Theory and Applications in Macroeconometric Modelling

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Abstract

The motivation behind this thesis is rooted in the critical need to enhance the understanding and application of Global Vector Autoregressive (GVAR) models in macroeconometric analysis, particularly in the context of global economic interconnectedness and regional economic differentiation within the United Kingdom. Despite the widespread adoption of GVAR models for their robustness in capturing global economic dynamics, there remains a notable research gap in their comparative effectiveness, ability to identify structural shocks, and application in regional economic analysis. This thesis is motivated by the imperative to address these gaps, thereby advancing the theoretical and practical utility of GVAR models in economic forecasting and policy formulation.

Research Questions Addressed:

Comparative Effectiveness: A significant gap in the literature is the lack of a comprehensive comparison of GVAR models with other macroeconometric frameworks. While various models are employed for forecasting and scenario analysis, their comparative effectiveness, especially in the context of GVAR's adaptability and robustness across diverse datasets, remains insufficiently explored. This thesis aims to fill this gap by providing a detailed comparative analysis, thereby positioning GVAR models within the broader macroeconometric modelling landscape.

Structural Shock Identification: The literature on GVAR models primarily utilises generalised impulse response functions (GIRFs), which, despite their practicality, fall short of distinguishing between shock types, leading to potential ambiguities in policy implications. This thesis addresses the critical need for a methodological shift towards identifying and analysing structural shocks in a manner that aligns GVAR models closer to DSGE models. By extending GVAR models to estimate structural shocks, this research contributes to refining

shock analysis and enhancing the interpretability of economic dynamics.

Regional Economic Analysis within the UK: Another profound gap is the absence of GVAR applications in dissecting regional economic dynamics within the UK. Existing macroeconometric models primarily focus on national or global scales, often overlooking the nuanced economic interplays at the regional level. This oversight is particularly significant in the context of the UK, where regional economies exhibit distinct characteristics and shock responses. By developing a GVAR-based regional model for the UK, this thesis pioneers a framework that provides deeper insights into regional economic interdependencies and the differential impacts of shocks, offering valuable guidance for region-specific policy interventions.

Theories Tested:

The research critically evaluates the theoretical underpinnings of GVAR models, comparing these with other macroeconometric frameworks such as unrestricted and structural VAR models, and Factor-Augmented VAR (FAVAR) models. It tests the hypothesis that GVAR models, when extended to identify structural shocks, can offer comparable, if not superior, insights into economic dynamics relative to DSGE models. Additionally, the thesis posits that a regional GVAR model can effectively capture the economic interdependencies and differential shock impacts across UK regions.

Methodologies Employed:

A mixed-method approach is adopted, comprising quantitative econometric analysis and qualitative theoretical exploration. The study employs comparative analysis, structural shock estimation techniques, and regional economic modelling using the GVAR framework. Methodological innovations include the extension of GVAR models for structural shock identification and the creation of a novel regional economic model for the UK.

Data Description:

The thesis utilises a comprehensive dataset encompassing global economic indicators, COVID-19 pandemic-related economic data, and regional economic data within the UK. This dataset facilitates a broad analysis of GVAR models' forecasting abilities and their effectiveness in structural shock identification and regional economic analysis.

Key Findings:

GVAR models demonstrate a comparative advantage in forecasting and scenario analysis across diverse economic datasets, showcasing superior adaptability and robustness.
The extension of GVAR models to estimate structural shocks enhances their analytical capabilities, aligning them closer to the insights provided by DSGE models, particularly evident in the analysis of COVID-19 pandemic data. The development of a GVAR-based regional model for the UK offers novel insights into regional economic interdependencies and the varied impacts of shocks, underscoring the importance of tailored regional policy interventions.

This thesis undertakes a comprehensive examination of Global Vector Autoregressive (GVAR) models, focusing on their theoretical underpinnings, comparative efficacy, and applicability in macroeconometric modelling, particularly in forecasting, structural shock identification, and regional economic analysis within the United Kingdom. The primary contributions include a critical comparison of GVAR models against established macroeconometric frameworks, an extension of GVAR models to facilitate structural shock identification paralleling Dynamic Stochastic General Equilibrium (DSGE) models, and the novel development of a GVAR-based regional model for the UK.

This thesis provides a comprehensive examination of the theory and application of Global

Vector Autoregressive (GVAR) models within the broader context of macroeconometric modelling. It begins by delving into various macroeconometric approaches including, unrestricted and structural VAR models, FAVAR models, and notably, the GVAR model itself. The study thoroughly explores the technicalities, empirical applications, and dynamic analysis inherent to these models, laying a particular emphasis on the GVAR approach and its comparative advantage in capturing global economic dynamics. Initiating with an analytical comparison, the study highlights the GVAR model's unique ability to capture global economic dynamics, demonstrating its enhanced adaptability and robustness in scenario analysis and forecasting across varied datasets. The research advances by extending GVAR models to estimate structural shocks, adopting a structural approach that integrates economic theory and methodological innovations, thus improving shock identification and analysis. This extension is exemplified through the analysis of economic data from the COVID-19 pandemic, illustrating the model's effectiveness in assessing the economic impacts of global shocks.

The thesis progresses by dissecting the economic theories guiding these models, focusing on structural cointegrating approaches, production technology, arbitrage, solvency, and liquidity conditions. It further investigates the GVAR model's forecasting abilities, comparing it with alternative macro models for scenario analysis and forecasting, highlighting its adaptability and robustness in handling diverse datasets.

A significant part of the research is dedicated to extending the GVAR model to estimate structural shocks, aiming to align its capabilities with Dynamic Stochastic General Equilibrium (DSGE) models. This includes a detailed examination of pre- and post-pandemic scenarios, offering insights into the model's versatility and effectiveness in capturing economic dynamics under varying conditions.

Furthermore, the thesis presents an empirical analysis of UK regions using the GVAR approach, marking a novel contribution to regional economic modelling. This model assesses the impact of various shocks across UK regions, providing a nuanced understanding of regional economic interdependencies and responses.

A significant innovation of this thesis is the creation of a GVAR-based model for the UK's regional economies, a pioneering effort that utilises the GVAR framework to explore economic dynamics and shock responses across the UK's diverse regions. This model provides a sophisticated analytical tool for policymakers and economists, enabling a more granular understanding of regional economic interdependencies and variations in shock impacts.

The findings reveal that the extended GVAR model offers a refined framework for understanding global and regional economic dynamics, outperforming comparable models in terms of forecasting accuracy and shock analysis. The regional UK model uncovers pronounced disparities in shock impacts across regions, highlighting the necessity for tailored regional policy measures.

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Author’s declaration

I declare that all the material contained in this thesis is my own work.

1 Chapter 1 - Literature review on macroeconometric models

1.1 Introduction

As economies grow bigger and more interconnected, the conduct of economic policy also becomes more complex as it is harder to understand in terms of the transmission mechanism and the impact on other economic components such as output and employment.
To properly understand the nature of economic policy and its transmission, economists and policymakers utilise macroeconometric models to organise their thinking and disentangle the interrelationships between variables such as inflation and interest rates example.

Current approaches to modelling the global and national economy include a few approaches such as dynamic stochastic general equilibrium modelling (DSGE) and various types of Vector Autoregressive (VAR) models. Of these, the GVAR is closely related to the VAR modelling literature first proposed by Sims (1980).

Considering the failure of previous macro models, many solutions have been put forth and one of the most promising approaches is the method of Global Vector Autoregressive (GVAR) since its creation in 2004 by Pesaran, Schuermann and Weiner (abbreviated as PSW) 2004. The GVAR approach is closely related to the VAR modelling approach proposed by Sims (1980) but provides a relatively simple yet effective way. Compared to empirical DSGE models which can model a few countries but often do not treat them as a whole system, GVAR provides a more complete method that allows the user to include many countries under a single large model while explicitly allowing interactions among the countries. GVAR's capability to accommodate many individual countries; their respective economic variables and model them in one coherent framework has been very attractive to study the effects of economic shocks from one economic variable of a country to other variables in the rest of the model. For example, Chudik and Pesaran (2016) have pointed out that GVAR is one of the main techniques used to understand interlinkage across individual countries.

Numerous applications can be found at policy institutions such as the International Monetary Fund (IMF), European Central Bank (ECB) etc.

This thesis conducts a critical and rigorous examination of the theory and application of Global Vector Autoregressive (GVAR) models. With a surge in complex global interconnections, understanding the dynamics and implications of various macroeconomic shocks has become paramount. The GVAR model, known for its comprehensive approach to modelling economies worldwide, serves as a focal point for this research.

1.2 Research Gaps and Problem:

Despite its extensive use, the GVAR model's comparative effectiveness, structural shock identification, and regional adaptability remain underexplored. This thesis identifies these gaps as the core research problem, particularly focusing on the model's ability to predict and analyse economic shocks compared to other models like and its application to regional economic analysis within the UK.

Model comparison

Currently there are many works on modelling and forecasting the global economy using the GVAR approach. For example, Pesaran et al (2009) looks into incorporating financial variables in the global model to improve economic forecasts; Assenmacher (2013) modelling the small but interconnected Swiss economy for forecasting purposes or forecasting inflation and output in South Africa (De Waal et al,2015); forecasting local and regional labour market by Schanne (2015) etc or forecasting output growth using PMI indices (Chudik et al, 2016).

For FAVAR models by identified by Bernanke, Boivin, and Eliasz (2005), this are also used for forecasting such as oil prices (Binder, 2020), consumer inflation in Brazil (Figueiredo, 2013), India (Dua and Goel, 2023), financial variables such as the yield curve (Vieira et al

2017) , monetary policy effectiveness (Fernald et al, 2014) or carbon prices (Chevallier, 2010). remains sparse. However, there is no direct comparison with other models, such as GVAR as both are suitable for a data-rich modelling environment but using two distinctive approaches. This thesis aims to bridge this gap by employing a methodological framework that juxtaposes these models' forecasting capabilities and their efficacy in responding to economic shocks. This research extends the comparative analysis to include impulse response functions (IRFs) to assess the models' shock response, providing a nuanced understanding of each model's strengths and limitations in economic forecasting and shock analysis.

Structural Shock Identification

The majority of the GVAR literature uses generalised impulse response functions (GIRFs) such as the papers identified in previous section. This due to the convenience of offering a practical solution to examining the dynamic responses of economic variables to shocks. This method's appeal lies in its ability to bypass the need for individual parameter restrictions required by orthogonal impulse response functions (IRFs), a significant advantage in models featuring numerous variables. However, GIRFs' lack of structural distinctions between shock types can lead to ambiguous interpretations and potentially misleading policy implications, highlighting a critical issue in GVAR literature where the convenience of GIRFs might obscure the real economic impact of analysed shocks.

Kim (2013) identifies a significant drawback of using GIRFs in VAR models, which is their dependence on extreme identifying assumptions. GIRFs assume that each variable in the model can be considered as if it were ordered first, a condition met only if the model's covariance matrix is diagonal. This extreme identification can lead to inconsistencies across different variables' responses, unless the covariance matrix's off-diagonal elements are zero, suggesting no contemporaneous correlations between variables. Such inconsistencies can result in misleading economic inferences, emphasising the necessity of employing normal orthogonalised impulse response functions (OIRFs). OIRFs offer a consistent description of the economic model under more realistic assumptions about variable interactions and covariances when restrictions are applied.

The potential for GIRFs to provide superficial analyses has led to an increasing acknowledgement of the need for a balance that aligns the identification of structural shocks, based on economic theory, with the application of meaningful restrictions on estimated parameters. Ensuring that economic interpretations from the model are accurate and meaningful requires a methodological equilibrium.

In another paper by Luca Benati (2010) critically examines the reliability of policy counterfactuals based on VARs against those derived from DSGE models. It argues that VAR-based counterfactuals often fail to accurately capture the impacts of changes in monetary policy rules (e.g., Taylor rules) on the economy's reduced-form properties. Through systematic investigation using standard New Keynesian models, the study demonstrates that VAR counterfactuals can significantly misestimate the effects of monetary policy changes, leading to potentially substantial errors. This unreliability stems from VARs' inability to incorporate cross-equation restrictions imposed by rational expectations—a fundamental aspect highlighted by Sargent's (1979) critique of VARs. The paper emphasises that VARs' effectiveness in policy analysis is fundamentally limited due to their reliance on unknown structural characteristics of the data-generating process. Consequently, it advocates for the estimation of DSGE models as a more reliable approach for assessing policy counterfactuals, arguing that DSGE models, by design, accommodate the underlying economic theory and structural relationships more accurately.

In response, the proposed thesis suggests a structural approach to econometric modelling, specifically through estimating a DSGE-type New Keynesian rational expectations model. This approach, incorporating key elements like the IS curve, Phillips curve, and Taylor's rule, aims to offer a simplified yet structurally sound framework that overcomes to model the economy and identify the shocks in the model to be orthogonal to each other. This by passes GIRFs' limitations and enhances the analysis by clarifying the economic implications of various shocks.

Regional applications

The intricate web of global interdependence has increasingly highlighted the interconnectedness of economies, both at a national and regional level. This phenomenon is particularly pronounced in the context of the United Kingdom, where economic policies and shocks can have varied impacts across its constituent countries: England, Wales, Scotland, and Northern Ireland. Despite this, there exists a conspicuous research gap in applying Global Vector Autoregressive (GVAR) models to dissect the regional economic dynamics within the UK. This gap stems from a historical focus on national or global economic models, which, while valuable, often gloss over the nuanced economic interplays and shock absorptions capacities at the regional level.

The body of existing macroeconometric literature has put forth numerous models aimed at understanding the linkages and responses between countries to economic shocks. These models, however, seldom drill down into the regional effects within a singular nation, especially one as economically diverse as the UK. Models such as those developed by Garratt et al. (2006) have made significant strides in modeling national and global economies through cointegration and long-run structural modeling. These models adeptly capture the long-run equilibrium dynamics between variables, providing a framework that aligns with economic theories. However, they fall short of dissecting the UK into its constituent regions, instead treating it as a monolithic entity. This aggregation masks the distinct economic landscapes and shock responses inherent to each UK region, a limitation that this paper seeks to address.

Moreover, regional analysis within the UK is complicated by the unique degree of autonomy and economic heterogeneity among its regions, a factor not adequately captured by existing models. The devolution process has endowed regions like Scotland, Wales, and Northern Ireland with certain powers, thereby necessitating a more granular approach to economic modeling that considers these political and economic nuances.

This paper proposes to bridge this research gap by employing a GVAR approach to model the UK's regional economies. The GVAR model is particularly suited for this task due to its ability to accommodate spatial spillovers and regional interdependencies. Unlike traditional models that might view economic regions as isolated entities, the GVAR framework recognizes the interconnectedness of regions and their susceptibility to both local and global economic shocks. By integrating regional economic variables and leveraging the concept of cointegration, this approach allows for a detailed analysis of how economic policies or global economic shifts impact UK regions differently.

The novelty of this research lies in its attempt to not only map the economic connections between UK regions but also to understand the varying responses to economic shocks. Such an analysis is crucial for policymakers who must navigate the delicate balance of national policies with regional implications. For instance, an oil price shock may have a disparate impact on Scotland compared to other regions due to its oil-dependent economy. Similarly, the effect of monetary and fiscal policies may unfold differently across regions, influenced by factors such as distance to economic centers like London, regional economic structures, and the strength of local industries.

To accomplish this, the paper will draw upon existing methodologies while introducing new variables and frameworks suitable for the UK's regional context. By modeling the UK regions based on physical distances, economic ties, and spatial dependencies, this research will provide a more nuanced understanding of regional economic dynamics. The methodology will incorporate the spatial autoregressive models and adapt them to the GVAR framework, allowing for a comprehensive analysis of regional economic interdependencies.

In essence, this paper aims to contribute to the literature by providing a detailed, region-specific economic model of the UK using the GVAR approach. This model will not only fill a significant gap in existing research but also offer valuable insights for policymakers, economists, and scholars interested in the complex interplay of regional economies within a unified national framework. By doing so, it aspires to pave the way for more informed, regionally attuned economic policies that reflect the unique characteristics and needs of each UK region.

1.3 Aims & Objectives:

The aim is to enhance the theoretical and practical understanding of GVAR models by:

a) Historically and econometrically comparing GVAR with other macroeconometric models.

b) Extending GVAR to identify structural shocks, aligning its capabilities closer to those of rational expectation models.

c) Developing a pioneering regional UK economic model using the GVAR framework to aid policymakers in shock analysis.

1.4 Research Questions:

- How does GVAR compare with other macroeconometric models in terms of forecasting ability and shock analysis?

- Can GVAR be extended to identify structural shocks comparable to those in rational expectation models, and what are the implications of such an extension?
- How can GVAR be applied to create a regional economic model for the UK, and what insights does it provide for different regions?

1.5 Contributions:

This thesis contributes to the literature in the following ways:

a) It provides a comprehensive comparison of GVAR models with other macroeconometric models, shedding light on its forecasting prowess and scenario analysis capability.

b) It extends the GVAR model into a structural framework; comparable to a DSGE model enhancing its utility in identifying and comparing shocks, particularly with the inclusion of COVID-19 data.

c) It introduces a first-of-its-kind regional UK model using the GVAR approach, offering policymakers a tool for assessing shock impacts across different UK regions, thereby contributing novel insights and methodologies to regional economic analysis and policy formulation.

1.6 Literature review on macroeconometric approaches

The following sections aim to illustrate and review different macroeconometric approaches, including Dynamic Stochastic General Equilibrium (DSGE) modelling; Vector Autoregressive (VAR) models such as standard VAR, FAVAR and Panel VAR; and the long-run structural Global VAR (GVAR) approach. Comparisons and contrasts between these techniques and GVAR will also be provided. The macroeconomic theories underlying the long-run structural methodology employed in GVAR modelling will then be covered in the subsequent chapter.

1.6.1 DSGE / New-Keyensian Rational Expectation model

Dynamic Stochastic General Equilibrium (DSGE) models serve as a pivotal reference in my thesis due to their comprehensive approach to incorporating microeconomic foundations into macroeconomic analysis. Specifically, the rational expectations framework within DSGE models, where agents form expectations about the future based on all available information and the understanding of the economy's structure, underpins much of modern macroeconomic theory. This is exemplified in the log-linearised version of a rational expectations DSGE model, which simplifies the analysis by linearising the model equations around a steady state. Such models permit the examination of how economies respond to various shocks under the assumption that agents optimally adjust their expectations and behaviours based on their understanding of the economy. This theoretical underpinning is crucial for grounding the empirical analysis in solid economic theory, even when the primary focus of the research is on the Global Vector Autoregressive (GVAR) model.

The GVAR model, in contrast, is geared towards capturing the interdependencies and co-movements of multiple economies within a global framework, making it exceptionally well-suited for analysing international economic dynamics. Unlike DSGE models, which are often focused on a single economy or a stylised version of the global economy, GVAR models empirically estimate the interactions among a wide range of countries, considering both endogenous and exogenous variables to reflect real-world complexities. While DSGE models offer insights into the theoretical mechanisms driving economic fluctuations and policy responses, GVAR models provide a more direct empirical assessment of international linkages and transmission mechanisms of economic policies and shocks across countries.

Within this thesis, I have demonstrated the innovative integration of a New Keynesian type log-linearised Rational Expectations (RE) model within a Global Vector Autoregressive (GVAR) framework. Specifically, key components of the New Keynesian model, such as the Taylor rule, Phillips Curve, and IS Curve, were estimated in conjunction with a GVAR model. This approach allowed for a nuanced analysis that combines the theoretical underpinnings of macroeconomic policy analysis — represented by the Taylor rule's prescription for monetary policy, the Phillips Curve's insight into inflation dynamics, and the IS Curve's depiction of the relationship between real interest rates and output — with the empirical strength of the GVAR model in capturing global economic interdependencies. The basic New Keynesian Rational Expectations (RE) Dynamic Stochastic General Equilibrium (DSGE) model is a cornerstone of contemporary macroeconomic analysis, encapsulating the essence of how policy, expectations, and market imperfections interact within an economy. At its core, this model comprises three fundamental equations: the Taylor rule, which describes how central banks set nominal interest rates in response to deviations of inflation from its target and output from its potential; the Phillips Curve, which links inflation to output gaps and expected future inflation, capturing the dynamics of price adjustments; and the IS Curve, which illustrates the relationship between real interest rates and output, emphasising the effects of monetary policy on economic activity through investment and consumption.

Regarding DSGE for forecasting, Edge and Gurkaynak (2011) have found that DSGE models are very poor for forecasting GDP growth and inflation but it was mainly due to the wrong specification of the model and concluded the failure of the forecast for the financial crisis should be not used to judge models. Earlier, Adolfson et al. (2007) and Edge et al. (2010) compared DSGE with other less complex models such as VAR for forecasting performance and found that simple VAR and VECM are better at forecasting, particularly with Bayesian estimation techniques, see Herbst and Schorfheide (2015), DSGE model can also be used for forecasting. However, Gürkaynak et al. (2013) compared the standard, mainstream DSGE model in Smets and Wouters (2007)with a typical simple AR model and VAR model with out-of-sample data and found that DSGE models are poorer for short-run forecasting but better at the long-run.

From an econometric perspective, DSGE models typically involve calibration or estimation techniques to align the model with macroeconomic realities or estimate parameters directly. Shocks in DSGE are interpreted within the model's structural framework, allowing for a detailed understanding of propagation mechanisms. Conversely, GVAR models utilise statistical methods appropriate for time-series data across countries, focusing on the empirical identification and estimation of shocks through techniques like impulse response functions. The propagation of shocks in GVAR models emphasises the international spillover effects and interconnectedness of economies.

Generalised impulse response functions (GIRFs) are commonly employed in GVAR modelling to analyse the propagation of shocks through the interconnected global system. Specifically, GIRFs trace how shocks to an individual variable or country transmit and influence all other endogenous variables over time. Unlike traditional impulse responses, GIRFs do not rely on an assumed ordering of variables in the vector autoregression. This makes them more flexible and robust when modelling multi-country dynamics where the ordering is ambiguous.

However, an important limitation is that GIRFs cannot be directly compared to shocks specified in dynamic stochastic general equilibrium (DSGE) models. This is because GIRFs are not structural in nature - they do not derive from underlying economic theory but rather statistical associations between variables. As such, GIRFs lack the strong theoretical foundation required to precisely interpret identified shocks in economic terms, as is possible within DSGE frameworks where shocks represent parameterised theoretical constructs like technology or preference disturbances.

Whilst GIRFs offer a non-structural means of examining dynamic responses without ordering assumptions, their economic interpretation is limited compared to DSGE shocks which have been specifically defined according to optimisation-based macroeconomic modelling.

In Chapter 4, this comparison issue between GIRFs and DSGE shocks is directly addressed. Specifically, the GVAR methodology is employed to estimate a reduced-form New Keynesian-style macroeconomic model that bears strong conceptual similarities to DSGE frameworks. By structurally modelling the global economy in this manner within the GVAR, the identified shocks can then be meaningfully interpreted and compared against perturbations characterised in the DSGE literature. This application of the GVAR technique aims to bridge the gap between its usual non-structural impulse analysis and the theoretical shock specifications common to optimisation-based modelling approaches. By leveraging the strengths of both strands of econometrics, valuable insights into international transmission mechanisms can be gained.

1.6.2 Unrestricted - reduced form VAR model

The VAR model is a simple and widely used model for multivariate time series analysis. It consists of a system of regression equations - the equation below shows a basic VAR model of order 2 (with 2 lags). From this model below, we can see that the y matrix at time t simply equals parts of its lags (t-1 and t-2) plus a stochastic element ut which contains the residuals of this equation (elements that could not be fitted). Using this in an economic context, for example, we have the three economic variables, say real GDP growth t, inflation rate t and the interest rate. In this case, the VAR model simply regresses three variables using their lags as well as the lags of every 2 other model variables. This renders the exclusion of the incredible identification of the traditional SEM approach (Sims, 1980).

The model:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + u_t$$

(1.1)

where

$$y_t = \begin{pmatrix} \Delta_t \\ \pi_t \\ i_t \end{pmatrix}, A_i = \begin{bmatrix} a_{11,i} & a_{12,i} & a_{13,i} \\ a_{21,i} & a_{22.i} & a_{23.i} \\ a_{31,i} & a_{32,i} & a_{33,i} \end{bmatrix}, u_t = \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix}, i = 1, 2$$

(1.2)

The model above is also known as a reduced form, defined as the current values only depending on its lagged values and other lagged model values. As seen above, it is a neat way of capturing the dynamic for a system of related time series data. This VAR model can also be seen as a finite-order approximation of its underlying data-generating process (DGP). As seen in the literature, the VAR models have been proven to be very useful for summarising the data, and forecasting and also applied for cointegration analysis should such a long-run relationship exist in the data. Except for the estimated parameters A_1 and A_2 (using standard methods such as least squares or maximum likelihood) which tell us how much the current Y values depend on the previous lags. However, the VAR model does not inform much meaningful economic relationship among the variables.

1.6.3 Structural VAR model

The VAR(p) model above has shown us that it could summarise the data well however it does not tell the relationship between the variables at time t i.e. the instantaneous relations.

$$B_0 yt = B1yt{-}1 + \ldots B_p yt{-}p + w_t$$

(1.3)

Consider the equation model above which contains three more terms namely: B_0, B_1 and B_p. Here the B_0 matrix represents the instantaneous relations among y_t and B_i; i = 1; 2 … p representing the slope coefficients. Here we also have a $K \times 1$ vector wt which represents a vector of mean zero structural shocks, which is serially uncorrelated with a diagonal covariance matrix $\sum w$ of full rank such that the number of shocks coincides with the number of variables. An important assumption (given correct estimation) is that these structural shocks in wt are unrelated to other elements in the vector. This fact implies that independent movement in the vector can be assigned to the particular element in w_t caused by that shock. The structural shocks cannot be recovered from the above equation given that there are more parameters to be estimated than equations available in the system. However, if the restriction is applied for the elements in B_0 then the structural shocks can then be recovered from the reduced form model. For example, using the examples above we have three economic variables i.e. real GDP growth Δ_t, inflation rate π_t and the interest rate i_t and we would like to know the effects of an interest rate shock on these variables for a central bank. This is not feasible as there are not enough equations for the estimation of the unknown parameters. However, if we place a restriction on the B_0 such that we have:

$$\begin{pmatrix} a_{12} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} = B_0$$

(1.4)

In this case, we assume that the central bank sets interest rates by looking at the fluctuation in real GDP growth Δ_t, inflation rate π_t only while interest rate i_t is the instrument it uses. Restriction (set to zeros) is then applied to the elements in B_0 so that there would be no contemporaneous impact of it on it but only from Δ_t and π_t. Given the data and also the restriction applied, we can then recover the structural shocks by multiplying the SVAR mode with the inverse of B_0 namely B_0^{-1} . It is now clear to see that we only need B_0. Therefore if the matrix B_0 can be solved so that we can obtain the estimates of B_1 and B_i; i = 1, 2 … p and w_t = $B_0\, u_t$, we can then say that the SVAR model can be identified. This is commonly referred to as the identification problem in the macroeconometric literature[1]. It is now easy to see that any meaningful interpretation of an SVAR analysis rests on the credible identification applied. Using the example from (Sims, 1992) for example, recursive ordering was used to obtain the Cholesky factor for the identification which relies on the ordering of the economic variables; for example, interest will first affect equity price then inflation and in the end GDP growth. The recursive ordering allows identification but the values from such order are not unique and could also be criticised as ad hoc, depending on the economic reasoning used.

1.7 Curse of dimensionality

As a rule of thumb, the minimum number of restrictions needed for estimating the SVAR model is the difference between the number of unknown and known elements. Given that restriction enables the estimation of the SVAR model, however, it is also the largest culprit for the undesirability of using VAR for global macroeconomic modelling. Typical global models constructed with the traditional SEM approach often contain hundreds of variables and equations. Therefore we can see that the straightforwardness of VAR models is constrained by their computational limitations. As the variables of interest and the size of

[1] For standard demonstration of the identification in SVAR see (Favero, 2001) and technical summaries of various
identification strategies in (Kilian and Lütkepohl, 2017)

economies also increase in the model, the parameters in each equation of the model to be estimated follow the rule of mp(N+1) (See, Garret et al. 2004), which implies explicitly, that if we have 6 macro variables, 31 economies and a lag order of 2, this means we will need 384 parameters to be estimated for each equation. This is practically impossible as there isn't enough data series for such an estimation. This problem has become known as 'the curse of dimensionality'.

Due to this limitation, the typical VAR models are used for a small set of variables for analysis. However, there is a motivation to incorporate more variables and relevant data into the VAR model. Consider measuring the output gap for example. The notion of the output gap does not have a direct economic measurement as it is made up of a host of individual economic variables such as industrial productions in various industrial sectors. As such, often there is no single economically equivalent variable that could be used when this notion encapsulates many individual variables. In this case, there is no clear rule to exclude any potentially relevant variables in the model but this would render the normal VAR model inestimable. If variables are ignored due to computational difficulties then, the result could be a VAR model that is informationally deficient and misspecified. Another motivation for employing a larger VAR model is the desire to have more understanding of policy shocks on a more disaggregated level for a specific sector, concerning the whole economy. For example. (Bernanke et al., 2005) proposed the FAVAR method for identifying the impact of monetary policy on individual industries.

In general, there are two approaches to this problem, one is via Factor-Augmented VAR and also the Global VAR approach. Essentially the FAVAR model shrinks the large dimensional datasets into common factors but summarises the information contained within. These factors are then used in the VAR model which could also be used for policy analysis with impulse response analysis.

Another approach, namely the DSGE models, is motivated from a different angle, starting with microeconomic theory and then fitting the data around such theoretical models. However, due to its limit on computation, most models in the literature are for 1 or 2 countries only and with a high aggregation.

1.8 FAVAR model

The next few sections are devoted to the exposition of the methodologies in the order of the motivation behind, FAVAR framework, factors selection with principle components, the specification and estimation of the model and also structural identification for structural impulse responses.

1.8.1 Structural FAVAR model

Recall the problem of identification in the unrestricted VAR model and consequently, typical VAR models used for policy analysis include a small set of economic variables. In this case, this is suboptimal as the missing variables from the model due to limits on the computation could lead to informational deficiency. The formation of the impulse responses and shocks computed would also be misled by the omitted variables. The relevance of a particular variable to the empirical model is also difficult to determine at times. Some concepts such as ′ economic output gap′ and ′ inflation ′ cannot be measured without error. Such concepts are themselves formed of highly aggregated information sets, therefore if the goal is to understand policy shocks on a more granular level then disaggregated data must be used to the extent that small unrestricted VAR models are no longer sufficient. This is particularly a problem as the number of regressors cannot exceed the number of observations.

In the following sections, we show how factor models can be used to condense the information from vast datasets while retaining as much information as possible. We then show how the estimated factors are incorporated into the FAVAR model for structural analysis.

1.8.2 Two equations approach

$$y_t = (F_t^{'}, z_t^{'})'$$

$$x_t = \Lambda^F F_t + \Lambda^z Z_t + e_t$$

(1.5)

Observation equation - where x_t is a T by N panel data matrix which contains large datasets of economic and relevant variables. Z_t is the variable of interest that we are trying to explain ('endogenous ' variable and used for impulse response analysis) is linked to the sum of x_t contemporaneously (i.e. large datasets of economic and relevant variables). F_t is a T by K matrix of unobserved factors which summarise the important information in x_t.
Λ^F is the factor loadings.

$$B(L) \begin{bmatrix} F_t \\ z_t \end{bmatrix} = \omega_t$$

$$B_t = c + \sum_{p=1}^{P} \beta_p B_{t-p} + \omega_t$$

(1.6)

Essentially, the steps of estimating a FAVAR can be summarised in 5 steps below:

Step 1) Approximate F_t as K principal components of x_t where x_t is stationary and standardised.

Step 2) Rotate the principal components to obtain $\widehat{F}_t$.

Step 3) Estimate a FAVAR using $\widehat{F}_t$ and z_t and estimate the impulse response to a policy shock using a Cholesky decomposition.

Step 4) Calculate the impulse response of $\widehat{F}_t$ and z_t to the policy shock.

Step 5) Calculate the impulse response standard errors using the bootstrap method.

1.8.3 Principle component analysis

Following (Stock and Watson, 2002), Bernanke et al. (2005) also used a two-stage procedure that used principal component analysis (PCA) to estimate the factors before estimating the VAR model. Principal component analysis (PCA) is a procedure that converts a set of observations x_t which are potentially correlated to Z_t into a set of factors (to be plugged into the FAVAR model) of linearly uncorrelated variables called principal components or PCs. When the transformation is completed, the first PC would have the largest possible variance and the PCs after would contain the remaining variance in the data, which the PCs must be orthogonal to the preceding PCs.

$$\arg\min_{\hat{F}_t, \hat{\Lambda}_i} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_i - \Lambda_i F_t)^2$$

(1.7)

Essentially the PCA estimation above aims to find the minimum number of factors needed to explain the datasets, in which the distance between the factors is minimised and also orthogonal to each other so that they are distinct variations. The eigenvector associated with the largest eigenvalue indicates the direction in which the data has the most variance. Similarly, the second largest eigenvalue in the associated eigenvector is orthogonal to the largest eigenvector, in which the data has the largest remaining variance. As PCA is sensitive to the scale of the data, the common practice is to convert the data into stationary and also standardisation i.e :

$$Z_{ij} = \frac{X_{ij} - \bar{x_j}}{s_j}$$

(1.8)

Where X_{ij} from data for variable j in sample unit i , $\bar{x}_j$ for the sample mean for variable j and s_j for the sample standard deviation for variable j.

The PCs are then rotated so that they are orthogonal. The factors remain uncorrelated and variances are preserved. In terms of the number of PCs to be used in the models, common methods include looking at the scree plots of the PCAs (if available) visually or using formal statistics such as the information criteria in Bai and Ng (2002). However often, it is simply an exercise depending on the output such as the shocks on variables for impulse responses. For example in (Bernanke et al., 2005), the authors increased the number of PCs k until there is no change in impulse responses. They found that the first three principal components capture the information in the dataset sufficiently and additional PCs did not contribute much.

1.9 Estimation of FAVAR and structural Identification

Now recall that the observation equation below, where $B_t = \widehat{F}_t, Z_t$, from the estimation of the factors by the PCA ,we should now have the factors so that the rest of the equation can be estimated.

$$B_t = c + \sum_{p=1}^{P} \beta_p B_{t-p} + \omega_t$$

(1.9)

In this case, ordinary least squares (OLS) can be used to estimate the equation above. In the example from Bernanke et al. (2005) for example, the authors used Cholesky decompilations with ordering $\widehat{F}_t$ based on Z_t. For example, the variable of interest was the federal fund rates and the authors were interested in separating the economic variables into slow and fast-moving variables. The recursive ordering here implies that certain series such as equity prices, and price index are likely to be affected first therefore they are ordered last and with slow variables ranking first such as GDP. Similarly, if we are interested in the sole effect of monetary policy only, to identify such effect, recursive ordering can be applied below such that:

$$\left(f_t^{s'}, z_t^{s'}, r_t, f_t^{f'}, z_t^{f'}\right)'$$

(1.10)

Variables are grouped into slow and fast-moving groups (s for slow and f for fast) which implies that the factors are needed to be extracted separately from those two groups. When the variables above e.g. $f_t^{s'}$ and $f_t^{f'}$ are ranked above or below the interest rate, therefore the fast-moving factors can be instantaneously affected in a lower triangular recursive identification scheme. In this case, this restriction implies that the central bank which has the control of r_t couldn't be affected by the fast-moving variables as they react to the change in r_t instantaneously (within the period t, so that cannot be observed). Further restrictions can also be applied for the identification schemes, such as sign restriction or imposing zero factor loadings so that the impulse responses would react accordingly (see chapter 16, Kilian and Lütkepohl, 2017). Similarly, impulse responses can be obtained akin to other VAR-type models when after estimating the FAVAR model. Bootstrapping is often then used for approximating the distribution of the impulse responses, although there are no formal criteria for the draws required.

1.10 Panel VAR

1.10.1 Introduction

Panel VAR models generalise the standard univariate VAR models to allow for the analysis of data with both a time series and cross-sectional dimension (Canova and Ciccarelli, 2013). This enables modelling dynamic relationships between multiple variables observed over time for different heterogeneous entities. The specification allows for both autoregressive lags within entities as well as interdependencies across entities through lagged cross-sectional effects. It can also accommodate static contemporaneous relationships if error terms are correlated across entities.

A Panel VAR model is essentially a system of interrelated VAR models for each panel unit (e.g., countries, firms), allowing for heterogeneity and cross-sectional dependence. The general form of a k-th order Panel VAR for i=1,…N units and t=1,…,T time periods can be written as:

$$y_{it} = \alpha_i + \sum_{j=1}^{k} \Phi_j \, y_{i,t-j} + \epsilon_{it}$$

(1.11)

y_{it} is the vector of endogenous variables for unit i at time t.

α_i is the vector of individual fixed effects.

$\Phi_j$are the coefficient matrices for the j-th lag of the endogenous variables.

ϵ_{it} it is the error term.

However, directly estimating this unconstrained specification is unfeasible as the number of parameters vastly exceeds available time series observations, even for moderate numbers of entities and periods. Dimension reduction techniques are therefore critical for panel VAR applications. In a Bayesian approach, coefficients are treated as random variables with a prior specifying relationships between them. This hierarchical structure facilitates computation of posterior densities using efficient MCMC methods.Alternatively, unobserved common dynamic factors can be introduced that drive the coefficients over time and across entities. Specifying factor dynamics as a stochastic process casts the model in a state space form.

State space representations allow classical filtering techniques to be applied for consistent likelihood-based estimation. These dimension reduction methods enable tractable estimation while retaining the flexibility to model cross-sectional heterogeneity and dynamic interlinkages in multivariate cross-sectional time series. Either Bayesian dimension shrinkage utilising coefficient relationships or classical factor methods incorporating lower dimensional latent factors are essential to overcome obstacles posed by large parameter spaces in panel VAR modelling frameworks.

1.10.2 Compared with GVAR

GVARs and panel VARs are both modelling frameworks aimed at capturing interdependencies between heterogeneous economic units using a VAR style specification. In fact, GVAR is considered to be a special case of panel VAR, particularly suited for modelling international linkages.

However, they differ fundamentally in how they structure those interdependencies.
A panel VAR leaves the interdependencies between units completely unrestricted. It specifies each unit's variables as depending on their own lags as well as lags of all other units' variables. This allows for the most flexible modelling of dynamic spillovers but poses immense dimensionality challenges for estimation.

In contrast, a GVAR imposes restrictions on the interdependencies by modelling each unit's variables as depending on its own lags and weighted averages of other units' lagged values. This restricts dynamic spillovers between units to be proportional to the weights, in effect 'collapsing' the interdependency structure. It reduces dimensionality compared to an unconstrained panel VAR, producing a number of coefficients similar to separate country VARs.

However, the weights are predetermined and may imperfectly capture true interlinkages. Also, the proportionality constraint imposed on interdependencies may be violated if spillover patterns are more complex. In terms of estimation, a GVAR's parsimony enables more direct techniques than panel VARs require. However its restrictive structure could produce misleading results if interdependencies are better left flexible as in a panel VAR.

Both approaches face dimensionality issues but address them differently. Panel VARs utilise cross-sectional information flexibly through priors or factors, without restricting interactions. But this retains a large parameter space requiring intensive computation.

GVARs severely constrain interdependencies a priori through proportional weights. This drastic dimension reduction enables simpler estimation frameworks. However the restrictions imposed may misrepresent true dynamic interlinkages if these are more intricate. In applications where plausible economic weights can be defined and the proportionality assumption is reasonable, GVARs more directly model cross-sectional interdependencies. But panel VARs likely provide a more realistic characterisation of unrestricted interdependence structures at the cost of greater complexity and dimension reduction requirements.

1.10.3 Using GVAR over panel VAR

The GVAR model is specifically tailored for analysing global economic interdependencies. Its structure models each country's variables as dependent on its own lags as well as lags of weighted averages of other countries. This captures cross-border spillovers through weights reflecting factors like bilateral trade shares. This level of detailed modelling of international dynamics is not typically found in standard panel VAR models.

GVAR allows flexibility in how it captures cross-country relationships. Different weighting schemes can be used to proxy the nature and intensity of linkages between nations based on metrics such as trade, financial connections, or other factors. This flexibility is important for accurately representing real-world economic interactions between interconnected global economies. By explicitly modelling transmission channels between countries, GVAR can provide more accurate and nuanced forecasts of international economic activity. Such forecasts are essential for policymaking and business decisions operating in a global context. Capturing spillover effects through the weighting structure means GVAR incorporates how shocks and policies reverberate across borders.

For policymakers analysing impacts that transmit globally, understanding transmission pathways is crucial. GVAR's detailed multi-country structure allows examining these questions by modelling international feedback loops. This comprehensive framework supports scenario analysis and stress testing of policies in an interconnected world economy.

1.11 Long-run structural approach

As stated in Garratt et al. (2006c), (The long-run structural)... the approach is based on the desire to develop a macroeconometric model that has transparent theoretical foundations, providing insights on the behavioural relationships that underlie the functioning of the macroeconomy. Implicit in the modelling approach is the belief that economic theory is most informative about the long-run relationships, as compared to the short-run restrictions that are more contentious. the approach is based on the desire to develop a macroeconometric model that has transparent theoretical foundations, providing insights into the behavioural relationships that underlie the functioning of the macroeconomy. Implicit in the modelling approach is the belief that economic theory is most informative about the long-run relationships, as compared to the short-run restrictions that are more contentious.

At the outset, it is clear that the philosophy behind this approach is using macroeconomic theory in the long-run while 'letting the data speak' in the short-run as often in the cointegrating literature such as Hoover et al. (2008)but with a much stronger emphasis on the long-run with macroeconomic theory. This is in strong contrast to the ad-hoc and modular theories applied in large-scale SEMs and coherent but more restrictive DSGE models (thus limiting short-run dynamics as restricted by theory). While the approach is focused on the long-run restrictions, it is also possible to impose short-run restrictions to test and investigate specific theories (such as the impact on monetary shocks in the short-run) without impact on the long-run restrictions (or vice versa).

The approach begins with an explicit statement of a set of long-run relationships between the macroeconomic variables in the system. The long-run relationships among the variables are derived from macroeconomic theory and are then embedded within a VARX (vector autoregressive with exogeneity) model. The works on VARX were originally developed by Gali (1992), Crowder et al. (1999) and later fully developed by Pesaran et al. (2001b, 2006) and applied to national and global macroeconometric modelling in Pesaran et al. (2004). The main difference between an unrestricted VAR as in Sims (1980) is that VARX is augmented with weakly exogenous or long-run forcing (as defined in Engle et al. (1983) foreign variables such as oil price, and metal prices which are global and used by many other countries. This is built on the assumption that the individual macroeconomic series is not stationary and have a unit root. The long-run relationships are then derived from the theory associated with the cointegrating relationship between the variables and the existence of these cointegrating relationships imposes restrictions on a VAR model as a VARX Garratt et al. (p.7 2006a). This assumption can be tested as shown in di Mauro and Smith (2013)and this assumption is often correct. The economic rationale behind this is that each country is small relative to the world economy and mathematically allows multiple countries to be stacked together as a single GVAR model to be solved later.

Compared to the cointegrating VAR advanced by Johansen (1991), the long-run structural approach places more emphasis on macroeconomic theory to explicitly state cointegrating relations with the VARX models. The usual cointegrating VAR begins with an unrestricted VAR and then imposes restrictions on the long-run relations later in the analysis without a clear, a priori view of the economy's structural relations. While the latter works relatively well for a system that exists only one cointegrating relationship among the variables. It is often very difficult if not impossible be applied to when there are more than two cointegrating relations Garratt et al. (2006c).

The long-run structural approach explicitly requires the modeller to determine the long-run relationships in the form of individual VARX models (e.g. if there are 10 countries in the model then there will be 10 VARX models, each representing one country). When the models are estimated, the model possesses transparency that is often lost in the large-scale SEM and the approach here is much easier to be interpreted. Another important advantage of this approach is the clarified relationship between the short and long-run restrictions of the model which allows analysis of the effects of shocks much clearer. Combing the use of GIRF (details see 1.3.4), eliminates the need to order variables in the system. Compared to alternative methods, this avoids some of the difficulties such as rigid economic theory being used to impose restrictions which often resulted in a poor fit with data.

1.12 Global Vector Autoregressive model

The exposition of the approach in Garratt et al. (2006) was primarily aimed at modelling a single open economy and the authors used the UK as an example and link the national economy to the world via a VARX model augmented with foreign country economic variables. This also allowed analysis of shocks and the authors used impulse response functions to interpret the results. This approach was further developed when combing multiple countries into a single GVAR model. For example, Pesaran et al. (2004), Dees et al. (2007)showed how this can be done.

The GVAR approach can be described as a two-step process. The first step is built on the long-run structural approach above. This step assumes that there are N+1 countries in the global economy, indexed by i = 0, 1,. . . , N and the aim is to relate a set of country-specific variables e.g. GDP, inflation, interest rates etc. that are of interest to the modeller. As the model contains a large number of variables, it is best to represent using linear algebra as per the standard convention in the literature. The vector of interest denoted as x collects the macroeconomic variables specific to the individual countries of interest indexed by i and over time, indexed by t=0,1,. . . ,T. It also imposes the assumption of weak exogeneity of foreign country-specific and global variables. In other words, it assumes that the individual economy is relatively small in terms of the world economy except for the exception of the US (Dees, et al. 2007). The weak exogeneity is then tested empirically to see whether this assumption holds. Specifically, an individual country (economy) is represented by a VARX model (or in its error-correction form VECMX) which links the domestic economy (defined by a range of domestic macroeconomic variables) to foreign economies (defined by corresponding foreign variables) which are treated as weakly exogenous. The domestic and foreign economies are then linked via weights matrices that match the international linkages in trade.

For example, the weight of UK (domestic) is expected to have a large trade with the EU countries such as Germany (foreign), therefore it will have a larger weight than say, Malaysia. It should be noted that similar to the framework of an unrestricted VAR, the VARX model can also be written in its error-correction form VECMX which allows the differentiation of short and long-run effects. In particular, the long-run effects are being treated as co-integrating. The individual VECMX models are estimated separately for each country i, based on reduced rank regression (see Pesaran (2015) thus identifying the long-run effects or I(1) relationships that exist within and across the domestic variables and also the foreign economic variables. Thus, the total number of co-integrating relations and speed of adjustment for each country can be derived and given economic meaning.

The second step then stacks all individual country models together in a theoretically consistent manner that can be solved as a whole (for a brief introduction see di Mauro and Smith (2013)and for the full derivation of the method see Chudik and Pesaran (2016). The solution can be used for scenario analysis and forecasting as is usually done with alternative DSGE or VAR models. The GVAR model has numerous applications that are catered for policymakers such as traditional shock analysis and conditional forecasting, see di Mauro and Pesaran (2013b) for a number of applications and also Pesaran (2015) for a brief review of applications in the literature. Although the primary interest mentioned so far are based on individual countries with the world economy, this is not necessary as the basic units in a GVAR can be organised as regions (a collection of local countries etc.), industries, banks or sectors in any given economy. For example, papers from the ECB use a mixed cross-section GVAR model for country data to link with firm-level data (such as banks) Gross and Kok (2013, 2016). Although the individual models are estimated country by country, shocks can be transmitted across countries as each individual is connected to other foreign countries via the weight matrix. Therefore there are three channels of shock transmissions namely via 1) direct dependence of domestic variables on foreign variables (and also lagged values), 2) dependence of the region-specific variables on common global exogenous variables such as oil and material prices and 3) non-zero contemporaneous dependence of shocks in region i on the shocks in region j Garratt et al. (p.64 2006c).

1.13 The GVAR approach

In the case of GVAR, for example, when modelling the world economy, each country is represented by its equation with a VARX* model which links the domestic country with the foreign countries and also a set of global variables such as oil and metal prices. In the individual model, the domestic model is linked to the foreign economies with their respective trade weights. Economically this is an intuitive approach as clearly, say policy shocks from India will have a lot higher impact on its neighbour such as Sri Lanka (which has many trades directly with India) than on Paraguay for example. Given the general nature of interdependencies in the world economy (see Pesaran and Smith, 2006), it is supposed that all country-specific variables and common global observed factors such as oil and commodity prices should be treated as endogenously (as part of the system i.e. a closed world economy). As the parameters to be estimated in the GVAR model are now restricted by the trade weights therefore this allows for the computation. Therefore in this sense, it is similar to the FAVAR approach which is by extracting ′ common factors ′ from relative trade weights rather than a statistical method.

The GVAR objective of solving the curse of dimensionality is to impose a set of restrictions on the VAR model so that the model can be estimated practically while being consistent. The main restriction of the GVAR approach is by imposing the assumption of weak exogeneity of foreign country-specific and global variables. In other words, it assumes that the individual economy is relatively small in terms of the world economy except for the exception of the US (Dées et al., 2007). The weak exogeneity is then tested empirically to see whether this assumption holds. Specifically, an individual country (or economy) is represented by a VARX* model (or in its error-correction form VECMX*) which links the domestic economy (defined by a range of domestic macroeconomic variables) to foreign economies (defined by corresponding foreign variables) which are treated as weakly exogenous. The domestic and foreign economies are then linked via weights matrices that match the international linkages in trade. The second step then stacks all individual country models together in a theoretically consistent manner that can generate forecasts for all world economic variables simultaneously.

The rest of the associated parameters are similar to those in a normal VAR, which are to be estimated to give context to economic interpretations of the model. It should be noted that x_{it}^{*} as a vector that captures the foreign-specific macroeconomic variables that are related to domestic ones are constructed via a weight matrix. The scheme of the weight matrix can be designed to reflect the trade and/or financial linkages. For example, the weight of Britain (domestic) is expected to have a large trade with the EU countries such as Germany (foreign), therefore it will have a larger weight than say, Malaysia.

As mentioned above, GVAR is a two-step process. The first was to estimate the VARX* model country by country and the second is to stack all VARX* models together and to be solved as a whole.

1.14 Country-specific VARX* models

The first step of the GVAR approach is the formulation of the individual VARX* (vector autoregressive with exogeneity) model for every country. In this section, we present the general methodology for advanced in (Chudik and Pesaran, 2016)to model individual countries in the GVAR model applied to the model in this study. The approach assumes that there are N+1 countries in the global economy, indexed by i = 0, 1,. . . , N and the aim is to relate a set of country-specific variables e.g. GDP, inflation, interest rates etc. that are of interest to the study. The vector of interest is denoted as x_{it} collects the macroeconomic variables specific to the individual countries of interest indexed by i and over time, indexed by t = 0; 1, …, T. Following the notation and definitions given in di Mauro and Pesaran (2013, p.14-17), the general individual country model VARX* (2, 2) is represented as

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i1}x^*_{it} + \Lambda_{i1}x^*_{it-1} + \Lambda_{i2}x^*_{it-2} + u_{it}$$

(1.12)

x_{it} – is a vector with a dimension of $k_i \times 1$ of domestic macroeconomic variables indexed by individual country i and time as t; x^*_{it} is a vector with dimension of $k^*_i \times 1$ of foreign macroeconomic variables indexed by individual country i and time as t; u_{it} – is a serially uncorrelated and cross-sectionally weakly dependent process. The rest of the associated parameters are similar to those in a normal VAR, which are to be estimated to give context to economic interpretations of the model. It should be noted that x^*_{it} as a vector that captures the foreign-specific macroeconomic variables that are related to domestic ones are constructed via a weight matrix. Mathematically, this is defined as :

$$x^*_{it} = \sum_{J=0}^{N} w_{ij}x_{jt} \; ; \; w_{ii} = 0$$

(1.13)

where w_{ij}, where i being the domestic country and j as the foreign, are a set of weights that $w_{ii} = 0$ and when combining all the weights of i and j would become 1. The scheme of the weight matrix can be designed to reflect the trade and/or financial linkages. It should be noted that similar to the framework of an unrestricted VAR, the VARX* model can also be written in its error-correction form VECMX* which allows the differentiation of short and long-run effects. In particular, the long-run effects are being treated as co-integrating. The individual VECMX* models are estimated separately for each country i, based on reduced rank regression thus identifying the long-run effects or I(1) relationships that exist within the domestic x_{it} and across x_{it} and also the foreign economies x_{it}^*. Thus, the total number of co-integrating relations and speed of adjustment for each country can be derived and given economic meaning. The error correction form of the VARX* for country i a t i.e. VECMX* can be written as below:

$$\Delta x_{it} = c_{i0} - \alpha_i \beta_i' [z_{i,t-1} - \gamma_i (t-1)] + \Lambda_{i0} \Delta x_{it}^* + \Gamma_i \Delta z_{i,t-1} + u_{it} \tag{1.14}$$

Similar to a conventional VECM model, the VECMX* model above allows for the possibility of co-integration both within x_{it} and between x_{it} and x_{it}^* and consequently across x_{it} and x_{jt} for $i \neq j$. The VECMX* models are then estimated separately for each country depending on whether the variables are weakly exogenous (or long-run forcing) or integrated or order 1 i.e. I (1). From this, the number of co-integrating relations, r_i, the speed of adjustment coefficients, β_i and the co-integrating vectors.

1.15 Weak exogeneity

The distinction between exogeneity and endogeneity is uncommon in the VAR literature as variables are normally considered to be endogenous. In practice, the variables could be affected by other observable variables which are determined outside the system of interest. And as such, those variables are deemed exogenous or unmodelled variables. However, the definition of exogeneity is often not precise and subjectively depends on the research question being studied. In the paper by (Engle et al., 1983), formal definitions were outlined where there are different strengths of exogeneities. The variable is considered to be weakly exogenous say if we are interested in estimating a particular parameter vector γf rom x_t which is an exogenous variable and if the estimation properties do not suffer from conditioning on $x_t$rather than using a full model for the data generation process of all the variables involved.

It should be noted here that the rationale behind the GVAR approach to reduce the parameters for estimation is via the assumption of weak exogeneity of the foreign variables in the individual VARX* models. This implies that there is no feedback from the lagged endogenous variables to the exogenous variables in the VARX* model, allowing the restrictions of these lag coefficients to be zero. Effectively this is imposing a Granger non-causality from endogenous to exogenous variables. Effectively, when modelling a small open economy in a global setting, one can see that the said small economy is effectively weakly exogenous to the rest of the world. From an economic policy, the action from one country is likely to be less affecting the rest of the world than the rest of the world affecting that single country, thus the causality is travelling one way only, from the exogenous (e.g rest of the world or foreign countries) to endogenous (e.g. domestic country) and not another way round except the USA which is usually treated as the dominant country. Such assumption of weak exogeneity is often supported in the literature such by Pesaran et al., 2004, Dées et al., 2007, di Mauro and Smith, 2013 and it can be tested via the Johansen test (Johansen, 1991).

1.15.1 Solution strategy and the GVAR model

As mentioned in the introduction, the GVAR approach is a two-stage process. The first was to estimate the VARX* model country by country and the second is to stack all VARX* models together and to be solved as a whole. We now examined the solution to solve the model as outlined in di Mauro and Pesaran (ibid, p.16).

Recall the generic VARX* (2,2) model:

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i1}x_{it}^{*} + \Lambda_{i1}x_{it-1}^{*} + \Lambda_{i2}x_{it-2}^{*} + u_{it}$$

(1.15)

Where the definitions remain the same as defined before, we now introduce a few terms to solve the model as a whole. To form the GVAR model, we first introduce a new term z_{it} defines it as:

$$z_{it} = (x_{it}^{'}, x_{it}^{*'})'$$

(1.16)

z_{it} is simply a term that combines the domestic and foreign variables that help reduce the derivation of the full GVAR model. Further introducing 3 more terms, where they collect the respective regression coefficients and the co-integrating term.

We now have:

$$A_{i0} = (I_{ki}, -\Lambda_{i0}), A_{i1} = (\phi_{i1}, \Lambda_{i1}), A_{i2} = (\phi_{i2}, \Lambda_{i2})$$
$$A_{i0}Z_{it} = a_{i0} + a_{i1}t + A_{i1}Z_{it-1} + A_{i2}Z_{it-2} + u_{it}$$

(1.17)

Country-specific trade weights wij obtained can be now used to link matrices denoted as Wi I to obtain the relationship between the domestic and foreign economies. As we have introduced the new term zit is now:

$$Z_{it} = W_i x_t$$

(1.18)

Therefore we have:

$$A_{i0} W_i x_t = a_{i0} + a_{i1} t + A_{i1} W_i x_{t-1} + A_{i2} W_i x_{t-2} + u_{it}$$

(1.19)

Also recall that for i = 0, 1,. . . , N, which implies the equation above is individual country-specific and require stacking to solve for x t which links all individual models together. We now introduce a few more terms to tidy up the model:

$$G_0 = \begin{pmatrix} A_{00} W_0 \\ A_{10} W_1 \\ \vdots \\ A_{N0} W_N \end{pmatrix}, \quad G_1 = \begin{pmatrix} A_{01} W_0 \\ A_{11} W_1 \\ \vdots \\ A_{N1} W_N \end{pmatrix}, \quad G_2 = \begin{pmatrix} A_{02} W_0 \\ A_{12} W_1 \\ \vdots \\ A_{N2} W_N \end{pmatrix},$$

$$a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \quad a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \quad u_1 = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \vdots \\ u_{Nt} \end{pmatrix}$$

(1.20)

Thus

$$G_0 x_t = a_{i0} + a_1 t + G_1 x_{t-1} + G_2 x_{t-2} + u_{it}$$

(1.21)

As the term G_0 is a known non-singular matrix (invertible matrix). G_0 is called non–singular if there exists an n × n matrix G_0^{-1} such that $G_0 G_0^{-1} = I_n = G_0^{-1} G_0$. Thus, by multiplying its inverse, the term disappears and we now obtain the GVAR (2) model with 2 lags where:

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + F_2 x_{t-2} + \epsilon_{it} \tag{1.22}$$

where the new terms collect the inverse of G_0

$$F_1 = G_0^{-1} G_1, F_2 = G_0^{-1} G_2,$$
$$b_0 = G_0^{-1} a_0, b_1 = G_0^{-1} a_1 \ \epsilon_{it} = G_0^{-1} u_{it} \tag{1.23}$$

The GVAR model above can be solved recursively, see Pesaran, 2015. To summarise, as shown above, the GVAR model allows the interactions among the domestic and foreign economies through three diverse channels. The first is the contemporaneous and lagged dependence on domestic variables x_{it} on foreign variables x_{it}^*. In addition, it also allows the effect and dependence of domestic variables x it on global weakly exogenous variables such as oil and commodity prices. This can also be used as a simulation strategy that can reveal the contemporaneous effects of shocks from country *i* on *j*.

1.15.2 Diagnostics tests

Model specification

Having described the derivation of the individual VARX* (p; q) models and their stacking to form a GVAR (p) model, we now turn to the specification of the individual models.

1.15.3 Lag orders of individual VARX* models

Recall that a generic VARX* (p,q) model has lag orders p for both domestic lag orders q for foreign variables. The exact lag orders to be selected are similar to those employed in time series literature with Akaike information criterion (AIC) or the Schwarz Bayesian criterion (SBC). Currently, the main computational tools for lag order selection are embedded in the GVAR toolbox which will automatically show the lag orders selected by either AIC or SBC, whichever with the highest value. It should be noted that it does not matter whether the lag orders of p and q are equal. Restriction on the maximum lag order can also be imposed as a large order of lags will deplete the degrees of freedom, depending on the length of the time series working with.

1.15.4 Unit root test

A big advantage of the GVAR approach is the indifference to the stationarity / non-stationarity of the variables. However, unit root tests are still useful in the sense that it allows the identification of short-run and long-run relations (as cointegrating). Like many other papers in the literature, The augmented Dickey-Fuller test is used instead of the older standard Dickey-Fuller test. The ADF test was carried out at 95%, implying if the test statistic for the variable is more negative than the critical values then it will be rejected as there is no unit root. The test was carried out on the level, differenced, twice differenced, with the trend and without trend on all variables. Once the unit root had been tested, the corresponding co-integrating VARX* models are estimated as VECMX*. The next step is the identification of the co-integrating relationships within the individual models. The rank of co-integrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics (see Pesaran et al., 2001a).

1.15.5 Testing for weak exogeneity

As mentioned before, the main assumption in the GVAR approach is the weak exogeneity of the foreign variables x_{it}^* with respect to the respective VARX* model. As described in Pesaran et al., 2004, this assumption is compatible with a certain degree of weak dependence across

u_{it} (the residuals). Following the work on weak exogeneity testing by Johansen (1992) and Granger and Lin (1995), the weak exogeneity assumption implies no long-run feedback from $x_{it}$to x_{it}^*, suggesting that x_{it}^*error correction terms of the individual country VECMX* models do not enter in the marginal model of x_{it}^* (Smith and Galesi, 2014). This implies we can consistently estimate the VARX* models individually and later combine them together to form the GVAR. The proof of weak exogeneity implication on x_{it}^* can be seen in Pesaran (2015, ch.23, p.569). The test is a regression model described in Johansen (1992) and Harbo et al. (1998). The test employed by Dees et al 2007) is as follows:

$$\Delta x_{it,l}^* = a_{i,l} + \sum_{j=1}^{r_i} \delta_{ij,l} ECM_{ij,t-1} + \sum_{j=1}^{s_i} \phi'_{ik,l} \Delta x_{i,t-k} + \sum_{m=1}^{n_i} \Psi'_{im,l} \Delta \tilde{x}_{i,t-m}^* + \eta_{it,l} \tag{1.24}$$

where ECMij ,t1, j = 1,2,. . . , r_i are the estimated error-correction terms corresponding to the cointegrating terms found as shown in the previous section. It also should be noted that $\Delta x_{it,l}^*$ is the differenced vector collection of the foreign variables. This is a F-test for the significance of $\delta_{ij,l}$ =0, j = 1,2,. . . ,r_i above. While the lag orders of p and q were determined earlier via AIC or SIC.

1.15.6 Testing for structural breaks

Having considered the rather harmless integrated series in the previous section and also the possible violations of weak exogeneity and its treatment, we now turn to one of the most fundamental problems in econometric modelling. So far we have shown that the problems mentioned above can be mitigated but unfortunately; similarly to other time-series / econometric models, the GVAR is also susceptible to structural breaks The core concept of structural breaks is straightforward; it is referring to the unexpected sudden shift of the time-series. Consider a daily stock price time series where sudden shift is very common due to stock splits, unexpected announcements, overnight trading, oversea stock exchange performance etc. This renders the original time-series model unreliable as the time-series had shifted unexpectedly and therefore not within the range of the forecast, this also implies forecast errors with be greater. The problem of structural breaks had been discussed extensively in the literature since the 1960s by Quandt (1958, 1960) who proposed Sup F test that calculates the likelihood ratio test for a change in model parameters and also identifies the break date. The Sup F test was quite adaptable but only worked on univariate regression; nevertheless, it became the the basis for future research.

In the GVAR literature, mainly those in Pesaran et al (2004), Pesaran and Smith (2006), Dees et al (2007), Pesaran et al (2009), di Mauro and Pesaran (2013), Chudik and Pesaran (2014) had an extensive discussion of the problem. The GVAR Handbook by di Mauro and Pesaran (2013) had surveyed the existing strategy that The GVAR literature employed. These include several tests statistics to assess the structural stability of the estimated coefficients and error variances of the individual VARX* / VECMX* models. Specifically, the survey indicated the methods used are (p.21): the maximal OLS cumulative sum (CUSUM) statistic, and its mean square variant by Ploberger and Krämer (1992); a test for parameter constancy against non-stationary alternatives by Nyblom (1989); as well as sequential Wald type tests "of a one-time structural change at an unknown change point specifically"; also the QLR statistic by Quandt (1960), the MW statistic (Hansen, 1992), and the APW statistic (Andrews and Ploberger, 1994).'

1.16 Dynamic analysis

The main application of the VAR models for dynamic analysis is from the impulse response function (IRF) and also variance decompositions. In particular, IRF can answer scenario-type what-if questions such as what is the effect of a negative shock to the equity price on GDP in the US? Essentially the IRF calculates the effects or shocks on the path of the selected variables. Consider a generic univariate series:

$$y_t = \rho y_t - 1 + v_t; y_t = 0$$
(1.25)

Where the series begin with a value of 0 and took on a shock of vt. If we assume the shock happened at t = 1 then the series would become y1 = y0 + v1 = v. By using recursive substitution, we can define the time path of y1 following the initial shock as the impulse response function. In order words, it displays what happens to the variable y after a certain shock over time. This is of course rather simple as it involves only one variable. However, if there is more than one variable in the system then it becomes significantly more difficult to discover the shocks i.e. identify where is the shock coming from. This problem is commonly referred to as the identification problem.

The identification problem is often further complicated by the fact that the shocks could be correlated. For example, if two shocks vt and et are correlated and occur at the same time, it would be impractical to answer whether the series $y_t$has been affected by $v_t$as the series could be affected by both shocks. The traditional impulse response function employed in the literature is Sims's orthogonalised impulse responses (OIR) (Sims, 1980) which it takes on the idea above with the assumption of the shocks being orthogonalised i.e. independent of each other. The OIR is usually employed in small VAR systems where there is a small number of variables and lag orders. In addition, it also depends on the natural causal ordering of the variables in the VAR system. This particular requirement is mostly due to the use of Cholesky decomposition, which is not mathematically unique (Cochrane, 2005, p53). In summary, the standard OIR assumes that the errors are orthogonal and the response of one variable to the other shock is zero. This implies, in our GVAR model, if we are to use the OIR then it assumes shocks are not correlated to each other and are orthogonal. It further requires the order of the shocks to the system to be arranged properly in the variables. This means the dependent variable and for domestic variables vector x it has to be re-ordered so that it complies with the causal order of the shocks e.g. equity price before GDP to see the shocks. Also, it is highly infeasible as one may wish to check many scenarios with the impulse response function therefore, this became a major problem for dynamic analysis. To tackle this problem, there are several methods proposed; these include Bernanke (1986), Blanchard and Watson (1986), Sims (1986) which broadly relied on reduced-form VAR (as opposed to structural VAR), which identification is possible. Particularly, they place a priori restrictions on the covariance matrix of shocks guided by economic theories. There, however, remain some issues for identification of shocks GVAR as Pesaran (2015, p.916) had shown due to the model's number of variables and lag orders. In light of this difficulty, Pesaran et al, 2014, Pesaran and Smith (2006) and other GVAR literature had mainly adopted the generalised IRF (GIRF) approach proposed by Koop al. (1996) and Pesaran and Smith (1998).

The Generalised impulse response function (GIRF) relies on the ordering of the variables, as Pesaran (ibid.) had shown. This GIRF below is the model for one country model only. For example, to answer the question: what will happen to UK's economy should there be a negative interest rate shock in Germany? Using the definition of the GIRF (di Mauro and Smith, 2013) for a single country is given by

$$g_{\epsilon j}(h) = E(X_{t+h}|\epsilon_{jt} = \sqrt{\sigma_{jj}, I_{t-1}) - E(X_{t+h}|I_{t-1})} = \frac{R_h G_0^{-1} \sum e_j}{\sqrt{e_j' \sum e_j}}$$

(1.26)

Where the GIRF is defined as a vector of k x1 size as $g_{\epsilon j}(h)$, h as the time period, j is the index of the interested country, E (.|.) is the conditional mathematical expectation with respect to the VAR model, defined as the vector of $\mathbf{x}_t$ at h period upon the shock of ϵjt to country j at time t. The mathematical expectation is equal to the square of the shock at size σjj , pre-set to be 1 standard deviation i.e. $\sqrt{\sigma}jj$. In this case, I_{t-1}, simply referred as the full information set at t-1, which is defined as the collection of vector $\mathbf{x}_t$ at t-1. R_h being a vector of $kxk\ G_0^{-1}$ for connecting the variables together as the Cholesky factor. Last but not least, ej as the sector vector that selects the element of shocks. For example, if we wish to find out the effect of 1 standard deviation negative shock to the UK economy given by the US, then we can specify this shock with the ej mathematically, with 1 being selected; 0 not i.e. ej = (0; 0; . . . 1; 0. . . 0) .

The model above is specified for a single country and we now turn to the version which allows global or regional shocks. The model is given by:

$$g_m(h) = E(\mathbf{x}_{t+h}|\varepsilon^g_{m,t} = \sqrt{\sqrt{m' \sum m}, I_{t-1}}) - E(x_{t+h}|I_{t-1}) = \frac{R_h G_0^{-1} \sum m}{\sqrt{m' \sum m}}$$

(1.27)

Where the single country shock is ϵ_{jt} is replaced by $\epsilon^g_{m,t}$, which is defined as $m^t_{\epsilon t}$ with $\mathbf{m}$ being the vector of weights related to the global model or region. From this, the user can alter the weight specification according to the objective. The functions above allow the user to generate the time profiles of the shocks, which can be used to simulate scenarios. The final time series path given by the GIRF comes with upper and lower bounds defined by the confidence interval e.g. 95%. This is carried out by the method of bootstrapping which estimates the individual models repeatedly until the solution is stable; defined as when eigenvalues are less than or equal to 1. For the technical detail see Smith and Galesi (2014, p.149).

1.17 Empirical applications

Whilst the GVAR developed by Pesaran et al. (2004)[2] was intended for analysing credit risk among multiple countries. As indicated in the publication of The GVAR Handbook, there have been many applications developed since the initial publication. As mentioned previously, the ability to model many countries and their respective variables under a single, theory-consistent model that allows scenario analysis and conditional forecasting has been proven to be very popular among central bankers. Publicly accessible works from central banks with the GVAR method includes Ng and Eickmeier (2013) where the authors were interested in the credit supply shocks propagation via the GVAR method; it is further expanded in 2015 for identifying the specific US shocks by Eickmeier and Ng (2015). Chudik and Fratzscher (2011) from the European Central Bank also used the approach for the global transmission of the financial crisis from 2007 to 2009 with the GVAR model. Similar to those principles of the GVAR modelling laid down in Dées et al. (2007), Chudik and Fratzscher also employed the now standardised global model-identification of shocks and impulse response analysis procedure. Although the GVAR has its main application in international shock transmission, it is also capable of carrying out other applications in economics and finance such as Favero (2013) at Deutsche Bank used it to model and forecast government spread in the Euro area. Melecky and Podpiera (2012) at the World Bank, for example, used it for macroprudential stress testing for central banks in central and southeastern Europe. In another ECB paper, Bussière et al. (2009) used the GVAR model for modelling global trade flows and also the GIRFs to stimulate shocks. In more recent papers, Gross and Kok

[2] Although the GVAR approach is conceptually simple, it requires some programming skills since it handles large data sets and it is not yet incorporated in any of the mainstream econometric software packages. Fortunately, an open-source toolbox developed by Smith and Galesi together with a global macroeconomic data set, covering the period 1979–2013, can be obtained from the web https://sites.google.com/site/gvarmodelling/. This toolbox has greatly facilitated empirical research using the GVAR methodology and appeared to be the standard and only toolbox available for GVAR.

(2016)built a mixed-cross-section GVAR model that included 23 sovereigns and 41 international banks for which the authors modelled their credit default swap spreads. The paper concluded that should large shocks of a size similar to the euro crisis in 2011/2012, the effects would have been more pronounced and more synchronised across the countries and banks.

Due to its versatility in accommodating multiple countries and economic variables, there have been many applications published regarding international transmission and forecasting. For example, Garratt et al. (2016)looked at the performance of the G7 economies concerning global recessions. Galesi and Sgherri (2013)developed a GVAR model containing 27 countries in Europe and key economic powers such as China, Japan and the US and assess the relevance of international spillovers following the slowdown in US equity prices. Specifically, each country model is linked to others by a set of foreign variables such as bilateral bank lending exposures. The authors found that asset prices are the main channel through which shocks are transmitted in the short run while cost and credit supply are more important in the long run. In Galesi and Lombardi (2013), the authors assessed to what extent oil and food price shocks transmit to the inflationary outlook and the real economy with the GVAR model. The paper found that there are direct inflationary effects of oil price shocks affecting most developed countries but less for emerging economies. The food price increase also has significant inflationary effects but is particularly pronounced for emerging economies. In another paper, Greenwood-Nimmo et al. (2013)used a GVAR model for scenario-based forecasting and counterfactual analysis. The application used probabilistic forecasting to analyse global imbalances with conditional probability for a given event or a combination of events and found that GVAR models are particularly well-suited to scenario-based analysis when there are rich datasets. The research focused on more regional interlinkages is also seen in Han et al. (2016), Chen et al. (2017)Cashin et al. (2017b), Dreger and Zhang (2014), Feldkircher and Korhonen (2012), Ma et al. (2012), Osorio and Unsal

(2013)which looked at the impact on the rise of the Chinese economy to other countries in particular. Other regional applications also include ASEAN Tan (2016), European Union (Castrén et al., 2010, Backé et al., 2013, Dragomirescu-Gaina and Philippas, 2015, Feldkircher, 2015, Hájek and Horváth, 2016), Japan (Ganelli and Tawk, 2017), Middle East Mensi (2017), Nigeria Oyelami and Olomola (2016), Swiss Katrin (2013) and the US economy Georgiadis (2016), Subrahmanyam (2016)etc. A unique study by Cashin et al. (2017a), the paper investigated the impacts of El Nino weather shocks (measured by the Southern Oscillation Index (SOI) on world economies. As weather events are exogenous in nature, their shock has a profound impact and the authors found considerable heterogeneities in the responses to the shock with many experiencing a short-lived fall in economic performance while others experiencing a growth-enhancing effect due to an increase in short-term commodity price increases.

1.17.1 Canonical GVAR model for shock transmission

Although there are many different types of GVAR and its applications in the literature, most began in the now-canonical paper by Dées et al. (2007) which laid out the identification, estimation and specification strategy to building a GVAR model. In di Mauro and Smith (2013), the authors re-introduced this model and updated it with the latest data for 2013. In this section, we examine the model in this paper and also its finer technical details, particularly regarding the specification that were not discussed before.

The model in this study describes the relationships between and across 33 countries from 1979q1 – 2013q1, extending the study in Dées et al. (2007) by 7 quarters. The current model contains 33 countries of which 8 eurozone countries are grouped into the Euro Area and treated as one country (in the sense of a separate VARX model). This list of the countries in the model consists of the US, China, Japan, UK, Euro area (Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Fin- land), Canada, Australia, New Zealand, Sweden, Switzerland, Norway, Korea, Indonesia, Thailand, Philippines, Malaysia, Singapore, India, South Africa, Turkey, Saudi Arabia, Brazil, Mexico, Argentina, Chile and Peru. As it stands, it contains the bulk of the world's output at around 90% (di Mauro and Pesaran, 2013, p.18). It is not surprising that due to data quality and availability, semi- emerging economies such as Russia, Nigeria, Pakistan, and Vietnam are not selected. It should also be noted that, due to the strict requirement of the data, most African countries are not included in the model. The variables included in each individual VARX model for both domestic and foreign countries are real output, inflation, real exchange rate, real equity price, short-term interest rate, and long-term interest rate. Global common variables also included oil price, raw materials and metal prices.

Recall that a generic VARX (p,q) model has lag orders p for both domestic lag orders q for foreign variables. The exact lag orders to be selected are similar to those employed in time series literature with the Akaike information criterion (AIC) or the Schwarz Bayesian criterion (SBC). This is embedded in the GVAR toolbox and the largest values from AIC or SBC are selected for the lag orders. The table would the lag orders selected by either AIC or SBC, whichever value is the highest. It should be noted that it does not matter whether the lag orders of p and q are equal.

Unit root tests are then used to identify short-run and long-run relations (as in cointegration). Like many other papers in the literature, the Augmented Dickey-Fuller test is used instead of the older standard Dickey-Fuller test. The ADF test was carried out at 95%, implying if the test statistic for the variable is more negative than the critical values then it will be rejected as there is no unit root. The test was carried out on the level, differenced, twice differenced, with the trend and without trend on all variables. The results from the test indicate most variables have either I(0) or I(1) characteristics which are expected for the GVAR approach.

The next step is the identification of the cointegrating relationships within the individual models. The rank of cointegrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics (see Pesaran et al. 2000).

Testing for weak exogeneity As mentioned before, the main assumption in the GVAR approach is the weak exogeneity of the foreign variables x* with respect to the respective VARX model. As described in Pesaran et al. (2004), this assumption is compatible with a certain degree of weak dependence across the residuals. Following the work on weak exogeneity testing by Johansen (1991), the weak exogeneity assumption implies no long-run feedback from x it to x* , suggesting that x* error correction terms of the individual country VECMX models do not enter the marginal model of x* . This implies we can consistently estimate the VARX models individually and later combine them to form the GVAR. The proof of weak exogeneity implication on x* can be seen in Pesaran (p.569 2015). The test is a regression model described in Harbo et al. (1998). The regression was run on the foreign variables in the VARX models real output, inflation, equity price, short-term interest rate, and long-term interest rate. and also the global variables such as the price of the metal, oil and raw material with a 5% significance level. Based on all 208 regressions run, only 9 variables (4.3%) are unable to meet the assumption. This result is a slight increase from Pesaran (2004). As a result, the foreign long-term interest rate would not enter Australia, Brazil and Turkey in the VARX models.

Another important property in time-series analysis is the disruption from structural breaks. Hav- ing considered the integrated series in the previous section and also the possible violations of weak exogeneity and its treatment, we now turn to one of the most fundamental problems in econometric modelling. So far we have shown that the problems mentioned above can be mitigated but unfortunately; similarly to other time-series / econometric models, the GVAR is also susceptible to structural breaks. The core concept of structural breaks is straightforward; it is referring to the un- expected sudden shift of the time-series. Consider a daily stock price time series where a sudden shift is very common due to stock split, unexpected announcements, overnight trading, oversea stock exchange performance etc. This renders the original time-series model unreliable as the time-series had shifted unexpectedly and therefore not within the range of the forecast, this also implies forecast errors with be greater. The problem of structural breaks had been discussed extensively in the literature since the 1960s by Quandt (1958, 1960) who proposed Sup F test that calculates the likelihood ratio test for a change in model parameters and also identifies the break date. The Sup F test was quite adaptable but only worked on univariate regression; nevertheless, it became the basis for future research. In the GVAR literature, mainly those in Pesaran and Timmermann (2004), Pesaran et al. (2006), Dees et al. (2007), Pesaran et al. (2009) had an extensive discussion of the problem. The GVAR Handbook surveyed the existing strategy that was employed. These include several test statistics to assess the structural stability of the estimated coefficients and error variances of the individual VARX / VECMX models. Specifically, the survey indicated the methods used are (p.21): the maximal OLS cumulative sum (CUSUM) statistic, and its mean square variant by Ploberger and Krämer (1992); a test for parameter constancy against non-stationary alternatives by Nyblom (1989); as well as sequential Wald type tests "of a one-time structural change at an unknown change point specifically"; also the QLR statistic by Quandt (1960), the MW statistic Hansen (1992), and the APW statistic Andrews and Ploberger (1994).'

Although structural breaks occur more in the current model, overall it is similar to those described in the literature. As Dees et al.(2007) concluded, despite the evidence for some structural breaks they are mostly from the error variances which would not impact the application with impulse responses as it is based on the bootstrap method for median and confidence boundaries rather than just point estimates. It would not be surprising to find that the dates are mostly related to episodes of financial distresses as it is when volatility dominates.

The main application of the VAR models for dynamic analysis is from the impulse response function (IRF) and also variance decompositions. In particular, IRF can answer scenario-type what-if questions such as what is the effect of a negative shock to the equity price on GDP in the US. Essentially the IRF calculates the effects of shocks on the path of the selected variables. Consider a generic univariate series where the series begins with a value of 0 and took on a shock of vt. If we assume the shock happened at t =1 then the series would become v. By using recursive substitution, we can define the time path of y following the initial shock as the impulse response function. In order words, it displays what happens to the variable y after a certain shock over time. This is of course rather simple as it involves only one variable. However, if there is more than one variable in the system then it becomes significantly more difficult to discover the shocks i.e. identify where is the shock coming from. This problem is commonly referred to as the identification problem.

In light of this difficulty, Pesaran et al. 2014, Pesaran and Smith (2006) and other GVAR literature mainly adopted the generalised IRF (GIRF) approach proposed by Koop et al. (1996). The GIRF is no longer relying on the ordering of the variables. The studies used GIRFs to study the dynamic properties of the global model and graphs presenting the time-persistent profiles from different shocks applied were shown in the end indicating the effects of a particular shock on another variable. For example, the paper presented three different scenarios, 1) Negative one standard error real equity price shock from the US on real GDP, 2) Positive one standard error oil price shock on real GDP and 3) Positive one standard error increase of US real interest rate on inflation.

In the case of a negative one standard error equity price from the US, it is clear that it will have a negative impact on the largest economies including China, Japan, the Euro area, Korea, Saudi Arabia and the UK. Upon the impact, the strongest impact is on South Korea which could lead to an estimated 1% fall in its GDP. The heavy potential loss is mostly due to the trading weight of Korea with the US. It is also alarming that Korea's heavy influence by the US equity market could lead to a long-term effect of more than a 2% downfall in real GDP.

In the second scenario in which a positive oil price shock of 1 standard error magnitude was used to shock the world economies on their real GDP. During this simulation, the Latin American countries in the existing model are combined into a single region and compared to three other areas namely Euro, the UK and the US. Although both UK and US are net oil exporters, the rising price of oil price will temperately boost the economy in the form of the energy sector, but soon after 2 quarters, the impact becomes negative as it chases up with the price in the wider economy. The result from the GIRFs for the UK and US exhibit similar behaviour to the oil shocks in the 1970s and 2000s.The case of the Euro is poor; with an initial decrease in its GDP that could cost up to 3% of the output and does not stabilise until a year later. The ultimate winner here is the Latin America group, as many are oil exporters including Brazil, Peru and Venezuela, but similarly, the effect is diminished by the end of the first year, although it does accumulate an average growth from 5% to 1% as it stabilises.

The last scenario in which a positive shock from the real US interest rate on the real inflation rate. Here we have four different areas, Argentina, Canada, Euro and the US. From the shape of the graph, Argentina appears to be largely indifferent with equal size of confidence intervals on both sides. Although it is possible, it should be noted that the lack of debt information in the model had significantly discounted the effect; which saw Argentina defaulting on its debt in 2014 as it could no longer increase the cost of refinancing. The graph for Canada is more plausible as the US is its largest trading partner thus it would increase their inflation rate. This is also shown in the case of the Euro. While domestically, the US would receive a sharp growth of inflation up to 0.2% until its later stabilisation.

1.18 Concluding remarks

To conclude, we have reviewed the main macroeconometric models that have been used by academics and policymakers in policy analysis. Particular attention was paid to how macromodelling has evolved and the implication on the types of models to be used. To recap, we began with the early macroeconometric models which were large-scale SEMs that dominated until the 1970s. We then considered the disintegration of how economists model the world economy as implicated by Lucas and Sims. Since then, two strands of modelling approaches were used namely DSGE and VAR. Having reviewed these two models including their identification strategy and specification, GVAR was presented in which a detailed discussion was made on the methodology and applications. A canonical form of the GVAR model was also presented to illustrate the common formation and the applications for transmission analysis.

In the final section, the reader can see that the GVAR approach was used to identify monetary (and other) shocks and that their impacts can be estimated in different scenarios. We also noted that similar models that were covered previously were also applied to this problem. In particular, Boivin et al. (2010) provided a detailed review of how shocks are transmitted via different channels and how different models were used to model these dynamics. We have reviewed a few other publications that were focused on the monetary shocks with GVAR, however, what is lacking is that there are no comparisons made between GVAR and other models in this area. Although there are models that are similar such as SVAR and FAVAR which were compared comparative studies on GVAR have been lacking, perhaps due to its relatively recent adoption in the literature.

Another interesting topic to be investigated is the strategy of shock identification. As seen in the previous review, the strategy used in GVAR has so far been limited to Cholesky decompositions and sign restrictions. It would be very useful to compare with other identification methods that are commonly used such as contemporaneous restrictions, factor-augmented VAR (FAVAR) and estimated DSGE models Ramey (2016).

The comparison and potential integration of GVAR and DSGE approx. is also appealing. . Noted by Chudik and Pesaran (p.190 2016), GVAR provides a coherent reduced form VAR representation of the global economy and the solution of DSGE is a VAR model, therefore it will be useful to bring these two modelling methods together. For example, Dees et al. (2014), Smith (2013) had begun work in the direction and considered a number of issues such as the measurement of steady states in DSGE model, short-run analysis of shocks and also identification and estimation in light of rational expectation. Upcoming research could continue this line of enquiry by constructing a DSGE, FAVAR, GVAR with the same data and comparing the impulse response functions generated from macroeconomic shocks.

2 Chapter 2 – Guiding Economic Theories

2.1 The need for economic theories

Empirical modelling has become an essential tool in macroeconomics research due to the complexity of real-world economies. However, empirical work alone is not sufficient and requires theoretical guidance to ensure results are meaningful. This thesis applies global vector autoregressive (GVAR) models to conduct empirical analyses of international macroeconomic linkages. While the empirical nature of this work is evident in its methodology and applications, it is the underlying macroeconomic theories that provide the essential bedrock for its structure, interpretation, and conclusions.

GVAR models capture interdependencies across multiple economies through a global dataset within a structural VAR framework. While flexible for empirical work, flexibility alone does not provide answers to important economic questions. Economic theories offer insights into relationships between key variables and shape our understanding of transmission mechanisms. Guidance from theory was thus instrumental in specifying the GVAR model and interpreting subsequent results.

Macroeconomic theories offer several indispensable roles in guiding empirical work. Firstly, they provide a coherent framework that helps to structure empirical analysis. Theories give us models that hypothesise relationships between variables, allowing us to form predictions and understand complex dynamics in a structured manner. This theoretical grounding is particularly crucial in a GVAR framework, where the interaction between multiple countries and variables can be intricate and nuanced. Without a solid theoretical foundation, empirical work risks becoming a directionless foray into vast data, lacking in focus and interpretative power.

To guide the thesis's research, I will rely on Garratt, Lee, Pesaran and Shin et al (2006), particularly the chapters on National and global structural macroeconometric modelling (chapter 4); economic theories of the long run (chapter 5) and economic theories of the short run (chapter 6). The chapters here lay the foundation of the theories and justification of using macroeconomic theories on the long-run structural approach whether it is for one single open economy i.e. the case of VARX* (VAR with weak exogeneity) or in a global setting with GVAR. The rest of this chapter describes and discusses these macroeconomic theories to how they shape and allow interpretation of the subsequent empirical chapters.

The theories also guided the identification of structural disturbances through long-run and short-run restrictions in line with theory-consistent interpretations. The neoclassical growth paradigm supported the identification of country-specific productivity and government spending shocks as driving macroeconomic fluctuations. International finance theories regarding unhedged currency positions motivated the interpretation of exchange rate shocks. Theoretically, motivated identifications thus shed light on channels through which shocks transmit globally.

2.2 Structural cointegrating approach to macro modelling

Under the tradition of Sims (1980), unrestricted and restricted VAR modelling largely concentrates on characterising variable dynamics and uses impulse response analysis to illustrate variable reactions to structural shocks over time. Identifying structural shocks from estimated reduced form VAR shocks necessitates an economic theory of the short run addressing decision sequencing and information asymmetries. This focus on specific shock impacts and short-run dynamics differs from the structural cointegrating VAR method.

The structural cointegrating VAR approach emphasises long-run relationships existing between variables. This reflects economic theory typically being more informative on long-run, rather than short-run relationships, as theory is often silent on decision ordering, information sets, and rigidities (p.27, Garratt et al, 2006). The approach outlines "long-run structural errors" arising from economic theory characterising deviations from long-run relationships. It clarifies links between these and observable "long-run reduced form errors".

If theory insufficiently defines short-run behaviour, a more general short-run dynamic examination is needed without shock identification. Literature examines identified shock impacts, but identification difficulty increases in larger VARs. Alternatively, impulse responses to observable unit shocks can show time profiles without identification ambiguity.

Under this long-run structural approach, the Generalised Impulse Response Function (GIRF) can be applied to analyse unit shock impacts invariantly across orderings. Persistence profiles similarly examine system-wide shock influences invariantly. Identification problems emerge in decomposing observable shock impacts into unobserved supply, demand or monetary concepts necessitating economic restrictions. The structural cointegrating VAR approach remains valid supplemented with short-run restrictions. It emphasises long-run theory reflects less robust short-run theorising, but short-run theory could motivate restrictions within this valid framework. This issue and incorporating explicit short-run assumptions are discussed subsequently. For example, Jacobs and Wallis (2010) illustrated how this approach can be applied to modelling the UK economy nationally and also globally and Chudik and Pesaran (2016) surveyed an extensive list of applications following this approach in the form of GVAR.

2.3 Economic theory of the long-run

In this section, I rely on the economic theories of the long-run as outlined in chapter 4 of Garratt et al (2006). I discuss how this theoretical structure can be incorporated into a macroeconometric model. In doing so, I point out the testable long-run relations implied by the theoretical approach that can then be examined empirically.

In particular, I follow the theoretical framework for modelling a small open economy macroeconomically, with an emphasis on stock-flow equilibria, accounting identities, and arbitrage conditions, appropriately modified to allow for the risks associated with market uncertainties. The arbitrage conditions elucidate relationships between prices, interest rates, and asset returns across timeframes. This methodology differs from the intertemporal optimisation foundations underlying dynamic stochastic general equilibrium (DSGE) models but relates closely to this type of theoretical structure (see Giacomini, 2013). Both approaches yield comparable implications regarding long-run equilibrium linkages between key macroeconomic variables. By establishing arbitrage linkages connecting prices and returns intertemporally, this methodology offers insights parallel to those derived from DSGE optimisation foundations into long-term steady-state relationships in a macroeconomic system (p.30, Garratt et al, 2006). Below is an overview of the theories that are addressed individually.

Macroeconomic Modelling of a Small Open Economy - UK:

Production Technology and Output Determination:

It assumes constant returns to scale production function with labour and capital as inputs. Aggregate output is determined by a production function involving labour, capital stock, and technological progress.

Stock-Flow Equilibria: Refers to the balance between stocks (assets) and flows (transactions) in the economy.

Arbitrage Conditions: These ensure that no unexploited opportunities for profit exist and connect various markets like goods, services, and assets.

Accounting Identities and Stock-Flow Relations:
These are crucial for ensuring consistency within the macroeconomic framework. They cover various sectors like private, government, and foreign sectors.

Long-run Solvency Requirements:

The model assumes the private sector remains solvent in the long run, affecting how the long-run relationships between macroeconomic variables are modelled.

Arbitrage Conditions:
Purchasing Power Parity (PPP): This condition equates to the cost of a common basket of goods across countries when adjusted for the exchange rate.
Fisher Inflation Parity (FIP): Relates the nominal interest rate to the real interest rate and expected inflation.
Uncovered Interest Parity (UIP): Asserts that the expected returns of two investments in different currencies should be the same when adjusted for exchange rate changes.

Long-run Structural Approach:
The model emphasises long-run relationships derived from economic theory and stock-flow

equilibria, focusing on their implementation in macroeconometric models.

2.4 Production technology and output determination

The theory in Garratt (2006) on production and output assumes that aggregate output is determined according to the following constant returns to the scale production function in the labour N_t; capital stock K_t and A_t stands for an index of labour labour-augmenting technological progress which is composed of a deterministic component and a stochastic mean-zero component. As the UK economy is relatively small to the world, the technical progress is determined by the level of technological progress in the rest of the world A_t^* and is a function of η_{at} which represents stationary, mean zero disturbances capturing the effects of information lags or (transitory) legal impediments to technology flows across different countries.

$$\frac{\tilde{Y}_t}{P_t} = F(K_t, A_t N_t) = A_t N_t F\left(\frac{K_t}{A_t N_t},,, 1\right) \tag{2.1}$$

$$A_t = \gamma A_t^* \exp(\eta_{at}) \tag{2.2}$$

Assuming that per capita output in the rest of the world is also determined according to a neoclassical growth model, and using a similar line of reasoning as above, we have:

$$y_t - y_t^* = \ln(\gamma) + \ln(\lambda_t / , \lambda^*) + \ln[f(\kappa_t)/ f^*(\kappa_t^*)] + \eta_{at} + (\eta_{nt} - \eta_{nt}^*) \tag{2.3}$$

Where: Domestic are UK variables; starred variables refer to foreign countries. For example, $y_t$is total domestic output; $y_t^*$is total foreign output. γ_t is the productivity differentials based on fixed, initial technological endowments; where λ is a fraction of the population that is employed at the time; K_t denotes capital stock per effective labour unit; $f(K_t) = F(K_t, 1)$ is a well-behaved function that satisfies the Inada conditions, see Barro and Sala-i-Martin (1992);

η_{nt} represents a stationary, mean-zero process capturing the cyclical fluctuations of the unemployment rate around its steady-state value, $1 - \lambda$; η_{at} represents stationary, mean zero disturbances capturing the effects of information lags or (transitory) legal impediments to technology flows across different countries (see Pesaran, 2007 for further discussion).

The stochastic version of the neoclassical growth model significantly affects how the real rate of return is determined. Due to firms aiming for maximum profits, the real rate of return in the long-term equilibrium will align with the marginal product of capital.

2.5 Arbitrage conditions

In the model, market dynamics lead to a series of arbitrage conditions commonly included in various macroeconomic models, namely (relative) Purchasing Power Parity (PPP), Fisher Inflation Parity (FIP), and Uncovered Interest Parity (UIP). Each of these is examined sequentially.

Purchasing Power Parity revolves around the concept of goods market arbitrage, positing that the cost of a similar set of goods should equalise across countries when priced in the same currency. Factors such as differences in information, transportation costs, and trade barriers can cause significant short-term deviations from the absolute version of PPP. Over time, if these factors have a stable average effect, the price of the goods basket will eventually align in each country, illustrating the concept of 'relative PPP.' Long-term deviations from relative PPP are mainly attributed to the 'Harrod–Balassa–Samuelson (H–B–S) effect', where countries with faster productivity growth in the traded goods sector see a quicker increase in prices for a combination of traded and non-traded goods.

The Fisher Inflation Parity (FIP) relationship is a fundamental concept in macroeconomics that represents the equilibrium result of arbitrage activities between investing in bonds and physical assets. It essentially posits that investors will adjust their preferences between holding bonds and investing in physical assets based on the expected inflation rate and the nominal interest rate. The FIP asserts that the real interest rate (the nominal interest rate adjusted for inflation) should be consistent across different types of investments to prevent arbitrage opportunities. This means investors will continually rebalance their portfolios between bonds and physical assets until the return, adjusted for inflation, is equalised across these options. The FIP relationship is integral in understanding how inflation expectations affect investment decisions and the resulting equilibrium in financial and capital markets. It underscores the interplay between inflation, nominal interest rates, and real returns, illustrating how they align in a balanced economic setting.

The Uncovered Interest Parity (UIP) relationship forms the third arbitrage condition, focusing on the balance achieved through arbitrage between domestic and foreign bonds. It stipulates that any differences in interest rates between countries should be counterbalanced by anticipated changes in exchange rates, thus nullifying any potential for arbitrage opportunities. However, factors like transaction costs, risk premiums, and speculative behaviours can lead to temporary discrepancies from UIP in the short term. These elements might allow for some deviations from the expected equilibrium, as investors weigh the potential risks and returns of holding bonds in varying currencies against the backdrop of fluctuating exchange rates and interest differentials; thus it is defined as interest rate parity (IRP).

FIP

$$r_t = \ln(1+\rho) + \Delta p_t + \eta_{\mathrm{fip},t+1} + \eta_{\rho,t+1} + \eta_{\Delta\Delta p,t+1} + \eta^e_{p,t+1} + \eta^e_{\rho,t+1} \tag{2.4}$$

Where r_t is the nominal interest rate on domestic assets held from the beginning to the end of period t in the UK in logarithm and $\eta_{fip,t+1t}$ is the risk premium capturing the effects of money and goods market uncertainties on risk-averse agents; ϱ is the real rate of return on physical assets over the period t; p_t is the price index at t and e denotes the expectation.

$$\Delta p_t = \ln\left(1, +, \frac{\Delta P_t}{P_{t-1}}\right) \tag{2.5}$$

and

$$\eta_{\Delta\Delta p,t+1} = \ln\left(\frac{P_{t+1}}{P_t}, \bigg/ , \frac{P_t}{P_{t-1}}\right). \tag{2.6}$$

IRP

$$r_t = r_t^* + \eta_{\Delta e,t+1} + \eta_{\text{uip},t+1} + \eta_{e,t+1}^e \tag{2.7}$$

Where r_t is the nominal interest rate on domestic assets held from the beginning to the end of period t in the UK in logarithm; with * denoting the rest of the world; and $\eta_{uip,t+1t}$ is the risk premium associated with the effects of bond and foreign exchange uncertainties on risk-averse agents.

PPP

$$p_{t+1} = p_{t+1}^* + e_{t+1} + \eta_{\text{ppp},t+1} \tag{2.8}$$

Where p_{t+1} is the price index at *t+1* in the UK in logarithm; * denotes rest of world; e_{t+1} is the effective exchange rate, defined as the domestic price of a unit of foreign currency at the beginning of period *t+1* (so that an increase in the exchange rate represents a depreciation of the home country currency). $\eta_{ppp,t+1}$ is assumed to follow a stationary (or possibly trend-stationary) process capturing short-run variations in transport costs, information disparities, and the effects of tariff and non-tariff barriers.

2.6 Solvency and liquidity conditions

Another important is the neoclassical assumption built-in for the model which are the solvency and liquidity (real money balances) conditions. Solvency ensures that entities can meet long-term obligations, maintaining confidence and stability in economic relationships. Liquidity is essential for facilitating transactions and responding to short-term obligations.

To model these two conditions, Garratt et al (2006) relies on the stock-flow relationship and look at the GDP from an output-expenditure angle. The stock-flow relationship in an economy highlights the dynamic interaction between stocks, quantities measured at a point in time such as wealth or debt, and flows, which are quantities measured over time like income or savings. This concept is integral for understanding how the accumulation and depletion of resources occur over time. Stocks at the end of one period become the beginning stocks of the next, continually influenced by the economic flows.

In terms of output and expenditure, the relationship is pivotal in measuring an economy's production and spending. Output, typically represented as GDP, is a flow, reflecting the total economic activity within a period. Expenditure, another flow, includes consumption, investment, and other forms of spending that drive the economy. Investment specifically affects the capital stock, highlighting the direct link between the flow of current spending and future stock of capital. This relationship is critical for understanding economic growth and development.

Long-run solvency and liquidity in real money balances are also crucial aspects derived from stock-flow dynamics. Long-run solvency ensures that the stock of debt is manageable over time, aligning future income flows (like tax revenue) with the current stock of debt. It emphasises the sustainability of economic policies and practices. Liquidity, particularly in the form of real money balances, ensures that there are enough liquid assets to facilitate the economy's flow of transactions. As the economy grows and output increases, so does the need for liquid assets to support this activity. This balance between liquidity and economic activity is vital for maintaining economic stability and growth. Together, these concepts underscore the importance of understanding and managing the intricate balance between stocks and flows.

These two conditions can be combined to form the below equation (log-linear version, please consult Garratt et al 2006 for the full derivation i.e. chapter 4 in sections 4.3 and 4.4).

$$(h_t - y_t) = \ln(\mu) + \mu_1 t + \mu_2 r_t + \mu_3 y_t + \eta_{ly,t+1} + \eta_{hl,t+1} \tag{2.9}$$

Where h_t is the stock of high-powered money measured in sterling for the UK and in logarithm; y_t is total domestic expenditure and in logarithm; with unknown parameters μ_i , i = 1, 2, 3; r_t is the nominal interest rate on domestic assets held from the beginning to the end of period t in the UK in logarithm ; $\eta_{ly,t+1}$ is a stationary process, so that the ratio of total financial assets to the nominal income level is stationary and ergodic; $\eta_{hl,t+1}$ represents the effects of the short-run deviations from IRP and FIP are now subsumed into the more general stationary processes.

2.7 Econometric formulation of the model

In this section, we use the modelling detailed in the last section to develop an econometric expression that is rooted in the previously discussed long-run economic theory. For empirical purposes, they apply a log-linear approximation to the five long-run equilibrium relationships identified earlier in equations (2.8), (2.7),(2.3),(2.9) and (2.4), forming the theoretical long-run relationships integral to the model's framework. The full derivation of the equations is found in section 4.5 of Garratt et al (2006).

PPP

$$p_t - p_t^* - e_t = b_{10} + b_{11} t + \xi_{1,t+1}, \tag{2.10}$$

IRP

$$r_t - r_t^* = b_{20} + \xi_{2,t+1}, \tag{2.11}$$

Production technology and output determination

$$y_t - y_t^* = b_{30} + \xi_{3,t+1}, \tag{2.12}$$

Solvency and liquidity

$$h_t - y_t = b_{40} + b_{41}t + \beta_{44}r_t + \beta_{46}y_t + \xi_{4,t+1}, \tag{2.13}$$

IRP

$$r_t - \Delta p_t = b_{50} + \xi_{5,t+1}, \tag{2.14}$$

Note that lower case letters are in logarithm i.e. that $p_{t=}\ln(P_t)$ etc. The equations also allowed for intercept and trend terms (when appropriate) in order to ensure that (long-run) reduced form disturbances, $\xi_{i,t+1,} i = 1,2, \ldots,5$, have zero means that are related to the long-run structural disturbances which are shown below.

$$\begin{aligned}
\xi_{1,t+1} &= \eta_{\text{ppp},t} - b_{10} - b_{11}t, \\
\xi_{2,t+1} &= \eta_{\text{uip},t+1} + \eta^e_{e,t+1} + \eta_{\Delta e,t+1} - b_{20}, \\
\xi_{3,t+1} &= \eta_{at} + (\eta_{nt} - \eta^*_{nt}) + (\eta_{kt} - \eta^*_{kt}), \\
\xi_{4,t+1} &= \eta_{ly,t} + \eta_{hl,t}, \\
\xi_{5,t+1} &= \eta_{\text{fip},t+1} + \eta_{\rho,t+1} + \eta_{\Delta\Delta p,t+1} + \eta^e_{p,t+1} + \eta^e_{\rho,t+1}.
\end{aligned} \tag{2.15}$$

The above relationships between the long-run structural disturbances, η_i's, and the long-run reduced form disturbances, ξ_i's clearly show the difficulties involved in identifying the effects of changes in particular structural disturbances on the dynamic behaviour of the macroeconomy. For example, $\xi_{5,t+1,}$ is composed of the five structural disturbances representing the different factors that could be responsible for disequilibria between inflation and interest rates.

The five long-run relations of the model (definition of the long-run errors) can be written more compactly as

$$\boldsymbol{\xi}_t = \boldsymbol{\beta}' \mathbf{z}_{t-1} - \mathbf{b}_0 - \mathbf{b}_1 (t, -, 1), \tag{2.16}$$

where

$$\begin{gathered} \mathbf{Z}_t = (p_t^o, e_t, r_t^*, r_t, \Delta p_t, y_t, p_t - p_t^*, h_t - y_t, y_t^*)' \\ \mathbf{b}_0 = (b_{10}, b_{20}, b_{30}, b_{40}, b_{50},)', \quad \mathbf{b}_1 = (b_{11}, 0, 0, b_{41}, 0)', \\ \boldsymbol{\xi}_\mathbf{t} = (\xi_{1t,} \xi_{2t,} \xi_{3t,} \xi_{4t,} \xi_{5t})', \end{gathered} \tag{2.17}$$

Both b_0 and b_1 are parameter vectors.

p_t^o is introduced as the price of oil, as a global variable affecting both the UK and the rest of the world. This is referred to as 'long-run forcing' meaning that the UK or the rest of world is affected by oil prices but the oil price is not affected by them in turn. The characterisation of oil prices as a 'long-run forcing' factor broadens the methodology used to model oil price impacts seen in earlier instances of cointegrating VAR analyses, such as those by Johansen and Juselius (1992) or Pesaran and Shin (1996). In these prior models, the variation in oil price was considered a purely exogenous I(0) variable.

The vector β'' is a matrix that allows restrictions to be included if desired e.g. as in the example below. it is a r × m matrix of parameters that describes the r equilibrium relationships expected to hold between the m variables in z_t in the long run.

$$\boldsymbol{\beta}'' = \begin{pmatrix} 0 & -1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & -\beta_{44} & 0 & -\beta_{46} & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \end{pmatrix}. \tag{2.18}$$

Given the definition of the long-run errors i.e. equation (2.16), it can be re-written as a *(p-1)th* order vector error correction model below:

$$\Delta \mathbf{z}_t = \mathbf{a}_0 - \boldsymbol{\alpha\xi}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{z}_{t-i} + \mathbf{v}_t. \tag{2.19}$$

$$\Delta \mathbf{z}_t = \mathbf{a}_0 - \boldsymbol{\alpha}[\boldsymbol{\beta}', \mathbf{z}_{t-1}, -, \mathbf{b}_0, -, \mathbf{b}_1, (t, -, 1)] + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{z}_{t-i} + \mathbf{v}_t,$$

or

$$\Delta \mathbf{z}_t = \mathbf{a} + \mathbf{b}t - \boldsymbol{\alpha\beta}'\mathbf{z}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{z}_{t-i} + \mathbf{v}_t, \tag{2.20}$$

which is of the form of with a = a0 + α (b0 − b1) and b = αb. This model directly incorporates the forecasts of economic theory pertinent to long-term trends. Estimating a model of the form presented above is achievable through the long-run structural modelling approach outlined in Pesaran and Shin (2002) and Pesaran, Shin, and Smith (2000). It should be noted that this method not only yields estimates for the parameters but also facilitates a direct test of the long-term theory. Specifically, by initially imposing just exact identifying restrictions on the cointegrating relations in a VECM (p − 1) of the form it's ensured that there are r^2cointegrating relations among the series. Proceeding to estimate the model with the complete set of theoretical restrictions offers over-identifying restrictions that are testable.

2.8 Summary

This chapter begins with outlying the importance of economic theories to guide the investigation of empirical questions. It then proceeds to demonstrate the economic theories that are relied on for the long-run structural approach i.e. Production technology and output determination; Long-run solvency and liquidity requirements and arbitrage conditions. From these theories, their economic equations are presented and then log-linear transformed which can be solved by econometric techniques. In the end, the equation sets are re-formulated in vectors for compactness and then transformed into vector error correction models that can be used to model and test these long-run relationships. It is clear from here that the VECMs can easily be transformed into VARX* models in the previous chapter which form the basis of a full GVAR model.

3 Chapter 3 - Comparing Global VAR with alternative macro models for forecasting and scenario analysis

3.1 Abstract

Macroeconometric models such as Global Vector Autoregresive (GVAR), Factor-Augmented VAR (FAVAR) models are often constructed for analysing monetary policy shocks. However, the rationale behind the modelling is completely different. This paper aims to investigate how GVAR fares against other macro models. Interest is in forecasting and scenario analysis. This paper compares the forecasting ability of GVAR and shock response from impulse response functions (IRFs) by FAVAR. For the forecasting exercise, the ability is compared between a generic AR model with GVAR ex-ante and GVAR-ex post forecasts. For the scenario analysis, IRFs were constructed from GVAR, FAVAR models with various shocks. It is easy to see that certain properties are similar among the models such as the long run appears to be unaffected by a monetary shock or that the GDP is negatively affected by it. However, there are also a lot of discrepancies in the short run, particularly in the first 4 quarters. From this, we can conclude that the GVAR model fares best in forecasting that it explicitly allows error correction mechanisms among country models, this is reflected by the dynamic responses from each economy. On the other hand, the FAVAR results look more uniform in their values and shape. There is no ’true’ model to speak of compared to the true values in the forecasting application. Consequently, the IRFs inform us more about the underlying methodology and assumption of the models themselves than can be used to evaluate their accuracies. The paper concludes that the GVAR model is quite adaptable in terms of allowing the data to dictate the short run but also relying on more theory-led identification for the long run.

3.2 Introduction

The purpose of this chapter is to further the comparison of GVAR with other models with empirical testing. During the last chapter, the various models have been illustrated with their specifications and a comparison was made on the basis of their methodological similarities and differences. There is only so much that can be said about theoretical comparison, however. Therefore, to continue the comparison, empirical testing is needed to contrast the performance of the GVAR model with others. In this comparison exercise, we have already covered the theoretical basis of the GVAR and other macroeconometric models therefore the previous chapters should already serve as a foundation to understand their similarities and differences. In the following pages, we first begin examining the model comparison strategy used in the literature and empirical testing was made for the application of forecasting and impulse response analysis. Discussion and conclusion come in the end.

To summarise, the GVAR model can be used for two types of applications i.e. economic forecasting and scenario analysis. This is also akin to other macro models where they are also designed for such applications and as such, GVAR models can be compared based on these two applications. In this chapter, we begin by examining the forecasting power of the GVAR models. We begin by using a global data set and estimate two different GVAR models (the first one with a restriction on the interest rates and the second one with unrestricted interest rates) and forecast the data within the sample so that we have a benchmark on how well the forecasting power is. In the second step, we also compare the results from the forecasts of GVAR models to forecasts from the standard autoregressive model. Given the theoretical underpinning of the GVAR model and its emphasis on its ability to use the full information set available, it is our question to ask whether such extra information improves our forecasts. The conclusion from the empirical tests, however, shows that GVAR ex-ante forecasts fare no better than simple AR models. Out of 30 AR estimated models, only 15 forecasts from GVAR models had won against the AR forecasts in terms of lower root mean square (RMSE) error. Although the forecasting results are not particularly good for the GVAR model, the verdict on its forecast ability is inconclusive. For example, GVAR was found to be very effective for a few variables such as the exchange rates for a few countries. Further discussion in the latter part of this chapter.

The comparison of models based on scenario analysis is however less straightforward. The main difficulty is the absence of a ' true model ' and also a widely agreed objective measure. The logic behind forecast comparison is easy to grasp. The forecasting model with a minimal distance between the forecasts and actual results is better. Although this is the sole factor as other factors can increase the value of a forecasting tool such as the usability and the economic reasoning behind it. The case for scenario analysis is more complex, however. By definition, scenario analysis is conditional forecasting i.e. given that A happens, what will happen to B in time t+2, ceteris paribus. This is also not observable and cannot be compared directly in reality as the ceteris paribus cannot be fulfilled. Without such a true model that exists, we can only compare the relevant output i.e. impulse response analysis from the GVAR and similar macro models.

On the other hand, if we have the same set of data, we can then compare the methods of GVAR with FAVAR, since both are essentially VAR-type models that are designed to handle large datasets. Therefore, to aid the comparison of these models, an experiment was made for this chapter. The first experiment involved taking the datasets which were used for the estimation of a GVAR model (chapter 1, di Mauro and Smith, 2013) and then approximating the results with a FAVAR model, using the same datasets but following the logical specification of a FAVAR model, which would allow us to compare the results coming from two models, in the form of impulse response functions from monetary shocks. In the following chapter, we first begin evaluating GVAR's forecasting ability. In the second part, we also examine and compare GVAR with alternative models with IRFs. Diagnostics tests and further details regarding the forecasts and tests are included in the appendix.

3.3 Evaluating the forecasting ability of GVAR model

3.3.1 Comparing forecasts

Different users will have different forecasting needs. For example, an ordinary investor is likely to be interested in understanding how the variables of interest, such as equity prices are likely to be to adjust the portfolio. In this case, we can see that the forecast is served as a tool to illustrate what could happen in the future so that the investor could adapt to it. On the other hand, central bankers and government economists setting fiscal policies will likely use the forecast to act on it to alter the course of the future. In the first group, ordinary investors who are unlikely to yield the power to change the course of economic events will show adaptive behaviour, while the second group i.e. central bankers and government economists who can set economic policies are much more likely to affect the course of the economy, particularly in the near future. In this case, the second group show a retroaction behaviour, implying that the forecast they made would react to such forecast and change the action, therefore invaliding the forecast itself. These two very different behaviours, therefore, are two forms of forecasting i.e. conditional and unconditional forecasts. Unconditional forecasts are much more familiar with what is generally known as forecast i.e. a set of numbers forecasted about the future. It attempts to describe the most likely scenario, given the information we have now and in the past. On the other hand, conditional forecasts are based on specific and possibly unrealistic assumptions about the economic agents/variables to see what would happen in the future, given such restrictions. For example, the central bankers would be interested in knowing what would happen to the world economy if interest rates are lowered.

Summarising the economic forecasting literature such as (Armstrong, 2001, Carnot et al., 2011, Elliott and Timmermann, 2013, Granger and Newbold, 2014), we can see that the sole value of forecast can only be understood in relation to and in the context of guiding decisions in areas of economics and finance. For example, (p.265-308 Carnot et al., 2011) summarised a framework that is widely used in evaluating economic forecasts. It first looks at some of the conceptual issues i.e. how to compare forecasts (what is being compared), forecast accuracy and its measurement and potential errors. The variables being compared, for example, are not necessarily the same and there is a risk that a comparison is being made with ' oranges and apples '. To mitigate this, the variables of interest must be defined clearly so that comparisons can be made on the same basis. There is also model uncertainty in which, the models that are producing the forecasts are misspecified. In this case, the forecasts produced from such models would also be biased, either forecasting pressingly or vying in certain directions. To mitigate this, one can perform diagnostic tests on the estimated model itself to ensure that it is fit for forecasting purposes.

Accuracy is perhaps the most contentious issue with economic forecasts. This is also the value that is most attached to by their users and creators. Although far from straightforward, in general, we do have a 'true model' that a forecasting model can be used for comparison, therefore the problem of assessing the accuracy of the forecasting model itself is not particularly hard. The problem is in how to define the measurement of accuracy. Another closely related concept is that of quality. Say, if we have two competing forecasting models in front and both have the same equally well forecasts (as defined and measured for their accuracy), then we have to consider the extra information that the model can convey. This depends heavily on the user's purpose, however. If the user is simply interested in knowing the forecast i.e. possible outcome of the future, then a sophisticated model would not yield more value than a naïve approach which would also give forecast values, should it be more accurate than the sophisticated approach. During the rest of the paper, the focus is on the accuracy of the forecasts. The extra merits of employing GVAR, which gives larger information set than simply naïve forecasts will be discussed in the end.

3.3.2 Forecasting accuracy

As shown above, not only forecasts themselves are inherently difficult to make but also the accuracy of forecasts is also difficult to assess. To make the comparison as fair as possible, a suite of techniques is often used to provide checks on the forecast accuracy, so that the result does not solely depend on the comparison being made. Of the plethora of various comparison methods available, the following techniques would be used for this chapter to assess the accuracy of forecasts, in line with (p.270 Carnot et al., 2011).

3.3.3 Summary statistics

This is an intuitive way to understand and characterise the size of the forecast errors. The goal here is simple, compare the forecasts and the actual values and summarise the difference. Often three different summary statistics are used in the literature i.e. the mean error (ME) which is also known as the bias measure. It should be close to zero for a good forecast. It simply sums up the error (i.e. the difference between forecast values and actual values) and is divided by the forecast horizons. A similar concept of mean absolute error (MAE) is also used, which measures the same thing but in absolute values, therefore, say an overestimate of a forecast value, say +3 points, will be treated as the same as an underestimate of a forecasts value, say -3 points. Both would be treated as a positive +3 points error, thus giving a penalty to both directions equally.

Another method of summarising the difference and treating both positive and negative errors equally is squaring the errors, thus yielding positive values. This is equal to $\sqrt{\sum_1^T E_t^2/T}$ root mean squared error (RMSE). However, it should be noted that the unit of RMSE is based directly on the forecasts it has measured. For example, say we have two sequences of forecasts in front, one GDP per capita of a country (forecast of $35000 and actual result of $36000) and another one for GDP annual growth rate (say a forecast of 1.2% and actual result of 1.5%), by definition, the RMSE would be larger for GDP per capita as the base unit of it uses is larger than that of percentage in growth rate. Therefore RMSEs cannot be used for direct comparison across models. If we wish to compare RMSEs across different models with different values, we need to normalise the calculated RMSEs first. Similar to error differences, there are also several ways to normalise it. For this chapter, RMSEs were divided by the mean of the sum squared difference from the forecast horizon. Say a forecast horizon is 8 periods or two years (8 quarters), then we have n=8, the difference between forecast and actual would be squared. The RMSE would then be divided by this mean. Similar to other measures, the lower value the better value for the forecasting model and an exact forecast would give a perfect 0 value.

The table below shows the relationship between the two, where there are 8 forecast results for two different sequences. The first forecasts show each period increases by 1% per period, reaching 1.07 after 8 periods. The same increase is also applied to the second forecast sequence which begins a 0.10 and with an increase of 1% per period, reaching 0.11 after 8 periods. As the base unit values they begin with are different, the RMSE would be different for them.

If we consider the two forecast sequences to be the squared difference between the forecast and actual values, then we can see that the RMSE mean would punish the second sequence much harsher than the first, this is because, although both forecast errors grow by 1% each period, the 1% value increase is much bigger for the second sequence (since the base value is smaller). Although this is not ideal, it does allow comparison across forecast models while not being distorted by the base values.

Table 1 - RMSE vs RMSE/mean

1	2	3	4	5	6	7	8	RMSE	Std	Mean
1.000	**1.010**	**1.020**	**1.030**	**1.041**	**1.051**	**1.062**	**1.072**	**1.018**	**40.317**	**0.983**
0.1	**0.101**	**0.102**	**0.103**	**0.104**	**0.105**	**0.106**	**0.107**	**0.322**	**127.495**	**3.107**

3.3.4 The rank of RMSEs and Sum of RMSEs

We can then rank the ranks of RMSE, with the smallest being the best, and the biggest the worst. The above result shows that even though the RMSE can be normalised by dividing the mean, it can still favour those that have larger base values, to begin with. To mitigate this, there are two ways. Instead of comparing RMSE or RMSE / mean across models, we can compare the sum of RMSEs of several models together. For example, say if we have two GVAR models, GVAR00 and GVAR01, both estimated with the same data but with different specifications, then instead of comparing the individual country model within the GVAR models, we can compare the sum of RMSEs or RMSE/mean of GVAR00 with GVAR01. Since both would have the same amount of country models within and also the same variables, the sum of RMSEs for both models would not be distorted by the problems above. In this case, the comparison is much simpler with the mode that has the smallest RMSE being better.

3.3.5 Theil's U Test

Another measure that is not distorted is using Theil's U Test. It is similar to the above concepts. The formula below shows the calculation where P equals the forecast value and A is the actual value. First finds the sum of squared difference and then divided by the sum of squared actual values. This is a more ideal indicator for judging the relative quality of a forecast that takes into consideration the values of the variables of interest i.e. A2. In this case, a value of 0 would indicate a perfect forecast.

Table 2: Directional test

Difference 1&2	2&3	3&4	4&5	5&6	6&7	7&8	Positive	Negative	Positive difference	Negative difference
-0.00049	0.00175	0.00188	0.00124	0.00109	0.00048	0.0011	6	1	4	-4
0.0278	-0.00852	-0.00718	-0.00645	-0.01696	-0.00685	0.01158	2	5		

3.3.6 Directional tests

Another measurement that can be made in the direction of the forecast. Often, if the only interest of the user is in knowing whether a variable is going to go up or down, then the size of the forecast error is less important. In this case, all we need to measure is the direction of the forecast and the actual result. In a sequence of say, forecasts for 8 periods, any positive value would indicate a positive direction whereas a negative value would point to a negative direction. By comparing the sum of directions, we can understand whether the model over or underestimate compares to the actual direction of the results. The below example shows a sequence of forecasts for 8 periods and their actual values. If we take the difference period nearby periods, i.e. difference between the 1st and 2nd period, 2nd and 3rd etc., then we can tell the direction of the sequence and contrast to that of the forecasts. If the sum of the positive and negative directions of the forecast is equal to the actual results, then it would be perfect. The below example shows that from the forecast, there are 6 positive directions and only 1 negative. However the actual result was 2 positive and 5 negative, therefore the trend is quite the opposite. It should also be noted that, by definition, the difference between positive and negative directions would equal as if one forecast is overestimated then it must be underestimated from the actual result perspective. The summing of positive and negative directions provides a robustness check on the result to ensure that it was calculated correctly.

3.4 Comparison with naïve forecasts

Although the user will be able to compare different forecasts with the tools above, they often mean little in isolation and with no context as to whether the forecast errors are due to the model or the nature of the variables being difficult for prediction. In this case, a relative comparison can be made with GVAR and other so-called naïve models. The purpose of using naïve models is to see if the additional features from GVAR models can add value to forecast accuracy. Several popular naïve models can be used, for example, one can simply generate random numbers given certain parameters that describe the distribution of the variables with Monte Carlo or a simple model that simply goes up or down by a certain percentage. Therefore it is expected that GVAR must at least beat randomly generated forecasts as otherwise would prove the model useless. Similarly, a random walk model can also be used to compare whether the GVAR forecasts would be better. In this chapter, autoregressive models were estimated instead as it tends to be more accurate and would be significantly more meaningful than compared with randomly generated models. The forecasts of simple AR models solely rely on its lags therefore it should be the most simplistic but also practical alternative to GVAR models, instead of using random walks. The equation below shows the AR(p). Similar to other time series models, the estimation of the models would also be subjected to diagnosis checks such as augmented dicky fuller test for unit root and AIC / BIC lag selection etc. Similar to the ordinary linear regression model, it is assumed that the error terms are independently distributed based on a normal distribution with zero mean and a constant variance and that the error terms are independent of the y values.

$$y_i = \varphi_0 + \varphi_1 y_{i-1} + \varphi_1 y_{i-2} + \ldots + \varphi_1 y_{i-p} + \varepsilon_i \tag{3.2}$$

Comparing the RMSE of the AR model with the equivalent GVAR model would then allow us to gauge their performance. In the example below, we have two estimated GVAR models, GVAR0 and GVAR1, two AR models, one with ex-ante forecasts and the other one with ex-post forecasts. In total, there are four forecasts made[3]. On the right-hand side of the table, it ranks the RMSE of the respective models where the lowest is the best with the rank 1 and so forth. By taking the ratio of the RMSE of the GVAR and AR model, we then get a percentage. If the percentage is less than 100% i.e. the RMSE for GVAR is less than AR, then this is in favour of the GVAR model. On the other hand, AR would win if the percentage is higher than the GVAR RMSE. In the example below, the ratio is 57% and 58.13% respectively, therefore both beating the AR model.

Further to the GVAR models, two types of AR forecasts were made, with both ex-post and ex-ante. As ex-post is estimated with the latest available data, it tends to be much better than ex-ante models. The purpose here is not to compare directly with AR (ex-post) to the GVAR model, since such functionality is not currently available, but this allows us to see the potential room for improvement should we wish to conduct ′ nowcasting ′ with the latest available data as input. Another purpose of estimating ex-post forecast is that it shows how that particularly depends on the latest available data.

If the difference between ex-post and ex-ante is large and that the ex-post is much more accurate, then it shows that the time series being forecast is much more reliable on its latest data point instead of historical data and the foreign variables (since it is produced from itself hence autoregressive).

[3] It should be noted that ex post forecast is currently not available with the GVAR toolbox therefore this is not
featured.

3.5 Estimating the GVAR model

The first step of the GVAR approach is the formulation of the individual VARX* (vector autoregressive with exogeneity) model for every country. In this section, we present the general methodology advanced in Dees et al.(2007) to model individual countries in the GVAR model applied to the model in this study. The approach assumes that there are N+1 countries in the global economy, indexed by i = 0, 1, . . . , N and the aim is to relate a set of country-specific variables e.g. GDP, inflation, interest rates etc. that are of interest to the study. As the model contains a large number of variables, it is best to represent using linear algebra as per the standard convention in the literature. The vector of interest denoted as xit collects the macroeconomic variables specific to the individual countries of interest indexed by i and over time, indexed by t = 0, 1, . . . , T . Following the notation and definitions given in di Mauro and Pesaran (2013, p.14-17), the general individual country model VARX* (2, 2) is represented as xit – is a vector with a dimension of ki × 1 of domestic macroeconomic variables indexed by individual country i and time as t; x∗it – is a vector with dimension of ki × 1 of foreign macroeconomic variables indexed by individual country i and time as t; uit – is a serially uncorrelated and cross-sectionally weakly dependent process. The rest of the associated parameters are similar to those in a normal VAR, which are to be estimated to give context to economic interpretations to the model. It should be noted that x∗it as a vector that captures the foreign-specific macroeconomic variables that are related to domestic ones are constructed via a weight matrix. Mathematically, this is defined as , where wij, where i being the domestic country and j as the foreign, is a set of weights that wij = 0 and when combining all the weights of i and j would become 1. The scheme of the weight matrix can be designed to reflect the trade and/or financial linkages. For example, in our model, the weight of Britain (domestic) is expected to have a large trade with the EU countries such as Germany (foreign), therefore it will have a larger weight than say, Malaysia. It should be noted that similar to the framework of an unrestricted VAR, the VARX* model can also be written in its error-correction form VECMX* which allows the differentiation of short and long-run effects. In particular, the long-run effects are being treated as co-integrating. The individual VECMX* models are estimated separately for each country i, based on reduced rank regression thus identifying the long-run effects or I(1) relationships that exist within the domestic xit and across xit and also the foreign economies x∗it. Thus, the total number of cointegrating relations, speed of adjustment for each country can be derived and given economic meaning. The full derivation of the VECMX* can been seen in di Mauro and Pesaran (ibid, p.15) and is not repeated here.

The GVAR approach is a two-stage process. The first was to estimate the VARX* model country by country and the second is to stack all VARX* models together and to be solved as a whole. We now examined the solution to solve the model as outlined in di Mauro and Pesaran (ibid, p.16). Recall the generic VARX* (2,2) model:

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i1}x^*_{it} + \Lambda_{i1}x^*_{it-1} + \Lambda_{i2}x^*_{it-2} + u_{it}$$

(3.3)

Where the definitions remain the same as defined before, we now introduce a few terms to solve the model as a whole. To form the GVAR model, we first introduce a new term z_{it} define it as:

$$z_{it} = (x'_{it}, x^{*\prime}_{it})'$$

(3.4)

Therefore we have:

$$A_{i0}W_i x_t = a_{i0} + a_{i1}t + A_{i1}W_i x_{t-1} + A_{i2}W_i x_{t-2} + u_{it}$$

(3.5)

Also recall that for i = 0, 1,. . . , N, which implies the equation above is individual country-specific and require stacking to solve for x t which links all individual models together. We now introduce a few more terms to tidy up the model:

$$G_0 = \begin{pmatrix} A_{00}W_0 \\ A_{10}W_1 \\ \vdots \\ A_{N0}W_N \end{pmatrix}, \quad G_1 = \begin{pmatrix} A_{01}W_0 \\ A_{11}W_1 \\ \vdots \\ A_{N1}W_N \end{pmatrix}, \quad G_2 = \begin{pmatrix} A_{02}W_0 \\ A_{12}W_1 \\ \vdots \\ A_{N2}W_N \end{pmatrix},$$

$$a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \quad a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \quad u_1 = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \vdots \\ u_{Nt} \end{pmatrix}$$

(3.6)

thus

$$G_0 x_t = a_0 + a_1 t + G_1 x_{t-1} + G_2 x_{t-2} + u_t$$

(3.7)

As the term G_0 is a known non-singular matrix (invertible matrix). G_0 is called non–singular if there exists an n × n matrix G_0^{-1} such that $G_0 G_0^{-1} = I_n = G_0^{-1} G_0$. Thus, by multiplying its inverse, the term disappears and we now obtain the GVAR (2) model with 2 lags where:

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + F_2 x_{t-2} + \varepsilon_t$$

(3.8)

Where the new terms collect the inverse of G_0

$$F_1 = G_0^{-1} G_1, F_2 = G_0^{-1} G_2,$$

$$b_0 = G_0^{-1} a_0, b_1 = G_0^{-1} a_1 \; \epsilon_{it} = \; G_0^{-1} u_{it}$$

(3.9)

The GVAR model above can be solved recursively, see Pesaran, 2015. To summarise, as shown above, the GVAR model allows the interactions among the domestic and foreign economies through three diverse channels. The first is the contemporaneous and lagged dependence of domestic variables x_{it} on foreign variables x_{it}^*. In addition, it also allows the effect and dependence of domestic variables x_{it} on global weakly exogenous variables such as oil and commodity prices. This can also be used as a simulation strategy that can reveal the contemporaneous effects of shocks from country i on j.

3.6 Data sources and variables

The current model contains 33 countries of which 8 eurozone countries are grouped into the Euro Area and treated as one country (in the sense of a separate VARX* model). This list of the countries in the model consists of the US, China, Japan, UK, Euro area (Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland), Canada, Australia, New Zealand, Sweden, Switzerland, Norway, Korea, Indonesia, Thailand, Philippines, Malaysia, Singapore, India, South Africa, Turkey, Saudi Arabia, Brazil, Mexico, Argentina, Chile and Peru. As it stands, it contains the bulk of the world's output at around 90% (di Mauro and Pesaran, 2013, p.18). It is not surprising that due to data quality and availability, semi-emerging economies such as Russia, Nigeria, Pakistan, and Vietnam are not selected. It should also be noted that, due to the strict requirement of the data, unfortunately, most African countries are not included in the model. Relative young development of capital markets in emerging markets is also a big drawback for their exclusion. Therefore the current edition of the GVAR cannot yet accommodate but there are other models which could be useful such as the SEMs, particularly those developed by earlier econometrics for soviet economies (see Shapiro, 1977) and developing countries (see Klein, 1965) which have a lot less requirement on the datasets.

3.7 GVAR model and Datasets

As noted in the chapter introduction, in the first experiment, we use a standard GVAR that was estimated by (chapter 1, di Mauro and Smith, 2013). The datasets that were used are currently available to be accessed with the GVAR toolbox. In this section, we first describe the datasets and also the model estimated. The same estimated model would first be used for evaluating its forecasting ability. Then in the second part, it would be used for generating IRFs for shocks. We then proceed to illustrate the estimation of an approximated FAVAR model. In the end, we compare the results from the two models.

The datasets contain a large selection of countries and their corresponding economic variables. Currently, the database contains 33 countries, spanning from 1979 to 2013. The model in this study describes the relationships between itself and across 33 countries from 1979q1 – 2016q4. Similarly to Dees et al.(ibid.), the countries in the Eurozone are grouped and considered as 'Euro Area' in the model with its VARX* model. of which 8 eurozone countries are grouped into Euro Area and treated as one country (in the sense of a separate VARX* model). This list of the countries in the model consists of the US, China, Japan, UK, Euro area (Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland), Canada, Australia, New Zealand, Sweden, Switzerland, Norway, Korea, Indonesia, Thailand, Philippines, Malaysia, Singapore, India, South Africa, Turkey, Saudi Arabia, Brazil, Mexico, Argentina, Chile and Peru. As it stands, it contains the bulk of the world's output at around 90% (di Mauro and Pesaran, 2013, p.18). Due to data quality and availability, semi-emerging economies such as Russia, Nigeria, Pakistan, and Vietnam are not included.

In terms of variables, there are real output (quarterly in the natural log, seasonally adjusted, with 2015 indexed at 100 for all countries), inflation (constructed from local CPI index, quarterly in the natural log), real exchange rate (constructed from local currency against USD, where USD is set as 1, also in the quarter and natural log), real equity price index (from the local largest stock market index, quarterly and in the natural log), short term interest rate (constructed from the local central bank using interest rate, deposit rates, T-bill rates and money market rates, quarterly averages, in natural log, long term interest rate, constructed with interest rates, government securities and bonds, in quarterly averages and natural log. The datasets also include three global variables, namely oil price, raw material and metal price. The oil price is constructed with the Brent crude index, also quarterly and in log. Both raw material and metal prices are taken from primary commodity prices indices and also in the quarterly log.

It is important to note that, the compilation of the database has been kindly shared and allowed for academic usage, however, there are some missing data in the database which makes it difficult to account for the effects of some variables. For example, the real equity price index is not available to China and a few other countries. Also for the long-term interest rate, only a handful of countries publish the data therefore only advanced economies are included. As such, rather than having all 33 countries and the 6 variables plus 3 global variables = (33*6)+3 = 201-time series, we have only 178 series, with 23 series missing (201-178). As can see from the figure, only complete time series are available for real output and inflation, therefore in the second part for comparing IRFs, only these are the variables that would be used for model comparison. However, for the model estimation exercise, we would include all variables in two models.

Variable	**No. of time-series**
Real output	33
Inflation	33
Equity price	26
Exchange rate	33
Short term interest	32
Long term interest	18
Oil price	1
Material price	1
Metal price	1

Table 3 – Variables and number of time- series in the model

3.7.1 Lag orders of individual VARX* models

Recall that a generic VARX* (p,q) model has lag orders p for both domestic lag orders q for foreign variables. The exact lag orders to be selected are similar to those employed in time series literature with the Akaike information criterion (AIC) or the Schwarz Bayesian criterion (SBC). This is embedded in the GVAR toolbox and the largest values from AIC or SBC are selected for the lag orders.

The table above shows the lag orders selected by either AIC or SBC, whichever value is the highest. It should be noted that it does not matter whether the lag orders of p and q are equal. However, also due to data limitation, an upper limit of two lags is imposed for the test as higher lags would consume too much degree of freedom. This means during the test, the order of (0, 0), (1, 0), (0, 1), and (1, 1) tested for all countries. As the results from the table show, all countries either have the lag order of (2, 1) or (1, 1).

3.7.2 Unit root test

A big advantage of the GVAR approach is the indifference to the stationarity / non-stationarity of the variables. However, unit root tests are still useful in the sense that it allows the identification of short-run and long-run relations (as cointegrating). Like many other papers in the literature, the Augmented Dickey-Fuller test is used instead of the older standard Dickey–Fuller test. The ADF test was carried out at 95%, implying if the test statistic for the variable is more negative than the critical values then it will be rejected as there is no unit root. The test was carried out on the level, differenced, twice differenced, with the trend and without trend on all variables namely real output (y), inflation (price level, p), equity price (eq), an exchange rate (ep), short-term interest rate (rs), long-term interest rate (lr). The output of the original test on all variables (domestic and foreign) is carried out in MATLAB and the results are displayed in appendix C, with the notation of N meaning the null hypothesis of non-stationarity is not rejected and Rej for rejected. It can be summarised that the results from the test indicate most variables have either I(0) or I(1) characteristics which is ideal for the GVAR approach.

3.7.3 Testing for Cointegrating relationships

Once the unit root had been tested, the corresponding cointegrating VARX* models are estimated as VECMX*. The next step is the identification of the cointegrating relationships within the individual models. The rank of cointegrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics (see Pesaran et al. 2000). The summary of output from both tests is displayed above. The number of cointegrating relationships found is somewhat different to the result in Dees et al.(2007), however, this is expected as it is mostly due to newly revised data. Japan has the biggest difference between this estimation to those in Dees et al.(ibid.,17), with only 2 found here but 4 before while the rest remain similar with ± 1.

Table 4 - VARX order

Country	p	q
Argentina	2	1
Australia	1	1
Brazil	2	1
Canada	2	1
China	2	1
Chile	2	1
Euro	2	1
India	2	1
Indonesia	2	1
Japan	2	1
South 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

3.7.4 Testing for weak exogeneity

As mentioned before, the main assumption in the GVAR approach is the weak exogeneity of the foreign variables x_{it}^{*} concerning the respective VARX* model. As described in Pesaran et al.(2004), this assumption is compatible with a certain degree of weak dependence across u_{it} (the residuals). Following the work on weak exogeneity testing by Johansen (1992) and

Granger and Lin (1995), the weak exogeneity assumption implies no long-run feedback from x_{it} to x_{it}^*, suggesting that x_{it}^*error correction terms of the individual country VECMX* models do not enter in the marginal model of x_{it}^* (Smith and Galesi, 2014). This implies we can consistently estimate the VARX* models individually and later combine them together to form the GVAR. The proof of weak exogeneity implication on x_{it}^* can be seen in Pesaran (2015, ch.23, p.569). The test is a regression model described in Johansen (1992) and Harbo et al. (1998). The test employed by Dees et al.(2007) is as follows:

$$\Delta x_{it\ell}^* = a_{ij} + \sum_{j=1}^{r_i} \delta_{ij\ell} ECM_{ij,t-1} + \sum_{k=1}^{s_i} \Phi_{ikj}^{'} \Delta x_{i,t-k} + \sum_{m=1}^{n_i} \Psi_{im\ell ikj}^{'} \Delta \tilde{x}_{i,\ell-m} + \eta_{it\ell} \tag{3.10}$$

where ECMij ,t1, j = 1,2,. . . ,*ri* are the estimated error-correction terms corresponding to the cointegrating terms found as shown in previous section. It also should be noted that Δx_{itl}^* is the differenced vector collection of the foreign variables. This is a F-test for the significance of ij, = 0,j = 1,2,. . . ,*ri* above. While the lag orders of p and q were determined earlier via AIC.

The regression was run on the foreign variables in the VARX* models real output (y), inflation (price level, Dp), equity price (eq), short-term interest rate (rs), and long-term interest rate (lr). and also the global variables such as price of metal (pmetal), oil (poil) and raw material (pmat) with 5% significance level. Table on the next page shows the result of 208 regressions run and their F-statistics. Also reported is whether they are rejected or not. The cell of orange indicates it has surpassed the critical value at 5% (defined by its degree of freedom, shown in the second column) which means the assumption of weak exogeneity is not met. Based on all 208 regressions run, only 9 variables (4.3%) are unable to meet the assumption. This result is a slight increase from Pesaran (2004) and Dees et al.(2007). Therefore, for example, the foreign long-term interest rate would not enter Australia, Brazil and Turkey VARX* models. Similarly, this applies to other rejected variables.

3.7.5 Testing for structural breaks

Having considered the rather harmless integrated series in the previous section and also the possible violations of weak exogeneity and its treatment, we now turn to one of the most fundamental problems in econometric modelling. So far we have shown that the problems mentioned above can be mitigated but unfortunately; similarly to other time-series / econometric models, the GVAR is also susceptible to structural breaks The core concept of structural breaks is straightforward; it is referring to the unexpected sudden shift of the time-series. Consider a daily stock price time series where a sudden shift is very common due to stock split, unexpected announcements, overnight trading, oversea stock exchange performance etc. This renders the original time-series model unreliable as the time-series had shifted unexpectedly and therefore not within the range of the forecast, this also implies forecast errors with be greater. The problem of structural breaks had been discussed extensively in the literature since the 1960s by Quandt (1958, 1960) who proposed Sup F test that calculates the likelihood ratio test for a change in model parameters and also identifies the break date. The Sup F test was quite adaptable but only worked on univariate regression; nevertheless, it became the basis for future research. In the GVAR literature, mainly those in Pesaran et al.(2004), Pesaran and Smith (2006), Dees et al.(2007), Pesaran et al.(2009), di Mauro and Pesaran (2013), Chudik and Pesaran (2014) had an extensive discussion of the problem. The GVAR Handbook by di Mauro and Pesaran (2013) surveyed the existing strategy that The GVAR literature employed. These include several test statistics to assess the structural stability of the estimated coefficients and error variances of the individual VARX* / VECMX* models. Specifically, the survey indicated the methods used are (p.21): the maximal OLS cumulative sum (CUSUM) statistic, and its mean square variant by Ploberger and Krämer (1992); a test for parameter constancy against non-stationary alternatives by Nyblom

(1989); as well as sequential Wald type tests "of a one-time structural change at an unknown change point specifically"; also the QLR statistic by Quandt (1960), the MW statistic (Hansen, 1992), and the APW statistic (Andrews and Ploberger, 1994).' Compare to the results in Dees et al.(2007), we have 2 extra years and also two global variables included in the model. Therefore, it is expected that the increased sample period would increase the chance of structural. This prediction is confirmed by the tests described above. All tests begin with their standard version with their robust version carried out in arrears. Details of the structural break tests can be seen in the appendix. Although structural breaks occur more in the current model, overall it is similar to those described in the literature. It is fair to conclude that the robust versions of the tests are performed much better. As Dees et al.(2007) had concluded, despite the evidence for some structural breaks they are mostly from the error variances which would not impact the application with impulse responses as it is based on the bootstrap method for median and confidence boundaries rather than just point estimates. The tables below show the percentage of variables found to have breaks and also the estimated dates of the breaks. It is not surprising to find that the dates are mostly related to episodes of financial distresses as it is where volatility dominates.

3.8 Forecasting

Similar to most econometric models, one of the main outputs of the GVAR model is the forecasts of the economic variables. Recall that the GVAR is constructed by stacking multiple VARX* models. In our case, we have estimated 33 individual VARX* (p,q) models with variable lags and stacked them together and became a GVAR (2) model. We now show that forecasts can be made from the generic GVAR (p) and applied the method to our study. Recall that the individual VARX* (2,2) i.e. two lags for both domestic and foreign variables:

$$x_{it} = a_{i0} + a_{i1} t + \varphi_{i1} x_{i,t-1} + \varphi_{i2} x_{i,t-2} + \Lambda_{i1} x^*_{it} + \Lambda_{i1} x^*_{it-1} + \Lambda_{i2} x^*_{it-2} + u_{it}$$

(3.11)

Where x_{it}– is a vector with a dimension of ki × 1 of domestic macroeconomic variables indexed by individual country i and time as t; x^*_{it}– is a vector with a dimension of ki × 1 of foreign macroeconomic variables indexed by individual country i and time as and u_it – is a serially uncorrelated and cross-sectionally weakly dependent process. This can be re-written into:

$$A_i(L,\ P\ )W_ix_t = \phi_{it}$$

(3.12)

Where ϕ_it equals x_{it}, L as the lag operator; p as the domestic variable lag orders; W as weight matrix and x_t as the domestic variables denoted in t and i denotes the country. In other words, it is simply a re-statement of the VARX* model as a function of domestic variables with lag orders multiplied by their corresponding weights. Also recall that, once the VARX* models have been estimated individually, the next step is to stack the models together to form the GVAR model.

Again, using the notations in Dees et al.(2007), by stacking the individual VARX* models (written as ϕ_{it}), we obtain the GVAR (p) model as

$$G(L,\ p)x_t = \phi_t$$

(3.13)

Where

$$G(L,p) = \begin{pmatrix} A_0(L,p)W_0 \\ A_1(L,p)W_1 \\ \vdots \\ A_N(L,p)W_N \end{pmatrix}, \varphi_t = \begin{pmatrix} \varphi_{0t} \\ \varphi_{1t} \\ \vdots \\ \varphi_{Nt} \end{pmatrix}$$

(3.14)

The GVAR ex-ante forecast model has now formed and can be solved via a recursive method at any horizon N.

3.8.1 GVAR ex-ante forecasts

We now turn to the results produced by the estimated GVAR model. As mentioned before, there are 33 countries in total with 8 euro countries which will be estimated as one, therefore there are 26 country models. Each has its combination of lag orders up to a maximum of 2 as determined by AIC/ BIC. It should be noted not all VARX* models have equivalent lag orders nor the same set of domestic and foreign variables due to the specification tests of lag order and weak exogeneity in the last section. In the end, after removing the variables which did not meet the weak exogeneity assumption, we have 271 variables estimated placed in 26 VARX models and one auxiliary model for global variables such as oil price, metal and raw material price for 8 quarters i.e. 2 years. This means 2184 point estimates were created for all variables. For original output see appendix.

3.8.2 GVAR (conditional forecast) and GVAR1 (unconditional forecast)

As mentioned previously, forecasts can either be conditional or unconditional. In this case, we estimate two sets of forecasts from the same estimated GVAR model. Summary statistics like RMSEs were calculated to see which model is more accurate and whether the restrictions imposed improved the forecast accuracy. If there is a strong conviction or that the future values are already known for a variable in advance, then there is a case to impose such restrictions, fixing the values and letting other values be estimated in light of these restrictions. In this case, restrictions were placed on US short and long interest rates setting both at 1% for short and 2% for long. The GVAR forecasts (also denoted in GVAR0 for easy differentiation)with the restriction are simply shown as GVAR below while the one without restriction is displayed as GVAR1.

3.8.3 Forecasting models comparison

As there are too many forecasts produced and due to space limit, below shows only a small selection of the forecasts produced. Looking at the forecasts produced in the figure below for the US interest rate, for example, it is easy to see that the GVAR1 forecast was off by a big margin as it was calculated based on previous data, culminating in a negative interest rate lower each quarter. This is not the case in reality thus the GVAR0 forecasts, with the predetermined restrictions fared better than the GVAR1 forecasts. Compare the GVAR1 forecast to the AR (ex-ante) and we can see that the AR model is of no use in forecasting the interest rate movement. In this case, a more naive approach proved to be more useful than forecasts based on time series alone. In general, AR ex-ante forecasts and also unrestricted GVAR ex-ante forecasts are useless for forecasting interest rates. This is because interest rates are often decided in advance in light of possible future scenarios therefore it is retroaction based. Past influence is likely to be less useful. If we consider AR ex-post forecasts, then we can see that it is much better in its performance. In this case, we can conclude that, if we wish to improve the forecast on the interest rate, we can employ the latest figure thus it would be much closer to a nowcasting exercise.

Now consider other forecasts and let's take oil price, material and metal price for example. These prices are constantly changing daily, therefore there is not enough information reflected if we take them quarterly. The actual values for oil price fluctuated a lot from 4.0 (about $54 USD if we inverse the natural log) to 3.5 ($33) and back to near 4. None of the 4 forecast models provided a similar description of this trend as historical prices matter very little in this case. Similar summaries can also be drawn about material and metal prices.

Although in these two prices, the AR ex-post forecasts were much closer to actual results while it was also incorrect for the oil price. Now if we turn to the Argentina equity index we can see that the performances are now better with the GVAR forecasts. Both GVAR forecasts were indicating a downward trend while AR ex-ante was indicating no inaccurate trend. In the example for both Brazil GDP and UK equity index, both GVAR forecasts and AR ex-ante are no better than random guesses. In this case, it proves that the time series data itself did not provide much information and unless the latest actual data is considered as in the AR ex-post case, it shows that there are few values in terms of accuracy. In the example of China's inflation rate, it was fluctuating by a large amount which was not captured by the forecasts. However, the GVAR forecasts were able to provide a middle course and are the best compared to the AR ex-ante. In other interest rate forecasts, we can see that GVAR is often better than AR models, whether conditional or unconditional. This is possibly due to the extra information conveyed from the past and also the interrelationships between international central banks in which if one decides to decrease rates, it could trigger other central banks to follow. This element could not be captured by the AR models therefore the GVAR forecasts here are much better.

Since there are too many forecasts to compare with, it is more efficient to compare at a macro level. In this case, RMSEs were calculated for each model of which there are 271 in total. It has been mentioned previously that individual RMSEs should not be used for comparing across models. However, by summing up the totals, we can then use it to compare two GVAR forecasts and decide which is more accurate.

In both cases, we can see that the RMSEs for emerging markets tend to be more accurate than for developed markets. If we rank the RMSEs, where the best has the value of 1 and the worst has 271, then we would have a sum of 9453 ranks in total (1+2+3...+271). The below table shows, for example in GVAR0 model that the combined ranks for the Brazil forecasts are the best of all countries with a rank of 148 only, while USA has a much larger combined rank of 485. We then see that the same is true for Brazil where the combined ranks are now 92 and Switzerland became the worst at 525. This shows that setting restrictions on the interest rates had helped some countries but worse the forecasts for others. If we are to compare two models, we then find that GVAR0 has a sum of RMSE/mean of 43234 and GVAR1 of 32003. Therefore the RMSE/mean is much smaller for the GVAR1 model where the interest rates are left to be estimated by the time series. Now a paradox has appeared. Although setting restrictions on interest rates had increased accuracy for country interest rates, on the whole, it has failed to improve the overall accuracy. The below table summarises the RMSE/mean difference between GVAR and GVAR1 model ΔGvar0; Gvar1 = Gvar0 - Gvar1. Except for the case of the long interest rates (lr), all variables performed better for GVAR0 forecasts as the RMSEs are much smaller. Again, this proves the same conclusion from the previous paragraph.

If we now compare the AR (ex-ante) to GVAR models, we can now see that AR models forecast better in general as they all have smaller values. It is easy to conclude that GVAR forecasts are no better than AR models. However as mentioned before, this could be distorted by the initial values which it started, therefore Theil's U statistics were also calculated using the equation defined earlier. From this measurement, we can see that AR ex-post performed the best as expected with a sum of 7.76. However GVAR0 model now performs much better than GVAR1 with a sum of 11.07 over 19.56. In this case, GVAR0 was also better than AR ex-ante therefore proving that GVAR forecasts are better than a simplistic AR model if restrictions are not set.

3.8.4 Directional test

Using the method that was mentioned earlier, the directional test was used to check whether

GVAR forecasts can anticipate direction change and whether the forecasts are going up or down. Out of 931 forecast points made from the GVAR0 model (unrestricted model), there are 48% indicated a positive change and 52% negative change, no variable stayed the same course. This is in contrast with the 56% up and 44% down for the actual results, where also no variable stayed the same course in eight quarters (2 years). This implies that 8% of GVAR forecasts were overestimated and that 8% were underestimated. In other words, there were 77 incorrect calls by the GVAR model, indicating that it is correct for 92% of the time.

3.9 Summary and conclusion

In this section, we have examined the ability of GVAR for producing forecasts. When compared to simple AR models, the forecast accuracy is no better with RMSE/mean measures. Although Theil's U statistics show a different answer, indicating that GVAR0 is better than AR and GVAR1 by a significant margin. The discrepancy between the two is possible because RMSE/mean would punish errors when the magnitude is relatively big while Theil's U does not as it treats errors equally by the actual unit it is comparing to. In this case, it would be more robust to consider that Theil's U is more appropriate although RMSE/mean helps select GVAR0 over GVAR01, it is not too helpful when it comes to assessing accuracy across different models. This is also backed up by the directional test which indicates that GVAR is 92% accurate for forecasting directions.

Overall, it shows a mixed but positive picture of GVAR forecasts. Recall that earlier the discussion that forecasts should not be judged solely on their accuracy as the extra information conveyed could also be important. In this case, we have found evidence that GVAR forecasts are better than AR ex-ante forecasts and that it also provides a much richer background in terms of linking different economic variables together thus allowing a more detailed understanding for the user.

Table5 - GVAR country ranks

Country	Sum of Rank	Sum of RMSE_mean	Average of RMSE_mean
uk	503	4081.3	680.22
japan	496	3841.6	640.26
usa	485	4716.4	943.28
switz	485	1508.4	251.40
can	481	3587.5	597.92
euro	473	2577.7	429.62
safrc	459	2331.2	388.53
austlia	454	1996.5	332.75
kor	448	2825.4	470.89
swe	432	1842.0	307.01
india	432	1037.2	172.87
nzld	429	1147.4	191.24
nor	402	1667.3	277.88
thai	358	808.4	161.69
sing	349	2294.6	458.92
china	340	2011.7	502.93
phlp	326	572.6	114.51
indns	323	785.1	196.28
mal	313	1792.4	358.49
mex	253	492.2	123.05
chl	248	351.1	70.22
turk	219	446.6	111.65
sarbia	204	230.5	76.83
arg	199	108.9	21.77
per	165	90.5	22.62
bra	148	75.1	18.77
du_model	29	14.3	4.77
Grand Total	9453	43234.0	315.58

Table6 -GVAR variable ranks

Variable	Sum of Rank	Sum of RMSE_mean	Average of RMSE_mean
poil	1	1.9	1.95
pmetal	8	5.0	5.01
pmat	20	7.4	7.36

eq	434	169.0	8.90
ep	730	359.1	14.36
lr	1594	14415.3	1108.87
y	1764	2293.1	88.20
Dp	2245	5714.2	219.78
r	2657	20268.8	810.75
Grand Total	9453	43234.0	315.58

Table 7- Difference between GVAR0 and GVAR1 – the difference between the two models show that GVAR01 is worse than GVAR0 in all areas except long-term interest rate (lr).

Variable	Sum of RMSE_mean	Average of RMSE_mean	Max of RMSE_mean	Min of RMSE_mean	StdDevp of RMSE_mean
Dp	-1458.46	-56.09	-37.08	-6.53	-22.45
ep	-81.53	-3.26	-21.79	-0.46	-4.48
eq	-17.31	-0.91	-6.10	-1.18	-0.90
lr	-1417.68	-109.05	872.27	-62.54	145.06
pmat	-0.57	-0.57	-0.57	-0.57	0.00
pmetal	-0.68	-0.68	-0.68	-0.68	0.00
poil	-0.30	-0.30	-0.30	-0.30	0.00
r	-7965.58	-318.62	-819.88	-6.06	-288.36
y	-287.98	-11.08	61.86	-4.21	16.33
Grand Total	-11230.09	-81.97	99.23	-0.30	-114.54
Average	-1247.79	-55.62	5.30	-9.17	-17.20

Table 8 - Forecast evaluation with RMSE

Model	**Count of RMSE**	**Count of Rank**	**Average of RMSE**	**Average of Rank**	**StdDevp of RMSE**	**Max of RMSE**	**Min of RMSE**
AR (Ex Ante)	30	30	0.057	2.733	0.095	0.373	0.001
AR (EX Post)	30	30	0.043	1.600	0.096	0.394	0.000
GVAR	30	30	0.080	2.867	0.133	0.513	0.000
GVAR1	30	30	0.082	2.800	0.135	0.529	0.000
Grand Total	120	120	0.066	2.500	0.118	0.529	0.000

Table9- Theil's U statistics

Model	Sum of Theil's U	Count of Theil's U	Average of Theil's U	Max of Theil's U	Min of Theil's U2
Actual	0.0	30	0.0	0.0	0.0
AR (EX Post)	7.8	30	0.3	1.8	0.0
GVAR	11.1	30	0.4	1.9	0.0
AR (Ex Ante)	14.3	30	0.5	1.8	0.0
GVAR1	19.6	30	0.7	4.4	0.0
Grand Total	52.7	150.0	0.4	4.4	0.0

Table10 - Directional test – table shows the forecast under-predicted 8% for actual positive results and over-predicted 8% for actual negative results.

	Forecast		Actual	
Direction	Positive	Negative	Positive	Negative
No. observations	446	485	523	408
Percentage of total (n=931)	48%	52%	56%	44%
Forecast error	-8%	8%		

3.10 Impulse response analysis

3.10.1 Introduction

During the last section, the GVAR model was evaluated in terms of its forecasting ability. The basis for IRFs and their theoretical comparisons have been thoroughly explored in the previous chapter. This section aims to complement the last one and to further illustrate this comparison exercise by means of empirical testing with IRFs.

In this case, we have 33 individual VARX* (p,q) models. There are two lags for the individual VARX* model, namely, p lags for domestic variables and q lags for foreign variables. The exact lag orders to be selected are similar to those employed in time series literature with the Akaike information criterion (AIC) or the Schwarz Bayesian criterion (SBC). From the estimation, we can see that the lag structures for most countries are either 1 or 2 lags maximum for domestic variables but only 1 lag for all foreign variables. Unit root tests were also run for identification. Like many other papers in the literature, the Augmented Dickey-Fuller test is used instead of the older standard Dickey-Fuller test. The ADF test was carried out at 95%, implying if the test statistic for the variable is more negative than the critical values then it will be rejected as there is no unit root. The test was carried out on the level, differenced, twice differenced, with the trend and without trend on all variables namely real output (y), inflation (price level, p), equity price (eq), the exchange rate (ep), short-term interest rate (rs), long-term interest rate (LR). Once unit roots had been found, corresponding VARX* models were estimated as VECMX*. The next step is the identification of the cointegrating relationships within the individual models. The rank of cointegrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics.

Another important assumption is the weak exogeneity of the foreign variables concerning the domestic variables. Following the work on weak exogeneity testing by Johansen (1992) and Granger and Lin (1995), the weak exogeneity assumption implies no long-run feedback from x it to x* it, suggesting that x* it error correction terms of the individual country VECMX* models do not enter in the marginal model of x* (Smith and Galesi, 2014). This implies we can consistently estimate the VARX* models individually and later combine them to form the GVAR. The regression was run on the foreign variables in the VARX* models real output, inflation, equity price, short-term interest rate, and long-term interest rate. and also the global variables such as the price of the metal, oil and raw material with a 5% significance level. Based on all 178 regressions run, only 9 variables (5%) are unable to meet the assumption. Therefore, for example, the foreign long-term interest rate would not enter Australia, Brazil and Turkey VARX* models. Similarly, this applies to other rejected variables.

As described in the last chapter, impulse response functions can be used to estimate the shocks from an increase or decrease. In this case, the use of GIRF is preferred over OIRF as it does not depend on the ordering of the variables. In this case, we specify a shock of 1 positive standard error to the US interest rate and see what would happen to the rest of the 33 (including the US) economies. As the shock was applied to all variables and models, there are 178 GIRFs estimated for the horizon of 40 quarters, equivalent to 8 years. As there are too many IRFs run, therefore only a handful of samples are demonstrated here. For the comparison exercise, the countries Argentina, Brazil, China, Malaysia, Mexico, Peru, the UK and USA were used for their respective variables of real GDP and inflation.

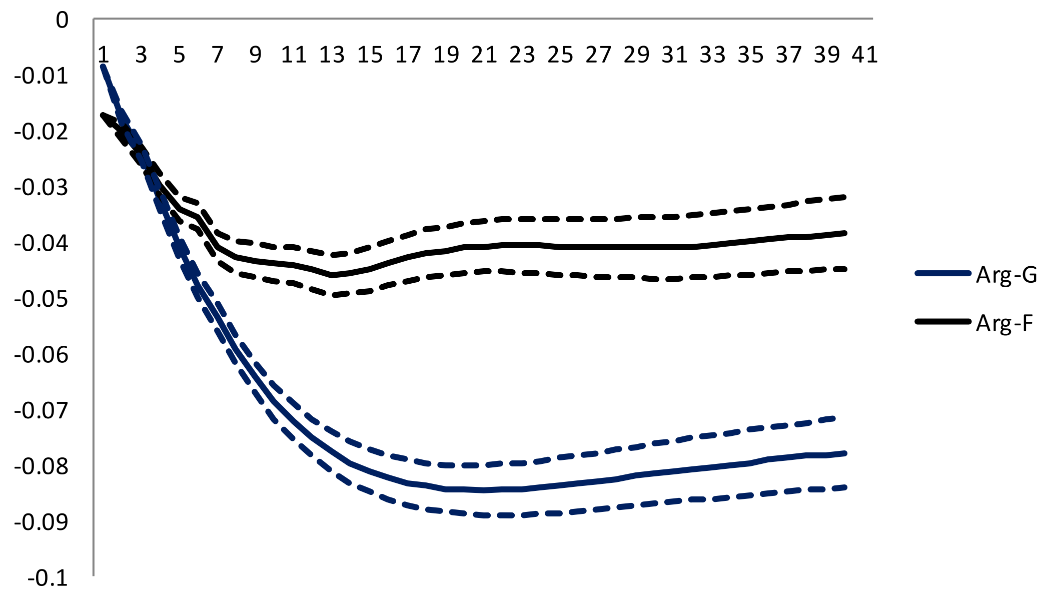
3.10.2 FAVAR model estimation

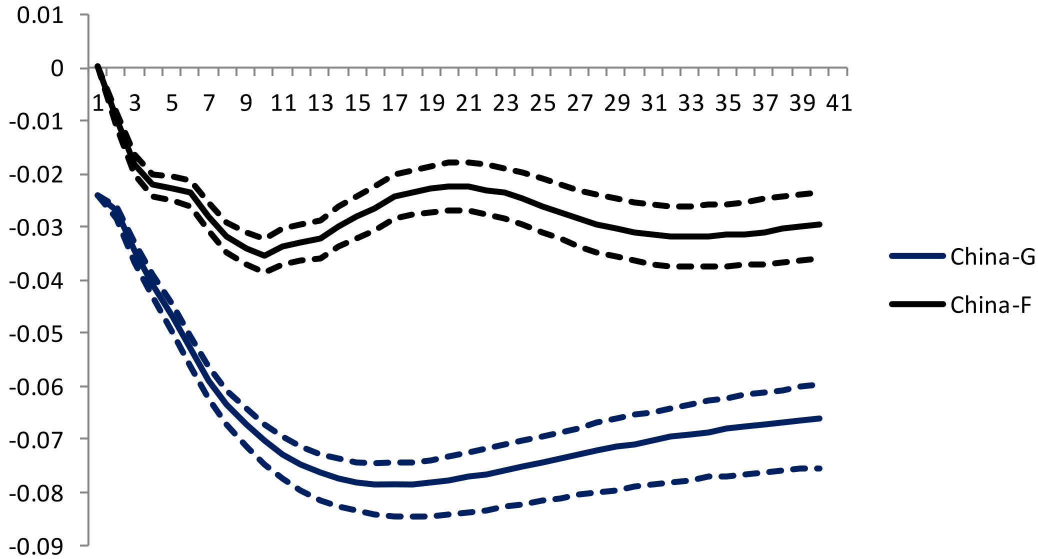
A two-stage process was used for the estimate of a FAVAR model from the GVAR datasets. First, PCA was used to estimate the numbers needed to represent the data and the data was then augmented into the VAR model for estimation and the IRFs are then created. The impulse response functions were then calculated, from the model variables. Before estimating the model, the data were first normalised. In this case, we would like to know the effect of a monetary shock of 1 standard error from the US on the rest of the economies. Therefore the nominal interest rate of the US was used as the endogenous variable. Recall that there are 178 time series from the datasets, as the US is itself a time series, therefore this is taken out from the total datasets for PCA estimation i.e. there are 177 time series for PCA. Then PCA was run and 3 factors were found to be the best fit for the data. From the output of the model, 4 factors were also used but did not increase the significance of the IRFs, therefore only 3 factors were used. Regarding the identification of the shocks, the main method is to separate the variables into either slow or fast moving. In the case of fast-moving variables such as interest rate and equity prices, the effect of any shock would have already been reflected in them before the next succession of data at t+1 i.e. if there is an increase in US interest rate, it would have been reflected well into the real equity data before the next quarter data is updated. Therefore these series are assumed to be affected by the increase contemptuously. This restriction is also applied in this estimation, similar to the one used in (Bernanke et al., 2005) where GDP and inflation are set as slow, while the rest of the data, oil price, material price, metal price, exchange rate, real equity price, interest rates (long and short) are set to be fast. IRFs are then produced, with a 1 positive standard error to the US short-term interest rate to the model variables, also with 40 periods. In terms of model lag, different tests were used to run the model from 1 to 16 lags (4 years). In the end, the lag of 7 periods was found to be the most significant with the ADF test, as additional lags did not add more to the results. The results are reproduced below for comparison with the GVAR model estimation.

3.10.3 Comparison of GVAR and FAVAR

The IRFs produced are listed in The IRFs used for comparison are listed below. The first figure summarises how GDP and inflation react from the countries reacted to the increase in short-term US interest rate. Looking at the graphs for GVAR - GDP and also FAVAR GDP, we can see that there is a consensus regarding the general direction of the shock. From the FAVAR estimation, we can see that all countries suffer from the shock and can decrease as much as 0.04 per cent point for most countries. In particular, we can see that South and Latin American countries are particularly affected. For example, Brazil, Peru, and Mexico fared worst. This is possible considering the strong trade links between the US and these countries. However, the particular effect on these countries is not that prominent, considering that other countries also suffer a similar decrease of around 0.03%. From these examples, we can see that all FAVAR IRFs for GDP are negative. If we compare this to the GVAR results, the results are also similar, we can see that most countries also trend downward. This is also true for most of the 33 countries in the model, although they are not reported here due to space limitations. However, there is also the case for Mexico and Peru which appear very differently from the GVAR model. In both cases, the increase in US interest rate thus causing an increase of the US dollars against the respective local currencies. Therefore, in that case, the strong exports from these countries to the US actually contributed to their economies compared to the FAVAR model. As the trade weights were explicitly included in the GVAR, that illustrates the possible scenarios for these countries which are particularly prominent for those influenced by the US.

Figure 1-6- GVAR-FAVAR - Selection of real GDP shocks on various countries. Arg-G is referring to the GVAR results while Arg-F is for FAVAR. The dashed lines represent 95% confidence intervals.

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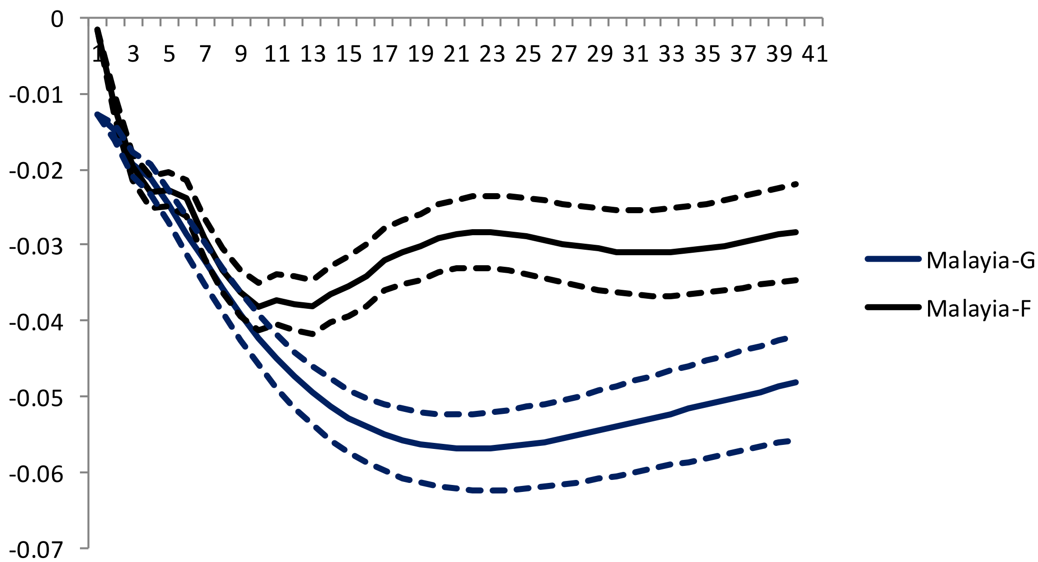
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
-0.08
-0.09
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
China-G
China-F


0
-0.01
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-0.04
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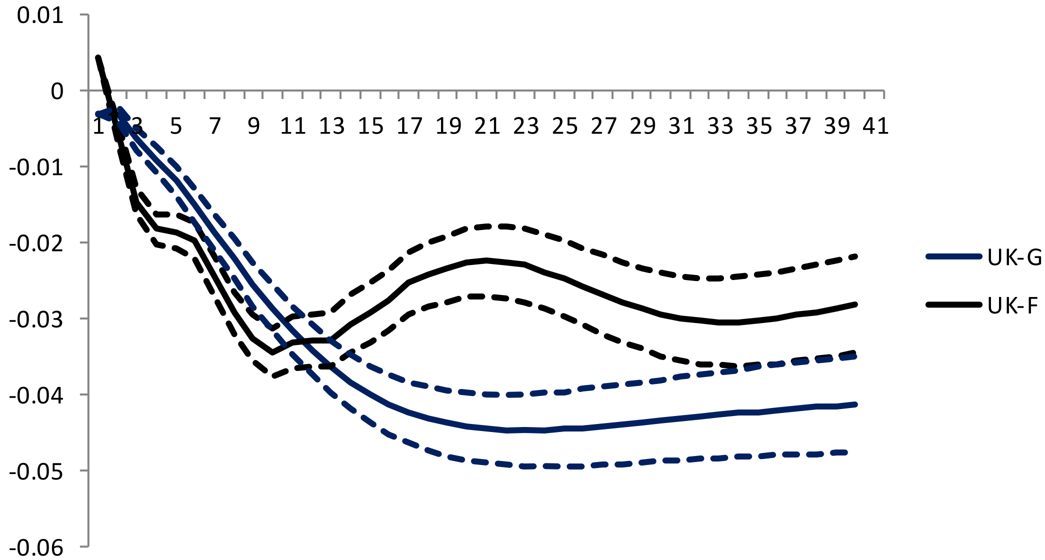
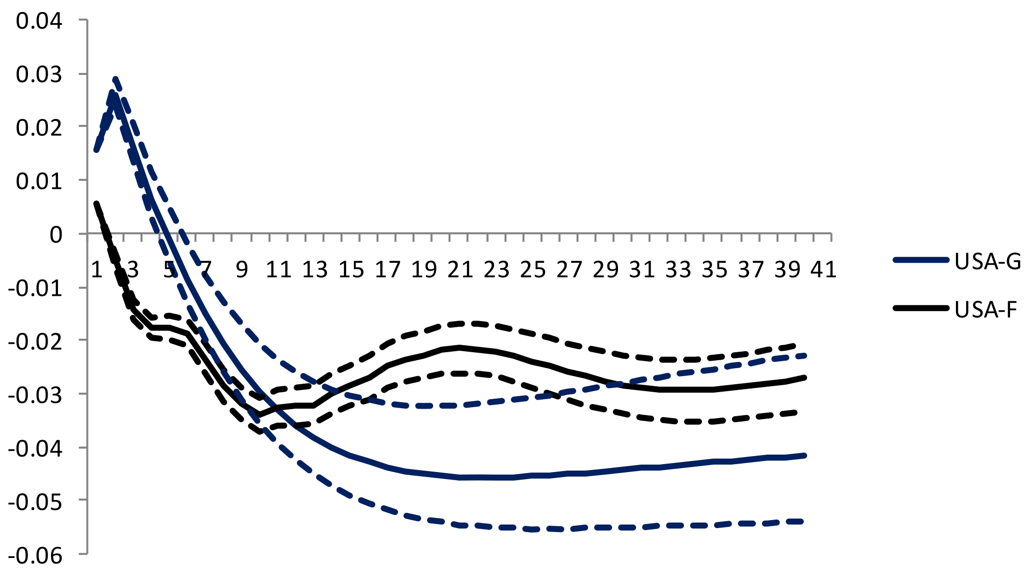
-0.06
-0.07
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
Malayia-G
Malayia-F



0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
UK-G
UK-F



0.04
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1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
USA-G
USA-F

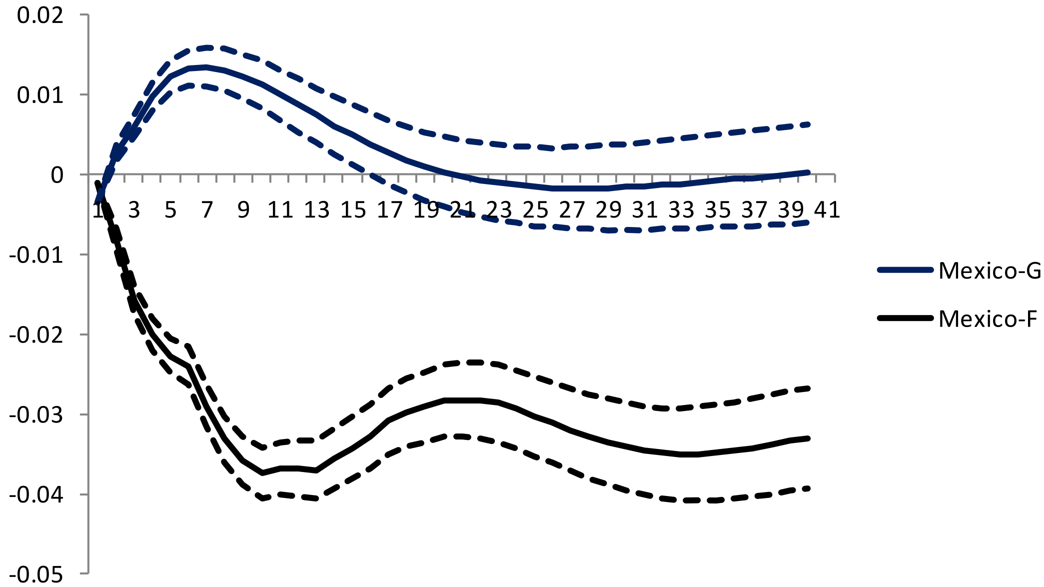
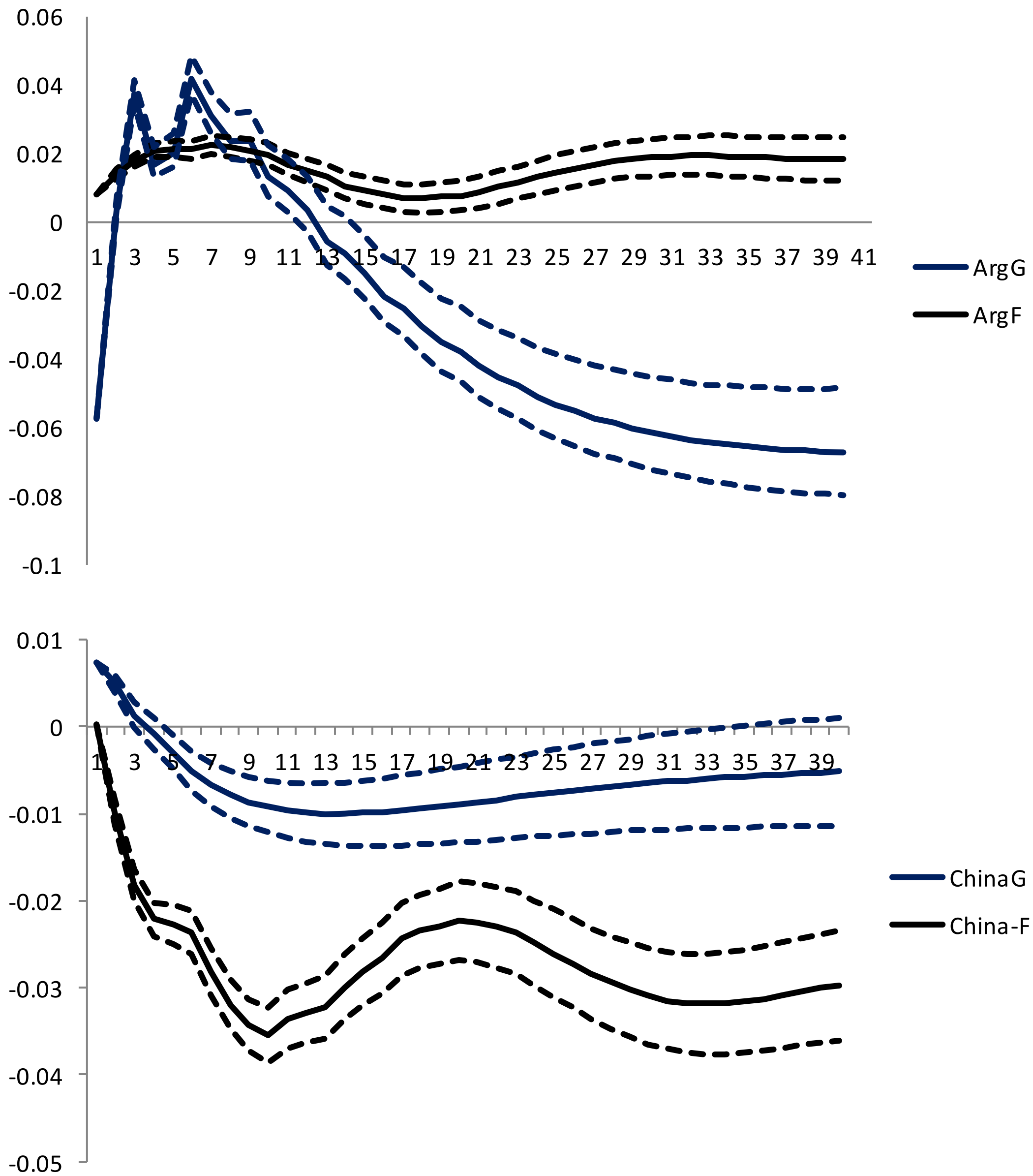
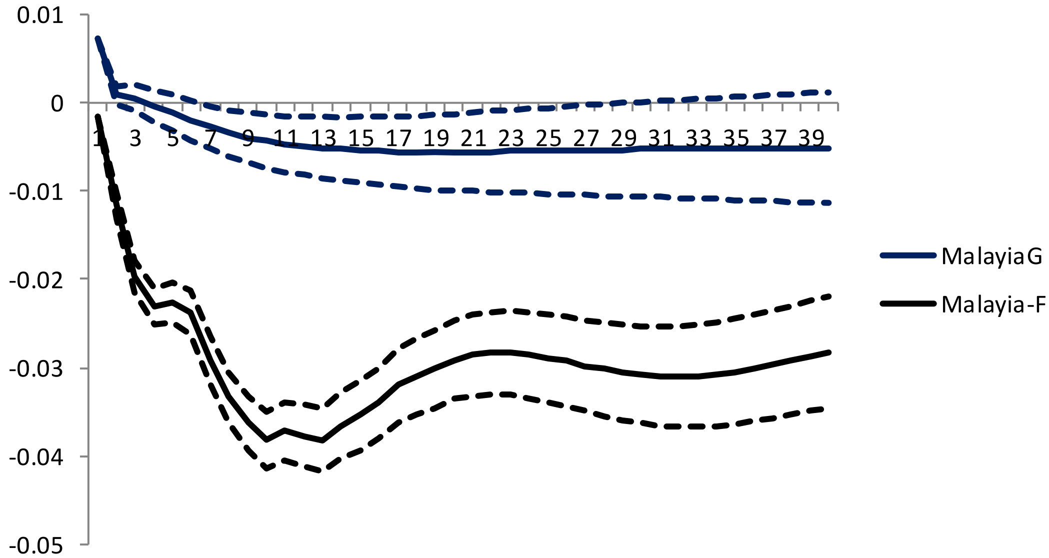

0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
Mexico-G
Mexico-F

Figure 7-12- GVAR-FAVAR - Selection of inflation shocks on various countries. Arg-G is referring to the GVAR results while Arg-F is for FAVAR. The dashed lines represent 95% confidence intervals.





0.01
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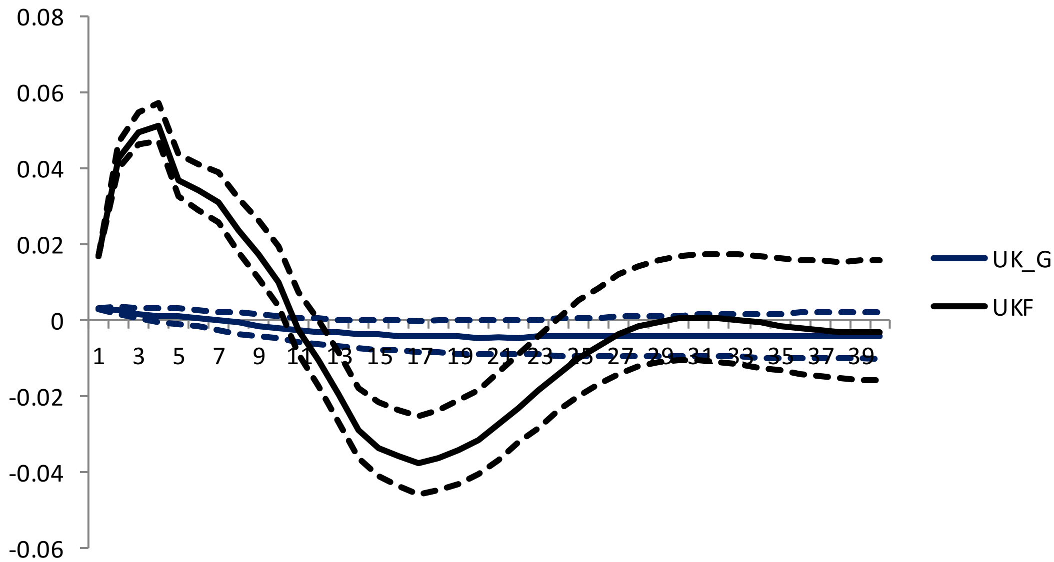
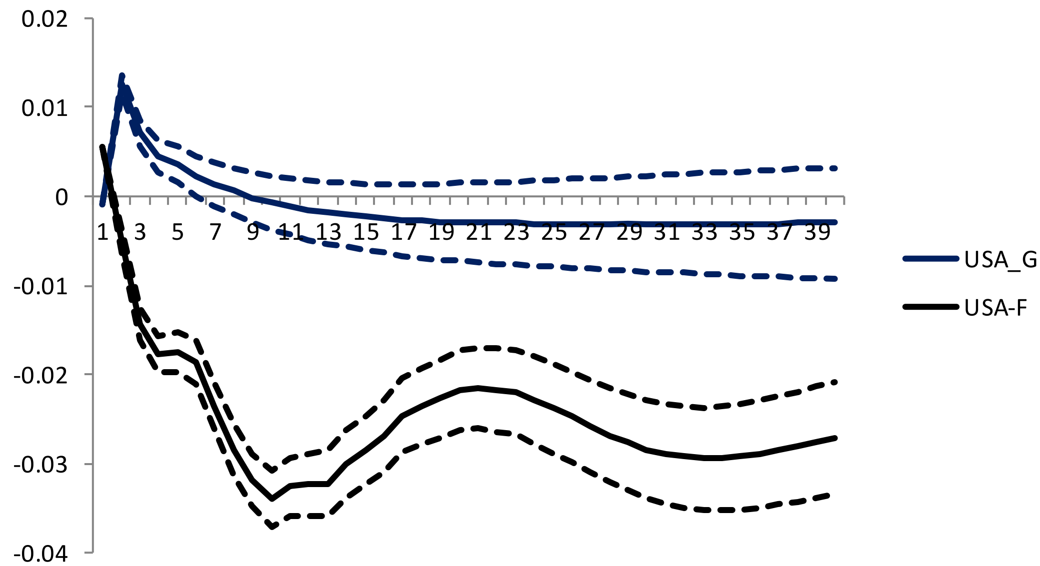
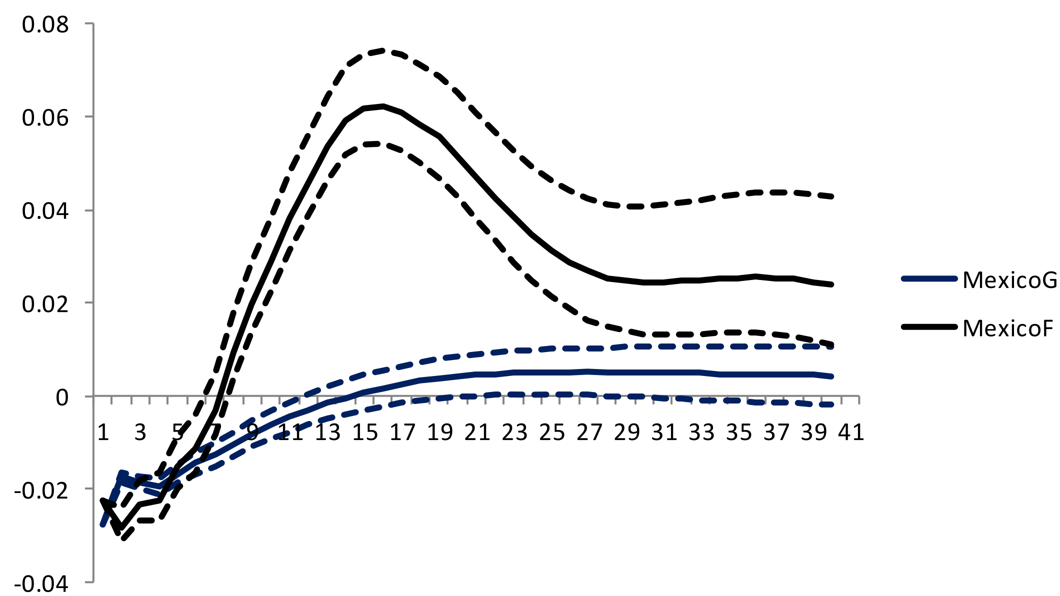
-0.01
-0.02
-0.03
-0.04
-0.05
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39
MalayiaG
Malayia-F



0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39
UK_G
UKF


0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39
USA_G
USA-F


0.08
0.06
0.04
0.02
0
-0.02
-0.04
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
MexicoG
MexicoF

While both models produced a similar outlook for GDP, the inflation shock was much more complicated. In the case of the GVAR model, most economies' inflation IRF did not respond much to an increase in the US interest rate, with most countries hovering around 0 impacts, except the case of Mexico, Argentina, Brazil and Peru. In particular with Peru, we can see that both IRFs behave very similarly, with the inflation peaking at 0.02 per cent and also a similar trajectory, growing positively before running negative and later picking up again. An interesting example is the so-called inflation puzzle produced in the US IRF. In this case, we can see that the inflation shot up by a small amount of 0.01 % before dropping down again. This puzzle was originally found in (Sims, 1992) and was solved by adding commodity prices. However, in this case, the inflation puzzle remains even though there are much more data used in this GVAR model so any transmission channel of interest shock should have been identified. Although it is worth noting that the effect is very insignificant at 0.01%, and sharply turns into negative. For example, (Dees et al., 2007), this paper had also found a similar phenomenon that could not be explained away by the data. The authors found that changing the order of the variables affected the IRFs, as documented by using OIRFs (see chapter 2). However, in this case, the IRFs were produced with GIRFs therefore the underlying variable order should not matter. In the case of the FAVAR inflation, it is much strong, with the price puzzle presenting in many countries, which could be affected due to the ordering of the slow/fast category of variables[4].

Another observation from this comparison is that the IRF values from the FAVAR models that to be higher than that in the GVAR model and the values are also more even. This could be because the shock is affecting all countries equally under the current identification scheme, in which no particular country is more prone to the effects. In the case of the GVAR model, due to the trade weights used to define the domestic and foreign economies, we can

[4] At the moment, there is no tool developed for using GIRFs with FAVAR models, therefore this could be further investigated

see that the effects on each country are more specific and individual whereas the ones from FAVARs are more spread out. In this case, we can conclude that the GVAR model allows a much stronger transmission of shocks among countries, specifically assigned by their respective trade weights. From this perspective, the FAVAR model appears to be much less nuanced.

3.11 Conclusion

The main contribution here is letting GVAR competes with other models with different benchmarks and tests, which is not done in the literature. This chapter has assessed and evaluated GVAR's ability to forecasting with a benchmark model with various tests. Impulse response functions were also used to compare with alternative models. Judging from the analysis above, it certainly shows that GVAR is capable of forecasting data and the extra information could potentially help. However, this is far from conclusive since its forecasting ability is not much better if not the same as a simple AR model. The emphasis for the value of the GVAR model then comes in its ability to include much available data coherently while also providing an adequate forecasting ability. The evaluation from impulse responses provides an extra check on the model itself and can be used to compare with alternative models. In this case, the IRFs show that certain properties are similar among different models such as the long run appears to be unaffected by a monetary shock or that the GDP is negatively affected by it. However, there are also a lot of discrepancies in the short-run, particularly in the first 4 quarters. From this, we can conclude that the GVAR model fares best in that it explicitly allows error correction mechanisms among country models, this is reflected by the dynamic responses from each economy.

4 Chapter 4 - Estimating Shocks in a New-Keynesian Rational Expectations model with the GVAR approach: Pre- and Post-Pandemic

Abstract:

This paper investigates the possibility of using the global VAR (GVAR) model to estimate a simple New Keynesian DSGE-type multi-country model. The long-run forecasts from an estimated GVAR model were used to calculate the steady-states of macro variables as differences. The deviations from the long-run forecasts were taken as the deviation from the steady-states and were used to estimate a simple NK open economy model with an IS curve, Philips curve, Taylor rule, and an exchange rate equation. The shocks to these equations were taken as the demand shock, supply shock, monetary shock, and exchange rate shock, respectively. An alternative model was constructed to compare the results from GVAR long-run forecasts. The alternative model used a Hodrick–Prescott (HP) filter to derive deviations from the steady-states. The impulsive response functions from the shocks were then compared to results from other DSGE models in the literature. Both GVAR and HP estimates produced dissimilar results, although the GVAR managed to capture more from the data, given the explicit co-integration relationships. For the IRFs, both GVAR and HP estimated DSGE models appeared to be as expected before the pandemic; however, if we include the pandemic data, i.e., 2020, the IRFs are very different, due to the nature of the policy actions. In general, NK-GVAR models appear to be much more versatile, and are able to capture dynamics that HP filters are not.

Keywords: global VAR; New Keynesian model; structural model; pandemic data

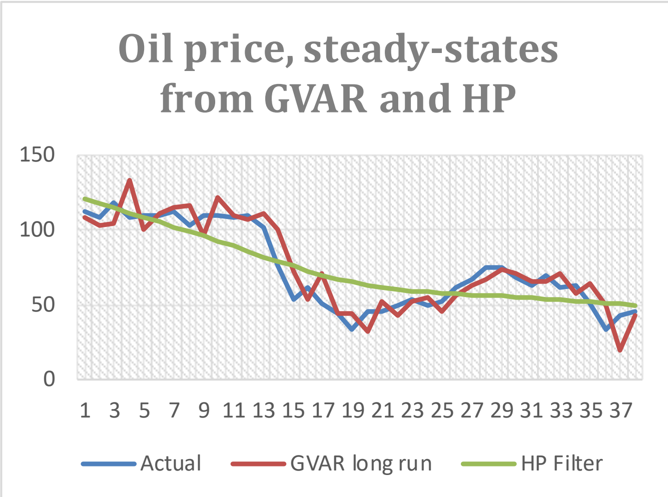
4.1 Introduction

The field of macroeconomics is dominated by DSGE-type models, mainly due to their ability to build from micro-foundations and, as a result, bypass Lucas' critique. Due to the highly non-linear nature and the intractability of the model, the majority of the literature is confined to studies of a single economy, or with a few countries included as a small open economy model. There has been slow progress in expanding the literature to a global-type method, such as the working paper by IMF Carabenciov et al., 2013 (1), while many works are confined to a regional scale. Recent literature on the impacts of Covid-19 has also faced a similar problem, where the models are built for a single country analysis or on a regional basis. As such, the global dynamic feedbacks between economic variables are limited. For example, Eichenbaum et al. (2021) (2) developed a macro-model for the US, with epidemic properties, to study the link between economic decisions (such as reducing consumption by agents to reduce the chance of infection and, therefore, extending the recession). The paper provides economic decisions and epidemic dynamics in the US, but this cannot be easily extended to other countries or on a global scale. The measurement of the global macroeconomic impacts is more suitable with the GVAR methodology. For example, Chudik, Mohaddes, Pesaran et al. (2021) (3) developed a threshold GVAR model to measure the macroeconomic effects of the pandemic on a global scale, with 33 countries and multiple regions.

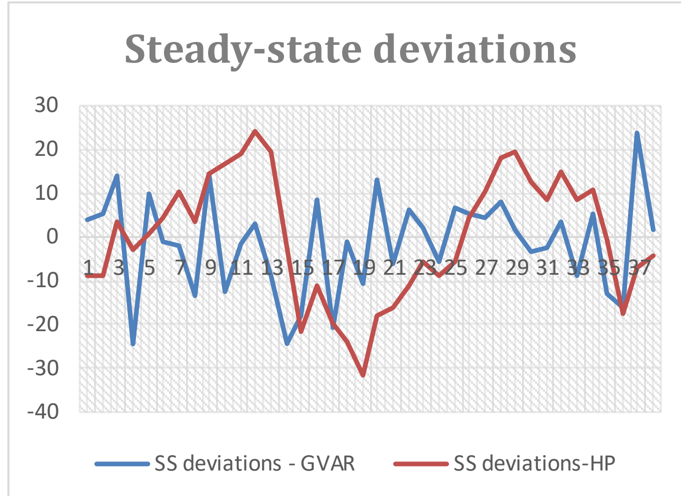
The global VAR framework from DDPS (Dées et al. 2013) (4) provides an approach that allows estimating a global model while limiting the problem of scale in the VAR literature (known as the causality of dimension). Instead of imposing restrictions separately on the individual equations, as seen in the SVAR literature, Global VAR attempts to solve the model as a whole.

Under this paradigm, many multi-country models have been built for macro and finance purposes. For example, in (Smith, 2013) (5) the handbook shows how a large GVAR model can be built with 30+ countries and a dozen variables for each country, spanning 50 years of data, etc. However, there is a common critique of the interpretations of the impulse response functions (IRFs) to VAR-type models, as they may not correspond to the economic theory directly. The same can be applied to IRFs generated in GVAR models, and this is referred to as the shock identification problem in the literature. On the other hand, DSGE models do generate shocks that can have such a clear interpretation, but extending them to a multi-country framework is very difficult.

To solve the shock identification problem of VARs, there are various approaches in the literature. These include structural VARs and identification by sign restrictions on the impulse responses. These approaches are particularly easy to implement if the model in question is small scale and as such, a clear and consistent identification regime can be applied. However, this can be difficult to implement in a large-scale model. Another approach offered a large-scale model, to close the gap between the GVAR and DSGE models by Dées, Pesaran, Smith, and Smith (2013) (4). The authors showed that, a multi-country rational expectations (RE) New Keynesian type model, which consists of three equations i.e., Phillips curve, IS Curve, and a Taylor rule, can be solved with the input of GVAR long-run forecasts. In a typical DSGE model, all shocks are in effect deviations from the steady-state values. Therefore, the modeller is required to estimate the steady-states, either from econometric applications or taking calibrated values from the existing literature. The authors in DPSS argue that the long-run forecasts produced from an estimated GVAR model can be used as the steady-states from which the shocks can be derived, and, as such, the shocks will now be given a clear economic interpretation, while satisfying Lucas' critique. In general, their paper covered the technical issues involved when estimating the DSGE model with GVAR inputs and provided a framework for this type of estimation. Similarly to other papers in the DSGE literature, this shows that global demand and supply shocks are the most important drivers of output, inflation, and interest rates in the long run. Financial impacts such as monetary and exchange rate shocks have only a short-run impact on the evolution of the world economy. This paper evaluated the framework that was given in the DPSS paper, and, first, re-estimated two GVAR models and used their long-run forecasts as the inputs for estimating two RE models. This was done by extending the datasets from the original paper from 2009 to 2020, including the pandemic and subsequent extreme swings. As an alternative, another RE model was estimated using steady-states from a Hodrick–Prescott (HP) filter for comparison. In the end, comparisons were made based on the estimated coefficients of the models and the DSGE literature. An example is shown below. The actual oil price is shown against the long-run forecast with GVAR and a filtered oil price series with a lambda of 1600, which is standard for quarterly data. It is easy to see that the HP filter often loses the granularity of the data and the cycles. As such, any cointegration relationships between series would be lost. Therefore, this paper hypothesizes that a DSGE-type NK model estimated with GVAR long-run forecast, instead of the standard HP filter, will perform better.



Steady-States Graph 1 - The graph above compares three steady-states.



Steady-States Graph 2 -Steady-state deviations from GVAR and HP.

4.2 Methodology

The list below shows the steps that were taken to estimate the RE models.

a. expanding the datasets from 2009 to 2020.

b. Establish individual VARX*/VECMX* models.

c. Estimate GVAR model from individual VARX*/VECM*.

d. Create GVAR long-run forecasts from the model.

e. Take the difference between GVAR long-run forecasts and actual data as the gap or deviation from the steady-states.

f. Use the deviation from steady-state values to estimate a rational expectation (RE) model.

g. Compare the estimated coefficients from the models.

h. Compute the IRFs from the model.

i. Alternative model/estimate the steady-states from HP filter.

j. Compare the results to the GVAR generated model.

k. Compare the results to the DSGE literature.

To estimate a DSGE model with GVAR inputs, the datasets were first extended by 11 years for all 33 countries and four variables. These variables were to be used for forming individual VARX* models and then solved together as a GVAR. For the HP estimated DSGE model, no GVAR model was solved, and all steady-states were estimated with HP. Details of the datasets are given in the next section.

The theory justifying using GVAR to estimate long-run forecasts and the deviation to steady-states, instead of the conventional HP filter, is detailed in DPSS. The first step of solving the GVAR is forming individual VARX* models. Each country has one equation relating itself to its domestic variables and foreign variables represented by a star *. Details are provided in the next section.

Once the long-run forecasts have been calculated, the difference between the actual values and the forecast is the gap or the deviation from the steady-states, with the long-run forecast being the steady-states. These deviations from steady-state values are then used in the DSGE model. Specifically, two DSGE models were estimated. One with the 2020 data and another model with the data to 2019 only. As an alternative, an HP filter was used to estimate the steady-states, instead of a GVAR long-run forecast. Deviations from the steady-states were calculated as above.

Comparisons were made at the end between the different models, in terms of their coefficients and the shapes of the IRFs. A specific comparison was also made to the DSGE literature.

4.3 Data

The datasets contain a large selection of countries and their corresponding economic variables. The database contains 33 countries, spanning from 1979 to 2021, extending the original by 11 years. The model in this study describes the relationships between itself and across 33 countries from 1979q1–2020q4. Similarly to Dées et al. (4), the countries in the Eurozone are grouped and considered as 'Euro Area' in the model with its VARX* model, of which eight eurozone countries are grouped into the Euro Area and treated as one country (in the sense of a separate VARX* model). The list of the countries in the model consists of the US, China, Japan, UK, Euro area (Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland), Canada, Australia, New Zealand, Sweden, Switzerland, Norway, Korea, Indonesia, Thailand, Philippines, Malaysia, Singapore, India, South Africa, Turkey, Saudi Arabia, Brazil, Mexico, Argentina, Chile, and Peru. As it stands, this contains the bulk of the world output, at around 90% on p.18, di Mauro and Pesaran, 2013 (6). Due to data quality and availability, semi-emerging economies such as Russia, Nigeria, Pakistan, and Vietnam are not included. In terms of variables, there are real outputs (quarterly in the natural log, seasonally adjusted, with 2015 indexed at 100 for all countries), inflation (constructed from local CPI index, quarterly in natural log), real exchange rates (constructed from local currency against USD, where USD is set as 1, also in the quarter and natural log), real equity price index (from the local largest stock market index, quarterly and in natural log), and short term interest rates (constructed from the local central bank using interest rate, deposit rates, T-bill rates and money market rates, quarterly averages, in natural log, long term interest rate, constructed with interest rates, government securities and bonds, in quarterly averages and natural log). The datasets also include three global variables, namely oil price, raw material price, and metal price. The oil price is constructed with the Brent crude index, also quarterly and in log. Both the raw material and metal prices are taken from primary commodity price indices, and also in a quarterly log. It is important to note that, the compilation of the database has been kindly shared and allowed for academic usage; however, there are some missing data in the database, which makes it difficult to account for the effects for some variables. For example, the real equity price index is not available for China and a few other countries. In addition, for the long-term interest rate, only a handful of countries publish data; therefore, only advanced economies are included. As such, rather than having all 33 countries and the 6 variables plus 3 global variables = (33 × 6) + 3 = 201 time series, we only have 178 series, with 23 series missing (201-178).

Similar to (Chudik, 2016) (11), we have modelled the variables accordingly, as:

$\boldsymbol{Y}_{it} = \ln(GDP_{it}/CPI_{it})$, $\boldsymbol{p}_{it} = \ln(CPI_{it})$, $\boldsymbol{eq}_{it} = \ln(EQ_{it}/CPI_{it})$, $\boldsymbol{e}_{it} = \ln(E_{it})$, $\boldsymbol{\varrho S}_{it} = 0.25\ln(1 + Rs_{it}/100)$,

$\boldsymbol{\varrho L}_{it} = 0.25\ln(1 + Rl_{it}/100)$, $\mathbf{O}_t = \ln(O_t)$, $\mathbf{M}_t = \ln(M_t)$, $\mathbf{MA}_t = \ln(MA_t)$,

where $\boldsymbol{Y}_{it}$ = Nominal Gross Domestic Product of country i during the period t, in domestic currency; CPI_{it} = Consumer Price Index in country i at time t; EQ_{it} = Nominal Equity Price Index; E_{it} = Exchange rate of country i at time t in terms of USD; $\boldsymbol{\varrho S}_{it}$ = Nominal short-term rate of interest per annum, in percent; **ϱL** $_{it}$ = Nominal long-term rate of interest per annum, in percent; **M**$_t$ = price of metals, **MA**$_t$ = price of materials and **O**$_t$ = Price of oil (in USD).

4.4 Estimating the GVAR Model

The first step of the GVAR approach is the formulation of the individual VARX* (vector autoregressive with exogeneity) models for each country. In this paper, the general methodology in Dées et al. (2007) (7) was followed to model individual countries in the GVAR model. The approach assumes that there are N + 1 countries in the global economy, indexed by i = 0, 1, …, N, and the aim is to relate a set of country-specific variables, e.g., GDP, inflation, interest rates, etc. Appendix A describes the statistical tests and specification of the models.

The vector of interest is denoted as x_{it}, collects the macroeconomic variables specific to the individual countries of interest indexed by i and over time, indexed by t = 0; 1; … ; T. Following the notation and definitions given in (6) p. 14–17, the general individual country model VARX* (2, 2) is represented as x_{it} is a vector with the dimension of $k_i \times 1$ of domestic macroeconomic variables indexed by individual country i and time as t; x_{it}^* is a vector with a dimension of $k_i \times 1$ of foreign macroeconomic variables indexed by individual country i and time as t; u_{it} is a serially uncorrelated and cross-sectionally weakly dependent process. It should be noted that x_{it} is a vector that captures the foreign-specific macroeconomic variables that are related to domestic ones constructed via a weight matrix. This is defined as ω_{ij}, where i being the domestic country and j as the foreign, are a set of weights that ω_{ij} = 0 and when combining all the weights of i and j become 1. The scheme of the weight matrix can be designed to reflect the trade and/or financial linkages. For example, in our model, the weight of Britain (domestic) is expected to have a large trade with the EU countries such as Germany (foreign); therefore, it will have a larger weight than say, Malaysia. It should be noted that similarly to the framework of an unrestricted VAR, the VARX* model can also be written in its error-correction form VECMX*, which allows the differentiation of short and long-run effects. In particular, the long-run effects are treated as co-integrating. The individual VECMX* models are estimated separately for each country i, based on reduced rank regression, thus, identifying the long-run effects or I(1) relationships that exist within the domestic x_{it} and across x_{it} and also the foreign economies x_{it}^*. Thus, the total number of co-integrating relations and speed of adjustment for each country can be derived and given economic meaning. The full derivation of the VECMX* can be seen in (6) p. 15 and is not repeated here.

The GVAR approach is a two-stage process. The first is to estimate the VARX* model country by country, and the second is to stack all VARX* models together, to be solved as a whole. We now examined the solution to solve the model, as outlined in (6) p. 16.

Recall the generic VARX* (2,2) model:

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i0}x^*_{it} + \Lambda_{i1}x^*_{it-1} + \Lambda_{i2}x^*_{it-2} + u_{it} \tag{4.1}$$

where the definitions remain the same as defined before, we now introduce a few terms to solve the model. To form the GVAR model, we first introduce a new term z_{it} define it as $z_{it} = (x_{it}, x^*_{it})'$
Therefore, we have

$$A_{i0}W_i x_t = a_{i0} + a_{i1}t + A_{i1}W_i x_{i,t-1} + A_{i2}W_i x_{i,t-2} + u_{it} \tag{4.2}$$

Moreover, recall that for i = 0, 1, …, N, which implies the equation above is individual country-specific and requires stacking to solve for x_t, which links all individual models together. We now introduce a few more terms to tidy up the model:

$$G_0 = \begin{pmatrix} A_{00}W_0 \\ A_{10}W_1 \\ \vdots \\ A_{N0}W_N \end{pmatrix}, \qquad G_1 = \begin{pmatrix} A_{00}W_0 \\ A_{11}W_1 \\ \vdots \\ A_{N1}W_N \end{pmatrix}, \qquad G_2 = \begin{pmatrix} A_{02}W_0 \\ A_{12}W_1 \\ \vdots \\ A_{N2}W_N \end{pmatrix},$$

$$a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \qquad a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \qquad u_1 = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \vdots \\ u_{Nt} \end{pmatrix} \tag{4.3}$$

Thus

$$G_0 x_t = a_{i0} + a_1 t + G_1 x_{t-1} + G_2 x_{t-2} + u_{it}$$
(4.4)

As the term G_0 is a known non-singular matrix (invertible matrix). G_0 is called non–singular if there exists an $n \times n$ matrix G_0^{-1} such that $G_0 G_0^{-1} = I_n = G_0^{-1} G_0$. Thus, by multiplying its inverse, the term disappears and we now obtain the GVAR (2) model with 2 lags where

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + F_2 x_{t-2} + \epsilon_{it}$$

(4.5)

where the new terms collect the inverse of G_0

$$F_1 = G_0^{-1} G_1, F_2 = G_0^{-1} G_2,$$
$$b_0 = G_0^{-1} a_0, b_1 = G_0^{-1} a_1 \ \epsilon_{it} = G_0^{-1} u_{it}$$
(4.6)

The GVAR model above can be solved recursively, see Pesaran, 2015 (8). Specifically, this paper used the GVAR toolbox for the solution.

4.5 Forecasting

Similar to most econometric models, one of the main outputs of the GVAR model is the forecasts of the economic variables. In our case, we have estimated 33 individual VARX* (p,q) models with variable lags, and stacked together they became a GVAR (2) model. We now show that forecasts can be made from the generic GVAR (p). Recall that the individual VARX* (2,2) has two lags for both domestic and foreign variables. This can be re-written into

$$A_i(L, P) W_i x_t = \varphi_{it}$$
(4.7)

where φ_{it} equals x_{it}, L is the lag operator; P is the domestic variable lag orders; W is the weight matrix, and x_t is the domestic variables denoted in t and i denotes the country. In other words, it is simply a re-statement of the VARX* model as a function of domestic variables with lag orders multiplied by their corresponding weights. Furthermore, recall that, once the VARX* models have been estimated individually, the next step is to stack the models together to form the GVAR model.

Again, using the notations in Dées et al. (2007) (7) by stacking the individual VARX* models (written as φ_{it}), we obtain the GVAR (p) model as

$$G(L,P)x_t = \varphi_{it}$$

(4.7)

where

$$G(L,p) = \begin{pmatrix} A_0(L,p)W_0 \\ A_1(L,p)W_1 \\ \vdots \\ A_N(L,p)W_N \end{pmatrix}, \varphi_t = \begin{pmatrix} \varphi_{0t} \\ \varphi_{1t} \\ \vdots \\ \varphi_{Nt} \end{pmatrix}$$

(4.8)

The GVAR ex-ente forecast model has now formed and can be solved via recursive method at any horizon N.

4.6 Empirical Results and Long-Run Forecasts

We now turn to the results produced by the estimated GVAR model. As mentioned before, there are 33 countries in total, with eight euro countries which will be estimated as one, therefore there are 26 country models. Each has its combination of lag orders, up to a maximum of two, as determined by

AIC/BIC. It should be noted that not all VARX* models have equivalent lag orders nor the same set of domestic and foreign variables, due to the specification tests of lag order and weak exogeneity in the last section. In the end, after removing the variables that did not meet the weak exogeneity assumption, we had estimated 271 variables, placed in 26 VARX models and one auxiliary model for global variables, such as oil price, metal, and raw material price for eight quarters, i.e., 2 years. This means 2184 point estimates were created for all variables.

Unit root test

An augmented Dickey–Fuller (ADF) test was carried out at 95%, implying that if the test statistic for the variable is more negative than the critical values, then it will be rejected, as there is no unit root. The test was carried out on level, differenced, twice differenced, with the trend, and without trend on all variables. Once the unit root had been tested, the corresponding co-integrating VARX* models were estimated as VECMX*. The next step is the identification of the co-integrating relationships within the individual models. The rank of co-integrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics.

Testing for weak exogeneity

The main assumption in the GVAR approach is the weak exogeneity of the foreign variables x_{it}^* with respect to the respective VARX* model. As described in (9), this assumption is compatible with a certain degree of weak dependence across u_{it} (the residuals). Following the work on weak exogeneity testing by Johansen (1992) (10) and Granger and Lin (1995) (11), the weak exogeneity assumption implies no long-run feedback from x_{it} to x_{it}^*, suggesting that x_{it}^* error correction terms of the individual country VECMX* models do not enter the marginal model of x_{it}^* (Smith and Galesi, 2014) (12). This implies we can consistently estimate the VARX* models individually and, later, combine them to form the GVAR. The proof of weak exogeneity implication on x_{it}^* can be seen in (8) ch. 23, p. 569). The test is a regression model described in (10). The test shows that the weak exogeneity assumption holds for the models.

Testing for structural breaks

Having considered the rather harmless integrated series in the previous section and also the possible violations of weak exogeneity and their treatment, we now turn to one of the most fundamental problems in econometric modelling. So far, we have shown that the problems mentioned above can be mitigated, but unfortunately, similarly to other time-series/econometric models, the GVAR is also susceptible to structural breaks. The core concept of structural breaks is straightforward, it refers to an unexpected sudden shift of the time-series. Consider a daily stock price time series, where sudden shifts are very common due to stock splits, unexpected announcements, overnight trading, oversea stock exchange performance, etc. This renders the original time-series model unreliable, as the time-series has shifted unexpectedly, therefore, not within the range of the forecast; this also implies forecast errors will be greater. The problem of structural breaks has been discussed extensively in the literature since the 1960s, after Quandt (1958) (13) proposed the Sup F test that calculates the likelihood ratio test for a change in model parameters and also identifies the break date. The Sup F test was quite adaptable, but only worked on univariate regression; nevertheless, it became the basis for future research.

The GVAR literature, mainly those in Pesaran et al. (2004) (9), Pesaran and Smith (2011) (14), Dées et al. (2007) (7), di Mauro and Pesaran (2013) (6), and Chudik and Pesaran (2014) (3), has an extensive discussion of the problem. The GVAR Handbook (6) surveyed the existing strategy that The GVAR literature employed. This includes several test statistics to assess the structural stability of the estimated coefficients and error variances of the individual VARX*/VECMX* models. Specifically, the survey indicated that the methods used are (p. 21): the maximal OLS cumulative sum (CUSUM) statistic and its mean square variant by Ploberger and Krämer (1992) (15); a test for parameter constancy against non-stationary alternatives by Nyblom (1989) (16); as well as sequential Wald type tests 'of a one-time structural change at an unknown change point specifically'; also the QLR statistic by Quandt (1960) (17), the MW statistic and the APW statistic (Andrews and Ploberger, 1994) (18). The test shows the data does not display structural breaks.

4.7 NK-GVAR Model

A standard NK (New Keynesian) type model is formed by three fundamental equations (see Gali, 2018, for the derivation and a standard treatment of this model). Firstly, the dynamic IS equation establishes a relationship between the current output gap and the expected output gap in the future. The output gap represents the disparity between actual output and the potential or "natural" output. It is also influenced by the discrepancy between the real interest rate and the natural rate of interest. The natural rate of interest and natural output are equilibrium values assuming fully flexible prices.

The second equation is the New Keynesian Phillips curve, which introduces the concept of expected inflation one period ahead and its impact on inflation. By incorporating an expectation term, this Phillips curve extends the conventional understanding of the relationship between inflation and the output gap.

The third relationship is an interest rate rule, which outlines how the nominal interest rate is determined. This equation is closely associated with the conduct of monetary policy. A commonly used approximation for monetary policy in advanced economies is the Taylor-type rule. It suggests that nominal interest rates should adjust based on the prevailing inflation rate and detrended output. However, the degree of tightness or looseness in monetary policy can deviate from historical patterns at a given time.

Together, these three equations provide the foundation for a standard NK type model, capturing the dynamics between output, inflation, and monetary policy in an economy with sticky prices but flexible wages.

The IS curve also includes exchange rate and foreign output gap variables. Similar to the literature, the exchange rate movement is captured with the US as the base currency. Following New Keynesian theory, all variables are measured as deviations from their steady-states. The dominant method is to treat the steady-states as constants with deterministic trends or measured with a HP filter. Here, two methods were used to measure the steady-states and, therefore, the deviations. The first is using the long-run forecasts from GVAR. The other is with an HP filter as an alternative. The economic advantage of using GVAR over HP, or any other statistical procedure, is that the long-run forecast should be able to capture any existing co-integrating relationships within the data and, as such, can be used as the steady-state. On the other hand, an HP filter exists as a simple statistical univariate de-trending procedure that does not capture any long-run relationships in the data. It removes short-term fluctuations associated with the business cycle. The filtered data is the steady-states from which the deviation will be calculated from the actual observed value. In other words, if the deviations from steady-states are represented by tildes, then:

$$\tilde{\pi}_{it} = \overline{\pi}_{it} - \pi_{it} \tag{4.9}$$

π_{it} is the actual data of inflation for country i and time t, say the Q1 of 2015, the variable $\overline{\pi}_{it}$ being the measured steady state for country i and time t either with GVAR long-run forecasts or HP filter. The difference between the two will be a gap or deviation from the steady state. The other variables included are output deviations $\tilde{y}_{it}$, interest rate deviations $\tilde{r}_{it}$, and real effective exchange rate deviations $\tilde{r}e_{it}$, with the exception of the US, as it uses USD as the base currency.

The Phillips curve (PC) is derived from the optimising behaviour of monopolistically competitive firms subject to nominal rigidities, which determines inflation deviations $\tilde{\pi}_{it}$, and takes the form:

$$\tilde{\pi}_{it} = \beta_{ib}\tilde{\pi}_{i,t-1} + \beta_{if}E_{t-1}(\tilde{\pi}_{i,t+1}) + \beta_{iy}\tilde{y}_{it} + \varepsilon_{i,st}, i = 0,1,\dots,N \tag{4.10}$$

where $E_{t-1}(\tilde{\pi}_{i,t+1})$ denotes the information available at time t − 1. No intercept is included in the equations, as the mean would be zero for any deviations from steady-state values. The error term $\varepsilon_{i,st}$ is then interpreted as a supply shock; therefore, given a full economic meaning as opposed to the residual terms in the previous GVAR model.

The IS equation takes the form of:

$$\tilde{y}_{it} = \alpha_{ib}\tilde{y}_{i,t-1} + \alpha_{ir}\left[\tilde{r}_{it} - E_{t-1}(\tilde{\pi}_{i,t+1})\right] + \alpha_{ie}\widetilde{re}_{it} + \alpha_{iy*}\widetilde{y^*}_{it} + \varepsilon_{i,dt}, i = 0,1,\dots,N \tag{4.11}$$

where $\varepsilon_{i,dt}$ is understood as a demand shock. The IS curve represents the aggregate demand. The equation is obtained by log-linearizing the Euler equation in consumption and substituting the result in the economy's aggregate resource constraint (see Dées, 2009 (14) for full derivation and Smith (38) for non-technical explanation). For this open economy model, the aggregate resource constraint will also contain net exports, which in turn will be a function of the real effective exchange rate, $\widetilde{re}_{it}$, and the foreign output gap, $\widetilde{y^*}_{it}$.

The Taylor rule takes the standard form, as below, and the error term is taken as a monetary policy shock $\varepsilon_{i,mt}$.

$$\tilde{r}_{it} = \gamma_{ib}\tilde{r}_{i,t-1} + \gamma_{i\pi}\tilde{\pi}_{it} + \gamma_{iy}\tilde{y}_{it} + \varepsilon_{i,mt}, i = 0,1, \dots, N \tag{4.12}$$

The log real effective exchange rate deviations are modelled as a stationary first-order autoregression. As such the ρ_i would be less than one.

$$\widetilde{re}_{it} = \rho_i \widetilde{re}_{i,t-1} + \varepsilon_{i,et}, i = 1,2, \dots, N \tag{4.13}$$

4.8 Model Estimation

There are commonly two approaches to estimating DSGE models in the literature: by generalised method of moments (GMM), or Bayesian methods. However, Bayesian estimation, in this case, is difficult, considering where N is large and as such the specification of multivariate priors over many parameters would be challenging. Therefore, for this model GMM is preferred. To further restrict the parameters of the equations, inequality constraints are also imposed. For example, the coefficient of the output gap in the Philips curve should be positive, but if it is negative then it will be constrained to be zero.

Regarding the identification of the parameters in the model, this paper follows the arguments in Canova and Sala (2009) (19), Koop et al. (2011) (20), and Dées et al. (2009) (7). They argue that the large country framework can provide new sources of identification that are not available in small, single closed economy models. This is identified via the use of cross-section averages of foreign variables as instruments. Individual country shocks, being relatively unimportant, will be uncorrelated with the cross-section averages as N becomes large. Global factors in the model, i.e., oil price, make the cross-section averages correlated with the included endogenous variables. The parameters of the multi-country model can be estimated consistently for each country separately by instrumental variables subject to the theory restrictions referred to above.

For this model, the following variables are used as instruments. Lagged values of the country-specific endogenous variables: $\tilde{y}_{i,t-1}$, $\tilde{\pi}_{i,t-1}$, $\tilde{r}_{i,t-1}$, $\widetilde{re}_{i,t-1}$. The current values at t for country-specific foreign variables $\widetilde{y^*}_{it}$, $\widetilde{\pi^*}_{it}$, $\widetilde{r^*}_{it}$ and the log oil price deviation $\widetilde{p^0}_{it}$

In this case, using normal Impulse Response Functions (IRFs) with restrictions informed by economic theories is advantageous over Generalized Impulse Response Functions (GIRFs) because it provides a more precise identification of structural shocks, which are central to understanding economic dynamics. Normal IRFs, by incorporating theoretical restrictions, align more closely with the underlying economic mechanisms, ensuring that the estimated responses are consistent with economic theory. This alignment enables researchers to derive more accurate and theoretically informed inferences about the impact of shocks on the economy. In contrast, GIRFs, due to their reliance on less restrictive identifying assumptions, may yield misleading inferences by generating response functions that are not consistent across different shocks unless the covariance matrix is diagonal (Kim, 2013). By adhering to the theoretical underpinnings of economic models, normal IRFs offer a more reliable tool for policy analysis and economic forecasting, enhancing the interpretability and relevance of the empirical findings.

The model is solved for all periods in the estimation sample, giving estimates of the shocks. Due to the size and complexity of the model, it is not possible to derive a unique analytical condition for the existence of a determinate solution. However, a unique solution exists after imposing these restrictions. Similar to the literature, the estimates of the structural parameters can be used to estimate the country-specific supply, demand, and monetary policy shocks εi,st, εi,dt, and εi,mt. These shocks are assumed to be pairwise orthogonal within each country for identification, but shocks of the same type may be correlated across countries. Below table 1 shows the averages of pairwise correlations across the four types of shocks in the model. The values are small; therefore, this is in line with the assumption of orthogonal shocks.

Table 1. Average pairwise correlations of shocks.

	Demand	Monetary	Real Ex	Oil
Supply	0.160	0.026	0.018	−0.069
Demand	-	0.039	0.000	0.001
Monetary	-	-	0.003	0.009

4.9 Shock Analysis

In this section, selected impulse responses are presented. The shocks here are not on the variables themselves but their deviation from steady-states. If the system is stable, then these shocks should converge to their steady-state values within a few years. This is true for the majority of the shocks, although this is not always the case; particularly, when shocks are applied to individual countries instead of regions. A few economically less-stable countries tend to exhibit short term volatility in their time-series, such as Argentina and Turkey. As such, the shocks to their variables tend to be more violent and less likely to cycle back to zero. In terms of the whole model, the largest eigenvalue of the system is 0.98 and many are complex; therefore, the path often cycles back to zero.

In total, four models were run. The below table 2 summarizes the model and its characteristics. In the first model, M1 was estimated for eight regions, containing eight regions and had five shocks. The period of data for M1 is between 1984Q2 to 2019Q4, in other words this excludes the pandemic data. A post-pandemic vision M2 was also estimated with the additional year of 2020. This model, M2, also contains an extra time-series for the Saudi Arabia model with short term rates. Saudi Arabia is usually not included for monetary purposes, as the country does not control the interest rate directly, rather the short-term repo rate offered by Saudi Arabian Monetary Authority is used as a proxy. This allows the negative global shock to be simulated, as the NK-GVAR model now contains all 33 countries; therefore, it is closed. This is otherwise not possible with other models, such as DPSS or M1. As an alternative to the NK-GVAR approach, two DSGE models were estimated with HP filtered steady-states, namely H1 and H2. While shocks are estimated individually on each country model, their impulse response functions are stacked together regionally. The following section investigates the shocks that were performed. In particular, the following shocks are presented. For the reference model, only a few shocks are available; therefore, they were included whenever possible.

Shocks

- Global Demand on oil price
- Oil Price shock on real exchange rate
- US rate on inflation
- Global demand on inflation
- Global demand on output
- Global supply on output
- Additional negative shocks

Table 2. Summary of estimated models.

Model Name	Type	Period	Countries	Number of Shocks	Additional Shocks	Remarks
DPSS	NK-GVAR	1980Q2–2006Q4	26	4-Oil, Demand, Supply and Monetary.		Reference model
M1	NK-GVAR	1984Q2–2019Q4	33—(8 regions)	5-Oil, Demand, Supply, Monetary and Exchange rate.		GVAR estimation. Most shocks are stable.
M2	NK-GVAR	1986Q2–2020Q4	33—(8 regions)	5-Oil, Demand, Supply, Monetary and Exchange rate.	Negative shock to global interest rates. Model includes short term rates from Saudi Arabia (derived from repo rates).	GVAR estimation. Some shocks are not stable.

H1	DSGE-HP	1987Q2–2019Q4	33—(8 regions)	5-Oil, Demand, Supply, Monetary and Exchange rate.	HP estimation. Most shocks are stable.
H2	DSGE-HP	1988Q2–2020Q4	33—(8 regions)	5-Oil, Demand, Supply, Monetary and Exchange rate.	HP estimation. Most shocks are not stable.

Global demand shock on oil price—Figure 1

A standard error positive shock (+1) was applied to all five models. However, the quadratic equations failed to solve for the oil price shocks with H1 and H2 models; therefore, they were not available. The DPSS takes the data up to 2011 when the oil prices were in the range of USD 100–110 per barrel for Brent oil. This contrasts with the recent low prices of 2019 and 2020. Brent was trading around USD 60 to 70 per barrel in 2019, with the extreme lows of USD 20 up to USD 50 in 2020. Negative prices happened in 2020 at the beginning of the lockdown, as physical stocks were in surplus, due to a lack of refineries to process them. At some point, the May future delivery was marked to USD -37.63 in April 2020. However, since the data in the model is on a quarterly basis, the short-lived negative prices had a smaller effect. The extreme price swings are reflected properly in the IRFs. A one standard error positive global demand shock was applied, and the responses were as expected. M2 with the 2020 prices showed the strongest response with over 5% per unit of SE of a demand shock. This is due to the volatile price swings in 2020, and the IRF responded as expected. The next two are DPSS (2011) and M1 (2019), which showed a modest 2% to 3% increase.

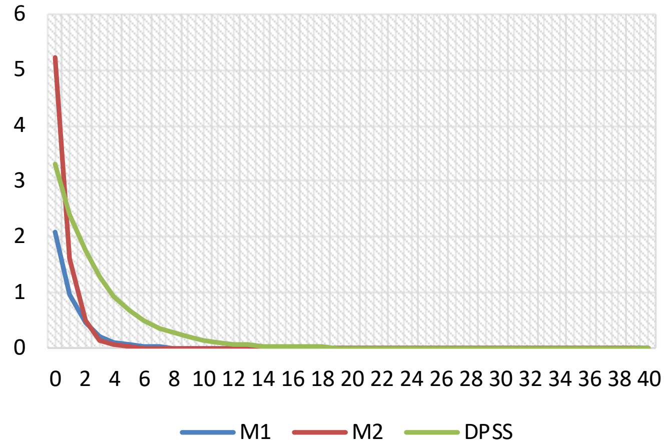


Figure 1. Positive shock to Global Demand on Oil price.

Oil Price shock on Real Exchange rate—Figure 2

Real exchange is not available for DPSS; therefore, they are not included for comparison. A positive oil price shock of one standard error was applied to all four models. For the NK-GVAR type models, both M1 and M2, as shown below, show that the real exchange rate tends to react strongly during the first few quarters to shocks, but often cycles back to steady-states a few quarters later. In particular, regions that are oil export-led, such as Latin America, Norway (ODC), and the UK, show that USD depreciate against them when oil prices increased. Conversely, big importers had their currencies depreciated against the USD, such as Japan (USD > JPY; therefore, showing a 1% increase of USD against JPY). Most regions, however, showed a low reaction, such as the Eurozone and ROW. This closely resembles what is observed in real life, as exchange rates tend to be stable around an equilibrium and should not drift, unless there is a strong economic situation, such as a currency devaluation. Including the 2020 data did not create much difference, although the effects were more pronounced for Latin America, but not significant. However, the DSGE-HP type models H1 and H2 showed IRFs that were not stable. This is shown in the graphs below, as none of the shocks apart from ROW returned to the steady-states; therefore, they are not stationary, nor stable enough to derive any conclusions. This is since using a HP filter diminished any meaningful cycles in the time-series; therefore, they have not captured any important features from history.

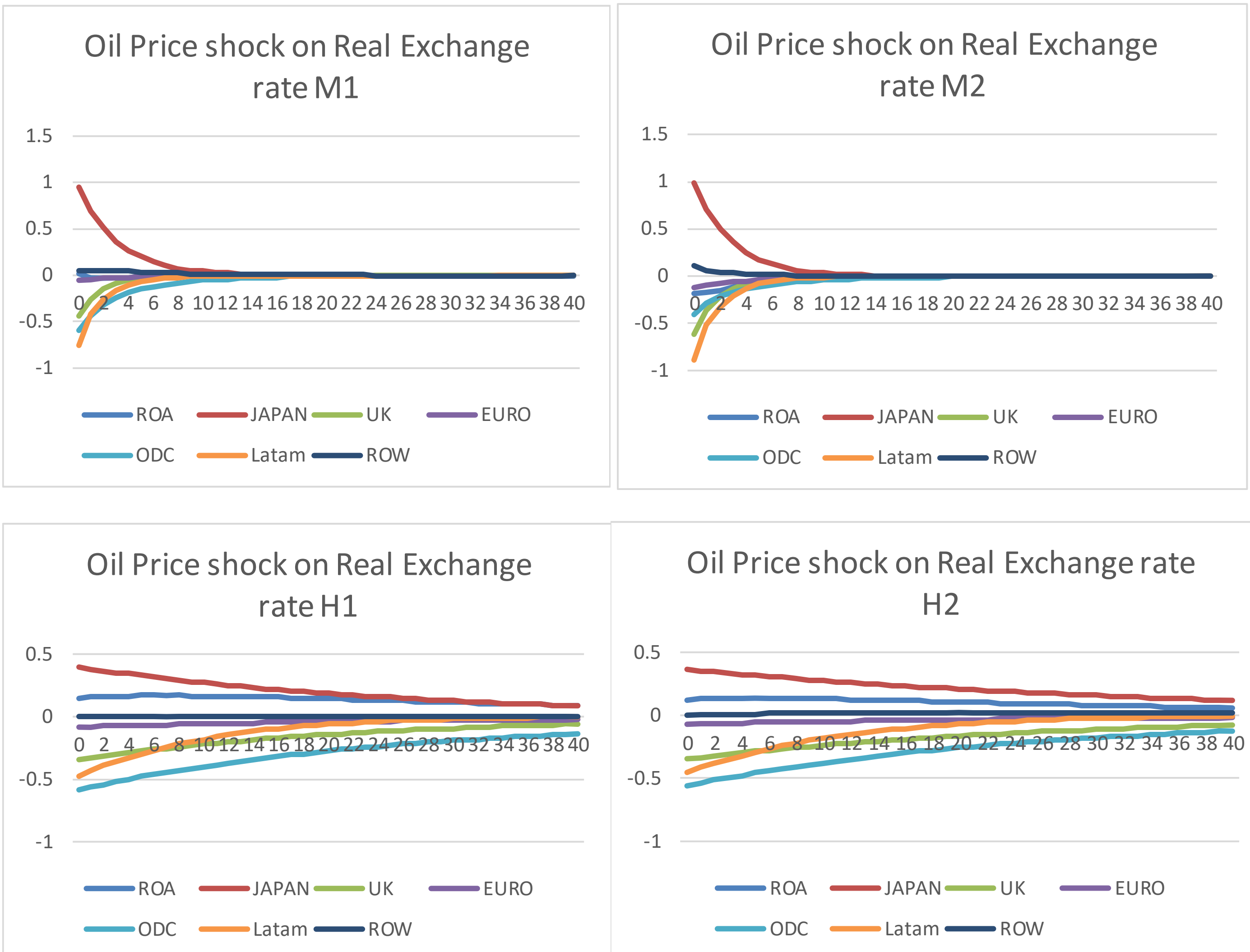
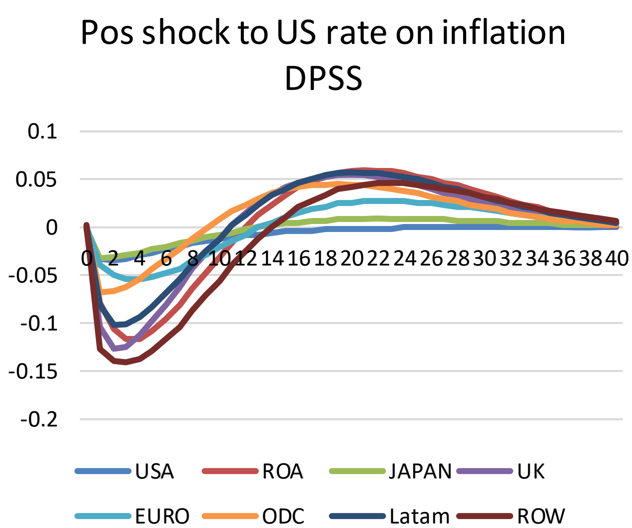
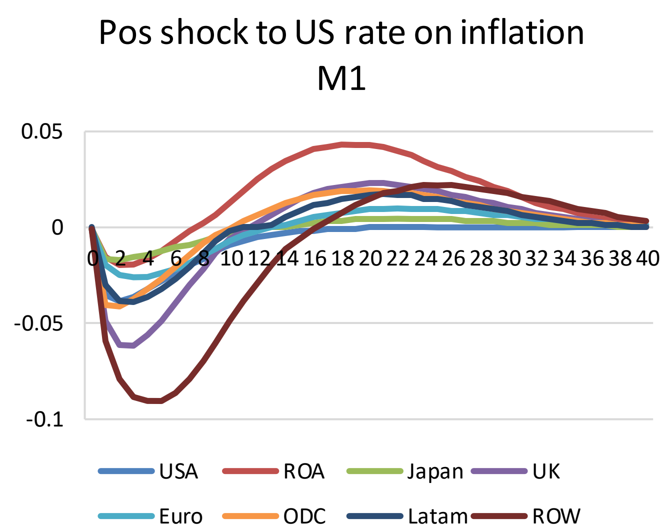


Figure 2. Positive oil price shock on real exchange rates.

US monetary shock on inflation - Figure 3

All five models (DPSS, M1, M2, H1, and H2) are available for monetary shock and inflation; therefore, this shock was applied to all of them. Due to the lack of interest rate for Saudi Arabia, a global shock (i.e., shocking all countries) is not possible here. Instead, a US positive shock was used. A positive one standard error was applied. This is in the range of 0.22 basis points for the DPSS model to 0.15 for the M1, M2, H1, and H2 models. As expected, the US monetary policy shock depressed inflation in the US and other countries. This is consistent with the standard results in the literature,. Inflation soon returned to close to the steady-state within a few years for DPSS and M1. However, the case is a little more complicated for H1, where, although the model shows similar IRFs, they do not converge back to the steady-states after 40 quarters. This is similar to the above oil shock, where the Eigenvalues do not allow a stable solution.





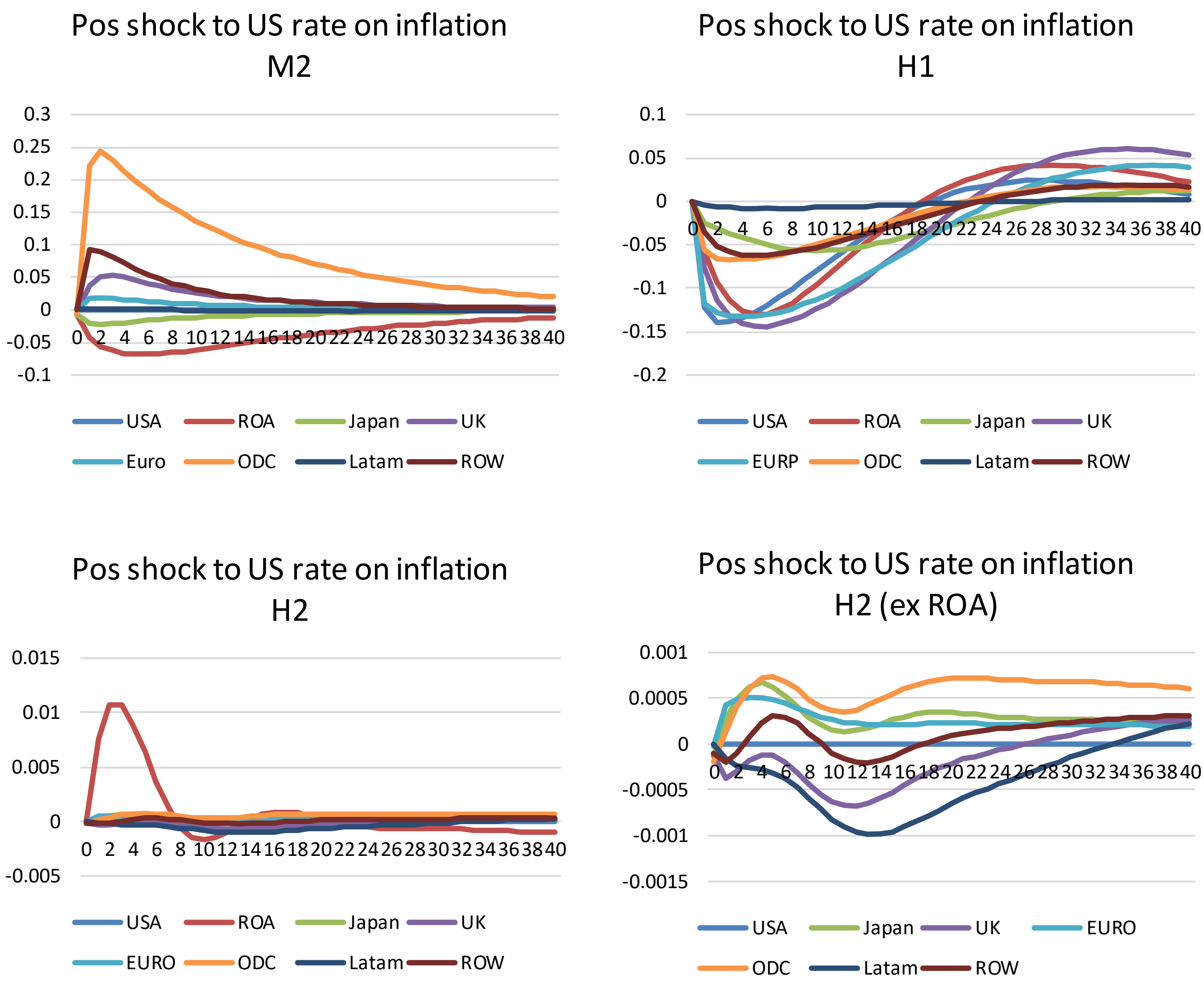


Figure 3. Positive monetary shock on inflation.

For DPSS and M1, by the fourth quarter, inflation for the US was −0.18% and output −0.50% below their steady-state values. This shape is similar to the paper of Smets and Wouters (2007, Figure 6) (21). Their model showed that a monetary policy shock would cause interest rates to go up, then slowly return to zero, whereas the models here show initially raised interest rates, that are then quickly offset by the effects of the relatively sharp falls in inflation. On average after four quarters, inflation is lower.

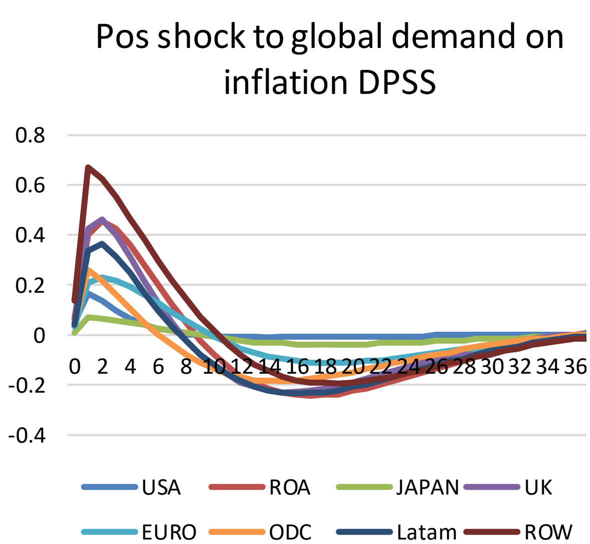
Relatively, US variables tend to return to their steady-state values when compared to other countries. This shows that a US monetary policy shock has a large global impact.

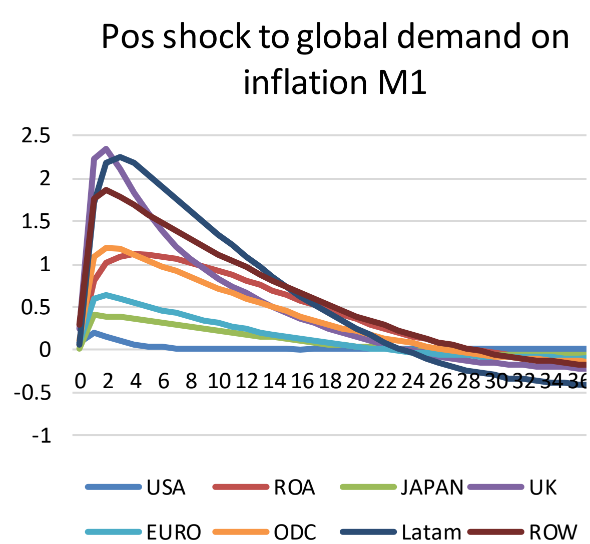
However, the cases for M2 and H2 are more complicated. The results from M2 show that the shocks cycle back to their steady-states relatively quickly. However, after including the data for 2020, the reaction of inflation to the interest raise is counterintuitive. Particularly for ODC, this showed a small but sharp spike in inflation. In general, except ROA and Japan, other areas showed inflation instead. This is probably as the majority of the countries have near or actual zero rates in their models. As such, any further increase would not show a significant decrease in inflation. Since the 2020 data show an abrupt decrease in interest rates globally and a strong decrease in inflation until the last quarter, the correlation between the two may be significant in the results here. The paradox of positive monetary shock and increase in inflation is a common problem in the VAR-shock literature. This was first noticed by Christiano et al. (1996) (9), but the 'price puzzle' was solved when introducing the commodity price index into the model.

One explanation has been attributed to the existence of a leading indicator for inflation, to which the central bank reacts and which is omitted from the VAR. The omission from the information set of a variable positively correlated with inflation and interest rates causes the VAR to be miss-specified; hence, the positive relation between inflation deviation and interest rates is observed. In theory, the extra channels from the international models, as well as global models of commodities, should capture the effect and inflation should show as negative instead. However, Pesaran et al. (2011) (14) also found this problem in their paper, and it could not be explained away by the extra time-series for different commodities. However, in the Covid-19 situation, the co-movement of lowering the interest rate and inflation affected the IRFs; therefore, the results were as shown below. For the DSGE–HP models, both show that their IRFs are unstable and did not converge to the steady-states. In particular, for H2, the majority of the models show indifference towards the shock, and their IRFs are not stable after 40 quarters.

Global demand shock on inflation - Figure 4

All five models (DPSS, M1, M2, H1, and H2) are available for demand shock and inflation; therefore, this shock was applied to all of them. A positive one standard error global shock was used, i.e., all countries had their demand equation shocked and the effect on inflation was tested for below. For DPSS, M1, and H1, all show the expected shape of a sharp increase in inflation, before smoothly falling to the steady-states. The majority of the shocks also cycle back to their steady-states, although some remain after 40 quarters. In particular, the UK, USA, and ROA (including China) show a strong and sharp increase in inflation when there is a global demand shock. This is like the situation in 2021, when there was a sudden demand for the economy from the previous slump in 2020. This was also very similar to the infla-tion observed in the majority of countries in 2021, after the first two waves of the pandemic and the global lockdowns and travel restrictions. This is also similar to the 2020 models, but to a lesser extent. In this case, both models are distorted by the one-off increase in in-flation seen in China due to the strict lockdowns. As such, both models have unusual shapes. Their IRFs are mostly stable and cycle back to the steady-states after 40 quarters. Taking ROA away, the models show a modest increase, before lowering to the steady-states. The effects are much less obvious than non-HP models, as their time-series lack the cyclical features after filtering.





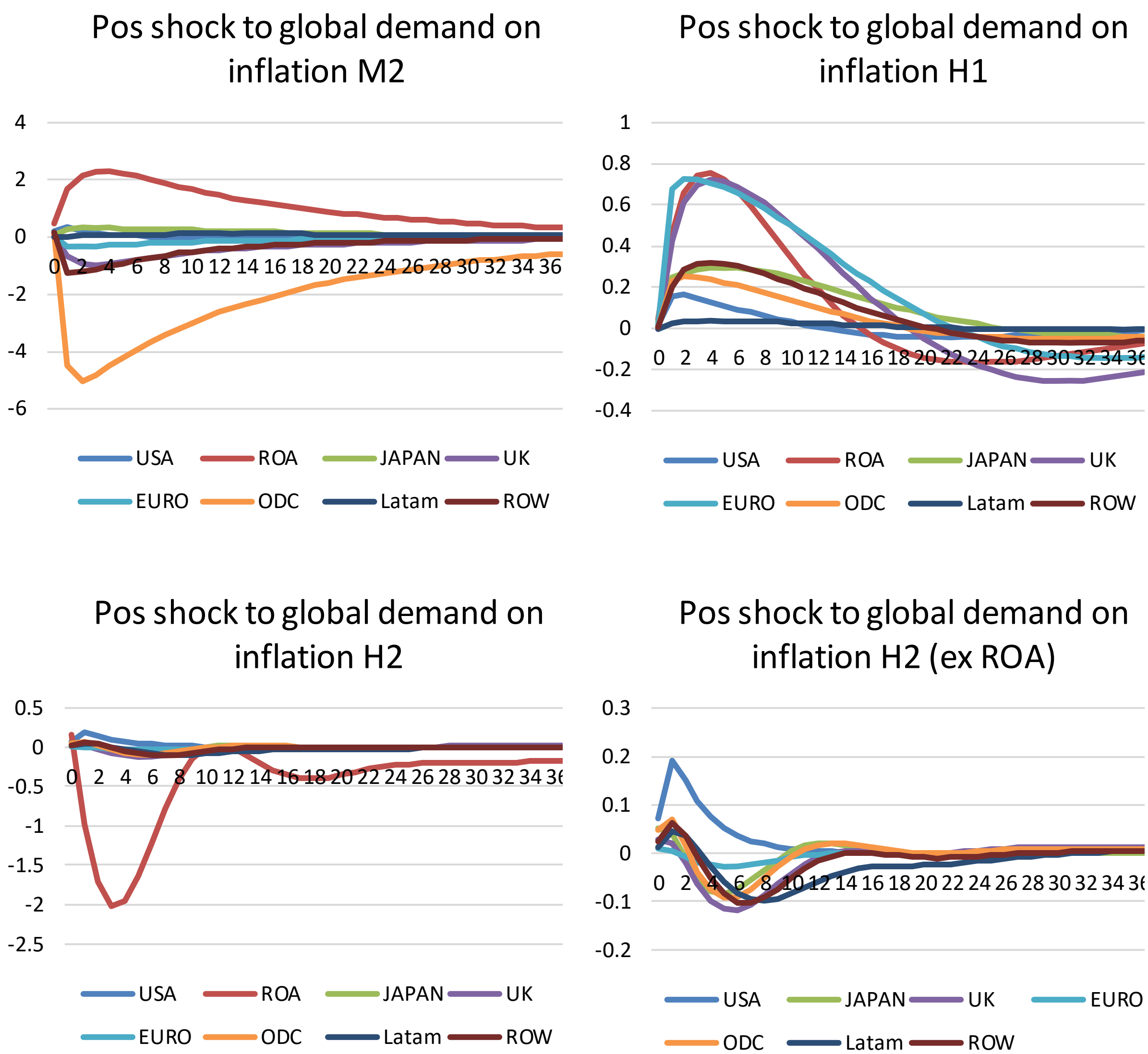
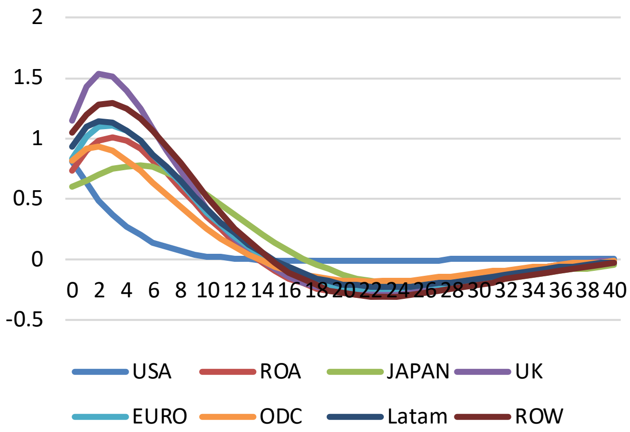


Figure 4. Positive global demand on inflation

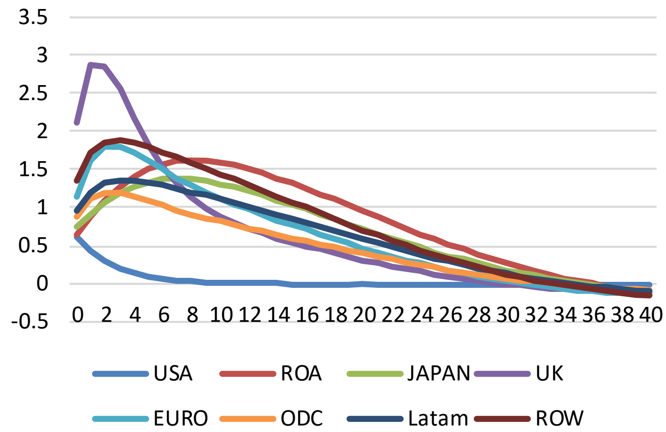
Global demand shock on output - Figure 5

All five models (DPSS, M1, M2, H1, and H2) are available for demand shock and output; therefore, this shock was applied to all of them. A positive one standard error global shock was used; i.e., all countries had their demand equation shocked and the effect on output was tested, as seen below. In general, the shapes are similar for the DPSS, NK-GVAR, and DSGE–HP type models. As expected, the output increased sharply upon impact, before settling down near or below the steady-states. The impact was in the range of 0.5% of output growth for Japan, to more than 1.5% for the UK in the second quarter. For the DPSS model, the shocks tended to revert after 4 to 5 years. This is due to the lower growth after the financial crisis and the beginning of the Euro crisis; therefore, the growth was the lowest among DPSS, M1, and H1. Prior to Covid-19, the growth was quite steady across all models; therefore, the M1 model showed the strongest growth and impact from a positive demand shock. The impact was also longer, lingering for 6 years. Similar shapes were also recorded for H1, but the peaks tended to be slower, and were only reached after 2–3 years. Given the sudden shock of the demand equation, the shocks should have moved quickly upon impact and decreased from the peak. As such, the DPSS and M1 provide better insights into actual growing paths. Including the 2020 data, both M2 and H2 models display a similar shape, but different paths of growth on output. Due to the extreme values in 2020, many region models had an initial boost, but immediately turned to negative growth once in the third quarter and after. The effect was particularly strong for M2 compared to H2, where the time-series were much smoother from the filter. The heavy infections in the US, ODC, and UK meant that lockdowns remained in place longer. As such, the economic impact was much stronger, and this affected their growth paths to negative, even after an initial increase. This, however, did not happen to ROA, for example; although China had initially discovered the virus, the impact was much weaker on the economy, as it experienced growth every year. As a result, the demand shock had a much stronger impact on ROA. This was, however, not captured in H2, as the sudden output gap (actual GDP minus HP steady-states) was much stronger than usual; therefore, actual growth was not predicted in this model.

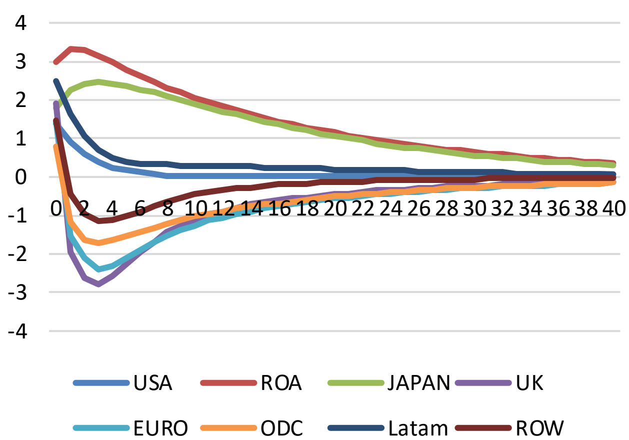
Pos Global Demand shock on output DPSS



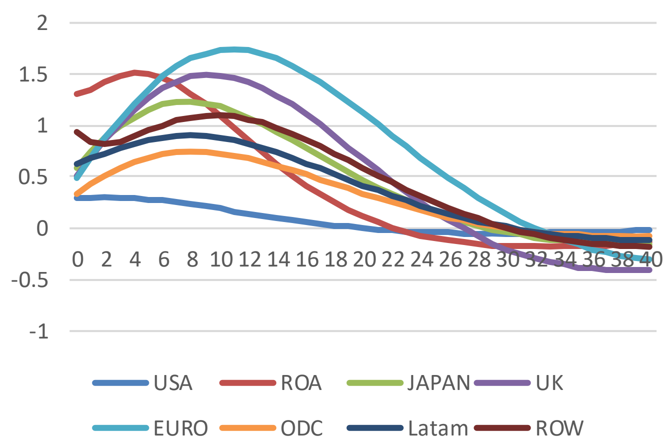
Pos Global Demand shock on output M1



Pos Global Demand shock on output M2



Pos Global Demand shock on output H1



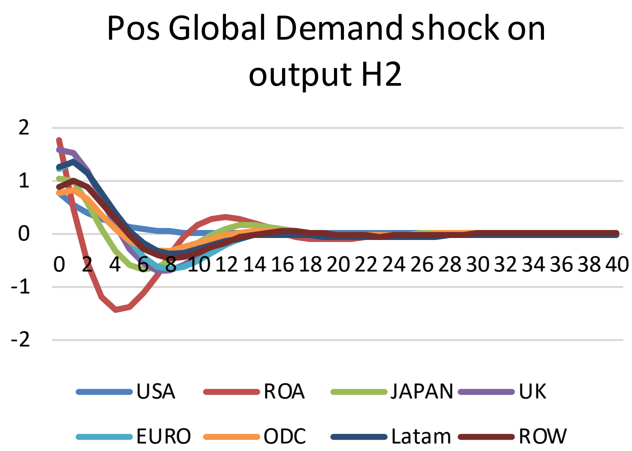
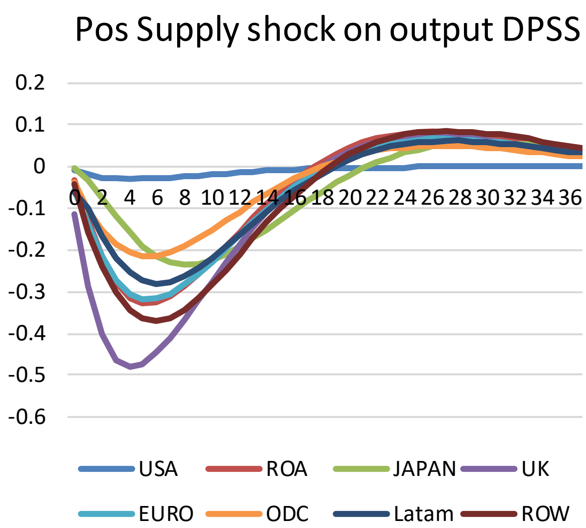
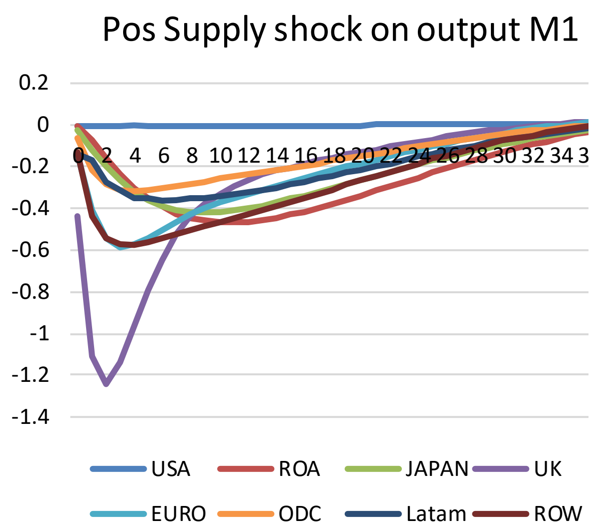


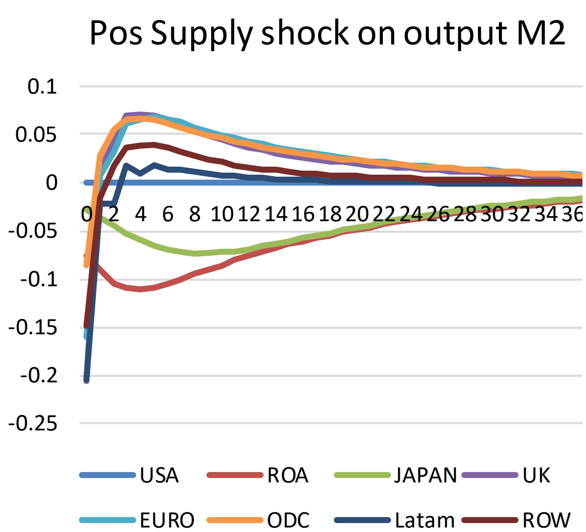
Figure 5. Positive global demand shock on output.

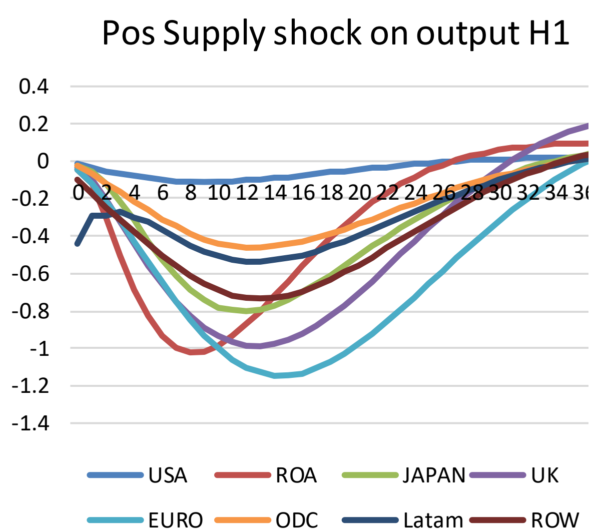
Supply shock on output - Figure 6

Next, a supply shock was applied to the output. This was done via a positive shock of one standard error to the Phillips curve. By definition, this shock causes inflation and interest rates to increase on impact, but here we are interested in the impact on output. The global supply shock also reduces output across all models; for the DPSS, with an average effect of −2.4% after four quarters. All regions suffered a decrease, except the US model. This was also true for the M1 and H1 models, although the updated data of M1 reflected a much stronger effect, with the UK in both models suffering the most. This was reflected in late 2021, with a double whammy of Brexit supply chain issues causing inflation and an increase of interest rate towards the end showing a similar effect. Regarding the pattern of dynamic adjustments, this model captured the deficiencies of importing for UK via the trade weight matrix and across trading partners. Both the DPSS and M1 also operated at a faster pace, as their effects slowed to steady-states after a few years. Qualitatively M1 also showed a similar pattern, but the speed was much slower and it took a few more years until it settled. However, for both H2 and M2 models, they exhibited a similar pattern of a sharp decrease, then a sharp bounce back to the steady-states. Perhaps not surprisingly, the extreme co-movements of decrease in inflation, interest rates, and output, and the sudden increase in inflation and output in the third and fourth quarters, reduced the impact of supply shocks to a sharp downturn, before recovering almost immediately. In this case, both models captured well the channels of supply shock transmission to output.









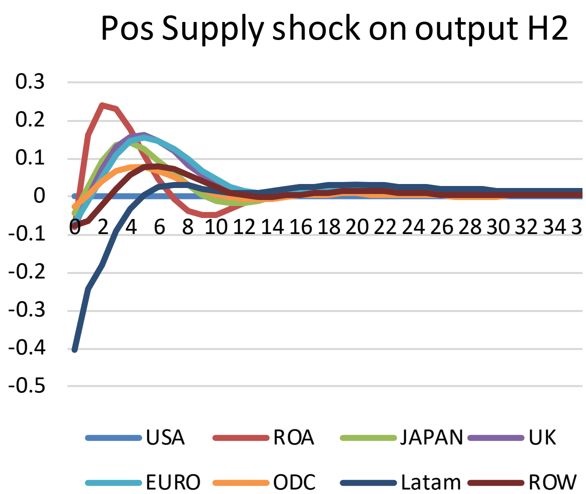
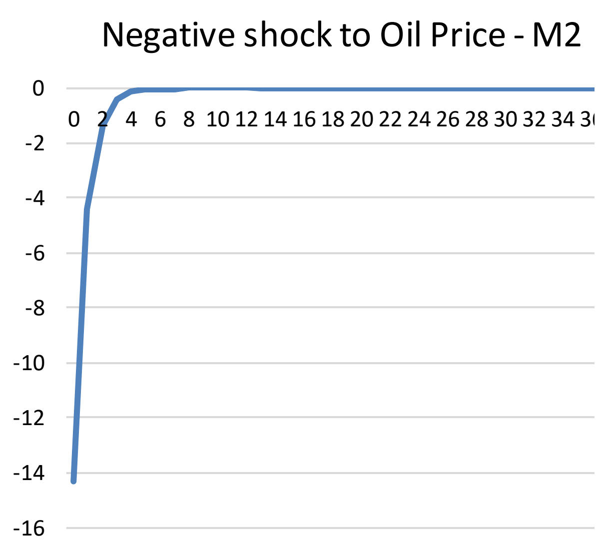


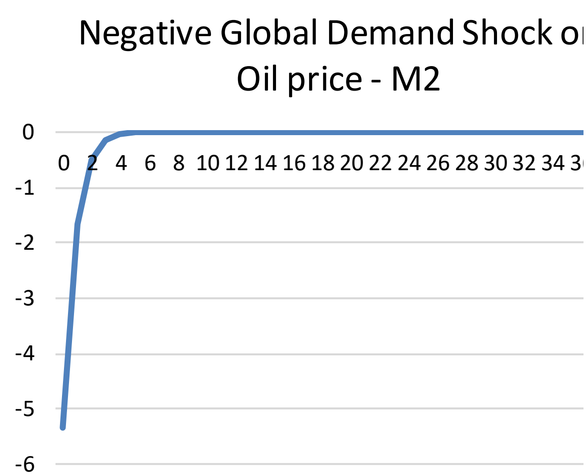
Figure 6. Positive supply shock on output.

Additional negative shocks with M2 - Figure 7

The shocks in the above sections form an exercise in understanding the impact of different shocks on the economy from a pre-and post-pandemic point of view. However, it is interesting to re-run some of the scenarios with negative shocks instead. As noted in the previous table, to stimulate a global interest rate shock, a completely closed model is required; therefore, the interest rate variable was approximated with repo for the Saudi Arabian model. In this section, for all models, there are eight regions (33 countries). Now that M2 contains all the pandemic data, it is expected to show a stronger impact on different variables given negative shocks. The first shock applied was a negative standard error in oil price. This was done for the oil price and the impact of oil price on real exchange rates. Not surprisingly, given the dramatic fall of the oil price in 2020, a 1 standard error drop in oil price shock saw a 14% drop on impact, although this sharply recovered to the steady-state levels. This is similar to the real oil price reaction in 2020, where it saw a sharp drop and recovery. Another shock was a negative global demand shock, and, similarly, this saw a drop in the oil price by about 5%. This is like the sudden emergence of the Omicron variant, where strict restrictions on travel were reintroduced in the fourth quarter of 2021 for most countries. This saw a sharp drop in oil price, from 5% to 10%, before recovering some losses. Another test considered, was a negative oil price shock to real exchange rates. This was as expected, as oil-importing regions such as Japan had appreciated against the USD, and oil-exporting currencies depreciated against the USD (USD was stronger; therefore, one dollar can exchange more currencies of Latam or ODC, hence, the increase). This was followed by a quick return to steady-states; therefore, this was as expected.

Lastly, an interesting exercise was performed on further rate decreases. First, in the UK scenario, where a sudden rate decrease happened, this would provide a small uplift to output for one quarter, before reversing the impact. If a global rate decrease shock happens, a similar effect is also felt. Here, the UK shock remained at a 0.3% increase in output for the global scenario. For all other countries, there was no discernible impact other than a weak growth in Japan and ROA. In both cases, the impact was about 0.05% to 0.025%, and soon reduced to steady-states. Zero and negative rates for Euro countries saw a minor decrease, and certainly had no growth impact.





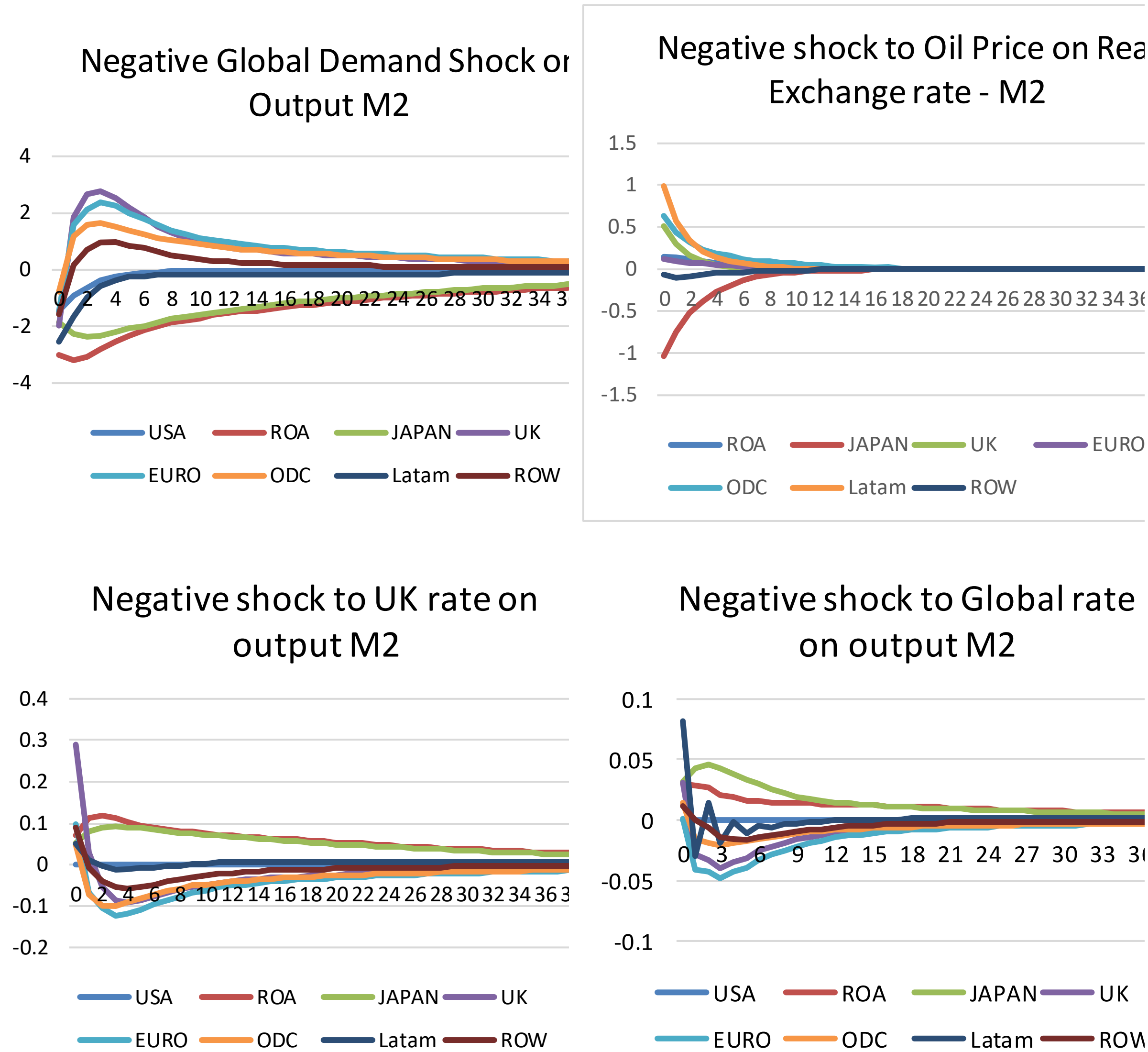


Figure 7. Additional negative shocks to M2.

4.10 Conclusions

This paper developed a NK-GVAR multi-country model that is consistent with the New Keynesian framework. Furthermore, it tested the supply, demand, and monetary policy shocks, before and after the pandemic. The results from impulse responses clearly show that the NK-GVAR is better than fitting the DSGE model with just HP filtered values, which is the norm in the literature. The impact and sudden changes in 2020 caused some of the impulse responses to react strongly and unexpectedly. However, the majority of the shocks are in line with expectations. This is particularly true for the NK-GVAR models, unlike the HP filtered ones, where some of the models could not converge; therefore, indicating misspecification. This implies that the outcome is consistent with the framework.

Supplementary Materials: For running GVAR model, the GVAR toolbox was used. https://sites.google.com/site/gvarmodelling/gvar-toolbox. For DSGE model replication, MMB was used. https://www.macromodelbase.com/.

5 Chapter 5 – An Empirical National-Regional Model

5.1 ABSTRACT

This paper develops a regional economic model for the UK and examines the impact of various shocks on the UK economy. The objective is to create a model capable of analysing the effects of monetary, fiscal, and oil shocks on the UK's regional economies. The methodology used is the Global Vector Autoregressive (GVAR) approach, which connects various UK regions based on their proximity and economic ties to London, the predominant economy. The model incorporates regional housing price indices (HPI), economic activity, and fiscal variables, along with national variables such as the UK interest rate and oil prices. The findings indicate a varied response to these shocks across different regions, with particularly distinct effects in regions further from London, such as Northern Ireland and Scotland.

5.2 INTRODUCTION

It is acknowledged that the interdependence between countries and regions is increasing. Economies have become more interconnected, evidenced by the monetary union and a unified monetary policy fostering economic commonality among member states. Yet, the reactions differ among these countries due to the diverse structures and policies each possesses. Within macroeconometric research, numerous models have been developed to illustrate and analyse the connections between countries and their responses to economic shocks. Nevertheless, the regional impact remains insufficiently explored. For instance, current research does not address the UK regions using the GVAR approach, which specifically accommodates cointegration and the interrelations between regions and global variables. This observation is particularly relevant to the United Kingdom, comprised of four primary countries: England, Wales, Scotland, and Northern Ireland. Although the UK is a unitary sovereign state, Northern Ireland, Scotland, and Wales have each acquired a measure of autonomy through devolution.

The motivation of this paper is to build a consistent model that can ask and answer counterfactual questions of the policymaker. While one policy may be beneficent to the country, it may not be the case for certain regions. For example, the oil price increase poses a drastically different response to Scotland than the rest of the country. Also important is the question of the effect of monetary and fiscal policy; whether regions experience the same effect and what is the time profile of the shock? Whether the shocks should be major or small? The undeniable economic and political capital of the UK is London which is by far the biggest of any city in the country. However, given the far distance of various regions to the capital, London can be seen as foreign as another country. The distance to the capital and other cities of various regions determines the connectedness of the regions. The connection between regions is economically important as it forms cross-section dependence that arises from contemporaneous dependence across space. This spatial dependence, for example, is the approach adopted to determine the correlations in the cross section by relating each unit to its neighbour(s). The spatial autoregressive models are examples of incorporating such processes for example (Cliff and Ord, 1973; Kelejian and Prucha, 2010; Holly, Pesaran and Yamagata (2011); Vansteenkiste and Hiebert (2011).

The proximity between places could be measured directly as physical distances but also in other areas such as social (Conley and Topa, 2002) or economic distances, such as trade flows (Conley,1999; Pesaran et al., 2004). In the context of modelling regions, the distances between regions can be approximated by the physical distances and transport. An example would be a commuting town in which the local housing market is partly determined by the commuters travelling to work to a neighbour town. In this paper, regions are modelled based on the physical linear distance between their regional capital to London similar to Holly et al (2010, 2011) and Vansteenkiste and Hiebert (2011). In other words, an economic boom happening in Manchester is much more likely to affect Leeds instead of Belfast for example.

While there isn't a regional UK model using the GVAR method, there are several approaches that are related in the literature. For example Garratt et al (2006) pioneered the long-run structural approach to modelling national and global economies using cointegration and long-run structural modelling. Long-run structural models using cointegration are considered structural in terms of using economic theories because they incorporate economic theory-based restrictions and long-run relationships into the modeling framework. Cointegration, which implies a stable long-run equilibrium relationship between variables, aligns with economic theories that describe the fundamental relationships between economic variables. By incorporating cointegration, these models capture the underlying economic structure and provide insights into the equilibrium dynamics of the economy. The inclusion of economic theory-based restrictions ensures that the estimated relationships are consistent with economic principles, enhancing the interpretability and policy relevance of the model. This approach is closely related to the GVAR approach but is set in only the national basis. The UK national model built in Garratt et al (2006, p. 191) uses a single equation of vector error correction model (VECM) to estimate the UK economy. The model uses data up to 2001 and has the following variables: real UK GDP per capita; domestic producer prices; domestic retail prices; domestic nominal interest rate and foreign variables such as producer prices of the OECD countries; UK effective nominal exchange rate (GBP vs EUR); foreign nominal interest rate; real OECD GDP per capita and oil price. Effectively the approach sets the UK national economy within the global context thus modelled the UK as an aggregated unit rather than regions. This approach provides an economic meaningful way of modelling the UK economy within the world economy, in this case, within the OECD world. However, as mentioned earlier, the local dynamics are lost as all regions are lumped together as a unit. As such this is not appropriate for understanding the regional economy for policy makers focusing on the UK only and calls for a regional approach.

In a paper by Jacob and Wallis (2010), the authors provided two models of the UK economy similar to above using cointegration, long-run structural modelling and weak exogeneity. The paper built a national-economy model (GLPS) and another the UK submodel of a global model using GVAR. The GLPS model is similar to Garret et al (2006) using the same approach but slightly different variables connecting the UK economy to other countries via domestic vs foreign GDP; interest ratees; inflation; exchange rates; money stock per capita and oil price etc. The VECM models represent reduced-form equations of the long-run economic theory, underlying the analysis establishes five long-term relationships or equilibrium conditions among these variables. The second model, the GVAR UK model puts the UK This is an updated and expanded version of the original GVAR model by Pesaran et al. (2004). It uses data from 1979q2 to 2003q4 and includes 33 countries. Among these, eight countries are part of the euro area and are combined into a single euro-area block. Therefore, the model consists of 26 individual country or regional submodels. Each country's model includes both domestic and foreign variables. The foreign variables specific to each country are calculated by combining data from foreign economies based on their trade shares with the home country. When solving the model, a globally consistent solution for the country-specific variables is obtained using the "link" matrix.

The models above show that the long-run approach can accommodate long-run economic theories and relationships within the model while relating the UK to the global economy. However there is a lack of more granular level looking the UK into separate regions while linked together.

Specifically, in a regional context like the UK, where economic activities are highly interconnected, GVAR models adeptly handle spatial spillovers and regional interlinkages. They allow for a nuanced understanding of how shocks or policy changes in one region can have ripple effects across others, acknowledging that regions are not isolated but economically integrated.

GVAR's strength lies in its structural design, which accommodates long-run relationships and equilibrium constraints across regions, ensuring that the model's predictions are not just short-term adjustments but also align with broader economic theories and long-term trends. This aspect is crucial for regional policy analysis, where understanding the long-term impact of economic policies on regional growth, employment, and inflation is as important as immediate effects.

Moreover, GVAR models are flexible in incorporating region-specific characteristics and exogenous variables, making them particularly useful for regional analysis. They can differentiate between the dominant economic influences of larger regions and the unique local factors of smaller areas, providing a comprehensive and detailed regional economic analysis. Thus, for countries like the UK, with distinct regional economic profiles, GVAR models offer a robust framework for understanding and forecasting regional economic dynamics.

This paper identifies and measures the responses of different regions in the UK, whether the shock originated nationally such as interest rate change or locally. Individual regions in a country are interlinked in a complex way through multiple channels such as producing or consuming resources (such as oil), political developments, labour and trade in goods and services. Even after allowing for such channels, there might still be residual interdependencies due to unobserved interactions and spillover effects not taken properly into account by using the common channels of interactions. The built model helps understand the heterogeneous responses of each region. To model a wide set of region variables, cointegration between regions must be considered as well as the shock transmission channels across regions. This requires consistent modelling of regional interdependencies to conduct counterfactual analyses. Specifically, the global vector autoregression (GVAR) approach was developed by Pesaran et al. (2004). It has been proven to be very useful to analyse interactions in the global macroeconomy and other networks where both the cross-section and the time dimensions are large.

Another aspect of forming the UK regional model is the dominance of the London economy. In this paper, the approach follows Chudik and Smith (2013) in which the authors compared two GVAR models; one treats the United States as a globally dominant economy (causality of effect goes from the US to foreign counterparts but not the other way round); one that treats the US as in a standard version of the GVAR model. The paper found support to model the US as the dominant economy and in the presence of a dominant economy, restrictions implied by the asymptotic analysis of a system without a dominant economy are no longer valid. This is due to the influence of the dominant model (US) would enter all individual models within the GVAR even if the country is not a major trade partner to the US, it would still be affected via its trading links to the world, which would then be affected by the US. Importantly the authors noted the trade-off between modelling the GVAR with or without a dominant unit has its cost in terms of degrees of freedom. The choice to use one GVAR over another was compared by means of persistent profiles (PPs) of system-wide shocks to the cointegrating relationships. If the dominant economy is left unmodelled as a dominant unit then the PPs would show as less stable before returning to zero.

The dominance of the economy can be confirmed by the weak-exogeneity test in which if a variable in an individual model is not weakly exogenous to others, then it is considered to be dominant and should be removed from the overall GVAR model. This dilemma is addressed in the methodology section in which a decision is needed to remove some variables.

5.3 DATA

To estimate the model, a dataset was constructed using various official publications. The monthly dataset spans from December 2000 to December 2019 (229 periods). The dataset contains all regions in the UK as defined by the International Territorial Level 1 (Office for National Statistics5) and their corresponding economic variables. The twelve regions are North East; North West; York and Humber; East Midlands; West Midlands; East; London; South East; South West; Wales; Scotland and Northern Ireland. The variables for each region are Gross value added (GVA); economic activity rate; house prices average; net fiscal balance (excluding North Sea oil and gas revenue), number of businesses; North Sea oil and gas Revenue. Two additional global variables representing on a national level are also included namely oil price (Brent) and UK interest rate.

One of the challenges of building the model is the data. Often data is not collected on a regional level but nationally such as inflation. In this case, some variables were converted from quarterly data into monthly etc (see table below). Another challenge is a net fiscal balance which is used to indicate fiscal shock. To include this in the model, two variables compiled by ONS were used. From these, oil revenue is derived to measure the fiscal dependence on oil revenue. Indexation was introduced to transform the data to remove the positive or negative sign originally assigned. Instead, a smaller index value indicates less tax revenue while a higher value indicates higher tax revenue.

It should be noted that the variables in the VARX* models are assumed to be weakly exogenous to each other. The 'idiosyncratic' shocks of the individual regional model should be cross-sectionally 'weakly correlated' and as a result, the weak exogeneity of the foreign region variables is ensured. The reason is that by conditioning the regional models on weakly exogenous foreign variables, the degree of correlation of the remaining shocks across regions should be minimal. This assumption is later tested and is true for 90% of the variables (see appendix A9). As both interest rate and oil price would be the same throughout the country, therefore, they are assigned as global variables. The national inflation rate was considered a global variable; however, it failed the weak exogeneity test for most regional models. Its inclusion also decreased the stability of the model therefore it was not used for the

5 https://geoportal.statistics.gov.uk/datasets/78c7b050aea44b04b0cab3d3e42d831b_0/explore

estimation. The inclusion of the house price index (not adjusted for inflation) in the model provides the information and as a proxy for inflation in each region. Regional employment data is also not included as this poses the same problem as it has failed weak exogeneity tests for many regional models. Instead, GVA and the number of businesses provide proxies for the general economy. Given the dimensions of the model i.e., 229 periods; 12 regions, 6 domestic/foreign variables and 2 global variables, it is important to ensure the model is stable, namely eigenvalues of the estimated model should be on or inside the unit circle. Persistence profiles (PPs) were also calculated to determine the time profiles of the effects of variable-specific shocks on the cointegrating relations in the GVAR model (Pesaran and Shin, 1996). PPs have a value of 1 on impact and should tend to zero as the horizon approaches infinity, this provides information on the speed at which the cointegrating relationships return to their equilibrium states. The calculated PPs and eigenvalues in appendix A10 provides evidence that the model is stable as the shocks approach near zero within the time horizon and all eigenvalues are within the unit circle.

Table 1 - Data in the model

Variable (short name)	**Data in model**	**Original dataset**	**Source**
Gross value added (y)	In natural log. Converted to monthly series.	Index 2019=100. Model-based estimates of quarterly GVA output in real terms.	Office for National Statistics Model-based early estimates of regional gross value added (GVA) in the regions of England, Wales, Scotland, and Northern Ireland
Economic activity rate (ea)	In natural log. The percentage using original data.	Percentage, monthly output.	Office for National Statistics HI01 - LFS headline indicators - People

House prices average (hpi)	In natural log. Index using original data.	Index, measure for UK residential properties. Monthly output. Seasonally adjusted. Not adjusted for inflation.	HM Land Registry UK House Price Index (UK HPI)
Fiscal balance index excluding oil and gas (fis)	In natural log. Index – converted original data into monthly. Switched sign – positive value indicates higher revenue received by region.	£ million. Yearly data. Used below series: Net Fiscal Balance excl. North Sea Oil & Gas revenues. A positive net fiscal balance indicates a deficit, while a negative net fiscal balance indicates a surplus	Office for National Statistics Country and Regional Public Sector Finances, FYE 2020: Net Fiscal Balance Tables
No of Businesses (biz)	In natural log. Converted to monthly series.	Number of businesses in the private sector; all businesses. Yearly data.	Office for National Statistics Business population estimates for the UK and Regions 2021
North Sea Oil and Gas Revenue index (og)	In natural log. Index, same method as (fis). Positive value indicates region	£ million. Yearly data. Calculated from table using below series Net Fiscal Balance excl. North Sea Oil & Gas revenues minus	Office for National Statistics Country and Regional Public Sector Finances, FYE 2020: Net Fiscal Balance Tables

	receiving revenue from oil and gas. Zero for London, West Midland and Wales.	Net Fiscal Balance (incl. North Sea Oil & Gas revenues by geographic area).	
Oil price (poil)	In natural log.	$, dollars per barrel. Monthly data. Europe Brent spot price FOB (free on board)	Reuters Source key: RBRTE
UK interest rate (r)	Value of 1 added to each period in order to transform the data into natural log. Converted to monthly series.	Percentage, interest rate as published quarterly.	Bank of England

5.4 METHODOLOGY

The first step of the GVAR approach is the formulation of the individual VARX* (vector autoregressive with exogeneity) models for each region. In this paper, the general methodology in Dées et al. (2007) was followed to model individual countries in the GVAR model. The approach assumes that there are N + 1 countries in the global economy, indexed by i = 0, 1, …, N, and the aim is to relate a set of country-specific variables, e.g., GDP, inflation, interest rates, etc. Appendices describe the statistical tests and specifications of the models.

The vector of interest is denoted as x_{it}, collects the economic variables specific to the individual regions of interest indexed by i and over time, indexed by t = 0; 1; … ; T. Following the notation and definitions given in Galesi and Smith (2014) p. 14–17, the general individual country model VARX* (2, 2) is represented as x_{it} is a vector with the dimension of $k_i \times 1$ of domestic economic variables indexed by individual region i and time as t; x_{it}^* is a vector with a dimension of $k_i \times 1$ of foreign (other regions) variables indexed by individual region i and time as t; u_{it} is a serially uncorrelated and cross-sectionally weakly dependent process. It should be noted that x_{it} is a vector that captures the foreign-specific economic variables that are related to domestic ones constructed via a weight matrix. This is defined as ω_{ij}, where i being the domestic region and j as the foreign, are a set of weights that ω_{ij} = 0 and when combining all the weights of i and j become 1.

Often in the GVAR literature, the scheme of the weight matrix is designed to reflect the trade and/or financial linkages between regions. However, such statistics are not collected by the ONS. As such for this paper, the geographic distance between is used instead like the wight matrix designed by (Vansteenkiste and Hiebert, 2011). This links each region spatially. For example, the economic significance is so large that it affects the whole country and all regions. The effect is particularly in the South East due to the proximity. By the same logic, the effect from Northern Ireland would be much smaller in London.

Given the dominance of London in other countries, it is modelled separately from other regions. Each regional model comprises three parts e.g. domestic, foreign and global (national). This implies that London exerts its influence on other regions but is not affected by them. This can be tested formally to confirm this assumption. For the London model, it does not include the following foreign variables i.e. GVA, HPI, oil and gas revenue nor global variables such as oil price and interest rate. This is based on estimations from weak exogeneity tests and persistent profiles. Effectively, the London model would fail the weak exogeneity if including the above foreign variables and a poor persistent profile indicating the model is misspecified.

It should be noted that similarly to the framework of an unrestricted VAR, the VARX* model can also be written in its error-correction form VECMX*, which allows the differentiation of short and long-run effects. In particular, the long-run effects are treated as co-integrating. The individual VECMX* models are estimated separately for each region i, based on reduced rank regression, thus, identifying the long-run effects or I(1) relationships that exist within the domestic x_{it} and across x_{it} and also the foreign regions x_{it}^*. The full derivation of the VECMX* can be seen in Smith and Galesi (2011), p. 15 and is not repeated here.

The GVAR approach is a two-stage process. The first is to estimate the VARX* model country by country, and the second is to stack all VARX* models together, to be solved as a whole. We now examined the solution to solve the model, as outlined in Ibid p. 16.

Following Galesi and Smith (2014) the generic VARX* (2,2) model:

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i1}x_{it}^* + \Lambda_{i1}x_{it-1}^* + \Lambda_{i2}x_{it-2}^* + u_{it} \tag{5.1}$$

where the model includes N+1 countries which are indexed by i=0, 1, 2, …, N; x_{it} is a $k_i \times 1$ vector of domestic variables; φ_{il} is a $k_i \times k_i$ matrix of lagged coefficients; Λ_{il} is $k_i \times k_i^*$matrix of coefficients associated with the foreign variables; $u_{it}$is a $k_i \times 1$vector of idiosyncratic shocks. Importantly $x_{it}^* = \sum_{J=0}^{N} w_{ij}x_{jt}; w_{ii} = 0$. By construction, the region-specific foreign variables are based on spatial weights which reflects the relative importance of economic developments in region j for region i.

To construct the link matrix weight matrix w_{ij} linking different regions together, the inverse distance weighting of the linear distance between regions was used. The first step was to find the linear distance between regional capitals e.g. The capital of Northern Ireland is Belfast and Wales is Cardiff etc. The full list of regional capitals used is listed in appendix (A5) . The coordinates used to determine the distance are from the official publication by Ordnance Survey. For example, the linear distance between Birmingham (West Midlands) and Bristol (South West) is 171.84 km. The complete matrix of distances between capitals is shown in the appendix (A6).

The sum of total IDW for each region is plotted below. Not surprisingly Scotland and Northern Ireland ranked the lowest indicating their relative geographic isolation from other regions. The North East and West Midlands are most connected spatially to the rest of the country.

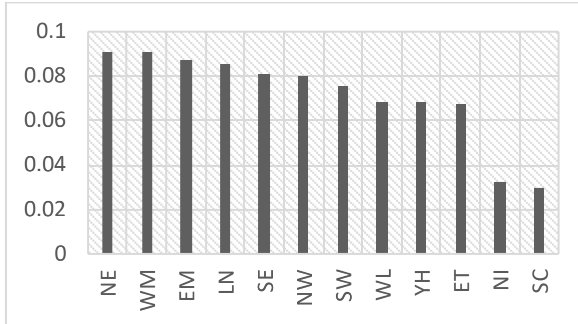


Figure 1 - Chart showing sum of regional IDW

Inverse distance weighting (IDW) was then used to determine the spatial weight between regions. This is done by using the formula $|(j-i)^{-1}|$, j (base capital) to i (foreign capital), where the value must be absolute. For example, the IDW between Leicester (East Midlands) and Edinburgh (Scotland) i.e. $|(0-392.412)^{-1}| = 0.0025$. Once IDW (matrix in appendix A7) is found for all regions (0 for diagonal elements e.g. NE and NE; SC and SC etc), the respective portion for each region is calculated to form the final weight matrix (appendix A8) such that each column sums to 1. For example, the absolute IDW between Leicester (East Midlands) and Edinburgh (Scotland) is 0.0025. The combined weight of all regions in the East Midlands column (East Midlands to other regions) is 0.0833. As such the weight for Scotland in the East Midlands column is 0.0025/0.0833 = 0.029 or 3% of the total IDW. Under this weighting scheme, it is easy to see that for example, spatially, South East is affected by London the most at 40.9% and Scotland the least at just 2%.

5.4.1 Estimating the GVAR model

Once the individual country models are estimated separately, given the weak exogeneity assumption discussed above, the GVAR model is solved simultaneously. To form the GVAR model, first, assume a VARX*(2,2) model:

$$A_{i0}W_i x_t = a_{i0} + a_{i1}t + A_{i1}W_i x_{i,t-1} + A_{i2}W_i x_{i,t-2} + u_{it} \tag{5.2}$$

Where $u_{it} = (x_{it}, x_{it}^*)'$; $A_{i0} = (I_{ki}, -\Lambda_{i0})$and $A_{i1} = (\varphi_{i1}, -A_{ij})$for j=1, …, p_i. The terms $W_i x_t$ contain the weights w_{ij} for construction of the country-specific foreign variables. These can be combined into $z_{it} = (W_i x_t)$, where W_i is a $(k_i \times k_i^*) \times k$ matrix and $k = \sum_{i=0}^{N} k_i$.

Moreover, recall that for i = 0, 1, …, N, which implies the equation above is individual region specific and requires stacking to solve for x_t, which links all individual models together. We can now introduce a few more terms to tidy up the model:

$$G_0 = \begin{pmatrix} A_{00} W_0 \\ A_{10} W_1 \\ \vdots \\ A_{N0} W_N \end{pmatrix}, \qquad G_1 = \begin{pmatrix} A_{01} W_0 \\ A_{11} W_1 \\ \vdots \\ A_{N1} W_N \end{pmatrix}, \qquad G_2 = \begin{pmatrix} A_{02} W_0 \\ A_{12} W_1 \\ \vdots \\ A_{N2} W_N \end{pmatrix},$$

$$a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \qquad a_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \qquad u_1 = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \vdots \\ u_{Nt} \end{pmatrix}$$

(5.3)

Thus

$$G_0 x_t = a_{i0} + a_1 t + G_1 x_{t-1} + G_2 x_{t-2} + u_{it}$$

(5.4)

As the term G_0 is a known non-singular matrix (invertible matrix). G_0 is called non–singular if there exists an n × n matrix G_0^{-1} such that $G_0 G_0^{-1} = I_n = G_0^{-1} G_0$. Thus, by multiplying its inverse, the term disappears and we now obtain the GVAR (2) model with 2 lags where:

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + F_2 x_{t-2} + \epsilon_{it}$$

(5.5)

where the new terms collect the inverse of G_0

$$F_1 = G_0^{-1}G_1, F_2 = G_0^{-1}G_2,$$
$$b_0 = G_0^{-1}a_0, b_1 = G_0^{-1}a_1\ \epsilon_{it} = G_0^{-1}u_{it}$$
(5.6)

The GVAR model above can be solved recursively, see Pesaran, 2015. Specifically, this paper used the GVAR toolbox for the solution.

5.4.2 Dominant unit

In addition to the standard GVAR model, this model also introduces a dominant unit for the global (national) variables. In this case, the global variables (oil price and interest rate) are modelled as a dominant unit, as defined by Chudik and Pesaran (2013) where the global variables enter all regional models. The non-dominant units i.e. the regional models; are conditioned on current and lagged values of the dominant variables, in addition to the foreign variables, x_{it}^*. In contrast, for the dominant unit only lagged values of the dominant variables are included as shown in (Galesi and Smith, 2014). The following VAR model specifies the global variables model. The global variables ω_t depends on its lags as determined by SIC or AIC but not the non-dominant units i.e. regional models.

$$\omega_t = \mu_0 + \mu_1 t + \Phi_{i1}\omega_{t-1} + \Phi_{p\omega}\omega_{t-p\omega} + \eta_t$$
(5.7)

Solving the GVAR augmented with a dominant unit is similar to the procedure above. The individual regional model VARX* (2,2) now becomes:

$$x_{it} = a_{i0} + a_{i1}t + \varphi_{i1}x_{i,t-1} + \varphi_{i2}x_{i,t-2} + \Lambda_{i1}x_{it}^* + \Lambda_{i2}x_{it-2}^* + \psi_{i1}\omega_{t-1} + \psi_{i2}\omega_{t-2} + u_{it}$$
(5.8)

Note that the global variables ω_t do not have the subscript i=0,1,…, N like the domestic and foreign variables. The global variables are treated similarly to the foreign variables for estimation purposes like the standard GVAR model. Explicitly, foreign and global variables are combined and treated jointly as weakly exogenous, using the reduced rank regression techniques for VECMX* models (p.154, Galesi and Smith, 2014).

5.5 Estimating Generalised Impulse response functions

Similar to the GVAR literature, GIRF was preferred in this model as it does not rely on the ordering of the variables. The paper emphasises the need for caution when utilising Generalised Impulse Response Functions (GIRFs) due to their reliance on extreme assumptions. However, it is important to recognise the potential advantages of using GIRFs as an alternative approach in vector autoregressive (VAR) models. There are several reasons why GIRFs can offer a better alternative.

Firstly, GIRFs demonstrate invariance to the ordering of variables within the VAR model, providing robustness and flexibility in analysis. Secondly, they allow for a comprehensive analysis of response functions, capturing the dynamic adjustments of all variables in the system and enabling a holistic understanding of their interrelationships. Additionally, GIRFs facilitate the identification of structural shocks, helping to uncover the underlying drivers of economic phenomena. GIRFs have been widely employed in empirical studies, demonstrating their practical applicability. Furthermore, comparing GIRFs with other approaches, such as orthogonalised impulse response functions (OIRFs), allows for a thorough examination of economic inferences and enhances the robustness of the findings.

Specifically, this paper used both domestic shocks and global shocks to illustrate the dynamics between regions and national variables. Using the definition of the GIRF , Ibid

$$\boldsymbol{g}_{\varepsilon j}(h) = E\left(\mathbf{x}_{t+h} \middle| \varepsilon_{jt} = \sqrt{\sigma_{jj}}, \boldsymbol{I}_{t-1}\right) - E(\mathbf{x}_{t+h} | \boldsymbol{I}_{t-1}),$$

(5.9)

$$= \frac{\boldsymbol{R}_h \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma} \boldsymbol{e}_j}{\sqrt{\boldsymbol{e}_j' \boldsymbol{\Sigma} \boldsymbol{e}_j}}$$

(5.10)

Where the GIRF is defined as a vector of k x1 size as $\boldsymbol{g}_{\varepsilon j}(h)$, h as the time period, j is the index of the interested country, E(.|.) being the conditional mathematical expectation with respect to the VAR model, defined as the vector of $\mathbf{x}_t$ at h period upon the shock of ε_{jt} to country j at time t. The mathematical expectation is equal to the square of the shock at the size σ_{jj}, pre-set to be 1 standard deviation i.e. $\sqrt{\sigma_{jj}}$. In this case, $\boldsymbol{I}_{t-1}$, simply referred to as the full information set at t-1, which is defined as the collection of vector $\mathbf{x}_t$ at t-1. $\boldsymbol{R}_h$ being a vector of $(k_i \times k_i)$ $\boldsymbol{G}_0^{-1}$for connecting the variables $\boldsymbol{\Sigma}$ as the Cholesky factor.

Last but not least, $\boldsymbol{e_j}$ as the sector vector that selects the element of shocks. For example, if we wish to find out the effect of 1 standard deviation negative shock to the Scotland GVAR given by London, then we can specify this shock with the $\boldsymbol{e_j}$ mathematically, with 1 being selected; 0 not i.e. $\boldsymbol{e_j}$ =(0, 0, … 1,0 …0) ′.

Global shocks were also used. This is done in the form of the dominant unit model e.g. a positive global one standard error shock to all the regional models. The GIRF of this shock is given by:

$$\boldsymbol{g}_m(h) = E\left(\mathbf{x}_{t+h} \middle| \varepsilon^g_{m,t} = \sqrt{\mathbf{m}', \boldsymbol{\Sigma}\mathbf{m}}, \boldsymbol{I}_{t-1}\right) - E\left(\mathbf{x}_{t+h} \middle| \boldsymbol{I}_{t-1}\right), \tag{5.11}$$

$$= \frac{\boldsymbol{R}_h \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma}\mathbf{m}}{\sqrt{\boldsymbol{m}'\boldsymbol{\Sigma}\mathbf{m}}} \tag{5.12}$$

Where the single country shock is ε_{jt} is replaced by $\varepsilon^g_{m,t}$, which is defined as $\mathbf{m}'\varepsilon_t$ with $\mathbf{m}$ being the vector of weights related to the global model or region.

5.6 EMPIRICAL RESULTS

Unit root tests

An augmented Dickey–Fuller (ADF) test was carried out at 95%, implying that if the test statistic for the variable is more negative than the critical values, then it will be rejected, as there is no unit root. The test was carried out on level, differenced, twice differenced, with the trend, and without trend on all variables. Once the unit root had been tested, the corresponding co-integrating VARX* models were estimated as VECMX*. The next step is the identification of the co-integrating relationships within the individual models. The rank of co-integrating relationships for each model is then computed using Johansen's trace and maximal eigenvalue statistics.

Testing for weak exogeneity

The main assumption in the GVAR approach is the weak exogeneity of the foreign variables $x_{it}^{*}$with respect to the respective VARX* model. this assumption is compatible with a certain degree of weak dependence across u_t (the residuals). Following the work on weak exogeneity testing by Johansen (1992) and Granger and Lin (1995), the weak exogeneity assumption implies no long-run feedback from x_t to x_{it}^{*}, suggesting that x_{it}^{*}error correction terms of the individual country VECMX* models do not enter the marginal model of x_{it}^{*} (Smith and Galesi, 2014). This implies we can consistently estimate the VARX* models individually and, later, combine them to form the GVAR. The proof of weak exogeneity implication on x_{it}^{*}can be seen in Pesaran (2015) p. 569. The test shows that the weak exogeneity assumption holds for the majority of the models. If we further remove the variables that have failed the test, the overall result remains similar as indicated by the persistent profiles.

Lag length and cointegrating relations

For each VARX* and VECMX*, the choice of lag length was based on the results of the Schwarz-Bayesian information criterion. For VECMX*, the possibility of several cointegrating relations, the rank for each country is chosen based on Johansen's trace and maximal eigenvalue statistics as set out in Pesaran et al. (2004). In addition, eigenvalues and persistence profiles (PPs) were used to determine the effects of variable-specific shocks on the cointegrating relations in the overall GVAR model. The results are in the appendix which shows a quick decline of the shock to zero, implying a stable model (A10).

Individual regional model specification

As a default, all regional models include all domestic, foreign and national variables. That is, for example, the Scotland model, includes the domestic variables of gross value added (y); economic activity rate (ea); house prices average (hpi); fiscal balance index excluding oil and gas (fis); number of businesses (biz); North Sea Oil and Gas Revenue index (og). It is also the equivalent of the foreign variables in its model as defined by the weight matrix. For global variables, the model includes oil price (poil) and UK interest rate (r).

Due to the dominance of the London economy; its modelling needs to be specified separately. As confirmed by weak-exogeneity test, the London model includes all the above domestic variables, but for foreign variables only economic activity rate (ea); fiscal balance index excluding oil and gas (fis); the number of businesses (biz) and no global variables. This implies that London is dependent mainly on its own domestic variables plus only a few foreign variables across the rest of the UK. Results are seen in the appendix.

Apart from the London models, some foreign variables have failed the test at 95%. However, their exclusion from the models did not significantly alter the model estimation as the number is relatively small. As such, similar to (di Mauro, Pesaran, 2013), the variables are retained, given that the performance of persistent profiles and other robustness checks did not change significantly given their absence.

5.7 Shock Analysis

In this section, selected impulse responses estimated with GIRF are presented. Impulses are presented over a time horizon of 60 periods i.e. 5 years. Specifically, five different shocks are presented below, showing the effect of either a positive or negative 1 standard error shock on different variables.

The below list shows the shocks presented in this section.

Shocks

- National 1 standard error positive shock to House prices average
- London 1 standard error positive shock to GVA
- Scotland 1 standard error positive shock to GVA
- Dominant unit model 1 standard error negative shock to UK interest rate
- Dominant unit model 1 standard error positive shock to oil price

National 1 standard error positive shock to House prices average – Fig 2

A standard error positive shock (+1) was applied to all individual models for the house price index (HPI). This is around a 1% increase in HPI for each regional model. From this shock, the majority of regional economies experienced an insignificant increase in GVA, notably Scotland although the effect is small at around 0.1% decrease. For economic activity, there is a heterogeneous response in each region with Northern Ireland showing the largest increase in economic activity at around 0.02% while East Midland showing the reverse at around -0.02%. For all other regions, there is no noticeable pattern or effect. This is like the number of businesses which is not show a uniform pattern. The first fiscal indicator, net fiscal balance (ex o&g) shows a much more uniform trend where most regions have a small negative impact. The worst affected is Scotland which is around 0.08% at the peak. A similar pattern can be observed for North Sea oil and gas revenue in which the majority of regions show a strong negative response. The worst affected is Scotland which has the lowest value of more than 5%. Another region that is reliant on oil and gas is Yorkshire and Humber with a 2% decrease. Compared to other variables, oil and gas revenue shows a much stronger reaction, given the past volatile changes in oil price. The most notable region in this shock is the reaction from the Scotland model. A shock to HPI is associated with a lower economic outlook in which, GVAR and fiscal variables have gone down, particularly the decrease in oil and gas revenue. To conclude, there is in general a negligible to a positive effect on most indicators, except Scotland where it has a negative association of oil and gas revenue with an increase in HPI.

London 1 standard error positive shock to GVA– Fig 3

In this shock, a positive one standard error or about 0.1% increase in GVA growth was applied to all regional models. For all regions, this is showing a uniform GVA growth from 0.1% to 0.3% at the end of 5 years horizon. Given the gravity of London's economy, this is not surprising as a positive shock is also felt in all other models. In general, the positive influence is also seen for economic activity, fiscal balance and HPI. However, the Scotland model exhibits a notable difference from the rest of the UK regions. Surprisingly this is associated with negative economic activity and also oil and gas revenue. Although the trend is negative for economic activity, it is a small magnitude of 0.2% while oil and gas revenue showed a sharp decrease of -6% before going back to -2%, reacting much more volatile to all other models. This again, suggests a divergence between the Scotland model and the rest of the UK as emphasized by the oil and gas price. It should be noted that GIRF does not suggest direct causality but a historical pattern that had happened given the present time-series data.

Scotland 1 standard error positive shock to GVA– Fig 4

Contrary to the London model, it would be interesting to examine the effect of the same shock but originated from the Scotland model. In this case, the effect is much smaller than the London shock. Overall the impact on GVA is positive for all regions except the London model but this is expected as the London model is restricted not to be influenced by the UK regions by design and as such, the effect entered into other channels, resulting in a slight negative trend. Economic activity and a number of businesses are also showing a weak effect of between 0 to 0.01%, although the Northern Ireland model is showing a somewhat lower effect, close to -0.2% at the end of the 5-year period. This suggests a competitive role of Northern Ireland in the Scotland model. As expected, given the positive shock to the GVA, both fiscal variables are showing a strong increase, up to a 15% increase in oil revenue. As noted above this does not suggest direct causality. Instead, this can be interpreted as, for Scotland to achieve a one standard error positive shock of the GVA, it needs a 15% increase in oil revenue to achieve a positive impact on its economy.

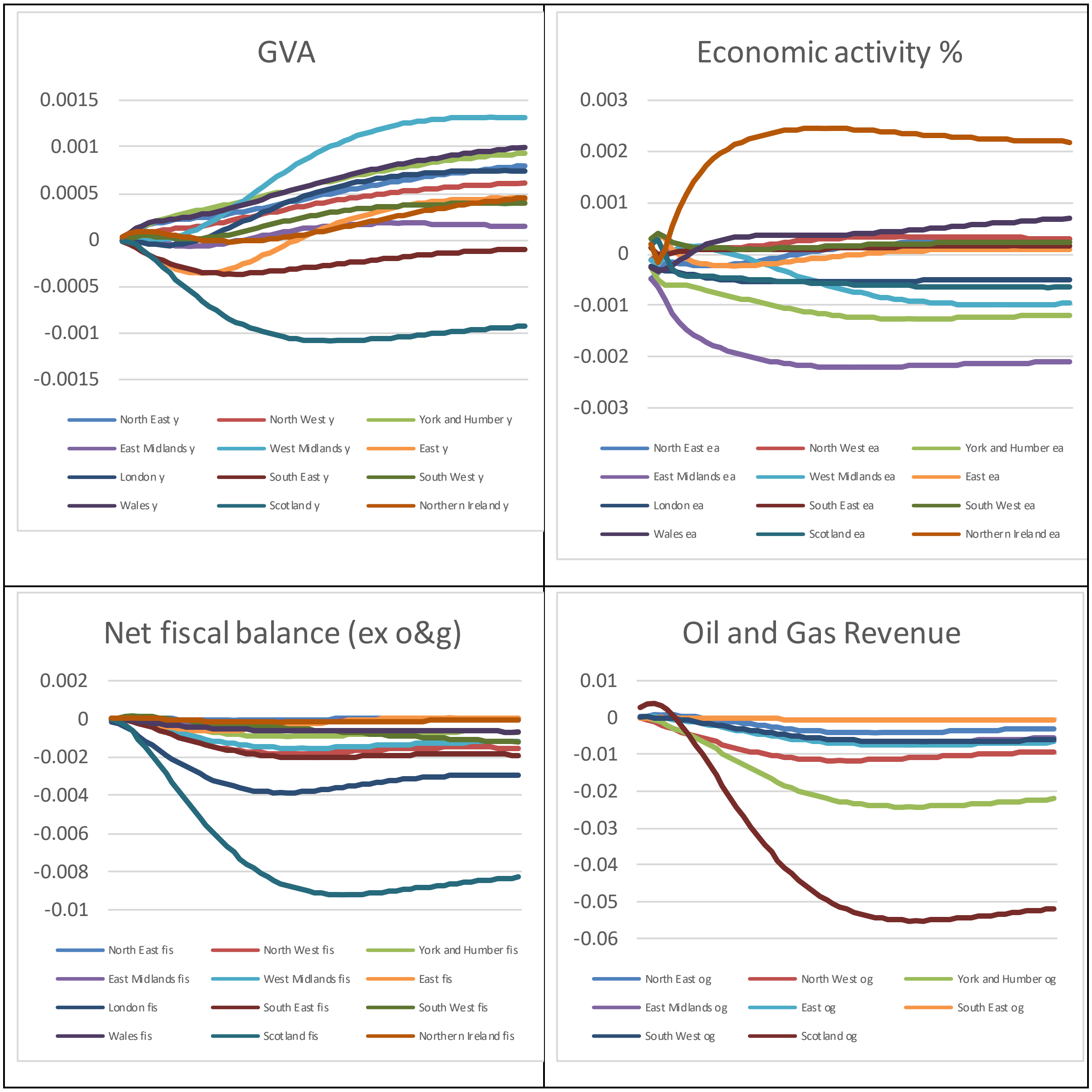
Dominant unit model 1 standard error negative shock to UK interest rate – Fig 5

The next two shocks presented originated from the global variables. The first one is the UK interest rate which was set to a negative shock of 1 standard deviation. A uniform pattern is seen for the GVA, fiscal variable (except Scotland) and HPI etc. A negative shock to the UK interest rate is associated with an initial impact of around -0.01% to -0.05% in all regions in the UK. The corresponding net fiscal balance is thus showing the same but with a bigger magnitude of between -1% to 3% for Scotland. The oil and gas revenue again is showing a high impact of negative 10% for Scotland. This is due to the history of interest decrease with the economic downturn, and as such, the majority of variables are showing a downward trend except for HPI. Given lower interest rates, property, in general, would rise which is shown here except for London which is restricted not to consider property prices from other regions and Northern Ireland which appears to have a separate market from the rest of the UK.

Dominant unit model 1 standard error positive shock to oil price – Fig 6

Lastly, a one positive standard error shock was applied to the oil price. Given the previously presented shocks, it is expected Scotland to have a major benefit from this shock and this is confirmed here. A clear increase is observed in Scotland's GVAR, net fiscal balance, oil and gas revenue and also HPI. For the rest of the UK, an increase in oil price ranges from slightly positive to negative. A particular divergence is seen in the HPI. Except for Scotland and Northern Ireland (which appears to have a separate housing market), more expensive oil price shows clearly weights on the housing market. Although it showed a slight increase for the Scotland model, it does not persist and reduces after the first 5 periods. The GVA and net fiscal balance are clear that it has a strong influence on Scotland's economy.

Figure – 2 National 1 standard error positive shock to House prices average


GVA
0.0015
0.001
0.0005
0
-0.0005
-0.001
-0.0015
North East y
North West y
York and Humber y
East Midlands y
West Midlands y
East y
London y
South East y
South West y
Wales y
Scotland y
Northern Ireland y
Economic activity %
0.003
0.002
0.001
0
-0.001
-0.002
-0.003
North East ea
North West ea
York and Humber ea
East Midlands ea
West Midlands ea
East ea
London ea
South East ea
South West ea
Wales ea
Scotland ea
Northern Ireland ea
Net fiscal balance (ex o&g)
0.002
0
-0.002
-0.004
-0.006
-0.008
-0.01
North East fis
North West fis
York and Humber fis
East Midlands fis
West Midlands fis
East fis
London fis
South East fis
South West fis
Wales fis
Scotland fis
Northern Ireland fis
Oil and Gas Revenue
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
North East og
North West og
York and Humber og
East Midlands og
East og
South East og
South West og
Scotland og

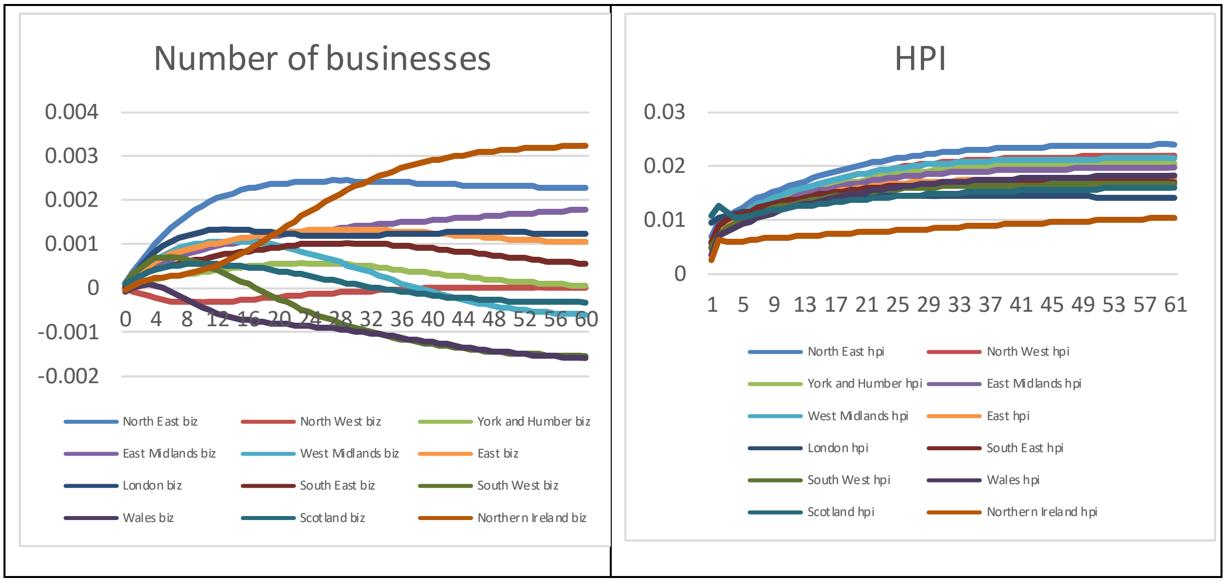
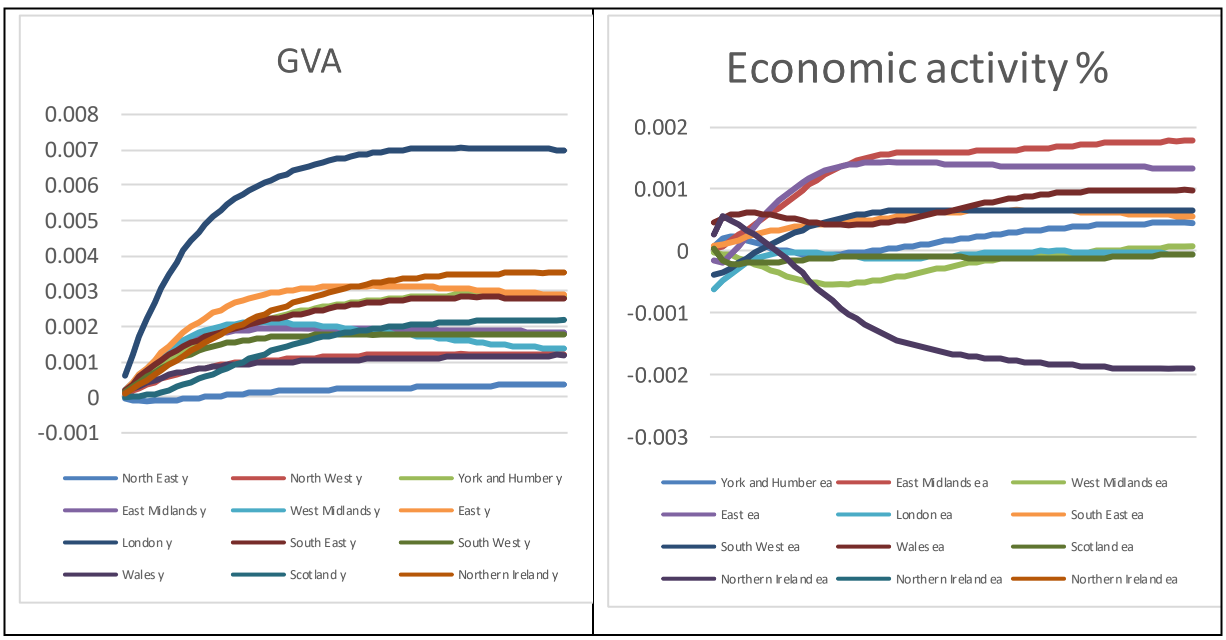


Figure – 3 London 1 standard error positive shock to GVA



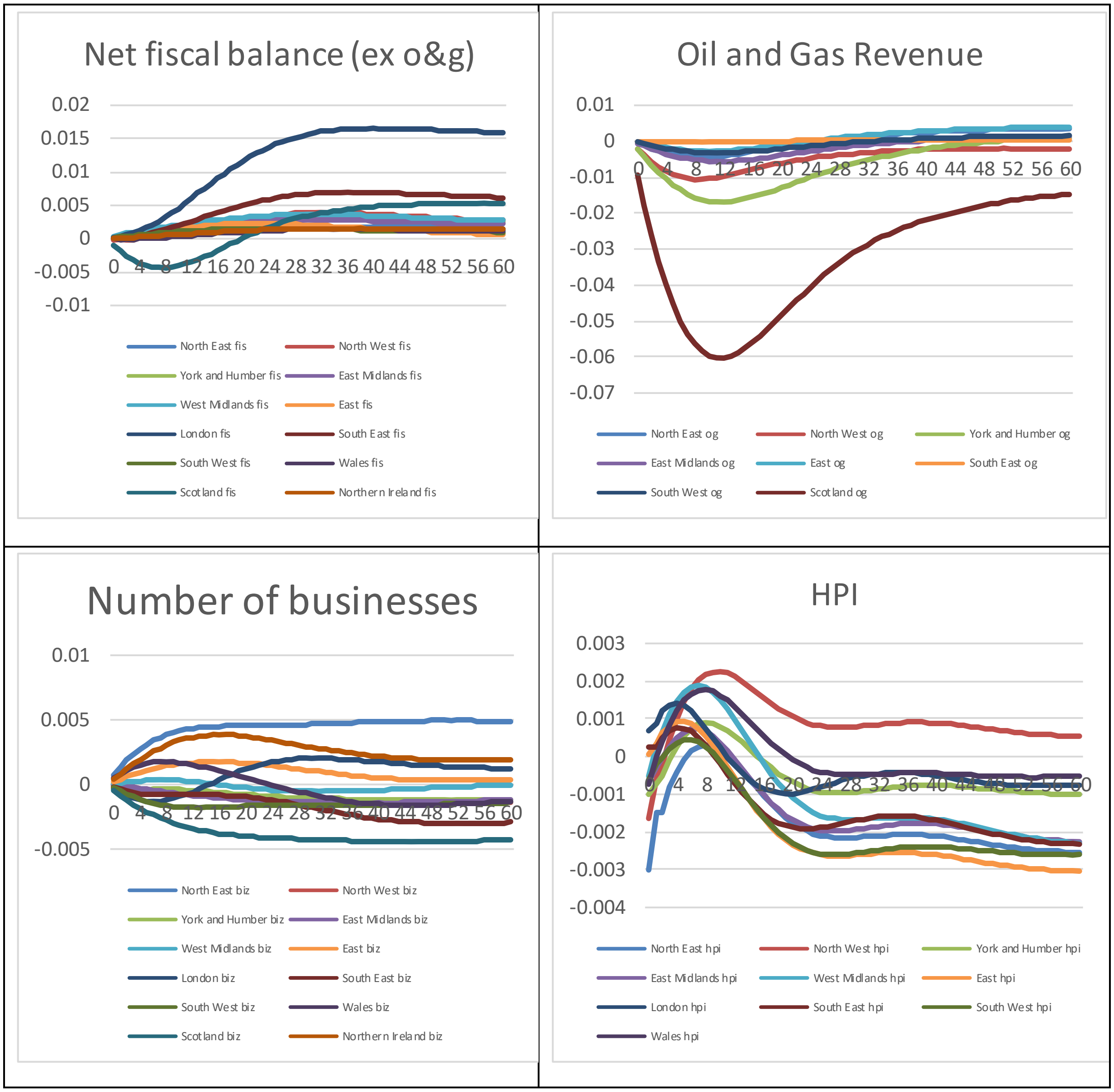
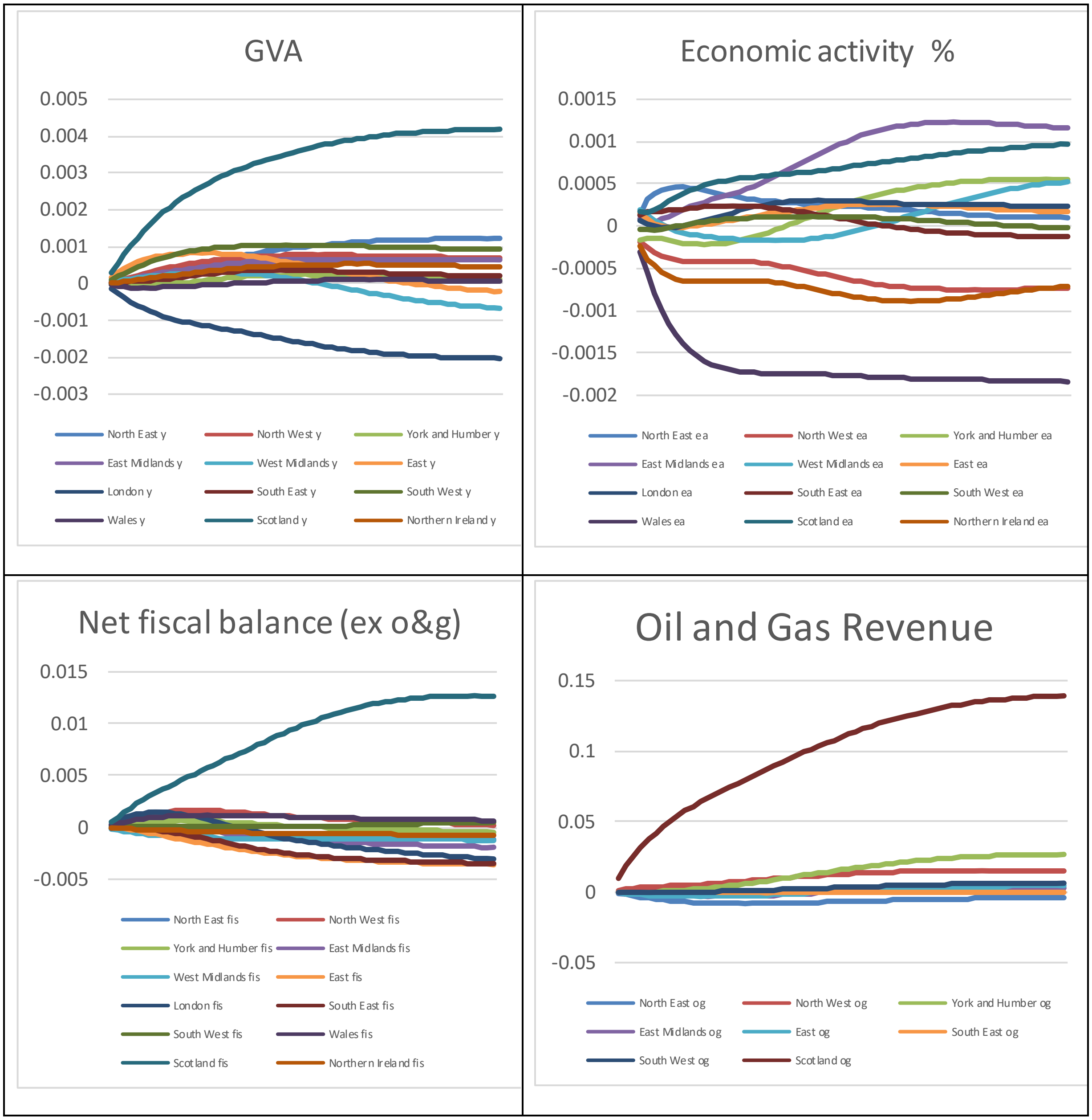

Net fiscal balance (ex o&g)
0.02
0.015
0.01
0.005
0
-0.005
-0.01
0 4 8 12 16 20 24 28 32 36 40 44 48 52 56 60
North East fis
North West fis
York and Humber fis
East Midlands fis
West Midlands fis
East fis
London fis
South East fis
South West fis
Wales fis
Scotland fis
Northern Ireland fis
Oil and Gas Revenue
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
0 4 8 12 16 20 24 28 32 36 40 44 48 52 56 60
North East og
North West og
York and Humber og
East Midlands og
East og
South East og
South West og
Scotland og
Number of businesses
0.01
0.005
0
-0.005
0 4 8 12 16 20 24 28 32 36 40 44 48 52 56 60
North East biz
North West biz
York and Humber biz
East Midlands biz
West Midlands biz
East biz
London biz
South East biz
South West biz
Wales biz
Scotland biz
Northern Ireland biz
HPI
0.003
0.002
0.001
0
-0.001
-0.002
-0.003
-0.004
0 4 8 12 16 20 24 28 32 36 40 44 48 52 56 60
North East hpi
North West hpi
York and Humber hpi
East Midlands hpi
West Midlands hpi
East hpi
London hpi
South East hpi
South West hpi
Wales hpi

Figure – 4 Scotland 1 standard error positive shock to GVA



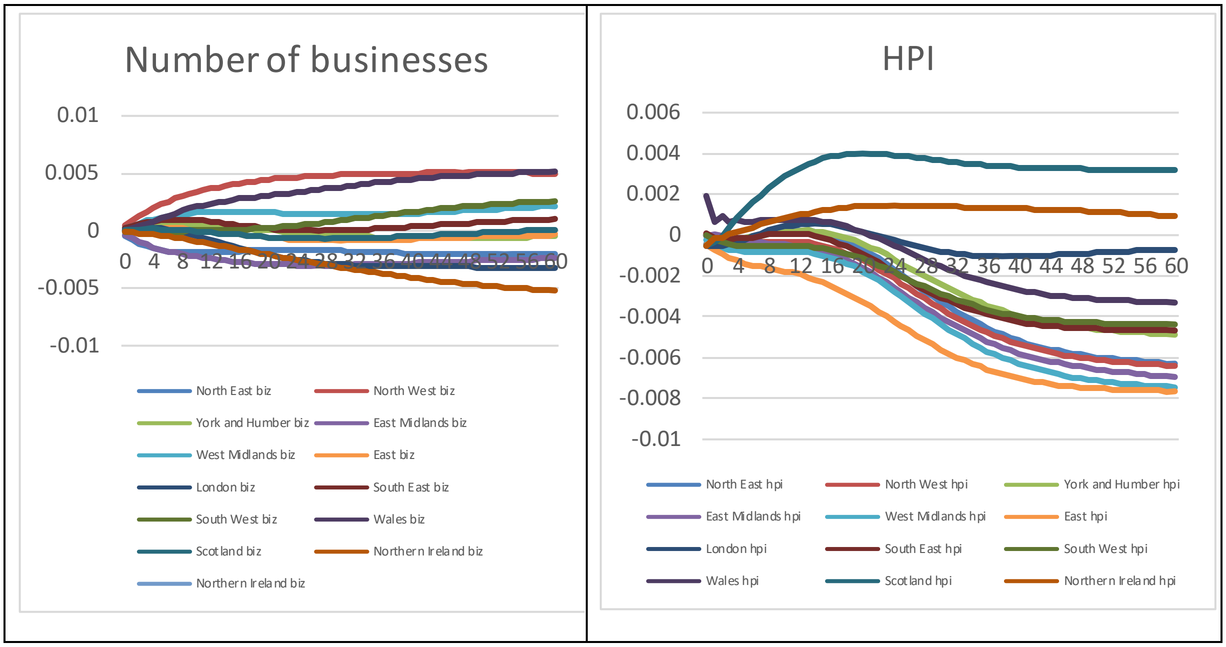
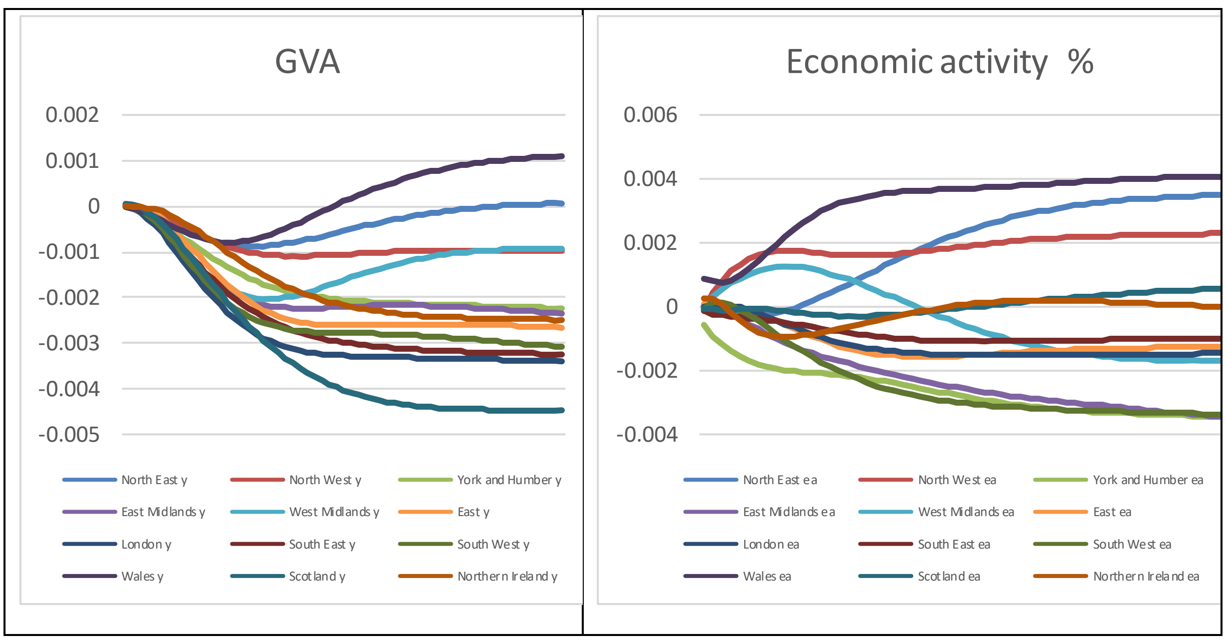


Figure – 5 Dominant unit model 1 standard error negative shock to UK interest rate



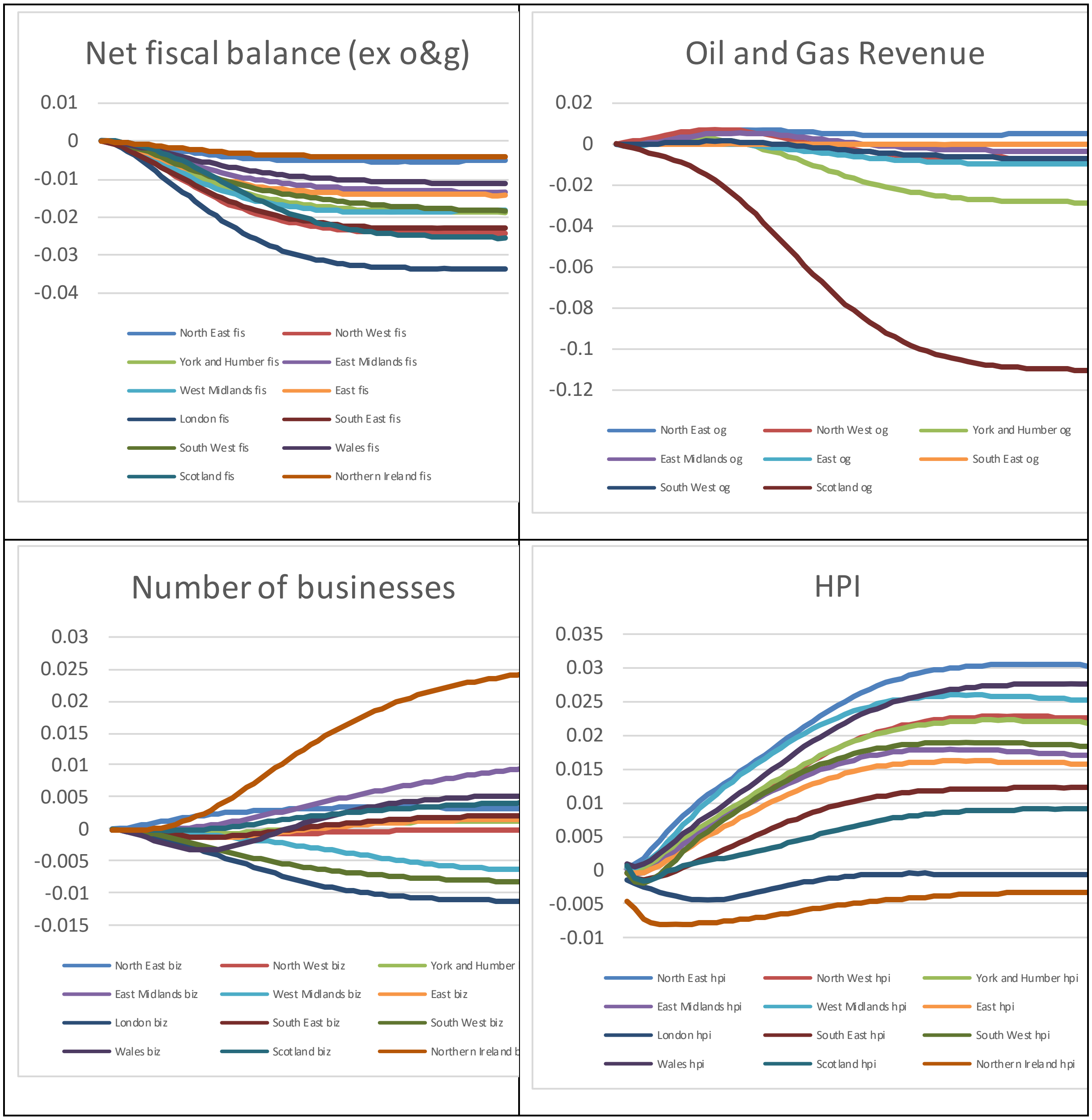
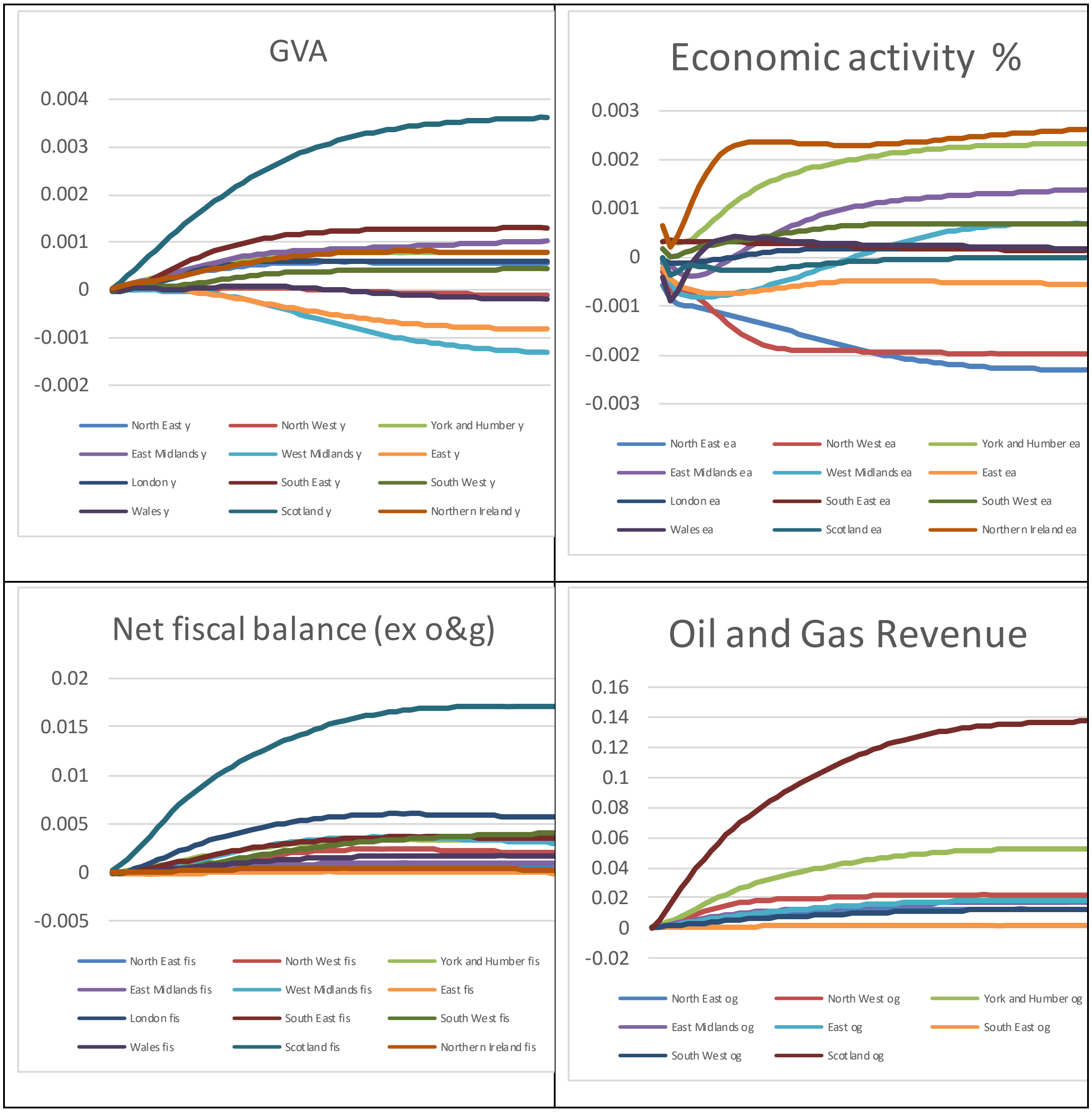
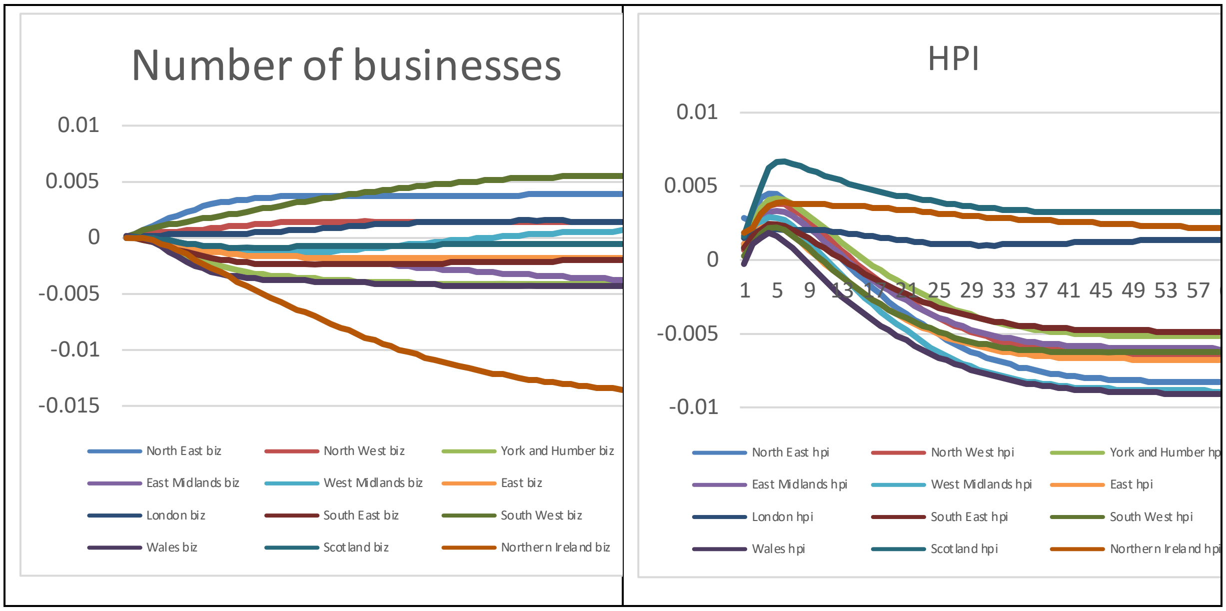

Net fiscal balance (ex o&g)
0.01
0
-0.01
-0.02
-0.03
-0.04
North East fis
North West fis
York and Humber fis
East Midlands fis
West Midlands fis
East fis
London fis
South East fis
South West fis
Wales fis
Scotland fis
Northern Ireland fis
Oil and Gas Revenue
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
North East og
North West og
York and Humber og
East Midlands og
East og
South East og
South West og
Scotland og
Number of businesses
0.03
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
North East biz
North West biz
York and Humber
East Midlands biz
West Midlands biz
East biz
London biz
South East biz
South West biz
Wales biz
Scotland biz
HPI
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
North East hpi
North West hpi
York and Humber hpi
East Midlands hpi
West Midlands hpi
East hpi
London hpi
South East hpi
South West hpi
Wales hpi
Scotland hpi
Northern Ireland hpi

Figure – 6 Dominant unit model 1 standard error positive shock to OIL PRICE





5.8 CONCLUSIONS AND DISCUSSION

This paper has contributed to the modelling literature in several ways. Firstly, papers using GVAR to study fiscal and monetary dynamics in a region are not many. This paper provides a way to model economic, fiscal and monetary elements from a regional perspective. Secondly, unlike others in the literature, the fiscal aspect is differentiated between oil and gas revenue and all other revenues. Instead of government expenditure, a net fiscal balance index was constructed. This allows for a more nuanced empirical analysis of different regions. Thirdly this paper has shown a way to model the UK regional economy by determining the dominance of the London region while linking all regions together while a weighting scheme. The effects of fiscal shocks are not often used in the GVAR literature such as (Ricci-Risquete and Ramajo-Hernandez, 2015) thus this paper contributes to this area.

As mentioned in the paper, the shocks from the GVAR and GIRF are in general not structural. Future research could focus on the structural identification of regional fiscal shocks, though the data may not be available and thus cannot be modelled directly. This could be an avenue of research, thus rendering the GIRFs comparable to structural shocks. There are works on identifying the shocks in a structural sense, constructing from a GVAR model, similar to the ones commonly found in the dynamic stochastic general equilibrium (DSGE) models literature such as Dées et al (2009, 2012), Pesaran and Smith (2011) and Kwok (2022).

Overall, this paper adopted a linear treatment for all data and as such, the non-linear method can be used to apply to the crisis period which had affected the UK economy deeply. Another direction of the research is on linking the UK regional economies to the wider world. This would involve more global variables to be modelled either as a collection of indices indicating economic linkage across the European Union and other regions. This will also require an expansion of the endogenous variables such as export and manufacturing index etc.

6 Chapter 6 - Final Conclusions and Directions for Further Research

This thesis has scrutinised critically and rigorously the theory and application of the application of Global vector Autoregressive (GVAR) models. The motivation of this thesis is to provide a thorough study and contribution to the theory and application of the Global vector Autoregressive (GVAR) models.

The main contributions of this work are in the following ways:

a) provided a comparison of this model historically and econometrically against other macroeconometric models in the literature;
b) extended the GVAR model into a role that is capable of identifying structural shocks similar to the DSGE model, therefore enabling comparisons between the two. Also shown the theory and application of this structural model with covid 19 data;
c) created a regional UK model which enables policymakers to assess shock impact in different regions across the UK. To my knowledge, this is the first kind of UK regional model using the GVAR approach.

The thesis begins by surveying the historical and current macroeconometric model literature. The second chapter reviews the technical methodologies behind each model. The third chapter compares the GVAR model with alternative macro models for forecasting and scenario analysis. This chapter found that GVAR is better at forecasting due to its advantage in modelling more data and variables. It also made a comparison of the impulse response analysis with DSGE and noted the difficulty of comparing the two. As a result of this difficulty, I have looked into the literature and extended the GVAR model into a structural model that is similar to a simple Keynesian model, enabling the estimate of structural shocks that is often impossible with the VAR literature. Having completed the theoretical studies of the model, the final chapter builds a complete fiscal and monetary model of the UK economy with different regions.

Paper 1 (Chapter 3) - Comparing Global VAR with alternative macro models for forecasting and

scenario analysis

Macroeconometric models such as Global Vector Autoregresive (GVAR), Factor-Augmented VAR (FAVAR) and Dynamic stochastic general equilibrium (DSGE) models are often constructed for analysing monetary policy shocks. However, the rationale behind the modelling is completely different. This chapter aims to investigate how GVAR fares against other macro models. My particular interest is in forecasting and scenario analysis. This paper compares the forecasting ability of GVAR and also shock response from impulse response functions (IRFs) by FAVAR and DSGE. For the forecasting exercise, the ability is compared between a generic AR model with GVAR ex-ante and GVAR-ex post forecasts. For the scenario analysis, IRFs were constructed from GVAR, FAVAR and DSGE models with various shocks. It is easy to see that certain properties are similar among the models such as the long run appears to be unaffected by a monetary shock or that the GDP is negatively affected by it. However, there are also a lot of discrepancies in the short run, particularly in the first 4 quarters. From this, we can conclude that the GVAR model fares best in forecasting that it explicitly allows error correction mechanisms among country models, this is reflected by the dynamic responses from each economy. On the other hand, the FAVAR results look more uniform in their values and shape. The comparison was also made with DSGE IRFs and shows that there is a certain consensus among the theory-driven versus the data-driven models. In contrast with forecasting, the scenario analysis provided by IRFs cannot be evaluated against real-world events. There is no 'true' model to speak of compared to the true values in the forecasting application. Consequently, the IRFs inform us more about the underlying methodology and assumption of the models themselves than can be used to evaluate their accuracies. The paper concludes that the GVAR model is quite adaptable in terms of allowing the data to dictate the short run but also relying on more theory-led identification for the long run.

The main contribution here is letting GVAR competes with other models with different benchmarks and tests, which is not done in the literature. Judging from the analysis above, it certainly shows that GVAR is capable of forecasting data and the extra information could potentially help. However, this is far from conclusive since its forecasting ability is not much better if not the same as a simple AR model. The emphasis on the value of the GVAR model then comes in its ability to include much available data coherently while also providing an adequate forecasting ability.

The evaluation from impulse responses provides an extra check on the model itself and can be used to compare with alternative models. In this case, the IRFs show that certain properties are similar among different models such as the long run appears to be unaffected by a monetary shock or that the GDP is negatively affected by it. However, there are also a lot of discrepancies in the short-run, particularly in the first 4 quarters.

One of the biggest limitations of this comparison is the identification of shocks. Similar to other VAR models in the literature, the identification of shocks is done either via some restrictions or specification of the model to derive the IRFs. In the sense of the DSGE literature, the shocks from the GVAR models are not 'structural' and cannot be relied on for conducting policy.

To overcome this problem, the next chapter builds on this limitation and focused on bridging the gap between GVAR and the structural literature.

Paper 2 (Chapter 4)

Estimating Structural Shocks with the GVAR-DSGE Model: Pre- and Post-Pandemic

This paper investigates the possibility of using the global VAR (GVAR) model to estimate a simple New Keynesian DSGE-type multi-country model. The long-run forecasts from an estimated GVAR model were used to calculate the steady-states of macro variables as differences. The deviations from the long-run forecasts were taken as the deviation from the steady-states and were used to estimate a simple NK open economy model with an IS curve, Philips curve, Taylor rule, and an exchange rate equation. The shocks to these equations were taken as the demand shock, supply shock, monetary shock, and exchange rate shock, respectively. An alternative model was constructed to compare the results from GVAR long-run forecasts. The alternative model used a Hodrick–Prescott (HP) filter to derive deviations from the steady-states. The impulsive response functions from the shocks were then compared to results from other DSGE models in the literature. Both GVAR and HP estimates produced dissimilar results, although the GVAR managed to capture more from the data, given the explicit co-integration relationships. For the IRFs, both GVAR and HP estimated DSGE models appeared to be as expected before the pandemic; however, if we include the pandemic data, i.e., 2020, the IRFs are very different, due to the nature of the policy actions. In general, NK-GVAR models appear to be much more versatile and can capture dynamics that HP filters are not.

This paper developed a NK-GVAR multi-country model that is consistent with the New Keynesian framework. Furthermore, it tested the supply, demand, and monetary policy shocks, before and after the pandemic. The results from impulse responses clearly show that the NK-GVAR is better than fitting the DSGE model with just HP filtered values, which is the norm in the literature. The impact and sudden changes in 2020 caused some of the impulse responses to react strongly and unexpectedly. However, the majority of the shocks are in line with expectations. This is particularly true for the NK-GVAR models, unlike the HP filtered ones, where some of the models could not converge; therefore, indicating misspecification. This implies that the outcome is consistent with the framework. To reinforce the comparison with the wider literature, comparisons were also made with the DSGE literature, which showed that all models reacted similarly to monetary policy shocks, despite differences in the specification and the year.

The biggest limitation of this paper is the fact that the GVAR-DSGE model is not always stable and is heavily dependent on the data (this limitation was mentioned in the paper) – the convergence of the estimation can be random. In the estimated models of the chapter, for example, the data ranging from 1987Q2–2019Q4 33 were estimated without issue. However, if the data is between 1988Q2–2020Q4 then the shocks are not stable and cannot be converged. This problem is partially solved when the data is stretched back i.e. 1986Q2–2020Q4 as the model can be solved but some shocks are not stable. This dependence on specific datasets has limited the application of the GVAR-DSGE model. Further research can look into solving this instability.

Paper 3 (Chapter 5)

An Empirical Analysis of UK Regions with Global Vector Autoregressive approach

This paper builds a UK regional economic model and measures the effects of various shocks on the

UK economy. The paper aims to construct a model that can analyse monetary, fiscal and oil shocks to the regional economies of the UK. The methodology employs the Global vector autoregressive (GVAR) approach which links different UK regions by their distances and linkages to the dominant economy of London. Regional housing price index (HPI), economic activities and fiscal variables. The model also contains the UK interest rate and oil price as national variables. This paper has found evidence of heterogeneous responses to various shocks in different regions, particularly in a region that is further away from London such as Northern Ireland and Scotland.

This paper has contributed to the modelling literature in several ways. Firstly, papers using GVAR to study fiscal and monetary dynamics in a region are not many. This paper provides a way to model economic, fiscal and monetary elements from a regional perspective. Secondly, unlike others in the literature, the fiscal aspect is differentiated between oil and gas revenue and all other revenues. Instead of government expenditure, a net fiscal balance index was constructed. This allows for a more nuanced empirical analysis of different regions. Thirdly this paper has shown a way to model the UK regional economy by determining the dominance of the London region while linking all regions together while a weighting scheme. The effects of fiscal shocks are not often used in the GVAR literature such as (Ricci-Risquete and Ramajo-Hernandez, 2015) thus this paper contributes to this area.

As mentioned in the paper, the shocks from the GVAR and GIRF are in general not structural. Future research could focus on the structural identification of regional fiscal shocks, though the data may not be available and thus cannot be modelled directly. This could be an avenue of research, thus rendering the GIRFs comparable to structural shocks. There are works on identifying the shocks in a structural sense, constructing from a GVAR model, similar to the ones commonly found in the dynamic stochastic general equilibrium (DSGE) models literature such as Dées et al (2009, 2012), Pesaran and Smith (2011) and Kwok (2022).

Overall, this paper adopted a linear treatment for all data and as such, the non-linear method can be used to apply to the crisis period which had affected the UK economy deeply. Another direction of the research is on linking the UK regional economies to the wider world. This would involve more global variables to be modelled either as a collection of indices indicating economic linkage across the European Union and other regions. This will also require an expansion of the endogenous variables such as export and manufacturing index etc.

6.1 Discussions and further research avenues

In critically examining the theory and application of Global Vector Autoregressive (GVAR) models, this thesis contributes significantly to the understanding of macroeconometric modelling. However, it acknowledges certain limitations and opens avenues for future research while also discussing the broad policy implications of its findings.

Theoretically, the thesis confronts the non-structural nature of shocks in GVAR models. Despite efforts to align GVAR with structural shocks akin to those in Dynamic Stochastic General Equilibrium (DSGE) models, the inherent statistical basis of GVAR poses challenges in interpreting and applying these shocks for policy-making. This is compounded by the model's stability and heavy reliance on data specificity. Particularly in scenarios incorporating extensive data variations such as the pandemic's impact, the model's performance can be unpredictably variable.

Methodologically, the thesis highlights the complexity and computational intensity of extended GVAR models. As they incorporate more sophisticated structural shocks, the models demand increased computational resources, potentially limiting their applicability in real-time analysis or in environments with constrained computational capacity. Additionally, the thesis notes the inherent difficulties in directly comparing GVAR model forecasts and shock responses with those from other models due to fundamental differences in underlying assumptions and methodologies.

Looking forward, the thesis identifies several promising research directions. Enhancing structural shock identification within GVAR models represents a significant area, potentially involving hybrid approaches that integrate economic theory into the statistical frameworks. Addressing model stability and robustness, particularly in the face of unpredictable economic conditions, is also crucial. Moreover, incorporating non-linear dynamics to better understand and predict economic downturns or crises, and expanding regional models to include more detailed global linkages, could significantly enhance the model's predictive power and applicability.

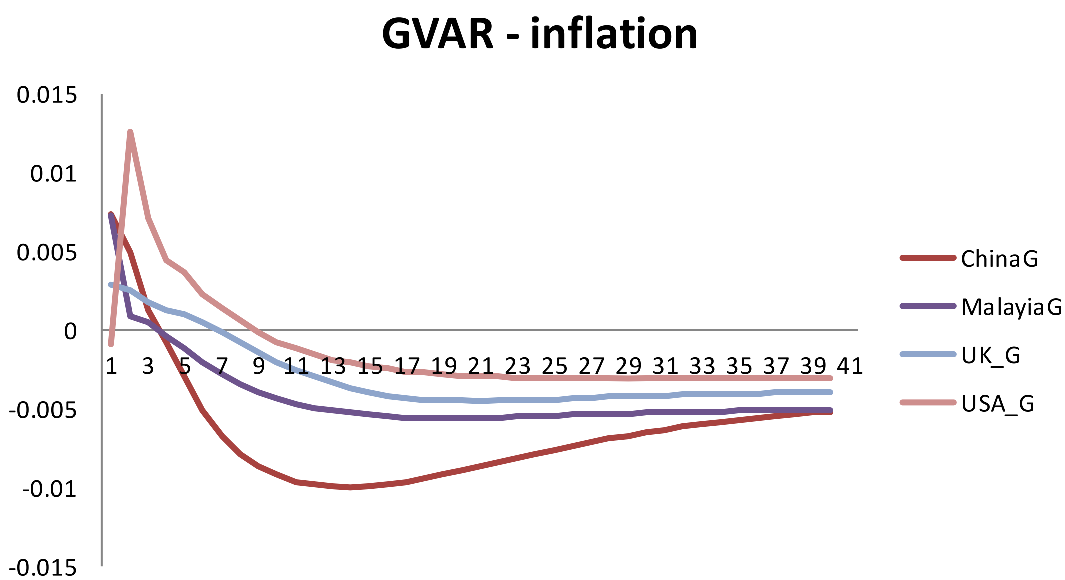
From a policy perspective, the thesis underscores several implications. The development of a regional UK model using the GVAR approach provides a nuanced tool for policymakers, enabling more tailored and effective regional economic policies. Understanding the transmission and impact of various shocks can enhance economic resilience and preparedness. While the adaptability of GVAR in forecasting and scenario analysis underscores its utility in policymaking, it is crucial for policymakers to consider the model's limitations, particularly the non-structural nature of shocks and comparative constraints. Nonetheless, the rich data-driven insights offered by GVAR models can significantly inform and refine policy formulation, provided there is a continued emphasis on developing robust and stable model specifications.

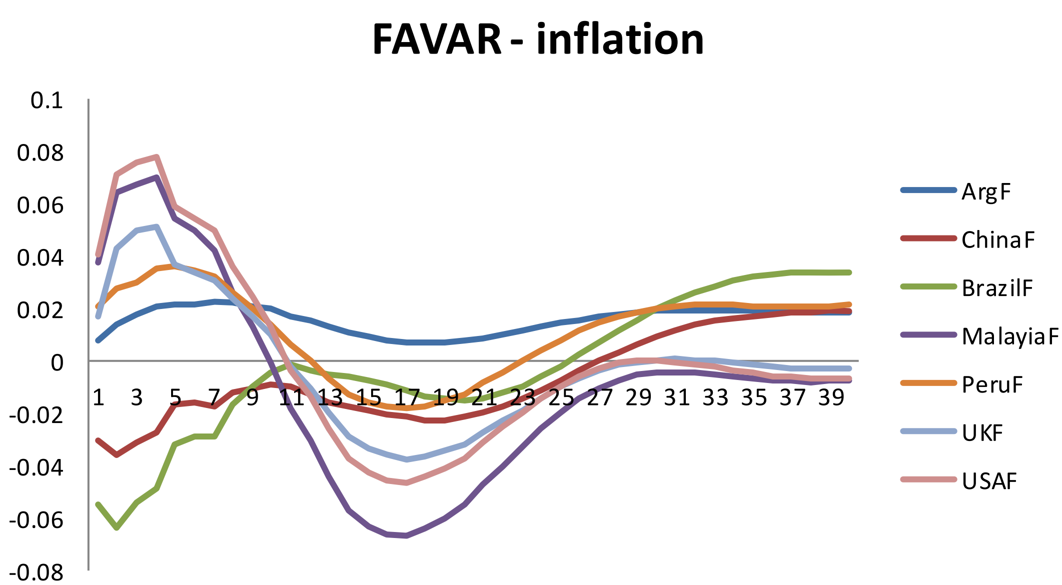
As an economist or policymaker in a central bank, regional analysis using the GVAR approach is particularly useful for understanding and managing the economic diversity within the UK. The UK's regions exhibit varied economic characteristics, industrial structures, and sensitivities to different types of shocks. For instance, a policy change or external shock may affect London's financial services industry differently from manufacturing in the Midlands or tourism in Scotland. Regional analysis allows for the assessment of such heterogeneous impacts, facilitating more informed and regionally sensitive monetary and fiscal policy decisions. It enables the identification of region-specific vulnerabilities and growth opportunities, aiding in targeted intervention strategies. By understanding regional dynamics, central bank policymakers can better gauge the aggregate and distributive impacts of national policy changes, ensuring more equitable and effective economic management across the UK's diverse economic landscape. This, in turn, contributes to more balanced regional development and national economic stability.

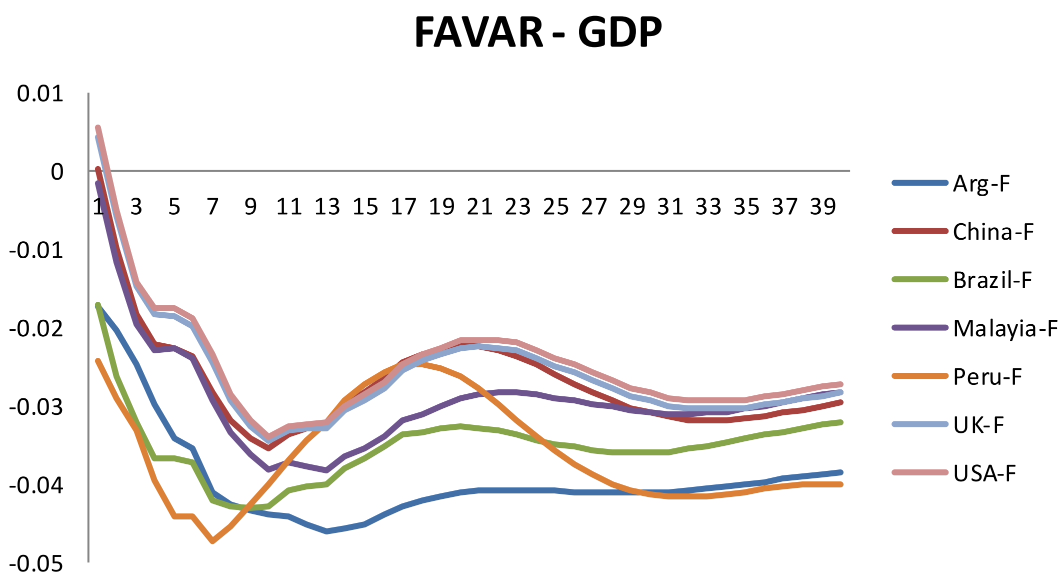
In conclusion, while the thesis acknowledges certain limitations in the GVAR approach, its extensive analysis contributes valuable insights into macroeconometric modelling, offering substantial groundwork for future research and policy formulation. As the field continues to evolve, addressing the highlighted limitations and exploring the identified avenues can significantly advance the understanding and application of GVAR models in capturing the complex dynamics of the global economy.

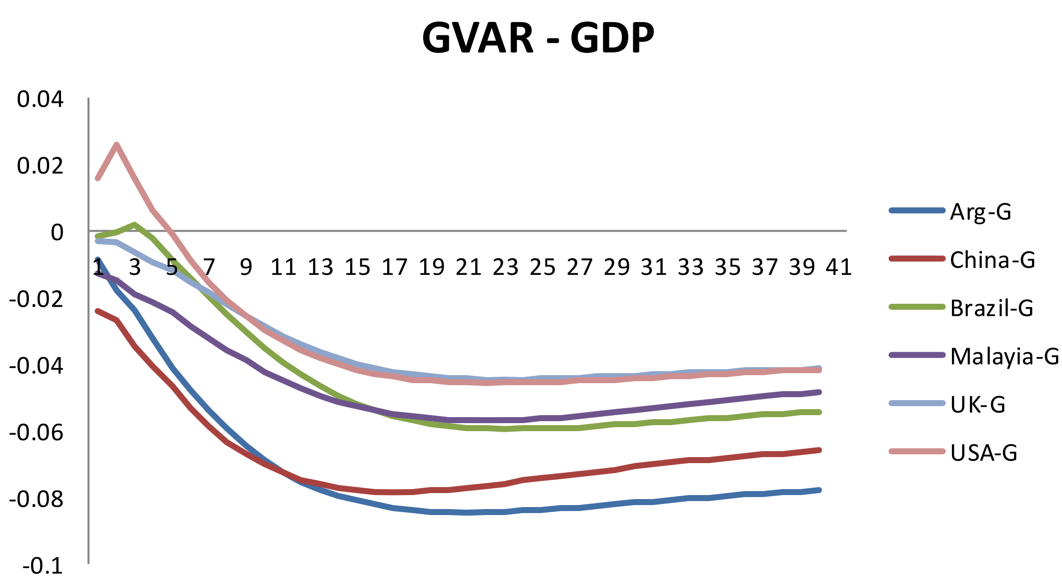
Appendix to chapter 3

Figures 1 – 4 . Shows the GVAR and FAVAR shocks to inflation and real GDP






FAVAR - GDP
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39
Arg-F
China-F
Brazil-F
Malayia-F
Peru-F
UK-F
USA-F


GVAR - GDP
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
Arg-G
China-G
Brazil-G
Malayia-G
UK-G
USA-G

Appendix to chapter 4

Table A1. 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
AUSTRIA	1	1
BELGIUM	1	1
BRAZIL	2	1
CANADA	1	1
CHINA	2	1
CHILE	2	1
FINLAND	2	1
FRANCE	2	1
GERMANY	2	1
INDIA	2	1
INDONESIA	2	1
ITALY	2	1
JAPAN	2	1
KOREA	2	1
MALAYSIA	1	1
MEXICO	1	1
NETHERLANDS	2	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
SPAIN	2	1
SWEDEN	2	1
SWITZERLAND	1	1
THAILAND	2	1
TURKEY	2	1
UNITED KINGDOM	2	1
USA	2	1

Table A2. No. of Co-integrating Relationships for the Individual VARX* Models.

Country	# Cointegrating Relations
ARGENTINA	2
AUSTRALIA	5
AUSTRIA	3
BELGIUM	2
BRAZIL	2
CANADA	4
CHINA	2
CHILE	2
FINLAND	2
FRANCE	3
GERMANY	3
INDIA	2
INDONESIA	3
ITALY	2
JAPAN	2
KOREA	4
MALAYSIA	2
MEXICO	3
NETHERLANDS	2
NORWAY	5
NEW ZEALAND	3
PERU	4
PHILIPPINES	3
SOUTH AFRICA	3
SAUDI ARABIA	3
SINGAPORE	2
SPAIN	3

SWEDEN	2
SWITZERLAND	3
THAILAND	3
TURKEY	1
UNITED KINGDOM	1
USA	2

Table A3. F-Statistics for the Serial Correlation Test of the VECMX* Residuals.

		Fcrit_0.05	**y**	**Dp**	**eq**	**ep**	**r**	**lr**
ARGENTINA	F(4,140)	2.44	1.16	0.98	1.05	0.75	0.89	
AUSTRALIA	F(4,142)	2.44	2.69	0.35	0.20	1.90	3.16	1.23
AUSTRIA	F(4,144)	2.43	3.86	1.34	3.29	3.18	0.68	7.25
BELGIUM	F(4,145)	2.43	2.47	1.96	1.48	5.03	5.36	1.92
BRAZIL	F(4,141)	2.44	2.77	2.28		0.63	1.09	
CANADA	F(4,143)	2.43	1.24	2.20	1.80	3.85	2.93	1.08
CHINA	F(4,141)	2.44	3.97	4.28		1.09	6.00	
CHILE	F(4,140)	2.44	1.12	2.29	1.27	2.14	0.34	
FINLAND	F(4,140)	2.44	1.37	4.98	2.33	1.52	1.80	
FRANCE	F(4,138)	2.44	1.39	3.50	0.34	0.26	2.31	3.02
GERMANY	F(4,138)	2.44	1.81	0.31	0.51	1.46	0.48	1.22
INDIA	F(4,139)	2.44	0.87	3.27	1.30	1.04	1.13	0.18
INDONESIA	F(4,140)	2.44	2.06	3.86		2.35	3.02	
ITALY	F(4,139)	2.44	4.00	2.12	1.04	0.59	2.05	2.40
JAPAN	F(4,139)	2.44	1.65	0.20	0.53	4.27	1.37	2.39
KOREA	F(4,137)	2.44	3.41	4.00	2.00	2.27	0.47	1.61
MALAYSIA	F(4,145)	2.43	0.71	0.19	1.91	3.82	2.84	
MEXICO	F(4,144)	2.43	2.35	1.27		1.18	2.21	
NETHERLANDS	F(4,139)	2.44	0.99	0.69	1.90	1.99	3.19	2.32
NORWAY	F(4,136)	2.44	2.36	1.64	1.25	1.43	1.99	3.50
NEW ZEALAND	F(4,138)	2.44	1.09	3.72	2.21	2.28	3.53	5.67

PERU	F(4,139)	2.44	2.56	4.69		3.02	6.10	
PHILIPPINES	F(4,139)	2.44	4.10	1.29	0.42	0.07	3.11	
SOUTH AFRICA	F(4,138)	2.44	3.73	2.98	1.07	2.30	1.02	0.79
SAUDI ARABIA	F(4,141)	2.44	19.56	1.21		0.78		
SINGAPORE	F(4,140)	2.44	2.32	2.21	2.12	1.48	3.86	
SPAIN	F(4,138)	2.44	4.07	3.01	1.01	1.80	1.63	1.45
SWEDEN	F(4,139)	2.44	0.99	4.96	4.09	1.89	2.03	3.07
SWITZERLAND	F(4,144)	2.43	5.93	4.06	1.37	2.00	1.01	1.68
THAILAND	F(4,139)	2.44	0.75	3.10	1.06	2.45	0.67	
TURKEY	F(4,142)	2.44	1.15	2.65		0.78	2.63	
UNITED KINGDOM	F(4,140)	2.44	1.56	1.98	0.67	2.79	1.21	0.66
USA	F(4,142)	2.44	1.05	1.45	0.99		4.59	0.50

Table A4. Average Pairwise Correlations -NK-GVAR (M1).

	Supply_Supply	Supply_Demand	Supply_MP	Supply_RE	Supply_Oil	Demand_Demand	Demand_MP	Demand_RE	Demand_Oil	MP_MP	MP_RE	MP_Oil	RE_RE	RE_Oil	Oil_Oil
OIL															1
USA	0.31	0.11	0.22	0.04	−0.03	0.04	0.05	−0.07	0.42	0.27	−0.05	0.10			
CHINA	0.02	0.01	−0.08	−0.07	−0.01	0.07	0.07	0.00	0.02	0.09	0.03	0.20	−0.04	0.01	
JAPAN	0.57	0.22	0.04	0.02	−0.05	0.09	0.13	0.02	0.14	0.26	−0.03	−0.05	−0.15	0.26	
UNITED KINGDOM	0.62	0.25	0.04	0.03	−0.18	0.23	0.05	0.02	−0.14	0.29	0.00	0.09	−0.01	−0.27	
AUSTRIA	0.62	0.24	0.02	0.04	−0.15	0.19	0.04	0.01	−0.11	0.34	0.00	0.19	−0.02	0.11	
BELGIUM	0.62	0.25	0.03	0.03	−0.18	0.21	0.05	0.03	−0.13	0.32	0.00	0.00	−0.01	0.10	
FINLAND	0.62	0.25	0.04	0.03	−0.17	0.05	0.01	−0.05	−0.13	0.30	0.01	0.01	−0.02	0.16	
FRANCE	0.63	0.25	0.05	0.03	−0.15	0.13	0.08	0.00	−0.05	0.31	0.00	−0.05	−0.03	0.06	
GERMANY	0.07	0.03	0.00	0.00	0.42	0.01	0.02	−0.01	0.08	0.30	0.00	0.02	−0.01	0.13	
ITALY	0.44	0.15	0.06	0.03	0.10	0.07	0.11	0.03	0.05	0.28	0.05	−0.09	0.01	−0.21	
NETHERLANDS	0.51	0.18	0.03	0.03	0.01	0.06	0.02	0.00	−0.12	0.31	0.00	0.09	−0.05	−0.18	
SPAIN	0.62	0.24	0.05	0.03	−0.09	0.06	0.05	0.02	−0.19	0.23	0.04	−0.09	0.03	−0.12	
NORWAY	0.53	0.20	0.03	0.01	−0.08	0.00	0.00	0.03	−0.02	0.11	0.01	−0.02	0.04	−0.23	
SWEDEN	0.62	0.25	0.04	0.03	−0.20	0.21	0.05	0.02	−0.14	0.24	0.01	0.10	0.05	−0.31	
SWITZERLAND	0.62	0.25	0.03	0.03	−0.18	0.04	0.05	0.02	0.05	0.10	−0.02	0.09	0.00	0.16	

AUSTRALIA	0.60	0.24	0.03	0.02	−0.11	0.05	0.05	−0.02	0.04	0.12	0.00	−0.01	0.09	−0.46
CANADA	0.60	0.24	0.05	0.02	−0.09	0.10	0.10	−0.03	0.03	0.24	−0.04	0.11	0.09	−0.50
NEW ZEALAND	0.62	0.24	0.04	0.03	−0.16	0.06	0.09	0.03	−0.04	0.09	0.01	−0.04	0.09	−0.33
ARGENTINA	0.10	0.04	0.04	−0.01	−0.06	−0.03	−0.04	0.00	0.09	0.07	0.03	0.01	−0.04	−0.08
BRAZIL	0.47	0.18	0.00	0.00	−0.12	0.08	0.04	0.05	−0.03	0.01	0.03	−0.07	0.06	−0.19
CHILE	0.29	0.07	0.06	0.02	0.04	0.01	0.05	0.05	−0.09	0.06	0.00	−0.09	0.09	−0.18
MEXICO	0.16	0.04	0.00	0.07	−0.17	0.00	0.10	−0.03	0.13	0.09	0.01	0.01	0.11	−0.47
PERU	−0.03	0.00	0.00	0.01	0.09	0.04	0.05	−0.01	−0.06	−0.08	−0.03	0.00	0.01	0.14
INDONESIA	−0.06	−0.03	−0.02	−0.01	−0.02	0.11	0.10	−0.01	−0.05	0.12	0.01	0.07	−0.01	−0.10
KOREA	0.62	0.24	0.05	0.03	−0.18	0.01	−0.04	−0.02	0.11	0.13	0.02	−0.04	0.04	−0.31
MALAYSIA	0.62	0.25	0.02	0.02	−0.16	0.07	0.07	−0.05	0.05	0.06	−0.01	0.04	0.09	−0.08
PHILIPPINES	0.62	0.25	0.03	0.03	−0.19	0.05	−0.02	−0.03	0.10	0.13	−0.01	−0.02	0.06	−0.08
SINGAPORE	0.56	0.23	0.05	0.02	−0.05	0.10	−0.03	−0.01	−0.12	0.22	0.00	0.07	0.06	−0.20
THAILAND	0.62	0.25	0.02	0.02	−0.13	0.00	0.00	−0.04	0.04	0.20	−0.04	0.11	0.03	0.14
INDIA	−0.13	−0.06	−0.11	−0.01	0.02	0.02	−0.09	0.01	0.04	0.10	0.02	−0.13	0.03	0.28
SOUTH AFRICA	0.18	0.05	0.10	0.01	0.14	0.06	0.02	0.03	−0.06	0.09	0.01	−0.18	0.01	−0.12
SAUDI ARABIA	−0.13	−0.05	−0.08	−0.01	0.04	0.00	0.06	0.01	0.11				−0.04	0.37
TURKEY	0.49	0.21	−0.02	0.02	−0.20	0.16	−0.01	0.03	0.03	0.03	0.02	−0.13	0.02	0.01

Table A5. Country Weights NK-GVAR.

Country	Dp_c	y_c	r_c	ep_c
ARGENTINA	0.010	0.010	0.010	0.010
AUSTRALIA	0.015	0.015	0.015	0.015
AUSTRIA	0.006	0.006	0.006	0.006
BELGIUM	0.007	0.007	0.007	0.007
BRAZIL	0.035	0.035	0.035	0.035
CANADA	0.024	0.024	0.024	0.024
CHINA	0.134	0.134	0.136	0.134
CHILE	0.004	0.004	0.004	0.004
FINLAND	0.003	0.003	0.004	0.003
FRANCE	0.039	0.039	0.039	0.039
GERMANY	0.054	0.054	0.054	0.054
INDIA	0.059	0.059	0.059	0.059

INDONESIA	0.016	0.016	0.016	0.016
ITALY	0.035	0.035	0.035	0.035
JAPAN	0.081	0.081	0.082	0.081
KOREA	0.024	0.024	0.025	0.024
MALAYSIA	0.007	0.007	0.007	0.007
MEXICO	0.028	0.028	0.029	0.028
NETHERLANDS	0.012	0.012	0.012	0.012
NORWAY	0.005	0.005	0.005	0.005
NEW ZEALAND	0.002	0.002	0.002	0.002
PERU	0.004	0.004	0.004	0.004
PHILIPPINES	0.006	0.006	0.006	0.006
SOUTH AFRICA	0.009	0.009	0.009	0.009
SAUDI ARABIA	0.011	0.011		0.011
SINGAPORE	0.004	0.004	0.004	0.004
SPAIN	0.026	0.026	0.027	0.026
SWEDEN	0.006	0.006	0.006	0.006
SWITZERLAND	0.006	0.006	0.006	0.006
THAILAND	0.010	0.010	0.010	0.010
TURKEY	0.018	0.018	0.018	0.018
UNITED KINGDOM	0.040	0.040	0.041	0.040
USA	0.260	0.260	0.263	0.260

Table A6. Regional Weights NK-GVAR.

Region	Country	Dp_c	y_c	r_c	ep_c
japan	japan	1.00	1.00	1.00	1.00
la	arg	0.12	0.12	0.12	0.12
la	bra	0.43	0.43	0.43	0.43
la	chl	0.05	0.05	0.05	0.05
la	mex	0.35	0.35	0.35	0.35
la	per	0.05	0.05	0.05	0.05

odc	nor	0.08	0.08	0.08	0.08
odc	swe	0.11	0.11	0.11	0.11
odc	switz	0.10	0.10	0.10	0.10
odc	austlia	0.26	0.26	0.26	0.26
odc	can	0.41	0.41	0.41	0.41
odc	nzld	0.04	0.04	0.04	0.04
restworld	safrc	0.24	0.24	0.33	0.24
restworld	sarbia	0.28	0.28		0.28
restworld	turk	0.48	0.48	0.67	0.48
uk	uk	1	1	1	1
usa	usa	1	1	1	1
euro	austria	0.032	0.032	0.032	0.032
euro	bel	0.038	0.038	0.038	0.038
euro	fin	0.019	0.019	0.019	0.019
euro	france	0.214	0.214	0.214	0.214
euro	germ	0.295	0.295	0.295	0.295
euro	italy	0.190	0.190	0.190	0.190
euro	neth	0.067	0.067	0.067	0.067
euro	spain	0.145	0.145	0.145	0.145
restasia	indns	0.061	0.061	0.061	0.061
restasia	kor	0.094	0.094	0.094	0.094
restasia	mal	0.026	0.026	0.026	0.026
restasia	phlp	0.022	0.022	0.022	0.022
restasia	sing	0.017	0.017	0.017	0.017
restasia	thai	0.038	0.038	0.038	0.038
restasia	india	0.226	0.226	0.226	0.226
restasia	china	0.517	0.517	0.517	0.517

Table A7. Oil model-NK-GVAR.

Country	Yvar	Xvar1	coeffs1	se1	t-ratio1	se_NW1	t-ratioNW1	LM_CHSQ(4)	GRsq
OIL	poil_c	poil_c(-1)	0.47	0.08	5.66	0.12	3.89	7.11	0.40

Table A8. Phillips Curve-NK-GVAR.

Country	coeffs1	coeffs2	coeffs3	t-ratio1	t-ratio2	t-ratio3
USA	0.06	0.91	0.14	0.55	4.77	3.09
CHINA	0.47	0.21	0.14	5.51	2.74	1.58
JAPAN	0.00	0.99	0.02			
UNITED KINGDOM	0.16	0.79	0.12	1.67	6.51	4.36
AUSTRIA	0.06	0.93	0.05			
BELGIUM	0.04	0.95	0.11			
FINLAND	0.35	0.62	0.04	4.05	5.16	2.65
FRANCE	0.09	0.86	0.06	0.76	6.24	2.27
GERMANY	0.04	0.00	0.09			
ITALY	0.18	0.81	0.00			
NETHERLANDS	0.18	0.57	0.07	1.95	3.89	2.18
SPAIN	0.08	0.91	0.04	0.69	6.08	1.78
NORWAY	0.06	0.93	0.03			
SWEDEN	0.04	0.87	0.15	0.36	5.64	3.38
SWITZERLAND	0.28	0.71	0.11			
AUSTRALIA	0.06	0.78	0.19	0.54	3.97	2.49
CANADA	0.16	0.74	0.08	1.69	6.67	2.88
NEW ZEALAND	0.00	0.99	0.10			
ARGENTINA	0.01	0.98	0.00			
BRAZIL	0.25	0.74	0.13			
CHILE	0.30	0.65	0.00			
MEXICO	0.41	0.58	0.00			
PERU	0.26	0.49	0.00			

INDONESIA	0.38	0.59	0.00			
KOREA	0.19	0.80	0.14			
MALAYSIA	0.03	0.96	0.04			
PHILIPPINES	0.29	0.70	0.16			
SINGAPORE	0.15	0.70	0.05	1.59	3.72	1.88
THAILAND	0.18	0.81	0.02			
INDIA	0.13	0.50	0.00			
SOUTH AFRICA	0.07	0.92	0.00			
SAUDI ARABIA	0.35	0.29	0.00			
TURKEY	0.11	0.74	0.27	0.93	1.64	1.28

Table A9. IS Curve-NK-GVAR.

Country	coeffs1	coeffs2	coeffs3	coeffs4	coeffs5	coeffs6
USA	0.69	−0.01	0.01			
CHINA	0.64	−0.43	0.43	0.00	0.00	0.22
JAPAN	0.71	−0.34	0.34	−0.05	0.05	0.27
UNITED KINGDOM	0.29	−0.49	0.49	0.09	−0.09	1.08
AUSTRIA	0.18	−0.49	0.49	−0.14	0.14	1.06
BELGIUM	0.15	−0.13	0.13	−0.11	0.11	1.00
FINLAND	0.09	0.00	0.00	0.12	−0.12	1.32
FRANCE	0.27	0.00	0.00	−0.04	0.04	0.73
GERMANY	0.06	−0.07	0.07	−0.05	0.05	1.27
ITALY	0.08	0.00	0.00	−0.21	0.21	0.57
NETHERLANDS	0.07	−0.03	0.03	0.00	0.00	0.82
SPAIN	0.24	0.00	0.00	−0.17	0.17	0.71
NORWAY	−0.09	0.00	0.00	−0.06	0.06	0.52
SWEDEN	0.04	−0.32	0.32	0.08	−0.08	1.21
SWITZERLAND	0.01	0.00	0.00	−0.03	0.03	0.79
AUSTRALIA	0.19	0.00	0.00	−0.01	0.01	0.53

CANADA	0.51	0.00	0.00	−0.02	0.02	0.81
NEW ZEALAND	0.03	0.00	0.00	−0.04	0.04	0.54
ARGENTINA	0.46	0.00	0.00	0.00	0.00	0.64
BRAZIL	0.09	−0.01	0.01	−0.04	0.04	1.20
CHILE	0.20	−0.29	0.29	−0.32	0.32	1.10
MEXICO	0.32	−0.15	0.15	−0.02	0.02	1.01
PERU	0.57	0.00	0.00	−0.02	0.02	0.32
INDONESIA	0.64	0.00	0.00	−0.11	0.11	1.23
KOREA	0.46	0.00	0.00	0.01	−0.01	0.39
MALAYSIA	0.20	0.00	0.00	0.00	0.00	1.52
PHILIPPINES	0.72	0.00	0.00	0.04	−0.04	0.63
SINGAPORE	0.06	−0.11	0.11	0.12	−0.12	1.46
THAILAND	0.67	0.00	0.00	0.04	−0.04	1.38
INDIA	0.27	0.00	0.00	−0.12	0.12	0.00
SOUTH AFRICA	0.56	0.00	0.00	−0.12	0.12	0.57
SAUDI ARABIA	0.50	0.00	−0.15	0.15	0.34	
TURKEY	−0.01	−0.22	0.22	−0.15	0.15	1.40

Table A10. Taylor rule-NK-GVAR.

Country	coeffs1	coeffs2	coeffs3	se1	se2	se3	t-ratio1	t-ratio2	t-ratio3
USA	0.92	0.15	0.02	0.03	0.05	0.01	34.94	3.00	1.77
CHINA	0.85	0.03	0.02	0.07	0.03	0.02	12.53	1.10	1.16
JAPAN	0.91	0.16	0.00	0.03	0.05		34.97	3.28	
UNITED KINGDOM	0.83	0.28	0.00	0.03	0.05		26.16	5.47	
AUSTRIA	0.96	0.00	0.03	0.03	0.06		31.14	0.50	
BELGIUM	0.94	0.11	0.03	0.03	0.06	0.01	30.14	1.81	2.15
FINLAND	0.90	0.20	0.02	0.03	0.05	0.01	34.26	4.22	2.43
FRANCE	0.84	0.24	0.03	0.04	0.06	0.01	23.69	4.08	2.17
GERMANY	0.85	0.10	0.03	0.04	0.07	0.01	20.95	1.47	2.98

ITALY	0.84	0.23	0.03	0.04	0.09	0.02	19.86	2.71	1.30
NETHERLANDS	0.95	0.02	0.04	0.03	0.06	0.01	28.82	0.27	3.40
SPAIN	0.92	0.09	0.01	0.04	0.07	0.02	24.23	1.24	0.57
NORWAY	0.84	0.11	0.04	0.07	0.06	0.03	12.79	1.70	1.41
SWEDEN	0.92	0.10	0.01	0.03	0.05	0.02	27.49	1.87	0.69
SWITZERLAND	0.49	0.03	0.07	0.06	0.04	0.01	8.73	0.67	6.50
AUSTRALIA	0.42	0.12	0.14	0.05	0.03	0.02	9.04	4.43	8.66
CANADA	0.80	0.29	0.00	0.04	0.05		22.38	5.49	
NEW ZEALAND	0.49	0.33	0.18	0.05	0.04	0.04	9.33	7.66	5.11
ARGENTINA	−0.27	0.28	0.00	0.12	0.12		−2.27	2.34	
BRAZIL	−0.61	1.51	0.00	0.14	0.22		−4.37	6.88	
CHILE	0.40	0.63	0.01	0.11	0.18	0.04	3.56	3.49	0.33
MEXICO	0.01	0.37	0.06	0.04	0.02	0.02	0.33	18.22	2.48
PERU	−0.19	0.39	0.04	0.18	0.11	0.22	−1.03	3.52	0.19
INDONESIA	0.67	0.22	0.10	0.04	0.04	0.02	16.27	4.88	4.69
KOREA	0.72	0.20	0.09	0.06	0.06	0.03	12.40	3.35	3.16
MALAYSIA	0.54	0.00	0.01	0.07	0.02		7.96	0.15	
PHILIPPINES	0.73	0.22	0.01	0.05	0.05	0.02	15.57	4.60	0.59
SINGAPORE	0.97	0.06	0.02	0.02	0.04	0.01	47.89	1.42	3.62
THAILAND	0.81	0.13	0.00	0.04	0.07		18.10	1.95	
INDIA	0.49	0.16	0.00	0.12	0.08		4.01	2.06	
SOUTH AFRICA	0.64	0.14	0.06	0.05	0.04	0.01	12.63	3.12	7.06
TURKEY	0.64	0.12	0.09	0.06	0.05	0.03	10.98	2.51	2.74

Table A11. Real Exchange equation NK-GVAR.

Country	coeffs1	coeffs2	coeffs3	se1	se2	t-ratio1	t-ratio2
USA	0.01			0.00		3.24	
CHINA	0.79	−0.79	1.00	0.05	0.05	15.07	15.07
JAPAN	0.73	−0.73	1.00	0.06	0.06	12.43	12.43
UNITED KINGDOM	0.58	−0.58	1.00	0.07	0.07	7.98	7.98

AUSTRIA	0.55	−0.55	1.00	0.07	0.07	7.94	7.94
BELGIUM	0.66	−0.66	1.00	0.06	0.06	10.60	10.60
FINLAND	0.58	−0.58	1.00	0.07	0.07	8.69	8.69
FRANCE	0.39	−0.39	1.00	0.08	0.08	5.02	5.02
GERMANY	0.49	−0.49	1.00	0.07	0.07	6.62	6.62
ITALY	0.49	−0.49	1.00	0.07	0.07	6.55	6.55
NETHERLANDS	0.73	−0.73	1.00	0.06	0.06	12.52	12.52
SPAIN	0.84	−0.84	1.00	0.05	0.05	17.99	17.99
NORWAY	0.42	−0.42	1.00	0.08	0.08	5.64	5.64
SWEDEN	0.71	−0.71	1.00	0.06	0.06	12.19	12.19
SWITZERLAND	0.49	−0.49	1.00	0.07	0.07	6.70	6.70
AUSTRALIA	0.59	−0.59	1.00	0.07	0.07	8.94	8.94
CANADA	0.84	−0.84	1.00	0.04	0.04	19.33	19.33
NEW ZEALAND	0.35	−0.35	1.00	0.07	0.07	4.90	4.90
ARGENTINA	0.54	−0.54	1.00	0.07	0.07	7.46	7.46
BRAZIL	0.28	−0.28	1.00	0.09	0.09	3.15	3.15
CHILE	0.52	−0.52	1.00	0.07	0.07	7.04	7.04
MEXICO	0.69	−0.69	1.00	0.06	0.06	11.84	11.84
PERU	0.59	−0.59	1.00	0.07	0.07	8.64	8.64
INDONESIA	0.48	−0.48	1.00	0.07	0.07	6.88	6.88
KOREA	0.73	−0.73	1.00	0.05	0.05	14.37	14.37
MALAYSIA	0.53	−0.53	1.00	0.07	0.07	7.60	7.60
PHILIPPINES	0.71	−0.71	1.00	0.06	0.06	11.80	11.80
SINGAPORE	0.66	−0.66	1.00	0.06	0.06	10.36	10.36
THAILAND	0.56	−0.56	1.00	0.07	0.07	8.02	8.02
INDIA	0.29	−0.29	1.00	0.08	0.08	3.66	3.66
SOUTH AFRICA	0.68	−0.68	1.00	0.06	0.06	11.56	11.56
SAUDI ARABIA	0.82	−0.82	1.00	0.05	0.05	16.54	16.54
TURKEY	0.20	−0.20	1.00	0.10	0.10	1.98	1.98

Appendix to chapter 5

Table A1. VARX* Order of individual models p = lag order of domestic variables, q = lag order of foreign variables.

	p	q
North East	2	2
North West	2	2
York and Humber	2	2
East Midlands	2	2
West Midlands	2	2
East	2	2
London	2	2
South East	2	2
South West	2	2
Wales	2	2
Scotland	2	2
Northern Ireland	2	2

Table A2. No. of Co-integrating Relationships for the Individual VARX* Models.

Region	# Cointegrating relations
North East	1
North West	1
York and Humber	1
East Midlands	1
West Midlands	1
East	1
London	1

South East	1
South West	1
Wales	1
Scotland	1
Northern Ireland	1

Table A3. Order of Weak Exogeneity Regression Equations

	p*	q*
North East	1	1
North West	1	1
York and Humber	1	1
East Midlands	1	1
West Midlands	1	1
East	1	1
London	1	1
South East	1	1
South West	1	1
Wales	1	1
Scotland	1	1
Northern Ireland	1	1

Table A4. Unit Root Tests for the Global Variables at the 5% Significance Level

Global Variables	Test	Critical Value	Statistic
poil (with trend)	ADF	-3.45	-2.11255
poil (with trend)	WS	-3.24	-2.14424
poil (no trend)	ADF	-2.89	-2.17854
poil (no trend)	WS	-2.55	-1.63432
Dpoil	ADF	-2.89	-5.95018
Dpoil	WS	-2.55	-6.12053
DDpoil	ADF	-2.89	-10.0465
Dpoil	WS	-2.55	-10.2126

r (with trend)	ADF	-3.45	-2.47846
r (with trend)	WS	-3.24	-2.64185
r (no trend)	ADF	-2.89	-1.85707
r (no trend)	WS	-2.55	-1.26796
Dr	ADF	-2.89	-3.32671
Dr	WS	-2.55	-3.42956
DDr	ADF	-2.89	-10.0477
Dr	WS	-2.55	-10.263

Table A5. Regional Capitals

Regions	Short name	Capital
North East	NE	Newcastle upon Tyne
North West	NW	Manchester
York and Humber	YH	Leeds
East Midlands	EM	Leicester
West Midlands	WM	Birmingham
East	ET	Cambridge
London	LN	London
South East	SE	Surrey
South West	SW	Bristol
Wales	WL	Cardiff
Scotland	SC	Edinburgh
Northern Ireland	NI	Belfast

Table A6 Linear distance between each regional capital (km)

	NE	NW	YH	EM	WM	ET	LN	SE	SW	WL	SC	NI
NE	0	56.238	98.275	76.141	57.177	173.466	212.793	221.438	172.8	182.045	337.472	308.763
NW	56.238	0	57.433	119.602	119.602	212.471	262.405	274.278	226.502	231.355	281.319	271.322
YH	98.275	57.433	0	132.522	148.187	209.569	273.087	291.457	269.991	280.273	261.073	298.359
EM	76.141	119.602	132.522	0	54.332	97.349	143.566	160.885	162.98	189.909	392.412	384.377
WM	57.177	119.602	148.187	54.332	0	140.649	162.653	171.84	121.355	141.265	395.156	355.171

ET	173.466	212.471	209.569	97.349	140.649	0	79.455	108.575	202.523	240.39	469.115	480.853
LN	212.793	262.405	273.087	143.566	162.653	79.455	0	30.123	169.759	211.249	533.645	517.746
SE	221.438	274.278	291.457	160.885	171.84	108.575	30.123	0	156.884	198.32	553.285	525.963
SW	172.8	226.502	269.991	162.98	121.355	202.523	169.759	156.884	0	41.58	497.206	230.018
WL	182.045	231.355	280.273	189.909	141.265	240.39	211.249	198.32	41.58	0	497.206	392.06
SC	337.472	281.319	261.073	392.412	395.156	469.115	533.645	553.285	497.206	497.206	0	230.018
NI	308.763	271.322	298.359	384.377	355.171	480.853	517.746	525.963	230.018	392.06	230.018	0

Table A7 Absolute Inverse distance weighting (IDW) of each region

	NE	NW	YH	EM	WM	ET	LN	SE	SW	WL	SC	NI
NE	0.0000	0.0178	0.0102	0.0131	0.0175	0.0058	0.0047	0.0045	0.0058	0.0055	0.0030	0.0032
NW	0.0178	0.0000	0.0174	0.0084	0.0084	0.0047	0.0038	0.0036	0.0044	0.0043	0.0036	0.0037
YH	0.0102	0.0174	0.0000	0.0075	0.0067	0.0048	0.0037	0.0034	0.0037	0.0036	0.0038	0.0034
EM	0.0131	0.0084	0.0075	0.0000	0.0184	0.0103	0.0070	0.0062	0.0061	0.0053	0.0025	0.0026
WM	0.0175	0.0084	0.0067	0.0184	0.0000	0.0071	0.0061	0.0058	0.0082	0.0071	0.0025	0.0028
ET	0.0058	0.0047	0.0048	0.0103	0.0071	0.0000	0.0126	0.0092	0.0049	0.0042	0.0021	0.0021
LN	0.0047	0.0038	0.0037	0.0070	0.0061	0.0126	0.0000	0.0332	0.0059	0.0047	0.0019	0.0019
SE	0.0045	0.0036	0.0034	0.0062	0.0058	0.0092	0.0332	0.0000	0.0064	0.0050	0.0018	0.0019
SW	0.0058	0.0044	0.0037	0.0061	0.0082	0.0049	0.0059	0.0064	0.0000	0.0241	0.0020	0.0043
WL	0.0055	0.0043	0.0036	0.0053	0.0071	0.0042	0.0047	0.0050	0.0241	0.0000	0.0020	0.0026
SC	0.0030	0.0036	0.0038	0.0025	0.0025	0.0021	0.0019	0.0018	0.0020	0.0020	0.0000	0.0043
NI	0.0032	0.0037	0.0034	0.0026	0.0028	0.0021	0.0019	0.0019	0.0043	0.0026	0.0043	0.0000
Sum	0.0910	0.0801	0.0682	0.0875	0.0907	0.0677	0.0855	0.0812	0.0759	0.0683	0.0296	0.0329

Table A8. Regional Weights – Final Weight Matrix

	NE	NW	YH	EM	WM	ET	LN	SE	SW	WL	SC	NI
NE	0.0000	0.2221	0.1492	0.1502	0.1927	0.0851	0.0550	0.0556	0.0763	0.0805	0.1001	0.0986
NW	0.1953	0.0000	0.2553	0.0956	0.0921	0.0695	0.0446	0.0449	0.0582	0.0633	0.1200	0.1122
YH	0.1118	0.2175	0.0000	0.0863	0.0744	0.0705	0.0428	0.0423	0.0488	0.0523	0.1294	0.1020
EM	0.1443	0.1044	0.1106	0.0000	0.2028	0.1517	0.0815	0.0766	0.0808	0.0771	0.0861	0.0792
WM	0.1921	0.1044	0.0989	0.2105	0.0000	0.1050	0.0719	0.0717	0.1086	0.1037	0.0855	0.0857
ET	0.0633	0.0588	0.0700	0.1175	0.0783	0.0000	0.1472	0.1135	0.0651	0.0609	0.0720	0.0633
LN	0.0516	0.0476	0.0537	0.0796	0.0677	0.1858	0.0000	0.4090	0.0776	0.0693	0.0633	0.0588
SE	0.0496	0.0455	0.0503	0.0711	0.0641	0.1360	0.3883	0.0000	0.0840	0.0739	0.0610	0.0579
SW	0.0636	0.0551	0.0543	0.0702	0.0908	0.0729	0.0689	0.0785	0.0000	0.3522	0.0679	0.1323
WL	0.0603	0.0540	0.0523	0.0602	0.0780	0.0614	0.0554	0.0621	0.3169	0.0000	0.0679	0.0776
SC	0.0325	0.0444	0.0562	0.0291	0.0279	0.0315	0.0219	0.0223	0.0265	0.0295	0.0000	0.1323
NI	0.0356	0.0460	0.0491	0.0297	0.0310	0.0307	0.0226	0.0234	0.0573	0.0374	0.1468	0.0000
Sum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table A9 weak exogeneity test – variables that failed the test is in bold

Region	F test	Fcrit_0.05	ys	eas	hpis	fiss	bizs	ogs	poil	r
North East	F(1,206)	3.887	**4.026**	0.004	0.631	0.329	0.179	1.185	0.582	0.480
North West	F(1,206)	3.887	0.174	0.027	0.290	0.007	0.010	0.574	0.101	1.887
York and Humber	F(1,206)	3.887	0.092	0.967	0.599	0.008	0.016	0.515	1.133	0.549
East Midlands	F(1,206)	3.887	0.085	1.533	0.358	1.000	0.032	2.104	**6.131**	0.035
West Midlands	F(1,207)	3.887	0.201	0.357	0.004	**5.179**	0.852	0.780	0.171	1.618
East	F(1,206)	3.887	0.008	0.156	2.601	**4.408**	0.193	0.352	0.386	**4.442**
London	F(1,207)	3.887		2.345		1.260	0.132			
South East	F(1,206)	3.887	0.019	0.006	0.001	0.695	1.534	1.151	**4.980**	0.007
South West	F(1,206)	3.887	0.000	0.000	2.159	**4.777**	0.361	0.108	0.529	2.029
Wales	F(1,207)	3.887	0.671	0.283	0.487	0.681	0.815	2.402	0.035	0.319
Scotland	F(1,206)	3.887	2.005	1.191	1.393	0.002	0.990	0.245	0.085	0.424
Northern Ireland	F(1,207)	3.887	0.708	0.001	2.955	0.131	0.941	0.517	0.856	0.175

Table A10 Persistent profiles

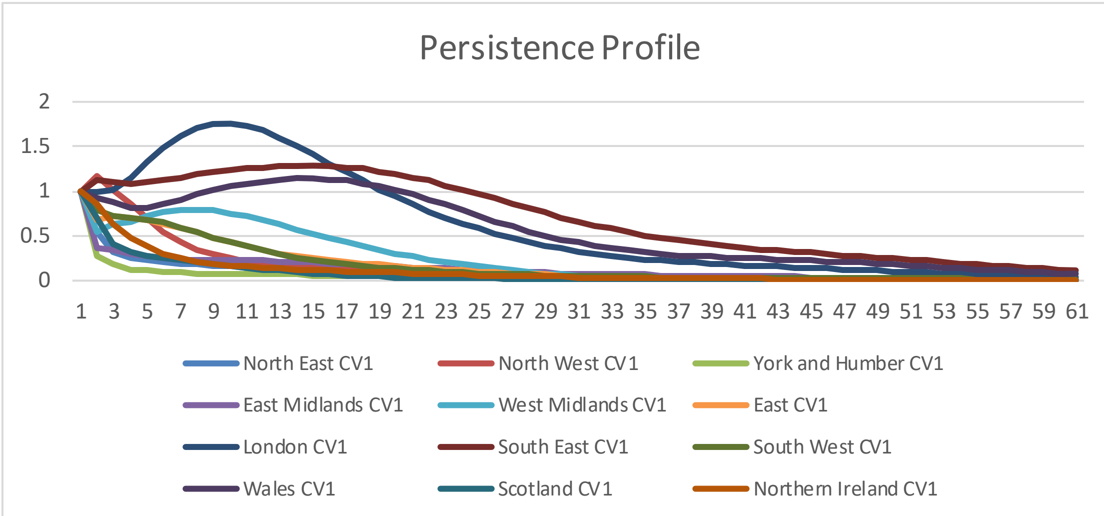


Table A11 Eigenvalues and eigenvectors (first twenty)

Eigenvalues of the GVAR Model in Descending Order	Corresponding Moduli
1.00000000000003 +0.00000000000010i	1
1.00000000000003 -0.00000000000010i	1
1	1
1.00000000000003 +0.000000000000001i	1
1.00000000000003 -0.000000000000001i	1
1.00000000000002 +0.000000000000002i	1
1.00000000000002 -0.000000000000002i	1
1	1
1	1
1.00000000000001 +0.000000000000001i	1
1.00000000000001 -0.000000000000001i	1
1.00000000000001 +0.000000000000001i	1
1.00000000000001 -0.000000000000001i	1
1	1
1.00000000000001 +0.000000000000004i	1

1.00000000000001 +0.00000000000000i	1
1.00000000000001 -0.00000000000000i	1
1.00000000000001 -0.00000000000004i	1

Table A12 F-Statistics for the Serial Correlation Test of the VECMX* Residuals

		Fcrit_0.05	y	ea	hpi	fis	biz	og
North East	F(6,193)	2.15	0.04	0.47	0.79	0.35	0.53	0.33
North West	F(6,193)	2.15	0.09	5.12	1.63	0.06	0.68	0.82
York and Humber	F(6,193)	2.15	0.04	2.18	2.08	0.29	0.14	0.12
East Midlands	F(6,193)	2.15	0.07	1.54	2.49	0.17	0.07	0.58
West Midlands	F(6,194)	2.15	0.06	0.61	2.41	0.21	0.25	
East	F(6,193)	2.15	0.17	3.11	2.51	0.13	0.01	0.15
London	F(6,204)	2.14	0.02	1.33	1.75	0.15	0.27	
South East	F(6,193)	2.15	0.45	1.54	3.16	0.48	0.64	0.51
South West	F(6,193)	2.15	0.03	2.57	2.52	0.17	0.60	0.12
Wales	F(6,194)	2.15	0.09	1.67	2.48	0.76	0.40	
Scotland	F(6,193)	2.15	0.05	1.35	2.07	0.04	0.51	0.17
Northern Ireland	F(6,194)	2.15	0.24	2.64	11.97	0.42	0.03	

Table A13 VEC Estimates of the Dominant Unit Model

	Intercept	dpoil_1	dr_1
dpoil	0.004	0.227	29.816
dr	0.000	0.000	0.803
	Fcrit_0.05	poil	r
F(6,214)	2.141	2.890	6.339

Table A14 – Weights of regional GVA. For example London accounts for 24% of combined GVA.

Data for constructing aggregation weights	
North East	0.0290

North West	0.0961
York and Humber	0.0663
East Midlands	0.0586
West Midlands	0.0739
East	0.0862
London	0.2357
South East	0.1477
South West	0.0740
Wales	0.0350
Scotland	0.0754
Northern Ireland	0.0219
Total	1

Table A15 Regional VARX* model Domestic variables

	OIL PRICE	**UK interest rate**
North East	1	1
North West	1	1
York and Humber	1	1
East Midlands	0	1
West Midlands	1	1
East	1	1
London	0	0

South East	0	1
South West	1	1
Wales	1	1
Scotland	1	1
Northern Ireland	1	1

Table A16 Regional VARX* model Domestic variables

	y	**ea**	**hpi**	**fis**	**biz**	**og**
North East	1	1	1	1	1	1
North West	1	1	1	1	1	1
York and Humber	1	1	1	1	1	1
East Midlands	1	1	1	1	1	1
West Midlands	1	1	1	1	1	
East	1	1	1	1	1	1
London	1	1	1	1	1	
South East	1	1	1	1	1	1
South West	1	1	1	1	1	1
Wales	1	1	1	1	1	
Scotland	1	1	1	1	1	1
Northern Ireland	1	1	1	1	1	

Table A17 Regional VARX* model Foreign variables

	ys	eas	hpis	fiss	bizs	ogs
North East	1	1	1	1	1	1
North West	1	1	1	1	1	1
York and Humber	1	1	1	1	1	1
East Midlands	1	1	1	1	1	1
West Midlands	1	1	1		1	1
East	1	1	1		1	1
London	0	1	0	1	1	0
South East	1	1	1	1	1	1
South West	1	1	1		1	1
Wales	1	1	1	1	1	1
Scotland	1	1	1	1	1	1
Northern Ireland	1	1	1	1	1	1

References for chapter 1

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