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The International Impact of Financial Shocks: A Global VAR and Connectedness Measures Approach

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Abstract

This paper examines the international impact of shocks to a large array of measures of financial frictions and financial stress. The methodology employed in this paper is twofold, it firstly utilities the Global VAR (GVAR) approach and then employs a set of Generalized Connectedness Measures (GCM) to summarise the results of this analysis. These two methodologies provide a way to rank the relative importance of different measures of financial shocks on countries and macroeconomic variables. The methodologies are applied to a data set of 17 countries, over the period 1981Q1 to 2013Q1, with 12 separate measures of financial frictions and financial stress. Utilising connectedness index measures, it is found that financial stress measures constructed from the corporate bond market are the most influential on global macroeconomic variables and that this result is also consistent across individual countries. It is found that many proposed measures of financial stress are not net transmitters of influence but are more dependent on external factors. The paper finds little evidence to support the use of credit as a financial shock variable as is common in the literature. This variable is found to be a weak transmitter of shocks and highly influenced by shocks to other variables.

1 Introduction

This paper focuses on three prominent issues, who's importance was underscored by the 2008 global financial crisis, firstly; the intensification of global linkages, secondly the importance of credit cycles and macro-financial interactions and thirdly the recognition that better measures of stresses in the financial system were needed. The paper will draw together the theoretical and empirical insights from these three separate research areas into a framework which will allow the interactions between global linkages, credit cycles and financial stress areas to be explored. The empirical approach will provide a means to distinguish the most influential measures of financial disruptions in the global economy. The methodologies that will be employed will be the GVAR framework as developed by di Mauro et al. (2007), henceforth DdPS (2007), and the Generalised Connectedness Measures framework as outlined in by Greenwood-Nimmo et al. (2015). These provide a flexible methodology and are particularly suited to the questions addressed in this paper.

The contribution of this paper is threefold; firstly the paper apples the connectedness measures approach of Greenwood-Nimmo et al. (2015) to rank the global influence of an array of measures of financial frictions and financial stress. This application of the methodology is an advancement on the work of Greenwood-Nimmo et al. (2015) as they apply the connectedness measures developed in their paper to a baseline GVAR model which is absent of financial shock measures. The connectedness methodology is particularly suited to the analysis of financial frictions and financial stress as it does not require onerous structural assumptions. In addition to this the methodology allows this ranking analysis to be broken down to the country and variable level. The second contribution is that in building towards these results the analysis proceeds in a way that further reduces the number of assumptions used in the estimation. Specifically the model is based on stationary time series and generalised impulse response functions. As opposed to previous studies[1] the model is not sensitive to the identification scheme used or the co-integrating relationships specified, as these do not need to be defined in the model in this paper. The approach taken, which is a departure

[1]See for example, Xu (2012), Eickmeier and Ng (2011), Guarda and Jeanfils (2012), Sanjani (2014), Goodhart and Hofmann (2008) and N'Diaye et al. (2010)

from the GVAR methodology that is standard in the literature, is particularly advantageous given that when including financial variables in a multi-country macroeconomic model the theoretical guidance for the appropriate structure to be employed is often unclear. This is also the case in relation to the nature of the long run relationship between the vast array of financial and the standard macroeconomic variables and so would complicate a co-integration based model. Thirdly, in terms of the contribution, further to dealing with the uncertainty as regards the interactions of the variables there is also a large degree of uncertainty regarding the macro-financial relationships among countries. This paper contributes to the modelling of these interactions as the methodologies employed provide a way to characterise the strength of the influence and dependence among countries without heavy reliance on structural assumptions.

The focus of this paper is on the international impact of financial shocks. As regards the previous literature this research area contains a relatively limited number of empirical papers, this is due to the necessary high dimension of this type of analysis (Eickmeier and Ng, 2011). In the literature two broad approaches to dealing with the dimensionality issue in international economic dynamics have been developed, the GVAR approach and the factor augmented VAR (FVAR) approach (Eickmeier and Ng, 2011). In this paper the GVAR approach, which is outlined in the next section, is used as it allows country specific dynamics to be explicitly modelled and the weights for foreign variables are data, not statistically, based (Eickmeier and Ng, 2011). The ability of the GVAR approach to model at the country level is an important feature as it allows a wider range of issues such as the strength of country specific financial linkages to be estimated (Bijsterbosch and Falagiarda, 2014). The GVAR model is built up from VAR models and in the context of the analysis in this paper the VAR based approach is particularly advantageous when analysing financial stress as it provides a rich representation of the complex potential interactions (Borio and Drehmann, 2011). The estimation results of the GVAR model will form the basis for construction of the connectedness measures.

Our results indicate that variables which proxy for the concept financial friction as in the Bernanke et al. (1999) model are the most influential sources of financial shocks. This result holds

both at the global level and at the level of most individual countries. It is also found that the credit variable is not an influential source of shocks but is more influenced by other financial shock variables, suggesting that credit may be an endogenous variable. This is contrary to much of the existing literature which gives a central role to analysing shocks to different measures of the quantity of credit in analysing the propagation of financial distress.

The remainder of this paper is structured as follows; the next two subsections will provide firstly; an overview of the literature related to the three issues that will be analysed in this paper and secondly; the existing empirical literature and how this literature informs the empirical approach. Section 2 will outline the empirical strategy. Section 3 will detail the empirical methodology. Section 4 will describe the data, the variables and the model used in the analysis. Section 5 will present the results and Section 6 will conclude.

1.1 Literature and Motivation

This paper will draw together three important themes in the macroeconomic literature, the first theme is that of the intensification of global financial linkages. As discussed in Lane (2012) there have been substantial changes in the global financial system since at least the 1980's. A major feature is that many markets have undergone a process of financial integration (Sgherri and Galesi, 2009). One measure of the scale of cross-border financial integration is the sum of foreign assets and foreign liabilities as a ratio of GDP, the international financial integration (IFI) ratio, (Lane, 2012). This ratio has increased from 68.5 percent in 1980 to a peak of 438.2 percent in 2007, before the financial crisis (Lane, 2012). Further to this Ciccarelli et al. (2012) states that in the past quarter of a century, global trade flows have grown at a much faster rate than world output and the volume of global financial flows has grown even faster than global trade [2].

This greater degree of financial integration and the better functioning financial intermediaries have been found, in general, to be associated with improved growth opportunities (Xu, 2012).

[2]Taking world gross external assets relative to world GDP as a measure of financial flows and comparing it to world trade to GDP in 1980 global financial flows and global trade were roughly equal at approximately a quarter of world GDP (Haldane, 2014). However, by 2010 global financial flows had grown to be nine times larger than global trade (Haldane, 2014)

This process does, however, have potential costs as well as benefits. While it has the potential to smooth the response of income to asymmetric shocks through cross-border asset diversification, these cross-border links may also expose financial institutions to shocks in an array of segmented markets and countries (Metiu et al., 2015). The increase in cross-border financial linkages could potentially allow these shocks to transmit internationally more easily that in a situation of low global financial integration. This dynamic is termed the "international finance multiplier" in Metiu et al. (2015).

These financial shocks have the potential to spillover to the real side of the economy. This has been evidenced by the 2008 global financial crisis with sharp drops in output and employment, heavy credit losses, falls in stock markets, increased volatility and a rise in risk aversion (Stock and Watson, 2012), (Ciccarelli et al., 2012).

In relation to the second issue highlighted by the global financial crisis, that of the importance of macro-financial linkages and credit, on the theoretical side, as noted in Goodhart and Hofmann (2008), many modern macroeconomic models contained no banks, no borrowing and no risk of default. As a result of this credit aggregates and asset prices played no role in the dynamics of these models [3]. The financial crisis changed the perception that macro-financial linkages were were of a lesser importance, as observed in Stock and Watson (2012), the shocks that produced the financial crisis were primarily financial disruptions. As a result of this, the link between financial distress and real outcomes that operate through capital, credit and/or liquidity has been repositioned as a major theme in macroeconomics and this literature has rapidly developed (Brzoza-Brzezina et al., 2013). On the theoretical side this literature developed from a line of research in macroeconomics that gives a central role to financial frictions and assumes that insolvency, high debt burdens, bankruptcy, asset price fluctuations, and bank failures are not just features of a declining economy, but major instigating factors (Iacoviello, 2005) [4].

[3] Chari (2011), postulates that this is likely due to a long period of financial stability experienced in many advanced economics up until the 2008 crisis.

[4] At present, broadly speaking, there are three main strands in the literature on incorporating financial frictions; each of which is based on introducing an agency problem between borrowers and lenders (Gertler and Kiyotaki, 2010). These mechanisms are cash-flow constraints, as detailed in Bernanke et al. (1999), collateral constraints, as detailed in Kiyotaki and Moore (1997), and constraints on the supply of external funding through financial intermediaries,

The third issue that will be integrated into the analysis in this paper is that of measuring stresses in the financial system. There is a large array of newly proposed measures of financial stress, the number of which have expanded rapidly since the financial crisis (Giglio et al., 2015). The large number of indicators that have been developed is in part in response the lack of proper indicators of financial instability available to policy makers both before and during the financial crisis (Kliesen et al., 2012). Some of these policy makers now have a legal obligation to manage financial stress; the Dodd Frank Act created a Financial Stability Oversight Council and an Office of Financial Research (Bisias et al., 2012). The directive of these institutions necessitates the prompt measurement of financial risk (Bisias et al., 2012). The large number of indicators is also due to the fact that financial stress is an unobservable latent condition and consequently there are many alternative ways to construct measures of it (Kliesen et al., 2012). Another issue in developing measures is the relative infrequency with which systemic financial shocks occur. This, coupled with the limited time span of financial data, makes identifying patterns and developing useful empirical and statistical indicators of financial crisis difficult (Bisias et al., 2012). On the importance of these measures, Bisias et al. (2012) outline circumstances in which improved techniques for measuring threats can significantly reduce the likelihood of macro-prudential policy mistakes.

Many of the issues highlighted are interrelated and, given the proliferation of theoretical and empirical contributions, involve potentially complex interactions between a broad set of variables. The analysis will necessarily be cross-country in nature owing to the internationalisation of the financial system, as discussed. This paper adopts the GVAR and GCM approach as it is particularity suited to quantify these complex and uncertain relationships.

1.2 Existing Empirical Literature

The traditional GVAR approach as outlined in Pesaran et al. (2004), henceforth PSW (2004), and DdPS (2007) was constructed primarily to analyse the impact of foreign influences on national

as detailed in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). The three approaches are differentiated by the mechanism used to generate the financial friction (Brunnermeier and Sannikov, 2014). The common feature among the models is the presence of a financial accelerator mechanism; where endogenous forces in credit markets amplify and propagate shocks to the real economy (Brunnermeier and Sannikov, 2014).

and regional economies (Garratt et al., 2012). This approach was developed as analysing global interactions and the impact of foreign variables on national and regional economies with a standard macroeconometric approach quickly becomes infeasible due to the large number of parameters to be estimated relative to the data series available (Garratt et al., 2012). The GVAR approach proposes a solution to this problem of modelling an array of economies in a consistent way through the construction of separate measures of foreign variables for each national economy or region in the model. These country specific foreign variables summarise the influence of all external variables on a particular economy (Garratt et al., 2012). Each of the foreign variables is constructed by weighting, typically according to trade data, the importance of that variable in other countries to a particular economy, so all influences are contained in a single variable (Garratt et al., 2012). This approach of summarising the foreign influences substantially reduces the number of parameters to be estimated.

There have been a number of recent studies that have utilised this GVAR methodology in studies on cross country financial linkages. Sgherri and Galesi (2009) use a 27 country GVAR model to analyse the time profile of the cross-country transmission of financial shocks. The countries covered in the analysis are European Countries plus the United States. The shocks analysed are equity shocks which emanate from the US[5]. They find that asset prices are the main transmission channel in the short run with cost and quantity of credit being longer term determinants. These conclusions are reached using generalised forecast error variance decompositions (GFEVD). It is found that for US variables' real equity prices explain most of the forecast error variance in the short run with real credit growth and real GDP growth becoming more important over time. They also find significant co-movement of equity prices and country specific credit effects. There is, however, an ordering of regions and the strong co-movement result does not hold for emerging European regions. This is taken as an indication of their low degree of financial integration with the rest of the world [6].

Xu (2012) employs a GVAR containing financial and real variables to investigate the interna-

[5]This analysis is done using monthly data over the years 1999-2008.

[6]Sgherri and Galesi (2009) use an alternative weighting scheme for the country-specific foreign variables. The weighting scheme they employ is constructed by bilateral bank lending exposures from consolidated foreign claims data as opposed to the trade based weights typically used in GVAR analysis.

tional transmission of a negative shock to the level of US credit and the role of credit in explaining business cycle fluctuations. The paper analyses a general decline in credit and does not identify it as a supply or demand side effect. The paper adds a bank credit variable, in levels, to a standard GVAR model[7]. It is found that there are strong spillovers internationally of a shock to US credit, with a particularly strong impact on the UK. The model predicts a fall in the short term interest rate in response to a credit shock. As in Sgherri and Galesi (2009) it is found that there are strong international impacts from a shock to US real equity prices. The inclusion of the credit variable is found to provide a significant improvement in the sample fit of the country-specific models, particularly for advanced economies [8]. The paper also highlights the importance of bank credit as an explanatory variable for growth, inflation and long term interest rate changes. Following the GVAR framework Eickmeier and Ng (2011) analyse the transmission of credit supply shocks in the US, the Euro area and Japan to other economies[9]. It is found that a negative credit supply shock to the private sector has a strong adverse effect on the domestic economy of the US and that this shock also propagates internationally. As in Xu (2012) there is a strong impact on the UK. Credit supply shocks in the model are identified by sign restriction [10].

Chudik and Fratzscher (2011) analyse two hypothesis for the global spread of the 2008 financial crisis, the liquidity hypothesis and pricing of risk hypothesis. To test the significance of these two transmission channels a GVAR model is used with shocks to the liquidity conditions and the risk appetite. In their analysis shocks originate from the US and shocks to liquidity are measured from the TED spread and shocks to the risk appetite are measured from the US VIX index. The authors draw on the literature on the time-varying risk of economic disaster and its impact on the business cycle and asset prices to identify the shocks. It is found that liquidity shocks were more important in advanced economies while the decline in the risk appetite was more important for emerging

[7]The analysis covers of 26 countries and is conducted quarterly over the years 1979 to 2006, just prior the global financial crisis.

[8]The importance of the credit variable is found to be related to the depth of the banking sector in each country, where credit to the private sector is taken as an indicator of banking development.

[9]The sample is expanded from that in Xu (2012) as it covers 33 countries and extends from 1983 to 2009, covering the beginning of the financial crisis.

[10]Financial weights are used in the model and it is found that these weights allow a better fit of the model to the data than the trade weights typically used.

economies and had a stronger impact on EU economies than other advanced countries. It was also found that the importance of US specific shocks on foreign equity markets roughly doubled in importance during the crisis.

On the inclusion of financial stress measures, Dovern and van Roye (2013) combine a GVAR model and a financial stress index[11]. Their financial stress measures are constructed using the assumption that the financial stress of a market is related to the volatility in that particular market (Dovern and van Roye, 2013). The measures are calculated for the banking sector the bond market and the foreign exchange market (Dovern and van Roye, 2013). They find that financial stress indicators display strong co-movement, especially in financially open compared to financially closed countries and that there is an increasing trend in the cross country correlation of their financial stress measures, indicating increased international financial integration. As in other studies it is found that US financial stress transmitted internationally and with a persistent negative effect on output.

Still looking at the question of cross-country financial linkages in to context of financial stress and financial frictions measures but not using the GVAR framework Metiu et al. (2015) analyse the role of financial frictions in facilitating the international propagation of US financial shocks[12]. The risk premium on US corporate bonds is used to proxy the financial friction and the data used is from the IMF stress index data set. The empirical results show that a positive shock to US financial frictions leads to a tightening of global financial conditions (Metiu et al., 2015). This is seen as a strong increase in uncertainty, proxied by an increase in global stock market volatility. The rise in the friction also leads to a global output contraction (Metiu et al., 2015). The results also maintain that the global corporate bond market is an additional transmission mechanism through which US financial shocks propagate as global corporate bond spreads rise significantly following the rise in US financial frictions.

In relation to studies focusing specifically on financial frictions measures, which are an important

[11]This is calculated from a dynamic factor model for 20 countries, at monthly frequency, from 1970 to 2012.

[12]This is preformed using a two-region threshold vector autoregression on monthly data covering the years 1984 to 2012.

variable in the theoretical literature, there have generally been based on analysing a single country. In a study of the US, focusing on financial shocks, Sanjani (2014) hypotheses that risk premiums are the central link between credit markets and the real side of the economy. Sanjani (2014) postulated that this is observable through the external finance premium. The paper uses a Bayesian estimation with a vector autoregression and New Keynesian models to analyse the interaction between the real business cycle and the credit market. Sanjani (2014) decomposes the credit spread into a default risk spread and a liquidity risk component. The results show that both the liquidity and default components of the credit spread are countercyclical. It is also shown that while default spread risk shocks have a large impact, a shock to liquidity risk has a more severe economic impact.

Specifically analysing the interaction between corporate bond credit spreads and economic activity in the US Gilchrist and Zakrajsek (2012) construct a credit spread index and find it to be a powerful predictor of economic activity. Then the index is constructed from firm level data and decomposes the spread into two components. These two components are the expected defaults which move in a countercyclical way and the excess bond premium, which represents cyclical deviations in changes in the relationship between default risk of the issuer and the pricing of their corporate bonds (Gilchrist and Zakrajsek, 2012). This decomposition shows that the changes in the excess bond premium are driven by shocks to the profitability of leveraged financial intermediaries, which can also be thought of as a measure of credit supply conditions[13]. The results show that a reduction in credit supply, from a change to the excess bond premium, has significant adverse macroeconomic consequences including a fall in asset prices. The result supports the theoretical predictions of a financial accelerator mechanism, from the financial frictions literature (Gilchrist and Zakrajsek, 2012) [14]. In keeping with this result on the importance of uncertainty for macroeconomic activity Ludvigson et al. (2015) find that, by using two constructed instrumental variables to first "disentangle" uncertainty shocks from shocks to real activity and secondly to disentangle macroeconomic uncertainty shocks from financial uncertainty shocks, there are strong effects from

[13]The predictive power of the indicator is reliant on the this component of the index (Gilchrist and Zakrajsek, 2012).

[14]There is also an observed comovement between the excess bond premium and the profitability of the US corporate sector and also the CDS spread (Gilchrist and Zakrajsek, 2012).

this financial uncertainty variable.

In terms of the financial stress indexes in Lall et al. (2009) these measures are used to identify periods of financial stress, to assess the impact of financial stress on the macroeconomy and to try to determine why some periods of financial stress lead to a major downturn and some do not. The analysis does not attempt to determine causality from financial variables to economic contractions but rather to provide a broad coverage of the potential channels and mechanisms through which financial stress affects the economy. On the accuracy of the financial stress measures, it is found using an event analysis based off the historical record of financial stress episodes that the measures are quite robust in capturing the main financial stress events (Lall et al., 2009). Lall et al. (2009) notes that although the index identified episodes of financial stress, only half the stress episodes identified are followed by contractions.

Applying the IMF financial stress index measures of Lall et al. (2009), Mittnik and Semmler (2014) analysis the interaction between industrial production and financial stress[15]. It is found that financial sector stress has a strong influence on economic activity, particularly stresses as measured by the TED spread, corporate bond spreads and a measure of stress in the banking sector, the "banks beta" (Mittnik and Semmler, 2014). This finding on the importance of the TED spread measure is also found in an analysis of the relevance of 30 systemic risk measures for forecasting adverse macroeconomic outcomes in Giglio et al. (2015)[16].

2 Empirical Motivation and Strategy

In this paper we will proceed by analysing the global significance of a wide range of financial shock measures as motivated by the existing literature. This will be done using a Global VAR

[15]This analysis uses a non-linear, multi regime vector autoregression approach (MRVAR) with Granger-causality and non-linear impulse response

[16]Using principal components quantile regression analysis is conducted in Giglio et al. (2015). They find that many of the measures do not match the broader historical context and record spikes a periods where there was no macroeconomic turmoil. It is also found that the individual measures, aside from the TED spread and equity volatility, have low predictive power for downturns in employment and industrial production but an aggregate measure preforms well. Giglio et al. (2015) observe that many of the variables used in the literature are better suited to recording occurrences of systemic risk rather than forecasting incidences of distress.

and Generalised Connectedness Measures approach, as described in Section 3, as this approach has a number of advantages in dealing with the empirical complications which are discussed in the previous literature. Before proceeding with the empirical analysis these issues are outlined below.

A large number of the studies cited rely on identifying restrictions, Metiu et al. (2015). Bijsterbosch and Falagiarda (2014) note that there has been a fast growing literature attempting to identify credit shocks through vector autoregression models. To identify spread shocks, Sanjani (2014), relies on a block ordering with variables categorised into a block of macroeconomic variables, a financial block and a spread block. Gilchrist and Zakrajsek (2012) use an identified VAR framework to analyse their decomposed bond spread. Although Xu (2012) uses generalised impulse response functions the empirical methodology still employs four exact identifying restrictions in the error correction structure of the model. Eickmeier and Ng (2011) use theoretically motivated sign restrictions on short run impulse responses [17]. Specifically this involves imposing sign restrictions on corporate bond spreads jointly with restrictions on the response of other domestic variables. These sign restrictions can be problematic, particularly when dealing with the comparatively new research field of the impact of financial shocks on macroeconomic variables as there is no settled theoretical modelling structure. As noted in, Jarociski and Makowiak (2013), aside from ordering, it is not even certain which variables should be included in a standard macro-financial model. As is noted in Borio and Drehmann (2011) "there are no satisfactory models of the economy as a whole linking balance sheets in the financial sector to macroeconomic variables". Indeed a number of papers in the literature note this difficulty, N'Diaye et al. (2010) notes the "enormous amount of identification" restriction needed to estimate their GVAR model with financial variables.

In the identification of shocks in the analysis of the interaction between house prices, credit and standard macroeconomic variables in Goodhart and Hofmann (2008), the authors note that the ordering credit and asset price variables is "somewhat arbitrary". In disentangling the effects stemming from changes in liquidity and the risk appetite in a GVAR model Chudik and Fratzscher (2011) state that "it is inherently difficult to identify meaningful measures of shocks to liquidity

[17] These are taken from DSGE models containing a banking sector.

and to risk appetite". In the dynamic factor model employed in Stock and Watson (2012) it is noted that given the high correlation of shocks particularly related to financial variables, separate interpretation can be difficult and they employ 18 instruments to identify structural shocks. In terms of credit supply dynamics, Bijsterbosch and Falagiarda (2014) note that the correct identification of credit supply dynamics is crucial for policy makers. In their paper on macro-financial linkages Guarda and Jeanfils (2012) note that for the financial variables used in their model that the exact ordering for the Choleski decomposition is not clear cut and that the theoretical literature does not have a clear guide for it. This uncertainty is further increased with the wide range of new variables that have been constructed to proxy for financial stress as among this broad array there is still a lack of agreement on precisely which measures should be used to measure stress (Kliesen et al. (2012)).

In light of these issues using a more general framework has a number of advantages in terms of the analysis in this paper. For this more general framework we combine the GVAR model with the connectedness measures approach of Greenwood-Nimmo et al. (2015). As discussed above there exists uncertainty in terms of the choice and also the identification ordering of variables in studies on macro-financial linkages. The Generalized Connectedness Measures proposed in Greenwood-Nimmo et al. (2015), which builds on the work of Diebold and Yilmaz (2009, 2014), are derived from generalised forecast error variance decompositions. The advantage of this approach is that the results generated are independent of the ordering of variables. Lanne and Nyberg (2014) state that generalised forecast variance decompositions are particularly useful when it is difficult to propose credible identifying restrictions. Furthermore, the GVAR approach combined with the connectedness measures allows a degree of quantification of the concept of "systemic risk" such as the importance of different countries and regions and the relative importance of different variables (Bisias et al. (2012)) [18]. Another advantage of employing the GVAR and GCM approaches is

[18]The importance of this is further discussed in Borio and Drehmann (2011) in their assessment of indicators of banking stress they note that many country level indicators of financial imbalance miss imbalances caused problems originating in foreign exposures. They note that particularly in a globalised world with an intensification of global linkages that indicators based on the assumption that financial institutions in a country are only exposed to cycles in that country are limited (Borio and Drehmann, 2011).

that in a cross country study of macro-financial linkages there is, as has been mentioned and as will be discussed in the subsequent section, a vast array of potential variables to consider. Even in benchmark GVAR macroeconomic models there is a considerable volume of statistical output produced and the addition of the variables from the array of macro-financial variables available will only add to this and make the traditional impulse response approach to detailing the models insights infeasible (Greenwood-Nimmo et al., 2015). This situation highlights another advantage, and in fact an original motivation for the GCM approach of Greenwood-Nimmo et al. (2015), that this empirical approach deals directly with the curse of "output dimensionality" and selectivity in the presentation of results. The GCM will provide a reductive method to summarising the output, this will permit a comprehensive reporting of the models results (Greenwood-Nimmo et al., 2015). This is particularly important in the context of the question in this paper due to the considerable complexity and uncertainty in the transmission channels in a dynamic global macro-financial model.

Utilising the connectedness measures approach yields the above mentioned advantages, but using the Greenwood-Nimmo et al. (2015) innovation on the Diebold and Yilmaz (2009, 2014) approach has a particular advantage for the questions of interest in this paper as it introduces a new stratum between individual variables and system-wide aggregates. This new stratum allows the connectedness measures to be employed at different aggregation levels and so look at the connection between countries, regions and in particular in our case between groups of variables within the model (Greenwood-Nimmo et al., 2015). This will allow measures of the cross-country dependence and influence of different measures of financial stress to be quantified.

3 Empirical Methodology

3.1 The GVAR Approach

As discussed previously the theoretical and empirical literature suggest the importance of macro-financial linkages as well as the increase in linkages across countries. A departure from the standard GVAR approach is taken in this paper in that although the GVAR approach is employed, as in

Lui and Mitchell (2013), the stationary versions of the variables are used. As the analysis will be based on a covariance stationary representation of a VAR model, it will not be necessary to specify error-correcting relationships among the variables, as is required in much of the literature using GVAR models. This is advantageous as with the uncertainty in the theoretical links between the macroeconomic and financial variables noted in the literature, it is not clear what the nature of the long run relationship's are among many of these variables[19].

Following the standard literature[20], it is supposed that there are $N+1$ countries or regions in the global economy, indexed by $i = 0, 1, ..., N$. Country 0 serves as the numeraire country and in keeping with the GVAR literature this is taken as the United States. The aim of the GVAR approach is to model a number of country specific macroeconomic variables over time, $t = 1, 2, ..., T$, and across the $N+1$ countries. While treating all country specific and global variables endogenously would be desirable given the interdependencies that may exist in the global economy, this would make estimation infeasible due to the "curse of dimensionality". To circumvent this issue, the GVAR approach imposes weak exogeneity of the foreign country-specific and global variables. This imposition implicitly assumes that the individual countries, aside from the US, are small with respect to the rest of the world. In this paper the data is used in stationary form and therefore as in Lui and Mitchell (2013), weak exogeniety will be assumed.

The empirical model of each individual country includes a set of domestic, foreign specific and global variables, the number of which can vary across countries. Considering the structure of an individual country VARX*(1,1) model, a VAR model with exogenous variables, for country i this is given by:

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

In this structure $\boldsymbol{x}_{it}$ is a $k_i \times 1$ vector of domestic variables, $\boldsymbol{x}^*_{it}$ is a $k^*_i \times 1$ vector of foreign variables, $\boldsymbol{a}_{i0}$ and $\boldsymbol{a}_{i1}t$ are the coefficients of the deterministics, in this case intercepts and linear trends, and $\boldsymbol{u}_{it}$ is a serially uncorrelated and cross-sectionally weakly dependent process. In terms of global

[19] Wickens (1996) outlines the importance specifying and incorporating a priori knowledge of the economic relationship among variables to counter the fundamental identification problem in cointegration analysis.

[20] See PSW (2004), DdPS (2007) and di Mauro and Pesaran (2013)

variables, such as oil prices, every global variable enters as endogenous (domestic) in one country only and exogenous (foreign-specific) in the rest. This variable will thus enter into either the vector $\boldsymbol{x}_{it}$ or the vector $\boldsymbol{x}^*_{it}$ in each country. The country-specific foreign variables $\boldsymbol{x}^*_{it}$ are constructed as weighted averages of the corresponding domestic variables of all other countries. These weights are also country specific where, $\boldsymbol{x}^*_{it} = \sum_{j=0}^{N} w_{ij}\boldsymbol{x}_{jt}$, where $w_{ij}, j = 0, 1...., N$, are a set of weights such that $w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1$. The trade weights capture the importance of country j for country $i's$ economy. The benchmark analysis in this paper will be preformed using weights estimated by bilateral trade data from the IMF Direction of Trade Statistics.

The GVAR model is solved by estimating the VARX* models on a country by country basis. Although this initial step done country by country, the GVAR model is then solved for all countries in totality and takes account of the fact that all variables are endogenous to the system as a whole. Taking the estimated coefficients and deterministics from the VARX* models the GVAR model is constructed by first defining the $(k_i + k^*_i) \times 1$ vector:

$$\boldsymbol{z}_{it} = (\boldsymbol{x}'_{it}, \boldsymbol{x}^{*'}_{it})' \tag{2}$$

Equation 2 for each country model can then be rewritten as:

$$\boldsymbol{A}_{i0}\boldsymbol{z}_{it} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1}t + \boldsymbol{A}_{i1}\boldsymbol{z}_{i,t-1} + \boldsymbol{u}_{it} \tag{3}$$

where

$$\boldsymbol{A}_{i0} = (\boldsymbol{I}_{ki}, -\boldsymbol{\Lambda}_{i0}),\ \boldsymbol{A}_{i1} = (\boldsymbol{\Psi}_{i1}, \boldsymbol{\Lambda}_{i1}) \tag{4}$$

The model collects all country-specific variables together into the $k\times1$ global vector $\boldsymbol{x}_t = (\boldsymbol{x}'_{0t}, \boldsymbol{x}'_{1t}, ..., \boldsymbol{x}'_{Nt})'$ where $k = \sum_{i=0}^{N} k_i$ is the total number of endogenous variables in the global model for $i = 1, 2, ..., N$. All country specific variables can be written in terms of this global vector of endogenous variables. This is done by using link matrices $\boldsymbol{W}_i$, which is a is a $(k_i + k^*_i) \times k$ matrix of fixed known constants which are defined by the country specific trade weights. This allows the country specific models to

be written in terms of the global vector of endogenous variables:

$$\boldsymbol{z}_{it} = \boldsymbol{W}_i \boldsymbol{x}_t, \ i = 0, 1, 2..., N, \tag{5}$$

The individual VARX* models can then be written in terms of the global vector:

$$\boldsymbol{A}_{i0}\boldsymbol{W}_i\boldsymbol{x}_t = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1}t + \boldsymbol{A}_{i1}\boldsymbol{W}_i\boldsymbol{x}_{t-1} + \boldsymbol{u}_{it} \tag{6}$$

Structuring the individual country models in this way allows for the final stage in the constructing the GVAR model, the stacking of the individual country models to yield a model for the global vector of endogenous variables. This global model is now given by:

$$\boldsymbol{G}_0\boldsymbol{x}_t = \boldsymbol{a}_0 + \boldsymbol{a}_1 t + \boldsymbol{G}_1\boldsymbol{x}_{t-1} + \boldsymbol{u}_t \tag{7}$$

where

$$\boldsymbol{G_0} = \begin{bmatrix} \boldsymbol{A}_{00}\boldsymbol{W}_0 \\ \boldsymbol{A}_{10}\boldsymbol{W}_1 \\ . \\ . \\ \boldsymbol{A}_{N0}\boldsymbol{W}_N \end{bmatrix}, \boldsymbol{G}_1 = \begin{bmatrix} \boldsymbol{A}_{01}\boldsymbol{W}_0 \\ \boldsymbol{A}_{11}\boldsymbol{W}_1 \\ . \\ . \\ \boldsymbol{A}_{N1}\boldsymbol{W}_N \end{bmatrix}, \boldsymbol{a_0} = \begin{bmatrix} \boldsymbol{a}_{00} \\ \boldsymbol{a}_{10} \\ . \\ . \\ \boldsymbol{a}_{N0} \end{bmatrix}, \boldsymbol{a_1} = \begin{bmatrix} \boldsymbol{a}_{01} \\ \boldsymbol{a}_{11} \\ . \\ . \\ \boldsymbol{a}_{N1} \end{bmatrix}, \boldsymbol{u_t} = \begin{bmatrix} \boldsymbol{u}_{0t} \\ \boldsymbol{u}_{1t} \\ . \\ . \\ \boldsymbol{u}_{Nt} \end{bmatrix} \tag{8}$$

Since $\boldsymbol{G}_0$ is a known non-singular matrix made up of the trade weights and parameter estimates of the individual country level models the reduced-form global model is obtained as:

$$\boldsymbol{x}_t = \boldsymbol{G}_0^{-1}\boldsymbol{a}_0 + \boldsymbol{G}_0^{-1}\boldsymbol{a}_1 t + \boldsymbol{G}_0^{-1}\boldsymbol{G}_1\boldsymbol{x}_{t-1} + \boldsymbol{G}_0^{-1}\boldsymbol{u}_t \tag{9}$$

This equation can be solved recursively and allows the interactions among different economies and variables to be modelled through an number of channels.

3.2 Dynamic Analysis and Connectedness

The GVAR model described in the previous section can be used to perform generalized impulse response function (GIRF) analysis and generalised forecast error variance decompositions (GFEVD) as described in Pesaran and Shin (1998). This is done to study the dynamic properties of the model and the time profile of variable specific shocks across economies (PSW 2004). An advantage of using GIRF as opposed to the orthogonalised impulse responses (OIR) of Sims (1980), is that the results will be invariant to the order in which the endogenous variables are stacked in $\boldsymbol{x}_{it}$ and also invariant to the ordering of the countries when constructing the global vector of endogenous variables, $\boldsymbol{x}_t$ (PSW 2004). As noted in PSW (2004) this non-invariance property of the OIR's is due to the standard non-uniqueness of the Choleski factor used in deriving the OIR's. PSW (2004) further note that in some cases OIR functions can be significantly impacted by the ordering of the variables in the GVAR model[21] [22]. In the context of this paper this observation of PSW (2004) is of particular relevance, this is because, as discussed in previous sections, in addition to there being no framework for an ordering of countries in a GVAR model, there is no-clear theoretical benchmark for ordering variables in a macroeconomic model when combining and array of macroeconomic and financial data.

The GIRF approach considers shocks to individual errors in $\boldsymbol{u}_t$, with the ν^{th} shock, for $\nu = 1, ..., k$, in $\boldsymbol{u}_t$ corresponding to the ζ^{th} variable, and thus the ζ^{th} equation, in the i^{th} country and integrates out the effects of the other shocks using the historically observed distribution of shocks (PSW 2004, di Mauro and Pesaran (2013)). The GIRF of $\boldsymbol{x}_t$ is given as:

$$GIRF(\boldsymbol{x}_t; u_{i\zeta t}, n) = E(\boldsymbol{x}_{t+n}|u_{i\zeta t} = \sqrt{\sigma_{ii,\zeta\zeta}}\Gamma_{t-1}) - E(\boldsymbol{x}_{t+n}|\Gamma_{t-1}) \tag{10}$$

where Γ_{t-1} is the information set at time $t-1$, n is the horizon and $\sigma_{ii,\zeta\zeta}$ is the diagonal element

[21] Pesaran and Shin (1998) note that GIRF and OIR will coincide in the case of the error variance matrix being diagonal.

[22] PSW (2004) highlight an alternative methodology in the macroeconometric literature for dealing with identification, that of "structural VAR" models. This approach is however very cumbersome when employing the GVAR approach as in a GVAR model with $N+1$ countries and k_i endogenous variables per country exact identification via a structural approach would require $k(k-1)/2$ theory-based restrictions (PSW 2004).

of the variance-covariance matrix $\sum_u$, corresponding to the ζ^{th} equation in the i^{th} country PSW (2004). The GIRF can be interpreted as the time profile of the effect of a one standard error shock hitting at time t (Lanne and Nyberg, 2014). This is obtained as the difference between expectations of the global vector of endogenous variables conditional on the shock and the information set Γ_{t-1}, and the expectations conditional only on the information set Γ_{t-1}, absent a shock (Lanne and Nyberg, 2014). The information set consists of a matrix of initial values required to compute the conditional expectations (forecasts), usually by simulation (Lanne and Nyberg, 2014)[23].

As discussed in Pesaran and Shin (1998) and Lanne and Nyberg (2014) the generalised impulses can be used to construct the GFEVD. However, as also discussed in Pesaran and Shin (1998) and Lanne and Nyberg (2014), the interpretation of the GFEVD of a shock is complicated by the fact that the contribution of the shocks to the forecast error variance of a given variable at horizon n do not sum to unity if the covariance matrix of the error $\boldsymbol{u}_t$ is not a diagonal matrix. A normalisation is typically employed to solve this issue. In this paper the same approach is taken, the formula for the GFEVD as proposed by Lanne and Nyberg (2014) is used as this formula is normalised by its construction as the denominator is the cumulative effect of all shocks. This normalisation restores the percentage interpretation of GFEVDs (Lanne and Nyberg, 2014). Following Lanne and Nyberg (2014) the GFEVD, is given as:

$$GFEVD(\boldsymbol{x}_{\zeta t}; u_{\nu t}; n) = \varphi^{(n)}_{\zeta \leftarrow \nu} = \frac{\sum_{s=0}^{n} (GIRF(\boldsymbol{x}_t; u_{i\nu t}, n))^2_{\zeta}}{\sum_{i=1}^{k} \sum_{s=0}^{n} (GIRF(\boldsymbol{x}_t; u_{i\nu t}, n))^2_{\zeta}} \tag{11}$$

In this formulation of the GFEVD the denominator measures the cumulative effect of all shocks while the numerator measures the cumulative effect of the ζ^{th} shock. In the context of the GVAR model, the formula thus measures the relative contribution of a shock to the ν^{th} equation in the i^{th} country to the total impact of all k shocks to the n periods ahead forecast error variance of the ζ^{th} element of $\boldsymbol{x}_t$ (Greenwood-Nimmo et al., 2015).

[23]One drawback of the GIRF as opposed to the OIR approach is that with GIRF there is no information on the reasons and or sources behind the shocks, they are simply shocks to a given equation in the model (Lanne and Nyberg, 2014).

The GFEVD's are used to construct the connectedness measures in this paper with the approach following the generalised connectedness measures as proposed in Greenwood-Nimmo et al. (2015). As discussed in Greenwood-Nimmo et al. (2015) the Diebold and Yilmaz (2014) framework is subject to a "processing constraints" and is suited to analysis with a single country with multiple variables or multiple countries with a single variable and not multi-country and global models which are the subject of this paper. To overcome this processing constant Greenwood-Nimmo et al. (2015) propose a re-normalisation and a block aggregation structure for the GFEVD's. As in Greenwood-Nimmo et al. (2015) when considering a model with $i = 0, 1, ..., N$ countries each of which are described by k_i variables, where $k = \sum_{i=1}^{N} k_i$, the use of the block aggregation exploits the fact that the GEFEVD's are invariant to the ordering of the variables in $\boldsymbol{x}_t$. Therefore the variables in $\boldsymbol{x}_t$ may be reordered to align with a country ordering, such as $\boldsymbol{x}_t = (\boldsymbol{x}'_{2,t}, \boldsymbol{x}'_{2,t}, ..., \boldsymbol{x}'_{N,t})'$. With the adjustments and the ordering by country the structure is written as:

$$\underset{(k\times k)}{\mathbb{C}_R^{(n)}} = k^{-1} \begin{bmatrix} \phi^{(n)}_{1\leftarrow 1} & \cdots & \phi^{(n)}_{1\leftarrow k_1} & \phi^{(n)}_{1\leftarrow k_1+1} & \cdots & \phi^{(n)}_{1\leftarrow k_1+k_2} & \cdots & \phi^{(n)}_{1\leftarrow k} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & \vdots \\ \phi^{(n)}_{k_1\leftarrow 1} & \cdots & \phi^{(n)}_{k_1\leftarrow k_1} & \phi^{(n)}_{k_1\leftarrow k_1+1} & \cdots & \phi^{(n)}_{k_1\leftarrow k_1+k_2} & & \phi^{(n)}_{k_1\leftarrow 1} \\ \phi^{(n)}_{k_1+1\leftarrow 1} & \cdots & \phi^{(n)}_{k_1+1\leftarrow k_1} & \phi^{(n)}_{k_1+1\leftarrow k_1+1} & \cdots & \phi^{(n)}_{k_1+1\leftarrow k_1+k_2} & & \phi^{(n)}_{k_1+1\leftarrow k} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & \vdots \\ \phi^{(n)}_{k_1+k_2\leftarrow 1} & \cdots & \phi^{(n)}_{k_1+k_2\leftarrow k_1} & \varphi^{(n)}_{k_1+k_2\leftarrow k_1+1} & \cdots & \phi^{(n)}_{k_1+k_2\leftarrow k_1+k_2} & & \phi^{(n)}_{k_1+k_2\leftarrow k} \\ \vdots & & & & & & \ddots & \vdots \\ \phi^{(n)}_{k\leftarrow 1} & \cdots & \phi^{(n)}_{k\leftarrow k_1} & \phi^{(n)}_{k\leftarrow k_1+1} & \cdots & \phi^{(n)}_{k\leftarrow k_1+k_2} & \cdots & \phi^{(n)}_{k\leftarrow k} \end{bmatrix}$$

Re-normalisation by dividing each element of the matrix by the number of variables means the interpretation of the (ζ^{th}, ν^{th}) element of the matrix $\mathbb{C}_R^{(n)}$ represents the proportion of the total n-step ahead forecast error variance of the system accounted for by the effect from variable ν to variable ζ (Greenwood-Nimmo et al., 2015). The resulting structure allows the matrix of GFEVD's to be easily partitioned when constructing connectedness measures between different

groups of countries and or variables. When arranged into b groups this will define the b^2 blocks of the matrix. Furthermore the re-normalisation maintains the percentage interpretation even when partitioning among different blocks of the matrix.

As described in Greenwood-Nimmo et al. (2015) the matrix can be reordered to support any block aggregation structure. These can be country level, regional or variable ordered blocks. This introduces a new stratum between which connectedness can be measured between countries and variables. These new measures made possible by the ordering include the Total To, Total From and net connectedness measure as well as the dependence index and influence index measures proposed in Greenwood-Nimmo et al. (2015). The Total From, Total To and net connectedness measures of the k-th group are defined as:

$$\mathcal{F}^{(h)}_{k\leftarrow\bullet} = \sum_{\ell=1,\ell\neq k}^{b} \boldsymbol{e'}_{mk}\boldsymbol{B}^{(h)}_{k\leftarrow\ell}\boldsymbol{e}_{m\ell}, \quad \mathcal{T}^{(h)}_{\bullet\leftarrow\ell} = \sum_{\ell=1,\ell\neq k}^{b} \boldsymbol{e'}_{m\ell}\boldsymbol{B}^{(h)}_{\ell\leftarrow k}\boldsymbol{e}_{mk}, \quad \mathcal{N}^{(h)}_{\bullet\leftarrow k} = \mathcal{T}^{(h)}_{\bullet\leftarrow k} - \mathcal{F}^{(h)}_{k\leftarrow\bullet} \tag{12}$$

Where $\boldsymbol{e'}_{mk}$ is an $mk\times 1$ column vector of ones, mk is the number of variables in a given country k and $\boldsymbol{B}$ represents a block in the structure. As each normalised forecast error variance decomposition represents the proportion of the total n-step ahead forecast error variance of the system accounted for by the effect from variable ν to variable ζ, $\mathcal{F}^{(h)}_{k\leftarrow\bullet}$ thus measures the total spillover from all other groups to group k by summing the normalised forecast error variance decompositions. Similarly $\mathcal{T}^{(h)}_{\bullet\leftarrow\ell}$ measures the total spillover to all other groups from group k (Greenwood-Nimmo et al., 2015). The two further measures proposed by Greenwood-Nimmo et al. (2015), the dependence index and influence index. At horizon h these measures are given respectively as:

$$\mathcal{O}^{(h)}_{k} = \frac{\mathcal{F}^{(h)}_{k\leftarrow\bullet}}{\mathcal{W}^{(h)}_{k\leftarrow k} + \mathcal{F}^{(h)}_{k\leftarrow\bullet}}, \quad \mathcal{I}^{(h)}_{k} = \frac{\mathcal{N}^{(h)}_{\bullet\leftarrow k}}{\mathcal{T}^{(h)}_{\bullet\leftarrow k} + \mathcal{F}^{(h)}_{k\leftarrow\bullet}}, \tag{13}$$

Where $\mathcal{W}^{(h)}_{k\leftarrow k}$ is the within-group forecast error variance contribution for the k-th group.

The dependence index where, $0 \leqslant \mathcal{O}^{(h)}_{k} \leqslant 1$, measures the relative importance of external

shocks to all shocks for the k-th group, the more important external shocks are the higher this index number will be. The influence index, $-1 \leqslant \mathcal{I}_k^{(h)} \leqslant 1$, has a threshold at zero whereby if $\mathcal{I}_k^{(h)} < 0$ the k-th group is a net shock recipient and if $\mathcal{I}_k^{(h)} > 0$ the group will be a net shock transmitter. A higher value of the influence index thus indicates a more dominant group.

4 Data, Variables and Model Specification

In this paper an attempt is made to use the longest time series possible so that the relationships among the variables can be tested over several business cycles (Kliesen et al., 2012). Although Sgherri and Galesi (2009) and N'Diaye et al. (2010) use monthly data in a macro-financial GVAR, and the FSI data are available monthly, the analysis in this paper will be conducted at a quarterly frequency. The longer time series resulting from using the data at this frequency has two advantages in relation to the analysis in this paper. Firstly, as already stated in Bisias et al. (2012), financial shocks occur relatively infrequently in the data so a longer series is desirable in attempting to quantify macro-financial relationships. In addition to allowing for a longer time series than monthly data, there is the benefit that, as noted in Canova (2007), with quarterly data the time aggregation should allow the issue of non-linearities to be abstracted from. This is important given that these non-linearities can be an important factor in monthly data, particularly in monthly financial data (Canova, 2007).

The database constructed for this paper draws heavily on the GVAR database [24]. The GVAR models in the paper will be estimated over the period 1981(1)-2013(1) and so will capture the period of the financial crisis and its aftermath. The data series finishes at the given date as this is the latest vintage available for the GVAR database. This database provides a consistent cross country macroeconomic database free from possible distortions from revisions to national accounts. As in Eickmeier and Ng (2011) the analysis will use an updated version of the data set used in DdPS (2007)[25]. Along with the variables from the GVAR database a number of financial variables

[24]For details of the GVAR database see di Mauro and Pesaran (2013) and DdPS (2007)

[25]This is taken from the GVAR Toolbox.

are added to the dataset to capture some of the variables which are indicated to be important in the theoretical and empirical literature on macro-financial linkages. The analysis will not however involve all countries available in this data set as once financial variables are added to the data set the number of usable countries reduces due to missing values in the financial data series. The analysis will begin with this initial reduced set of countries for which their is coverage of all the financial variables of interest [26].

One of the main sources for the financial data is the IMF financial stress index of Lall et al. (2009) are also used[27]. This is a uniform set of country specific time series measures which highlights periods of banking and financial distress across a broad range of advanced national economies. The index includes six measures; the inverted term spread, a measure of banking sector risk, a measure of counter-party risk (the TED spread), the corporate bond spread, stock market returns, stock return volatility and exchange rate volatility. The construction and sources of these measures are are outlined in detail in Lall et al. (2009). In this paper this measure will be used as a proxy for different types of financial stress episodes.

The TED spread is defined as the 3-month Libor rate minus the government short term rate and is used as a measure of stress in financial markets (Hull, 2012). This is because the Libor, the London interbank offer rate, is the rate at which banks are willing to lend to other banks and so an increase in the spread indicates an increased perception of the risks of bank insolvency (Thornton, 2009). As discussed in Hull (2012) over the course of the financial crisis this measure increased

[26]The final set of countries used are; Australia, Austria, Belgium, Canada, Finland, France, Germany, Italy, Ireland, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States.

[27]The substantial number of papers in the literature that attempt to identify causality in the impact of financial stress on the macroeconomy by constructing financial variables that can be thought of collectively as a financial conditions index (FCI) (Kliesen et al., 2012). This approach is found in Alessi and Detken (2009) where indicators of asset price booms are tested off periods they identify as boom periods from the historical record. Departing from this Lall et al. (2009) constructs a financial stress index (FSI) for advanced economies composed of six financial stress indexes. For a discussion on the similarities and differenced between FSI and FCI measures, see, Kliesen et al. (2012). It should be noted that this analysis is extended to emerging economies in Danninger et al. (2009). Many of the FSI and FCI measures are based on spreads. Throughout the 2008 financial crisis and its aftermath credit spreads came to prominence both as a measure of the stress in the financial system and for their predictive power for economic activity, particularly investors expectations of future economic outcomes (Gilchrist and Zakrajsek, 2012). This focus is motivated by theories that depart from the Modigliani Miller world of frictionless financial markets (Gilchrist and Zakrajsek, 2012). Another potentially important feature of the spread movements is that they may also represent shifts in the supply of credit (Gilchrist and Zakrajsek, 2012).

sharply and spiked at an all time high in October 2008. It then returned to normal levels, only to again increase during the Greek crisis. This pattern is seen in our data for most of the countries in the sample. The banking-sector beta is a measure of risk in the banking sector and is in line with the standard capital asset pricing model. The concept by which it measures banking sector risk is that if banking stocks move more than proportionately with the overall stock market then the banking sector is relatively risky (Danninger et al., 2009) [28]. In the financial stress indexes proposed by Lall et al. (2009) it is found that financial stress originating from banking stress is more likely to lead to strong and persistent downturns. In relation to the GVAR literature N'Diaye et al. (2010) find that a measure of bank distress has significant international spillovers and that the impact is larger in advanced economies.

The corporate bond spread variable is a proxy for risk in the corporate debt market (Lall et al., 2009). In the newest version of the IMF financial stress index, as used in this paper, the volatility measures have a changed definition from those found in Danninger et al. (2009) and Lall et al. (2009). The previously used GARCH(1,1) measure is replaced with volatility measured as the 6-month (backward looking) moving average of the squared month on month returns (Semmler and Chen, 2014). The inverted term spread which is the short minus the long term government rate is not included in the analysis as a spread variable, as used in Guarda and Jeanfils (2012), will be included in the model [29].

Moving on to measures not contained in the IMF database, a variable that is highlighted as important in strands of the theoretical literature, but that is unobservable, is the level of financial frictions. Hall (2012) notes that the crisis raised financial frictions by depleting the equity capital of financial institutions and that this resulted in a sharp fall in investment. The empirical literature related to the impact of a change in the overall level of financial frictions is more limited than that related to the other variables motivated by the financial friction literature. In a contribution

[28] Frictions from the banking sector are an important element in the financial frictions literature as they can also contribute to the propagation of shocks from the supply side (Xu, 2012). As discussed in Bisias et al. (2012) there has been a secular growth in the share of the US and global economy accounted for by the financial and insurance industries. These industries have grown monotonically since the 1980's and so it is likely that shocks to the financial system will have a larger impact now than in the past (Bisias et al., 2012).

[29] There is a high correlation between this spread variable and the inverted term spread.

to the empirical assessment of financial frictions that tries to develop a measure which is close to the concept of a financial friction proposed in the theoretical literature, Chari et al. (2007) find that financial frictions as modelled by a costly state verification approach as in Bernanke et al. (1999) or a credit market frictions model such as Carlstrom and Fuerst (1997) are equivalent to a growth model with an investment wedge. Utilising the conceptual basis of the investment wedge financial friction in Chari et al. (2007), Hall (2012) and Hall (2013). Hall (2013) proposes a number of measures of the financial frictions and find that these frictions account for the long period of high unemployment, depressed output and stifled investment in the period after the global financial crisis.

The long and short safe rate are used to calculate the various spreads as this follows the concept of the financial friction of Hall (2011) where the friction places a wedge between the return earned by savers and the borrowing rate. The three measures of frictions used in this paper coincide conceptually to those of Hall (2011) who presents a loan friction, a business investment friction and a mortgage friction. In the sample used in this paper these spreads increased during the financial crisis and remained high across a number of countries. The spreads calculated to capture the Hall (2011) measures differ in construction to what is common in the literature on cross country analysis. In Guarda and Jeanfils (2012) the spread between the short and long rate is used and is calculated on a country by country basis. This is not the approach taken in this paper for the Hall (2011) financial friction measures. For these measures, for example, in calculating the mortgage spread by country the safe rate is taken as the 10 year bond rate on German government bonds for a number of countries. This is done as in a number of countries sovereign sustainability issues meant that the country's own 10 year bond rate was volatile over the period and could not be considered as a measure of the safe return as utilised by Hall (2011) [30] [31].

In considering which variables are important in analysing macro-financial linkages the aforementioned theoretical literature and also the global financial crisis have highlighted an important

[30] For a description of the sources and construction of the data see appendix A.

[31] For example in the case of Spain and Italy the spread between mortgage interest rates and long term bonds turns sharply negative after the financial crisis due to changes on their respective 10 year government bond yields, However, when measured using the German rate the spread rises.

development in the financial system, that the role of credit has grown in many countries in the last number of decades (Xu, 2012). This growth is seen in that aggregate non-financial sector debt as percentage of GDP in advanced economies has increased from 167 percent in 1980 to 314 percent in 2009 (Cecchetti et al., 2011). The corporate sector accounted for 42 percentage points of this increase with households and governments accounting for 56 and 49 percentage points respectively (Cecchetti et al., 2011). This growth in credit, coupled with the global financial crisis, has lead to an expansion of research on the impact of credit shocks and a renewed interest in the credit and business cycles literature [32]. A number of studies have also highlighted the importance of credit in the international transmission of shocks [33]. It is seen that credit markets can not only be a source of disturbances but also an important propagator of disturbances (Bijsterbosch and Falagiarda, 2014). Balke (2000) notes a similar finding from the theoretical literature whereby in theoretical models of financial frictions, credit conditions need not be an important source of shocks to have relevance in the model as they are an important propagator of shocks.

From the empirical literature on the importance of credit, Lall et al. (2009) finds that initial conditions matter in determining whether a period of financial stress is followed by a downturn, in particular important preconditions are the borrowing ratios of non-financial corporates, the credit to GDP ratio of the household sector and the dynamics of credit and asset prices in the pre crisis period. This result is in line with the view of the Bank For International Settlements, as outlined in Leeper and Nason (2014), that deviation in credit to GDP ratios and house prices from trend are real time indicators of the risk of a financial crisis. In support of this view Leeper and Nason (2014) further point to a Bank of England estimates that a 1 per cent rise in the growth rate of the credit to GDP ratio raises the probability of a banking crisis in two years by 0.18 percentage points. Although the analysis in Lall et al. (2009) does not attempt identification the authors note

[32] See for example Xu (2012).

[33] Using a time varying parameter vector autoregression model, and identifying the shocks with the DSGE model of Gerali et al. (2010)), Bijsterbosch and Falagiarda (2014)) find that credit supply shocks have been an important driver of business cycle fluctuations.They also point to the long lasting negative effects of credit supply constraints on the economy with heterogeneity between stressed and non-stressed economics in this result. Ciccarelli et al. (2012) use a time varying panel Bayesian VAR approach with real and financial variables and counterfactual shocks to analyse macro-financial linkages across countries and over time. It is found that a tightening of the credit supply occurred in the 2008 financial crisis and that there were significant spillovers across countries.

that the results they find are consistent with the importance given to credit supply shocks as a key factor in the financial crisis.

There are two measures of credit considered in this paper. The first credit measure considered is the credit to GDP ratio. This is used as The Basel Committee on Banking Supervision (Bank For International Settlements, 2010) noted that extraordinary private credit growth often results in widespread default and financial instability and so the credit to GDP ratio is a useful system-wide benchmark (Bisias et al., 2012). The credit gap is the seacond credit measure used. It is also noted in Bisias et al. (2012) that Alessi and Detken (2009) find that indicators based on the private credit gap are the best early warning indicators of costly cycles [34]. Asset prices are included for a similar reason, Borio and Drehmann (2011) note that the coexistence of unusually rapid credit expansions and asset price increases are good indicators of a build up of financial stress [35].

To look in more detail at the evolution of the credit series over the sample period used in this paper, Figure 1 presents the average annualised growth rate of the ratio of credit to private non-financial corporates to GDP for a sub-sample of six countries. This sub-sample is indicative of the border trends in the full sample. The growth in this credit to GDP ratio series displays cyclical behaviour over the sample for most countries. The exception to this is Japan where the series displays a steady decline until up to the period just before the global financial crisis. The global financial crisis is the most striking feature of the series over the sample used as many countries display a persistent rise in the growth rate prior to the crisis and a spike in the early period of the crisis. This was followed by a sharp contraction in the mid to latter stages of the crisis. The full cross-country variation in the general pattern of the evolution of the growth in the credit ratio as highlighted in Figure 1 is seen in Figure 2. This figure shows the average growth rate of credit to GDP for a 4 year period before the crisis and for a 3 year period after financial crisis. It can be seen from this figure that of the sample of countries Ireland and Spain recorded the highest average credit growth pre crisis with the lowest being Germany and Japan. It is noteworthy that

[34]The credit gap used in this paper is that proposed in Alessi and Detken (2009) and is estimated by using the HP filter on the ration of credit to GDP with a very slow adjusting lambda, set to 100,000. Credit is this case is credit to private non-financial corporates from all sectors

[35]For the sources of the credit and asset price series see Appendix A.

by this measure the largest average reductions in credit to the private sector were recorded in the United States the United Kingdom, Germany, Norway and Japan. This group contains 4 out of the 5 largest economies in the world.

Asset prices are another variable highlighted as important in the theoretical literature. These are important as a collapse can be transmitted internationally through a deterioration in the balance sheets of connected institutions (Mittnik and Semmler, 2014) [36]. On the empirical side Guarda and Jeanfils (2012) in their analysis of macro-financial linkages find that financial shocks have a large contribution to real fluctuations and that shocks to asset prices are the most important source of these shocks. Looking specifically at the house price aspect of asset prices changes, Goodhart and Hofmann (2008) notes that in the pre crisis period that along with the observed growth in credit there was also a strong increase in house prices across a substantial number of countries. This link between credit and house prices may arise from collateral effects on credit demand as higher prices enhance borrowing capacities (Goodhart and Hofmann, 2008). Goodhart and Hofmann (2008) also highlights that this house price effect should be positive for credit growth due to the aggregate asymmetry between beneficiaries and those who lose out from a general house price increase. Hall (2011) outlines another aspect of house prices whereby years of stable and rising house prices made leveraged real estate assets seem a safe asset and many risk analysts assigned zero probability to a significant decline in house prices and so the unexpected decline impacted the economy as a substantial financial shock.

4.1 Variables

As in DdPS (2007) the macroeconomic variables are converted to real terms and the log-transformation is applied, the spread variables are not log transformed [37]. Following Canova (2007) we proceed

[36] This will occur as in the model of Kiyotaki and Moore (1997), when leverage constraints are binding a fall in asset values forces a immediate balance sheet contraction process.

[37] As stated in Mayr and Ulbricht (2007) the log-transformation is typically applied to macroeconomic data due to the use of the normality assumption. The transformation should limit the effects of heteroscedasticity and skewness in level data resulting in a more homogeneous series with a more stable variance (Mayr and Ulbricht (2007), Ltkepohl and Xu (2012) and Xu (2012)). In Shin and Kang (2001), taking a transformation compared to using levels is found to have very little effect on the in-sample time series estimation, the transformation does however improve the out of

by checking the degree of integration of each series by preforming unit root tests on the levels and differences of the series and then first difference the unit root variables until covariance stationary is achieved. This is important in this paper as a stationary version of the GVAR model will be used. As discussed in Canova (2007), the conventional view is that many macroeconomic time series are characterised by near unit root behaviour. Given this feature statistical tests for distinguishing between stationary and unit root processes have low power (Canova, 2007) [38]. Because of this Kwiatkowski et al. (1992) propose an alternative test baste in the null of stationary to be used in compliment with standard tests so as to assist in distinguishing stationary and unit root series. We utilise both types of tests to characterise the series used in this paper. For the unit root null test, the augmented Dickey-Fuller test is used and for the stationary null test the test proposed in Kwiatkowski et al. (1992) is used. As discussed in Zivot and Wang (2006) it is imperative to specifying unit root tests to characterise the trend properties of the data under consideration and the presence or absence of a constant [39]. The results of the unit root tests indicate, in line with the existing GVAR literature, that the variables; real output, inflation, the long and short run interest rate, the real exchange rate, real equity prices, the credit to GDP ratio, the house price index, real investment and real private consumption are all integrated of order one, $(I(1))$. The unit root tests indicate that these variables are stationary in their growth rates and so these are used in the estimation. The growth rate used is the year-on-year quarterly growth rate. The unit root tests indicate that some of the variables used in the model are stationary in their levels. Variables with this property include all the credit spread variables, the mortgage interest spread, the consumer spread, the corporate spread and the long minus short spread, all the IMF index measures and credit gap are shown to be $(I(0))$.

The selection of country specific variables to be used as variables or to be used in the construction of variables for the stationary country specific VAR models are the growth rate of real GDP of

sample forecasting performance of some variables (Ltkepohl and Xu (2012) and Xu (2012)).

[38]This point on the power of the tests is also discussed in Kwiatkowski et al. (1992) who note that many statistical tests propose as the null hypothesise that the series is a unit root process and so due to the tests low power result in a failure to reject the null. This may lead to series being designated unit root in error.

[39]In relation to unit root tests and transformations Ltkepohl and Xu (2012) and Xu (2012) not that in general in practice if a variable is classified as I(1) its transformation will also be I(1).

country i at time t, (y^g_{it}), the growth rate of the real exchange rate (e^g_{it}), the growth rate of the rate of inflation (π^g_{it}), the growth rate of real equity prices (q^g_{it}), the quarterly short term interest rate (ρ^S_{it}), the quarterly long term interest rate (ρ^L_{it}), the spread (sp_{it}), the growth in the house price index (hp^g_{it}), the mortgage interest rate spread (ms_{it}), the corporate borrowing spread (cps_{it}), the consumer borrowing spread (cs_{it}), the growth rate of credit to private non-financial corporates from all sectors $(cnfc^g_{it})$, the credit gap $(cgap_{it})$, the TED spread (ted_{it}), the "banking-sector-beta" $(beta_{it})$, corporate debt spread $(cbds_{it})$, stock market volatility (sv_{it}) and exchange market volatility (ev_{it}). More specifically, the variables are:

$$
\begin{aligned}
y^g_{it} &= ln(GDP_{it}/CPI_{it}) - ln(GDP_{i,t-4}/CPI_{i,t-4}), e^g_{it} = ln(FXDOL_{it}/CPI_{it}) - ln(FXDOL_{it-4}/CPI_{it-4}),\\
\pi^g_{it} &= \pi_{it} - \pi_{i,t-4},\ \pi_{it}\\
q^g_{it} &= ln(EQ_{it}/CPI_{it}) - ln(EQ_{i,t-4}/CPI_{i,t-4}),\ \rho^S_{it} = 0.25 \times ln(1 + R^S_{it}/100),\\
\rho^L_{it} &= 0.25 \times ln(1 + R^L_{it}/100),\ hp^g_{it} = ln(HPXI_{it}) - ln(HPXI_{i,t-4}),\\
ms_{it} &= bsmrg_{it} - safe^L_{it},\ cs_{it} = ircl_{it} - safe^S_{it},\ cps_{it} = corpb_{it} - safe^S_{it},\ sp_{it}\\
cnfc^g_{it} &= ln(CPNFCA_{it}/GDP_{it}) - ln(CPNFCA_{i,t-4}/GDP_{i,t-4})
\end{aligned}
$$

where GDP_{it} is nominal Gross domestic Product, CPI_{it} is the consumer price index, $FXDOL_{it}$ is the exchange rate in terms of US dollars, EQ_{it} is the nominal equity price index, R^S is the short term interest rate, R^L is the long term interest rate, $HPXI_{it}$ is the house price index, $bsmrg_{it}$ is the quarterly interest rate on building society mortgages, $ircl_{it}$ is the average quarterly interest rate on consumer loans, $corpb_{it}$ is the average quarterly corporate borrowing rate, $safe^L_{it}$ is a measure of the safe long term interest rate for country i at time t, $safe^S_{it}$ is the safe short term interest rate for country i at time t and $CNFCA_{it}$ is nominal credit to non-financial corporates from all sectors. The TED spread, the "banking-sector-beta", corporate debt spread, stock market volatility and exchange rate volatility measures are all taken directly from Lall et al. (2009) [40]. It should be

[40] For a discussion on the construction of these variables see (Danninger et al., 2009)

noted that as the spread variable, sp_{it}, is highly correlated with the inverted term spread, which is a measure of the slope of the yield curve, the inverted term spread variable form the IMF FSI measures is not used in the analysis. This variable is also a measure of banking sector risk (Lall et al., 2009)[41].

Along with the country specific variables the analysis will also include global variables. These are spread between the Aaa and Baa corporate bond yield ($Aaa-Baa_t$), the Gilchrist and Zakrajsek (2012) default risk (GZd_t) and excess bond premium ($GZebp_t$) and the growth rate of the log of the oil price index (oil_t^g) [42].

$$oil_{it}^g = ln(OIL_{it}) - ln(OIL_{i,t-4})$$

4.2 Model Specification

In constructing the country specific models, the analysis follows the standard approach in the GVAR literature as seen in DdPS (2007) and Xu (2012) whereby the US is considered the dominant economy in the model. In line with this approach and dealing firstly with all countries aside from the US, each country specific model will include a set of domestic variables, where available, and their foreign specific counterparts, termed country-specific foreign variables. For all countries, aside from the US, the country-specific foreign variables will include any global variables and will exclude the exchange rate as it will already be contained in the set of domestic variables. Given it is the dominant economy, the specification of the US mode differs accordingly. The global variables are included as endogenous variables in the US model. This allows macro variables to be influenced by the evolution of global variables such as the oil price (DdPS 2007). In relation to the financial variables the standard approach in the GVAR literature is again followed. Given the importance of the US financial variables in the global economy, the US country-specific foreign financial variables

[41] This is because banks generate income through intermediation between short-term and long-term assets and so a change in this spread can impact banks profitability (Lall et al., 2009).

[42] On the properties of these series, the oil price is non-stationary while the three spread variables are all stationary.

are not included in the US model as they are not considered long run forcing (weakly exogenous) with respect to the US domestic financial variables [43] (DdPS 2007). Following DdPS (2007) the country-specific foreign variables for the US for output and inflation are included in the US model. This is to capture possible second round effects of external shocks to the US [44] (DdPS 2007), (Xu, 2012). The analysis will begin by first constructing a benchmark model of the type used in DdPS (2007) and Guarda and Jeanfils (2012). The domestic and foreign variables for this model are shown in Table 1.

Once the variables to be included in the model are finalised, the appropriate lag order for the country-specific VARX for both the domestic and foreign variables, p_i and q_i respectively, are chosen (di Mauro and Pesaran, 2013). As in DdPS (2007), these are selected according to the Akaike information criterion [45]. As in Xu (2012) due to the limitations imposed by the sample size, p_{max} and q_{max} are not permitted to be no greater than two. As in (di Mauro and Pesaran, 2013) for the majority of countries, a VARX*(2,1) specification is deemed to be satisfactory. Also following Xu (2012) the models are estimated with unrestricted intercepts and restricted trend coefficients. In proceeding with the model specification the issue of structural breaks is abstracted from [46].

For the weights used in the GVAR model in this paper trade weights are selected for the reasons discussed in Xu (2012) which uses these instead of other possible measures such as financial linkages. Citing a variety of research papers Xu (2012) states that trade is the most important determinant of cross country linkages and international business cycle linkages (Xu, 2012). Xu (2012) notes that

[43] Supporting evidence for this assumption is provided in Xu (2012).

[44] Evidence supporting the weak exogeneity assumption required can be found in Xu (2012).

[45] This is a penalized likelihood approach which adds a term to the likelihood function of the model so that when estimating the parameters it is a complexity penalized likelihood function that is optimised (Sin and White, 1996).

[46] An important issue to consider when particularly with time series data with long sample sizes is the possibility of the presence of structural breaks (di Mauro and Pesaran, 2013). The importance of this issue in relation to macroeconomic time series is highlighted in Stock and Watson (1996). They do however also note that the conclusion on the presence or not of a structural break is dependent on the test employed (Stock and Watson, 1996). This point on the inconclusive nature of the best test of structural breaks is also noted in the GVAR literature and so following this literature a range of structural break tests are presented to assess the stability of the estimated coefficients and error variances of the country specific models. It should be noted that in the GVAR model, given that the country-specific models are specified conditional on foreign variables, this should, to an extent, alleviate problems of structural breaks (DdPS 2007). This is because with the presence of these variables the GVAR model can accommodate co-breaking and so the GVAR model may be more robust to structural breaks than compared to reduced-form single equation models (DdPS 2007).

given that there is a high degree of cross county correlation for financial and real variables mis-specification of weights will not have strong implications. Also in a GVAR model which contains financial variables; financial linkages will already be captured through the presence country specific foreign financial variables (Xu, 2012). In N'Diaye et al. (2010) alternative weighting schemes in the GVAR are again discussed, it is noted that in most of the GVAR literature trade weights are used or a narrow financial weights which only cover one type of relationship. N'Diaye et al. (2010) construct weights construct weights based on currency exposure measures of Lane and Shambaugh (2010)) which summarises five financial instruments. However, in robustness analysis using a variety of trade and financial weighting schemes N'Diaye et al. (2010) find that the results show little change between specifications. It is also the case that time series data on bilateral trade is much more readily available for a longer time period and a larger array of countries than bilateral financial data (Xu, 2012).

In utilising the connectedness measures framework to analyse the impact of different measures of financial stress a benchmark GVAR model will first be presented. This benchmark model will be used to compare connectedness results with this sample of countries to the analysis in Greenwood-Nimmo et al. (2015). This comparison is of interest as in contrast to this paper Greenwood-Nimmo et al. (2015) utilises the full set of available countries in the GVAR database and preforms the analysis with non-stationary data. To this benchmark model a measure of credit will then be added. This is because, as has previously been discussed, there is a growing empirical literature highlighting the importance of the information content of credit for business cycle fluctuations and financial crises (Borio et al., 2013). With the benchmark model now inclusive of a measure of credit the analysis will proceed by employing the connectedness measures framework to analyse the impact of the different measures of financial shocks that will be added to this model. The set of variables to be used in the benchmark model and those that will be added as measures of financial shocks are outlined in Table 2. As outlined in the previous section, this set of variables encompasses a broad range of liquidity, banking stress, volatility and asset price measures.

Once the financial variables that are the most influential have been identified, by utilising the

connectedness analysis, for all these variables the analysis can then be expanded to a broader range of countries where data is available. This is because, initially, many countries were excluded from the analysis as no data was available for a large number of the financial stress and financial friction measures. It will be seen that the connectedness analysis will exclude many of the financial shock measures as having little global influence, a reduced set of financial shock variables will then be under consideration.

5 Results

In conducting the analysis in this section a benchmark model is first established to assess the comparability of the results with the original GVAR and GCM approach given the use of stationary data and a different sample of countries. This comparison is contained in Appendix B. The consistency of results that is found supports the use and comparability of this benchmark model when proceeding with the inclusion of financial variables. To this benchmark model a credit variable is added. The choice of credit measure and its and effect are outlined in Appendix C.

Turing to the analysis of the relative global importance of the array of financial shock variables, this will involve the GVAR model being estimated in accordance with the equation structure outlined in Table 2 [47]. This will allow the dependence and influence index measures from the connectedness measures framework to be calculated for each of the shock variables in turn, in a benchmark GVAR model with credit. The connectedness measure framework is then applied to summarise these results. In relation to the origin of the shocks, as the US is the dominant economy in the model all shocks are shocks to the US domestic series of each variable [48]. To look at the impact of variables the bloc aggregation structure of the matrix of forecast error variance decompositions is changed from a country based structure to a variable based grouping structure. The

[47] The forecast horizon h used for all of the connectedness measures presented in this paper will be set at $h = 4$. This follows the discussion of alternative choices of horizon, when using quarterly data, in Greenwood-Nimmo et al. (2015). In Greenwood-Nimmo et al. (2015) it is found that in the large majority of cases the choice of forecast horizon is unlikely to exert a decisive influence on the results of the connectedness measures and also that in most cases the connectedness measures converge to their long run value after 3-5 quarters.

[48] This is in keeping with the much of the existing GVAR literature.

results of this analysis for the dependence and influence index measures are shown in Figure 3.

These measures show the dependence and influence of each variable when included separately in the benchmark model with credit. From the figure it can be seen that the most influential variables are the bond spread measures, the two measures proposed by Gilchrist and Zakrajsek (2012), (henceforth the GZ measures), and the Aaa-Baa corporate bond spread. The other influential variables, albeit at a relatively much reduced magnitude, are the exchange rate volatility measure, the spread measure and the corporate bond spread measure from the IMF's financial stress index measures. All other measures of financial stress/financial frictions are net shock recipients. It is noteworthy that two of the least influencing measures are house prices and the mortgage spread, this could be because as noted in Dees (2015) that housing markets are influenced predominantly by country specific factors, and so in a connectedness analysis it would be expected that their global influence measure will be low. This result for the GZ measures and the Aaa-Baa spread is congruent to the result found in papers not using the GVAR framework, such as Giglio et al. (2015) where the GZ measures and the default spread (what they term the Aaa-Baa spread) frequently Granger cause other variables and not the reverse. In their analysis on the predictive power of an array of systemic risk measures for the lower tail of macroeconomic shock the GZ measures were also found to have significant predictive power. The results of Sanjani (2014) are also in line with those in this paper as in decomposing the credit spread liquidity risk shocks are found to have a severe economic impact.

The results of the connectedness measures analysis as presented thus far suggest that credit can be thought of as an endogenous variable in the model as it records a very low influence score and a high dependence. This result holds both at the at the global economy level, and at the individual country level where the shock to US credit is shown to have a very weak influence. As per the interpretation of Gilchrist and Zakrajsek (2012) of the link between their measure and the financial frictions literature of Bernanke et al. (1999), Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010) and Hall (2011), our results also suggest that it is shocks to a measure of the financial friction and not shocks to the level of credit that are of importance. This result would be

in keeping with the theoretical literature on macroeconomic variables, credit and financial frictions and is contrary to the approach employed by many papers in the empirical financial shocks literature which proceed by shocking a measure of credit [49]. From the perspective of the collateral constraints seam of the financial frictions literature as outlined in Kiyotaki and Moore (1997), Iacoviello (2005) and empirically in Hall (2011), it is the size of the financial friction that is of most importance not the amount of credit. In this theoretical literature the presence of a stock of borrowing in steady state depends on the existence of a financial friction not vise versa.

Figures 4-6 show how the influence of these financial shocks varies by country. It is notable that the cross-country variation in the pattern of of which measures are influential and which are not is quite homogenious across most of the countries. This is in line with the findings of Guarda and Jeanfils (2012), that the effect of financial shocks on the real economy is fairly uniform across countries. They note that this is in line with much of the previous literature. The general pattern of a high recorded measure for the GZ variables ad the Aaa-Baa spread measures and lower values for the other variables holds across countries. It is seen that Canada is much more influenced for almost all variables compared to other countries due to its close linkages with the US. Switzerland and Ireland as small open-economies with a relatively large financial sector, record a much higher influence from a shock to US stock market volatility than other countries. In relation to the other financial shock measures, aside from the GZ variables and the Aaa-Baa spread, Germany, Japan, Ireland and Switzerland record more sensitivity to the US TED spread and the US Banking Beta banking sector stress measures than other countries in the sample.

The relative aggregate impact of the three the three most influential financial shock measures, the GZ default risk measure, the GZ excess bond premium measure and the Aaa-Baa corporate bond spread, are shown in Figure **??**. The shocks are ordered by the impact of the default risk measure.

As previously noted, the connectedness measures indicate that the most influential variables in the benchmark model are the equity price and the oil price. Figure 8 shows the magnitude

[49] See Xu (2012) and Eickmeier and Ng (2011).

of the influence index measure of the two GZ measures and the Aaa-Baa spread relative to the other benchmark variables in the model. The negative figure for output should not be taken as a lack of importance, it is because it is heavily influenced by other variables and so this will reduce its influence index number. This graph is constructed using the TO connectedness measure and again takes advantage of the connectedness measure flexibility in switching between a country and variable level ordering of the matrix of generalised forecast error variance decompositions. This measure shows the the macroeconomic and financial variables of Germany are most impacted by a shock the the default risk and excess bond premium. Surprisingly given its proximity and strong economic linkages for this particular type of shock Canada is the second least impacted, with Ireland being the least impacted. This is in keeping with the results in Greenwood-Nimmo et al. (2015) where there is a diverse range of dependence and influence measures among economies. This diverse reaction among different countries can depend on a broad array of factors such as differences in measures of macroeconomic fundamentals and financial integration (Adler and Mora, 2012). This result is of particular interest in the context of country level financial stability as it indicated that although there there may be a clear ranking found of which variables are most influential at the global level there can still be an unexpected diversity among countries as regards which variables are important for influencing the outcomes of each individual country.

In relation to the sign and magnitude of the impact of the financial shocks the strongest impact is from a rise in the default component of the corporate bond spread on the equity price index. This result of the strong response of the equity price index may be due to the forward looking nature of stock prices, that they anticipate the changes in output, indeed in empirical forecasting exercises GDP growth is found to be highly correlated with the lagged stock price changes (Nalewaik, 2010). For each of the variable the effect on the credit to GDP variable is positive. It is probable that this occurs because in the data, as can be seen from Figure 1, this ratio spikes during the early crisis periods and only begins to contract in the years after the onset of the crisis.

6 Conclusions

This paper analyses cross-country macro-financial interactions through looking at a variety of measures of financial stress and financial frictions. The framework employed allows this complex set of interactions to be analyses in a single model and for the results to be condensed down to a more limited range of summary measures that can be presented in a more stylised and less selective way. This framework has significant advantage in relation to analysing these types of interaction due to the large amount of uncertainty regarding their measurement, transmission mechanisms and possible identification structures. The contribution of the paper is that this is the first paper which utilises the GVAR and connectedness measures frameworks to gain an insight into the global transmission and influence of different types of financial shock and it does this in a way which minimises the amount of assumptions and restrictions required.

In testing an array of financial stress and financial friction measures in a large global VAR model combined with connectedness measures it is found that many proposed measures are net receiver of shocks and not net transmitters. In particular the connectedness measures suggest, in line with the theoretical literature, that the measure of credit is an endogenous variable in the model. The measures found to be most influential on other macroeconomic variables are liquidity measures as constructed from the corporate bond market. The component of this bond spread which found to be most influential is that which is most closely aligned to the concept of a financial friction from the financial frictions literature. This finding on the importance of this financial friction measure is supported in other studies. There is also a considerable degree of consistency in the cross-country reaction to US originating financial shocks.

These results contribute to the literature on the measurement and influence of financial shocks, the cross-country variation in the impact of the shocks among economies warrants further investigation as there are a number hypothesis on the variables that determine this reaction.

7 Appendix A. Data Sources

The variables GDP, the price level, equity price index, exchange rate, short and long term interest rates as well as the oil price index are all drawn from the latest version of GVAR database as outlined in DdPS (2007). For Finland the series for the interest rate on long term government bonds is not contained in the original GVAR database. This is because in the case of Finland the series used for the other countries 'Interest Rates, Government Securities, Government Bonds' from the IMF International Financial Statistics only begins in Q1 1988. This series is included in the analysis in this paper and is back dated using data from the OECD Economic outlook and the OECD Main Economic Indicators. The series used are 'Finland, Long-Term Interest Rate On Government Bonds, AR, SA' and 'Finland, Long-Term Government Bond Yields, 10-Year, Main (Including Benchmark), Yield 10-Year Government Benchmark Bonds'. Both series are sourced from Datastream. The correlation between the IMF bond series for Finland and the two OECD bond series is above 0.99.

The data source for the house price index for all countries is the Oxford Economics 'House Price Index' and is sourced from Datastream. An alternative house price measure also from Datastream is the 'Residential Property Prices' series from the Bank for International Settlements. The Oxford Economics series was selected as it covered more countries relevant to the sample in this paper and the correlation between these two house price indexed was above 0.99 for most countries.

The data for the credit series all come from the Bank For International Settlements. The series used for credit to private non-financial corporates from all sectors is, 'Credit to Nonfinl Corps from all Sectors'.

Data for the global corporate bond yield variable is taken from Datastream with the variables being 'United States Corp Bonds Moodys Seasoned BAA' and 'United States Corp Bonds Moodys Seasoned AAA'.

For the majority of countries, for the investment variable, the series used is "Gross Fixed Capital Formation, Total, Current Prices, AR, SA" from the OECD Economic Outlook and is sourced from

Datastream. However, for Ireland this series only begins in Q1 1990.

8 Appendix B. Model Comparison

To illustrate the connectedness estimation results and to provide a comparison with the analysis of Greenwood-Nimmo et al. (2015) in advance of proceeding with the analysis of the financial shock variables, the results of the connectedness measures analysis of the benchmark model with no financial factors is shown in Table 3. The variables used in the benchmark model are outlined in Table 1. Large values of the Total To connectionless measure indicates that a shock to a country's variables has a strong impact on the other countries variables. From this measure the United States is the dominant economy in the model with spillovers from the US to the other economies accounting for 8.5% of all the four-quarters-ahead forecast error variance of the system. This results adds to the empirical justification of focusing on US based shocks as is done in much of the GVAR literature and in the broader literature on financial shocks. In the sample used in this paper the economies with a weak impact on other economies are Canada and Switzerland. These results are a close match to Greenwood-Nimmo et al. (2015) who notes that the impact measure tends to be weaker in small open economies which belong to significant free trade areas. Higher values of the Total From connectedness measure indicated an economy is more strongly effected by other economies. This measure also reveals the dominant role of the US as it has the lowest value of all countries in the sample, indicating it is the least influenced by external factors. The dependence and influence index confirm this pattern with the US and Japan the least impacted by external shocks, The United States and the oil price are the strongest transmitters of global shocks in the sample. For the US it should be noted that the connectedness measures suggest that by far the most important variable for shock transmission is the US equity price index. This result was found in Greenwood-Nimmo et al. (2015) which revealed the substantial spillover from financial markets to real activity throughout the sample period. The US equity price result has also bee seen in the GVAR literature, in Sgherri and Galesi (2009) and Xu (2012).

The consistency of this benchmark model with that of Greenwood-Nimmo et al. (2015) is interesting to note as not only is the model in this paper estimated on a reduced sample of countries, this model also employs stationary as opposed to non-stationary data, as is used in Greenwood-Nimmo et al. (2015).

9 Appendix C. The Credit Variable

With the introduction of the credit variable to the benchmark model in our analysis it is found that, whether it be the growth of the credit to GDP ratio or the HP filtered credit gap, its inclusion improves the fit of almost all country specific models [50]. More specifically, the average of the adjusted R-squared measures across the country-specific models increased from 0.83 without credit to 0.86 and 0.88, respectively, with the credit gap and credit to GDP measure included. Figure 9 shows the difference in the adjusted R-squared measure between the benchmark model and the models including the two alternative measures of credit. It can be seen that the credit to GDP ratio improves the fit of all country-specific models by more than the credit gap measure. Taking the adjusted R-squared as a measure of the fit of the model, it can also be seen that in the case of Austria and the Netherlands the inclusion of the credit gap measure reduces the fit compared to the basic model. Based on these estimates, the credit to GDP ratio is taken as the credit measure to be used in all models when proceeding to the financial shocks analysis. From the connectedness measures framework, Figure 10 shows the changes in the dependence and influence index measures for each country resulting from the inclusion of the credit variable. The influence of the UK and the US as a transmitter of shocks increases while their dependence decreases [51]. The influence of Germany and Japan reduces with the introduction of the credit variable.

[50] This improvement of fit from the introduction of credit is also found in Xu (2012).

[51] This also occurs for Italy but this is because the Influence index measure was increasing from a low initial value.

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Table 1: Benchmark Model and Financial Variables

Country	Domestic Variables	Foreign Variables
US	$y^g_{US,t}, \pi^g_{US,t}, q^g_{US,t}, sp_{US,t}, oil^g_t$	$y^{*g}_{US,t}, \pi^{*g}_{US,t}, e^{*g}_{US,t}$
Rest of the World	$y^g_{it}, \pi^g_{it}, q^g_{it}, e^g_{it}, sp_{it}$	$y^{*g}_{it}, \pi^{*g}_{it}, q^{*g}_{it}, sp*_{it}, oil^g_{it}$

Table 2: Benchmark Model and Financial Variables

Benchmark Model						Credit	Shock Variable
y^g_{it}	π^g_{it}	e^g_{it}	q^g_{it}	sp_{it}	oil^g		
y^g_{it}	π^g_{it}	e^g_{it}	q^g_{it}	sp_{it}	oil^g	$cnfc^g_{it}$	
y^g_{it}	π^g_{it}	e^g_{it}	q^g_{it}	sp_{it}	oil^g	$cnfc^g_{it}$	cps_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	ted_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$beta_{it}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	cs_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	hp^g_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	ms_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$cbds_{it}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	sv_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	ev_{it}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$GZebp_t$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	GZd_t
y^g_{it}	π^g_{it}	e^g_{it}	q^g_{it}	sp_{it}	oil^g	$cnfc^g_{it}$	$Aaa - Baa_t$

Table 3: Connectedness measures Among Countries, Four-Quarters Ahead

	To	From	Dep	Inf
Australia	2.90	3.68	0.63	-0.12
Austria	3.18	4.83	0.82	-0.21
Belgium	6.16	4.86	0.83	0.12
Canada	2.77	4.45	0.76	-0.23
Finland	4.33	4.32	0.73	0.00
France	4.86	4.88	0.83	0.00
Germany	6.10	4.81	0.82	0.12
Italy	3.98	4.59	0.78	-0.07
Japan	3.19	3.53	0.60	-0.05
Netherlands	3.51	4.95	0.84	-0.17
Norway	3.70	4.78	0.81	-0.13
Spain	4.47	4.39	0.75	0.01
Sweden	3.01	4.86	0.83	-0.24
Switzerland	2.91	4.82	0.82	-0.25
United Kingdom	5.30	4.41	0.75	0.09
United States	8.50	2.83	0.60	0.50
Oil	3.26	0.41	0.35	0.78
Ireland	3.57	4.35	0.74	-0.10
Average	4.21	4.21	0.74	0.00
Average (excl. oil)	4.26	4.43	0.76	-0.04

Figure 1: The One Year Average Growth in Credit

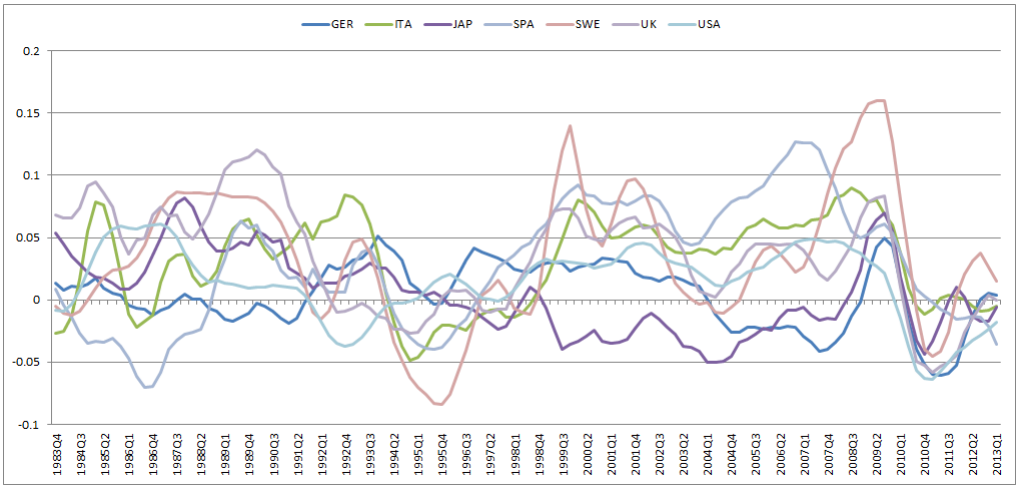


Figure 2: Growth in Credit Pre and Post Financial Crisis

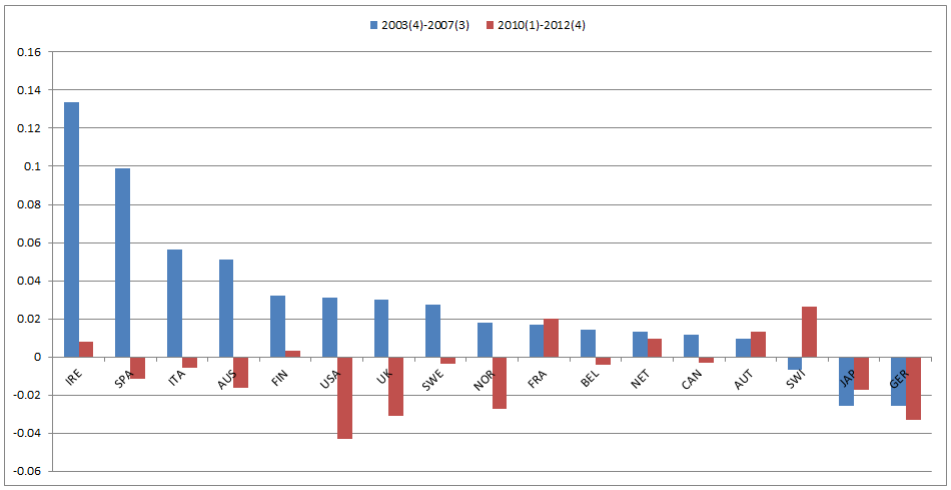
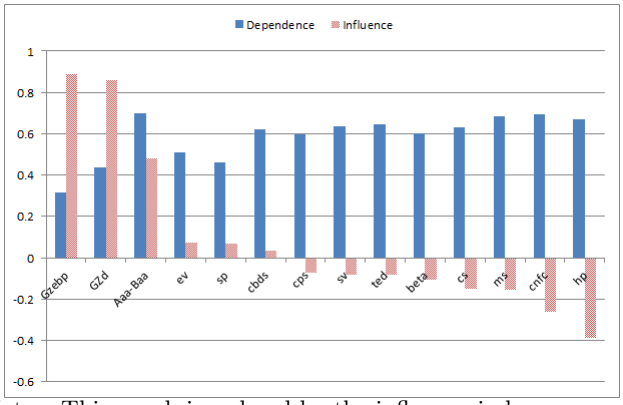


Figure 3: Influence of Financial Variables



Notes: This graph is ordered by the influence index measure and displays the cross country influence and dependence index measures from an array of financial shocks originating from the US. The results are obtained by running the baseline model and adding a different financial shock variable each time, with replacement.

Figure 4: Magnitude of Influence Across Countries (1)

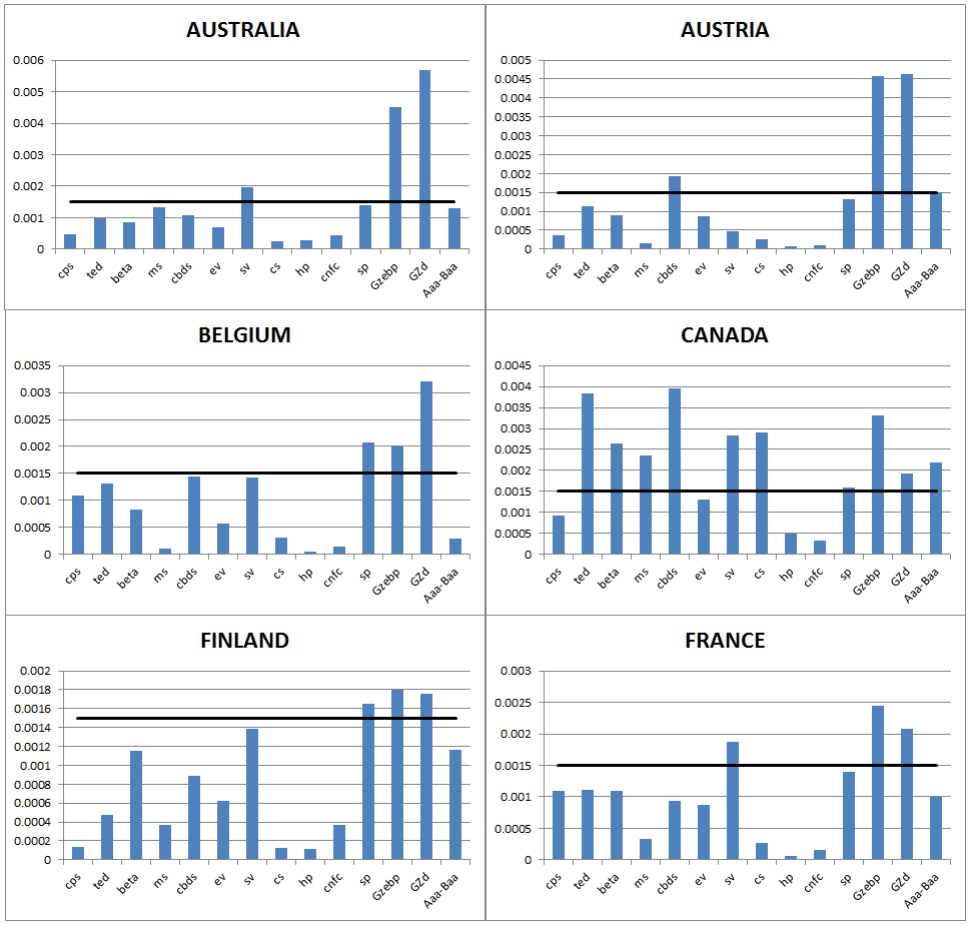


Figure 5: Magnitude of Influence Across Countries (2)

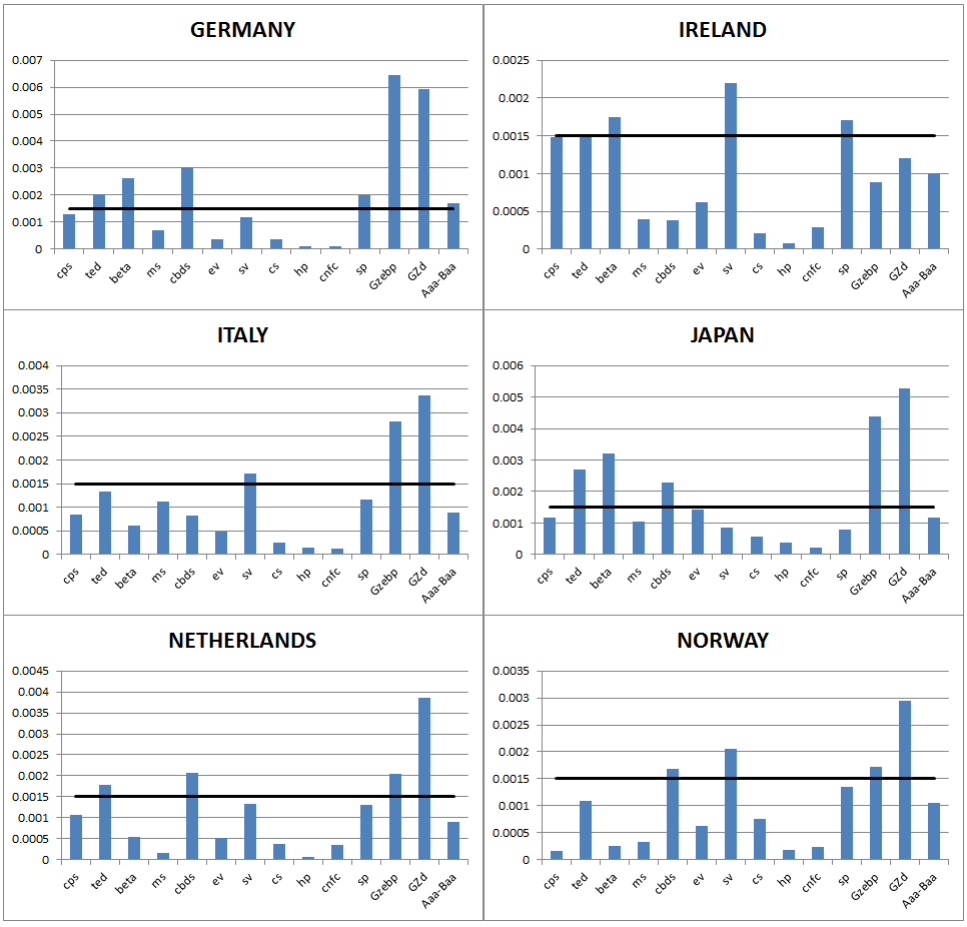


Figure 6: Magnitude of Influence Across Countries (3)

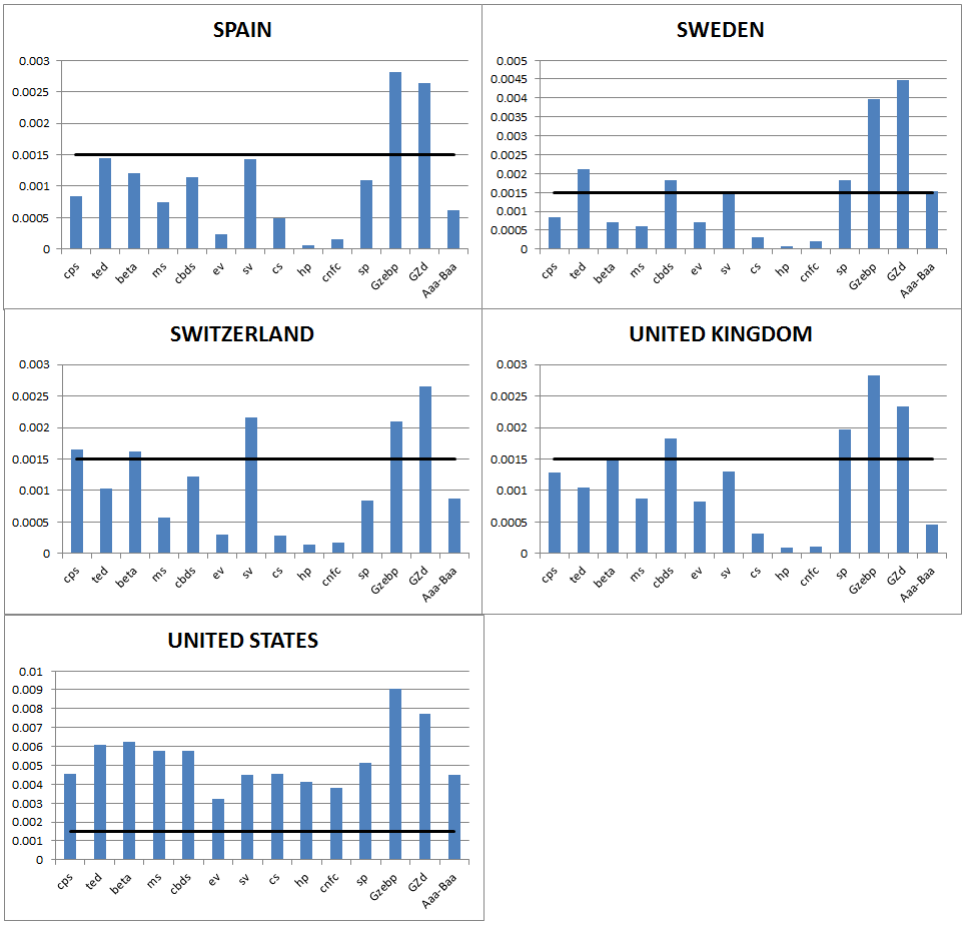
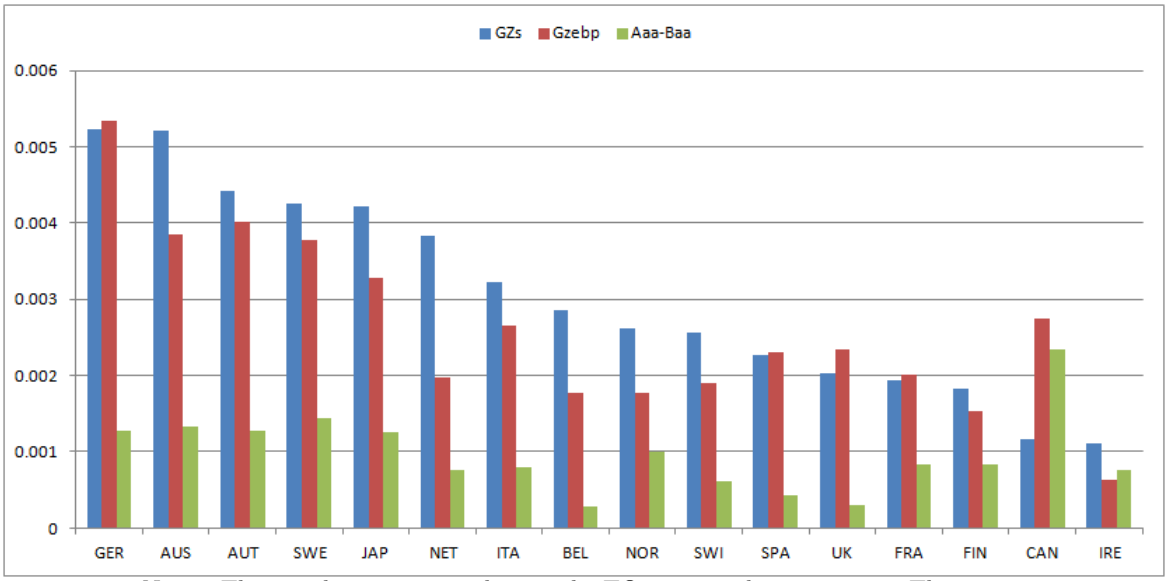


Figure 7: Impact of Shocks to Selected United States Financial Variables



Notes: This graph is constructed using the TO connectedness measure. This measures the aggregate impact on a countries macroeconomic and financial variable's of a shock a particular financial variable.

Figure 8: Magnitude of Influence Across Variables

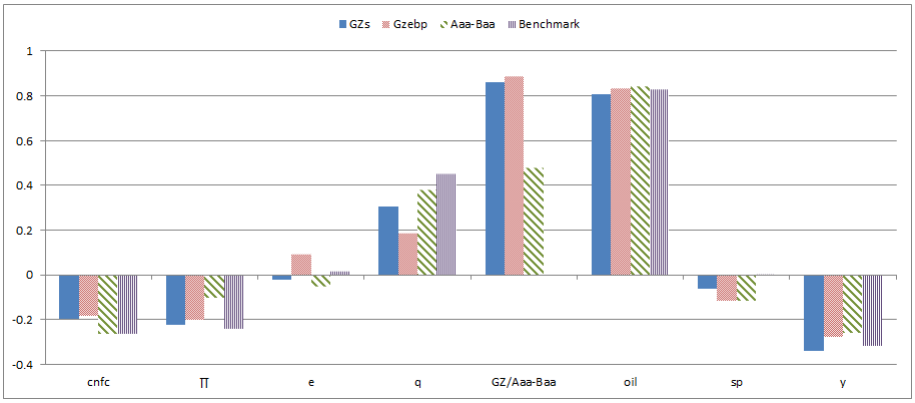
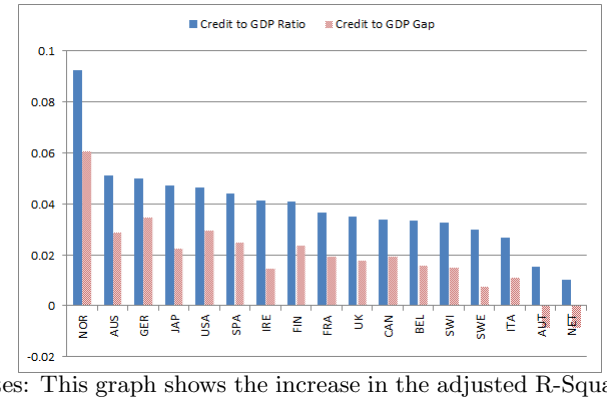


Figure 9: Credit and Models Fit



Notes: This graph shows the increase in the adjusted R-Squared statistic from the country level VAR models that comes from the addition of the different credit variables.

Figure 10: Change in Dependence, Influence from Credit