUSUM statistic (**PK sup**) and its mean square variant (**PK msq**); the Nyblom (1989) test statistic (**Nyblom**); the Quandt's (1960) likelihood ratio statistic (**QLR**) in its Wald form; the mean Wald statistic (**MW**) of Hansen (1992) and Andrews and Ploberger (1994); the Andrews and Ploberger (1994) Wald statistic based on the exponential average (**APW**). The heteroskedasticity-robust version of the Nyblom test and the sequential Wald statistics (**QLR, MW, APW**) are also given. The **str_stab_breakdates** worksheet contains the structural break dates corresponding to the **QLR** statistic (see Figure 6.19)**.**

Figure 6.18 Structural stability test statsitics

output

	A	B	C	D	E	F	G
1	Structural Stability Tests: Statistics						
2							
3	Variables	y	Dp	eq	ep	r	lr
4							
5	PK sup						
6	ARGENTINA	1.211050	0.552904	0.499638	0.652704	0.530360	
7	AUSTRALIA	0.339170	0.727678	0.775128	0.746712	1.091395	1.181049
8	BRAZIL	0.597111	1.011235		0.619804	1.051252	
9	CANADA	0.931660	0.852747	0.902225	0.729457	0.573825	0.581064
10	CHINA	1.065266	0.549221		0.897223	1.411978	
11	CHILE	0.546631	0.733600	0.632817	0.780524	0.637031	
12	EURO	0.843678	0.559081	0.649786	0.627323	1.007642	0.487360
13	INDIA	0.652090	0.786847	0.719306	0.694003	0.654998	
14	INDONESIA	0.472393	0.445557		0.690398	0.644067	
15	JAPAN	1.341639	0.700500	1.274319	0.383667	0.975343	0.786540
16	KOREA	0.568871	0.514160	0.714356	0.426189	0.457017	0.571595
17	MALAYSIA	0.891038	0.447484	0.877999	0.763524	1.265208	
18	MEXICO	0.477428	0.412557		0.432400	0.577798	
19	NORWAY	0.820671	0.339662	0.444827	0.918436	0.501874	0.573529
20	NEW ZEALAND	1.039157	0.508795	0.905146	0.604997	0.778220	0.447315
21	PERU	0.385724	0.440807		0.431901	0.760464	
22	PHILIPPINES	0.809205	0.643440	0.821656	0.884197	0.710771	
23	SOUTH AFRICA	0.335797	0.652463	0.659460	0.834450	0.550766	0.529784
24	SAUDI ARABIA	0.608436	0.480177		0.468997		
25	SINGAPORE	0.786513	0.829458	0.513049	0.872022	0.595997	
26	SWEDEN	1.151266	0.731871	1.077293	0.684317	0.953855	0.598976
27	SWITZERLAND	0.800530	0.480671	1.181237	0.733986	0.540963	0.588790
28	THAILAND	0.967613	0.617045	0.599212	0.994977	0.775991	
29	TURKEY	0.629811	0.638289		0.866001	0.654950	
30	UNITED KINGDOM	1.100799	0.598795	0.814504	0.324243	0.702998	0.754371
31	USA	0.994302	0.729550	0.798150		0.444189	0.548524
32							
33	PK msq						
34	ARGENTINA	0.351507	0.027446	0.059766	0.088466	0.043114	
35	AUSTRALIA	0.023073	0.066401	0.118396	0.099875	0.150152	0.254374

str_stab_stats / str_stab_breakdates / DUmodel_VAR&coint

Finally, if the bootstrap was performed, the program prints the bootstrapped critical values at 90%, 95% and 99%, for all the aforementioned test statistics in the **str_stab_cvals** worksheet (see Figure 6.20). Note that the worksheets in the interface file are not in alphabetical order; **str_stab_cvals** is the last worksheet of the file.

Figure 6.19 Break dates for structural stability tests

output

	A	B	C	D	E	F	G
1	Structural Stability Tests: Break Dates for QLR Tests						
2							
3	Variables	y	Dp	eq	ep	r	lr
4	ARGENTINA	1994Q3	1990Q2	1985Q4	1989Q3	1990Q1	
5	AUSTRALIA	1984Q3	1989Q1	1988Q4	1986Q3	1986Q2	1988Q2
6	BRAZIL	1990Q1	1989Q3		1998Q4	1989Q3	
7	CANADA	1987Q1	1999Q1	1985Q1	2003Q3	1987Q1	1984Q3
8	CHINA	1994Q4	1988Q3		1990Q4	1996Q1	
9	CHILE	1986Q1	1984Q4	1985Q1	2003Q3	1984Q4	
10	EURO	1988Q1	1996Q3	1999Q3	1999Q2	1984Q3	1985Q2
11	INDIA	1997Q2	1998Q4	1993Q2	1991Q3	1994Q4	
12	INDONESIA	1984Q4	1997Q3		1998Q1	1984Q4	
13	JAPAN	2008Q1	1991Q3	1991Q2	1998Q3	1984Q3	1995Q4
14	KOREA	2001Q1	1984Q4	1988Q4	1997Q3	1997Q1	1984Q3
15	MALAYSIA	1988Q2	2008Q1	1998Q3	1995Q1	1998Q2	
16	MEXICO	1984Q3	1988Q1		1995Q1	1988Q1	
17	NORWAY	1985Q2	2001Q2	1990Q3	2003Q2	1992Q3	1990Q1
18	NEW ZEALAND	1986Q4	1986Q4	1990Q4	1997Q2	1986Q4	1986Q3
19	PERU	1991Q1	1990Q4		1991Q2	1990Q2	
20	PHILIPPINES	1986Q1	1991Q2	1986Q3	1984Q3	1984Q4	
21	SOUTH AFRICA	1985Q2	1985Q1	1984Q4	1989Q1	1985Q2	1989Q2
22	SAUDI ARABIA	1989Q4	1989Q4		1986Q3		
23	SINGAPORE	2008Q1	1984Q3	1991Q1	1997Q2	1984Q3	
24	SWEDEN	1984Q4	1991Q2	1984Q3	2000Q1	1985Q1	1987Q4
25	SWITZERLAND	2007Q4	1986Q1	1986Q4	2002Q2	1987Q3	2000Q3
26	THAILAND	2008Q1	1984Q3	1990Q3	1998Q2	1994Q4	
27	TURKEY	1994Q1	1994Q1		1985Q1	1994Q2	
28	UNITED KINGDOM	1984Q3	1991Q2	1992Q4	2006Q3	1991Q3	1985Q1
29	USA	1984Q3	2002Q2	2000Q3		1984Q3	1984Q3
30							

str_stab_breakdates / DUmodel_VAR&coint / DUmodel_VECM_est

Figure 6.20 Critical values for structural stability tests

output.xls

	A	B	C	D	E	F	G	H	I	J	K	L
1	Structural Stability Tests: Critical Values											
2												
3	Critical Values	y_90%	Dp_90%	eq_90%	ep_90%	r_90%	lr_90%	y_95%	Dp_95%	eq_95%	ep_95%	r_95
4												
5	PK sup											
6	ARGENTINA	0.991871	0.634015	1.045655	1.101679	0.608815		1.004973	0.707061	1.125318	1.115392	0.693
7	AUSTRALIA	0.499974	0.530716	0.650385	0.659442	0.682170	0.969247	0.523505	0.580770	0.692706	0.719778	0.814
8	BRAZIL	0.945982	0.646172		0.862773	0.836563		1.066941	0.684892		1.007655	0.988
9	CANADA	0.987956	1.006957	0.995769	1.107739	0.937622	0.980703	1.102739	1.112016	1.065396	1.168305	1.012
10	CHINA	1.003560	0.791855		0.927209	0.926638		1.116402	0.833750		1.050467	0.988
11	CHILE	0.839785	0.927681	1.051754	0.987220	0.597320		0.909700	1.051772	1.148395	1.079695	0.630
12	EURO	1.048923	0.984287	1.004503	0.976081	0.965575	0.985808	1.109082	1.075839	1.077938	1.040271	1.051
13	INDIA	0.962904	0.615337	0.859324	1.032193	0.720626		1.042108	0.709002	0.935843	1.089641	0.844
14	INDONESIA	0.769262	0.491347		0.774481	0.765962		0.870601	0.525747		0.858829	0.859
15	JAPAN	0.983272	0.715552	1.076346	0.985685	0.850035	1.083377	1.152519	0.783849	1.199147	1.092950	0.947
16	KOREA	0.553781	0.662908	0.903853	0.911916	0.734367	0.962292	0.596158	0.696070	0.991782	1.011266	0.783
17	MALAYSIA	0.967078	0.632974	1.058083	1.041633	0.971175		0.990301	0.691624	1.137656	1.167790	1.039
18	MEXICO	0.603636	0.483963		0.927438	0.799893		0.632467	0.508334		1.015743	0.915
19	NORWAY	0.904336	0.612113	0.857324	1.000781	0.865921	0.873185	0.994734	0.655345	0.932942	1.076502	0.930
20	NEW ZEALAND	0.973404	0.990414	1.153700	1.044298	0.733619	0.834984	1.030761	1.082925	1.252477	1.203985	0.816
21	PERU	0.444014	0.475429		0.479854	0.468258		0.496676	0.494364		0.501094	0.475
22	PHILIPPINES	0.959906	0.895579	1.065662	0.981153	0.687431		1.012995	0.954541	1.122195	1.134142	0.795
23	SOUTH AFRICA	0.629934	0.705361	0.950829	0.989209	0.921324	0.831044	0.660142	0.747303	1.055798	1.072221	1.052
24	SAUDI ARABIA	0.847368	0.519630		0.712303			0.935694	0.577940		0.804641	
25	SINGAPORE	1.027086	0.874304	0.833636	0.834822	1.012030		1.201513	0.917688	0.965702	0.956199	1.070
26	SWEDEN	0.989814	0.909852	0.909695	0.979901	0.773358	0.849977	1.071929	0.979315	0.969191	1.131672	0.855
27	SWITZERLAND	0.875727	0.604756	0.934091	0.885421	0.720328	0.924347	1.019765	0.707692	0.995457	0.968508	0.772
28	THAILAND	0.908161	0.611597	0.696034	0.851306	0.976157		1.060186	0.672040	0.857300	0.894611	1.047
29	TURKEY	0.976055	0.776553		1.021794	1.033418		1.052136	0.884146		1.186409	1.105
30	UNITED KINGDOM	0.875080	0.619909	0.974409	0.575572	0.943637	1.025104	1.049235	0.667410	1.022685	0.616170	0.979
31	USA	0.891736	0.680158	1.047416		0.914699	0.821614	1.059797	0.779174	1.135575		0.949
32												
33	PK msq											
34	ARGENTINA	0.246973	0.069464	0.269814	0.322234	0.065179		0.307078	0.086835	0.331894	0.384706	0.078
35	AUSTRALIA	0.033962	0.037228	0.061622	0.076560	0.090460	0.216061	0.041583	0.050349	0.097154	0.100681	0.109

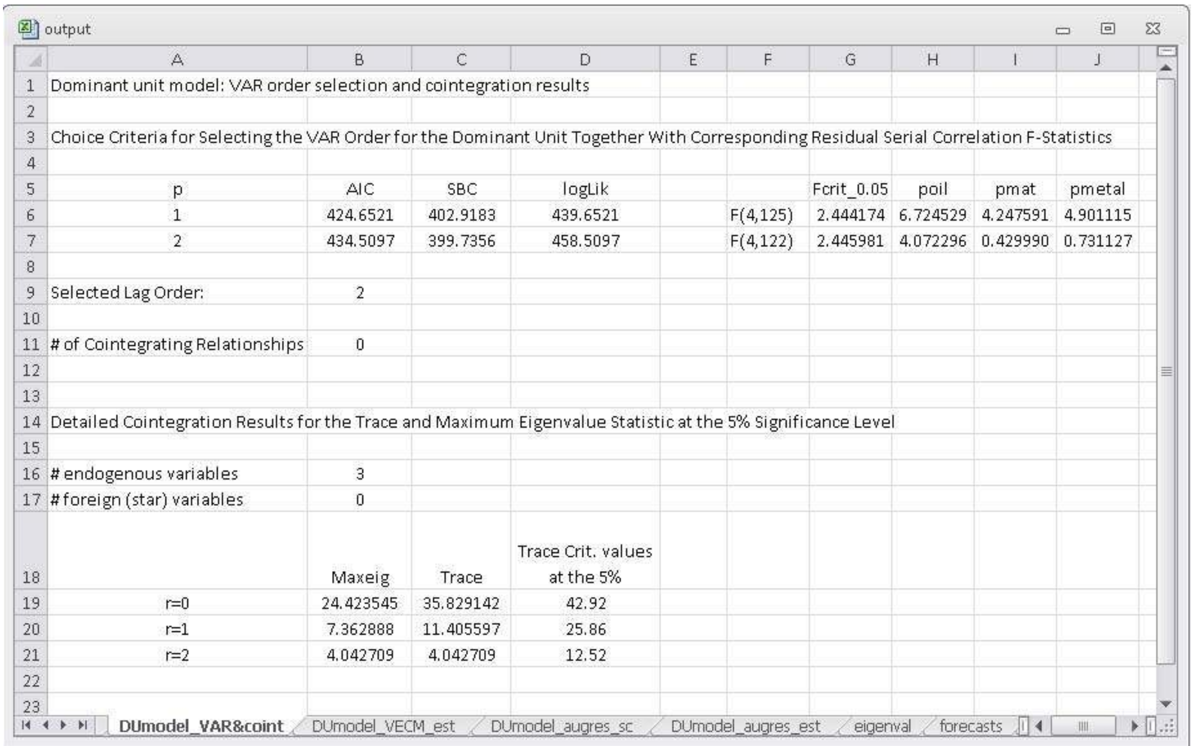
str_stab_cvals

- **Dominant unit model estimation**

  Output associated with the VEC model when the dominant unit model is multivariate

  - If you chose to perform the information criterion based lag order selection the worksheet **DUmodel_VAR&coint** will be created. The top panel of the worksheet contains the Akaike (**AIC**), the Schwartz Bayesian (**SBC**) and the log-likelihood (**logLik**) statistics for the associated VAR model (see Figure 6.21). These are computed for all possible lag order specifications, where the maximum lag order is defined by the value inputted in cell G14 of the DOMINANT UNIT worksheet. In addition, the F-statistics for testing the residual serial correlation of the individual VAR model equations are computed (column F onwards) with the corresponding 95% critical values (column G) and degrees of freedom (column F). The bottom panel of the worksheet contains both the trace and maximum eigenvalue statistics used for determining the dimension of the cointegration space of the VECM model, as well as the critical values for the trace statistic. Tests are conducted using (by default) the trace statistic at the 5% level of significance. The critical values are obtained from Mackinnon, Haug and Michelis (1999). This output sheet will not be exported if the program is run with the **Run the program with pauses** function disabled. If **no** is selected in the **Lag order selection** field this sheet will be exported, though it will not contain the residual serial correlation F-statistics.

Figure 6.21 VAR order selection and cointegration results for the dominant unit model



	A	B	C	D	E	F	G	H	I	J
1	Dominant unit model: VAR order selection and cointegration results									
2										
3	Choice Criteria for Selecting the VAR Order for the Dominant Unit Together With Corresponding Residual Serial Correlation F-Statistics									
4										
5	p	AIC	SBC	logLik			Fcrit_0.05	poil	pmat	pmetal
6	1	424.6521	402.9183	439.6521		F(4,125)	2.444174	6.724529	4.247591	4.901115
7	2	434.5097	399.7356	458.5097		F(4,122)	2.445981	4.072296	0.429990	0.731127
8										
9	Selected Lag Order:	2								
10										
11	# of Cointegrating Relationships	0								
12										
13										
14	Detailed Cointegration Results for the Trace and Maximum Eigenvalue Statistic at the 5% Significance Level									
15										
16	# endogenous variables	3								
17	# foreign (star) variables	0								
18		Maxeig	Trace	Trace Crit. values at the 5%						
19	r=0	24.423545	35.829142	42.92						
20	r=1	7.362888	11.405597	25.86						
21	r=2	4.042709	4.042709	12.52						
22										
23										

  - If the dominant unit model is multivariate, **DUmodel_VECM_est** will be exported by default containing the estimated coefficients of the VEC model and the F-statistics for the serial correlation test of the residuals (see Figure 6.22).

Figure 6.22 VEC estimates of the dominant unit model

VEC Estimates of the Dominant Unit Model

	Intercept	Trend	poil_1	pmat_1	pmetal_1	dpoil_1	dpmat_1	dpmetal_1
dpoil	0.004614	0	0	0	0	0.117951	-0.031867	0.392887
dpmat	0.002561	0	0	0	0	0.002364	0.078046	0.209604
dpmetal	0.005613	0	0	0	0	-0.014278	-0.058154	0.395598

F- Statistics for the Serial Correlation Test of the VECM Residuals

	Fcrit_0.05	poil	pmat	pmetal
F(4,126)	2.443591	5.705918	1.441923	0.127902

Output associated with the augmented VEC or univariate model

- If you chose to perform the information criterion based lag order selection the worksheet **DUmodel_augres_sc** will be created. This worksheet contains the Akaike (**AIC**), the Schwartz Bayesian (**SBC**) and the log-likelihood (**logLik**) statistics for each of the augmented VEC equations or the univariate model. These are computed for all possible lag order specifications, where the maximum lag order(s) are defined by the value(s) inputted in columns P (and AD in the case of feedback variables) of the DOMINANT UNIT worksheet. In addition, the F-statistics for testing the residual serial correlation of the individual model equations are computed (column H onwards) with the corresponding 95% critical values (column I) and degrees of freedom (column H), see Figure 6.23. If the dominant unit model is multivariate and no feedback variables are included (as selected in cell Y87 of the MAIN worksheet), this output sheet will not be exported. The same is true if **no** is selected in the **Lag order selection** field or if the program is run with the **Run the program with pauses** function disabled.

Figure 6.23 Choice criteria for selecting the order of the augmented regressions together with corresponding residual serial correlation F-statistics

Choice Criteria for Selecting the Order of the Augmented Regression(s) Together With Corresponding Residual Serial Correlation F-Statistics

	ptilde	qtilde	AIC	SBC	logLik		Fcrit_0.05	Fstat
poil	1	1	69.7818	61.0883	75.7818	F(4,124)	2.444766	5.896475
poil	1	2	68.1309	56.5696	76.1309	F(4,121)	2.446603	4.396178
poil	2	1	75.2907	62.2842	84.2907	F(4,120)	2.447237	1.452215
poil	2	2	75.4048	59.5079	86.4048	F(4,118)	2.448536	0.438928
pmat	1	1	197.3089	188.6154	203.3089	F(4,124)	2.444766	2.130011
pmat	1	2	196.0224	184.4610	204.0224	F(4,121)	2.446603	1.628073
pmat	2	1	194.0353	181.0287	203.0353	F(4,120)	2.447237	1.308277
pmat	2	2	193.3210	177.4241	204.3210	F(4,118)	2.448536	1.852481
pmetal	1	1	142.0214	133.3278	148.0214	F(4,124)	2.444766	0.2172
pmetal	1	2	141.1453	129.5839	149.1453	F(4,121)	2.446603	0.202764
pmetal	2	1	139.4696	126.4630	148.4696	F(4,120)	2.447237	1.01954
pmetal	2	2	139.3789	123.4820	150.3789	F(4,118)	2.448536	0.11549

– **DUmodel_augres_est** contains the estimated coefficients of the augmented VEC or univariate model, and the F-statistics for the serial correlation test of the residuals (see Figure 6.24).

Figure 6.24 OLS estimates of the augmented dominant unit regressions

output.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	OLS Estimates of Augmented Regressions												
2													
3	dpoil	Intercept	dpoil_1	dpmat_1	dpmetal_1	dpoil_2	dpmat_2	dpmetal_2	dy˜_1	dDp˜_1	dy˜_2	dDp˜_2	
4		-0.027764	0.253271	-0.012090	0.395647	-0.292616	-0.189707	-0.270284	0.836484	-3.451325	2.742880	3.036836	
5	dpmat	Intercept	dpoil_1	dpmat_1	dpmetal_1	dy˜_1	dDp˜_1						
6		-0.008834	-0.016378	0.045498	0.194686	1.208957	1.449065						
7	dpmetal	Intercept	dpoil_1	dpmat_1	dpmetal_1	dy˜_1	dDp˜_1						
8		-0.014919	-0.034250	-0.105369	0.362385	2.132385	1.000133						
9													
10													
11													
12	F-Statistics for the Serial Correlation Test of Residuals												
13													
14		Fcrit_0.05	poil	pmat	pmetal								
15	F(4,124)	2.444766	0.438928	2.130011	0.217200								
16													
17													

DUmodel_augres_est / eigenval / forecasts / conditional forecasts / cov_shrinkage / cwgts / rwgts / PP / PP_bs_median

- **Eigenvalues of the GVAR**

  Eigenval contains the eigenvalues (column A) and their corresponding moduli (column G) of the GVAR model (see Figure 6.25).

Figure 6.25 Eigenvalues and corresponding moduli of the GVAR model

output.xls

	A	B	C	D	E	F	G	H
1	Eigenvalues of the GVAR Model in Descending Order						Corresponding Moduli	
2								
3	1.00000000000001 +0.00000000000000i						1	
4	1.00000000000001 -0.00000000000000i						1	
5	1						1	
6	1						1	
7	1						1	
	⋮						⋮	
70	1						1	
71	1						1	
72	1						1	
73	0.97478185						0.974781847	
74	0.94818411						0.948184111	
75	0.90089835						0.905563323	
76	0.90072764032362 +0.09345935154394i						0.905563323	
77	0.90072764032362 -0.09345935154394i						0.900898349	
78	0.87250278459882 +0.14405486640548i						0.884314940	
79	0.87250278459882 -0.14405486640548i						0.884314940	
80	0.85530823775170 +0.03019329189398i						0.863171513	
81	0.85530823775170 -0.03019329189398i						0.863171513	
82	0.85406478771627 +0.12505358394351i						0.855841000	
83	0.85406478771627 -0.12505358394351i						0.855841000	
84	0.84684994						0.849308088	
85	0.84502676083384 +0.08517042890356i						0.849308088	

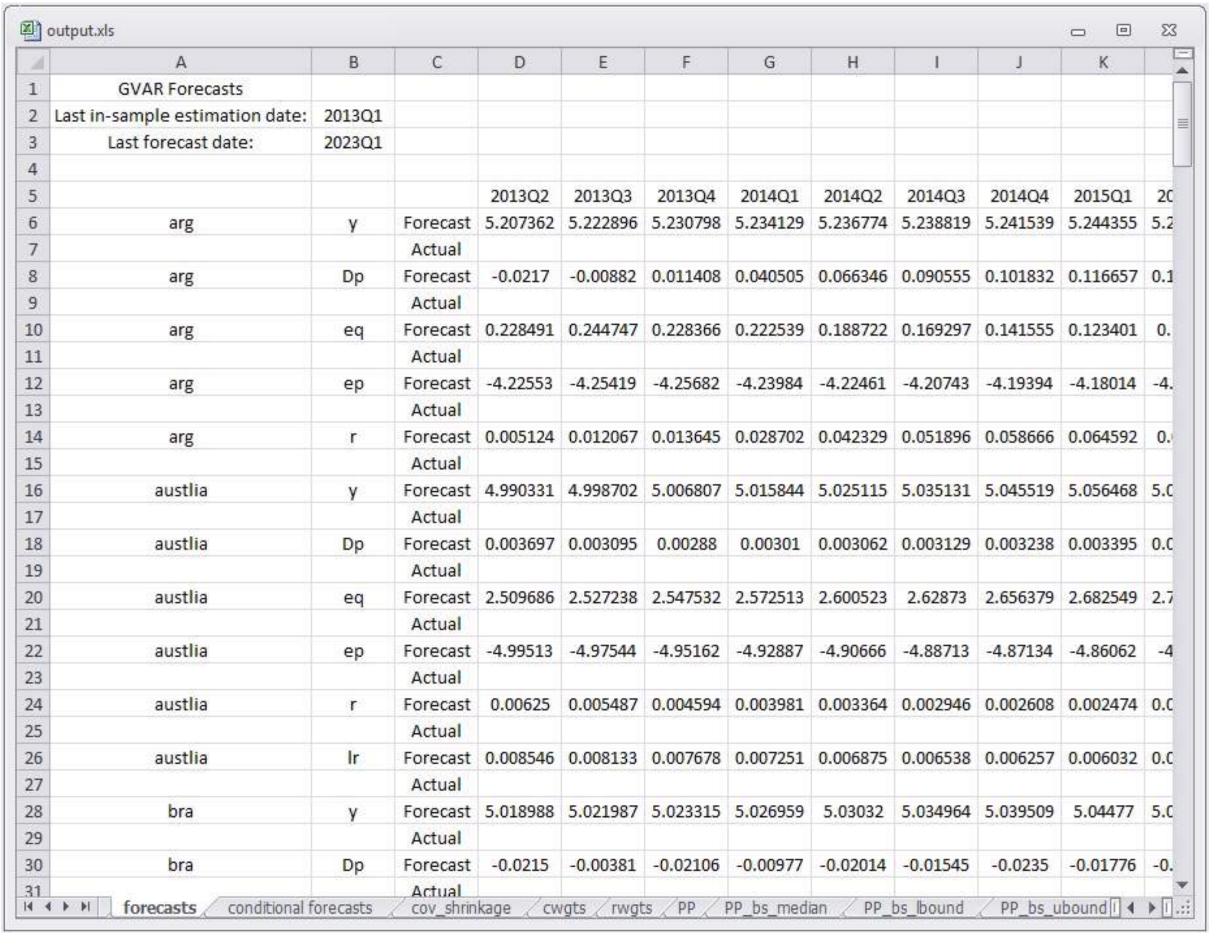
eigenval / forecasts / conditional forecasts / cov_shrinkage / cwgts / rwgts / PP

- **GVAR forecasts**

  – **Ex-ante forecasts**

  If you have chosen to generate ex-ante forecasts of the GVAR model, then the results are stored in the worksheet **forecasts** (see Figure 6.26). The program prints the last in-sample estimation date (cell B2) and the last forecast date (cell B3). Forecasts of each variable of the GVAR model are printed along with the actual values, if these overlap with the selected forecast horizon, i.e. if the last observation (cell U15) of the estimation sample predates the final available observation (cell Z15).

Figure 6.26 GVAR forecasts



output.xls

	A	B	C	D	E	F	G	H	I	J	K	
1	GVAR Forecasts											
2	Last in-sample estimation date:	2013Q1										
3	Last forecast date:	2023Q1										
4												
5				2013Q2	2013Q3	2013Q4	2014Q1	2014Q2	2014Q3	2014Q4	2015Q1	20
6	arg	y	Forecast	5.207362	5.222896	5.230798	5.234129	5.236774	5.238819	5.241539	5.244355	5.2
7			Actual									
8	arg	Dp	Forecast	-0.0217	-0.00882	0.011408	0.040505	0.066346	0.090555	0.101832	0.116657	0.1
9			Actual									
10	arg	eq	Forecast	0.228491	0.244747	0.228366	0.222539	0.188722	0.169297	0.141555	0.123401	0.
11			Actual									
12	arg	ep	Forecast	-4.22553	-4.25419	-4.25682	-4.23984	-4.22461	-4.20743	-4.19394	-4.18014	-4.
13			Actual									
14	arg	r	Forecast	0.005124	0.012067	0.013645	0.028702	0.042329	0.051896	0.058666	0.064592	0.
15			Actual									
16	austlia	y	Forecast	4.990331	4.998702	5.006807	5.015844	5.025115	5.035131	5.045519	5.056468	5.0
17			Actual									
18	austlia	Dp	Forecast	0.003697	0.003095	0.00288	0.00301	0.003062	0.003129	0.003238	0.003395	0.0
19			Actual									
20	austlia	eq	Forecast	2.509686	2.527238	2.547532	2.572513	2.600523	2.62873	2.656379	2.682549	2.7
21			Actual									
22	austlia	ep	Forecast	-4.99513	-4.97544	-4.95162	-4.92887	-4.90666	-4.88713	-4.87134	-4.86062	-4
23			Actual									
24	austlia	r	Forecast	0.00625	0.005487	0.004594	0.003981	0.003364	0.002946	0.002608	0.002474	0.0
25			Actual									
26	austlia	lr	Forecast	0.008546	0.008133	0.007678	0.007251	0.006875	0.006538	0.006257	0.006032	0.0
27			Actual									
28	bra	y	Forecast	5.018988	5.021987	5.023315	5.026959	5.03032	5.034964	5.039509	5.04477	5.0
29			Actual									
30	bra	Dp	Forecast	-0.0215	-0.00381	-0.02106	-0.00977	-0.02014	-0.01545	-0.0235	-0.01776	-0.
31			Actual									

forecasts / conditional forecasts / cov_shrinkage / cwgts / rwgts / PP / PP_bs_median / PP_bs_lbound / PP_bs_ubound

  – **Conditional forecasts**

  If you have chosen to generate conditional forecasts of the GVAR model, then the results are stored in the worksheet **conditional forecasts** (see Figure 6.27). Once again, the program prints the last in-sample estimation date (cell B2) and the last forecast date (cell B3). Conditional forecasts for all variables in the GVAR model are printed over the selected forecast horizon, along with the actual values if applicable. For the country variables subjected to restrictions (i.e. predefined values), it is these values that appear over this horizon.

Figure 6.27 GVAR conditional forecasts

output.xls [Compatibility Mode]

	A	B	C	D	E	F	G	H
1	GVAR Conditional Forecasts							
2	Last in-sample estimation date:	2013Q1						
3	Last forecast date:	2014Q1						
4								
5				2013Q2	2013Q3	2013Q4	2014Q1	
6	arg	y	Forecast	5.202710	5.202824	5.202919	5.201644	
7			Actual					
8	arg	Dp	Forecast	-0.135320	-0.017114	-0.005535	0.015584	
9			Actual					
10	arg	eq	Forecast	0.396211	-0.104155	-0.171099	-0.313607	
11			Actual					
12	arg	ep	Forecast	-4.231895	-4.161387	-4.105381	-4.053225	
13			Actual					
14	arg	r	Forecast	-0.043518	0.008055	-0.013658	0.018498	
15			Actual					
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	
262	usa	y	Forecast	4.845323	4.840051	4.838761	4.839529	
263			Actual					
264	usa	Dp	Forecast	0.012648	0.006842	0.000908	-0.001832	
265			Actual					
266	usa	eq	Forecast	2.089294	1.901063	1.760093	1.665789	
267			Actual					
268	usa	r	Forecast	0.01	0.01	0.01	0.01	
269			Actual					
270	usa	lr	Forecast	0.02	0.02	0.02	0.02	
271			Actual					
272	du_model	poil	Forecast	4.606303	4.544194	4.619017	4.644195	
273			Actual					
274	du_model	pmat	Forecast	4.892653	4.893427	4.884219	4.871820	
275			Actual					
276	du_model	pmetal	Forecast	5.255711	5.266666	5.267171	5.257464	
277			Actual					
278								

conditional forecasts / cov_shrinkage / cwgts / rwgts / PP / PP_bs_median

- **Summary information related to shrinkage of the covariance matrix**

  Information regarding shrinkage of the covariance matrix used for computing point and bootstrap estimates and for generating the bootstrap data is summarised and reported in **cov_shrinkage** (see Figure 6.28).

Figure 6.28 Summary information relating to shrinkage of the covariance matrix

output.xls

	A	B	C	D
1	Shrinkage of Covariance Matrix			
2				
3	Covariance matrix for point and bootstrap estimates:			
4	- used original selected covariance matrix (no shrinkage performed)			
5				
6	Covariance matrix for bootstrap data generation:			
7	-- shrinkage was performed			
8	-- internally computed shrinkage parameter =	0.375463		
9				
10				
11				

cov_shrinkage / cwgts / rwgts / PP / PP_bs_median

- **Country and regional weights for aggregation**

  The computed country-specific and regional (PPP-GDP, in our example) weights for aggregation of the regional variables and the country-specific GIRFs and GFEVDs are reported in **cwgts** (see Figure 6.29) and **rwgts** respectively (see Figure 6.30).

Figure 6.29 Country weights for aggregation

output

Country Weights

Country	y	Dp	eq	ep	r	lr
ARGENTINA	0.010712	0.010712	0.015030	0.014022	0.010849	
AUSTRALIA	0.015569	0.015569	0.021846	0.020380	0.015769	0.025805
BRAZIL	0.035902	0.035902		0.046997	0.036364	
CANADA	0.022367	0.022367	0.031385	0.029279	0.022655	0.037072
CHINA	0.168676	0.168676		0.220807	0.170848	
CHILE	0.005059	0.005059	0.007098	0.006622	0.005124	
EURO	0.172757	0.172757	0.242410	0.226148	0.174981	0.286337
INDIA	0.066648	0.066648	0.093520	0.087246	0.067507	
INDONESIA	0.017293	0.017293		0.022638	0.017516	
JAPAN	0.069054	0.069054	0.096896	0.090395	0.069943	0.114454
KOREA	0.023325	0.023325	0.032729	0.030534	0.023625	0.038660
MALAYSIA	0.006890	0.006890	0.009667	0.009019	0.006978	
MEXICO	0.029058	0.029058		0.038038	0.029432	
NORWAY	0.004700	0.004700	0.006596	0.006153	0.004761	0.007791
NEW ZEALAND	0.002150	0.002150	0.003017	0.002815	0.002178	0.003564
PERU	0.004588	0.004588		0.006006	0.004647	
PHILIPPINES	0.005834	0.005834	0.008186	0.007637	0.005909	
SOUTH AFRICA	0.008666	0.008666	0.012161	0.011345	0.008778	0.014364
SAUDI ARABIA	0.012713	0.012713		0.016641		
SINGAPORE	0.004606	0.004606	0.006463	0.006030	0.004665	
SWEDEN	0.006055	0.006055	0.008497	0.007927	0.006133	0.010037
SWITZERLAND	0.006186	0.006186	0.008680	0.008097	0.006265	0.010252
THAILAND	0.009582	0.009582	0.013445	0.012543	0.009705	
TURKEY	0.019108	0.019108		0.025013	0.019354	
UNITED KINGDOM	0.036414	0.036414	0.051096	0.047668	0.036883	0.060355
USA	0.236089	0.236089	0.331278		0.239129	0.391309

cwgts rwgts PP PP_bs_median PP_bs_lbound

Figure 6.30 Regional weights for aggregation

	A	B	C	D	E	F	G	H
1	Regional Weights							
2								
3	Region	Country	y	Dp	eq	ep	r	lr
4	china	china	1	1		1	1	
5	euro	euro	1	1	1	1	1	1
6	japan	japan	1	1	1	1	1	1
7	la	arg	0.125549	0.125549	0.679233	0.125549	0.125549	
8	la	bra	0.420800	0.420800		0.420800	0.420800	
9	la	chl	0.059290	0.059290	0.320767	0.059290	0.059290	
10	la	mex	0.340584	0.340584		0.340584	0.340584	
11	la	per	0.053777	0.053777		0.053777	0.053777	
12	odc	austlia	0.388384	0.388384	0.388384	0.388384	0.388384	0.388384
13	odc	can	0.557971	0.557971	0.557971	0.557971	0.557971	0.557971
14	odc	nzld	0.053645	0.053645	0.053645	0.053645	0.053645	0.053645
15	restasia	indns	0.256087	0.256087		0.256087	0.256087	
16	restasia	kor	0.345405	0.345405	0.464308	0.345405	0.345405	1
17	restasia	mal	0.102023	0.102023	0.137143	0.102023	0.102023	
18	restasia	phlp	0.086390	0.086390	0.116130	0.086390	0.086390	
19	restasia	sing	0.068207	0.068207	0.091687	0.068207	0.068207	
20	restasia	thai	0.141888	0.141888	0.190732	0.141888	0.141888	
21	restworld	india	0.622097	0.622097	0.884931	0.622097	0.705853	
22	restworld	safrc	0.080892	0.080892	0.115069	0.080892	0.091783	1
23	restworld	sarbia	0.118659	0.118659		0.118659		
24	restworld	turk	0.178351	0.178351		0.178351	0.202363	
25	restweurope	nor	0.277451	0.277451	0.277451	0.277451	0.277451	0.277451
26	restweurope	swe	0.357435	0.357435	0.357435	0.357435	0.357435	0.357435
27	restweurope	switz	0.365114	0.365114	0.365114	0.365114	0.365114	0.365114
28	uk	uk	1	1	1	1	1	1
29	usa	usa	1	1	1		1	1

- **Persistence profiles**

  The program stores the point estimates of the persistence profiles in the **Effect_PPs** worksheet (see Figure 6.31). If the bootstrap has been conducted, bootstrap median estimates together with bootstrap lower and upper bounds are reported in **Effect_PPs_BS_median**, **Effect_PPs_BS_lbound** and **Effect_PPs_BS_ubound,** respectively (see Figure 6.32). Note that 90% bootstrapped confidence bands are given.

Figure 6.31 Persistence profiles

output.xls

Persistence Profile of the Effect of System-Wide Shocks to the Cointegrating Relations of the GVAR Model

	ARGENTINA	ARGENTINA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	BRAZIL	BRAZIL	CANADA
Horizon	CV1	CV2	CV1	CV2	CV3	CV4	CV5	CV1	CV2	CV1
0	1	1	1	1	1	1	1	1	1	1
1	0.883835	0.389994	1.018493	0.196790	0.927776	0.961674	0.942833	1.764574	0.761594	0.314053
2	0.146015	0.100177	0.954489	0.177509	0.748527	0.643589	0.944652	0.752843	0.287704	0.243508
3	0.362423	0.216735	0.962463	0.182240	0.659624	0.441766	0.997052	0.114129	0.032863	0.175587
4	0.056541	0.039116	0.974976	0.142309	0.554888	0.283399	1.063835	0.672283	0.044921	0.159522
5	0.032236	0.066833	0.811326	0.112822	0.390253	0.194473	1.001101	0.431447	0.015902	0.164969
6	0.036742	0.033098	0.755046	0.099090	0.324688	0.152829	0.984137	0.042871	0.009353	0.153485
7	0.012351	0.008185	0.676940	0.080924	0.241650	0.154480	0.938811	0.094922	0.005189	0.140803
8	0.006848	0.010146	0.530041	0.067169	0.160680	0.170422	0.807505	0.165933	0.007003	0.135590
9	0.005885	0.010109	0.443869	0.055857	0.116462	0.160693	0.724378	0.045278	0.006219	0.123798
10	0.005978	0.003121	0.344594	0.043139	0.081203	0.171044	0.615580	0.009491	0.002538	0.115068
11	0.003976	0.001683	0.252411	0.034425	0.060432	0.162234	0.493151	0.044873	0.001492	0.104711
12	0.001179	0.003371	0.192097	0.026437	0.046785	0.142210	0.404193	0.028669	0.001703	0.091582
13	0.001592	0.001747	0.137922	0.019332	0.042855	0.135487	0.311576	0.006535	0.001270	0.081406
14	0.001724	0.000491	0.099508	0.014473	0.039419	0.113368	0.234410	0.006988	0.000208	0.070628
15	0.000328	0.000759	0.073733	0.010636	0.035950	0.093332	0.177563	0.010409	0.000304	0.060002
16	0.000239	0.000623	0.057076	0.007917	0.036852	0.079072	0.130000	0.005864	0.000560	0.051143
17	0.000588	0.000322	0.046014	0.006076	0.033565	0.060092	0.096191	0.000622	0.000108	0.042680
18	0.000189	0.000116	0.038704	0.004933	0.030433	0.046009	0.072618	0.002324	0.000043	0.035315
19	0.000076	0.000178	0.035671	0.004176	0.028320	0.034863	0.056917	0.003033	0.000173	0.029156
20	0.000167	0.000199	0.031860	0.003620	0.023682	0.024731	0.046103	0.000482	0.000079	0.023801
21	0.000123	0.000053	0.029010	0.003334	0.019962	0.017803	0.039069	0.000293	0.000026	0.019408
22	0.000076	0.000065	0.026952	0.003011	0.016521	0.012739	0.034882	0.000986	0.000041	0.015831

PP | PP_bs_median | PP_bs_lbound | PP_bs_ubound | overid_restr_logLik | str_stab_cvals

Figure 6.32 Persistance profiles: Bootstrap median estimates with 90 per cent bootstrap error bounds

output.xls

Persistence Profile of the Effect of System-Wide Shocks to the Cointegrating Relations of the GVAR Model - Bootstrap Median estimates

	ARGENTINA	ARGENTINA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	BRAZIL	BRAZIL	CANADA	CA
Horizon	CV1	CV2	CV1	CV2	CV3	CV4	CV5	CV1	CV2	CV1	
0	1	1	1	1	1	1	1	1	1	1	
1	2.729946	1.554516	0.957894	0.335756	1.206597	1.216702	0.828358	2.783121	2.777860	0.346845	0.
2	0.672398	0.519148	0.804623	0.253305	0.739698	0.707296	0.747820	2.289139	1.710401	0.308852	0.
3	1.474823	0.403752	0.759214	0.259023	0.684563	0.513558	0.743446	0.281196	0.346357	0.232485	0.
4	0.675966	0.743698	0.885131	0.172139	0.621810	0.387047	0.866137	1.646659	0.754567	0.220787	0.
5	0.143999	0.417007	0.643596	0.132892	0.443847	0.335242	0.753878	2.094286	0.447452	0.296188	0.
6	0.194048	0.106202	0.596240	0.124466	0.380813	0.232620	0.738352	0.353107	0.141692	0.273131	0.
7	0.358317	0.399462	0.673888	0.112713	0.346682	0.220869	0.837021	0.647152	0.153288	0.256149	0.
8	0.276640	0.488083	0.483187	0.090471	0.266215	0.285062	0.646250	1.608234	0.525625	0.287777	0.
9	0.079187	0.114090	0.424472	0.088626	0.178204	0.173103	0.587772	0.716604	0.288370	0.246092	0.
10	0.324347	0.162715	0.387797	0.070479	0.150570	0.161568	0.595323	0.350464	0.102919	0.227186	0.
11	0.308957	0.320092	0.292283	0.053512	0.161707	0.208581	0.432910	1.151350	0.312102	0.242471	0.
12	0.056319	0.185757	0.227333	0.049616	0.095443	0.123996	0.405492	0.987971	0.288580	0.211230	0.

PP_bs_median | PP_bs_lbound | PP_bs_ubound | overid_restr_logLik | str_stab_cvals

output.xls

Persistence Profile of the Effect of System-Wide Shocks to the Cointegrating Relations of the GVAR Model - Bootstrap Lower bounds

	ARGENTINA	ARGENTINA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	BRAZIL	BRAZIL	CANADA	CA
Horizon	CV1	CV2	CV1	CV2	CV3	CV4	CV5	CV1	CV2	CV1	
0	1	1	1	1	1	1	1	1	1	1	
1	1.026996	0.291548	0.551365	0.210908	0.777055	0.738152	0.486388	1.238051	0.746554	0.231315	0.
2	0.304115	0.113353	0.436900	0.134869	0.435584	0.376128	0.350089	0.481707	0.497495	0.177789	0.
3	0.449636	0.060791	0.374133	0.105824	0.311171	0.268555	0.356977	0.110594	0.069373	0.120262	0.
4	0.205390	0.051517	0.439981	0.091004	0.294453	0.189711	0.348056	0.564226	0.055676	0.094257	0.
5	0.057040	0.070536	0.301690	0.056250	0.211148	0.148614	0.257888	0.512561	0.044201	0.135962	0.
6	0.042976	0.022460	0.248130	0.051122	0.166134	0.088272	0.242834	0.077371	0.045679	0.102752	0.
7	0.041945	0.024310	0.312877	0.042324	0.144300	0.095416	0.288958	0.163303	0.023673	0.096212	0.
8	0.052452	0.028475	0.174902	0.030746	0.100884	0.131612	0.182670	0.325154	0.068811	0.107729	0.
9	0.019929	0.023416	0.116028	0.029513	0.075941	0.059215	0.159222	0.092825	0.042800	0.073999	0.
10	0.032453	0.011445	0.123065	0.026971	0.056589	0.058989	0.167633	0.051782	0.010579	0.059626	0.
11	0.024416	0.014555	0.124477	0.018395	0.051296	0.075761	0.127241	0.114688	0.019604	0.065279	0.
12	0.011865	0.015510	0.056483	0.013187	0.034616	0.042920	0.097063	0.079345	0.024036	0.050379	0.

PP_bs_median | PP_bs_lbound | PP_bs_ubound | overid_restr_logLik | str_stab_cvals

output.xls

Persistence Profile of the Effect of System-Wide Shocks to the Cointegrating Relations of the GVAR Model - Bootstrap Upper bounds

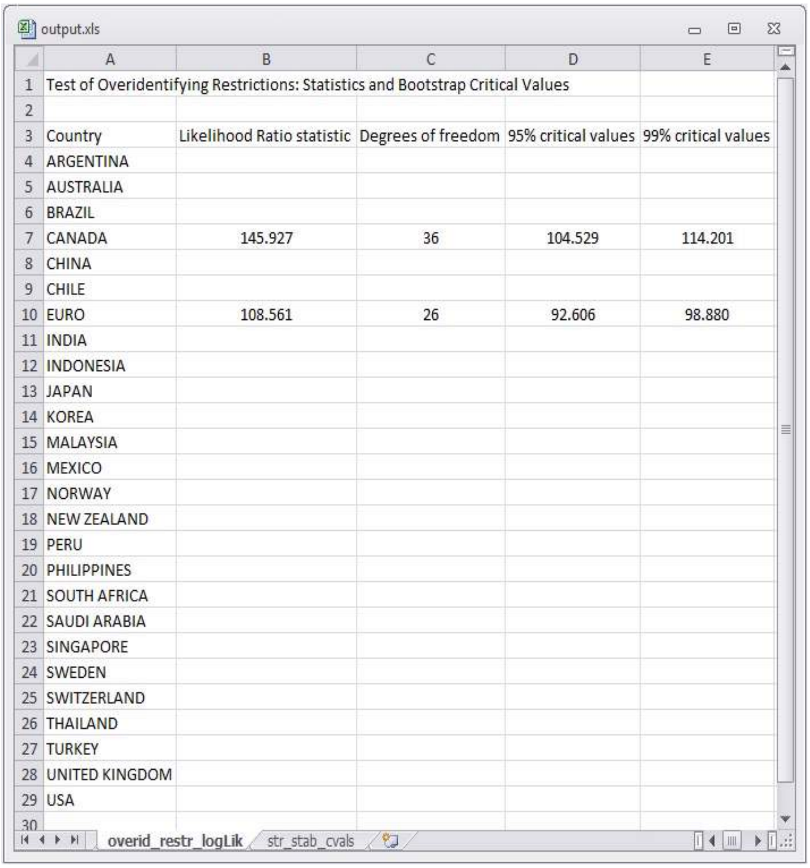
	ARGENTINA	ARGENTINA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	AUSTRALIA	BRAZIL	BRAZIL	CANADA	CA
Horizon	CV1	CV2	CV1	CV2	CV3	CV4	CV5	CV1	CV2	CV1	
0	1	1	1	1	1	1	1	1	1	1	
1	4.396236	6.732502	1.507431	0.552526	2.103164	2.116724	1.256137	6.798384	10.604401	0.468791	0.
2	1.437401	2.225694	1.368297	0.512895	1.265135	1.061390	1.266903	12.427685	5.681046	0.510493	1.
3	4.208557	2.936373	1.454010	0.528391	1.250446	0.906548	1.393079	2.474886	1.558237	0.421883	0.
4	1.905212	2.885603	1.715254	0.355695	1.340862	0.701884	1.775326	3.750754	4.264647	0.413436	1.
5	0.331053	1.247798	1.250154	0.305342	0.995485	0.689344	1.643495	8.238368	2.185679	0.516268	1.
6	0.862276	0.519165	1.252472	0.312878	0.907651	0.490263	1.751321	2.550711	0.539398	0.530854	1.
7	1.227173	1.672801	1.483407	0.314904	0.821219	0.515144	2.050124	1.514014	2.284394	0.474274	1.
8	1.018757	2.330757	1.144634	0.247280	0.766924	0.685734	1.626591	5.728531	3.218759	0.590181	1.
9	0.440774	0.743469	1.037826	0.245117	0.530798	0.507950	1.591412	5.402435	1.317734	0.532415	1.
10	1.377850	1.227676	0.994139	0.190872	0.458899	0.513343	1.678070	1.603976	1.235379	0.548393	2.
11	1.023920	2.273404	0.907057	0.165352	0.438907	0.571392	1.051850	3.718929	2.918513	0.626757	2.
12	0.471886	1.186516	0.756810	0.167163	0.318136	0.418418	1.218814	6.008073	1.540812	0.545243	2.

PP_bs_median | PP_bs_lbound | PP_bs_ubound | overid_restr_logLik | str_stab_cvals

- **Overidentifying restrictions test**

  If you have chosen to test for overidentifying restrictions, the likelihood ratio statistic (column B), the corresponding degrees of freedom (column C) and the associated bootstrapped critical values, 95% and 99% (columns D-E), are reported in the **overid_restr_logLik** worksheet (see Figure 6.33). Recall that this worksheet will only be exported if the user has carried on with the dynamic analysis and the bootstrap has been enabled.

Figure 6.33 Likelihood ratio statistics and bootstrap critical values for overidentifying restrictions test on the cointegrating vectors


output.xls

	A	B	C	D	E
1	Test of Overidentifying Restrictions: Statistics and Bootstrap Critical Values				
2					
3	Country	Likelihood Ratio statistic	Degrees of freedom	95% critical values	99% critical values
4	ARGENTINA				
5	AUSTRALIA				
6	BRAZIL				
7	CANADA	145.927	36	104.529	114.201
8	CHINA				
9	CHILE				
10	EURO	108.561	26	92.606	98.880
11	INDIA				
12	INDONESIA				
13	JAPAN				
14	KOREA				
15	MALAYSIA				
16	MEXICO				
17	NORWAY				
18	NEW ZEALAND				
19	PERU				
20	PHILIPPINES				
21	SOUTH AFRICA				
22	SAUDI ARABIA				
23	SINGAPORE				
24	SWEDEN				
25	SWITZERLAND				
26	THAILAND				
27	TURKEY				
28	UNITED KINGDOM				
29	USA				
30					

overid_restr_logLik / str_stab_cvals

6.1.2 The countrydata.xls file

The program exports all domestic, foreign and global variables to **countrydata.xls** for each country/region in the GVAR model (see Figure 6.34) including the dominant unit. A worksheet is created for the individual countries/regions, and these are labelled according to their names. For each country/regional model, time series of the variables are arranged by column. The ordering of the exported series is domestic variables, then foreign ones, and finally global variables. If a particular variable is not available for a specific country, the program looks for the next available series and exports it. These Excel files can be imported into any other software package to perform detailed country-specific analysis if desired.

Figure 6.34 Individual country data: Domestic, foreign-specific and global variables

countrydata

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	date	y	Dp	eq	ep	r	lr	ys	Dps	eqs	rs	lrs	poil	pmat	pmetal
2	1979Q2	4.149594	0.023241	0.696633	-4.155041	0.020743	0.023864	3.773493	0.032616	0.986516	0.022640	0.022929	3.433544	4.148960	4.200168
3	1979Q3	4.154957	0.025758	0.717955	-4.216458	0.022621	0.024768	3.781906	0.044569	0.965817	0.023969	0.023369	3.576322	4.272871	4.198063
4	1979Q4	4.165486	0.027551	0.655949	-4.256379	0.025203	0.025965	3.796633	0.034890	0.935334	0.025984	0.025955	3.696729	4.220098	4.305733
5	1980Q1	4.175451	0.032778	0.667306	-4.270745	0.028111	0.028189	3.805994	0.046018	0.939123	0.028172	0.027822	3.661658	4.311326	4.431295
6	1980Q2	4.169854	0.024979	0.643103	-4.297900	0.030323	0.028859	3.800870	0.040516	0.933236	0.027036	0.026837	3.643353	4.207531	4.284341
7	1980Q3	4.166282	0.025395	0.698367	-4.314543	0.028534	0.028600	3.806145	0.029156	0.981389	0.026631	0.026615	3.550055	4.289884	4.277811
8	1980Q4	4.166649	0.026840	0.749635	-4.271393	0.029028	0.030003	3.812233	0.031882	1.000758	0.028932	0.027563	3.679337	4.284165	4.195716
9	1981Q1	4.168499	0.030160	0.765135	-4.210865	0.029291	0.031271	3.820902	0.032869	0.977039	0.030253	0.028494	3.666904	4.204844	4.135575
10	1981Q2	4.173195	0.027089	0.752319	-4.132561	0.034325	0.033997	3.826664	0.030576	0.994478	0.030518	0.029374	3.561324	4.181515	4.082994
11	1981Q3	4.175081	0.026395	0.698703	-4.108231	0.035933	0.035373	3.837623	0.033496	0.934595	0.035420	0.030978	3.571967	4.122315	4.049079
12	1981Q4	4.176647	0.027582	0.611609	-4.170611	0.033911	0.034344	3.839450	0.025021	0.901366	0.034459	0.030814	3.605037	4.108267	4.004547
13	1982Q1	4.180445	0.023560	0.633780	-4.136194	0.032274	0.033546	3.840839	0.024802	0.872851	0.034079	0.029713	3.474382	4.130567	3.987907
14	1982Q2	4.181364	0.023775	0.581117	-4.134658	0.032958	0.032893	3.848787	0.023425	0.835763	0.034159	0.028648	3.535427	4.123548	3.893332
15	1982Q3	4.176969	0.021299	0.509827	-4.104834	0.030470	0.032644	3.850586	0.028222	0.842618	0.032976	0.027067	3.514316	4.107813	3.871532
16	1982Q4	4.178204	0.020788	0.508820	-4.102420	0.029725	0.031365	3.856538	0.024195	0.938197	0.032977	0.024478	3.511951	4.057183	3.864445
17	1983Q1	4.184694	0.018952	0.589039	-4.118974	0.027251	0.029542	3.865317	0.023439	1.009241	0.033046	0.024252	3.380749	4.055756	3.979404
18	1983Q2	4.192894	0.017804	0.678583	-4.091631	0.027127	0.029309	3.880656	0.023790	1.102646	0.036006	0.023627	3.395761	4.139160	4.085738
19	1983Q3	4.197203	0.018124	0.704498	-4.043352	0.027438	0.029639	3.895565	0.028289	1.120990	0.035030	0.024514	3.426576	4.220844	4.127331
20	1983Q4	4.206710	0.019327	0.726038	-4.041892	0.026834	0.029519	3.912387	0.028406	1.119271	0.034763	0.024141	3.372183	4.261962	4.087199
21	1984Q1	4.214474	0.016761	0.811151	-4.061551	0.025745	0.028524	3.932390	0.026580	1.153480	0.035833	0.024095	3.393073	4.282072	4.063485
22	1984Q2	4.209900	0.014357	0.804130	-4.054141	0.024592	0.028242	3.942792	0.028783	1.127506	0.036001	0.025163	3.387143	4.321841	4.001832
23	1984Q3	4.220301	0.012260	0.817499	-3.998934	0.024309	0.027432	3.955928	0.028808	1.119561	0.039712	0.025369	3.335108	4.284158	3.893744
24	1984Q4	4.223459	0.013983	0.854556	-3.966163	0.024249	0.025677	3.968284	0.028028	1.138426	0.039227	0.024380	3.316097	4.210952	3.879541
25	1985Q1	4.227079	0.015465	0.952883	-3.934819	0.023615	0.024467	3.980874	0.031415	1.199597	0.041699	0.024805	3.323724	4.067875	3.890182
26	1985Q2	4.236543	0.014436	1.027621	-3.987240	0.023289	0.024399	3.992431	0.035638	1.206625	0.043005	0.024226	3.296801	4.110594	3.911686

EURO / INDIA / INDONESIA / JAPAN / KOREA / MALAYSIA / MEXICO / NORWAY / NEW ZEALAND / PERU / PHILIPPINES / SOUTH AFRICA / S

6.1.3 The overid_restr.xls file

The **overid_restr.xls** file contains the overidentifying restrictions imposed during the cointegration analysis of the country-specific models, as shown in Figure 5.30.

6.1.4 The ExF_lb_restr.xls file

The **ExF_lb_restr.xls** file contains any ‘additional’ lower bounds imposed during the computation of the ex-ante forecasts, as shown in Figure 5.51. These lower bounds are those imposed on any variables in addition to the interest rate variables, assuming that the latter have been separately submitted to lower bound restrictions. If no additional lower bounds are imposed during the computation of the ex-ante forecasts this file will not be produced, as in our earlier demonstration.

6.1.5 The con_forc_restr.xls file

The **con_forc_restr.xls** file contains the restrictions (i.e. the prespecified values) defined for the country/countries of interest over the restriction horizon, as shown in Figure 5.53.

6.1.6 The TC_trend_restr.xls file

The **TC_trend_restr.xls** file contains the trend restrictions imposed during the Trend/Cycle decomposition of the GVAR, as shown in Figure 5.55.

6.1.7 The TCdecomposition.xls file

The **TCdecomposition.xls** file contains all domestic and global variables for each country/region in the GVAR used in the estimation of the individual models including the dominant unit model, and their permanent and transitory components, as shown in Figure 6.35. The permanent components are reported in the worksheet named with **_p** and the transitory/cyclical components are reported in the worksheet named with **_c.** The latter are equal to the deviations from the steady states[1] and are used in multicountry New Keneysian modelling (see Dees, Pesaran, Smith and Smith, 2013).

Figure 6.35 Trend/Cycle decompostion output

TCdecomposition.xls

Date	ARGENTINA	AUSTRALIA	BRAZIL	CANADA	CHINA	CHILE	EURO	INDIA	INDONESIA	JAPAN	KOREA	MALAYSIA	MEXICO	NC
1979Q2														
1979Q3														
1979Q4														
1980Q1	-0.030725	0.036303	0.065647	0.029220	0.031860	-0.091862	0.009161	0.018654	-0.038122	-0.002336	0.030770	-0.017269	-0.026320	-0.
1980Q2	-0.021746	-0.006203	0.061446	0.017319	0.041399	-0.104707	0.013690	0.000017	-0.032534	-0.005331	0.026899	-0.041879	-0.043360	-0.
1980Q3	0.015252	-0.021778	0.046112	0.000721	0.031227	-0.040613	0.016057	-0.009772	-0.039207	0.016315	0.009340	-0.032997	-0.018210	-0.
1980Q4	0.005893	0.034381	0.047277	0.021071	0.014573	0.014880	-0.007494	0.018857	-0.061299	0.013036	-0.096005	-0.066552	-0.024380	-0.
1981Q1	0.001007	0.022753	0.052659	0.046014	0.049864	0.044632	0.024857	-0.002946	0.008938	0.050007	-0.036400	-0.031503	-0.018503	-0.
1981Q2	-0.015003	0.043780	0.036579	0.039916	0.014037	0.103152	0.000896	0.009375	0.002121	0.043467	-0.041169	-0.036186	0.028951	-0.
1981Q3	-0.016533	0.072661	0.043986	0.036270	0.000212	0.176132	0.004207	0.015383	-0.002805	0.032794	-0.080029	-0.006547	0.053907	-0.
1981Q4	0.000903	0.020574	0.061401	0.014224	0.061534	0.201279	0.055858	-0.035358	0.074957	0.090767	0.038512	0.041007	0.075888	-0.
1982Q1	-0.017888	0.012699	0.055801	0.004862	0.054850	0.163283	0.054395	-0.040547	0.067435	0.076613	-0.016050	0.065657	0.099322	-0.
1982Q2	-0.007549	0.011114	0.015934	0.005803	0.019823	0.195212	0.025999	-0.037536	0.067758	0.050640	-0.026604	0.049896	0.063707	-0.
1982Q3	-0.047862	-0.023538	-0.036578	-0.008245	-0.006872	0.093510	0.024974	-0.042326	0.071341	0.053855	0.000727	0.049291	0.088846	0.
1982Q4	-0.033914	-0.067383	-0.045487	-0.027673	0.014584	-0.013934	-0.012521	-0.022450	0.029286	0.036462	0.023211	-0.004485	-0.041089	-0.
1983Q1	-0.060639	-0.129072	-0.054505	-0.032896	0.036453	0.016506	0.003663	-0.040521	0.021950	0.063860	0.002333	-0.000050	-0.006727	-0.
1983Q2	-0.040983	-0.127731	-0.046044	-0.025176	0.026915	0.025891	-0.001687	-0.034844	0.082433	0.060479	0.039107	0.016955	-0.027786	-0.
1983Q3	-0.049064	-0.085385	-0.028244	-0.015605	0.022681	-0.012451	0.005410	-0.034497	0.064811	0.058147	0.054883	0.043682	-0.004955	-0.
1983Q4	-0.050010	-0.087902	-0.018925	-0.010376	0.037669	0.027985	0.014039	-0.044012	0.104141	0.067309	0.049224	0.063197	-0.006813	-0.
1984Q1	-0.034315	-0.061114	-0.025815	-0.003334	0.015518	0.067729	0.019226	-0.040055	0.110422	0.056641	0.046741	0.074924	0.004610	0.
1984Q2	0.016352	-0.037504	-0.013209	-0.004273	-0.025665	0.055008	0.019758	-0.030113	0.066407	0.037898	0.011161	0.058940	0.000532	0.
1984Q3	-0.000434	-0.027030	-0.020523	-0.000532	-0.047650	0.088503	-0.005668	-0.009466	0.087546	0.010435	-0.010541	0.023617	-0.008188	-0.
1984Q4	-0.057213	-0.040818	-0.041524	-0.014648	-0.062214	-0.005317	-0.022549	0.004293	-0.004149	-0.010994	-0.016315	-0.014061	-0.056077	-0.
1985Q1	-0.073328	-0.059026	-0.010308	-0.014087	-0.008884	0.051852	0.019651	-0.028346	0.050377	0.029896	0.034495	0.032225	-0.030628	0.
1985Q2	-0.117371	-0.036552	0.006377	-0.010969	0.033926	-0.044283	0.028672	-0.055464	0.059756	0.064792	0.069381	0.052839	-0.005097	0.
1985Q3	-0.090761	-0.045429	-0.032746	-0.008218	-0.004678	-0.020325	-0.003416	-0.034608	0.005860	0.021786	0.008756	-0.010201	-0.002010	-0.
1985Q4	-0.070827	-0.018750	-0.023341	-0.006690	-0.011614	0.062062	-0.004152	-0.026181	0.014581	0.007757	-0.011416	0.003416	-0.015092	-0.

r / lr / poil / pmat / pmetal / y_p / Dp_p / eq_p / ep_p / r_p / lr_p / poil_p / pmat_p / pmetal_p / y_c / Dp_c / eq_c / ep_c / r_c

6.1.8 The GIRFs and GFEVDs folders

The **GIRFs** and **GFEVDs** folders contain results specific to the chosen shocks carried out. The program creates one subfolder for each simulation performed, and the subfolder is labelled according to the type of performed shock.

In each subfolder of **GIRFs**, the program creates **irfs.xls**, containing the point estimates of the generalised impulse response functions (see Figure 6.36). If regional aggregation is performed, the program creates **rirfs.xls**, containing the point estimates aggregated according to the selected regions as defined in Section 5.11.6. If the bootstrap is performed, the program creates **irfs_bs.xls**, (see Figure 6.37) containing the bootstrap median estimates and the associated 90% bootstrap confidence bands for the generalised impulse response functions. If both regional aggregation and the bootstrap are performed, the program creates **rirfs_bs.xls**, containing the bootstrap median

[1]The program performs a check on this equality and will report an error message if this is not satisfied.

estimates and the associated 90% bootstrap confidence bands for the generalised impulse response functions aggregated according to the selected regions. The output for the generalised forecast error variance decompositions (in the folder GFEVDs) is exported in the same manner described above. The following figures illustrate how the output will appear in these spreadsheets. In the case of structural GIRFs and GVEFDs the name of the folders become **SGIRFs** and **SGFEVDs.** Similarly for the orthogonalised IRFs and FEVDs, they become **OIRFs** and **OFEVDs.** The names of the subfolders and their included files are the same in all cases as mentioned above for the **GIRFs** and **GFEVDs**. The title in cell A1 of the **irfs.xls** and **irfs_bs.xls** files as illustrated in the figures below will also reflect the selected type of impulse response functions (the same for the forecast error variance decomposition).

Figure 6.36 Country level generalised impulse responses of a negative unit 1 s.e. global shock to real equity prices

irfs.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Generalized Impulse Response Functions													
2	One s.e. Negative Global Shock to REAL EQUITY PRICES													
3	Point Estimates													
4			0	1	2	3	4	5	6	7	8	9	10	
5	ARGENTINA	y	-0.00165	-0.00313	-0.00375	-0.00434	-0.00451	-0.00459	-0.00454	-0.00434	-0.00429	-0.00423	-0.00416	-0.(
6	ARGENTINA	Dp	-0.01389	-0.01804	0.00149	-0.01512	-0.01427	-0.00791	-0.01853	-0.01441	-0.01363	-0.01893	-0.01477	-0.(
7	ARGENTINA	eq	-0.09966	-0.12598	-0.13963	-0.13009	-0.14045	-0.13608	-0.12878	-0.13309	-0.12899	-0.12855	-0.13186	-0.:
8	ARGENTINA	ep	0.00025	0.01914	0.02089	0.02039	0.02420	0.02231	0.02126	0.02171	0.01968	0.01980	0.02003	0.(
9	ARGENTINA	r	-0.01074	0.00852	0.00658	-0.00443	0.00516	-0.00049	-0.00329	0.00192	-0.00291	-0.00208	0.00017	-0.(
10	AUSTRALIA	y	-0.00011	-0.00065	-0.00078	-0.00098	-0.00116	-0.00139	-0.00172	-0.00205	-0.00245	-0.00289	-0.00330	-0.(
11	AUSTRALIA	Dp	-0.00006	0.00017	0.00007	-0.00005	-0.00011	-0.00014	-0.00020	-0.00024	-0.00028	-0.00032	-0.00035	-0.(
12	AUSTRALIA	eq	-0.04397	-0.05309	-0.05605	-0.05843	-0.06131	-0.06360	-0.06625	-0.06953	-0.07271	-0.07568	-0.07799	-0.(
13	AUSTRALIA	ep	0.01176	0.01222	0.00762	0.00194	-0.00378	-0.00914	-0.01313	-0.01566	-0.01705	-0.01746	-0.01732	-0.(
14	AUSTRALIA	r	-0.00032	-0.00027	-0.00016	-0.00008	0.00001	0.00006	0.00008	0.00008	0.00004	-0.00001	-0.00006	-0.(
15	AUSTRALIA	lr	-0.00007	-0.00007	0.00003	0.00010	0.00014	0.00016	0.00018	0.00019	0.00018	0.00017	0.00015	0.(
16	BRAZIL	y	-0.00135	-0.00170	-0.00170	-0.00224	-0.00247	-0.00283	-0.00307	-0.00306	-0.00321	-0.00326	-0.00322	-0.(
17	BRAZIL	Dp	0.00196	-0.00920	-0.01179	-0.01505	-0.01536	-0.01281	-0.01337	-0.01185	-0.01038	-0.01096	-0.00984	-0.(
18	BRAZIL	ep	0.02785	0.04089	0.04532	0.04912	0.04897	0.04868	0.04853	0.04748	0.04772	0.04810	0.04820	0.(
19	BRAZIL	r	-0.00206	-0.01128	-0.01120	-0.01458	-0.01174	-0.01072	-0.01144	-0.00865	-0.00880	-0.00903	-0.00738	-0.(
20	CANADA	y	-0.00043	-0.00188	-0.00299	-0.00374	-0.00410	-0.00418	-0.00411	-0.00393	-0.00370	-0.00347	-0.00323	-0.(
21	CANADA	Dp	-0.00054	-0.00004	-0.00009	-0.00016	-0.00015	-0.00010	-0.00006	0.00001	0.00006	0.00009	0.00014	0.(
22	CANADA	eq	-0.04928	-0.06237	-0.06841	-0.07157	-0.07271	-0.07217	-0.07117	-0.07020	-0.06945	-0.06895	-0.06846	-0.(
23	CANADA	ep	0.01120	0.01271	0.01389	0.01606	0.01815	0.01996	0.02166	0.02324	0.02475	0.02616	0.02737	0.(
24	CANADA	r	-0.00010	-0.00015	-0.00030	-0.00046	-0.00053	-0.00057	-0.00057	-0.00054	-0.00050	-0.00046	-0.00040	-0.(
25	CANADA	lr	0.00023	0.00030	0.00027	0.00023	0.00018	0.00014	0.00011	0.00009	0.00008	0.00006	0.00005	0.(
26	CHINA	y	0.00124	0.00173	0.00225	0.00261	0.00303	0.00339	0.00350	0.00358	0.00363	0.00360	0.00360	0.(
27	CHINA	Dp	0.00063	0.00075	0.00105	0.00116	0.00122	0.00127	0.00121	0.00116	0.00111	0.00102	0.00097	0.(
28	CHINA	ep	-0.00231	-0.00613	-0.00839	-0.01072	-0.01215	-0.01319	-0.01429	-0.01480	-0.01523	-0.01567	-0.01580	-0.(
29	CHINA	r	-0.00020	-0.00017	-0.00007	0.00001	0.00009	0.00016	0.00020	0.00023	0.00024	0.00024	0.00024	0.(
30	CHILE	y	-0.00061	-0.00230	-0.00327	-0.00442	-0.00477	-0.00508	-0.00532	-0.00525	-0.00528	-0.00530	-0.00522	-0.(
31	CHILE	Dp	0.00049	0.00193	0.00193	0.00217	0.00208	0.00205	0.00201	0.00195	0.00195	0.00194	0.00192	0.(

Sheet1 Sheet2 Sheet3 Point Estimates

Figure 6.37 Country level generalised impulse responses of a negative unit 1 s.e. global shock to real equity prices: Bootstrap median estimates with 90 per cent bootstrap error bounds

irfs_bs.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M	
1	Generalized Impulse Response Functions													
2	One s.e. Negative Global Shock to REAL EQUITY PRICES													
3	Median Estimates													
4			0	1	2	3	4	5	6	7	8	9	10	
5	ARGENTINA	y	-0.00154	-0.00274	-0.00219	-0.00209	-0.00163	-0.00192	-0.00247	-0.00217	-0.00216	-0.00213	-0.00178	-0.C
6	ARGENTINA	Dp	-0.02043	-0.02753	-0.01489	-0.01748	-0.02285	-0.01029	-0.01892	-0.01937	-0.01063	-0.01745	-0.01682	-0.C
7	ARGENTINA	eq	-0.09974	-0.11930	-0.14595	-0.13171	-0.14232	-0.13805	-0.12717	-0.14057	-0.13486	-0.13383	-0.14066	-0.1
8	ARGENTINA	ep	-0.00142	0.01758	0.02293	0.02036	0.02075	0.02044	0.01933	0.01955	0.02000	0.01888	0.02027	0.0
9	ARGENTINA	r	-0.01521	-0.00438	0.00355	-0.00841	0.00115	-0.00090	-0.00696	0.00382	-0.00204	-0.00382	0.00170	-0.C
10	AUSTRALIA	y	-0.00014	-0.00099	-0.00119	-0.00152	-0.00174	-0.00179	-0.00211	-0.00224	-0.00262	-0.00288	-0.00317	-0.C
11	AUSTRALIA	Dp	0.00021	0.00031	0.00018	0.00003	-0.00011	-0.00015	-0.00019	-0.00021	-0.00022	-0.00023	-0.00022	-0.C
12	AUSTRALIA	eq	-0.04470	-0.05071	-0.05530	-0.05725	-0.05953	-0.06033	-0.06226	-0.06594	-0.06773	-0.07069	-0.07377	-0.C
13	AUSTRALIA	ep	0.01213	0.01250	0.00909	0.00415	-0.00088	-0.00400	-0.00625	-0.00700	-0.00595	-0.00487	-0.00409	-0.C
14	AUSTRALIA	r	-0.00037	-0.00026	-0.00022	-0.00021	-0.00017	-0.00013	-0.00013	-0.00013	-0.00019	-0.00024	-0.00024	-0.C
15	AUSTRALIA	lr	-0.00008	-0.00004	0.00005	0.00012	0.00013	0.00015	0.00016	0.00016	0.00015	0.00012	0.00010	0.0
16	BRAZIL	y	-0.00121	-0.00124	-0.00135	-0.00135	-0.00162	-0.00173	-0.00214	-0.00204	-0.00214	-0.00220	-0.00207	-0.C
17	BRAZIL	Dp	-0.00497	-0.01973	-0.03732	-0.04434	-0.04661	-0.04008	-0.04071	-0.04114	-0.03719	-0.03527	-0.03891	-0.C

Sheet1 Sheet2 Sheet3 Median Estimates Lower Bounds Upper Bounds

irfs_bs.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M	
1	Generalized Impulse Response Functions													
2	One s.e. Negative Global Shock to REAL EQUITY PRICES													
3	Lower Bounds													
4			0	1	2	3	4	5	6	7	8	9	10	
5	ARGENTINA	y	-0.00380	-0.00633	-0.00890	-0.00919	-0.01034	-0.01037	-0.01042	-0.01044	-0.01053	-0.01065	-0.01090	-0.C
6	ARGENTINA	Dp	-0.04018	-0.08356	-0.04221	-0.06575	-0.07306	-0.04691	-0.07154	-0.06797	-0.05494	-0.08637	-0.06663	-0.C
7	ARGENTINA	eq	-0.15074	-0.17845	-0.20790	-0.19435	-0.22380	-0.21322	-0.20113	-0.23444	-0.21445	-0.22580	-0.24032	-0.2
8	ARGENTINA	ep	-0.01569	-0.00348	-0.00635	-0.01264	-0.01024	-0.01092	-0.01243	-0.01187	-0.01498	-0.01412	-0.01399	-0.C
9	ARGENTINA	r	-0.06290	-0.02619	-0.02161	-0.05592	-0.03154	-0.03142	-0.04724	-0.03421	-0.03798	-0.04650	-0.03601	-0.C
10	AUSTRALIA	y	-0.00095	-0.00221	-0.00294	-0.00362	-0.00417	-0.00473	-0.00572	-0.00654	-0.00714	-0.00762	-0.00822	-0.C
11	AUSTRALIA	Dp	-0.00057	-0.00025	-0.00043	-0.00064	-0.00076	-0.00075	-0.00086	-0.00085	-0.00099	-0.00105	-0.00106	-0.C
12	AUSTRALIA	eq	-0.05223	-0.06542	-0.07536	-0.08407	-0.09205	-0.09600	-0.09776	-0.10785	-0.11159	-0.11416	-0.11960	-0.1
13	AUSTRALIA	ep	0.00696	0.00400	-0.00120	-0.00649	-0.01289	-0.01738	-0.02255	-0.02437	-0.02771	-0.03053	-0.03261	-0.C
14	AUSTRALIA	r	-0.00068	-0.00067	-0.00072	-0.00070	-0.00075	-0.00075	-0.00078	-0.00093	-0.00101	-0.00125	-0.00145	-0.C
15	AUSTRALIA	lr	-0.00020	-0.00027	-0.00022	-0.00017	-0.00019	-0.00018	-0.00020	-0.00023	-0.00023	-0.00025	-0.00030	-0.C
16	BRAZIL	y	-0.00289	-0.00360	-0.00396	-0.00504	-0.00530	-0.00613	-0.00672	-0.00612	-0.00637	-0.00714	-0.00701	-0.C
17	BRAZIL	Dp	-0.01998	-0.05992	-0.08269	-0.08968	-0.10132	-0.09828	-0.10044	-0.10448	-0.09254	-0.09452	-0.09654	-0.C

Sheet1 Sheet2 Sheet3 Median Estimates Lower Bounds Upper Bounds

irfs_bs.xls

	A	B	C	D	E	F	G	H	I	J	K	L	M	
1	Generalized Impulse Response Functions													
2	One s.e. Negative Global Shock to REAL EQUITY PRICES													
3	Upper Bounds													
4			0	1	2	3	4	5	6	7	8	9	10	
5	ARGENTINA	y	0.00123	0.00087	0.00228	0.00230	0.00317	0.00352	0.00331	0.00338	0.00385	0.00348	0.00378	0.0
6	ARGENTINA	Dp	-0.00352	0.01215	0.03334	0.01156	0.02292	0.03914	0.01311	0.02193	0.03567	0.01356	0.02614	0.0
7	ARGENTINA	eq	-0.07269	-0.07410	-0.08284	-0.07936	-0.08015	-0.07953	-0.06790	-0.07049	-0.07547	-0.06895	-0.07851	-0.C
8	ARGENTINA	ep	0.01494	0.04204	0.04761	0.05324	0.05509	0.05724	0.06059	0.06030	0.06295	0.06527	0.06686	0.0
9	ARGENTINA	r	0.02381	0.02682	0.02767	0.02301	0.03840	0.02614	0.02648	0.04302	0.02520	0.03164	0.03689	0.0
10	AUSTRALIA	y	0.00059	0.00017	0.00036	0.00025	0.00042	0.00044	0.00038	0.00052	0.00079	0.00078	0.00097	0.0
11	AUSTRALIA	Dp	0.00084	0.00074	0.00064	0.00059	0.00039	0.00045	0.00041	0.00033	0.00041	0.00038	0.00044	0.0
12	AUSTRALIA	eq	-0.03724	-0.03965	-0.04085	-0.03890	-0.03774	-0.03679	-0.04021	-0.04207	-0.04382	-0.04335	-0.04299	-0.C
13	AUSTRALIA	ep	0.01621	0.01880	0.01956	0.01710	0.01599	0.01446	0.01404	0.01382	0.01485	0.01656	0.01931	0.0
14	AUSTRALIA	r	-0.00013	0.00001	0.00018	0.00024	0.00035	0.00047	0.00051	0.00058	0.00053	0.00050	0.00050	0.0
15	AUSTRALIA	lr	0.00005	0.00012	0.00026	0.00033	0.00033	0.00035	0.00040	0.00041	0.00041	0.00041	0.00038	0.0
16	BRAZIL	y	0.00053	0.00081	0.00141	0.00153	0.00101	0.00110	0.00074	0.00092	0.00110	0.00092	0.00102	0.0
17	BRAZIL	Dp	0.01061	0.01154	0.00065	-0.00531	-0.00483	0.00564	0.00691	0.00808	0.01650	0.01547	0.01273	0.0

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If you have chosen to plot the graphs at the settings stage, the program will create additional files containing both tables and graphs of the simulated shocks. The same procedure is used as described above: graphs (see Figure 6.38) and corresponding tables are created at the country-level and regional-level (if regional aggregation is performed) for the point estimates, and bootstrap median estimates together with 90% bootstrap confidence bands, if the bootstrap has been enabled (see Figure 6.39). The following figures illustrate how the graphs will appear.

Figure 6.38 Graph of country level responses of a negative unit 1 s.e. global shock to real equity prices on real equity prices

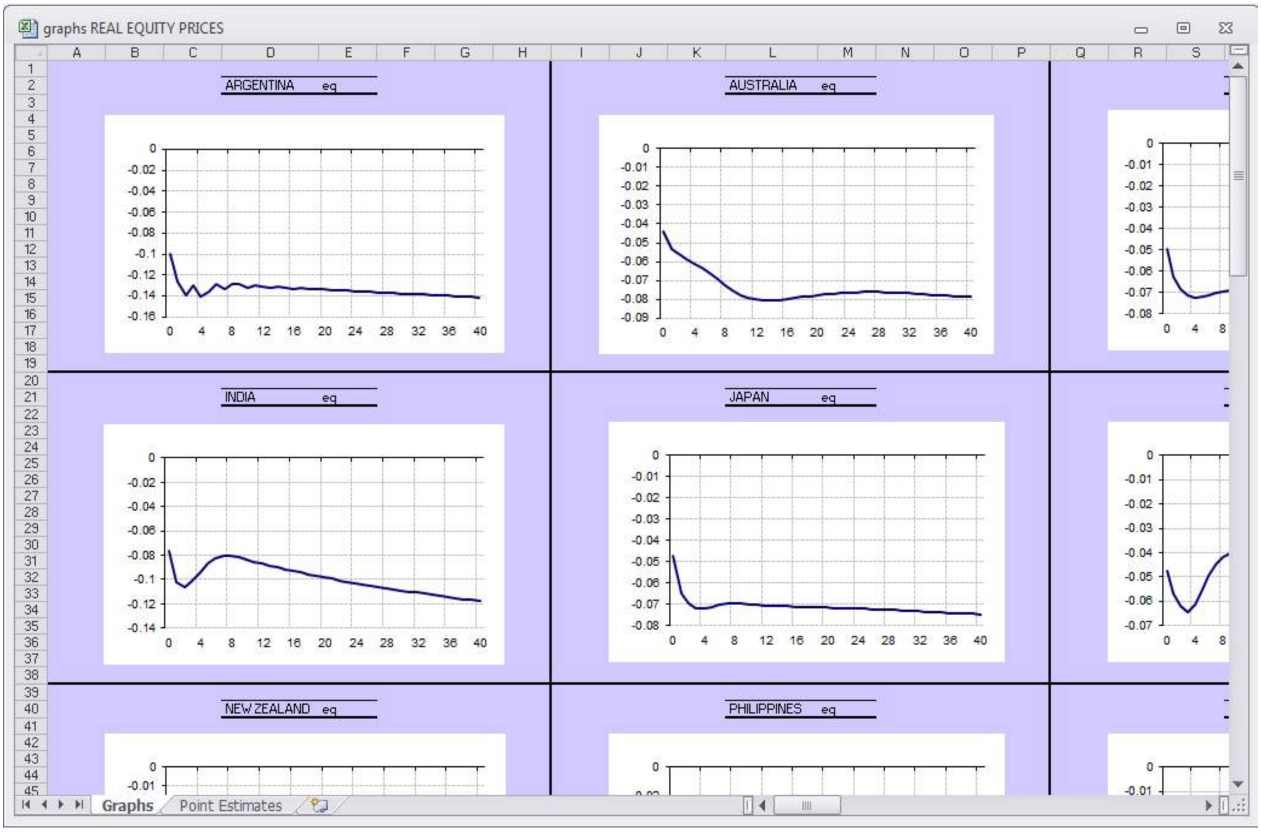
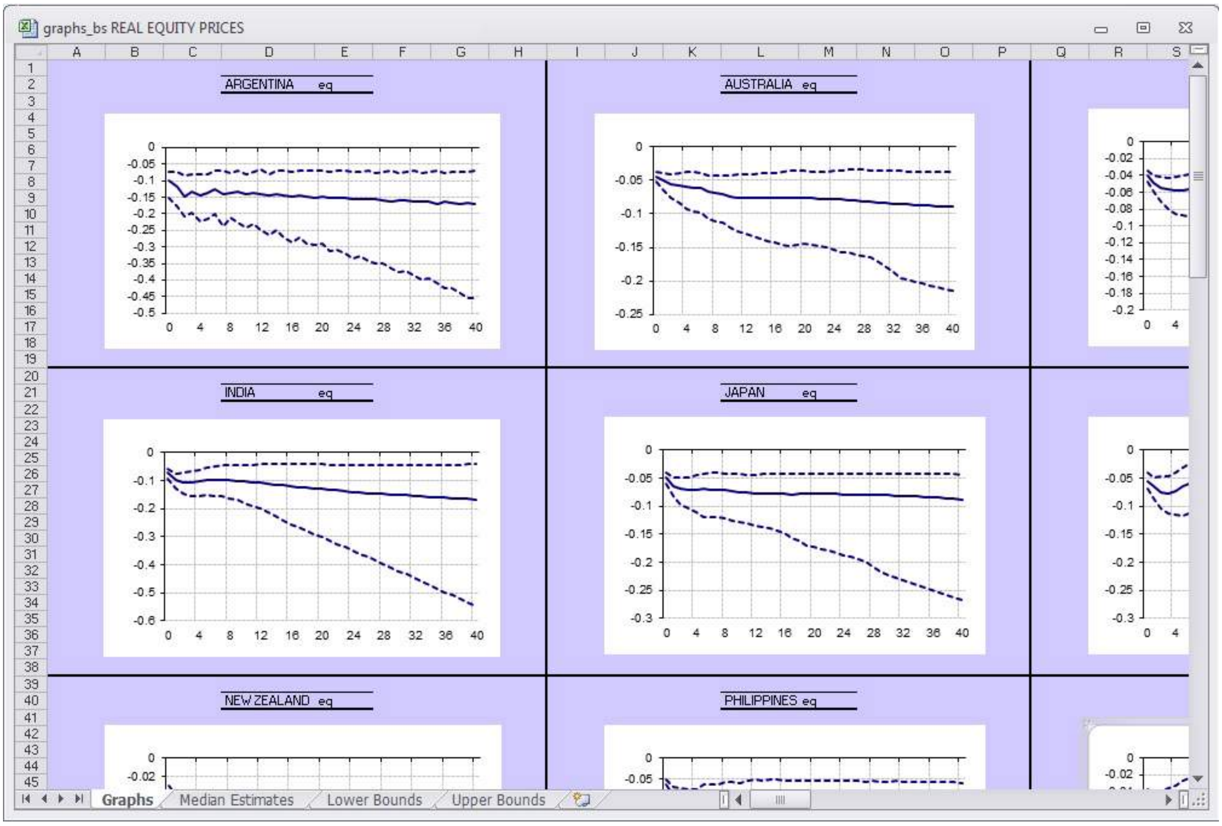


Figure 6.39 Graph of country level responses of a negative unit 1 s.e. global shock to real equity prices on real equity prices: Bootstrap median estimates with 90 per cent bootstrap error bounds



6.2 Organising the output

Now that the analysis is concluded, we recommend that you move your results, to avoid them being overwritten if you rerun the analysis. We suggest doing the following:

1. Open **GVAR_Toolbox2.0****Output**\\ and move **'Output Folder name chosen'**\\ into a directory of your choice, for example **GVAR_Toolbox2.0****Samples**\\.
2. Open **GVAR_Toolbox2.0**\\ and move the **interface file used** into the directory chosen in step 1.
3. Open **GVAR_Toolbox2.0****Flows**\\, and move **flows.xls** into the directory chosen in step 1.

Your folder **GVAR_Toolbox2.0****Samples****'Output Folder name chosen'**\\ now contains all the data, settings, and results of your performed GVAR analysis.

7. REFINING YOUR GVAR SPECIFICATION

The final choice of the GVAR model specification should be arrived at based on a satisfactory performance of the model in terms of stability (related to the eigenvalues of the GVAR model), persistence profiles and impulse response functions. Thus, it is anticpated that users will need to adjust settings and rerun the GVAR program several times before being satisfied with the results. It is recommended that the user initially runs the GVAR program without changes to the values selected by the program during the interim stages, looks carefully at the output, and only then decides what adjustments to make. Below is a list of suggestions to guide you in this process:

1. When to reconsider the specification of the individual models:

    i. If the GVAR model is unstable, i.e. there is at least one eigenvalue that lies above the unit circle in the presence of unit roots (allowing for the possibility of rounding error), or on or above the unit circle in the case of no unit root behaviour in the underlying variables.

    ii. When the persistence profiles do not converge to zero even after about 40 periods or when they do converge to zero they do so in a manner that clearly indicates a problem in the underlying individual model specifications. Note that assessment of the persistence profiles should be based on the sample covariance matrix without any restrictions imposed or any shrinkage performed.

    iii. When the impulse responses do not stabilise after about 40 periods.

2. Ways in which to reconsider the specification of the individual models:

    i. Increasing or decreasing the number of cointegrating relations of the individual VARX* models.

        Most commonly a decrease is required. The persistent profiles are a good guide in selecting which country to start from: it is usually the one that displays the largest non-convergent behaviour.[1]

    ii. Increasing the lag order of the domestic and/or foreign variables.

        Using the Akaike information criterion to select the lag orders of the individual models is typically a good starting point. Thereafter, care should be taken when increasing the lag order of the domestic and/or foreign variables for a particular country, as this can result in non-convergent persistence profiles and/or pronounced cyclical behaviour of the impulse responses.

3. Specification of the foreign variables

    Care should be exercised when selecting the foreign variables for countries which play an important role in the world economy, such as the US, as this can affect the dynamics of the GVAR considerably. The weak exogeneity test provides guidance on this, although further exclusion of variables in such countries may be required, based on the inspection of the persistence profiles and impulse responses.

[1] It is often the case that the resulting number of cointegrating relations is too high for a single country, causing the persistent profiles for a number of countries to behave badly.

4. Provided that conditions of stability and convergence are met, a sound GVAR model specification would be one that delivers sensible impulse responses and other output in line with what one would expect from economic theory (where applicable).

8. TROUBLESHOOTING

If a problem occurs, you have to relaunch the program, which is particularly time-consuming if you get an error message very close to the end. The most common issues are human error when inputting information and deleting or modifying existing links between Excel and Matlab that are hidden within the Excel interface file.

For this reason, you must take great care when:

- Defining the settings in the interface file and entering data. There is no time limit during the pauses, so you can check carefully for errors or for anything that you may have selected which you did not mean to.
- Deleting input within the interface file especially when building your own GVAR model.

If you do get an error message:

- Check that you have entered a choice for all the required settings of the GVAR and that all choices are compatible.
- Look for typing mistakes in the interface file (and flows.xls file, if you are using a program-built weight matrix). Common errors include mistyping names, typing a space after a name[1], not always entering names in the same order, inputting data into blank cells where only 1s should be replaced.
- Finally, to ensure that you have not deleted or modified any links between Excel and Matlab, start from a new interface file and input all the required information again paying extra attention this time.

Note that problems can be caused by errors made in the data or settings anywhere in the process up to the point where the error message appears. For example, if an error message is triggered by a problem at step seven, the error may be anywhere in steps one to seven, so all those stages will need checking, not just step seven. It is worth remembering that you can disable the functionality of each procedure (by selecting 0 rather than 1), which could help you identify where you have made a potential error.

This program has been thoroughly tested by its providers using a variety of datasets and experimental scenarios. However, we accept the possibilty of bugs in the program, which have not been predicted and accommodated. If you have checked that the error is not with your computer or your data and you still get an error message, you can contact us at gvar.helpdesk@gmail.com for technical support. Please attach:

- The error message(s) from the Matlab command window prompt
- The associated interface and flows files if these are different from the ones already included in the toolbox.

A log of amended items are (and will continue to be) posted at https://sites.google.com/site/gvarmodelling/gvar-toolbox/changelog.

[1]This is perhaps the most common error, and also the hardest to spot, so extra attention is required when entering names.

Part II

Technical Appendices

A: ECONOMETRIC METHODS

At the core of the GVAR modelling framework lies a set of individual VARX* models, combined in such a way to give rise to the global VAR model. We begin by introducing a simple VARX* structure.[2]

A.1 A simple VARX* structure

Consider a set of countries $i = 0, 1, 2, ..., N$, with country 0 taken as the reference country. For country i, abstracting from deterministics and higher order lags, consider the VARX*$(1, 1)$ structure

$$\mathbf{x}_{it} = \mathbf{\Phi}_i \mathbf{x}_{i,t-1} + \mathbf{\Lambda}_{i0} \mathbf{x}^*_{it} + \mathbf{\Lambda}_{i1} \mathbf{x}^*_{i,t-1} + \mathbf{u}_{it},$$

$$\begin{aligned} \mathbf{x}_{it} &: k_i \times 1 \text{ vector of domestic variables} \\ \mathbf{x}^*_{it} &: k^*_i \times 1 \text{ vector of foreign variables} \end{aligned}$$

where

$$\mathbf{x}^*_{it} = \sum_{j=0}^{N} w_{ij} \mathbf{x}_{jt},\ w_{ii} = 0,$$

with w_{ij}, $j = 0, 1, ..., N$ a set of weights such that $\sum_{j=0}^{N} w_{ij} = 1$, and $\mathbf{u}_{it}$ are cross sectionally weakly correlated such that $\bar{\mathbf{u}}_{it} = \sum_{j=0}^{N} w_{ij} \mathbf{u}_{jt} \xrightarrow{p} \mathbf{0}$, as $N \to \infty$ (where $\xrightarrow{p}$ denotes convergence in probability). In the explanations that follow, unless otherwise specified, fixed weights are used.

A.2 An example of domestic and foreign variables

The domestic and foreign variable vectors could contain, for example, the following variables:

$$\mathbf{x}_{it} = \begin{pmatrix} y_{it} \\ \Delta p_{it} \\ \rho^S_{it} \end{pmatrix}, \quad \mathbf{x}^*_{it} = \begin{pmatrix} y^*_{it} \\ \Delta p^*_{it} \\ \rho^{S*}_{it} \end{pmatrix},$$

where

$$\begin{aligned} y_{it} &= \ln(GDP_{it}/CPI_{it}), \\ \Delta p_{it} &= p_{it} - p_{i,t-1},\ p_{it} = \ln(CPI_{it}), \\ \rho^S_{it} &= 0.25 \ln(1 + R^S_{it}/100), \end{aligned}$$

GDP_{it} is the nominal gross domestic product, CPI_{it} the consumer price index, R^S_{it} is the annualised short rate, and

$$\begin{aligned} y^*_{it} &= \Sigma_{j=0}^{N} w_{ij} y_{jt}, \\ \Delta p^*_{it} &= \Sigma_{j=0}^{N} w_{ij} \Delta p_{jt}, \\ \rho^{S*}_{it} &= \Sigma_{j=0}^{N} w_{ij} \rho^S_{jt}. \end{aligned}$$

[2]See also Garratt, Lee, Pesaran, and Shin (2006) for a textbook treatment of the GVAR.

Note that when constructing the foreign variables, if the corresponding domestic variables of some countries are not available due to data constraints, the weights are reweighted such that they sum to one. This is also the case when domestic variables are not included in certain countries during the specification stage (the associated country variable data are treated as not available by the program).[3]

A.3 Constructing weight matrices

A.3.1 Country level

Below we describe how the weights, w_{ij}, used for the computation of the foreign variables and solving the GVAR are constructed from the flows data. The weights used throughout the illustration are trade weights but the same procedure applies to financial or any other weights used. In the case of trade weights, w_{ij} is the share of country j in the trade (exports plus imports) of country i.

Consider a set of seven countries: US, UK, Norway, Switzerland, Sweden, Finland, Australia and New Zealand. Table A.1 below shows the country-level trade relationship between the countries. The primary countries are given in the first column, with their corresponding trading partners given in the remaining columns.

Table A.1 Country level trade relationships in US dollars

	US	UK	NOR	SWE	FIN	AUST	NZ	Total
US	0	47014	4322	6485	2900	13947	2441	77109
UK	49418	0	13750	7474	2683	3786	841	77952
NOR	5021	16713	0	8223	1719	154	23	31853
SWE	6412	8230	12190	0	7313	1015	74	35234
FIN	3114	2601	1559	7503	0	361	39	15177
AUST	13648	6029	207	1063	440	0	6030	27417
NZ	2542	825	18	95	58	5271	0	8809

For example, the total trade that Norway has with the other six countries is 31853.

The country level trade shares are constucted by dividing the total trade of each country i by the amount of trade with country j, such that the i^{th} row sums to one, for all i. These are given in Table A.2.

Table A.2 Country level trade shares

	US	UK	NOR	SWE	FIN	AUST	NZ
US	0	0.610	0.056	0.084	0.038	0.181	0.032
UK	0.634	0	0.176	0.096	0.034	0.049	0.011
NOR	0.158	0.525	0	0.258	0.054	0.005	0.001
SWE	0.182	0.234	0.346	0	0.208	0.029	0.002
FIN	0.205	0.171	0.103	0.494	0	0.024	0.003
AUST	0.498	0.220	0.008	0.039	0.016	0	0.220
NZ	0.289	0.094	0.002	0.011	0.007	0.598	0

[3] The weight matrix exported to the output.xls file is the one that corresponds to the full set of domestic variables for which data are available.

The GVAR program reads this matrix in columns, not rows (as is more typical). Thus if the country level trade share matrix is imported into the interface file by the user, it must be done in such a way that each *column* sums to one. Furthermore, it should contain all the individual countries included in the GVAR model, unless the user is interested in working with regions. In this case the corresponding regional share matrix would need to be imported, constructed as described below.

A.3.2 Regional level

Under the program-built weight matrix option, if you have previously defined regions (in columns H-J of the MAIN interface worksheet), the program will construct the regional level trade share matrix as follows.

Suppose we would like to aggregate five of the above seven set of countries into two regions (NORD and ANZ). The former consists of the Nordic countries Norway, Sweden and Finland, and the latter includes Australia and New Zealand. The NORD trade with ANZ is 1666 which is obtained by adding up all trade from the NORD perspective (rows) with ANZ (columns) 154+23+1015+74+361+39, as shown in Table A.3 below.

Table A.3 Regional level trade relationships in US dollars

	US	UK	NORD	ANZ	Total
US	0	47014	13707	16388	77109
UK	49418	0	23907	4627	77952
NORD	14547	27544	38507	1666	82264
ANZ	16190	6854	1881	11301	36226

The NORD intraregional trade is 38507 and is obtained by adding up all trade from the NORD perspective (rows) with NORD (columns), 8223+1719+12190+7313+1559+7503. Similarly the ANZ intraregional trade is 11301.

The regional level trade relationships are then used to compute the regional-level trade share matrix given in Table A.4. Thus, the ANZ share for NORD is 0.038=1667/(82265-38507).

Table A.4 Regional level trade shares

	US	UK	NORD	ANZ
US	0	0.610	0.178	0.213
UK	0.634	0	0.307	0.059
NORD	0.332	0.629	0	0.038
ANZ	0.650	0.275	0.075	0

Note that as for the country level share matrix, the regional share matrix is constructed such that $w_{ii} = 0$, where i denotes either a country or a region, and the sum of the i^{th} row sums to one, for all i. The regional share matrix is then used by the program in its transposed form, i.e. each *column* sums to one, and exported as output in the same way.[4]

[4]For the rows of the share matrices in Tables A.2 and A.4 that do not exactly sum to one, this is due to rounding errors.

A.4 Constructing country-specific and regional aggregation weights

Two sets of weights are constructed for aggregation purposes in our earlier demonstration using PPP-GDP figures: country-specific weights and regional weights. The country-specific weights are computed by dividing the PPP-GDP figure of each country by the total sum across countries, such that the weights add up to one across the countries. These are used for the computation of global shocks (i.e. shocks to a variable across all countries) in impulse response analysis and forecast error decompositions. For the regional weights, the PPP-GDP figure of each country within a region is divided by the total sum across that region, such that the weights add up to one within the region. These are used for computation of regional variables, regional shocks (i.e. shocks to a variable across all countries within a particular region) and regional aggregation of impulse responses and forecast error variance decompositions.

A.5 Constructing regional variables

The regional variables, for example y_{it} and Δp_{it}, can be constructed from the country-specific variables $y_{i\ell t}$, $\Delta p_{i\ell t}$ using the following weighted averages

$$y_{it} = \sum_{\ell=1}^{N_i} w_{i\ell}^0 y_{i\ell t},\ \Delta p_{it} = \sum_{\ell=1}^{N_i} w_{i\ell}^0 \Delta p_{i\ell t},$$

where $y_{i\ell t}$ denotes output of country ℓ in region i and $w_{i\ell}^0$ are, for example as in DdPS, PPP-GDP weights for a given year or based on an average computed over several years. The weights used to aggregate countries into a region (PPP-GDP weights) are not the same as the weights used to create the foreign variables (trade weights), as seen in our earlier demonstration.

A.6 Unit root tests

The GVAR program reports standard ADF unit root t-statistics as well as those based on weighted symmetric estimation of ADF type regressions, introduced by Park and Fuller (1995). The latter tests, denoted by WS, exploit the time reversibility of stationary autoregressive processes in order to increase their power performance. Leybourne, Kim and Newbold (2005) and Pantula, Gonzalez-Farias and Fuller (1995) provide evidence of superior performance of the weighted symmetric test statistic compared to the standard ADF test or the GLS-ADF test proposed by Elliot, Rothenberg and Stock (1996). The lag length employed in the ADF and WS unit root tests can be selected either by the Akaike information criterion (AIC) or the Schwartz Bayesian (SBC) criterion. Results of the ADF and WS statistics are provided for the level, first differences and second differences of all the country and/or region-specific domestic and foreign, as well as global variables. A constant is included in the regressions of the first and second differences by default.

A.7 Lag order selection of the individual VARX* models

Abstracting from any global observed variables, the individual VARX*(p_i,q_i) models are expressed in their general form as

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{\Phi}_{i1}\mathbf{x}_{i,t-1} + ... + \mathbf{\Phi}_{ip_i}\mathbf{x}_{i,t-p_i} + \mathbf{\Lambda}_{i0}\mathbf{x}^*_{it} + \mathbf{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + ... + \mathbf{\Lambda}_{iq_i}\mathbf{x}^*_{i,t-q_i} + \mathbf{u}_{it}, \quad \text{(A.1)}$$

for $i = 0, 1, 2, ..., N$.[5] The lag orders p_i and q_i of the domestic and foreign variables respectively, can be selected using the Akaike information criterion (AIC) or the Schwarz Bayesian criterion (SBC). These are computed as follows:

- Akaike information criterion:

$$AIC_{i,pq} = -\frac{Tk_i}{2}(1 + \log 2\pi) - \frac{T}{2}\log\left|\hat{\Sigma}_i\right| - k_i s_i, \quad \text{(A.2)}$$

- Schwartz Bayesian information criterion:

$$SBC_{i,pq} = -\frac{Tk_i}{2}(1 + \log 2\pi) - \frac{T}{2}\log\left|\hat{\Sigma}_i\right| - \frac{k_i s_i}{2}\ln T, \quad \text{(A.3)}$$

where the first two terms in equations (A.2) and (A.3) correspond to the maximised value of the log-likelihood function with $\hat{\Sigma}_i = \sum_{t=1}^{T} \widehat{\mathbf{u}}_{it}\widehat{\mathbf{u}}'_{it'}/T$ computed based on the estimated residuals $\widehat{\mathbf{u}}_{it}$ of the individual VARX* models given by (A.1), T is the sample size, $|\cdot|$ is the determinant of $\hat{\Sigma}_i$, k_i and k_i^* are the number of domestic and foreign variables respectively in the individual models and $s_i = k_i p_i + k_i^* q_i + 2$. The model with the highest AIC or SBC value is chosen.

A.8 Estimation of the individual VARX* models

For country i, consider the VARX*(2,2) structure

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{\Phi}_{i1}\mathbf{x}_{i,t-1} + \mathbf{\Phi}_{i2}\mathbf{x}_{i,t-2} + \mathbf{\Lambda}_{i0}\mathbf{x}^*_{it} + \mathbf{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + \mathbf{\Lambda}_{i2}\mathbf{x}^*_{i,t-2} + \mathbf{u}_{it}. \quad \text{(A.4)}$$

The error correction form of the VARX*(2,2) specification can be written as

$$\Delta\mathbf{x}_{it} = \mathbf{c}_{i0} - \boldsymbol{\alpha}_i\boldsymbol{\beta}'_i[\mathbf{z}_{i,t-1} - \boldsymbol{\gamma}_i(t-1)] + \mathbf{\Lambda}_{i0}\Delta\mathbf{x}^*_{it} + \mathbf{\Gamma}_i\Delta\mathbf{z}_{i,t-1} + \mathbf{u}_{it}, \quad \text{(A.5)}$$

where $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$, $\boldsymbol{\alpha}_i$ is a $k_i \times r_i$ matrix of rank r_i and $\boldsymbol{\beta}_i$ is a $(k_i + k_i^*) \times r_i$ matrix of rank r_i. By partitioning $\boldsymbol{\beta}_i$ as $\boldsymbol{\beta}_i = (\boldsymbol{\beta}'_{ix}, \boldsymbol{\beta}'_{ix*})'$ conformable to $\mathbf{z}_{it}$, the r_i error correction terms defined by the above equation can be written as

$$\boldsymbol{\beta}'_i(\mathbf{z}_{it} - \boldsymbol{\gamma}_i t) = \boldsymbol{\beta}'_{ix}\mathbf{x}_{it} + \boldsymbol{\beta}'_{ix*}\mathbf{x}^*_{it} - (\boldsymbol{\beta}'_i\boldsymbol{\gamma}_i)\,t,$$

which allows for the possibility of cointegration both within $\mathbf{x}_{it}$ and between $\mathbf{x}_{it}$ and $\mathbf{x}^*_{it}$, and consequently across $\mathbf{x}_{it}$ and $\mathbf{x}_{jt}$ for $i \neq j$.

[5] In the presence of any global observable variables included in the GVAR model (e.g. the oil price), contemporaneous and lag values of these variables would also appear on the right hand side of equation (A.1) $i = 0, 1, 2, ..., N$.

For estimation, $\mathbf{x}_{it}^*$ are treated as 'long-run forcing' or $I(1)$ weakly exogenous with respect to the parameters of the VARX* model (also known as the conditional model).[6] The VARX* models are estimated separately for each country conditional on $\mathbf{x}_{it}^*$, using reduced rank regression, taking into account the possibility of cointegration both within $\mathbf{x}_{it}$ and across $\mathbf{x}_{it}$ and $\mathbf{x}_{it}^*$. This way, the number of cointegrating relations, r_i, the speed of adjustment coeffifients, $\boldsymbol{\alpha}_i$, and the cointegrating vectors $\boldsymbol{\beta}_i$ for each country model are obtained.

Conditional on a given estimate of $\boldsymbol{\beta}_i$, the remaining parameters of the VARX* model are consistently estimated by OLS based on the following equation

$$\Delta\mathbf{x}_{it} = \mathbf{c}_{i0} + \boldsymbol{\delta}_i ECM_{i,t-1} + \boldsymbol{\Lambda}_{i0}\Delta\mathbf{x}_{it}^* + \boldsymbol{\Gamma}_i\Delta\mathbf{z}_{i,t-1} + \mathbf{u}_{it}, \tag{A.6}$$

where $ECM_{i,t-1}$ are the error correction terms corresponding to the r_i cointegrating relations of the i^{th} country model.

More specifically, once the variables to be included in the individual country VARX* models have been selected, the lag orders of the domestic and foreign variables, p_i and q_i respectively, are chosen according to either the AIC or the SBC or can be inputted by the user. It should be noted that for each model, p_i and q_i need not be the same. The lag order of the GVAR, denoted by p, is computed as the maximum of the maximum lag order of p_i and q_i across all countries i.

Then, the corresponding cointegrating VARX* models are estimated and the rank of their cointegrating space is determined using the error-correction form of the individual country models given by (A.5). The rank of the cointegrating space for each country/region is computed using Johansen's trace and maximal eigenvalue statistics as set out in Pesaran, Shin and Smith (2000) for models with weakly exogenous $I(1)$ regressors. The final selection of the rank orders is determined by the trace statistic**,** which in small samples is known to have better power properties than the maximal eigenvalue statistic.

A.8.1 Deterministics of the VECMX* models

The current version of the toolbox provides three options regarding the treatment of the deterministic components in the VECMX* estimation of the individual models. For consistency the same naming as appears in the literature is employed for these (see for example Pesaran, Shin and Smith (2000) and MacKinnon, Haug, and Michelis (1999)):

- Case II: restricted intercepts and no trend coefficients
- Case III: unrestricted intercepts and no trend coefficients
- Case IV: unrestricted intercepts and restricted trend coefficients

For cases II and IV, the intercept and trend coefficients respectively are restricted to lie in the cointegrating space.

In most macro-economic applications of interest, where the variables of interest contain deterministic trend components, and the corresponding long run multiplier matrix ($\boldsymbol{\Pi}_i = \boldsymbol{\alpha}_i\boldsymbol{\beta}_i'$) is rank deficient, the appropriate vector error correction model is given by case IV, where the trend coefficients are restricted. In cases where the variables of interest do not contain deterministic trends, Case II is the appropriate error correction model.

[6] In the presence of any global observable variables in the GVAR model, for the estimation of the country-specific models these variables can be combined with the foreign specific variables $\mathbf{x}_{it}^*$ and treated jointly as weakly exogenous.

Note that despite the fact that a deterministic trend is not included in the VECMX* model for case III, the levels of the domestic variables will be trended due to the drift coefficients. It is possible to define case IV for certain countries and case II and III for others. A formal test of whether cointegrating relations are trended can be performed by testing for co-trending restrictions (see Section A.10 for details).

A.9 Testing for residual serial correlation

For the residual serial correlation test consider the ℓ^{th} equation of the estimated i^{th} country error correction model given by

$$\Delta x_{it,\ell} = \hat{\mu}_{i\ell} + \sum_{j=1}^{\hat{r}_i} \hat{\gamma}_{ij,\ell} E\hat{C}M_{ij,t-1} + \sum_{n=1}^{\hat{p}_i-1} \hat{\boldsymbol{\varphi}}'_{in,\ell} \Delta \mathbf{x}_{i,t-n} + \sum_{s=0}^{\hat{q}_i-1} \hat{\boldsymbol{\vartheta}}'_{is,\ell} \Delta \mathbf{x}^*_{i,t-s} + e_{it,\ell}, \quad \text{(A.7)}$$

which can be written more compactly as

$$y_{it,\ell} = \hat{\boldsymbol{\theta}}'_{i\ell} \mathbf{z}_{it} + e_{it,\ell}, \quad \text{(A.8)}$$

where $y_{it,\ell} = \Delta x_{it,\ell}$, $\mathbf{z}_{it} = (1, E\hat{C}M'_{ij,t-1}, \Delta\mathbf{x}'_{i,t-n}, \Delta\mathbf{x}'^{*}_{i,t-s})'$, $E\hat{C}M_{ij,t-1}$, $j = 1, 2, ..., r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found for the i^{th} country model, and $\hat{\boldsymbol{\theta}}_{i\ell} = (\hat{\mu}_{i\ell}, \hat{\gamma}_{ij,\ell}, \hat{\boldsymbol{\varphi}}'_{in,\ell}, \hat{\boldsymbol{\vartheta}}'_{is,\ell})'$. Let $e_{it,\ell}$ be the residuals from the estimated model (A.8) and $\hat{\sigma}^2_{i\ell} = T^{-1} \sum_{t=1}^{T} e^2_{it,\ell}$ the corresponding estimated error variance.

The F-statistic for the residual serial correlation test is the F-version of the familiar Lagrange Multiplier (LM) statistic (see Godfrey 1978a, 1978b), also known as 'modified LM' statistic, and is computed according to the following formula

$$F_{i\ell,SC}(p_{ei}) = \left(\frac{T - \kappa_i - p_{ei}}{p_{ei}} \right) \left(\frac{\chi^2_{i\ell,SC}(p_{ei})}{T - \chi^2_{i\ell,SC}(p_{ei})} \right) \overset{a}{\sim} F_{p_{ei}, T-\kappa_i-p_{ei}},$$

where T is the sample size, κ_i is the number of regressors or dimension size of the $\hat{\boldsymbol{\theta}}_{i\ell}$ vector, and p_{ei} is the lag order of the error process $e_{it,\ell}$.[7]

The expression for $\chi^2_{i\ell,SC}(p_{ei})$ is given by

$$\chi^2_{i\ell,SC}(p_{ei}) = T \left(\frac{\mathbf{e}'_{i\ell} \mathbf{Q}_{i\ell} (\mathbf{Q}'_{i\ell} \mathbf{M}_{iz} \mathbf{Q}_{i\ell})^{-1} \mathbf{Q}'_{i\ell} \mathbf{e}_{i\ell}}{\mathbf{e}'_{i\ell} \mathbf{e}_{i\ell}} \right) \overset{a}{\sim} \chi^2_{p_{ei}},$$

where

$$\mathbf{M}_{iz} = \mathbf{I}_T - \mathbf{Z}_i (\mathbf{Z}'_i \mathbf{Z}_i)^{-1} \mathbf{Z}'_i,$$

$$\mathbf{e}_{i\ell} = \mathbf{y}_{i\ell} - \mathbf{Z}_i \hat{\boldsymbol{\theta}}_{i\ell} = (e_{i1,\ell}, e_{i2,\ell}, ..., e_{iT,\ell})',$$

$\mathbf{y}_{i\ell} = (y_{i1,\ell}, y_{i2,\ell}, ..., y_{iT,\ell})'$, $\mathbf{Z}_i = (\mathbf{z}_{i1}, \mathbf{z}_{i2}, ..., \mathbf{z}_{iT})'$, $\boldsymbol{\theta}_{i\ell} = (\boldsymbol{\theta}_{i1,\ell}, \boldsymbol{\theta}_{i2,\ell}, ..., \boldsymbol{\theta}_{iT,\ell})'$ and

$$\mathbf{Q}_{i\ell} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ e_{i1,\ell} & 0 & \cdots & 0 \\ e_{i2,\ell} & e_{i1,\ell} & \cdots & 0 \\ \vdots & e_{i2,\ell} & & \vdots \\ \vdots & \vdots & & e_{i,T-p_{ei}-1,\ell} \\ e_{i,T-1,\ell} & e_{i,T-2,\ell} & \cdots & e_{i,T-p_{ei},\ell} \end{bmatrix}.$$

[7] Hereafter, $\overset{a}{\sim}$ signifies that asymptotically the statistic under consideration, here $F_{i\ell,SC}(p_{ei})$, follows the given distribution, here $F_{p_{ei},T-\kappa_i-p_{ei}}$.

The F-statistics provided by the program for testing residual serial correlation at the VARX* order selection stage are based on the residuals from the estimated VARX*(p_i, q_i) models given in (A.1).

A.10 Testing for co-trending restrictions

A test of whether the cointegrating relations are trended (co-trending restrictions) can be carried out by testing the following r_i restrictions

$$\boldsymbol{\beta}_i'\boldsymbol{\gamma}_i = \mathbf{0},$$

within equation (A.5). The relevant test statistic is given by

$$LR(\boldsymbol{\beta}_i'\boldsymbol{\gamma}_i = \mathbf{0}) = 2\{\ell(\hat{\boldsymbol{\theta}}_i; r_i) - \ell(\widetilde{\boldsymbol{\theta}}_i; r_i)\} \overset{a}{\sim} \chi^2_{r_i}, \tag{A.9}$$

where $\boldsymbol{\theta}_i = vec(\boldsymbol{\beta}_i)$, $\ell(\hat{\boldsymbol{\theta}}_i; r_i)$ is the maximised value of the log-likelihood function when the cointegrating relations are just identified, and $\ell(\widetilde{\boldsymbol{\theta}}_i; r_i)$ is the maximised value of the log-likelihood function obtained subject to the just-identified restrictions plus the additional r_i co-trending restrictions. Under the co-trending null hypothesis, $LR(\boldsymbol{\beta}_i'\boldsymbol{\gamma}_i = \mathbf{0})$ is asymptotically chi-square distributed, χ^2, with r_i degrees of freedom.

This test can easily be implemented using the output from the GVAR program. Having defined the individual model specifications and imposed case IV for estimation of the VECMX* models, $\ell(\hat{\boldsymbol{\theta}}_i; r_i)$ is given under the log-likelihood column heading in the ECMS_stats worksheet of the output.xls file**.** The loglikelihood, $\ell(\widetilde{\boldsymbol{\theta}}_i; r_i)$, can be obtained in the same way by rerunning the model and imposing case III for estimation of the individual country models, keeping the model specifications unchanged. The likelihood ratio statistic given by (A.9) can then be computed and compared against the $\chi^2_{r_i}$ distribution using the usual 95% critical value.

A.11 Testing for overidentifying restrictions on the cointegrating vectors

To develop a global model with a theoretically coherent foundation one may wish to incorporate long-run structural relationships, suggested by economic theory in the otherwise unrestricted country-specific models. In what follows, abstracting from any deterministics for simplicity, we illustrate how overidentifying restrictions can be imposed and tested within the context of a simple country specification (see also Dees, Holly, Pesaran and Smith, 2007).

Consider the i^{th} country-specific model that consists of the following domestic and foreign variables

$$\mathbf{x}_{it} = \begin{pmatrix} y_{it} \\ \Delta p_{it} \\ ep_{it} \\ \rho^S_{it} \end{pmatrix}, \quad \mathbf{x}^*_t = \begin{pmatrix} y^*_{it} \\ \Delta p^*_{it} \\ \rho^{S*}_{it} \end{pmatrix},$$

expressed in logs, where y_{it}, Δp_{it}, ep_{it} and ρ^S_{it} are real output, inflation, the real exchange rate and the short-term interest rate respectively, and $y^*_{it}, \Delta p^*_{it}$ and ρ^{S*}_{it} are the corresponding foreign variables.

Suppose that the rank obtained by the reduced rank regression estimation is $r_i = 2$. The corresponding cointegrating relations have the form

$$\beta_{i,11}y_{it} + \beta_{i,12}\Delta p_{it} + \beta_{i,13}ep_{it} + \beta_{i,14}\rho_{it}^{S} + \beta_{i,15}y_{it}^{*} + \beta_{i,16}\Delta p_{it}^{*} + \beta_{i,17}\rho_{it}^{S*} \sim I(0),$$
$$\beta_{i,21}y_{it} + \beta_{i,22}\Delta p_{it} + \beta_{i,23}ep_{it} + \beta_{i,24}\rho_{it}^{S} + \beta_{i,25}y_{it}^{*} + \beta_{i,26}\Delta p_{it}^{*} + \beta_{i,27}\rho_{it}^{S*} \sim I(0).$$

Exact identification requires $r_i^2 = 4$ restrictions, that is two restrictions per cointegrating vector, where each vector is given by the coefficients of the associated cointegrating relation. The exact identifying restrictions imposed by the program are those based on the identity matrix. Now suppose we want to test the validity of the following cointegrating relations suggested by economic theory, namely the Fisher equation and the uncovered interest parity, given by

$$\rho_{it}^{S} - \Delta p_{it} \sim I(0),$$
$$\rho_{it}^{S} - \rho_{it}^{S*} \sim I(0).$$

These long run relations admit the following cointegrating vectors

$$\boldsymbol{\beta}_{i1} = \begin{pmatrix} 0 & -1 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}',$$
$$\boldsymbol{\beta}_{i2} = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 0 & -1 \end{pmatrix}',$$

and imply fourteen restrictions, four of which are required for exact identification. Therefore, the number of overidentifying restrictions is $m_i r_i - r_i^2 = (7 \times 2) - 4 = 10$, where m_i is the total number of domestic and foreign variables (including any deterministics, if these are present) that enter the cointegrating space.

The likelihood ratio statistic is used to test whether these ten overidentifying restrictions are valid. Let $\boldsymbol{\theta}_i = vec(\boldsymbol{\beta}_i)$ where $\boldsymbol{\beta}_i = (\boldsymbol{\beta}_{i1}, \boldsymbol{\beta}_{i2}, ..., \boldsymbol{\beta}_{ir_i})$. Denote by $\hat{\boldsymbol{\theta}}_i$ the maximum likelihood (ML) estimator of $\boldsymbol{\theta}_i$ obtained subject to the r_i^2 exactly-identifying restrictions, and by $\widetilde{\boldsymbol{\theta}}_i$ the ML estimator of $\boldsymbol{\theta}_i$ obtained under the total number of restrictions $m_i r_i$.

Under the null hypothesis that the over-identifying restrictions hold the log-likelihood ratio statistic, $\mathcal{LR}$, is defined by

$$\mathcal{LR} = 2\{\ell_T(\hat{\boldsymbol{\theta}}_i; r_i) - \ell_T(\widetilde{\boldsymbol{\theta}}_i; r_i)\} \overset{a}{\sim} \chi^2_{m_i r_i - r_i^2},$$

where $\ell_T(\hat{\boldsymbol{\theta}}_i, r_i)$ and $\ell_T(\widetilde{\boldsymbol{\theta}}_i, r_i)$ is the maximised value of the log-likelihood function under exact-identifying restrictions and the total number of restrictions, respectively.

The log-likelihood ratio statistic is asymptotically distributed as a χ^2 variate with degrees of freedom equal to the number of over-identifying restrictions. However, in small samples, and to take account of the global interactions, the critical values for the $\mathcal{LR}$ statistic are computed by bootstrapping the GVAR (see Section A.22 for details). For each bootstrap replication b, the vector error-correction model given by (A.5) is estimated for each country i, $i = 0, 1, ..., N$. For the b^{th} replication the $\mathcal{LR}$ statistic is then computed as

$$\mathcal{LR}^{(b)} = 2\{\ell_T^{(b)}(\hat{\boldsymbol{\theta}}_i; r_i) - \ell_T^{(b)}(\widetilde{\boldsymbol{\theta}}_i; r_i)\}, \text{ for } b = 1, 2, ...$$

These statistics are sorted in ascending order and the value that exceeds 95% of the bootstrapped statistics yields the appropriate 95% critical value for testing the over-identifying restrictions.

The over-identifying restrictions inputted by the user should be imposed simultaneously on each of the selected countries. Where none are imposed, countries are estimated subject to exact-identifying restrictions. Note that the current version of the program does not permit testing of the purchasing power parity relation.

If one chooses to test for the validity of long-run economic theory relations, the number of economic relations to be tested must equal the corresponding rank orders of the individual models. For example, if one country has rank equal to three, three theory-based cointegrating relations must be tested. One cannot test for two long run relations and simply exactly-identify the remaining cointegrating relation. To test for two long run relations for that particular country, one needs to reduce its number of cointegrating relations from three to two at the model specification stage. If the number of potential candidates for long run theory relations is greater than the number of cointegrating relationships for a particular country, then the ultimate choice should be based on careful inspection of the persistence profiles and impulse responses as will be discussed later.

Furthermore, if the user would like to allow, for example, the coefficient of inflation to be unrestricted in the Fisher equation, that is $\boldsymbol{\beta}_{i1} = \begin{pmatrix} 0 & \beta_{i,12} & 0 & 1 & 0 & 0 & 0 \end{pmatrix}'$, then $\beta_{i,12}$ would need to be estimated outside the GVAR program using other software (for example Microfit or Eviews), and replaced by its estimated value, $\hat{\beta}_{i,12}$, at the stage of inputting the over-identifying restrictions. Once long run restrictions have been imposed on the cointegrating vectors, all output thereafter including weak exogeneity test results, impact elasticities, average cross section correlations, structural stability statistics, impulse responses and forecast error decompositions, is computed based on the overidentified betas.

A.12 Testing for weak exogeneity

The main assumption underlying the estimation of the individual country VARX* models is the weak exogeneity of $\mathbf{x}_{it}^*$ with respect to the long run parameters of the conditional model defined by (A.5). This assumption is compatible with a certain degree of weak dependence across $\mathbf{u}_{it}$, as discussed in Pesaran, Shuermann and Weiner (2004). Following Johansen (1992) and Granger and Lin (1995), the weak exogeniety assumption in the context of cointegrating models implies no long run feedback from $\mathbf{x}_{it}$ to $\mathbf{x}_{it}^*$, without necessarily ruling out lagged short run feedback between the two sets of variables. In this case, $\mathbf{x}_{it}^*$ is said to be 'long run forcing' for $\mathbf{x}_{it}$, which implies that the error correction terms of the individual country VECMX* models do not enter in the marginal model of $\mathbf{x}_{it}^*$. A formal test of this assumption for the country-specific foreign variables (the 'star' variables) and the observed global variables is conducted along the lines described in Johansen (1992) and Harbo, Johansen, Nielsen and Rahbek (1998). This involves a test of the joint significance of the estimated error correction terms in auxiliary equations for the country-specific foreign variables, $\mathbf{x}_{it}^*$. In particular, for each ℓ^{th} element of $\mathbf{x}_{it}^*$ the following regression is carried out

$$\Delta x_{it,\ell}^* = a_{i\ell} + \sum_{j=1}^{r_i} \delta_{ij,\ell} E\hat{C}M_{ij,t-1} + \sum_{s=1}^{p_i^*} \boldsymbol{\phi}_{is,\ell}' \Delta \mathbf{x}_{i,t-s} + \sum_{s=1}^{q_i^*} \boldsymbol{\psi}_{is,\ell}' \Delta \widetilde{\mathbf{x}}_{i,t-s}^* + \eta_{it,\ell},$$

where $E\hat{C}M_{ij,t-1}$, $j = 1, 2, ..., r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found for the i^{th} country model, and p_i^* and q_i^* are the orders of the lagged changes for the domestic and foreign variables, respectively. Based on the earlier demonstration, $\Delta\widetilde{\mathbf{x}}_{it}^* = (\Delta\mathbf{x}_{it}'^*, \Delta ep_{it}^*, \Delta p_t^o, \Delta p_t^{rm}, \Delta p_t^m)'$ for $i = 1, ..., N$ where p_t^o, p_t^{rm} and p_t^m is the price of oil, raw material and metal, respectively. For the US $(i = 0)$, $\Delta\widetilde{\mathbf{x}}_{0t}^* = (\Delta\mathbf{x}_{0t}'^*, \Delta p_t^o, \Delta p_t^{rm}, \Delta p_t^m)'$ as the term Δep_{0t}^* is included in $\Delta\mathbf{x}_{0t}^*$ from the outset. The test for weak exogeneity is an F-test of the joint null hypothesis that $\delta_{ij,\ell} = 0$, $j = 1, 2, ..., r_i$ in the above regression.

The lag orders p_i^* and q_i^* need not be the same as the orders p_i and q_i of the underlying country-specific VARX* models. They can either be selected by an information criterion such as the AIC or the SBC, or imposed by the user. Increasing q_i^*, typically reduces the number of significant outcomes for a specific country.

Thus, testing for weak exogeneity involves the marginal model of $\mathbf{x}_{it}^*$, that is, the model for the foreign variables. Note that the specification of the marginal model is independent of that of the conditional model (A.5). Lag order selection of the weakly exogenous regression equations is performed in the same way as described in Section A.7 for the VARX* models.

A.13 Contemporaneous effects of foreign variables on their domestic counterparts

The contemporaneous effects of foreign variables on their domestic counterparts are provided together with t-ratios computed based on standard, as well as White and Newey-West adjusted variance matrices. These contemporaneous effects are given by the estimated coefficients on the contemporaneous foreign specific variables and can be interpreted as impact elasticities between domestic and foreign variables. They are particularly informative as regards the international linkages between the domestic and foreign variables. High elasticities between these variables imply strong co-movements between the two. Consider the ℓ^{th} equation of the estimated i^{th} country error correction model given by (A.7). The White and Newey-West adjusted variance estimates of the individual VECMX* regressors collected in $\boldsymbol{\theta}_{i\ell}$ (see Section A.9) are computed as follows:

A.13.1 Heteroskedasticity-consistent variance estimator

The program computes a degrees of freedom corrected version of White's (1980) heteroskedasticity-consistent variance estimator for $\boldsymbol{\theta}_{i\ell}$ using the following formula:

$$\widehat{HCV}(\hat{\boldsymbol{\theta}}_{i\ell}) = \left(\frac{T}{T-\kappa_i}\right)(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\left(\sum_{t=1}^{T} e_{it,\ell}^2 \mathbf{z}_{it}\mathbf{z}_{it}'\right)(\mathbf{Z}_i'\mathbf{Z}_i)^{-1},$$

where T, κ_i, $e_{it,\ell}$, $\mathbf{z}_{it}$ and $\mathbf{Z}_i$ are defined as in Section A.9.

A.13.2 Newey-West variance estimator

The Newey-West variance estimator (Newey and West, 1987) is computed, allowing for a small sample correction, according to the following formula:

$$\hat{V}(\hat{\boldsymbol{\theta}}_{i\ell}) = \left(\frac{T}{T-\kappa_i}\right)(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\hat{\mathbf{S}}_{iT,\ell}(\mathbf{Z}_i'\mathbf{Z}_i)^{-1},$$

where

$$\hat{\mathbf{S}}_{iT,\ell} = \hat{\boldsymbol{\Omega}}_{i0,\ell} + \sum_{j=1}^{m} w(j,m)(\hat{\boldsymbol{\Omega}}_{ij,\ell} + \hat{\boldsymbol{\Omega}}_{ij,\ell}'),$$

in which

$$\hat{\boldsymbol{\Omega}}_{ij,\ell} = \sum_{t=j+1}^{T} \hat{e}_{it,\ell}\hat{e}_{i,t-j,\ell,}\mathbf{z}_{it}\mathbf{z}_{i,t-j}',$$

and $w(j,m)$ is the 'lag window'. The *Bartlett window* is used as the lag window given by

$$w(j,m) = 1 - \frac{j}{m+1}, \qquad j = 1, 2, ..., m.$$

The 'window size' or the 'truncation point', m, is specified as $m = [4(T/100)^{2/9}]$, where $[.]$ denotes the integer part of m.

A.14 Average pairwise cross-section correlations

One of the key assumptions of the GVAR modelling approach is that the 'idiosyncratic' shocks of the individual country models should be cross-sectionally 'weakly correlated', so that $Cov(\mathbf{x}_{it}^{*}, u_{it}) \rightarrow 0$, with $N \rightarrow \infty$, and as a result the weak exogeneity of the foreign variables is ensured. Direct tests of weak exogeneity assumptions discussed earlier indirectly support the view that the idiosyncratic shocks could only be weakly correlated. The program output provides direct evidence on the extent to which this is likely to be true. The basic idea is that by conditioning the country-specific models on weakly exogenous foreign variables, viewed as proxies for the 'common' unobserved global factors, it is reasonable to expect that the degree of correlation of the remaining shocks across countries/regions will be modest. These residual interdependencies could reflect, for example, policy and trade spillover effects.

A simple diagnostic of the extent to which the country-specific foreign variables have been effective in reducing the cross-section correlation of the variables in the GVAR model is provided by the average pairwise cross-section correlations for the levels and first differences of the endogenous variables of the model, as well as those of the associated residuals over the selected estimation period. These are computed as follows: for every country for each given variable, the pairwise correlation of that country with each of the remaining countries is computed, and averaged across countries.

A.15 Structural stability tests

A number of structural stability tests, similar to those considered by Stock and Watson (1996), are computed to detect the possibility of the presence of breaks. Among them Ploberger and Krämer's (1992) maximal OLS cumulative sum (CUSUM) statistic, denoted by $PK_{\sup}$ and its mean square variant PK_{msq}. The $PK_{\sup}$ statistic is similar to the CUSUM test suggested by Brown, Durbin and Evans (1975), although the latter is based on recursive rather than OLS residuals. Also included are tests for parameter constancy against non-stationary alternatives proposed by Nyblom (1989), denoted by $\mathfrak{N}$, as well as sequential Wald type tests of a one-time structural change at an unknown change point. The latter include the Wald form of Quandt's (1960) likelihood ratio statistic (QLR), the mean Wald statistic (MW) of Hansen (1992) and Andrews and Ploberger (1994), and the Andrews and Ploberger (1994) Wald statistic based on the exponential average (APW). The heteroskedasticity-robust version of the Nyblom and sequential Wald tests is also provided. The critical values of the tests are computed under the null of parameter stability using the bootstrap samples obtained from the solution of the GVAR(p) model as described in Section A.22.1. Note that the critical values employed in Stock and Watson (1996) are for the case of predetermined regressors and are therefore not applicable in the GVAR context.

In what follows, for expositional purposes, we abstract from the index i and re-introduce it at a later stage. For the structural stability tests, consider the compact version of the ℓ^{th} equation of the estimated i^{th} error correction model given by

$$y_{\ell t} = \boldsymbol{\theta}'_{\ell t}\mathbf{z}_t + e_{\ell t}. \tag{A.10}$$

Note that contrary to equation (A.8), the parameter coefficients of (A.10), defined by $\boldsymbol{\theta}_{\ell t} = (\mu_{\ell t}, \gamma_{j\ell t}, \boldsymbol{\varphi}'_{n\ell t}, \boldsymbol{\vartheta}'_{s\ell t})'$, can now change over time. The null hypothesis for all the considered tests is that of parameter constancy, that is $\boldsymbol{\theta}_{\ell t} = \boldsymbol{\theta}_{\ell}$. The alternative varies, depending on the test, from non-stationarity (e.g. random walks) to a one-time change at an unknown break point for the sequential Wald type statistics, or some systematic movement in the parameters which are all considered to be subject to change.

Tests based on the cumulative sum of OLS residuals

The maximal OLS CUSUM statistic proposed by Ploberger and Krämer (1992) is similar to Brown, Durbin and Evans' (1975) CUSUM statistic, although it is computed using OLS rather than recursive residuals. The mean square version of this test is also considered. Let $\zeta_T(\delta) = \hat{\sigma}_\ell^{-1}T^{-1/2}\sum_{s=1}^{[T\delta]} e_{\ell s}$, where $[\cdot]$ is the greatest integer function, then

$$PK_{\text{sup}} = \sup_{\delta\in[0,1]} \left|\zeta_{\ell T}(\delta)\right|,$$

$$PK_{msq} = \int_0^1 \zeta_{\ell T}(\delta)^2 d\delta.$$

Random walk alternatives

Nyblom (1989) specifies as the alternative that $\boldsymbol{\theta}_{\ell t}$ follows a random walk, that is, $\boldsymbol{\theta}_{\ell t} = \boldsymbol{\theta}_{\ell,t-1} + \boldsymbol{\eta}_{\ell t}$, where $\boldsymbol{\eta}_{\ell t}$ is iid and uncorrelated with error term in equation (A.10), and proposes the following statistic

$$\mathfrak{N}_\ell = T^{-2}\sum_{t=1}^{T} \mathbf{S}'_{\ell t}\hat{\mathbf{V}}_\ell^{-1}\mathbf{S}_{\ell t} \tag{A.11}$$

where $\mathbf{S}_{\ell t} = \sum_{s=1}^{t} \mathbf{z}_s e_{\ell s}$ and $\hat{\mathbf{V}}_\ell = (T^{-1}\sum_{t=1}^{T} \mathbf{z}_t\mathbf{z}'_t)\hat{\sigma}_\ell^2$. The heteroskedasticity-robust version of the $\mathfrak{N}_\ell$ statistic is obtained by replacing $\hat{\mathbf{V}}_\ell$ in (A.11) with $\tilde{\mathbf{V}}_\ell = T^{-1}\sum_{t=1}^{T} e_{\ell t}^2\mathbf{z}_t\mathbf{z}'_t$.

Sequential Wald statistics

(i) Quandt (1960) likelihood ratio (QLR) statistic in Wald form

$$QLR = \sup_{\delta\in(\delta_0,\delta_1)} F_{\ell T}(\delta),$$

(ii) The mean Wald statistic (Hansen (1992), Andrews and Ploberger (1994))

$$MW = \int_{\delta_0}^{\delta_1} F_{\ell T}(\delta)d\delta,$$

(iii) The exponential average Wald statistic by Andrews and Ploberger (1994)

$$APW = \ln\{\int_{\delta_0}^{\delta_1} \exp(F_{\ell T}(\delta)/2)d\delta\}.$$

To obtain the Wald statistic $F_{\ell T}(\delta)$ of these tests for a break at $t = m$, where $\delta = m/T$ or $m = [T\delta]$, equation (A.10) is initially estimated under the null of no structural change. The resulting sum of squares is defined as $\mathcal{R}_\ell = \mathbf{e}'_\ell \mathbf{e}_\ell$, where $\mathbf{e}_\ell = (e_{\ell 1}, e_{\ell 2,}..., e_{\ell T})'$. The model with a one-time break at $t = m$ is given by

$$\text{Subsample 1:}\ \ y_{\ell t} = \boldsymbol{\theta}'_{1\ell}\mathbf{z}_t + \varepsilon_{1\ell t},\ t = 1, 2, ..., m \tag{A.12}$$

$$\text{Subsample 2:}\ \ y_{\ell t} = \boldsymbol{\theta}'_{2\ell}\mathbf{z}_t + \varepsilon_{2\ell t},\ t = m+1, ..., T. \tag{A.13}$$

Let $e_{1\ell t}$ and $e_{2\ell t}$ be the residuals from the OLS estimation of (A.12) and (A.13), respectively. Define $\mathcal{R}_{1\ell} = \mathbf{e}'_{1\ell}\mathbf{e}_{1\ell}$ and $\mathcal{R}_{2\ell} = \mathbf{e}'_{2\ell}\mathbf{e}_{2\ell}$. Then,

$$F_{\ell T}(\delta) = (T - 2\kappa)\frac{\mathcal{R}_\ell - \mathcal{R}_{\ell 1} - \mathcal{R}_{\ell 2}}{\mathcal{R}_{\ell 1} + \mathcal{R}_{\ell 2}},$$

where κ is the dimension of the $\boldsymbol{\theta}_{j\ell}$ $j = 1, 2$ vector, and $\delta \in [\delta_0, \delta_1]$ with $\delta_1 = 1 - \delta_0$. The value for δ_0 (the trimming parameter) is set to 0.15 in the MAIN worksheet of the demo interface files. Any change in this value should take into account the number of available observations, together with the maximum number of regressors included in the individual VARX* models.

The heteroskedasticity-robust version of the sequential Wald tests is given by

$$F_T(\delta) = (\hat{\mathbf{b}}_1 - \hat{\mathbf{b}}_2)'\mathbf{Q}_\ell^{-1}(\hat{\mathbf{b}}_1 - \hat{\mathbf{b}}_2),$$

where

$$\begin{aligned}\hat{\mathbf{b}}_1 &= (\mathbf{Z}'_1\mathbf{Z}_1)^{-1}\mathbf{Z}'_1\mathbf{Y}_{1\ell},\\ \hat{\mathbf{b}}_2 &= (\mathbf{Z}'_2\mathbf{Z}_2)^{-1}\mathbf{Z}'_2\mathbf{Y}_{2\ell},\end{aligned}$$

and

$$\begin{aligned}\mathbf{Q}_\ell = {} & (\mathbf{Z}'_1\mathbf{Z}_1)^{-1}(\sum\nolimits_{t=1}^{m} e^2_{\ell t}\mathbf{z}_t\mathbf{z}'_t)(\mathbf{Z}'_1\mathbf{Z}_1)^{-1} + \\ & (\mathbf{Z}'_2\mathbf{Z}_2)^{-1}[(\sum\nolimits_{t=1}^{T} e^2_{\ell t}\mathbf{z}_t\mathbf{z}'_t) - (\sum\nolimits_{t=1}^{m} e^2_{\ell t}\mathbf{z}_t\mathbf{z}'_t)](\mathbf{Z}'_2\mathbf{Z}_2)^{-1},\end{aligned}$$

with $\mathbf{Z} = (\mathbf{z}'_1, ..., \mathbf{z}'_T)'$ and $\mathbf{Y}_\ell = (y_{\ell 1}, ..., y_{\ell T})'$. Subscripts 1 and 2 refer to equations (A.12) and (A.13), respectively.

A.16 Solving the GVAR model

A.16.1 Solution

Although estimation is done on a country by country basis, the GVAR model is solved for the world as a whole (in terms of a $k \times 1$ global variable vector, $k = \sum_{i=0}^{N} k_i$), taking account of the fact that all the variables are endogenous to the system as a whole.

Specifically, after estimating the individual country VECMX* models as described in Section A.8 the corresponding VARX* models are recovered. Starting from the estimated country-specific VARX*(p_i, q_i) models

$$\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \boldsymbol{\Phi}_{i1}\mathbf{x}_{i,t-1} + ... + \boldsymbol{\Phi}_{ip_i}\mathbf{x}_{i,t-p_i} + \boldsymbol{\Lambda}_{i0}\mathbf{x}^*_{it} + \boldsymbol{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + ... + \boldsymbol{\Lambda}_{iq_i}\mathbf{x}^*_{i,t-q_i} + \mathbf{u}_{it}, \tag{A.14}$$

define $\mathbf{z}_{it}$ by

$$\mathbf{z}_{it} = \begin{pmatrix} \mathbf{x}_{it} \\ \mathbf{x}^*_{it} \end{pmatrix}.$$

Assuming that $p_i = q_i$ for ease of exposition, write (A.14) for each economy as

$$\mathbf{A}_{i0}\mathbf{z}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{A}_{i1}\mathbf{z}_{it-1} + ... + \mathbf{A}_{ip_i}\mathbf{z}_{it-p_i} + \mathbf{u}_{it},$$

where

$$\mathbf{A}_{i0} = (\mathbf{I}_{k_i}, -\mathbf{\Lambda}_{i0}), \quad \mathbf{A}_{ij} = (\mathbf{\Phi}_{ij}, \mathbf{\Lambda}_{ij}) \text{ for } j = 1, ..., p_i.$$

We can then use the so called link matrices $\mathbf{W}_i$, defined by the trade weights w_{ij}, to obtain the identity

$$\mathbf{z}_{it} = \mathbf{W}_i\mathbf{x}_t, \tag{A.15}$$

where $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ is the $k \times 1$ vector which collects all the endogenous variables of the system, and $\mathbf{W}_i$ is a $(k_i + k_i^*) \times k$ matrix.[8]

Using the identity given by (A.15) it follows that

$$\mathbf{A}_{i0}\mathbf{W}_i\mathbf{x}_t = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{A}_{i1}\mathbf{W}_i\mathbf{x}_{t-1} + ... + \mathbf{A}_{ip_i}\mathbf{W}_i\mathbf{x}_{t-p_i} + \mathbf{u}_{it}, \text{ for } i = 0, 1, 2, ..., N,$$

and these individual models are then stacked to yield the model for $\mathbf{x}_t$ given by

$$\mathbf{G}_0\mathbf{x}_t = \mathbf{a}_0 + \mathbf{a}_1\mathbf{t} + \mathbf{G}_1\mathbf{x}_{t-1} + ... + \mathbf{G}_p\mathbf{x}_{t-p} + \mathbf{u}_t, \tag{A.16}$$

where

$$\mathbf{G}_0 = \begin{pmatrix} \mathbf{A}_{00}\mathbf{W}_0 \\ \mathbf{A}_{10}\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_{N0}\mathbf{W}_N \end{pmatrix}, \ \mathbf{G}_j = \begin{pmatrix} \mathbf{A}_{0j}\mathbf{W}_0 \\ \mathbf{A}_{1j}\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_{Nj}\mathbf{W}_N \end{pmatrix} \text{ for } j = 1, ..., p,$$

$$\mathbf{a}_0 = \begin{pmatrix} \mathbf{a}_{00} \\ \mathbf{a}_{10} \\ \vdots \\ \mathbf{a}_{N0} \end{pmatrix}, \ \mathbf{a}_1 = \begin{pmatrix} \mathbf{a}_{01} \\ \mathbf{a}_{11} \\ \vdots \\ \mathbf{a}_{N1} \end{pmatrix}, \mathbf{u}_t = \begin{pmatrix} \mathbf{u}_{0t} \\ \mathbf{u}_{1t} \\ \vdots \\ \mathbf{u}_{Nt} \end{pmatrix},$$

and $p = \max p_i$ across all i. In general $p = \max(\max p_i, \max q_i)$.

Since $\mathbf{G}_0$ is a known non-singular matrix that depends on the trade weights and parameter estimates, premultiplying (A.16) by $\mathbf{G}_0^{-1}$, the GVAR(p) model is obtained as

$$\mathbf{x}_t = \mathbf{b}_0 + \mathbf{b}_1\mathbf{t} + \mathbf{F}_1\mathbf{x}_{t-1} + ... + \mathbf{F}_p\mathbf{x}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{A.17}$$

where

$$\mathbf{b}_0 = \mathbf{G}_0^{-1}\mathbf{a}_0, \ \mathbf{b}_1 = \mathbf{G}_0^{-1}\mathbf{a}_1,$$
$$\mathbf{F}_j = \mathbf{G}_0^{-1}\mathbf{G}_j, \ \ j = 1, ..., p, \ \boldsymbol{\varepsilon}_t = \mathbf{G}_0^{-1}\mathbf{u}_t.$$

Equation (A.17) can be solved recursively and used for a variety of purposes. There are no restrictions placed on the covariance matrix $\mathbf{\Sigma}_\varepsilon = \mathbf{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}'_t)$, unless one specifically decides to do so.

[8] Any global observable variables entering in one or more of the individual country models as weakly exogenous can be resolved through the $\mathbf{W}_i$ matrix, providing they also enter as a domestic variable in one country model. Solution of the GVAR model in the more general case is covered in Section A.24.

A.16.2 An example of constructing the ‘link’ matrices

Consider a global model composed of three countries in three variables, say output (y), inflation (Dp) and the nominal exchange rate (e), all in logs. We have

$$\mathbf{x}_t = \begin{pmatrix} \mathbf{x}_{0t} \\ \mathbf{x}_{1t} \\ \mathbf{x}_{2t} \end{pmatrix} = \begin{pmatrix} y_{0t} \\ \Delta p_{0t} \\ y_{1t} \\ \Delta p_{1t} \\ e_{1t} \\ y_{2t} \\ \Delta p_{2t} \\ e_{2t} \end{pmatrix}, \quad \mathbf{z}_{0t} = \begin{pmatrix} y_{0t} \\ \Delta p_{0t} \\ y_{0t}^* \\ \Delta p_{0t}^* \\ e_{0t}^* \end{pmatrix}, \quad \mathbf{z}_{it} = \begin{pmatrix} y_{it} \\ \Delta p_{it} \\ e_{it} \\ y_{it}^* \\ \Delta p_{it}^* \end{pmatrix}, \quad i = 1, 2.$$

The foreign variables are computed as

$$\begin{aligned} y_{it}^* &= \sum_{j=0}^{2} w_{ij} y_{jt}, \ \Delta p_{it}^* = \sum_{j=0}^{2} w_{ij} \Delta p_{jt}, \\ e_{0t}^* &= w_{01} e_{1t} + w_{02} e_{2t}, \end{aligned}$$

where

$$\begin{gathered} w_{00} = w_{11} = w_{22} = 0, \\ w_{01} + w_{02} = 1, \ \ w_{10} + w_{12} = 1, \ \ w_{20} + w_{21} = 1. \end{gathered}$$

The link matrix $\mathbf{W}_i$ for each country is a $(k_i + k_i^*) \times k$ matrix of fixed (known) constants defined in terms of the country specific weights, w_{ij}, where k_i and k_i^* are the number of domestic and foreign variables respectively, and $k = \sum_{i=0}^{N} k_i$, such that the identity given by (A.15) holds. Thus, in this example $\mathbf{W}_i$ is a 5×8 matrix for each i given by

$$\mathbf{W}_0 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & w_{01} & 0 & 0 & w_{02} & 0 & 0 \\ 0 & 0 & 0 & w_{01} & 0 & 0 & w_{02} & 0 \\ 0 & 0 & 0 & 0 & w_{01} & 0 & 0 & w_{02} \end{pmatrix} = \begin{pmatrix} \mathbf{I}_2 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & w_{01}\mathbf{I}_3 & w_{02}\mathbf{I}_3 \end{pmatrix},$$

$$\mathbf{W}_1 = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ w_{10} & 0 & 0 & 0 & 0 & w_{12} & 0 & 0 \\ 0 & w_{10} & 0 & 0 & 0 & 0 & w_{12} & 0 \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \mathbf{I}_3 & \mathbf{0} & \mathbf{0} \\ w_{10}\mathbf{I}_2 & \mathbf{0} & w_{12}\mathbf{I}_2 & \mathbf{0} \end{pmatrix},$$

$$\mathbf{W}_2 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ w_{20} & 0 & w_{21} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{20} & 0 & w_{21} & 0 & 0 & 0 & 0 \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_3 \\ w_{20}\mathbf{I}_2 & w_{21}\mathbf{I}_2 & \mathbf{0} & \mathbf{0} \end{pmatrix}.$$

Using the above expressions for $\mathbf{W}_i$, one can easily verify that $\mathbf{z}_{it} = \mathbf{W}_i \mathbf{x}_t$ for each i.

A.17 Eigenvalues

Consider the GVAR(p) model given by (A.17). We can write the GVAR(p) representation of (A.17) in the form

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{x}_{t-1} \\ \vdots \\ \vdots \\ \mathbf{x}_{t-p+1} \end{bmatrix} = \begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_2 & \dots & \mathbf{F}_{p-1} & \mathbf{F}_p \\ \mathbf{I}_k & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_k & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_k & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{x}_{t-2} \\ \vdots \\ \vdots \\ \mathbf{x}_{t-p} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{0} \\ \vdots \\ \vdots \\ \mathbf{0} \end{bmatrix},$$

which is a GVAR(1) model, but in the $kp \times 1$ vector of random variables $\mathbf{X}_t = (\mathbf{x}'_t, \mathbf{x}'_{t-1}, ..., \mathbf{x}'_{t-p+1})'$, namely

$$\mathbf{X}_t = \mathbf{F}\mathbf{X}_{t-1} + \mathbf{E}_t,$$

where $\mathbf{F}$ is now the $kp \times kp$ companion coefficient matrix

$$\mathbf{F} = \begin{pmatrix} \mathbf{F}_1 & \mathbf{F}_2 & \dots & \mathbf{F}_{p-1} & \mathbf{F}_p \\ \mathbf{I}_k & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_k & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_k & \mathbf{0} \end{pmatrix},$$

and $\mathbf{E}_t = (\boldsymbol{\varepsilon}'_t, \mathbf{0}', ..., \mathbf{0}')'$ is the $kp \times 1$ vector of error terms.

The eigenvalues of the GVAR model, denoted by $\lambda_{eig} = a \pm bi$, are computed as the eigenvalues of the companion matrix $\mathbf{F}$ by solving the determinantal equation

$$|\mathbf{I}_{kp}\lambda_{eig} - \mathbf{F}| = 0. \tag{A.18}$$

Their corresponding moduli are computed as $\mathrm{mod}(\lambda_{eig}) = \sqrt{a^2 + b^2}$. In the case of I(1), cointegrated variables the roots of equation (A.18) should lie inside and at most on the unit circle.

A.18 Persistence profiles

Persistence profiles (PPs) refer to the time profiles of the effects of system or variable-specific shocks on the cointegrating relations in the GVAR model (Pesaran and Shin, 1996). PPs have a value of unity on impact, while they should tend to zero as the horizon $n \to \infty$, if the vector under consideration is a valid cointegrating vector. They provide information on the speed with which the cointegrating relationships return to their equilibrium states.

Consider again the GVAR(p) model given by (A.17). The moving average representation of (A.17) is given by

$$\begin{aligned} \mathbf{x}_t &= \mathbf{d}_t + \sum_{s=0}^{\infty} \mathbf{A}_s \boldsymbol{\varepsilon}_{t-s} \qquad (A.19) \\ &= \boldsymbol{\varepsilon}_t + \mathbf{A}_1\boldsymbol{\varepsilon}_{t-1} + \mathbf{A}_2\boldsymbol{\varepsilon}_{t-2} + ... \end{aligned}$$

where $\mathbf{d}_t$ represents the deterministic component of $\mathbf{x}_t$, and $\mathbf{A}_s$ can be derived recursively as

$$\mathbf{A}_s = \mathbf{F}_1\mathbf{A}_{s-1} + \mathbf{F}_2\mathbf{A}_{s-2} + ... + \mathbf{F}_p\mathbf{A}_{s-p}, \; s = 1, 2, ... \tag{A.20}$$

with $\mathbf{A}_0 = \mathbf{I}_m$, $\mathbf{A}_s = \mathbf{0}$, for $s < 0$.

In the context of the GVAR, the cointegrating relations are given in terms of the country-specific variables, namely $\boldsymbol{\beta}_i'\mathbf{z}_{it}$, whilst the variables in the GVAR are given by $\mathbf{x}_t$. Using the identity $\mathbf{z}_{it} = \mathbf{W}_i\mathbf{x}_t$, which provides the mapping between $\mathbf{z}_{it}$ and $\mathbf{x}_t$, from equation (A.19) we have that

$$\mathbf{z}_{it} = \mathbf{W}_i\mathbf{d}_t + \mathbf{W}_i\mathbf{A}_0\boldsymbol{\varepsilon}_t + \sum_{s=1}^{\infty}\mathbf{W}_i\mathbf{A}_s\boldsymbol{\varepsilon}_{t-s}.$$

The PPs of $\boldsymbol{\beta}_{ji}'\mathbf{z}_{it}$, with respect to a system-wide shock to $\boldsymbol{\varepsilon}_t$, are obtained as

$$\mathcal{PP}(\boldsymbol{\beta}_{ji}'\mathbf{z}_{it}; \boldsymbol{\varepsilon}_t, n) = \frac{\boldsymbol{\beta}_{ji}'\mathbf{W}_i\mathbf{A}_n\boldsymbol{\Sigma}_\varepsilon\mathbf{A}_n'\mathbf{W}_i'\boldsymbol{\beta}_{ji}}{\boldsymbol{\beta}_{ji}'\mathbf{W}_i\mathbf{A}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{A}_0'\mathbf{W}_i'\boldsymbol{\beta}_{ji}}, n = 0, 1, 2, ... \tag{A.21}$$

where $\boldsymbol{\beta}_{ji}'$ is the j^{th} cointegrating relation in the i^{th} country $(j = 1, 2, ..., r_i)$, n is the horizon and $\boldsymbol{\Sigma}_\varepsilon$ is the covariance matrix of $\boldsymbol{\varepsilon}_t$. The $\mathbf{A}_n$ matrices are calculated based on (A.20).

A.19 Impulse response analysis

Impulse responses refer to the time profile of the effects of variable-specific shocks or identified shocks (such as monetary policy or technology shocks, identified using a suitable economic theory) on the future states of a dynamical system and thus, on all the variables in the model. The impulse responses of shocks to specific variables considered for the GVAR model are the generalised impulse response functions (GIRFs), introduced in Koop, Pesaran and Potter (1996) and adapted to VAR models in Pesaran and Shin (1998).

A.19.1 Generalised impulse response functions

Consider the model obtained during the solution of the GVAR expressed in terms of the country specific errors given by (A.16).

The GIRFs are based on the definition

$$\mathcal{GIRF}(\mathbf{x}_t; u_{i\ell t}, n) = E(\mathbf{x}_{t+n}|u_{i\ell t} = \sqrt{\sigma_{ii,\ell\ell}}, \mathcal{I}_{t-1}) - E(\mathbf{x}_{t+n}|\mathcal{I}_{t-1}),$$

where $\mathcal{I}_{t-1}$ is the information set at time $t-1$, $\sigma_{ii,\ell\ell}$ is the diagonal element of the variance-covariance matrix $\boldsymbol{\Sigma}_u$ corresponding to the ℓ^{th} equation in the i^{th} country, and n is the horizon.

On the assumption that $\mathbf{u}_t$ has a multivariate normal distribution[9], it follows that the GIRFs of a unit (one standard error) shock at time t to the ℓ^{th} equation in the above model on the j^{th} variable at time $t+n$ is given by the j^{th} element of

$$\mathcal{GIRF}(\mathbf{x}_t; u_{\ell t}, n) = \frac{\mathfrak{e}_j'\mathbf{A}_n\mathbf{G}_0^{-1}\boldsymbol{\Sigma}_u\mathfrak{e}_\ell}{\sqrt{\mathfrak{e}_\ell'\boldsymbol{\Sigma}_u\mathfrak{e}_\ell}}, n = 0, 1, 2, ...; \ell, j = 1, 2, ..., k, \tag{A.22}$$

where $\mathfrak{e}_\ell = (0, 0, ..., 0, 1, 0, ...0)'$ is a selection vector with unity as the ℓ^{th} element in the case of a country-specific shock. For a regional shock say to equity, $\mathfrak{e}_\ell$ has PPP-GDP weights that sum to one corresponding to the equity shocks of each of the countries that belong to the selected region, and zeros elsewhere. For a global shock to equity, $\mathfrak{e}_\ell$ has PPP-GDP weights that sum to one, corresponding to the equity shocks of each of the $N+1$ countries and zeros elsewhere. Note that

[9]This result also holds in non-Gaussian but linear settings where the conditional expectation can be assumed to be linear.

if equity prices are not available for a particular country, the PPP-GDP weights are reweighted to sum to one. The $\mathbf{A}_n$ matrices are calculated based on (A.20).

While GIRFs are invariant to the ordering of the variables, one needs to be cautious when interpretating the effect of shocks using GIRFs as they allow for correlation of the error terms (the error terms are not orthogonal).

A.19.2 Structural impulse responses

The user has the option to identify shocks to a single country within the GVAR model or to identify shocks to all countries.

Identification of shocks to a single country

Below we illustrate the identification of shocks to the US economy. To this end, the US model is placed first, or reordered if this is not the case from the outset. Following Sims (1980), alternative orderings of the variables within the US model can then be considered. In selecting the ordering of the variables economic theory can be a useful guide. The outcome of this exercise will be invariant to the ordering of the rest of the variables in the GVAR model, so long as the contemporaneous correlations of these shocks are left unrestricted (both in relation to themselves and with respect to the US shocks). The ordering of the rest of the variables in the GVAR model will be important for the analysis of the US structural shocks only if short-run overidentifying restrictions are imposed on the parameters of the models.

Consider the VARX*(p_0, q_0) model for the US

$$\begin{aligned}\mathbf{x}_{0t} &= \mathbf{a}_{00} + \mathbf{a}_{01}t + \mathbf{\Phi}_{01}\mathbf{x}_{0,t-1} + ... + \mathbf{\Phi}_{0p_0}\mathbf{x}_{0,t-p_0} \\ &\quad + \mathbf{\Lambda}_{00}\mathbf{x}^*_{0t} + \mathbf{\Lambda}_{01}\mathbf{x}^*_{0,t-1} + ... + \mathbf{x}^*_{0,t-q_0} + \mathbf{u}_{0t}.\end{aligned}$$

Let $\mathbf{v}_{0t}$ be the structural shocks given by

$$\mathbf{v}_{0t} = \mathbf{P}_0\mathbf{u}_{0t},$$

where $\mathbf{P}_0$ is a $k_0 \times k_0$ matrix of coefficients to be identified. The identification conditions using the triangular approach of Sims (1980) require $\mathbf{\Sigma}_{\mathrm{v}0} = Cov(\mathbf{v}_{0t})$ to be diagonal and $\mathbf{P}_0$ to be lower triangular. Let $\mathbf{Q}_0$ be the upper Cholesky factor of $Cov(\mathbf{u}_{0t}) = \mathbf{\Sigma}_{u0} = \mathbf{Q}_0'\mathbf{Q}_0$ so that $\mathbf{\Sigma}_{\mathrm{v}0} = \mathbf{P}_0\mathbf{\Sigma}_{u0}\mathbf{P}_0'$, with $\mathbf{P}_0 = (\mathbf{Q}_0')^{-1}$. Under this orthogonalisation scheme $Cov(\mathbf{v}_{0t}) = \mathbf{I}_{k_0}$.

Premultiplying the GVAR model (A.16) by

$$\mathbf{P}^0_{G_0} = \begin{pmatrix} \mathbf{P}_0 & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{k_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_{k_N} \end{pmatrix},$$

it follows that

$$\mathbf{P}^0_{G_0}\mathbf{G}_0\mathbf{x}_t = \mathbf{P}^0_{G_0}\mathbf{G}_1\mathbf{x}_{t-1} + ... + \mathbf{P}^0_{G_0}\mathbf{G}_p\mathbf{x}_{t-p} + \mathbf{v}_t,$$

where $\mathbf{v}_t = (\mathbf{v}_{0t}', \mathbf{u}_{1t}', ..., \mathbf{u}_{Nt}')'$ and

$$\mathbf{\Sigma}_{\mathrm{v}} = Cov\left(\mathbf{v}_t\right) = \begin{pmatrix} V(\mathbf{v}_{0t}) & Cov(\mathbf{v}_{0t}, \mathbf{u}_{1t}) & \cdots & Cov(\mathbf{v}_{0t}, \mathbf{u}_{Nt}) \\ Cov(\mathbf{u}_{1t}, \mathbf{v}_{0t}) & V(\mathbf{u}_{1t}) & \cdots & Cov(\mathbf{u}_{1t}, \mathbf{u}_{Nt}) \\ \vdots & \vdots & & \vdots \\ Cov(\mathbf{u}_{Nt}, \mathbf{v}_{0t}) & Cov(\mathbf{u}_{Nt}, \mathbf{u}_{1t}) & \cdots & V(\mathbf{u}_{Nt}) \end{pmatrix},$$

with

$$V(\mathbf{v}_{0t}) = \mathbf{\Sigma}_{\mathrm{v},00} = \mathbf{P}_0\mathbf{\Sigma}_{u,00}\mathbf{P}_0',$$
$$Cov(\mathbf{v}_{0t},\mathbf{u}_{jt}) = Cov(\mathbf{P}_0\mathbf{u}_{0t},\mathbf{u}_{jt}) = \mathbf{P}_0\mathbf{\Sigma}_{u,0j}.$$

By using the definition of the generalised impulse responses with respect to the structural shocks given by

$$\mathcal{SGIRF}(\mathbf{x}_t; \mathrm{v}_{\ell t}, n) = E(\mathbf{x}_{t+n}|\mathcal{I}_{t-1,}\mathfrak{e}_\ell'\mathbf{v}_t = \sqrt{\mathfrak{e}_\ell'\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}) - E(\mathbf{x}_{t+n}|\mathcal{I}_{t-1}),$$

it follows that for a structurally identified shock, $\mathrm{v}_{\ell t}$, such as a US monetary policy shock the GIRF is given by

$$\mathcal{SGIRF}(\mathbf{x}_t; \mathrm{v}_{\ell t}, n) = \frac{\mathfrak{e}_j'\mathbf{A}_n(\mathbf{P}_{G_0}^0\mathbf{G}_0)^{-1}\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}{\sqrt{\mathfrak{e}_\ell'\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}}, n = 0, 1, 2, ...; \ell, j = 1, 2, ..., k, \tag{A.23}$$

where $\mathbf{\Sigma}_{\mathrm{v}}$ is the covariance matrix of the structural shocks and $\mathbf{P}_{G_0}^0\mathbf{G}_0$ is defined by the identification scheme used to identify the shocks.

Identification of shocks to all countries

This option requires the user to select the ordering of all the $N+1$ countries and k variables included in the GVAR, and then proceeds with the computation of the usual orthogonalised impulse response functions. It is reasonable once again for the US to be placed first followed by the remaining countries. Then the orthogonalised impulse response functions based on (A.16) are given by

$$\mathcal{OIRF}(\mathbf{x}_t; u_{\ell t}^*, n) = \mathfrak{e}_j'\mathbf{A}_n\mathbf{G}_0^{-1}\mathbf{Q}\mathfrak{e}_\ell, n = 0, 1, 2, ...; \ell, j = 1, 2, ..., k, \tag{A.24}$$

where $u_{\ell t}^*$ is an orthogonalised residual, and $\mathbf{Q}$ is a lower triangular matrix obtained by the Cholesky decomposition of $\mathbf{\Sigma}_u^0 = \mathbf{Q}\mathbf{Q}'$, with $\mathbf{\Sigma}_u^0$ the covariance matrix corresponding to the re-ordered residuals $\mathbf{u}_t^0$. The covariance matrix is therefore required to be positive definite when computing the orthogonalised IRFs. The results of the OIRFs will depend on the specific country/variable ordering.

A.20 Forecast error variance decomposition

Traditionally the forecast error variance decomposition of a VAR model is performed on a set of orthogonalised shocks, whereby the contribution of the j^{th} orthogonalised innovation to the mean square error of the n-step ahead forecast of the model is calculated. In the case of the GVAR, the shocks across countries, that is u_{it} and u_{st} for $i \neq s$, are not orthogonal. In fact, there is evidence that on average the shocks across countries are positively correlated. The standard application of the orthogonalised FEVD to the GVAR model is therefore not valid. An alternative approach (that is invariant to the ordering of the variables), would be to consider the proportion of the variance of the n-step forecast errors of $\mathbf{x}_t$ which is explained by conditioning on the non-orthogonalised shocks u_{jt}, $u_{j,t+1}$,..., $u_{j,t+n}$, for $j = 1, ..., k$, while explicitly allowing for the contemporaneous correlations between these shocks and the shocks to the other equations in the system.

Analogously to the GIRFs, the generalised forecast error variance decomposition (GFEVD) of shocks to specific variables in equation (A.16) can be derived as

$$\mathcal{GFEVD}(\mathbf{x}_{(\ell)t}; u_{(j)t}, n) = \frac{\sigma_{jj}^{-1}\sum_{s=0}^{n}\left(\mathfrak{e}_\ell'\mathbf{A}_s\mathbf{G}_0^{-1}\boldsymbol{\Sigma}_u\mathfrak{e}_j\right)^2}{\sum_{s=0}^{n}\mathfrak{e}_\ell'\mathbf{A}_s\mathbf{G}_0^{-1}\boldsymbol{\Sigma}_u\mathbf{G}_0^{-1\prime}\mathbf{A}_s'\mathfrak{e}_\ell}, \text{ for } n = 0, 1, 2, ... \tag{A.25}$$

and $\ell = 1, ..., k$, which gives the proportion of the n-step ahead forecast error variance of the ℓ^{th} element of $\mathbf{x}_t$ accounted for by the innovations in the j^{th} element of $\mathbf{x}_t$.[10] Notice that due to the non-diagonal form of $\boldsymbol{\Sigma}_u$, the elements of $\mathcal{GFEVD}(\mathbf{x}_{(\ell)t}; u_{(j)t}, n)$ across j need not sum to unity. GFEVDs of regional and global shocks can also be computed, where these shocks are defined in exactly the same way as for the GIRFs.

Under structural identification of the shocks to a single country, similar to the GIRFs, we have

$$\mathcal{SGFEVD}(\mathbf{x}_{(\ell)t}; \mathrm{v}_{(j)t}, n) = \frac{\sigma_{jj}^{-1}\sum_{s=0}^{n}\{\mathfrak{e}_\ell'\mathbf{A}_s(\mathbf{P}_{G_0}^0\mathbf{G}_0)^{-1}\boldsymbol{\Sigma}_{\mathrm{v}}\mathfrak{e}_j\}^2}{\sum_{s=0}^{n}\mathfrak{e}_\ell'\mathbf{A}_s(\mathbf{P}_{G_0}^0\mathbf{G}_0)^{-1}\boldsymbol{\Sigma}_{\mathrm{v}}(\mathbf{P}_{G_0}^0\mathbf{G}_0)^{-1\prime}\mathbf{A}_s'\mathfrak{e}_\ell}, \text{ for } n = 0, 1, ... \tag{A.26}$$

In the case of orthogonalised shocks

$$\mathcal{OFEVD}(\mathbf{x}_{(\ell)t}; u_{(j)t}^*, n) = \frac{\sum_{s=0}^{n}\{\mathfrak{e}_\ell'\mathbf{A}_s\mathbf{G}_0^{-1}\mathbf{Q}\mathfrak{e}_j\}^2}{\sum_{s=0}^{n}\mathfrak{e}_\ell'\mathbf{A}_s\mathbf{G}_0^{-1}\boldsymbol{\Sigma}_u\mathbf{G}_0^{-1\prime}\mathbf{A}_s'\mathfrak{e}_\ell}, \text{ for } n = 0, 1, ... \tag{A.27}$$

where as for the OIRFs $u_{(j)t}^*$ is an orthogonalised residual and $\mathbf{Q}$ is a lower triangular matrix obtained by the Cholesky decomposition of $\boldsymbol{\Sigma}_u^0 = \mathbf{Q}\mathbf{Q}'$, with $\boldsymbol{\Sigma}_u^0$ the covariance matrix corresponding to the re-ordered residuals $\mathbf{u}_t^0$. The covariance matrix is therefore required to be positive definite when computing the orthogonalised FEVD. $\mathcal{OFEVD}(\mathbf{x}_{(\ell)t}; u_{(j)t}^*, n)$ can be viewed as measuring the proportion of the n-step ahead forecast error variance of variable ℓ, which is accounted for by the orthogonalised innovations in variable j.

As with the SGIRFs and OIRFs, the SGFEVD in (A.26) and the OFEVD in (A.27) are not invariant to the ordering of the variables in the structurally identified country and all variables in the GVAR, respectively.

A.20.1 Derivation of the generalised forecast error variance decomposition

Consider the MA representation (A.19) of the GVAR model. The forecast error of predicting $\mathbf{x}_{t+n}$ conditional on the information at time $t-1$ is given by

$$\boldsymbol{\xi}_t(n) = \sum_{l=0}^{n}\mathbf{A}_l\boldsymbol{\varepsilon}_{t+n-l}, \text{ for } n = 0, 1, 2, ...$$

[10] Formula (A.25) corresponds to performing GFEVD for the errors, $\mathbf{u}_{it}$, in the country-specific models. GFEVD can also be performed for the errors of the global model, $\boldsymbol{\varepsilon}_t$.

where the $\mathbf{A}_l$ matrices are computed using (A.20), and the total forecast error covariance matrix is

$$\boldsymbol{\Omega}_n = \sum_{l=0}^{n} \mathbf{A}_l \boldsymbol{\Sigma}_\varepsilon \mathbf{A}_l'.$$

In what follows, we will consider the forecast error covariance matrix of predicting $\mathbf{x}_{t+n}$ conditional on the information at time $t-1$, and the contemporaneous and expected future shocks to the j^{th} equation, $\varepsilon_{jt}, \varepsilon_{j,t+1}, ..., \varepsilon_{j,t+n}$. The forecast error of predicting $\mathbf{x}_{t+n}$ in this case is given by[11]

$$\boldsymbol{\xi}_t^j(n) = \sum_{l=0}^{n} \mathbf{A}_l \left[\boldsymbol{\varepsilon}_{t+n-l} - E(\boldsymbol{\varepsilon}_{t+n-l}|\varepsilon_{j,t+n-l})\right]. \tag{A.28}$$

Assuming that $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Sigma}_\varepsilon)$ we obtain that

$$E(\boldsymbol{\varepsilon}_{t+n-l}|\varepsilon_{j,t+n-l}) = (\sigma_{jj}^{-1}\boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j)\varepsilon_{j,t+n-l}, \tag{A.29}$$

for $j = 1, .., k$ and $l = 0, 1, .., n$, where $\mathfrak{e}_j$ is a $k \times 1$ selection vector with its element corresponding to the j^{th} variable in $\mathbf{x}_{t+n}$ equal to unity and zeros elsewhere. Substituting (A.29) in (A.28) yields

$$\boldsymbol{\xi}_t^j(n) = \sum_{l=0}^{n} \mathbf{A}_l(\boldsymbol{\varepsilon}_{t+n-l} - \sigma_{jj}^{-1}\boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j \varepsilon_{j,t+n-l}),$$

and the forecast error covariance matrix in this case becomes

$$\boldsymbol{\Omega}_n^j = \sum_{l=0}^{n} \mathbf{A}_l \boldsymbol{\Sigma}_\varepsilon \mathbf{A}_l' - \sigma_{jj}^{-1} \sum_{l=0}^{n} \mathbf{A}_l \boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j \mathfrak{e}_j' \boldsymbol{\Sigma}_\varepsilon \mathbf{A}_l'.$$

The decline in the n-step ahead forecast error variance of $\mathbf{x}_t$ as a result of conditioning on the expected future shocks to the j^{th} equation is given by

$$\Delta_{jn} = \boldsymbol{\Omega}_n - \boldsymbol{\Omega}_n^j = \sigma_{jj}^{-1} \sum_{l=0}^{n} \mathbf{A}_l \boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j \mathfrak{e}_j' \boldsymbol{\Sigma}_\varepsilon \mathbf{A}_l'.$$

Obtaining the change Δ_{jn} of the n-step ahead forecast error variance of $\mathbf{x}_t$ with respect to the ℓ^{th} variable as

$$\Delta_{(\ell)jn} = \mathfrak{e}_\ell' \left(\boldsymbol{\Omega}_n - \boldsymbol{\Omega}_n^j\right) \mathfrak{e}_\ell = \sigma_{jj}^{-1} \sum_{l=0}^{n} \left(\mathfrak{e}_\ell' \mathbf{A}_l \boldsymbol{\Sigma}_\varepsilon \mathfrak{e}_j\right)^2 \ , \ell, j = 1, .., k,$$

and scaling it by the n-step ahead forecast error variance of the ℓ^{th} variable of $\mathbf{x}_t$ yields the GFEVD formula for the errors in the global model. However, as in the case of impulse response analysis, GFEVD is performed for the errors in the country-specific models, $\mathbf{u}_{it}$, in which case the above derivation can be easily adjusted using (A.16) to yield (A.25). The formula for the case of structural shocks follows similarly.

[11]Note that as the $\boldsymbol{\varepsilon}_t s$ are serially uncorrelated, $E(\boldsymbol{\varepsilon}_{t+n-l}|\varepsilon_{jt}, \varepsilon_{j,t+1}, ..., \varepsilon_{j,t+n}) = E(\boldsymbol{\varepsilon}_{t+n-l}|\varepsilon_{j,t+n-l})$, $l = 0, 1, ..., n$.

A.21 Covariance matrix selection and estimation

In the above formulas for the PPs, IRFs and FEVDs, an estimate of the covariance matrix, $\mathbf{\Sigma}_u$, of the stacked country specific residuals $\mathbf{u}_t$ is required. The covariance matrix, $\mathbf{\Sigma}_u$, can be consistently estimated by

$$\hat{\mathbf{\Sigma}}_u = \sum_{t=1}^{T} \hat{\mathbf{u}}_t \hat{\mathbf{u}}_t' / T,$$

and since $\boldsymbol{\varepsilon}_t = \mathbf{G}_0^{-1}\mathbf{u}_t$, $\hat{\mathbf{\Sigma}}_\varepsilon$ can be computed as

$$\hat{\mathbf{\Sigma}}_\varepsilon = \mathbf{G}_0^{-1} \hat{\mathbf{\Sigma}}_u \mathbf{G}_0^{-1\prime} = \sum_{t=1}^{T} \hat{\boldsymbol{\varepsilon}}_t \hat{\boldsymbol{\varepsilon}}_t' / T. \tag{A.30}$$

A.21.1 Selecting the covariance matrix

The user can select between the following covariance matrices for computation of PP, IRF and FEVD point and bootstrap estimates:

- The sample covariance matrix, $(\hat{\mathbf{\Sigma}}_u)$
- The block diagonal covariance matrix, $Bdiag(\hat{\mathbf{\Sigma}}_u)$: Restricts all cross-country error covariances in $\hat{\mathbf{\Sigma}}_u$ to zero
- The block diagonal covariance matrix with exception country, $BEdiag(\hat{\mathbf{\Sigma}}_u)$: Restricts all cross-country error covariances in $\hat{\mathbf{\Sigma}}_u$ to zero except for one country of the user's choice. If that country is for example the US, then non-zero error covariances will only exist between the US and all the remaining countries.

The default option is the sample covariance matrix. The block diagonal covariance matrix and that with an exception country are restricted versions of the sample covariance matrix. These restrictions may be of interest in particular situations.

A.21.2 Positive definiteness of the covariance matrix estimator

If the dimension of the endogenous variables in the GVAR model, k, is larger than the time series dimension, T, $\hat{\mathbf{\Sigma}}_u$ is not guaranteed to be a positive definite matrix. This is an important consideration when computing bootstrapped error bands for the impulse responses, or bootstrapped critical values for the structural stability tests and overidentifying restrictions test of the cointegrating vectors, under the bootstrap approach 'inverse' that will be discussed below. It is also an issue for the computation of the OIRF point estimates, given that a positive definite covariance matrix is required to perform the Cholesky decomposition as seen earlier.

A number of approaches have been suggested in the literature to deal with this probem. The GVAR Toolbox 2.0 incorporates the Ledoit and Wolf (2004, LW) type shrinkage approach on the correlation matrix as proposed in Bailey, Pesaran and Smith (2014, BPS), where further details can be found together with a review of the literature. BPS show that this approach works reasonably well, particularly when the inverse covariance matrix is of interest. This version of the toolbox also allows the user to implement the 'naive' shrinkage approach included in version 1.1. though in a slightly modified form, to be discussed below. Both shrinkage approaches ensure that the size of the shock when conducting impulse response analysis remains unchanged. Moreover, they can be applied to any of the covariance matrices listed above.

LW shrinkage on the correlation matrix

Consider the sample covariance estimator

$$\hat{\boldsymbol{\Sigma}}_u = T^{-1}\sum_{t=1}^{T}\hat{\mathbf{u}}_t\hat{\mathbf{u}}_t' = (\hat{\sigma}_{ij}),$$

where $\hat{\mathbf{u}}_t$ is the vector of stacked residuals from the estimated country-specific models

$$\hat{\mathbf{u}}_t = \hat{\mathbf{G}}_0\mathbf{x}_t - \hat{\mathbf{a}}_0 - \hat{\mathbf{a}}_1\mathbf{t} - \hat{\mathbf{G}}_1\mathbf{x}_{t-1} - ... - \hat{\mathbf{G}}_2\mathbf{x}_{t-p}.$$

Also let

$$\hat{\mathbf{D}} = diag\left(\hat{\boldsymbol{\Sigma}}_u\right),$$

and note that the corresponding sample correlation matrix $\hat{\mathbf{R}}_u = (\hat{\rho}_{ij})$ can be written as

$$\hat{\mathbf{R}}_u = \hat{\mathbf{D}}^{-1/2}\hat{\boldsymbol{\Sigma}}_u\hat{\mathbf{D}}^{-1/2} = (\hat{\rho}_{ij}),$$

where by construction $\hat{\rho}_{ii} = 1$ and

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{\sqrt{\sum_{t=1}^{T}\hat{u}_{it}^2}\sqrt{\sum_{t=1}^{T}\hat{u}_{jt}^2}}, \text{ for } i \neq j.$$

Shrinkage is performed on the correlation matrix yielding the following shrinkage estimator

$$\widetilde{\mathbf{R}}_u(\lambda) = \lambda\mathbf{I}_N + (1-\lambda)\hat{\mathbf{R}}_u, \tag{A.31}$$

where the shrinkage parameter $\lambda \in [0,1]$. The optimal value of the shrinkage parameter λ that minimizes the squared Frobenius norm of the error of estimating $\mathbf{R}_u$ by $\widetilde{\mathbf{R}}_u$ is given by

$$\hat{\lambda}^* = 1 - \frac{\sum\sum_{i\neq j}\hat{\rho}_{ij}\left[\hat{\rho}_{ij} - \frac{\hat{\rho}_{ij}(1-\hat{\rho}_{ij}^2)}{2T}\right]}{\frac{1}{T}\sum\sum_{i\neq j}(1-\hat{\rho}_{ij}^2)^2 + \sum\sum_{i\neq j}\left[\hat{\rho}_{ij} - \frac{\hat{\rho}_{ij}(1-\hat{\rho}_{ij}^2)}{2T}\right]^2}.$$

In small samples, values of $\hat{\lambda}^*$ can be obtained that fall outside the range $[0,1]$. To avoid such cases, if $\hat{\lambda}^* < 0$ then $\hat{\lambda}^*$ is set to 0, and if $\hat{\lambda}^* > 1$ it is set to 1, or $\hat{\lambda}^{**} = \max(0, \min(1, \hat{\lambda}^*))$. For further details of the derivations see BPS.

The associated shrinkage covariance matrix is then obtained as

$$\widetilde{\boldsymbol{\Sigma}}_u = \hat{\mathbf{D}}^{1/2}\widetilde{\mathbf{R}}_u(\hat{\lambda}^*)\hat{\mathbf{D}}^{1/2}. \tag{A.32}$$

From (A.31) and (A.32) it is easy to see that the value $\hat{\lambda}^* = 0$ recovers the sample covariance matrix, that is no shrinkage is performed. The value $\hat{\lambda}^* = 1$ leads to the sample covariance matrix becoming a diagonal matrix, that is retaining only its diagonal values with all remaining elements set to zero. The computed $\hat{\lambda}^*$ will always yield a covariance matrix that is positive definite when $\hat{\lambda}^* \neq 0$.

It should be noted that the idea of shrinkage is not just to achieve non-singularity, when $k > T$, but also to obtain a more reliable estimate of the covariance matrix $\mathbf{\Sigma}_u$. That is, even in the case where the covariance matrix is invertible, one may still wish to use the shrinkage option. For example, computation of the PP, IRF and FEVD (excluding OIRF and OFEVD) point estimates does not require a covariance matrix that is positive definite.

When shrinkage is applied, the shinkage estimator of the selected covariance matrix is used to compute the PPs, IRFs and FEVDs in the corresponding expressions given earlier.

Naive shrinkage

The naive shrinkage estimator is expressed as a convex combination of $\hat{\mathbf{\Sigma}}_u$ and $diag(\hat{\mathbf{\Sigma}}_u)$, which shrinks the sample covariance matrix towards its diagonal in order to obtain a positive definite matrix. It is given by

$$\widetilde{\mathbf{\Sigma}}_u(\lambda) = \lambda diag\left(\hat{\mathbf{\Sigma}}_u\right) + (1-\lambda)\hat{\mathbf{\Sigma}}_u, \quad 0 \leq \lambda \leq 1, \tag{A.33}$$

which could be equivalently expressed in terms of the sample correlation matrix as in (A.31). Thus, shrinking the covariance matrix in (A.33) is equivalent to shrinking the correlation matrix in expression (A.31).

The name 'naive' is attributed to the shrinkage parameter being arbitrarily defined so as to render $\widetilde{\mathbf{\Sigma}}_u$ positive definite rather than computed based on some minimisation criterion. As earlier, a shrinkage parameter of $\lambda = 0$ will leave the selected covariance matrix in tact, i.e. no shrinkage will be imposed, while $\lambda = 1$ will lead to the sample covariance matrix becoming a diagonal matrix, with various degrees of shrinkage applied for intermediate values of λ.

It should be noted that naive shrinkage is only included in this version of the toolbox so that users are able to replicate results obtained in earlier versions. It does not serve as one of the main options of the toolbox and for this reason it is of limited functionality, as seen earlier. It should further be noted that in previous versions of the toolbox this shrinkage estimator was given by

$$\widetilde{\mathbf{\Sigma}}_u(\xi) = (1-\xi) diag\left(\hat{\mathbf{\Sigma}}_u\right) + \xi\hat{\mathbf{\Sigma}}_u, \quad 0 \leq \xi \leq 1,$$

so that $\xi = 1 - \lambda$ or $\lambda = 1 - \xi$.

A.22 Bootstrapping the GVAR

The GVAR model is bootstrapped in order to obtain:

- The empirical distribution of the PPs, IRFs and FEVDs and the associated error bands
- The empirical distribution of the likelihood ratio statistic for testing over-identifying restrictions on the cointegrating vectors
- The empirical distribution of the structural stability statistics for testing for structural breaks.

The covariance matrix selected among the options listed in Section A.21.1 is used both for computing the point and bootstrap estimates of the PPs, IRFs and FEVDs, as well as for generating the bootstrap data.

A.22.1 Generating the bootstrap data

Suppose we would like to bootstrap the GVAR model and the sample covariance matrix $\hat{\mathbf{\Sigma}}_u$ has been selected to estimate $\mathbf{\Sigma}_u$. A bootstrap sample for the k variables in the GVAR model, $\mathbf{x}_t^{(b)}$, is constructed based on

$$\mathbf{x}_t^{(b)} = \hat{\mathbf{b}}_0 + \hat{\mathbf{b}}_1 \mathbf{t} + \hat{\mathbf{F}}_1 \mathbf{x}_{t-1} + \hat{\mathbf{F}}_2 \mathbf{x}_{t-2} + \hat{\mathbf{G}}_0^{-1} \hat{\mathbf{u}}_t^{(b)},$$

by resamping the estimated GVAR residuals $\hat{\mathbf{u}}_t$ to obtain $\hat{\mathbf{u}}_t^{(b)}$.

Two approaches are available for resampling $\hat{\mathbf{u}}_t$ in the current version of the toolbox as described below. Prior to any resampling the residuals are recentered to ensure that their bootstrap population mean is zero.

Inverse option

This approach initially orthogonalises the estimated residuals $\hat{\mathbf{u}}_t$ by using the inverse of the Cholesky factor, $\mathbf{Q}$, associated with the Cholesky decomposition of the sample covariance matrix $\hat{\mathbf{\Sigma}}_u = \hat{\mathbf{Q}}\hat{\mathbf{Q}}'$ (or of $\widetilde{\mathbf{\Sigma}}_u$ defined earlier if the sample covariance matrix is not positive definite). This is achieved by premultiplying $\hat{\mathbf{u}}_t$ by $\hat{\mathbf{Q}}^{-1}$ so that an iid set of residuals, $\hat{\boldsymbol{\eta}}_t$, is obtained, where $\hat{\boldsymbol{\eta}}_t = \hat{\mathbf{Q}}^{-1}\hat{\mathbf{u}}_t$. Resampling with replacement is then performed on the kT elements of the matrix obtained from stacking the vectors $\hat{\boldsymbol{\eta}}_t$, for $t = 1, 2, ..., T$. The bootstrap error vector is obtained as $\hat{\mathbf{u}}_t^{(b)} = \hat{\mathbf{Q}}\hat{\boldsymbol{\eta}}_t^{(b)}$, where $\hat{\boldsymbol{\eta}}_t^{(b)}$ is the $k \times 1$ vector of re-sampled values from $\{\hat{\eta}_{jt}\}_{j=1,2,...,k;t=1,2,...,T}$. The covariance matrix is therefore required to be positive definite under this option.

Shuffle option

Another option for obtaining the bootstrap errors, $\hat{\mathbf{u}}_t^{(b)}$, is to simply take random draws with replacement from the in-sample residual vectors $\{\hat{\mathbf{u}}_1, \hat{\mathbf{u}}_2, ..., \hat{\mathbf{u}}_T\}$. The bootstrap errors obtained in this way will have the same distribution and covariance structure as that observed in the original sample. However, this procedure is subject to the criticism that it could introduce serial dependence at longer forecast horizons if the pseudo-random draws are made from the same set of relatively small T vector of residuals. On the plus side, it does not require use of the inverse of the selected covariance matrix. Thus, under this option the GVAR program will not perform shrinkage on the selected covariance matrix (except when computing the OIRFs), should the covariance matrix not be positive definite.

A.22.2 Computing critical values and impulse response bounds

For each bootstrap replication $b = 1, 2, ..., B$, having estimated the individual country models using the simulated data $\mathbf{x}_t^{(b)}$, the GVAR is reconstructed and solved as described earlier, and the impulse responses are calculated based on the formulas (A.22), (A.23) and (A.24) as $\mathcal{GIRF}_{j,n}^{(b)}$, $\mathcal{SGIRF}_{j,n}^{(b)}$, $\mathcal{OIRF}_{j,n}^{(b)}$ for $n = 0, 1, 2, \ldots$, respectively. These statistics are then sorted in ascending order, and the $(1-\alpha)100\%$ confidence interval is calculated by using the $\alpha/2$ and $(1-\alpha/2)$ quantiles, say $q_{\alpha/2}$ and $q_{(1-\alpha/2)}$, respectively, of the bootstrap distribution of $\mathcal{GIRF}_{j,n}$, $\mathcal{SGIRF}_{j,n}$ and $\mathcal{OIRF}_{j,n}$. The empirical distributions of the persistence profiles and forecast error variance decomposition are derived similarly, based on the formulas in Sections A.18 and A.20. The upper and lower confidence bounds are computed based on the number of bootstrap replications defined by the user. If a bootstrap replication does not yield a stable GVAR solution (i.e. eigenvalues less than or equal to one), then a new bootstrap sample is computed until the number of bootstrap replications that satisfy the stability condition reaches that specified by the user.[12]

In the same manner, to compute the critical values of the structural stability tests outlined in Section A.15, for each bootstrap replication b, using the bootstrap samples $\mathbf{x}_t^{(b)}$, the ℓ^{th} equation of the i^{th} individual error correction model

$$\Delta x_{it,\ell}^{(b)} = \mu_{i\ell}^{(b)} + \sum\nolimits_{j=1}^{\hat{r}_i} \gamma_{ij,\ell}^{(b)} ECM_{ij,t-1}^{(b)} + \sum\nolimits_{n=1}^{\hat{p}_i-1} \hat{\boldsymbol{\varphi}}_{in,\ell}^{\prime(b)} \Delta \mathbf{x}_{i,t-n}^{(b)} + \sum\nolimits_{s=0}^{\hat{q}_i-1} \boldsymbol{\vartheta}_{is,\ell}^{\prime(b)} \Delta \mathbf{x}_{i,t-s}^{*(b)} + e_{it,\ell}^{(b)},$$

is estimated for $\ell = 1, ..., k_i$, where k_i is the number of domestic variables for the i^{th} country and $E\hat{C}M_{ij,t-1}^{(b)}$, $j = 1, 2, ..., r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found for that country based on the actual data, and the statistics $PK_{\sup}^{(b)}$, $PK_{msq}^{(b)}$, $\mathfrak{N}_{\ell}^{(b)}, QLR^{(b)}, MW^{(b)}$ and $APW^{(b)}$ are then computed. These statistics are sorted in ascending order and their value which exceeds 95% of the observed statistics represents the appropriate 95% critical value for the structural stability tests. The same procedure applies for computing the critical values of the test for overidentifying restrictions on the cointegrating vectors.

A.23 Detailed workings of the toolbox related to shrinkage

In what follows the detailed workings of the toolbox related to shrinkage are outlined. All cell referencing refers to the MAIN worksheet of the interface file.

A.23.1 Workings of the toolbox under LW shrinkage on the correlation matrix

Assuming that cell **EI33** is empty:

- If the bootstrap is not enabled:
  - Under the **GIRFs** or **SGIRFs** option, the program will perform shrinkage when computing the point and bootstrap estimates if **Perform shrinkage on the correlation matrix for point and boot estmates** is set to **1,** and the value of the internally computed shrinkage parameter will be exported to cell **EH33**. If it is set to **0** no shrinkage will be performed.
  - Under the **OIRFs** option, the program will first check whether the selected (original) covariance matrix is positive definite.
    - If the covariance matrix is positive definite the program will perform shrinkage when computing the point and bootstrap estimates if **Perform shrinkage on the correlation matrix for point and bootstrap estimates** is set to **1,** and will export the value of the internally computed shrinkage parameter to cell **EH33**. If it is set to **0** no shrinkage will be performed.

[12] In the event where bootstrap samples continually fail to satisfy the stability condition, the program will terminate after generating twice the number of bootstrap replications specified by the user. The bootstrap results will then be computed based on the available number of 'stable' bootstrap replications, if sufficient.

    * If the covariance matrix is not positive definite the program will pause and you will be instructed through the Matlab command window to ensure that the **Perform shrinkage on the correlation matrix for point and bootstrap estimates** field is set to **1**. The program will then carry on to perform shrinkage exporting the value of the shrinkage parameter to cell **EH33**.

- If the bootstrap is enabled:
  - If the bootstrap approach **inverse** is selected, the program will check whether the selected (original) covariance matrix is positive definite or not.
    * If the covariance matrix is positive definite shrinkage will be performed according to **Perform shrinkage on the correlation matrix** selection fields. For example, it could be that the **Perform shrinkage on the correlation matrix for point and bootstrap estimates** field is set to **0** so no shrinkage will be performed on the correlation matrix for computing point and bootstrap estimates. At the same time, the **Perform shrinkage on the correlation matrix for bootstrap data generation** field could be set to **1,** in which case shrinkage will be performed on the correlation matrix when generating the bootstrap data and the internally computed shrinkage parameter will be exported to cell **EH33**.
    * If the covariance matrix is not positive definite, you will be instructed through the Matlab command window to select **1** in the **Perform shrinkage on the correlation matrix for bootstrap data generation** field to ensure that shrinkage is performed in this case. You can choose to either retain your selection associated with the **Perform shrinkage on the correlation matrix for computing point and bootstrap estimates** field or change it**.** If **0** is selected no shrinkage will be performed when computing point and bootstrap estimates; if **1** is selected shrinkage will be performed. In accordance with the selections provided, the program will carry on to perform shrinkage and export the internally computed shrinkage parameter to cell **EH33**.
  - If the bootstrap approach **shuffle** is selected:
    * If **GIRFs** or **SGIRFs** are chosen information in the shrinkage panel is not applicable and any selected options will be ignored. No shrinkage is performed when computing the point and bootstrap estimates and when generating the bootstrap data.
    * If **OIRFs** are chosen the program will check whether the selected (original) covariance matrix is positive definite or not.
      · If the covariance matrix is positive definite information in the shrinkage panel is not applicable and any selected options will be ignored. No shrinkage is performed when computing the point and bootstrap estimates and when generating the bootstrap data.
      · If the covariance matrix is not positive definite, the program will proceed as under the bootstrap approach **inverse,** the difference being that you are required to set to **1** both **Perform shrinkage on the correlation matrix** fields, namely for computing the point and bootstrap estimates and for generating the bootstrap data. This will ensure that shrinkage is performed in both cases.

A.23.2 Workings of the toolbox under naive shrinkage

Providing **Run the program with pauses** is set to **0** in the main settings of the MAIN worksheet of the interface file and an appropriate value is provided in cell **EI33**:

- If the bootstrap is not enabled:
  - Under the **GIRFs** or **SGIRFs** option, the program will perform naive shrinkage when computing the point and bootstrap estimates if **Perform shrinkage on the correlation matrix for point and boot estmates** is set to **1,** using the value provided in cell **EI33** as the shrinkage parameter. If it is set to **0** no shrinkage will be performed.
  - Under the **OIRFs** option, the program will first check whether the selected (original) covariance matrix is positive definite.
    - If the covariance matrix is positive definite the program will perform naive shrinkage when computing the point and bootstrap estimates if **Perform shrinkage on the correlation matrix for point and bootstrap estimates** is set to **1,** using the shrinkage value provided in cell **EI33**. If it is set to **0** no shrinkage will be performed.
    - If the covariance matrix is not positive definite the program will pause and you will be instructed through the Matlab command window to ensure that the **Perform shrinkage on the correlation matrix for point and bootstrap estimates** field is set to **1**. The program will then carry on to perform shrinkage using the shrinkage parameter value provided in cell **EI33**. If the value provided does not result in a positive definite covariance matrix, the program will pause and request you to increase it until positive definiteness of the covariance matrix is achieved.
- If the bootstrap is enabled:
  - If the bootstrap approach **inverse** is selected, the program will check whether the selected (original) covariance matrix is positive definite or not.
    - If the covariance matrix is positive definite then the shrinkage parameter value provided in cell **EI33** will be used to perform any shrinkage defined by the **Perform shrinkage on the correlation matrix** selection fields. For example, the **Perform shrinkage on the correlation matrix for point and bootstrap estimates** field could be set to **0** implying no shrinkage will be performed on the correlation matrix for computing point and bootstrap estimates, while the **Perform shrinkage on the correlation matrix for bootstrap data generation** field could be set to **1,** and so shrinkage will be performed on the correlation matrix when generating the bootstrap data.
    - If the covariance matrix is not positive definite, you will be instructed through the Matlab command window to select **1** in the **Perform shrinkage on the correlation matrix for bootstrap data generation** field to ensure that shrinkage is performed in this case. You can choose to either retain your selection associated with the **Perform shrinkage on the correlation matrix for computing point and bootstrap estimates** field or change it**.** If **0** is selected no shrinkage will be performed when computing point and bootstrap estimates; if **1** is selected shrinkage will be performed. In accordance with the selections provided, the

program will carry on to perform shrinkage according to the value of the shrinkage parameter in cell **EI33**. If this value does not yield a positive definite covariance matrix, the program will pause and require you to increase it until positive definiteness of the covariance matrix is achieved.

– If the bootstrap approach **shuffle** is selected the same steps apply as for LW shrinkage.

A.24 Including a dominant unit in the GVAR

Consider the case where one of the units in the GVAR model is known to be dominant, in the sense defined by Chudik and Pesaran (2012, CP). Denote the variables in the dominant unit by the $m_\omega \times 1$ vector of observables $\boldsymbol{\omega}_t$. In the context of an infinite dimensional stationary vector autoregressive model, CP show that the dominant unit acts as a dynamic factor in the regression equations for the non-dominant units. Therefore, the dynamic models for the non-dominant units should be conditioned on current and lagged values of the dominant variables, in addition to the foreign (starred) variables, $\mathbf{x}_{it}^*$. In contrast, in modelling the dominant unit only lagged values of the dominant variables need be included. See Smith and Yamagata (2011) for the inclusion of a dominant unit in a stationary GVAR model.

In practice, the weak exogeneity of the dominant variables, $\boldsymbol{\omega}_t$, for the estimation of the long run relations in the non-dominant units needs to be tested, similar to the tests of weak exogeneity applied to the foreign variables in the GVAR. As in the standard GVAR model, country (unit) specific models can be tested for cointegration treating the variables in the dominant unit as weakly exogenous.

In general one would expect that the variables of the dominant unit enter all the models for the non-dominant units, but in practice the variables of the dominant unit might be excluded if their inclusion in a particular (non-dominant) model proves to be statistically insignificant.[13]

A.24.1 Modelling the dominant unit

In modelling the dominant unit we distinguish between two cases, namely when the dominant unit does not contain any lagged feedbacks from the rest of the GVAR model, and when there are lagged feedbacks. In both cases we start with testing for possible cointegration amongst the elements of $\boldsymbol{\omega}_t$ using the Johansen procedure. To this end we consider the following VAR(p_ω) specification for the dominant unit

$$\boldsymbol{\omega}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \boldsymbol{\Phi}_1 \boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Phi}_{p_\omega} \boldsymbol{\omega}_{t-p_\omega} + \boldsymbol{\eta}_t, \tag{A.34}$$

where p_ω is selected by an information criterion, such as the AIC or SBC, or imposed by the user. If $\boldsymbol{\omega}_t$ contains I(1) variables then these may be cointegrated, and equation (A.34) under case IV (unrestricted intercept, restricted trend) admits the following error correction representation

$$\Delta\boldsymbol{\omega}_t = \mathbf{c} - \boldsymbol{\alpha}_\omega \boldsymbol{\beta}_\omega' [\boldsymbol{\omega}_{t-1} - \boldsymbol{\kappa}(t-1)] + \textstyle\sum_{j=1}^{p_\omega - 1} \boldsymbol{\Gamma}_j \Delta\boldsymbol{\omega}_{t-j} + \boldsymbol{\eta}_t, \tag{A.35}$$

where $\boldsymbol{\alpha}_\omega$ and $\boldsymbol{\beta}_\omega$ are $m_\omega \times\, r_\omega$ vectors, and r_ω denotes the number of cointegrating relations. Denote the $r_\omega \times 1$ vector of error correction terms by $\boldsymbol{\xi}_{\omega,t-1} = \boldsymbol{\beta}_\omega' [\boldsymbol{\omega}_{t-1} - \boldsymbol{\kappa}(t-1)]$, and its estimate by $\hat{\boldsymbol{\xi}}_{\omega,t-1} = \hat{\boldsymbol{\beta}}_\omega' [\boldsymbol{\omega}_{t-1} - \hat{\boldsymbol{\kappa}}(t-1)]$. Then the remaining parameters of (A.34) are consistently estimated by OLS applied to

$$\Delta\boldsymbol{\omega}_t = \mathbf{c} + \boldsymbol{\delta}\hat{\boldsymbol{\xi}}_{\omega,t-1} + \textstyle\sum_{j=1}^{p_\omega - 1} \boldsymbol{\Gamma}_j \Delta\boldsymbol{\omega}_{t-j} + \boldsymbol{\eta}_t,$$

[13] Note that a dominant unit should not enter as an endogenous variable in the models for the non-dominant units.

where $\hat{\boldsymbol{\xi}}_{\omega,t-1}$ are taken as given (estimated in the first stage).

In the second stage, the above ECM specification can be used as is without any additional feedback effects, or alternatively can be augmented with lagged changes of the variables in the rest of the GVAR model. This is achieved by first constructing a set of global variables, defined by $\widetilde{\mathbf{x}}_t = \widetilde{\mathbf{W}}\mathbf{x}_t$, where $\mathbf{x}_t$ is the $k \times 1$ vector of the variables included in the models for the non-dominant units, and $\widetilde{\mathbf{W}}$ is an $m_{\widetilde{x}} \times k$ matrix of weights used in constructing the global variables, $\widetilde{\mathbf{x}}_t$. The elements of the weight matrix $\widetilde{\mathbf{W}}$ denoted by w_{is}, where $s = 1, ..., \max_i(k_i)$ (recall that k_i is the country-specific domestic variables in the GVAR), in the most general case can contain different weights for each of the s variables (one example is PPP-GDP weights or any other weights specified by the user), such that $\widetilde{x}_{st} = \sum_{i=0}^{N} w_{is}x_{ist}$ and $\Sigma_{i=0}^{N} w_{is} = 1$.[14] It is important to recognise that in modelling the dominant unit, the contemporaneous values of $\widetilde{\mathbf{x}}_t$ can not be included in the model, since $\widetilde{\mathbf{x}}_t$ is not weakly exogenous for the parameters of the model of the dominant unit.

When N is sufficiently large the inclusion of lagged changes of $\widetilde{\mathbf{x}}_t$ in the model for $\boldsymbol{\omega}_t$ is redundant, since $\boldsymbol{\omega}_t$ and its lagged values are already included in the models for $\mathbf{x}_{it}$, and as $N \to \infty$, $\widetilde{\mathbf{x}}_t$ and $\boldsymbol{\omega}_t$ will become highly correlated - if $\boldsymbol{\omega}_t$ is truly dominant. But improvements can be obtained in small samples by including lagged changes of $\widetilde{\mathbf{x}}_t$, namely $\Delta\widetilde{\mathbf{x}}_{t-s}$, for $s = 1, 2, ...$ in the above ECM specification for the dominant unit so that

$$\Delta\boldsymbol{\omega}_t = \mathbf{c} + \boldsymbol{\delta}\hat{\boldsymbol{\xi}}_{\omega,\, t-1} + \textstyle\sum_{j=1}^{\widetilde{p}-1}\boldsymbol{\Gamma}_j\Delta\boldsymbol{\omega}_{t-j} + \sum_{j=1}^{\widetilde{q}-1}\boldsymbol{\Theta}_j\Delta\widetilde{\mathbf{x}}_{t-j} + \boldsymbol{\eta}_t. \tag{A.36}$$

In this augmented ECM specification the estimated ECM terms, $\hat{\boldsymbol{\xi}}_{\omega,\, t-1}$, are those computed from (A.35), while new lag orders are defined for the lagged changes of $\boldsymbol{\omega}_t$ and $\widetilde{\mathbf{x}}_t$, $\widetilde{p}$ and $\widetilde{q}$ respectively. Conditional on $\hat{\boldsymbol{\xi}}_{\omega,t-1}$, (A.36) can be consistently estimated by OLS. The lag orders $\widetilde{p}$ and $\widetilde{q}$ can be selected by an information criterion, such as the AIC or SBC, or imposed by the user.

Following estimation, equation (A.36) can be expressed in the form

$$\boldsymbol{\omega}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \boldsymbol{\Phi}_1\boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Phi}_{\widetilde{p}}\boldsymbol{\omega}_{t-\widetilde{p}} + \boldsymbol{\Lambda}_1\widetilde{\mathbf{x}}_{t-1} + ... + \boldsymbol{\Lambda}_{\widetilde{q}}\widetilde{\mathbf{x}}_{t-\widetilde{q}} + \boldsymbol{\eta}_t, \tag{A.37}$$

which will be used in establishing the dynamic properties of the global model in what follows.

When the dominant unit model is univariate, i.e. $m_\omega = 1$, then it can either be estimated in levels based on the regression (in the case of a trend)

$$\omega_t = \mu_0 + \mu_1 t + \phi_1\omega_{t-1} + ... + \phi_{\widetilde{p}}\omega_{t-\widetilde{p}} + \boldsymbol{\lambda}_1'\widetilde{\mathbf{x}}_{t-1} + ... + \boldsymbol{\lambda}_{\widetilde{q}}'\widetilde{\mathbf{x}}_{t-\widetilde{q}} + \eta_t,$$

or in first differences

$$\Delta\omega_t = c + \textstyle\sum_{j=1}^{\widetilde{p}-1}\gamma_j\Delta\omega_{t-j} + \sum_{j=1}^{\widetilde{q}-1}\boldsymbol{\theta}_j'\Delta\widetilde{\mathbf{x}}_{t-j} + \eta_t.$$

Note that in the case of the model in first differences a constant is always included in the regression.

In the baseline case for the dominant unit where the model does not contain the lagged changes of the global variables (namely $\Delta\widetilde{\mathbf{x}}_{t-j}$ for $j = 1, 2, ..\widetilde{q} - 1$), the lag orders are set at the level of the VAR model, (A.34). It is not appropriate to specify lag orders that are specific to the individual elements of $\boldsymbol{\omega}_t$. This is because the application of the Johansen approach does not allow for different lag orders across the different equations in the VAR. In any case if the model for the dominant unit does not contain any other variables, it does not make sense to change the specification of the dynamics of the model. But when augmenting the individual equations of the model for the dominant unit with $\Delta\widetilde{\mathbf{x}}_{t-j}$ it is reasonable to allow specification of equation-specific

[14]The current version of the toolbox accommodates only fixed weights for construction of the feedback variables.

lag orders for $\Delta\boldsymbol{\omega}_{t-j}$ and $\Delta\widetilde{\mathbf{x}}_{t-j}$. To this end denote the ℓ^{th} element of $\boldsymbol{\omega}_t$ by $\omega_{t\ell}$ and the s^{th} element of $\hat{\boldsymbol{\xi}}_{\omega,t-1}$ by $\hat{\xi}_{\omega,s,\,t-1}$, and consider the following general specification

$$\Delta\omega_{t,\ell} = c_\ell + \sum\nolimits_{s=1}^{r_\omega} \delta_{s,\ell}\hat{\xi}_{\omega,s,\,t-1} + \sum\nolimits_{j=1}^{\widetilde{p}_\ell-1} \boldsymbol{\gamma}'_{j,\ell}\Delta\boldsymbol{\omega}_{t-j} + \sum\nolimits_{j=1}^{\widetilde{q}_\ell-1} \boldsymbol{\theta}'_{j,\ell}\Delta\widetilde{\mathbf{x}}_{t-j} + \eta_{t,\ell}, \qquad \text{(A.38)}$$

for $\ell = 1, 2, ..., m_\omega$. Note that in this case, the augmentation of the equations with $\Delta\widetilde{\mathbf{x}}_{t-j}$ is likely to alter the order of the lags of $\Delta\boldsymbol{\omega}_{t-j}$. The lag orders $\widetilde{p}_\ell$ and $\widetilde{q}_\ell$ can be selected by an information criterion, such as the AIC or SBC, or imposed by the user. Finally, in the case where a subset of equations of (A.36) do not include any feedback variables, each corresponding equation is estimated based on (A.38) without the inclusion of the $\Delta\widetilde{\mathbf{x}}'s$.

A.24.2 Solving the GVAR in the presence of a dominant unit

Consider the following VARX*(p_i, q_i) structure for the i^{th} country-specific model

$$\begin{aligned}\mathbf{x}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \boldsymbol{\Phi}_{i1}\mathbf{x}_{i,t-1} + ... + \boldsymbol{\Phi}_{ip_i}\mathbf{x}_{i,t-p_i} + \boldsymbol{\Lambda}_{i0}\mathbf{x}^*_{it} + \boldsymbol{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + ... + \boldsymbol{\Lambda}_{iq_i}\mathbf{x}^*_{i,t-q_i} + \\ &\quad +\boldsymbol{\Psi}_{i0}\boldsymbol{\omega}_t + \boldsymbol{\Psi}_{i1}\boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Psi}_{iq_i}\boldsymbol{\omega}_{t-q_i} + \mathbf{u}_{it}, \qquad \text{(A.39)}\end{aligned}$$

for $i = 0, 1, ..., N$. Note that for specification and estimation purposes $\boldsymbol{\omega}_t$ is treated as a foreign variable in the GVAR toolbox, this includes sharing the same lag order, q_i, as the foreign variables. As mentioned earlier, for estimation of the country-specific models given by (A.39) $\mathbf{x}^*_{it}$ and $\boldsymbol{\omega}_t$ can be combined and treated jointly as weakly exogenous, using the reduced rank regression techniques for VECMX* models discussed in the preceding sections. Then, following Section A.16.1, we can solve for the global $k \times 1$ variable vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ by stacking the individual country equations and 'dispensing' with the foreign variables $\mathbf{x}^*_{it}$ through the identity $\mathbf{z}_{it}= \mathbf{W}_i\mathbf{x}_t$, with $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$, where $\mathbf{W}_i$ are the link matrices defined by the trade weights w_{ij}. However, because $\boldsymbol{\omega}_t$ does not enter as a domestic variable in any country-specific model $\mathbf{x}_{it}$, we cannot 'dispense' with this variable via the link matrices.

Expressing (A.39) in terms of $\mathbf{z}_{it}$ and assuming for simplicity of exposition that $p_i = q_i$ we have

$$\begin{aligned}\mathbf{G}_{i0}\mathbf{z}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{G}_{i1}\mathbf{z}_{i,t-1} + ... + \mathbf{G}_{ip_i}\mathbf{z}_{i,t-p_i} \\ &\quad +\boldsymbol{\Psi}_{i1}\boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Psi}_{iq_i}\boldsymbol{\omega}_{t-q_i} + \mathbf{u}_{it}, \qquad \text{(A.40)}\end{aligned}$$

with $\mathbf{G}_{i0} = (\mathbf{I}_{k_i}, -\boldsymbol{\Lambda}_{i0})$ and $\mathbf{G}_{ij} = (\boldsymbol{\Phi}_{ij}, \boldsymbol{\Lambda}_{ij})$, for $j = 1, ..., p_i$, and using the identity $\mathbf{z}_{it}= \mathbf{W}_i\mathbf{x}_t$, for $i = 0, 1, ..., N$, (A.40) can be written as

$$\begin{aligned}\mathbf{G}_{i0}\mathbf{W}_i\mathbf{x}_t &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{G}_{i1}\mathbf{W}_i\mathbf{x}_{t-1}+... + \mathbf{G}_{ip_i}\mathbf{W}_i\mathbf{x}_{t-p_i} + \boldsymbol{\Psi}_{i0}\boldsymbol{\omega}_t + \\ &\quad +\boldsymbol{\Psi}_{i1}\boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Psi}_{iq_i}\boldsymbol{\omega}_{t-q_i} + \mathbf{u}_{it}.\end{aligned}$$

These individual models are then stacked to yield the model for $\mathbf{x}_t$ given by

$$\mathbf{G}_0\mathbf{x}_t = \mathbf{a}_0 + \mathbf{a}_1 t + \mathbf{G}_1\mathbf{x}_{t-1} + ... + \mathbf{G}_p\mathbf{x}_{t-p} + \boldsymbol{\Psi}_0\boldsymbol{\omega}_t + \boldsymbol{\Psi}_1\boldsymbol{\omega}_{t-1} + ... + \boldsymbol{\Psi}_2\boldsymbol{\omega}_{t-q} + \mathbf{u}_t, \quad \text{(A.41)}$$

where both the contemporaneous and lagged values of $\boldsymbol{\omega}_t$ now appear on the right hand side of

(A.41) with $p = \max(p_i)$ and $q = \max(q_i)$ and

$$\mathbf{G}_0 = \begin{pmatrix} \mathbf{G}_{00}\mathbf{W}_0 \\ \mathbf{G}_{10}\mathbf{W}_1 \\ \vdots \\ \mathbf{G}_{N0}\mathbf{W}_N \end{pmatrix},\ \mathbf{G}_j = \begin{pmatrix} \mathbf{G}_{0j}\mathbf{W}_0 \\ \mathbf{G}_{1j}\mathbf{W}_1 \\ \vdots \\ \mathbf{G}_{Nj}\mathbf{W}_N \end{pmatrix},\ j = 1, ..., p,$$

$$\mathbf{a}_0 = \begin{pmatrix} \mathbf{a}_{00} \\ \mathbf{a}_{10} \\ \vdots \\ \mathbf{a}_{N0} \end{pmatrix},\ \mathbf{a}_1 = \begin{pmatrix} \mathbf{a}_{01} \\ \mathbf{a}_{11} \\ \vdots \\ \mathbf{a}_{N1} \end{pmatrix}, \mathbf{u}_t = \begin{pmatrix} \mathbf{u}_{0t} \\ \mathbf{u}_{1t} \\ \vdots \\ \mathbf{u}_{Nt} \end{pmatrix}.$$

The $\boldsymbol{\eta}_t$ and $\mathbf{u}_t$ innovations are assumed to be uncorrelated.

Defining the $(k+m_\omega)\times 1$ vector $\mathbf{y}_t = (\mathbf{x}_t', \boldsymbol{\omega}_t')'$, equations (A.37) and (A.41) for $p = \widetilde{p} = \widetilde{q} = q$ can be written as

$$\mathbf{H}_0\mathbf{y}_t = \mathbf{h}_0 + \mathbf{h}_1 t + \mathbf{H}_1\mathbf{y}_{t-1} + ... + \mathbf{H}_p\mathbf{y}_{t-p} + \boldsymbol{\zeta}_t, \tag{A.42}$$

where

$$\begin{aligned} \mathbf{H}_0 &= \begin{bmatrix} \mathbf{G}_0 & -\boldsymbol{\Psi}_0 \\ \mathbf{0}_{m_\omega\times k} & \mathbf{I}_{m_\omega} \end{bmatrix},\ \mathbf{h}_0 = \begin{bmatrix} \mathbf{a}_0 \\ \boldsymbol{\mu}_0 \end{bmatrix},\ \mathbf{h}_1 = \begin{bmatrix} \mathbf{a}_1 \\ \boldsymbol{\mu}_1 \end{bmatrix}, \\ \mathbf{H}_j &= \begin{bmatrix} \mathbf{G}_j & \boldsymbol{\Psi}_j \\ \boldsymbol{\Lambda}_j\tilde{\mathbf{W}}_j & \boldsymbol{\Phi}_j \end{bmatrix}, j = 1, ..., p, \qquad \boldsymbol{\zeta}_t = \begin{bmatrix} \mathbf{u}_t \\ \boldsymbol{\eta}_t \end{bmatrix}, \end{aligned}$$

or

$$\mathbf{y}_t = \mathbf{c}_0 + \mathbf{c}_1 t + \mathbf{C}_1\mathbf{y}_{t-1} + ... + \mathbf{C}_p\mathbf{y}_{t-p} + \mathbf{H}_0^{-1}\boldsymbol{\zeta}_t, \tag{A.43}$$

with

$$\mathbf{c}_j = \mathbf{H}_0^{-1}\mathbf{h}_j,\ j = 0, 1; \mathbf{C}_j = \mathbf{H}_0^{-1}\mathbf{H}_j,\ j = 1, ..., p.$$

In general, the lag order of $\mathbf{y}_t$ will be determined by the maximum lag order $\max(\max(p, \widetilde{p}), \max(q, \widetilde{q}))$.

The properties of the global model including eigenvalues, persistence profiles, impulse responses, variance decompositions are now determined by the $\mathbf{y}_t$ process. Also, bootstrapping the GVAR is performed in terms of the $\boldsymbol{\zeta}_t$ innovations. Below, the persistence profiles and impulse response functions are briefly presented for the GVAR model given by $\mathbf{y}_t$. The rest of the formulas and analysis associated with this model, and corresponding individual country models $\mathbf{x}_{it}$, are the same as those described earlier in Part II of this document and will therefore be omitted.

Persistence profiles

Let the infinite moving average representation of (A.43) be given by

$$\begin{aligned} \mathbf{y}_t &= \mathbf{d}_t + \sum_{s=0}^{\infty} \mathbf{B}_s\boldsymbol{\epsilon}_{t-s} \\ &= \boldsymbol{\epsilon}_t + \mathbf{B}_1\boldsymbol{\epsilon}_{t-1} + \mathbf{B}_2\boldsymbol{\epsilon}_{t-2} + ... \end{aligned} \tag{A.44}$$

where $\mathbf{d}_t$ represents the deterministic component of $\mathbf{y}_t$, $\boldsymbol{\epsilon}_t = \mathbf{H}_0^{-1}\boldsymbol{\zeta}_t$ and $\mathbf{B}_s$ can be derived recursively as

$$\mathbf{B}_s = \mathbf{C}_1\mathbf{B}_{s-1} + \mathbf{C}_2\mathbf{B}_{s-2} + ... + \mathbf{C}_p\mathbf{B}_{s-p},\ s = 1, 2, ... \tag{A.45}$$

with $\mathbf{B}_0 = \mathbf{I}_{k+m_\omega}$, $\mathbf{B}_s = \mathbf{0}$, for $s < 0$.

The cointegrating relations of the individual country models, $\dot{\boldsymbol{\beta}}_i'\dot{\mathbf{z}}_{it}$, are given in terms of the country-specific variables where $\dot{\mathbf{z}}_{it} = (\mathbf{x}_{it}', \mathbf{x}_{it}^{*\prime}, \boldsymbol{\omega}_t')'$ and $\dot{\boldsymbol{\beta}}_i = (\boldsymbol{\beta}_{ix}', \boldsymbol{\beta}_{ix^*}', \boldsymbol{\beta}_{i\omega}')'$ is the $(k_i + k_i^* + m_\omega) \times r_i$ matrix of cointegrating vectors, whilst the variables in the GVAR are given by $\mathbf{y}_t$. The identity $\dot{\mathbf{z}}_{it} = \dot{\mathbf{W}}_i\mathbf{y}_t$, provides the mapping between $\dot{\mathbf{z}}_{it}$ and $\mathbf{y}_t$, where $\dot{\mathbf{W}}_i$ is a $(k_i + k_i^* + m_\omega) \times (k + m_\omega)$ matrix given by

$$\dot{\mathbf{W}}_i = \begin{bmatrix} \mathbf{W}_i & \mathbf{0}_{k\times m_\omega} \\ \mathbf{0}_{m_\omega \times k} & \mathbf{I}_{m_\omega} \end{bmatrix}, \tag{A.46}$$

and $\mathbf{W}_i$ are the usual $(k_i + k_i^*) \times k$ link matrices defined in Section A.16.

Note that if a country does not include the dominant unit variables as weakly exogenous then $\mathbf{I}_{m_\omega}$ in (A.46) becomes a matrix of zeros. From equation (A.44) we then have that

$$\dot{\mathbf{z}}_{it} = \dot{\mathbf{W}}_i\mathbf{d}_t + \dot{\mathbf{W}}_i\mathbf{B}_0\boldsymbol{\epsilon}_t + \sum_{s=1}^{\infty}\dot{\mathbf{W}}_i\mathbf{B}_s\boldsymbol{\epsilon}_{t-s},$$

and the PPs of $\dot{\boldsymbol{\beta}}_i'\dot{\mathbf{z}}_{it}$ with respect to a system-wide shock to $\boldsymbol{\epsilon}_t$ are obtained as

$$\mathcal{PP}(\dot{\boldsymbol{\beta}}_{ji}'\dot{\mathbf{z}}_{it}; \boldsymbol{\epsilon}_t, n) = \frac{\dot{\boldsymbol{\beta}}_{ji}'\dot{\mathbf{W}}_i\mathbf{B}_n\boldsymbol{\Sigma}_\epsilon\mathbf{B}_n'\dot{\mathbf{W}}_i'\boldsymbol{\beta}_{ji}}{\boldsymbol{\beta}_{ji}'\dot{\mathbf{W}}_i\mathbf{B}_0\boldsymbol{\Sigma}_\epsilon\mathbf{B}_0'\dot{\mathbf{W}}_i'\boldsymbol{\beta}_{ji}}, n = 0, 1, 2, \dots .$$

where $\dot{\boldsymbol{\beta}}_{ji}'\dot{\mathbf{z}}_{it}$ is the j^{th} cointegrating relation in the i^{th} country $(j = 1, 2, ..., r_i)$, n is the horizon, and $\boldsymbol{\Sigma}_\epsilon$ is the $(k + m_\omega) \times (k + m_\omega)$ covariance matrix of $\boldsymbol{\epsilon}_t$. The $\mathbf{B}_n$ matrices are computed based on (A.45).

Similalry, the PPs of the cointegrating relations for the dominant unit model, $\boldsymbol{\beta}'\boldsymbol{\omega}_t$, with respect to a system-wide shock to $\boldsymbol{\epsilon}_t$ are given by

$$\mathcal{PP}(\boldsymbol{\beta}_j'\boldsymbol{\omega}_t; \boldsymbol{\epsilon}_t, n) = \frac{\boldsymbol{\beta}_j'\mathbf{W}\mathbf{B}_n\boldsymbol{\Sigma}_\epsilon\mathbf{B}_n'\mathbf{W}'\boldsymbol{\beta}_j}{\boldsymbol{\beta}_j'\mathbf{W}\mathbf{B}_0\boldsymbol{\Sigma}_\epsilon\mathbf{B}_0'\mathbf{W}'\boldsymbol{\beta}_j}, n = 0, 1, 2, \dots ,$$

where $\boldsymbol{\beta}_j'\boldsymbol{\omega}_t$ is the j^{th} cointegrating relation in the dominant unit model $(j = 1, 2, ..., r_\omega)$ with $\boldsymbol{\beta}$ the cointegrating vector obtained from (A.35) and $\mathbf{W} = (\mathbf{0}_{m_\omega \times k}, \mathbf{I}_{m_\omega})$.

Generalised impulse response functions

Using the infinite moving average representation in (A.44), the generalised impulse response function (GIRF) of (A.43) in the case of a one standard error shock defined by $v_t = \mathbf{b}'\boldsymbol{\zeta}_t$ at time t over the horizon $h = 0, 1, 2, ...$ is given by

$$\mathcal{GIRF}(h, \mathbf{y}_t; v_t) = E\left(\mathbf{y}_{t+h}|v_t = \sqrt{\mathbf{b}'\boldsymbol{\Omega}_\zeta\mathbf{b}}, \mathcal{I}_{t-1}\right) - E\left(\mathbf{y}_{t+h}|\mathcal{I}_{t-1}\right),$$

where $\mathbf{b}$ is a $(k + m_\omega) \times 1$ selection vector of the PPP-GDP weights with non-zero values only for the elements associated with the variable to be shocked for the countries involved, scaled to sum to unity, and $\mathcal{I}_{t-1}$ is the information set up to time $t-1$. Under the assumption that $\boldsymbol{\zeta}_t$ has a multivariate normal distribution or the conditional expectations can be assumed linear, the GIRF can be derived as

$$\mathcal{GIRF}(h, \mathbf{y}_t; v_t) = \frac{\mathbf{B}_h\mathbf{H}_0^{-1}\boldsymbol{\Omega}_\zeta\mathbf{b}}{\sqrt{\mathbf{b}'\boldsymbol{\Omega}_\zeta\mathbf{b}}},\ h = 0, 1, 2, \dots ,$$

where the $\mathbf{B}_h$ matrices are computed based on (A.45). For suitable choices of $\mathbf{b}$, one can consider country specific shocks, regional specific shocks, and global variable shocks including shocks to the global exogenous variables.

Structural impulse responses

The SGIRFs and OIRFs are obtained along the lines described in Section A.19.2 with the dominant unit placed first which is a natural ordering. In particular:

Identification of shocks to a single block To obtain the SGIRFs, the dominant unit is required to be placed first followed by say the US economy (or whichever other country of interest) as in the example of Section A.19.2. The variables within each unit/country should be ordered as desired by the user. For identification purposes, both the dominant unit and the US economy will be considered as a single 'block'. The results will be invariant to the ordering of the rest of the countries.

Consider the following specification for the dominant unit model

$$\boldsymbol{\omega}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 t + \boldsymbol{\Phi}_1 \boldsymbol{\omega}_{t-1} + \boldsymbol{\Lambda}_1 \tilde{\mathbf{x}}_{t-1} + \boldsymbol{\eta}_t,$$

and the US model

$$\mathbf{x}_{0t} = \mathbf{a}_{00} + \mathbf{a}_{01} t + \boldsymbol{\Phi}_{01} \mathbf{x}_{0,t-1} + \boldsymbol{\Phi}_{02} \mathbf{x}_{0,t-2} + \boldsymbol{\Lambda}_{00} \mathbf{x}^*_{0t} + \boldsymbol{\Lambda}_{01} \mathbf{x}^*_{0,t-1} + \mathbf{u}_{0t}.$$

Let $\dot{\mathbf{x}}_t = (\boldsymbol{\omega}'_t, \mathbf{x}'_{0t})'$ be a $(m_\omega + k_0) \times 1$ vector with

$$\dot{\mathbf{x}}_t = \dot{\mathbf{a}}_0 + \dot{\mathbf{a}}_1 t + \dot{\boldsymbol{\Phi}}_1 \dot{\mathbf{x}}_{t-1} + \dot{\boldsymbol{\Phi}}_2 \dot{\mathbf{x}}_{t-2} + \dot{\boldsymbol{\Lambda}}_0 \dot{\mathbf{x}}^*_t + \dot{\boldsymbol{\Lambda}}_1 \dot{\mathbf{x}}^*_{0,t-1} + \dot{\mathbf{u}}_t,$$

where

$$\begin{aligned}
\dot{\mathbf{a}}_0 &= \begin{pmatrix} \boldsymbol{\mu}_0 \\ \mathbf{a}_{00} \end{pmatrix}, \; \dot{\mathbf{a}}_1 = \begin{pmatrix} \boldsymbol{\mu}_1 \\ \mathbf{a}_{01} \end{pmatrix}, \\
\dot{\boldsymbol{\Phi}}_1 &= \begin{pmatrix} \boldsymbol{\Phi}_1 & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Phi}_{01} \end{pmatrix}, \; \dot{\boldsymbol{\Phi}}_2 = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Phi}_{02} \end{pmatrix}, \\
\dot{\boldsymbol{\Lambda}}_0 &= \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda}_{00} \end{pmatrix}, \; \dot{\boldsymbol{\Lambda}}_1 = \begin{pmatrix} \boldsymbol{\Lambda}_1 & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda}_{01} \end{pmatrix}, \\
\dot{\mathbf{u}}_t &= \begin{pmatrix} \boldsymbol{\eta}_t \\ \mathbf{u}_{0t} \end{pmatrix}.
\end{aligned}$$

The analysis then follows in the same manner as in Section A.19.2.

Specifically, let $\dot{\mathbf{v}}_t$ be the structural shocks given by

$$\dot{\mathbf{v}}_t = \mathbf{P} \dot{\mathbf{u}}_t,$$

where $\mathbf{P}$ is a $(m_\omega + k_0) \times (m_\omega + k_0)$ matrix of coefficients to be identified. The identification conditions using the triangular approach of Sims (1980) require $\boldsymbol{\Sigma}_{\dot{v}} = Cov(\dot{\mathbf{v}}_t)$ to be diagonal and $\mathbf{P}$ to be lower triangular. Let $\mathbf{Q}$ be the upper Cholesky factor of $Cov(\dot{\mathbf{u}}_t) = \boldsymbol{\Sigma}_{\dot{u}} = \mathbf{Q}'\mathbf{Q}$ so that $\boldsymbol{\Sigma}_{\dot{v}} = \mathbf{P}\boldsymbol{\Sigma}_{\dot{u}}\mathbf{P}'$, with $\mathbf{P} = (\mathbf{Q}')^{-1}$. Under this orthogonalisation scheme $Cov(\dot{\mathbf{v}}_t) = \mathbf{I}_{(m_\omega + k_0)}$.

Premultiplying the GVAR model (A.42) by

$$\mathbf{P}_{H_0} = \begin{pmatrix} \mathbf{P} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{k_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_{k_N} \end{pmatrix},$$

it follows that

$$\mathbf{P}_{H_0}\mathbf{H}_0\mathbf{y}_t = \mathbf{P}_{H_0}\mathbf{H}_1\mathbf{y}_{t-1} + \mathbf{P}_{H_0}\mathbf{H}_2\mathbf{y}_{t-2} + \mathbf{v}_t,$$

where $\mathbf{v}_t = (\dot{\mathbf{v}}_t', \mathbf{u}_{1t}', ..., \mathbf{u}_{Nt}')'$ and

$$\mathbf{\Sigma}_{\mathrm{v}} = Cov\left(\mathbf{v}_t\right) = \begin{pmatrix} V(\dot{\mathbf{v}}_t) & Cov(\dot{\mathbf{v}}_t, \mathbf{u}_{1t}) & \cdots & Cov(\dot{\mathbf{v}}_t, \mathbf{u}_{Nt}) \\ Cov(\mathbf{u}_{1t}, \dot{\mathbf{v}}_t) & V(\mathbf{u}_{1t}) & \cdots & Cov(\mathbf{u}_{1t}, \mathbf{u}_{Nt}) \\ \vdots & \vdots & & \vdots \\ Cov(\mathbf{u}_{Nt}, \dot{\mathbf{v}}_t) & Cov(\mathbf{u}_{Nt}, \mathbf{u}_{1t}) & \cdots & V(\mathbf{u}_{Nt}) \end{pmatrix},$$

with

$$V(\dot{\mathbf{v}}_t) = \mathbf{\Sigma}_{\dot{\mathrm{v}}} = \mathbf{P}\mathbf{\Sigma}_{\dot{u}}\mathbf{P}',$$
$$Cov(\dot{\mathbf{v}}_t, \mathbf{u}_{jt}) = Cov(\mathbf{P}\dot{\mathbf{u}}_t, \mathbf{u}_{jt}) = \mathbf{P}\mathbf{\Sigma}_{\dot{u},j}.$$

By using the definition of the generalised impulse responses with respect to the structural shocks given by

$$\mathcal{SGIRF}(\mathbf{y}_t; \mathrm{v}_{\ell t}, n) = E(\mathbf{y}_{t+n}|\mathcal{I}_{t-1,}\mathfrak{e}_\ell'\mathbf{v}_t = \sqrt{\mathfrak{e}_\ell'\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}) - E(\mathbf{y}_{t+n}|\mathcal{I}_{t-1}),$$

it follows that for a structurally identified shock, $\mathrm{v}_{\ell t}$, such as a US monetary policy shock the GIRF is given by

$$\mathcal{SGIRF}(\mathbf{y}_t; \mathrm{v}_{\ell t}, n) = \frac{\mathfrak{e}_j'\mathbf{B}_n(\mathbf{P}_{H_0}\mathbf{H}_0)^{-1}\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}{\sqrt{\mathfrak{e}_\ell'\mathbf{\Sigma}_{\mathrm{v}}\mathfrak{e}_\ell}}, n = 0, 1, 2, ...; \ell, j = 1, 2, ..., k + m_\omega,$$

where $\mathbf{\Sigma}_{\mathrm{v}}$ is the covariance matrix of the structural shocks and $\mathbf{P}_{H_0}\mathbf{H}_0$ is defined by the identification scheme used to identify the shocks.

Identification of shocks to all countries This option similar to Section A.19.2 requires the user to select the ordering of all the $N+1$ countries plus the dominant unit, as well as that of the $m_\omega + k$ variables included in the GVAR. As in the SGIRF case the dominant unit should be placed first, followed by the US and the remaining countries.

Similar to the non-dominant unit case, the orthogonal impulse response functions are given by

$$\mathcal{OIRF}(\mathbf{y}_t; \zeta_{\ell t}^*, n) = \mathfrak{e}_j'\mathbf{B}_n\mathbf{H}_0^{-1}\mathbf{Q}\mathfrak{e}_\ell, n = 0, 1, 2, ...; \ell, j = 1, 2, ..., k,$$

where $\zeta_{\ell t}^*$ is an orthogonalised residual, and $\mathbf{Q}$ is a lower triangular matrix obtained by the Cholesky decomposition of $\mathbf{\Sigma}_\zeta^0 = \mathbf{Q}\mathbf{Q}'$ where $\mathbf{\Sigma}_\zeta^0$ denotes the covariance matrix corresponding to the re-ordered residuals $\boldsymbol{\zeta}_t^0$.

A.25 GVAR forecasts

A.25.1 Ex-ante forecasts

Without loss of generality, consider the GVAR(2) model[15] given by

$$\mathbf{x}_t = \mathbf{b}_0 + \mathbf{b}_1 t + \mathbf{F}_1\mathbf{x}_{t-1} + \mathbf{F}_2\mathbf{x}_{t-2} + \varepsilon_t. \quad \text{(A.47)}$$

[15] If a dominant unit model is included in the GVAR then $\mathbf{x}_t$ simply needs to be replaced by $\mathbf{y}_t$ given by equation (A.43). This applies to both the GVAR forecasts and the trend/cycle decomposition of the GVAR that follows.

The point forecasts are computed recursively by

$$\boldsymbol{\mu}_h = \hat{\mathbf{b}}_0 + \hat{\mathbf{b}}_1 (T+h) + \hat{\mathbf{F}}_1 \boldsymbol{\mu}_{h-1} + \hat{\mathbf{F}}_2 \boldsymbol{\mu}_{h-2}, \text{ for } h = 1, 2, ... \tag{A.48}$$

with initial values $\boldsymbol{\mu}_0 = \mathbf{x}_T$ and $\boldsymbol{\mu}_{-1} = \mathbf{x}_{T-1}$, where h is the forecast horizon.

The point forecasts can be equivalently expressed in terms of the companion form of the GVAR. The companion form of (A.47) is given by

$$\begin{pmatrix} \mathbf{x}_t \\ \mathbf{x}_{t-1} \end{pmatrix} = \begin{pmatrix} \mathbf{F}_1 & \mathbf{F}_2 \\ \mathbf{I}_k & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{x}_{t-1} \\ \mathbf{x}_{t-2} \end{pmatrix} + \begin{pmatrix} \mathbf{b}_0 + \mathbf{b}_1 t \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{0} \end{pmatrix},$$

or

$$\mathbf{X}_t = \mathbf{F}\mathbf{X}_{t-1} + \mathbf{D}_t + \mathbf{E}_t,$$

where k is the number of endogenous variables in the GVAR model.

Hence

$$\mathbf{X}_{T+h} = \mathbf{F}^h \mathbf{X}_T + \sum_{\ell=0}^{h-1} \mathbf{F}^{\ell} \mathbf{D}_{T+h-\ell} + \sum_{\ell=0}^{h-1} \mathbf{F}^{\ell} \mathbf{E}_{T+h-\ell}, \tag{A.49}$$

and

$$\mathbf{x}_{T+h} = \mathcal{S}\mathbf{X}_{T+h}, \tag{A.50}$$

where $\mathcal{S} = \begin{pmatrix} \mathbf{I}_k & \mathbf{0}_{k\times k} \end{pmatrix}$.

Conditional on the initial values, $\mathbf{X}_T$, the point forecasts $\boldsymbol{\mu}_h$ equivalently to (A.48) are given by

$$\boldsymbol{\mu}_h = \mathcal{S}\mathbf{F}^h \mathbf{X}_T + \sum_{\ell=0}^{h-1} \mathcal{S}\mathbf{F}^{\ell} \mathbf{D}_{T+h-\ell}. \tag{A.51}$$

We will refer to these point forecasts as the ex-ante GVAR forecasts, formed conditional on the information set $\mathcal{I}_T$ with $\boldsymbol{\mu}_h = E\left(\mathbf{x}_{T+h} \left| \mathcal{I}_T \right.\right)$, in order to distinguish them from the conditional forecasts that will be discussed in the next section.

The GVAR toolbox can be used to obtain forecasts from different GVAR models estimated over alternative sample periods, as in Pesaran, Schuermann and Smith (2009a). Following these authors, the forecasts can then easily be pooled outside the program.

Imposing lower bound restrictions

To avoid negative forecasts of any interest rate variables included in the GVAR model, particularly with the use of the most recent GVAR database, the toolbox offers the option of subjecting the forecasts of such variables in all countries to an internally specified lower bound. The user is encouraged to make use of this feature when defining the relevant settings in the interface file. Specifically, a lower bound of $R_{\min} = 0.25$ is imposed on the nominal (per annum) interest rate (both short and long, assuming these are included in the GVAR model) of all countries. Following DdPS, this lower bound is then subjected to the transformation $(1/m)\ln(1 + R_{\min}/100)$, where m is the data frequency used in the GVAR. This transformation is the same as that made to the nominal (per annum) interest rate of the GVAR database at source level, prior to importing the data into the GVAR interface. The lower bound and associated transformation can be changed within the gvar.m program at the beginning of Section 4.4 (entitled: ‘GVAR forecasts’).

To see how the lower bound is applied to the ex-ante forecasts in practice, define the $k \times 1$ lower bound vector $\mathbf{x}_{lb}$ that contains the ‘transformed’ lower bound value, $(1/m)\ln(1 + R_{\min}/100)$, in the position of the interest rate(s) in all countries and a very large negative value elsewhere. At forecast horizon $h = 1,$ the $k \times 1$ vector of forecasts $\boldsymbol{\mu}_1$ computed based on (A.48) is compared to $\mathbf{x}_{lb}$ for each element $\ell = 1, .., k$. If $\mu_{1,\ell} < x_{lb,\ell}$ then $\mu_{1,\ell}$ is set to the lower bound value $x_{lb,\ell}$, else its value is retained. Denote the 'new' forecast for horizon $h = 1$ by $\boldsymbol{\mu}_1'$. It is this new forecast that is then used for the computation of $\boldsymbol{\mu}_2$ in (A.48). The same procedure is applied for all h, eventually yielding non-negative point forecasts for the interest rates over all horizons, with the lowest value that of the lower bound.

The toolbox also offers the option of subjecting the ex-ante forecasts of additional country-specific variables to lower bounds, which are then added to the lower bound vector $\mathbf{x}_{lb}$. In this case the 'transformed' lower bound value(s) need to be provided by the user during one of the pauses of the program, as described earlier in this document.

A.25.2 Conditional forecasts

Consider the solution of the GVAR model given say by A.47. Suppose we would like to compute forecasts based on this model conditional on a set of restrictions, i.e. imposing predefined values for selected variables over the forecast horizon and beyond. Let H denote the forecast horizon, $h = 1, 2, ..., H$, and $\bar{H}$ the restrictions horizon, $j = 1, 2, ..., \bar{H}$. For example, having estimated the GVAR model over the period 1979Q2-2013Q1, assume that we would like to obtain GVAR conditional forecasts for the next four quarters, that is 2013Q2-2014Q1 (i.e. $H = 4$), conditional on prespecified values for the US short and long-term interest rate variables, namely r^S_{0t} and r^L_{0t}, imposed over the period 2013Q2-2014Q1 (i.e. $\bar{H} = 4$). It is important to note that these restrictions have to be imposed on all selected GVAR country variables over the same $\bar{H}$ horizon, and have to be such that $H \leq \bar{H}$. For conditional forecasts using the GVAR model see also Pesaran, Smith and Smith (2007).

In this case, forecasts of the global model are obtained subject to a set of restrictions, which can be written more generally as

$$\boldsymbol{\Psi}\mathbf{x}_{T+j} = \mathbf{d}_{T+j},\ j = 1, 2, ..., \bar{H}, \tag{A.52}$$

where $\boldsymbol{\Psi}$ is a suitably defined $m \times k$ matrix, m is the number of variables to be restricted, and $\mathbf{d}_{T+j}$ is a $m \times 1$ vector of known constants. Assuming that: (i) there is only one observed global variable in the GVAR model, the oil price (p^o_t), included as endogenous in the US model; (ii) no dominant unit model is included; (iii) the variables in the US are given by the ordered vector $\mathbf{x}_{0t} = (y_{0t}, Dp_{0t}, eq_{0t}, r^S_{0t}, r^L_{0t}, p^o_t)'$, we have $m = 2$ with $k_0 = 6$ (the number of endogenous variables in the US model). The matrix $\boldsymbol{\Psi}$ is then defined as

$$\underset{2\times k}{\boldsymbol{\Psi}} = \begin{pmatrix} \mathbf{0}_{1\times(k-k_0)} & 0 & 0 & 0 & 1 & 0 & 0 \\ \mathbf{0}_{1\times(k-k_0)} & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}, \tag{A.53}$$

and $\mathbf{d}_{T+j} = (r^S_{0,T+j}, r^L_{0,T+j})'$, $j = 1, 2, ..., \bar{H}$, contains the predefined values for the US short and long run interest rates for each future quarter j.

Point forecasts of $\mathbf{x}_{T+h}$ under the restrictions are given by

$$\mu^*_h = E\left(\mathbf{x}_{T+h} \left|\mathcal{I}_T, \boldsymbol{\Psi}\mathbf{x}_{T+j} = \mathbf{d}_{T+j},\ j = 1, 2, ..., \bar{H}\right.\right),\ \text{for } h = 1, 2, ..., H.$$

In deriving the expectations it is assumed that the restrictions do not affect the GVAR parameters, $\mathbf{F}_i$, $i = 1, 2$ and the covariance matrix, $\boldsymbol{\Sigma}_\varepsilon$, associated with the residuals, $\boldsymbol{\varepsilon}_t$, of the GVAR model A.47.

Firstly consider that the ex-ante forecasts are normally distributed so that

$$\mathbf{x}_{T+h} \left|\mathcal{I}_T \right. \sim N(\boldsymbol{\mu}_h, \boldsymbol{\Omega}_{hh}),$$

where $\mathbf{\Omega}_{hh}$ is given by

$$\mathbf{\Omega}_{hh} = \mathcal{S}\sum_{\ell=0}^{h-1}\mathbf{F}^{\ell}\mathbf{\Sigma}\mathbf{F}'^{\ell}\mathcal{S}', \tag{A.54}$$

with

$$\mathbf{\Sigma} = \begin{pmatrix} \mathbf{\Sigma}_{\varepsilon} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix}, \tag{A.55}$$

and $\mathbf{\Sigma}_{\varepsilon}$=$Cov(\boldsymbol{\varepsilon}_{T+h-i})$.

Using (A.49) we have

$$\mathbf{x}_{T+h} = \boldsymbol{\mu}_h + \boldsymbol{\xi}_{T+h}, \tag{A.56}$$

where

$$\boldsymbol{\xi}_{T+h} = \sum_{\ell=0}^{h-1}\mathcal{S}\mathbf{F}^{\ell}\mathbf{E}_{T+h-\ell}.$$

The restrictions now imply that

$$\mathbf{\Psi}\boldsymbol{\xi}_{T+j} = \mathbf{d}_{T+j} - \mathbf{\Psi}\boldsymbol{\mu}_j \text{ for } j = 1, 2, ..., \bar{H}. \tag{A.57}$$

Setting $\mathbf{g}_j = \mathbf{d}_{T+j} - \mathbf{\Psi}\boldsymbol{\mu}_j\ \forall j$, (A.57) can be written as

$$(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi})\boldsymbol{\xi}_{\bar{H}}= \mathbf{g}_{\bar{H}},$$

where $\boldsymbol{\xi}_{\bar{H}}= (\boldsymbol{\xi}'_{T+1}, \boldsymbol{\xi}'_{T+2}, ..., \boldsymbol{\xi}'_{T+\bar{H}})'$ and $\mathbf{g}_{\bar{H}}= (\mathbf{g}'_1, \mathbf{g}'_2, ..., \mathbf{g}'_{\bar{H}})'$.

Under joint normality of the shocks, we have, for $h = 1, ..., H \leq \bar{H}$,

$$\begin{aligned} & E\left(\boldsymbol{\xi}_{T+h}\left|\mathcal{I}_T, \mathbf{\Psi}\mathbf{x}_{T+j} = \mathbf{d}_{T+j},\ j = 1, ..., \bar{H}\right.\right) \\ = \ & E\left(\boldsymbol{\xi}_{T+h}|\mathcal{I}_T, (\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi})\boldsymbol{\xi}_{\bar{H}}= \mathbf{g}_{\bar{H}}\right) \\ = \ & (\mathfrak{s}'_{h\bar{H}}\otimes\mathbf{I}_k)\mathbf{\Omega}_{\bar{H}}(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi}')[(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi})\mathbf{\Omega}_{\bar{H}}(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi}')]^{-1}\mathbf{g}_{\bar{H}}, \end{aligned}$$

where $\mathfrak{s}_{h\bar{H}}$ is a $\bar{H} \times 1$ selection vector with unity as its h^{th} element and zeros elsewhere, and $\mathbf{\Omega}_{\bar{H}}$ is the $k\bar{H} \times k\bar{H}$ matrix

$$\mathbf{\Omega}_{\bar{H}} = \begin{pmatrix} \mathbf{\Omega}_{11} & \mathbf{\Omega}_{12} & \cdots & \mathbf{\Omega}_{1\bar{H}} \\ \mathbf{\Omega}_{21} & \mathbf{\Omega}_{22} & \cdots & \mathbf{\Omega}_{2\bar{H}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{\Omega}_{\bar{H}1} & \mathbf{\Omega}_{\bar{H}2} & \cdots & \mathbf{\Omega}_{\bar{H}\bar{H}} \end{pmatrix}. \tag{A.58}$$

The diagonal elements of $\mathbf{\Omega}_{\bar{H}}$, that is $\{\mathbf{\Omega}_{ii}\}_{i=1}^{\bar{H}}$, are given by (A.54), while the off-diagonal elements can be expressed as

$$\mathbf{\Omega}_{ij} = \begin{cases} \mathcal{S}(\sum_{\ell=0}^{i-1}\mathbf{F}^{\ell}\mathbf{\Sigma}\mathbf{F}'^{\ell})\mathbf{F}'^{(j-i)}\mathcal{S}', & i < j \\ \mathcal{S}\mathbf{F}^{(i-j)}(\sum_{\ell=0}^{j-1}\mathbf{F}^{\ell}\mathbf{\Sigma}\mathbf{F}'^{\ell})\mathcal{S}', & i > j \end{cases}$$

where $\mathbf{\Sigma}$ is defined by (A.55).

Hence, the conditional point forecasts are given by

$$\boldsymbol{\mu}_h^* = \boldsymbol{\mu}_h + (\mathfrak{s}'_{h\bar{H}}\otimes\mathbf{I}_k)\mathbf{\Omega}_{\bar{H}}(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi}')[(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi})\mathbf{\Omega}_{\bar{H}}(\mathbf{I}_{\bar{H}}\otimes\mathbf{\Psi}')]^{-1}\mathbf{g}_{\bar{H}}.$$

The above can be easily modified to accommodate the specification of the GVAR model used in the first part of this document for demonstration purposes. This requires replacing $\mathbf{x}_{T+j}$ with $\mathbf{y}_{T+j}$ and adjusting the restrictions matrix $\mathbf{\Psi}$. The computation of the conditional forecasts is based on the sample covariance matrix $\hat{\mathbf{\Sigma}}_{\varepsilon}$ computed as in (A.30) without any restrictions imposed on this matrix or any shinkage performed.

Note that the current version of the toolbox does not impose lower bound restrictions on the conditional forecasts. This will be dealt with in a future release of the toolbox.

A.26 Trend/Cycle decomposition of the GVAR

A further option available by this version of the toolbox is the decomposition of the variables in the GVAR model into trends and cycles, with the trends further decomposed into deterministic and stochastic components. The stochastic components will be present only if the underlying GVAR contains unit roots. The decomposition can be viewed as a multivariate version of the well known Beveridge-Nelson (BN) permanent/transitory decomposition, but has the advantage that it is characterised fully in terms of the observables.

Denote the $k \times 1$ vector of endogenous variables in the global economy by $\mathbf{x}_t$, and consider the decomposition of $\mathbf{x}_t$ into permanent $\mathbf{x}_t^P$, and cyclical/transitory components, $\mathbf{x}_t^C$ of the form $\mathbf{x}_t = \mathbf{x}_t^P + \mathbf{x}_t^C$. The permanent component may be further sub-divided into deterministic and stochastic components, $\mathbf{x}_t^P = \mathbf{x}_{dt}^P + \mathbf{x}_{st}^P$. Following Garratt, Robertson and Wright (2006, GRW), the deterministic and the stochastic trend components of $\mathbf{x}_t$ can be defined respectively by

$$\mathbf{x}_{dt}^P = \boldsymbol{\mu} + \mathbf{g}t,$$

where $\boldsymbol{\mu}$ and $\mathbf{g}$ are $k \times 1$ vectors of fixed constants, and t is a deterministic time trend, and

$$\mathbf{x}_{st}^P = \lim_{h\to\infty} E_t\left(\mathbf{x}_{t+h} - \mathbf{x}_{d,t+h}^P\right) = \lim_{h\to\infty} E_t\left[\mathbf{x}_{t+h} - \boldsymbol{\mu} - \mathbf{g}(t+h)\right],$$

where $E_t(.)$ denotes the expectations operator conditional on the information available at time t, taken to include at least $\{\mathbf{x}_t, \mathbf{x}_{t-1}, ..., \mathbf{x}_0\}$. That is, the permanent-stochastic component, $\mathbf{x}_{st}^P$, is *uniquely* defined as the 'long-horizon forecast' (net of the permanent-deterministic component). For further details see GRW and Dees, Pesaran, Smith and Smith (2009).

Now consider the global error correction form of the GVAR given by

$$\mathbf{G}\Delta\mathbf{x}_t = \mathbf{a} - \widetilde{\boldsymbol{\alpha}}\widetilde{\boldsymbol{\beta}}'\left[\mathbf{x}_{t-1} - \boldsymbol{\gamma}(t-1)\right] + \sum_{i=1}^{p-1}\boldsymbol{\Gamma}_i\Delta\mathbf{x}_{t-i} + \mathbf{u}_t, \tag{A.59}$$

where $\mathbf{G}$ is a $k \times k$ matrix that reflects the contemporaneous interdependencies across countries, $\boldsymbol{\gamma}$ is a $k \times 1$ vector of fixed constants, $\widetilde{\boldsymbol{\alpha}}$ is the $k \times r$ block-diagonal matrix of the global loading coefficients, with diagonal elements $\boldsymbol{\alpha}_j$, with $r = \sum_{i=1}^N r_i$ and r_i is the cointegrating rank for country i, and $\widetilde{\boldsymbol{\beta}}$ is the global $k \times r$ cointegrating matrix[16]: $\widetilde{\boldsymbol{\beta}} = \begin{pmatrix} \mathbf{W}_1'\boldsymbol{\beta}_1, & \mathbf{W}_2'\boldsymbol{\beta}_2, & \ldots, & \mathbf{W}_N'\boldsymbol{\beta}_N \end{pmatrix}$.

To derive the permanent components, the global error correction model, (A.59), can be expressed in terms of the VAR(p) specification

$$\mathbf{x}_t = \mathbf{b}_0 + \mathbf{b}_1 t + \sum_{i=1}^{p}\boldsymbol{\Phi}_i\mathbf{x}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{A.60}$$

where

$$\mathbf{b}_0 = \mathbf{G}^{-1}(\mathbf{a} - \widetilde{\boldsymbol{\alpha}}\widetilde{\boldsymbol{\beta}}'\boldsymbol{\gamma}),\ \mathbf{b}_1 = \mathbf{G}^{-1}\widetilde{\boldsymbol{\alpha}}\widetilde{\boldsymbol{\beta}}'\boldsymbol{\gamma},\ \boldsymbol{\varepsilon}_t = \mathbf{G}^{-1}\mathbf{u}_t,$$

$$\boldsymbol{\Phi}_1 = \mathbf{G}^{-1}(\mathbf{G} + \boldsymbol{\Gamma}_1 - \widetilde{\boldsymbol{\alpha}}\widetilde{\boldsymbol{\beta}}'),\ \boldsymbol{\Phi}_i = \mathbf{G}^{-1}(\boldsymbol{\Gamma}_i - \boldsymbol{\Gamma}_{i-1}),\ i = 2, ..., p-1,\ \boldsymbol{\Phi}_p = -\mathbf{G}^{-1}\boldsymbol{\Gamma}_{p-1}.$$

[16]Note that for the deterministic trend properties of the variables to be the same in the global model as in the underlying country-specific models $\widetilde{\boldsymbol{\alpha}}\widetilde{\boldsymbol{\beta}}'\boldsymbol{\gamma} = \begin{pmatrix} (\boldsymbol{\alpha}_1\boldsymbol{\beta}_1'\mathbf{W}_1\boldsymbol{\gamma})', & (\boldsymbol{\alpha}_2\boldsymbol{\beta}_2'\mathbf{W}_2\boldsymbol{\gamma})', & \ldots, & (\boldsymbol{\alpha}_N\boldsymbol{\beta}_N'\mathbf{W}_N\boldsymbol{\gamma})' \end{pmatrix}'$ where $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ are the loading coefficients and the cointegrating matrix, respectively, of the individual country models.

Using (A.60) the solution of $\mathbf{x}_t$ can also be expressed as

$$\mathbf{x}_t = \boldsymbol{\mu} + \mathbf{g}t + \mathbf{C}(1)\mathbf{s}_{\varepsilon t} + \mathbf{C}^*(L)\boldsymbol{\varepsilon}_t,$$

where

$$\boldsymbol{\mu} = \mathbf{x}_0 - \mathbf{C}^*(L)\boldsymbol{\varepsilon}_0,\ \mathbf{s}_{\varepsilon t} = \sum_{j=1}^{t}\boldsymbol{\varepsilon}_j,\ \mathbf{C}^*(L) = \sum_{j=0}^{\infty}\mathbf{C}_j^* L^j,$$

$$\mathbf{C}_j = \mathbf{C}_{j-1}\boldsymbol{\Phi}_1 + \mathbf{C}_{j-2}\boldsymbol{\Phi}_2 + \cdots + \mathbf{C}_{j-p}\boldsymbol{\Phi}_p, \text{ for } j = 1, 2, ...,$$

with $\mathbf{C}_0 = \mathbf{I}_k$, $\mathbf{C}_1 = -(\mathbf{I}_k - \boldsymbol{\Phi}_1)$, and $\mathbf{C}_j = \mathbf{0}$ for $j < 0$; $\mathbf{C}_j^* = \mathbf{C}_{j-1}^* + \mathbf{C}_j$, for $j = 1, 2, ...$, with $\mathbf{C}_0^* = \mathbf{C}_0 - \mathbf{C}(1)$, and $\mathbf{C}(1) = \sum_{j=0}^{\infty}\mathbf{C}_j$.[17] Hence, it is easily seen that

$$\mathbf{x}_{st}^P = \lim_{h\to\infty} E_t\left[\mathbf{x}_{t+h} - \boldsymbol{\mu} - \mathbf{g}(t+h)\right] = \mathbf{C}(1)\sum_{j=1}^{t}\boldsymbol{\varepsilon}_j,$$

which is the multivariate version of the Beveridge-Nelson (BN) stochastic trend component.[18] Note that $\mathbf{x}_{st}^P$ is uniquely determined from the time series observations on $\mathbf{x}_t$ and its lagged values. The identification problem with the BN decomposition discussed in the literature relates to separating the k shocks, $\boldsymbol{\varepsilon}_t$, into permanent (supply) or transitory (demand) shocks. A general discussion of this problem is provided by Pagan and Pesaran (2008).

The permanent-stochastic component can now be estimated directly from the parameters of the GVAR as $\hat{\mathbf{x}}_{st}^P = \hat{\mathbf{C}}(1)\sum_{i=1}^{t}\hat{\boldsymbol{\varepsilon}}_i$. The transitory component, $\widehat{\mathbf{x}}_t^C$, the deviation from steady state, can then be estimated as

$$\hat{\mathrm{v}}_t = \mathbf{x}_t - \hat{\mathbf{x}}_{st}^P = \hat{\boldsymbol{\mu}} + \hat{\mathbf{g}}t + \widehat{\mathbf{x}}_t^C,$$

with $\hat{\boldsymbol{\mu}}$ and $\hat{\mathbf{g}}$ in turn estimated from the OLS regressions

$$\hat{\mathrm{v}}_{i,\ell t} = \mu_{i\ell} + g_{i\ell}t + \xi_{i,\ell t},\ i = 1, 2, ..., N;\ \ell = 1, ..., k_i, \tag{A.61}$$

for variable ℓ in country i.[19] In this way, a number of trend restrictions of interest are also able to be imposed. The estimated transitory component, $\hat{\mathbf{x}}_t^C$, is then the residual from the above regressions, that is $\widehat{\mathbf{x}}_t^C = (\hat{\boldsymbol{\xi}}_1', \hat{\boldsymbol{\xi}}_2' ..., \hat{\boldsymbol{\xi}}_N')'$.

The above decomposition of the GVAR can be used to obtain estimates of the deviation from the permanent component/steady states $\widetilde{\mathbf{x}}_t = \mathbf{x}_t - \mathbf{x}_t^P$ required as input data in multi-country New Keynesian (NK) modelling (Dees, Pesaran, Smith and Smith (2013, DPSS)). Measured as the permanent component in a multivariate version of the BN decompostion of $\mathbf{x}_t$, the steady states reflect the structure of the full GVAR model of the economy, including the variables chosen, the lag orders selected, the cointegrating relations imposed and the treatment of deterministic elements. Changing any of these will change the estimated decomposition. This seems a desirable feature as compared to statistical procedures like the Hodrick-Prescott filter where the estimate is invariant to the form of the economic model. However, where there is uncertainty about the form of the model and the appropriate sample to be used for estimation, one could use some form of model averaging

[17]For the computation of $C(1)$ the toolbox uses $j = 0, ..., 1000$.

[18]It is worth noting that the long run expectations can be derived with respect to other information sets, such information dated $t-1$ or earlier. In such cases the long run expectations will not coincide with the permanent component in the BN decomposition.

[19]If all variables in the GVAR model (including any dominant unit model) are estimated under case II, no trend term is included in (A.61) for any variable. Note that if the actual data do contain a linear trend, then the trend/cycle estimates will not be reliable.

to obtain a more robust decomposition. For more details regarding multi-country New Keynesian (MCNK) modelling see DPSS (2013).

It should be noted that when performing the above decomposition using a similar specification of the GVAR as DdPS (where the US is the numeraire country), given that the US real exchange rate variable does not enter the GVAR model as an endogenous variable, $\widetilde{ep}$ for the US ($\widetilde{ep}_{0t}$) is not directly obtainable. To obtain $\widetilde{ep}_{0t}$ note that $e_{0t} = 0$, $\widetilde{ep}_{0t} =$ -$\widetilde{p}_{0t}$. It is important that possible stochastic trends in the log US price level are appropriately taken into account when computing $\widetilde{p}_{0t}$. This is achieved by first estimating $\widetilde{Dp}_{0t}$ and then cumulating the values of $\widetilde{Dp}_{0t}$ to obtain $\widetilde{p}_{0t}$ up to an arbitrary constant. Specifically, -$\widetilde{p}_{0t}$ is constructed from $\widetilde{Dp}_{0t}$ taking the initial value from the p_{0t} (actual) series. The $\widetilde{p}_{0t}$ variable is subsequently demeaned before setting $\widetilde{ep}_{0t}$ =-$\widetilde{p}_{0t}$.

A.27 Time-varying weights in GVAR modelling

The use of time-varying weights affects the computation of the foreign variables that enter the individual models, and the solution of the GVAR model, in the way outlined in this section. All other procedures described thus far remain the same.

A.27.1 Country-specific models

Consider the VARX*(1,1) model abstracting from deterministics and common observed factors for ease of exposition

$$\mathbf{x}_{it} = \mathbf{\Phi}_i \mathbf{x}_{i,t-1} + \mathbf{\Lambda}_{i0}\mathbf{x}^*_{it} + \mathbf{\Lambda}_{i1}\mathbf{x}^*_{i,t-1} + \mathbf{u}_{it}. \tag{A.62}$$

The foreign variables are defined as weighted averages in terms of predetermined weight matrices $\mathbf{W}_{ij,t}$ of order $k^*_i \times k_j$ at time t given by

$$\mathbf{x}^*_{it}(\mathbf{W}_{i,\tau(t)}) = \sum_{j=0}^{N} \mathbf{W}_{ij,\tau(t)}\mathbf{x}_{jt} = \mathbf{W}_{i,\tau(t)}\mathbf{x}_t, \tag{A.63}$$

where $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ is a $k \times 1$ vector of the endogenous variables ($k = \Sigma^N_{i=0} k_i$), and $\mathbf{W}_{it} = (\mathbf{W}_{i0,t}, \mathbf{W}_{i1,t}, ..., \mathbf{W}_{iN,t})$. Therefore, (A.62) can be written as

$$\mathbf{x}_{it} = \mathbf{\Phi}_i \mathbf{x}_{i,t-1} + \mathbf{\Lambda}_{i0}\mathbf{W}_{i,\tau(t)}\mathbf{x}_t + \mathbf{\Lambda}_{i1}\mathbf{W}_{i,\tau(t-1)}\mathbf{x}_{t-1} + \mathbf{u}_{it}. \tag{A.64}$$

The weights could be based on bilateral trade or capital flows. When the same set of weights are used across all variables in a given economy then the k^*_i rows of $\mathbf{W}_{ij,\tau(t)}$ will be identical, except for possible differences in scaling. For example, three year moving average trade weights could be used with the weights reset at the start of each year and kept fixed through a given year, which can be specified in terms of $\tau(t)$. If a fixed set of weights are used over time then $\tau(t)$ will be fixed and will not change with t. It is important that for each choice of the weights, $\mathbf{W}_{i,\tau(t)}$, $\mathbf{x}^*_{it}(\mathbf{W}_{i,\tau(t)})$ and its lagged value is constructed according to (A.63). It is not necessarily the case that $\mathbf{x}^*_{i,t-1}$ is equal to the lagged value of $\mathbf{x}^*_{it}$. This is the case only if the weights are fixed across all time periods.

For a given set of weights, the country-specific models can then be tested for cointegration and estimated for each i. Using the sample $\mathbf{x}_t$, $t = 1, 2, ..., T$, such estimates can be denoted by $\hat{\mathbf{\Phi}}_i(\mathbf{W}_{NT})$, $\hat{\mathbf{\Lambda}}_{i0}(\mathbf{W}_{NT})$ and $\hat{\mathbf{\Lambda}}_{i1}(\mathbf{W}_{NT})$, where $\mathbf{W}_{NT} = \{\mathbf{W}_{it}, i = 0, 1, ..., N; t = 1, 2, ..., T\}$ with associated country-specific residuals given by

$$\hat{\mathbf{u}}_{it}(\mathbf{W}_{NT}) = \mathbf{x}_{it} - \hat{\mathbf{\Phi}}_i(\mathbf{W}_{NT})\mathbf{x}_{i,t-1} - \hat{\mathbf{\Lambda}}_{i0}(\mathbf{W}_{NT})\mathbf{W}_{i,\tau(t)}\mathbf{x}_t - \hat{\mathbf{\Lambda}}_{i1}(\mathbf{W}_{NT})\mathbf{W}_{i,\tau(t-1)}\mathbf{x}_{t-1}.$$

A.27.2 Solving the GVAR model for a given weight matrix

Having estimated the country-specific parameters using the time-varying weights, the estimated country-specific models can now be combined and solved for *any* given trade weights either from a particular year or from an average over a set of years. In what follows we shall denote such a weight matrix by $\mathbf{W}_i^0$ and show how to solve the GVAR with the estimates of the unknown parameters based on time varying weights.

Let $\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}) = (Vec(\hat{\boldsymbol{\Phi}}_i(\mathbf{W}_{NT}))', Vec(\hat{\boldsymbol{\Lambda}}_{i0}(\mathbf{W}_{NT}))', Vec(\hat{\boldsymbol{\Lambda}}_{i1}(\mathbf{W}_{NT}))')'$ and use the $k_i \times k$ selection matrix $\mathbf{S}_i$ such that

$$\mathbf{x}_{it} = \mathbf{S}_i \mathbf{x}_t.$$

Then using (A.64) we have

$$\begin{aligned}
\mathbf{S}_i \mathbf{x}_t &= \hat{\boldsymbol{\Phi}}_i(\mathbf{W}_{NT})\mathbf{S}_i \mathbf{x}_{t-1} + \hat{\boldsymbol{\Lambda}}_{i0}(\mathbf{W}_{NT})\mathbf{W}_i^0 \mathbf{x}_t + \hat{\boldsymbol{\Lambda}}_{i1}(\mathbf{W}_{NT})\mathbf{W}_i^0 \mathbf{x}_{t-1} + \breve{\mathbf{u}}_{it}, \\
[\mathbf{S}_i - \hat{\boldsymbol{\Lambda}}_{i0}(\mathbf{W}_{NT})\mathbf{W}_i^0]\mathbf{x}_t &= [\hat{\boldsymbol{\Phi}}_i(\mathbf{W}_{NT})\mathbf{S}_i - \hat{\boldsymbol{\Lambda}}_{i1}(\mathbf{W}_{NT})\mathbf{W}_i^0]\mathbf{x}_{t-1} + \breve{\mathbf{u}}_{it}, \\
\mathbf{G}_i(\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}), \mathbf{W}_i^0)\mathbf{x}_t &= \mathbf{H}_i(\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}), \mathbf{W}_i^0)\mathbf{x}_{t-1} + \breve{\mathbf{u}}_{it}, \qquad \text{(A.65)}
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{G}_i(\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}), \mathbf{W}_i^0) &= \mathbf{S}_i - \hat{\boldsymbol{\Lambda}}_{i0}(\mathbf{W}_{NT})\mathbf{W}_i^0, \\
\mathbf{H}_i(\hat{\boldsymbol{\theta}}_i(\mathbf{W}_{NT}), \mathbf{W}_i^0) &= \hat{\boldsymbol{\Phi}}_i(\mathbf{W}_{NT})\mathbf{S}_i - \hat{\boldsymbol{\Lambda}}_{i1}(\mathbf{W}_{NT})\mathbf{W}_i^0.
\end{aligned}$$

Note that $\breve{\mathbf{u}}_{it}$ will *not* be the same as $\hat{\mathbf{u}}_{it}(\mathbf{W}_{NT})$, unless at time t we have $\mathbf{W}_{i,\tau(t-1)} = \mathbf{W}_i^0$, which can only occur when the weights are fixed.

Stacking (A.65) for $i = 0, 1, ..., N$ we obtain

$$\mathbf{G}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)\mathbf{x}_t = \mathbf{H}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)\mathbf{x}_{t-1} + \breve{\mathbf{u}}_t,$$

where

$$\begin{aligned}
\mathbf{G}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0) &= (\mathbf{G}_0'(\hat{\boldsymbol{\theta}}_0(\mathbf{W}_{NT}), \mathbf{W}_0^0), \mathbf{G}_1'(\hat{\boldsymbol{\theta}}_1(\mathbf{W}_{NT}), \mathbf{W}_1^0), ..., \mathbf{G}_N'(\hat{\boldsymbol{\theta}}_N(\mathbf{W}_{NT}), \mathbf{W}_N^0))' \\
\mathbf{H}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0) &= (\mathbf{H}_0'(\hat{\boldsymbol{\theta}}_0(\mathbf{W}_{NT}), \mathbf{W}_0^0), \mathbf{H}_1'(\hat{\boldsymbol{\theta}}_1(\mathbf{W}_{NT}), \mathbf{W}_1^0), ..., \mathbf{H}_N'(\hat{\boldsymbol{\theta}}_N(\mathbf{W}_{NT}), \mathbf{W}_N^0))',
\end{aligned}$$

$$\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}) = (\hat{\boldsymbol{\theta}}_0'(\mathbf{W}_{NT}), \hat{\boldsymbol{\theta}}_1'(\mathbf{W}_{NT}), ..., \hat{\boldsymbol{\theta}}_N'(\mathbf{W}_{NT}))', \ \mathbf{W}^0 = (\mathbf{W}_0^0, \ \mathbf{W}_1^0, ..., \mathbf{W}_N^0).$$

and $\breve{\mathbf{u}}_t = (\breve{\mathbf{u}}_{0t}', \breve{\mathbf{u}}_{1t}', ..., \breve{\mathbf{u}}_{Nt}')$.

Therefore,

$$\mathbf{x}_t = \mathbf{F}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)\mathbf{x}_{t-1} + \mathbf{G}^{-1}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)\breve{\mathbf{u}}_t, \qquad \text{(A.66)}$$

where

$$\mathbf{F}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0) = \mathbf{G}^{-1}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0)\mathbf{H}(\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT}), \mathbf{W}^0).$$

The covariance matrix of the stacked country-specific residuals $\widetilde{\mathbf{u}}_t$ can be consistently estimated by

$$\breve{\boldsymbol{\Sigma}}_u = \sum_{t=1}^{T} \breve{\mathbf{u}}_t \breve{\mathbf{u}}_t'/T.$$

Shrinkage can then be applied to $\breve{\boldsymbol{\Sigma}}_u$ similar to $\hat{\boldsymbol{\Sigma}}_u$ in the case of fixed weights. Abstracting from parameter uncertainty and taking the value of $\hat{\boldsymbol{\theta}}(\mathbf{W}_{NT})$ as given and 'true', the computation of the PPs, GIRFs and GFEVDs is based on the formulas given by (A.21), (A.22) and (A.25) respectively. Bootstrapping is based on equation (A.66) and follows in the same manner described in Section A.22.1.

Link matrices in the case of time-varying weights

The trade flows included in the GVAR database are the annual trade flows beginning in 1980, while the sample data of DdPS for the domestic and global variables begin in 1979Q2 (an observation is lost due to the construction of inflation from the price level data).

Under the option of time-varying weights, the first choice the user has to make is to define the size of the window to average across when constructing the time-varying weights. If a three year average is selected, then the weights are constructed as shown below:

Date of trade share matrices	Three year weighted averages
1979	1980-1981-1982
1980	1980-1981-1982
1981	1980-1981-1982
1982	1980-1981-1982
1983	1981-1982-1983
1984	1982-1983-1984
1985	1983-1984-1985
1986	1984-1985-1986
1987	1985-1986-1987
1988	1986-1987-1988
1989	1987-1988-1989
1990	1988-1989-1990
$\vdots$	$\vdots$

so that 1982 weights are the average of 1980, 1981 and 1982 weights, 1983 weights are the average of 1981, 1982 and 1983 weights and so on. As there is no trade data available prior to 1980, the 1979, 1980 and 1981 weights contain the same three year average as 1982. These $\mathbf{W}_{NT}$ weights (using the above notation) are then used to estimate the country-specific models. If annual weights are chosen as opposed to three year averages, then:

Date of trade share matrices	Single year (annual) weight matrix dates
1979	1980
1980	1980
1981	1981
1982	1982
1983	1983
1984	1984
1985	1985
1986	1986
1987	1987
1988	1988
1989	1989
1990	1990
$\vdots$	$\vdots$

Next, the user is required to select a year to solve the GVAR model. Any year can be chosen corresponding to the years covering the estimation sample. Suppose one selects the year 1988 to solve the model, then the user has two options: either to use the three year weighted average corresponding to year 1988 that is 1986-1988 as shown above, or to use single year (annual) weights corresponding to 1988. In the latter case, the weights are simply trade shares constructed from the underlying 1988 trade flows.

B: COMPILATION, REVISION AND UPDATING OF THE GVAR DATABASE (1979Q1-2013Q1)

B.1 Data sources

This version of the GVAR dataset revises and extends up to 2013Q1 the last available GVAR dataset (the '2011 Vintage') available at: https://sites.google.com/site/gvarmodelling/data. This updated dataset (1979Q1-2013Q1) will be referred to as the '2013 Vintage'.

The 2013 Vintage is obtained by extrapolating forward (using growth rates) the data of the 2011 Vintage from 2004Q1, unless otherwise specified. Therefore, data from 1979Q1 to 2003Q4 are typically the same in both the 2011 and the 2013 Vintages, while it may differ from 2004Q1 to 2011Q2. This strategy is adopted to be sure to include in the update possible data revisions and to have an overlapping window to evaluate the goodness of the update.

The construction of the 2013 Vintage, relies on the International Financial Statistics (IFS) database, the Inter-American Development Bank Latin Macro Watch database (IDB LMW hereafter),[20] and Bloomberg data. In previous versions of the GVAR database, Datastream was used instead of Bloomberg. Table B.1 at the end of this section provides the Datastream codes corresponding to the Bloomberg series used.

B.1.1 Real GDP

For compiling the 2013 Vintage Real GDP countries are divided into three groups. First, those for which quarterly and seasonally adjusted data are available. Second, those for which quarterly data are available, but are not seasonally adjusted. Third, those for which only annual data are available.

For the first group, the IFS data were used (Concept: Gross Domestic Product, Real Index, Quarterly, 2005 = 100) for Australia, Canada, France, Germany, Italy, Japan, Netherlands, New Zealand, South Africa, Spain, Switzerland, United Kingdom, and United States.[21] The 2013 Vintage real GDP was extrapolated using quarterly growth rates of the IFS series from 2004Q1 to 2013Q1.

For the second group, the IFS data were used (Concept: Gross Domestic Product, Real Index, Quarterly, 2005 = 100) for Austria, Belgium[22], Finland, India, Indonesia, Korea, Malaysia, Singapore, Sweden, Thailand, and Turkey. When IFS data were not available, gaps were filled using Bloomberg data: India in 2011Q2 (Ticker: INQGGDPY Index) and Singapore in 2000Q2, 2000Q3 and 2011Q2 (Ticker: SGDPYOY Index). These series were seasonally adjusted using Eviews, applying the National Bureau's X12 program as described in Section B.2.2. As in the first group, the dataset was extended with forward extrapolation of the 2011 Vintage using quarterly growth rates of the adjusted IFS series from 2004Q1 to 2013Q1.

[20] The IDB LMW data is publicly available beginning in 1990 and can be downloaded from http://www.iadb.org/Research/LatinMacroWatch/lmw.cfm, where more information about the data can be found.

[21] All series in the IMF IFS database have been reclassified. The concepts used here correspond to the ones used for the 2009 Vintage real GDP, namely 99BVRZF, 99BVPZF and BVPZF.

[22] The IFS data reports seasonal adjusted data for Belgium from 1999Q1 onward, thus no seasonal adjustment was made after all.

For Saudi Arabia the annual seasonally unadjusted IFS data (Concept: Gross Domestic Product, Real index, Annually, 2005 = 100) were interpolated to obtain the quarterly values (see Section B.3 for details on this procedure). This series was then treated as the quarterly seasonally unadjusted data.

For the Latin American countries, namely for Argentina, Brazil, Chile, Mexico, and Peru, the IDB LMW data were used (Concept: GDP, Real Index SA) and the series were updated in the same manner described for the quarterly seasonally adjusted data. For Philippines, the quarterly rate of change of the seasonal adjusted real GDP index (Source: Bloomberg. Ticker: PHNAGDPS Index) was used to extrapolate forward the 2011 Vintage real GDP from 2004Q1 to 2013Q1. For Norway, the series from IFS continued to show evidence of seasonality after seasonal adjustment. The series from OECD (Ticker: GPSA, Concept: Growth rate compared to previous quarter, seasonally adjusted) was used instead, and the 2011 Vintage real GDP was extrapolated forward using this growth rate from 2004Q1 to 2013Q1.

As no institution publishes a quarterly real GDP Index for China, it has to be compiled from a nominal GDP series. The National Bureau of Statistics (NBS) of China releases quarterly nominal GDP series without seasonal adjustment.[23] Accordingly, a quarterly real GDP index for China was constructed as follows. First, the nominal GDP series from NBS was seasonally adjusted, as described in Section B.2.2. Then, the following formula was used:

$$\begin{aligned} \log(RGDP_1) &= \log\left(\frac{GDP_1}{CPI_1}\right) && \text{for } t=1 \\ \log(RGDP_t) &= \log(RGDP_{t-1}) + \log\left(\frac{GDP_t}{GDP_{t-1}}\right) - \log\left(\frac{CPI_t}{CPI_{t-1}}\right) && \text{for } t>1 \end{aligned}$$

where CPI is defined in Section B.1.2. The series was updated in the same manner as described for the quarterly seasonally adjusted data.

B.1.2 Consumer price index

In order to create the 2013 Vintage CPI, IFS data (Concept: Consumer Prices, All items, Quarterly, 2005 = 100) were collected for all countries with the exception of China.[24] For the series that did not need seasonal adjustment, the quarterly growth rates were used to extrapolate forward the 2011 Vintage from 2004Q1 to 2013Q1. Following the procedure in Section B.2, the following countries were seasonally adjusted: Austria, Belgium, Canada, Chile[25], Finland, France, Germany, India, Indonesia, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, South Africa, Spain, Sweden, Switzerland, Thailand, United Kingdom[26], United States. The quarterly rate of change of the adjusted IFS series was used to extrapolate forward the 2011 Vintage CPI from 2004Q1 to 2013Q1, in order to obtain the 2013 Vintage.

For China, Bloomberg data (Ticker: CNCPIYOY Index, quarterly rate of change of CPI index, NSA) were used. First, the quarterly rate of change was seasonally adjusted using Eviews, applying the National Bureau's X12 program. The Bloomberg rate of change was used to create a series in levels which was then seasonally adjusted following the procedure in Section B.2.2. Then, the

[23]For further information see: http://www.stats.gov.cn/english/statisticaldata/Quarterlydata/. The NBS series can be accessed from Datastream, ticker: CH GDP (DS CALCULATED) CURN.

[24]The series in the IMF IFS database have been reclassified. The concept used here corresponds to the IFS CPI 64zf (level) series, which is the one used in the 2009 Vintage CPI.

[25]For Chile the Quarterly 2009 = 100 index was used as it was the only available data.

[26]Note that the UK inflation series has changed since August 2011. Instead of "Retail Price Index", IMF has started to publish "the Consumer Price Index", which was previously published as "the Harmonized Consumer Price Index", as the official inflation series of UK.

2013 Vintage CPI for China was obtained by forward extrapolation of the 2011 Vintage using the rate of change of the adjusted Bloomberg series from 2004Q1 to 2013Q1.

B.1.3 Equity price index

Updated equity price series are from Bloomberg. A quarterly average of the MSCI Country Index in local currency was obtained for each of the following countries: Argentina, Australia, Austria, Belgium, Canada, Chile, Finland, France, Germany, India, Italy, Japan, Korea, Netherlands, Norway, New Zealand, Philippines, South Africa, Spain, Sweden, Switzerland, Thailand, United Kingdom, and United States.[27] For Malaysia, as the standard MSCI Index is not available, a local currency stock market index (Source: Bloomberg, Ticker: MXMY Index) was used instead. The quarterly average was computed based on the closing price of the last Wednesday of each month. That is, the last Wednesday was used for each month, then a simple average of these Wednesday prices was computed for the first three months of the year to obtain the first quarterly price index. Then an average of the Wednesday values for the next three months was computed to obtain the second quarterly price index and so on. Finally, the 2013 Vintage equity price index was obtained by forward extrapolation of the 2011 Vintage using the rate of change of the new series from 2004Q1 to 2013Q1.

B.1.4 Exchange rates

Exchange rate series are from Bloomberg. A quarterly average of the nominal bilateral exchange rates vis-a-vis the US dollar (units of foreign currency per US dollar) was obtained for each country.[28] The quarterly average was computed based on the closing value of the last Wednesday of each month, as described for the equity price index. The 2013 Vintage exchange rate was obtained by forward extrapolation of the 2011 Vintage using the rate of change of the new series from 2004Q1 to 2013Q1.

The exchange rate series of the euro economies refer to the pre-euro exchange rate (i.e. national currency per dollar). To denominate them in euro, the quarterly average of the euro exchange rate vis-a-vis the US dollar was used (Source: Bloomberg. Ticker: EUR Curncy). The 1999Q1 value of this series was then used as the base value, which was extrapolated backwards using the rate of change of the series denominated in national currency. From 1999Q1 to 2013Q1 the growth rates (and level) of the euro economies are the same and equal to the quarterly average of the euro exchange rate vis-a-vis the US dollar.

B.1.5 Short-term interest rates

IFS is the main source of data for the short-term interest rates. Consistent with the 2009 Vintage, IFS data were used for Argentina, Chile, China, and Turkey (Concept: Interest Rates, Deposit

[27] To construct a MSCI Country Index, every listed security in the market is identified. Securities are free float adjusted, classified in accordance with the Global Industry Classification Standard (GICS), and screened by size, liquidity and minimum free at (Source: MSCI Barra, www.mscibarra.com).

[28] The list of Bloomberg tickers is as follows: ARS JPMQ Curncy, AUD BGN Curncy, ATS CMPN Curncy, BEF CMPN Curncy, BRL BGN Curncy, CAD BGN Curncy, CNY BGN Curncy, CLP BGN Curncy, COP BGN Curncy, FIM CMPN Curncy, FRF CMPN Curncy, DEM BGN Curncy, INR CMPN Curncy, IDR BGN Curncy, ITL BGN Curncy, JPY BGN Curncy, KRW BGN Curncy, MYR BGN Curncy, MXN BGN Curncy, NLG CMPN Curncy, NOK BGN Curncy, NZD BGN Curncy, PEN BGN Curncy, PHP BGN Curncy, ZAR BGN Curncy, SAR BGN Curncy, SGD BGN Curncy, ESP CMPN Curncy, SEK BGN Curncy, CHF BGN Curncy, THB BGN Curncy, TRY BGN Curncy, GBP BGN Curncy, VEF BGN Curncy.

Rate); for New Zealand and Peru (Concept: Interest Rates, Discount Rate); for Canada, Malaysia, Mexico, Philippines, South Africa, Sweden, UK and US (Concept: Interest Rates, Treasury Bill Rate); and for Australia, Brazil, Finland, Germany, Indonesia, Italy, Japan, Korea, Norway, Singapore, Spain, Switzerland, and Thailand (Concept: Interest Rates, Money Market Rate).[29]

For Austria, Belgium, France, and the Netherlands no data were available for any of these series from 1999Q1 when the euro was introduced. The country specific IFS Money Market Rate was used from 1979Q1 to 1998Q4 and the series was completed to 2011Q2 using the corresponding data for Germany as the representative euro area interest rate. From 2012Q2 onward the IFS stopped publishing the German interest rate. The rest of the data were completed by extrapolating forward using the rate of change of the Euribor from Bloomberg (Ticker: EUR003M) from 2012Q3 to 2013Q1.

For India, quarterly averages of daily Bloomberg data (India Treasury Bill 3-Month Yield. Ticker: GINTB3MO Index) are constructed in the same way as the quarterly exchange rate series.[30] When IFS data were not available, gaps were filled using Bloomberg data: Norway in 2007Q1 and from 2009Q4 to 2011Q2 (Ticker: NKDRC CMPN Curncy), Philippines in 2003Q4, 2005Q4, 2006Q4 and 2008Q2 (Ticker: PH91AVG Index). The 2011 Vintage short-term interest rates are extended with these series from 2004Q1 to 2013Q1.

B.1.6 Long-term interest tates

The IFS data (Concept: Interest Rates, Government Securities, Government Bonds) were used to extend the series for all 18 countries for which long-term interest rate data were available, namely Australia, Austria, Belgium, Canada, France, Germany, Italy, Japan, Korea, Netherlands, New Zealand, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom, and United States.[31] The 2011 Vintage long-term interest rates are extended with these series from 2004Q1 to 2013Q1.

B.1.7 Oil price index

For the oil price index a Brent crude oil price from Bloomberg was used (Series: Current pipeline export quality Brent blend. Ticker: CO1 Comdty). To construct the quarterly series, the average of daily closing prices was obtained for all trading days within the quarter. The quarterly rate of change of this new series was used to extrapolate forward the 2011 Vintage oil price index from 2004Q1 to 2013Q1.

B.1.8 Other commodities: Agricultural raw material and metals price indices

The agricultural raw material and metals price indices were both taken from the IMF's Primary Commodity Prices monthly data.[32] Because the IMF data starts in 1980, the series were

[29] All series in the IMF IFS database have been reclassified. The concepts used here correspond to the ones used in the 2009 Vintage for the short term interest rates, namely the 60Lzf series, the 60Czf series, the 60Bzf series, and the 60zf series.

[30] This is an indicative Treasury Bill Rate polled daily by Bloomberg from various sources. The constructed series is not exactly equal to the original DdPS series, however it is very close.

[31] All series in the IMF IFS database have been reclassified. The concepts used here correspond to the ones used in the 2011 Vintage for the long term interest rates, namely the 61zf series.

[32] http://www.imf.org/external/np/res/commod/index.aspx.

extrapolated backwards to 1979 using the growth rate of the monthly price indices (2010 = 100) from the World Bank.[33] Monthly averages of the indices were taken for each quarter.

B.1.9 PPP - GDP data

The main source for construction of the country specific PPP-GDP weights is the World Development Indicator database of the World Bank. The GDP in Purchasing Power Parity terms in current international dollars (Ticker: NY.GDP.MKTP.PP.CD) was downloaded for all countries from 2009 to 2012.[34]

B.1.10 Trade matrix

To construct the trade matrices, the IMF Direction of Trade statistics was used. For all the countries considered the matrix of Exports and Imports (c.i.f.) was downloaded at the annual frequency. The data for 2011 and 2012 average of Exports and Imports were appended to the trade matrices associated with the 2011 Vintage.

Table B.1 Bloomberg tickers and corresponding Datastream codes

Series	Bloomberg Name	Datastream Name	Code
Philippines Real GDP	PHNAGDPS Index	GDP Index, NSA	PHGDP...D
Equity Price Indices	CNT MSCI Index	Total Market Index	CNT TOTMK
Exchange Rates	CNT CURNCY	Exchange Rates	CNT GTIS US $
India Treasury Bill 3-Month	GINTB3MO Index	91 Day T-Bill Primary Middle Rate	INPTB91
Oil Price	CO1 Comdty	Brent Crude	LCRINDX

B.2 Seasonality

B.2.1 Assessing the joint significance of seasonal effects

To asses the joint significance of the seasonal components for real output, real consumption and the price level the following procedure was used:

1. Let S_1, S_2, S_3 and S_4 be the usual seasonal dummies, such that S_i, $i = 1, 2, 3, 4$, takes the value of 1 in the i^{th} quarter and zero in the remaining three quarters.

2. Construct $S_{14} = S_1 - S_4$, $S_{24} = S_2 - S_4$, $S_{34} = S_3 - S_4$.

3. Run a regression of Δy (where the lower case denotes the natural logarithm of the corresponding variable) on an intercept and S_{14}, S_{24}, S_{34}. Denote the OLS estimates of S_{14}, S_{24} and S_{34} by a_1, a_2 and a_3.

4. Asses the joint significance of the seasonal components by testing the hypothesis that $a_1 = a_2 = a_3 = 0$ using the F-statistic.

[33] Prospects of commodity markets, “The Pink Sheet” historical data: http://go.worldbank.org/4ROCCIEQ50.

[34] WDI data was not available for Argentina in 2011 and 2012. The growth rate of 2010 was used in both cases to fill the gaps.

5. In cases where the null hypothesis was rejected at the 10% level, seasonal adjustment was performed on the log-difference of the original series using the X-12 procedure as described below.

B.2.2 Method of seasonal adjustment

To seasonally adjust the $log(GDP)$ series (assumed to be an I(1) process), first $\Delta\log(GDP)$ is seasonally adjusted using the X-12 quarterly seasonal adjustment method in Eviews under the additive option, to obtain $\Delta\log(GDP)_{SA}$. Then using the first observation of the raw series $log(GDP)$ (levels, not seasonally adjusted) the seasonally adjusted log changes, $\Delta\log(GDP)_{SA}$, are cumulated to obtain the log adjusted series $log(GDP)_{SA}$. Finally, the seasonal adjusted level series is obtained by taking the exponential of $log(GDP)_{SA}$.

Consider now the updating of seasonally adjusted series and suppose seasonally adjusted series from 1979Q1 to 2011Q2 are available, which one wishes to update to 2013Q1. The raw series are downloaded, for example from 2000Q1 to 2013Q1, and are first seasonally adjusted with the procedure described above. Then, the seasonally adjusted new series, in growth rates, are used to update the original seasonally adjusted series. To avoid possible abrupt changes in the updated series, two years of the original series were also overwritten for all variables. Specifically, all series were updated from 2004Q1 to 2013Q1.

B.3 Interpolation

Let X_t, $t = 0, 1, 2, ..., T$ be the annual observations compiled as averages of m time-disaggregated observations, x_{it}, $i = 1, 2, ..., m$, $t = 1, 2, ..., T$, such that

$$X_t = \sum_{i=1}^{m} x_{it}. \tag{B.1}$$

The objective is to estimate a relatively smooth set of observations, x_{it}, $i = 1, 2, ..., m$ that satisfy the above constraint. We confine ourselves to pure interpolation methods (namely without using any related economic time series) and assume that the underlying disaggregated observations are generated by the following time-varying first-order autoregressive process:

$$\begin{aligned}
x_{t1} &= \rho_t x_{t-1,m} + \mu_t \\
x_{t2} &= \rho_t x_{t1,m} + \mu_t \\
&\vdots \\
x_{tm} &= \rho_t x_{t,m-1} + \mu_t.
\end{aligned}$$

Solving for $x_{t+1,i}$ recursively forward yields

$$x_{t+1,i} = \rho_{t+1}^{i} x_{tm} + \mu_{t+1}\frac{(1-\rho_{t+1}^{i})}{(1-\rho_{t+1})}, \text{ for } i = 1, 2, ..., m.$$

Substituting these in the constraint (B.1) it follows that

$$X_t = \rho_{t+1}\frac{(1-\rho_{t+1}^{m})}{(1-\rho_{t+1})}x_{tm} + \frac{m\mu_{t+1}}{1-\rho_{t+1}} - \rho_{t+1}\frac{(1-\rho_{t+1}^{m})}{(1-\rho_{t+1})^2}\mu_{t+1}.$$

It is easily verified that the interpolations, $x_{t+1,i}$, do in fact exactly add up to the annual data, X_{t+1}.

The uniformly distributed interpolated series, $x_{t+1,i} = X_{t+1}/m$, for $i = 1, 2, ..., m$, correspond to the case where $\rho_{t+1} = 0$. The geometrically (exponentially) interpolated series is adopted here, which is obtained by setting $\mu_{t+1} = 0$. Other intermediate cases can also be entertained, though they tend to generate very similar outcomes for the applications typically considered in our context.

For the exponential interpolation, ρ_{t+1} is computed as the solution to

$$X_{t+1} = \rho_{t+1}\frac{(1-\rho_{t+1}^m)}{(1-\rho_{t+1})}x_{tm} \tag{B.2}$$

where x_{tm} is the observation at the end of the previous year. This formulation is suitable when interpolating the level of the variables (indices) rather than the growth rates and is applicable to I(1) variables.

To solve for ρ_{t+1}, let $\lambda_{t+1,m} = X_{t+1}/x_{tm}$, and write (B.2) in the expanded form

$$\rho_{t+1}^m + \rho_{t+1}^{m-1} + ... + \rho_{t+1} = \lambda_{t+1,m}, \text{ for } t = 0, 1, ..., \tag{B.3}$$

with

$$\lambda_{1,m} = X_1/x_{0m} = m(X_1/X_0).$$

It follows that

$$x_{t+1,i} = x_{tm}\rho_{t+1}^i, \ t = 0, 1, ...; i = 1, 2, ...m.$$

To proceed it is required to solve the m^{th} order polynomial equation given by (B.3). For example, interpolating quarterly observations from annual series implies solving the quartic equation (for $m = 4$)

$$\rho_{t+1}^4 + \rho_{t+1}^3 + ... + \rho_{t+1} - \lambda_{t+1,4} = 0. \tag{B.4}$$

To solve the quartic equation of the general form

$$A_4z^4 + A_3z^3 + A_2z^2 + A_1z + A_0 = 0$$

or

$$z^4 + a_3z^3 + a_2z^2 + a_1z + a_0 = 0 \tag{B.5}$$

with $a_i = A_i/A_4$, $i = 0, 1, 2, 3$, $z = x - a_3/4$ is substituted in (B.5) which yields

$$x^4 + px^2 + qx + r = 0, \tag{B.6}$$

where

$$p = a_2 - \frac{3}{8}a_3^2, \ q = a_1 - \frac{1}{2}a_2a_3 + \frac{1}{8}a_3^3$$
$$r = a_0 - \frac{1}{4}a_1a_3 + \frac{1}{16}a_2a_3^2 - \frac{3}{256}a_3^4.$$

In order to solve equation (B.6), it needs to be made factorable, which leads to the solution of the following cubic equation

$$u^3 + b_2u^2 + b_1u + b_0 = 0, \tag{B.7}$$

where

$$b_2 = -p, \ b_1 = -4r, \ b_0 = 4pr - q^2.$$

The cubic equation (B.7) has only one real root if the discriminant D is greater than zero, where D is defined by

$$D = Q^3 + R^2$$

and

$$Q = \frac{3b_1 - b_2^2}{9}, R = \frac{9b_1 b_2 - 27b_0 - 2b_2^3}{54}.$$

If $D > 0$, the unique real root is given by

$$u_1 = (R + \sqrt{D})^{1/3} - \frac{Q}{(R + \sqrt{D})^{1/3}} - \frac{1}{3}.$$

Then, by using the above solution to the cubic polynomial, u_1, the following quadratic equations arise

$$x^2 + \sqrt{u_1 - p}x + \frac{1}{2}u_1 - \frac{q}{2\sqrt{u_1 - p}} = 0 \tag{B.8a}$$

$$x^2 - \sqrt{u_1 - p}x + \frac{1}{2}u_1 + \frac{q}{2\sqrt{u_1 - p}} = 0. \tag{B.8b}$$

If x_r is a real solution of the pair of quadratics (B.8a) and (B.8b), then $x_r - a_3/4$ is a real solution to the quartic equation (B.5). Thus, a real solution to (B.4) is given by

$$\rho_{t+1} = x_{r,t+1} - 1/4.$$

However, multiple real solutions can arise from the solution of the quartic equation defined by (B.5).

Consider two real solutions of (B.5), a and b. Let $\{y_{i1}^a, y_{i2}^a, y_{i3}^a, y_{i4}^a, ...\}$ and $\{y_{i1}^b, y_{i2}^b, y_{i3}^b, y_{i4}^b, ...\}$ be the levels of the interpolated series based on the choice of the roots a and b, respectively. In this case, define

$$\Delta_a = \frac{\left|\ln(y_{i1}^a / y_{i1-1,4}^a)\right| + \left|\ln(y_{i21}^a / y_{i1}^a)\right| + \left|\ln(y_{i41}^a / y_{i3}^a)\right| + ...}{4}$$

$$\Delta_b = \frac{\left|\ln(y_{i1}^b / y_{i1-1,4}^b)\right| + \left|\ln(y_{i21}^b / y_{i1}^b)\right| + \left|\ln(y_{i41}^b / y_{i3}^b)\right| + ...}{4}$$

and choose a if $\Delta_a < \Delta_b$, otherwise b.

Part III

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