Financial sector bailouts, sovereign bailouts, and the transfer of credit risk*

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Abstract

We develop an empirical network model to study credit risk spillovers among a group of eighteen sovereigns and their financial sectors from 2006–2015. Initially a net source of credit risk, the financial sector becomes a net recipient after the 2008 financial sector bailouts in many countries. Fiscal fundamentals explain much of the heterogeneity in financial-sovereign spillovers over this period. The subsequent European sovereign bailouts disrupt the feedback between sovereign risk and local financial sector risk. Depending on the initial fiscal position of the target country, sovereign bailouts may also disrupt international credit risk spillovers originating from the target sovereign.

JEL Classification: C58, E44, G01, G12

Keywords: Financial crisis; Debt crisis; Financial–sovereign linkages; Credit risk transmission; Network modeling

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1 Introduction

Many systemically important financial institutions received government assistance during the Global Financial Crisis (GFC) to support their balance sheets and prevent insolvency. These measures eased concerns over systemic risk in the short term. The cost, however, was that a great deal of private sector credit risk was transferred onto the public sector during a period when public debt was growing rapidly. This combination ultimately led to the sovereign debt crisis in Europe and to a resurgence of systemic risk driven by the adverse feedback between sovereign and financial sector credit risk. The interplay of public and private risk is now one of the foremost challenges facing policymakers and regulators in the world’s advanced economies, yet much remains unknown about the sovereign–financial nexus.

We make two contributions in this paper. First, we develop a sophisticated model of the global credit risk network that provides a vivid representation of the time-varying codependence between sovereign and financial sector credit risk, both on a national and global scale. Second, we evaluate the impact of both financial sector and sovereign bailouts on the credit risk network and we show that much of the heterogeneity across countries can be explained by fiscal fundamentals.

Credit risk is typically measured using either bond yield spreads or credit default swap (CDS) spreads. A CDS operates like an insurance contract that allows a bondholder to pay a premium to transfer the default risk of the bond onto the protection seller over a given period. The CDS market is widely believed to be the leading forum for credit risk price discovery and the five-year tenor is considered to be among the most liquid ([Blanco et al., 2005](#); [Gyntelberg et al., 2018](#)). Consequently, we employ CDS spreads with a tenor of five years as our preferred measure of credit risk. Our CDS data is sourced from IHS Markit and covers the period January 2006 to July 2015 at daily frequency for a cross-section of eighteen countries and 202 banks domiciled within these countries.

An important feature of the CDS data is the high degree of comovement observed in the cross-section. For example, during our sample period, the correlation between the German and U.S. sovereign CDS spreads is 0.84, the correlation between the German sovereign CDS spread and the CDS spread for Deutsche Bank is 0.88 and the correlation

between the CDS spreads for Deutsche Bank and Société Générale is 0.92. Such a high degree of codependence is typical over this period despite the fact that credit spreads should rapidly adjust to reflect idiosyncratic variations in default risk. A significant portion of this comovement derives from the dependence of credit spreads on common factors, including liquidity and investor risk appetite (e.g., [Pan and Singleton, 2008](#); [Longstaff et al., 2011](#); [Fender et al., 2012](#); [Ang and Longstaff, 2013](#)). In addition to the role of local and global factors, bilateral spillovers among bond markets may contribute to the observed comovement of credit spreads (e.g., [Gande and Parsley, 2005](#); [Alter and Schüller, 2012](#); [Alter and Beyer, 2014](#)). It is these bilateral credit risk spillovers that are central to our analysis.

A great deal of research effort has been devoted to modeling credit spreads. Since the GFC, the development of techniques to model the joint evolution of sovereign and financial sector credit risk has emerged as an important focus among policy institutions, with increasing emphasis on holistic approaches that recognize the importance of bidirectional spillover effects and their potential to generate feedback loops and destabilizing spirals (e.g., [International Monetary Fund, 2013](#), pp. 65-6). Therefore, it is natural that empirical network models are prominent in this literature (e.g., [Billio et al., 2012](#); [Alter and Beyer, 2014](#); [Demirer et al., 2017](#)). These models are built on the theoretical literature in which network structure is emphasized as an important determinant of aggregate outcomes in economics and finance (e.g., [Leitner, 2005](#); [Acemoglu et al., 2012, 2015](#)).

We follow in this tradition and develop a model that is among the most detailed in the literature to date, containing both sovereign and financial sector credit spreads for eighteen countries that collectively account for the large majority of global economic and financial activity. Our model is rooted in the connectedness framework of [Diebold and Yilmaz \(2009, 2014\)](#) and [Demirer et al. \(2017\)](#) — hereafter collectively the **DY** framework — in which the forecast error variance decomposition of a vector autoregressive (VAR) model is used to construct a weighted directed network that summarizes the pairwise relations among entities in the model. This approach has two desirable features. First, unlike Granger-causal networks of the type considered by [Billio et al. \(2012\)](#), which are directed but unweighted, **DY** networks measure both the direction and the strength of

credit risk spillovers between entities. Second, because the network is derived from a VAR system, it is robust to the omitted variables problem that affects networks derived from a set of bivariate regression models.¹

Ours is not the first application of the DY framework to study credit risk or the interaction between sovereigns and the financial sector. For example, [Demirer et al. \(2017\)](#) analyze the volatility connectedness of the global bank network and show that major global bank stocks and ten-year sovereign bonds became tightly intertwined during the European sovereign debt crisis. Furthermore, [Alter and Beyer \(2014\)](#) and [Bostanci and Yilmaz \(2015\)](#) both develop DY network models to examine the cross-sectional linkages among CDS spreads. While [Bostanci and Yilmaz \(2015\)](#) focus on sovereign CDS spreads, [Alter and Beyer \(2014\)](#) consider the interaction of sovereign and financial sector CDS spreads. However, unlike these studies which mainly focus on characterizing the network and measuring spillover activity, our focus is primarily on understanding the heterogeneity among countries in the credit risk network.

Partly due to our disaggregate focus, our implementation of the DY framework offers two notable refinements to the literature. First, in recognition of the factor structure in the CDS data discussed above, we employ a considerably more sophisticated set of daily controls than is typically used. We include: (i) the daily stock market return and the sovereign term spread for each country to control for domestic macrofinancial conditions; (ii) the Treasury–Eurodollar (TED) spread and an appropriate European counterpart to control for variations in liquidity; and (iii) the equity and Treasury variance risk premia to account for variations in the willingness of equity and fixed income investors to bear risk. Accounting for global and local factors in this way is important if we are to measure changes in the intensity of bilateral credit risk spillovers without simply picking up comovements induced by exposure to common shocks. This contrasts with [Bostanci and Yilmaz \(2015\)](#), who do not include controls, and with [Alter and Beyer \(2014\)](#), whose controls mostly account for global but not local factors.²

¹A well-known problem in the context of bivariate Granger causality tests is that one may detect a first order connection between entities a and b which are, in fact, not directly connected to one-another but are both connected to another entity, c , which is excluded from the bivariate regression.

²The network model developed by [Bostanci and Yilmaz \(2015\)](#) contains sovereign CDS spreads for a large group of up to 54 developed and emerging sovereigns (data limitations necessitate the removal of some sovereigns over some sample periods). Given that sovereign CDS spreads rapidly impound

Second, given that our model is large and that we estimate over rolling samples to capture time-variation in the structure of the credit risk network, we test the performance of several strategies to alleviate the degrees of freedom problem in estimation. Most applications of the [DY](#) framework rely on simple VAR models, which are susceptible to overfitting as the dimension of the model becomes large. [Greenwood-Nimmo et al. \(2015\)](#) were the first to apply global VAR estimation in this context, using cross-sectional averages of the explanatory variables to reduce the number of freely estimated parameters. In a similar vein, [Demirer et al. \(2017\)](#) introduced shrinkage and selection estimators into the [DY](#) literature, implementing the elastic net regularisation of [Zou and Hastie \(2005\)](#). However, to the best of our knowledge, ours is the first paper to address the uncertainty surrounding the estimation strategy for the underlying VAR model, to systematically assess the relative performance of a set of candidate models and to select an optimal estimation strategy in a rule-based manner.

Our first finding is that the 2008 financial sector bailouts changed the role of sovereigns in the global credit risk network. Prior to the bailouts, on average, sovereigns absorbed credit risk from the financial sector. After the bailouts, however, many sovereigns became significant sources of risk. [Acharya, Drechsler, and Schnabl \(2014, hereafter ADS\)](#) offer a theoretical treatment of this issue featuring an adverse feedback loop between financial sector credit risk and sovereign credit risk. The loop starts with rising credit risk in the financial sector. Should the government perceive that the risk to financial stability is sufficiently severe, then it will bail-out distressed financial institutions. The bailouts reduce credit risk in the financial sector at the cost of increased sovereign credit risk, which raises the government’s funding cost and compromises its fiscal position. This, in turn, reduces the future value of the sovereign guarantee of the financial sector while simultaneously reducing the value of the financial sector’s holdings of sovereign debt. This combination causes a resurgence of financial sector credit risk, with the result that both sovereign credit risk and financial sector credit risk start moving in the same direction in

information on shocks affecting alternative asset classes, [Bostanci and Yilmaz](#) argue that it may be unnecessary to control for conditions in other asset markets when using the [DY](#) method in a model with such rich cross-sectional coverage. However, given that the cross-sectional coverage of our model is considerably smaller than that of [Bostanci and Yilmaz \(2015\)](#) — our analysis focuses on 18 countries compared to their 54 — it is important that we control for both local and global factors.

a mutually reinforcing manner.

Empirical evidence of this adverse feedback effect has been provided by [Alter and Schüller \(2012\)](#) using bivariate Granger causality tests and impulse response analysis and by [ADS](#) using a variety of panel data regression models. [Alter and Beyer \(2014\)](#) were the first to document sovereign–financial feedback effects using a variant of the [DY](#) framework in which contagion indices are constructed using restricted impulse response functions. Our results add to this body of evidence. We show that the [ADS](#) feedback loop manifests as a cycle in the sovereign–financial credit risk network, with the net credit risk spillover from the i th financial sector to the i th sovereign typically starting from a small positive value, rising rapidly during the GFC, falling sharply at the time of the bailouts and remaining negative for a period thereafter before returning to a positive value. The amplitude and duration of the cycle displays marked heterogeneity, with a particularly stark distinction between the European core and the GIIPS (Greece, Ireland, Italy, Portugal and Spain). In the core countries, the period during which the net financial–sovereign credit risk spillover is negative is typically short-lived and the magnitude of the net spillover effect is weak. Among the GIIPS, the negative part of the cycle is generally sustained for several years and the net spillover from the sovereign to the financial sector is much stronger. Based on auxiliary panel data regressions, we show that these differences can be well explained by cross-sectional differences in fiscal fundamentals, notably the behavior of the debt-to-GDP ratio and the government’s structural budget balance, which is strongly consistent with the emphasis in [ADS](#) on the fiscal costs of financial sector bailouts.

Next, we show that the sovereign bailouts received by Greece, Ireland, Portugal and Spain between 2010 and 2012 exerted a calming effect on the global credit risk network. We find that the bailouts systematically weaken spillovers between the target sovereign (the sovereign that received the bailout) and its domestic financial sector, thereby disrupting the adverse feedback loop documented by [ADS](#). This is an important result as it implies that sovereign bailouts improve financial stability within the target country. We show that the Irish, Portuguese and Spanish bailouts also helped to alleviate international credit risk spillovers originating from the target sovereigns, which suggests

that these bailouts may have reduced the contagion risk posed by these countries. However, we find little evidence that the Greek bailouts weakened international credit risk spillovers from the Greek sovereign. We argue that the contrast between the Greek bailouts and the other GIIPS bailouts can be understood in relation to the fiscal fundamentals of the target sovereign immediately prior to the bailouts. We show that the fiscal position of Greece was considerably weaker than that of the other GIIPS countries at the time of its first bailout. Efforts to curb public spending in Greece failed to reduce the debt-to-GDP ratio due to their contractionary influence on the economy. This leads us to conclude that the efficacy of a sovereign bailout will be diminished if the fiscal fundamentals of the target country are “too weak” to start with.

This paper proceeds in five sections. In Section 2, we introduce the data used to estimate our model. Section 3 covers our implementation of the DY framework. Our main estimation results, including a suite of robustness exercises, are presented in Section 4. We conclude in Section 5. Additional technical details are provided in the appendix. The Data Supplement provides further information on our dataset.

2 Measuring credit risk

Our model includes the following $N = 18$ countries: Austria, Australia, Belgium, China, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, Russia, Spain, Sweden, the U.K. and the U.S. Our dataset is sampled at daily frequency over the period 1/3/2006 to 7/27/2015. For each country in our model, we include a set of credit spreads, as well as indicators of macrofinancial conditions.

2.1 Sovereign and financial sector credit spreads

2.1.1 The first difference of the sovereign CDS spread

We measure the change in sovereign credit risk for the i th country using the first difference of the five-year sovereign CDS spread. In line with the CDS market conventions outlined by Bai and Wei (2017), we work with USD-denominated CDS in all cases except for the U.S., where we employ euro-denominated CDS. In addition, following Bai and Wei,

we use CDS contracts with a complete restructuring clause for each sovereign except for Australia, where we use modified restructuring as the data are more complete.

Sovereign CDS data for Greece are unavailable from 3/9/2012 to 6/6/2013. At this time, Greek sovereign CDS ceased trading on a running spread in favour of points upfront in light of the adverse conditions in the market for Greek sovereign debt. In addition, the Greek sovereign CDS spread rose above 10,000bps on 2/15/2012 and reached 23,189bps by 3/8/2012. These extreme observations largely reflect illiquidity and they introduce large outliers into the dataset, which may compromise the stability of the estimated model. Consequently, from 2/15/2012 to 6/6/2013 inclusive, we substitute the Greek sovereign CDS spread with the yield spread between the five-year Greek government bond and the five-year German Bund. The bond yield spread is a natural substitute for the CDS spread as both are widely used as credit risk measures in the literature (e.g., [Caporin et al., 2018](#), [ADS](#)) and the two are related by a theoretical no-arbitrage condition ([Duffie, 1999](#); [Fontana and Scheicher, 2016](#)).

In practice, the Greek sovereign CDS and bond yield spreads comove closely and provide a comparable signal, sharing a common sample correlation of 0.935. This is apparent in Figure 1(a), where the two series are plotted together. To avoid introducing discontinuities, for estimation we re-scale the bond yield spread such that it exactly meets the end points of the available CDS data, as shown in panel (b). Note that, given that our results are derived from rolling regression analysis, our use of the Greek yield spread from 2/15/2012 to 6/6/2013 has no effect on rolling samples that do not include this period. Furthermore, to verify that our treatment of the Greek data does not distort our findings for the other countries in the sample, we also report results for the model excluding Greece altogether.

— Insert Figure 1 about here —

2.1.2 The first difference of a synthetic financial sector CDS spread

We track changes in financial sector credit risk in the i th country using a synthetic sector-wide CDS spread, as in [ADS](#). Unlike [ADS](#), who focus exclusively on banks, we also include insurers as there were several notable bailouts in this sector during the GFC,

including AIG in the U.S. and Fortis in the Benelux countries. To construct the index for the i th country, we compute an equally-weighted average³ of the CDS spreads for firms that satisfy the following criteria: (i) they have USD-denominated five-year CDS spread data in the Markit database that covers at least 10% of our sample observations and that accords with the corporate CDS market conventions documented by [Bai and Wei \(2017\)](#); (ii) they are classified by Markit as financial firms; (iii) they are classified as either banking or insurance firms in Bureau van Dijk’s Osiris database;⁴ (iv) they are identified by Markit as operating in the i th country; and (v) they hold assets of USD 10 billion or more in at least one year of our sample period.

While we focus on firms with publicly traded equity, there are two notable exceptions: (i) in Austria, we include data for Raiffeisen Zentralbank as otherwise our index would be based on a single firm; and (ii) in China, we use data for four large state-sponsored banks as there are not enough CDS data for privately held Chinese banks to construct a meaningful index. Similarly, rather than simply dropping failed banks from the sample, we include CDS data for several institutions that became state-owned as a result of the crisis, such as the Irish Bank Resolution Corporation. Consequently, our dataset is somewhat broader than that of [ADS](#), whose sample includes 36 European banks. Furthermore, our dataset includes the large majority of banks considered by [Demirer et al. \(2017\)](#). A complete list of the 202 financial institutions used to construct our financial sector credit spreads is in the Data Supplement.

³Our use of an equally-weighted average follows the approach of [ADS](#). We also experimented with an asset-weighted average, which is conceptually similar to the market-capitalisation-weighted European bank CDS index constructed by [Gray and Jobst \(2011\)](#). To avoid gradually down-weighting those banks whose asset values contracted the most due to losses incurred in the GFC (i.e., the worst affected banks that were most likely to require assistance) we limited our attention to time-invariant weights. In practice, the choice of weighting scheme does not strongly affect the resulting index due to the strong positive correlation among the CDS spreads for the set of financial institutions in each country. The mean correlation between the equally-weighted and asset-weighted indices across all eighteen countries is 0.973 and the median is 0.989.

⁴In a small number of cases, we manually add firms whose data does not appear in Osiris. Notable examples include ABN Amro and Fortis, both of which played important roles in the GFC. In these cases, we obtain asset data directly from publicly available financial reports.

2.2 Controlling for local conditions in each country

2.2.1 The first difference of the term spread

We define the term spread as the spread between the ten-year and ninety-day government bond yields. The term spread approximates the slope of the yield curve and conveys valuable information about the stance of monetary policy and about macroeconomic fundamentals, including changes in output growth and inflation expectations. In several cases, there are missing observations in the ninety-day bond yield data, in which case we use zero coupon yields from Bloomberg instead.

2.2.2 The daily log-return of the broad stock index

The daily log-return on the broad stock index provides a further measure of the economic performance of the i th country.

2.3 Controlling for global conditions

2.3.1 The first difference of the equity and Treasury variance risk premia

Changes in the risk appetite of investors played an important role in the propagation of the GFC (e.g., [Chudik and Fratzscher, 2011](#)). The variance risk premium (VRP) popularized by [Bollerslev et al. \(2009\)](#) is widely used as a measure of risk appetite. The VRP is defined as the difference between the one-month-ahead implied variance and the realized variance. Under this definition, the VRP is typically positive, with higher values indicating a reduced risk appetite. The VRP is most commonly constructed for equity indices but it can also be computed for other asset classes, including sovereign bonds ([Choi et al., 2017](#)). We include the first difference of the equity VRP for the S&P 500, which is constructed using the square of the VIX and an estimate of bipower variation in the S&P 500 obtained from the Oxford Man Institute’s Realized Library ([Heber et al., 2009](#)). In addition, we include the first difference of the bond VRP for the ten-year U.S. Treasury note, which is computed using the square of the Chicago Board Options Exchange TYVIX index and a corresponding realized volatility index, which was

generously shared with us by J.P. Morgan.⁵

2.3.2 The first difference of U.S. and eurozone interbank spreads

Funding liquidity constraints have also been highlighted as an important factor in both the GFC and the sovereign debt crisis (e.g., [Greenwood-Nimmo et al., 2016](#); [Pelizzon et al., 2016](#)). During the GFC, the TED spread rose abruptly and remained at high levels from mid-2007 until early-2009, reflecting a marked shift in perceived counterparty risk among U.S. banks at this time. A similar although slightly more muted pattern can be seen in the spread between the Euribor and the ninety-day German T-bill yield (the Euribor-DeTBill spread). Unlike the TED spread, the Euribor-DeTBill spread widens again in 2011–2012, reflecting illiquidity among European banks during the sovereign debt crisis. It then falls rapidly in response to the European Central Bank’s substantial long-term refinancing operations in December 2011 and February 2012. By including the first difference of both the TED spread and the Euribor-DeTBill spread in the model, we are able to control for the effect of a range of monetary policy interventions on the credit risk network, which may otherwise obscure the effects of the financial sector and sovereign bailouts that are our primary concern.

2.4 Properties of the data

In Table 1, we provide elementary summary statistics for the dataset. Time series plots of the data and detailed descriptive statistics including pairwise correlations and stationarity tests are included in the Data Supplement. Each of the series used in estimation is stationary and displays limited autocorrelation. The most striking feature of Table 1 is the high level of volatility in the GIIPS relative to the other European countries in our sample. The only country to display a comparable level of volatility is Russia, which experienced a deep domestic crisis during the GFC and severe geopolitical uncertainty related to the 2008 Russo-Georgian War and the subsequent conflict with Ukraine.

⁵Following [Bekaert and Hoerova \(2014\)](#), we experimented with an alternative version of the VRPs, which employs a forecast of the realized variance generated from the same augmented specification of [Corsi’s \(2009\)](#) heterogeneous autoregressive model used by [Bekaert and Hoerova](#). Our estimation results are robust to this change. Full details are available upon request.

— Insert Table 1 here —

To verify that our sovereign and financial sector credit spreads behave similarly to the data used by ADS, we replicate one of the core phenomena that the authors document in Figure 2. Given that ADS only consider European countries, we gather this group on the left of each panel and the non-European countries on the right. Focusing on the time-varying interaction between European bank and sovereign credit spreads over the period from 1/1/2007 to 6/30/2010, ADS identify three key phases. In phase I, from January 2007 until late September 2008 (before the financial sector bailouts), financial sector credit spreads climbed rapidly as a result of the financial crisis, while sovereign credit spreads remained largely stable. In phase II, from late September to October 2008 (during the bailouts), financial sector credit spreads fell substantially and sovereign credit spreads climbed, indicating a transfer of risk from the banks to the sovereigns. Finally, in phase III (after the bailouts), both bank and sovereign credit spreads increased, as elevated sovereign risk fed back onto the financial sector. This pattern is prevalent among the European countries in our sample and Figure 2 is qualitatively and quantitatively similar to the charts presented by ADS.

— Insert Figure 2 here —

3 Modeling the credit risk network

To fix notation, let the $N = 18$ countries in the model be indexed by $i = 1, 2, \dots, N$. For the i th economy, we observe the $k \times 1$ vector of endogenous variables, $\mathbf{x}_{it}$:

$$\mathbf{x}_{it} = (\Delta g_{it}, \Delta b_{it}, \Delta s_{it}, \Delta \ln(q_{it}))', \quad (1)$$

where time periods are indexed by $t = 1, 2, \dots, T$, g_{it} is the sovereign credit spread, b_{it} is the financial sector credit spread, s_{it} is the term spread and q_{it} is the stock index. In addition, we observe the $k^{**} \times 1$ vector of global control variables, $\mathbf{x}_t^{**}$:

$$\mathbf{x}_t^{**} = (\Delta l_t^{US}, \Delta l_t^{EU}, \Delta v_t^{TY}, \Delta v_t^{EQ})', \quad (2)$$

where l_t^{US} and l_t^{EU} denote the TED spread and its European counterpart and where v_t^{TY} and v_t^{EQ} denote the Treasury and equity variance risk premia, respectively.

3.1 The DY framework

The first step in implementing the [DY](#) framework is the specification of an approximating model for the dynamics of the $K = Nk + k^{**}$ vector $\mathbf{z}_t = (\mathbf{x}'_{1t}, \dots, \mathbf{x}'_{Nt}, \mathbf{x}_t^{**})'$. The approximating model can be any model with an approximate VAR representation, a class that includes the entire VAR family, as well as a variety of micro-founded general equilibrium models. The general form of the approximating model is as follows:

$$\mathbf{z}_t = \mathbf{a} + \sum_{\ell=1}^P \mathbf{C}_\ell \mathbf{z}_{t-\ell} + \mathbf{v}_t, \quad (3)$$

where $\mathbf{a}$ is a vector of intercepts, $\mathbf{C}_\ell$ is the ℓ -th autoregressive parameter matrix and $\mathbf{v}_t$ is a vector of zero-mean residuals with covariance matrix $\mathbf{\Omega}$. We elaborate on our estimation strategy below but equation (3) is sufficient to derive the connectedness measures.

[Diebold and Yilmaz \(2014\)](#) demonstrate that the generalized forecast error variance decomposition (GVD) of equation (3) forms a weighted digraph that summarizes the pairwise relations among the elements of $\mathbf{z}_t$.⁶ The (i, j) th element of the h -step-ahead GVD matrix, $\mathbf{\Theta}^{(h)}$, is defined as follows:

$$\theta_{i \leftarrow j}^{(h)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^h (\mathbf{e}_i' \mathbf{R}_\ell \mathbf{\Omega} \mathbf{e}_j)^2}{\sum_{\ell=0}^h (\mathbf{e}_i' \mathbf{R}_\ell \mathbf{\Omega} \mathbf{R}_\ell' \mathbf{e}_i)} \quad i, j = 1, 2, \dots, K, \quad (4)$$

where σ_{jj} is the j th diagonal element of $\mathbf{\Omega}$, $\mathbf{e}_i$ is a selection vector whose i -th element is one with zeros elsewhere and $\mathbf{R}_i$ is the i th parameter matrix of the moving average representation of equation (3), which is obtained recursively as $\mathbf{R}_i = \mathbf{C}_1 \mathbf{R}_{i-1} + \mathbf{C}_2 \mathbf{R}_{i-2} + \dots + \mathbf{C}_P \mathbf{R}_{i-P}$, where $\mathbf{R}_0 = \mathbf{I}_K$ and $\mathbf{R}_j = \mathbf{0}_K$ for $j < 0$.

Given that $\sum_{j=1}^K \theta_{i \leftarrow j}^{(h)} > 1$ if the covariance matrix, $\mathbf{\Omega}$, is non-diagonal, [DY](#) apply the row-sum normalisation $d_{i \leftarrow j}^{(h)} = \theta_{i \leftarrow j}^{(h)} / \sum_{j=1}^K \theta_{i \leftarrow j}^{(h)}$, such that $\sum_{j=1}^K d_{i \leftarrow j}^{(h)} = 1$ for $i =$

⁶[Diebold and Yilmaz \(2009\)](#) show that the adjacency matrix may be derived from the orthogonalized forecast error variance decomposition, where orthogonalisation is achieved by Cholesky factorisation. However, when working with financial data sampled at daily frequency, reliance on a Wold-causal identification scheme is problematic, as theoretical support for a particular recursive ordering is likely to be weak. Consequently, the order-invariance of the GVD is a highly desirable property in this context.

$1, 2, \dots, K$. Consequently, $d_{i \leftarrow j}^{(h)}$ is interpreted as the proportion of the h -step ahead forecast error variance (FEV) of variable i that is explained by shocks to variable j . The complete network can be summarized as follows:

$$\mathcal{D}^{(h)} = \begin{bmatrix} d_{1 \leftarrow 1}^{(h)} & \cdots & d_{1 \leftarrow k}^{(h)} & d_{1 \leftarrow k+1}^{(h)} & \cdots & d_{1 \leftarrow 2k}^{(h)} & \cdots & \cdots & d_{1 \leftarrow K}^{(h)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & & \vdots \\ d_{k \leftarrow 1}^{(h)} & \cdots & d_{k \leftarrow k}^{(h)} & d_{k \leftarrow k+1}^{(h)} & \cdots & d_{k \leftarrow 2k}^{(h)} & \cdots & \cdots & d_{k \leftarrow K}^{(h)} \\ d_{k+1 \leftarrow 1}^{(h)} & \cdots & d_{k+1 \leftarrow k}^{(h)} & d_{k+1 \leftarrow k+1}^{(h)} & \cdots & d_{k+1 \leftarrow 2k}^{(h)} & \cdots & \cdots & d_{k+1 \leftarrow K}^{(h)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & & \vdots \\ d_{2k \leftarrow 1}^{(h)} & \cdots & d_{2k \leftarrow k}^{(h)} & d_{2k \leftarrow k+1}^{(h)} & \cdots & d_{2k \leftarrow 2k}^{(h)} & \cdots & \cdots & d_{2k \leftarrow K}^{(h)} \\ \vdots & & \vdots & \vdots & & \vdots & \ddots & & \vdots \\ \vdots & & \vdots & \vdots & & \vdots & & \ddots & \vdots \\ d_{K \leftarrow 1}^{(h)} & \cdots & d_{K \leftarrow k}^{(h)} & d_{K \leftarrow k+1}^{(h)} & \cdots & d_{K \leftarrow 2k}^{(h)} & \cdots & \cdots & d_{K \leftarrow K}^{(h)} \end{bmatrix} \quad (5)$$

It will generally be the case that the network is asymmetric, i.e., $d_{i \leftarrow j}^{(h)} \neq d_{j \leftarrow i}^{(h)}$. So-called “own variable effects” (also referred to as “loops”) lie on the prime diagonal of $\mathcal{D}^{(h)}$, while the bilateral spillover from entity j to entity i occupies the (i, j) th position. The net spillover from entity i to entity j is defined as $d_{i-j}^{(h)} = d_{j \leftarrow i}^{(h)} - d_{i \leftarrow j}^{(h)}$, while the total spillover from entity i to entities j and k is defined as $d_{(j+k) \leftarrow i}^{(h)} = d_{j \leftarrow i}^{(h)} + d_{k \leftarrow i}^{(h)}$.

3.2 The approximating model

We consider the following candidate estimation frameworks for the approximating model: (i) simple VAR; (ii) global VAR (Pesaran et al., 2004); and (iii) VAR with shrinkage and variable selection (Zou and Hastie, 2005). Each of these models has been used in the DY literature but little attention has been paid to their relative performance. This is an interesting issue because the DY approach is often applied to large systems where steps must be taken to tackle the overfitting problem of the simple VAR model. Global VAR (GVAR) does this by exploiting the cross-section dimension of the dataset, while shrinkage and selection techniques do so by imposing a penalty within the estimator’s objective function.

3.2.1 The simple VAR model

Provided that there are sufficient degrees of freedom, the VAR model in equation (3) can be estimated directly by the ordinary least squares method. This is the most common approach to the implementation of the DY framework, although it is susceptible to overfitting as the dimension of the model becomes large. For a K variable system with P lags where each equation includes an intercept and no other deterministic terms, one must freely estimate $K^2P + K$ parameters.

3.2.2 The global VAR model

One way to address the overfitting problem is via GVAR. A GVAR model is constructed by combining N country-specific VARX models, the i th of which expresses the $k \times 1$ vector of country-specific variables, $\mathbf{x}_{it}$, as a function of its own lags, the contemporaneous and lagged values of a corresponding $k \times 1$ vector of foreign variables, $\mathbf{x}_{it}^*$, and the contemporaneous and lagged values of the $k^{**} \times 1$ vector of global controls, $\mathbf{x}_{it}^{**}$. For the i th economy, the vector of foreign variables is defined as $\mathbf{x}_{it}^* \equiv (\Delta g_{it}^*, \Delta b_{it}^*, \Delta s_{it}^*, \Delta \ln(q_{it}^*))' = \mathbf{W}_i' \mathbf{x}_t$, where $\mathbf{x}_t = (\mathbf{x}_{1t}', \mathbf{x}_{2t}', \dots, \mathbf{x}_{Nt}')'$ is of dimension $Nk \times 1$ and $\mathbf{W}_i$ is a $k \times Nk$ matrix of country-specific weights that reflect the bilateral interaction between country i and countries $j = 1, 2, \dots, N, j \neq i$. Consequently, $\mathbf{x}_{it}^*$ represents the rest of the world from the perspective of country i . Pesaran et al. (2004) show that one may stack the N country-specific models to form a large VAR model, which may be completed by the addition of a marginal VAR for $\mathbf{x}_t^{**}$. The resulting GVAR model is of the form of equation (3). A thorough derivation of our GVAR model is presented in the Appendix.

The weighting scheme is a key element of the GVAR model. We consider the following three cases that emphasize different aspects of the international linkages between countries:

(i) Trade Weights. We use bilateral trade averages over 2006–2015 to capture the trade relations among countries (see Dees et al., 2007). Data on bilateral trade is obtained from the IMF’s Direction of Trade Statistics.

(ii) GDP Weights. We measure the relative economic mass of a country using its GDP in purchasing power parity (PPP) terms. We compute PPP-GDP weights over the

2006–2015 period using data from the World Bank’s World Development Indicators.

(iii) Financial Weights. Trade linkages and economic mass may not reflect financial linkages, so we also develop a financial weighting scheme (see [Galesi and Sgherri, 2013](#)). Using the IMF’s Coordinated Portfolio Investment Survey, we construct financial weights for the 2006–2015 period based on the U.S. dollar value of total derived bilateral portfolio liabilities (we use derived liabilities instead of asset holdings as the data are more complete).

3.2.3 The VAR model with elastic net regularization

An alternative way to solve the overfitting problem that does not rely on cross-sectional aggregation is via shrinkage and/or variable selection. Among the most common methods is the least absolute shrinkage and selection operator (LASSO) of [Tibshirani \(1996\)](#). LASSO works by augmenting the least squares objective function with an L_1 penalty term. In this respect, LASSO is conceptually similar to the ridge regression of [Hoerl and Kennard \(1970\)](#), in which an L_2 penalty term is applied for regularization of ill-posed problems. Both of these estimators are nested within the elastic net (EN) framework proposed by [Zou and Hastie \(2005\)](#), which is essentially a weighted combination of LASSO and ridge regression. Estimators in this family have been applied to macroeconomic VARs by [Furman \(2014\)](#) and have been used in the financial connectedness literature by [Bostanci and Yilmaz \(2015\)](#) and [Demirer et al. \(2017\)](#).

Following [Furman \(2014, p. 16\)](#), we note that a high-dimensional VAR model of the form of equation (3) can be estimated directly with the EN on an equation-by-equation basis, such that the degree of penalisation is chosen optimally for each equation. For the i th equation of (3), abstracting from deterministic terms and assuming a lag order of one, the EN estimator solves the following minimisation problem:

$$\hat{\phi}_i^{EN} = \arg \min_{\phi} \left(\sum_{t=1}^T \left(z_{it} - \sum_{j=1}^K \phi_{ij} z_{j,t-1} \right)^2 + \lambda_i \sum_{j=1}^K (\alpha |\phi_{ij}| + (1 - \alpha) \phi_{ij}^2) \right), \quad (6)$$

where $\lambda_i > 0$ and $\alpha \in [0, 1]$. EN reduces to ridge regression if $\alpha = 0$ and to LASSO if $\alpha = 1$ and it represents an intermediate case for $0 \leq \alpha \leq 1$.

We select λ_i from a fine grid of 100 points by five-fold cross validation. In principle,

one may also tune α by cross-validation. However, in practice, its value is often fixed a priori and is then subjected to robustness testing. This is the approach that we pursue for two reasons. First, allowing the values of both α and λ_i to vary across rolling samples is likely to introduce excess noise into the resulting spillover estimates. Second, from a practical perspective, tuning α in this way incurs a substantial computational cost, which is prohibitive in our case. For the baseline case where we include Greece, our VAR model in equation (3) contains $K = 76$ equations, each of which must be estimated for every rolling sample. Given that the time dimension of our dataset is $T_{max} = 2,495$ trading days and assuming a rolling sample of $w = 250$ trading days, we must therefore estimate $K(T_{max} - w + 1) = 170,696$ equations. In light of the computational cost, we limit our attention to $\alpha \in (0, 0.25, 0.50, 0.75, 1)$, which nests the grid used by [Furman \(2014\)](#), along with the LASSO and ridge regression estimators.

4 Empirical analysis

In this section, we present the results of our empirical analysis. First, we evaluate the relative performance of our nine candidate models based on their one-step-ahead predictive accuracy. We then provide an overview of the network topology based on the winning model. This provides a frame of reference for the rest of the paper, which focuses on two questions. First, how do financial sector bailouts affect the interaction of financial sector and sovereign credit risk and what explains the variation across countries? Second, how do sovereign bailouts affect the credit risk network and what explains the variation across bailout episodes?

4.1 Assessing the relative performance of the models

We assess the relative performance of our candidate models based on their out-of-sample predictive accuracy, which we measure using the one-step-ahead root mean squared forecast error (RMSFE). In Table 2, we report the proportion of rolling samples in which each model is ranked within the top three models. The models are organized into groups according to the way that they address the overfitting problem: (i) by shrinkage and

selection in the case of LASSO and elastic net; (ii) by means of cross-sectional aggregation in the case of GVAR; (iii) by shrinkage only in the case of ridge regression; and (iv) without shrinkage or selection in the case of the simple VAR model.

— Insert Table 2 here —

The LASSO model achieves the smallest forecast error in 22% of rolling samples, more than any other model considered. In practice, the performance of the LASSO and EN models is very similar. This is reflected in the cumulative relative RMSFE (RRMSFE), the values of which are clustered very close to one, although the EN models marginally outperform the LASSO by this measure. We provide a more detailed comparison of the models’ relative forecasting performance in Figure 3, which reports frequency plots of $1 + \ln(r_{js})$, where r_{js} is the RRMSFE of the j th model against the benchmark LASSO model in the s th rolling sample. If $r_{js} < 1$ ($r_{js} > 1$), then the j th model outperforms (is outperformed by) the benchmark model in the s th rolling sample.

— Insert Figure 3 here —

The frequency plots for the EN models in Figure 3 are highly peaked around 1, indicating that they all perform comparably to the LASSO model throughout our sample and that the choice of α does not exert a strong influence on the results. By contrast, the frequency plots for the GVAR models are considerably more dispersed, with substantial mass above 1. The underperformance of the GVAR models relative to the LASSO and EN models indicates that the parameter matrices of the unobserved data-generating process are likely to be sparse in practice. GVAR models constructed using dense weight matrices will typically yield a poor approximation of a sparse system and this is likely to compromise their forecasting performance, as well as any functions of the model parameters, including the DY connectedness measures. Lastly, as the models that do the least to tackle the overfitting problem, it is not surprising that the ridge regression and simple VAR models are the worst performing models that we consider, with the peaks of both histograms lying substantially above 1. Given that the LASSO and EN models perform so similarly and that the LASSO is ranked first in more rolling samples than any other model, we adopt the LASSO as our preferred model.

4.2 Visualizing the structure of the credit risk network

In Figure 4, we provide a visualization of the strongest linkages in the sovereign–financial credit risk network at two different points in time. Panel (a) shows the structure of the network evaluated over the 250 trading days beginning at the start of our sample and ending on 12/18/2006, prior to the GFC. Panel (b) depicts the structure of the network evaluated over the 250 trading day sample ending with the Portuguese request for aid on 4/6/2011. The figure demonstrates how the overall structure of the network changes from the pre-crisis period to the height of the debt crisis. In addition, by comparing the Portuguese bailout sample against a pre-crisis benchmark, we are able to highlight the changing role of Portugal in the global credit risk network.⁷

— Insert Figure 4 here —

Both panels of Figure 4 are derived from a network estimated using a rolling sample of 250 trading days and a forecast horizon of 10 trading days. As we will demonstrate below when working with simpler figures, the properties of the network do not depend strongly on the choice of window length and horizon. The (i, j) th edge shows the total spillover from the j th sovereign and the j th financial sector to the i th sovereign and the i th financial sector. The strength of the (i, j) th edge is denoted by its thickness and the size of the i th node is proportional to the sum of spillovers between the i th sovereign and the i th financial sector, including loops (spillovers from an entity onto itself). To enhance the clarity of the figures, spillovers weaker than 3% of FEV have been suppressed.

An emergent stylized fact in the network literature is that financial networks become more strongly connected in times of systemic stress (e.g., [Billio et al., 2012](#); [Demirer et al., 2017](#)). This effect can be seen clearly by comparing Figures 4(a) and 4(b). In the pre-GFC period, the majority of bilateral connections are relatively weak and within-country effects are the dominant force in the system. Nonetheless, the European countries form a discernible cluster and many of the strongest linkages exist between countries in the European core, including Austria, France, Germany and the Netherlands. In the case of Portugal, the strongest bilateral connection is with Germany, which is

⁷Our choice to focus on Portugal is illustrative given its experience during the debt crisis and its subsequent bailout but it is also arbitrary. Detailed results for other cases are available upon request.

consistent with the convergence of Portugal with the European core at this time. In addition, spillovers between Portugal and both Spain and Ireland are weaker than 3% of FEV at this time and are therefore not shown. The contrast with the Portuguese bailout period in panel (b) is striking. Within-country effects have weakened across the board and bilateral credit risk spillovers have intensified substantially, in line with [Ang and Bekaert's \(2002\)](#) observation of increased financial market comovements under adverse conditions. The European cluster is more strongly interconnected than in the pre-crisis period and spillovers among the GIIPS have strengthened markedly. Bilateral spillovers with respect to Portugal have risen sharply, with particularly strong connections to all of the other GIIPS countries, including Spain and Ireland.

Figure 4 highlights the extent to which the structure of the credit risk network changes during our sample period but it reveals nothing about the dynamics of this change. To this end, in Figure 5, we report three spillover measures on a rolling sample basis that serve to frame our subsequent analysis. Panel (a) shows the evolution of the average bilateral credit risk spillover between all of the financial sectors in the system. Panel (b) shows the average bilateral credit risk spillover among the sovereigns in the system. Finally, panel (c) shows the net credit risk spillover between the financial sector and the sovereigns at the global level (i.e., the net spillover from all eighteen national financial sectors to all eighteen sovereigns). These three spillover measures provide a compact summary of credit risk transmission within and between the financial and public sectors.

— Insert Figure 5 here —

In each panel of Figure 5, the spillover measure computed using a 250-day rolling sample and a forecast horizon of ten days is shown as a fine black line. Given that the variables selected by the LASSO may change from one rolling sample to the next, the spillover measures can be somewhat volatile. Consequently, a smoothed version computed using a 21-day centered moving average is shown as a heavy black line. As well as being an aid to visualization, the smoothed series helps to draw attention to the slow moving — or trend — component of spillover activity. Furthermore, the results of several robustness tests are summarized in the figure. In keeping with the robustness exercises in [Greenwood-Nimmo et al. \(2016\)](#), the gray band reports the range of values taken by the

smoothed spillover measure as the window length is varied in the set $w = \{200, 250, 300\}$ days and the forecast horizon is varied over $h \in \{5, 10, 15\}$ days. In addition, the dashed line shows the smoothed spillover measure from a model that excludes Greece. The results of these robustness tests strongly support our earlier assertion regarding the insensitivity of the estimated network to alternative choices of window and horizon. Furthermore, the similarity of the aggregate spillover measures reported in Figure 5, whether or not Greece is included in the sample, suggests that our use of Greek bond spread data during the period when the Greek CDS data are unavailable does not exert a decisive influence on our results.

Figure 5(a) reveals a sharp increase in financial sector credit risk spillovers in mid-2007. This coincides with the failure of two Bear Stearns hedge funds, an event that triggered acute concerns over counterparty credit risk in the U.S. financial sector. The surge in financial sector credit risk transmission starts on 6/19/2007 and peaks on 8/1/2007. Two points are noteworthy. First, financial sector spillover activity significantly leads the TED spread, which does not start to climb strongly until 8/8/2007 and does not peak until 8/20/2007. This lead-lag relation, which is maintained over much of our sample period, indicates that network-based measures of credit risk transmission in the financial sector can provide more timely signals of counterparty risk than interbank interest rate spreads. Second, spillover activity rises much more rapidly than it falls, a finding reminiscent of the long literature on asymmetry in volatility and which reflects the asymmetry of market participants' responses to good and bad news.

Financial sector credit risk spillovers remain elevated from mid-2007 until the end of 2009, a period that covers the principal events of the GFC. By contrast, Figure 5(b) reveals that credit risk spillovers among sovereigns rise later and remain elevated for longer. The largest surge in sovereign credit risk spillovers occurs on 11/21/2007, which is consistent with the start of the financial crisis period identified by Kalbaska and Gatkowski (2012) and which coincides with the emergence of an upward trend in sovereign CDS spreads and a marked widening of both Chinese and Russian credit spreads. In line with the sovereign credit risk dynamics documented by ADS, another large jump in sovereign credit risk spillovers occurs shortly after the financial sector bailouts in October

2008. Over the rest of our sample, sovereign credit risk spillovers remain considerably above their pre-GFC level, exhibiting a gradual decline that is interrupted on several occasions, including by the sovereign crises and bailouts among the GIIPS. Nonetheless, at the end of our sample period, sovereign credit risk transmission is considerably stronger than it was prior to the GFC.

Finally, Figure 5(c) shows the aggregate net credit risk spillover from the financial sector to all sovereigns in our sample. The plot reveals a clear change in the nature of the spillover between the financial sector and the sovereigns, which is strongly consistent with the ADS mechanism. Early in our sample period, as the financial crisis deepens, credit risk transmission from the financial sector to the sovereigns intensifies. This changes with the financial sector bailouts, after which we observe a net transmission of credit risk from the sovereigns to the global financial sector. Sovereigns remain a net source of risk until 2013, a period that covers the Irish, Portuguese and Spanish sovereign bailouts and two Greek sovereign bailouts.

4.3 Financial sector bailouts and the rise of sovereign risk

The aggregate results in Figure 5 offer a broad characterisation of the dynamics of credit risk transmission during the GFC and the ensuing sovereign debt crisis but disaggregate analysis is required to fill in the detail. We first focus on the financial sector bailouts and the associated transfer of credit risk onto the sovereigns. In Figure 6, we report the net credit risk spillover from the i th financial sector to the i th sovereign. Figure 6 differs from Figure 5(c) not just because it is disaggregate but also because it does not show spillovers from the j th financial sector to the i th sovereign for $j \neq i$.⁸ Nonetheless, the same characteristic cyclical pattern of net financial–sovereign spillovers is apparent for many countries. Furthermore, as with the aggregate results in Figure 5, we find little evidence that our results are sensitive to our modeling choices or to the exclusion of Greece from the sample.

— Insert Figure 6 here —

⁸Note that these cross-border spillovers from a financial sector to foreign sovereigns are generally weak as financial sector guarantees are rarely international in scope, which implies that the direct exposure of the i th sovereign to the j th financial sector is typically small for $j \neq i$.

Among the European countries, with the exception of France, Greece and Norway, the net credit risk transfer from the national financial sector to the sovereign is positive in the period immediately prior to the bailouts and negative thereafter. The timing of the sign change aligns closely with the bailout period in each case. For Greece and France, the same general pattern is apparent but there is no sign change. For Greece, the net spillover is initially negative and becomes more negative after the financial sector bailouts, while for France the net spillover is initially positive and weakens after the bailouts.

There are notable differences between our results for the GIIPS and the other European countries. These differences may be seen most clearly by viewing the evolution of the net financial–sovereign credit risk spillover as a cycle (henceforth the [ADS](#) cycle). For each of the European countries in our sample, [Table 3](#) shows the peak and trough values of the [ADS](#) cycle, its amplitude (the difference between the peak and the trough) and the share of sample observations during which the net financial–sovereign spillover is negative. There is a relatively close correspondence between the amplitude of the cycle and the proportion of negative net spillovers, the latter of which is related to the duration of the cycle. Overall, the results in [Table 3](#) indicate that the [ADS](#) cycle has been stronger and longer lasting in the GIIPS than in the rest of Europe.

— Insert [Table 3](#) here —

As well as the contrast between the European core and periphery, several interesting results arise among the five non-European countries shown in the bottom row [Figure 6](#). First, Australia does not display a marked [ADS](#) cycle, reflecting its relatively benign experience during the GFC. The U.S. also displays a muted [ADS](#) cycle, which most likely derives from the perceived safety of U.S. sovereign debt. The same is not true of Japan, however, where the high government debt-to-GDP ratio coupled with weak growth are likely to contribute to the sustained credit risk transmission from the sovereign to the financial sector that we observe from 2009 onwards. Finally, China and Russia experience strong and sustained net credit risk transfer from the sovereign to the financial sector. In China, this most likely reflects the fact that the banks in our sample are majority state-owned, which weakens the distinction between sovereign risk and financial sector risk. By contrast, the transmission of risk from the Russian sovereign to its financial

sector likely reflects the fact that Russia defaulted on its sovereign debt as recently as 1998 and that the adverse effects of the GFC in Russia were exacerbated by geopolitical uncertainty related to the Russo-Georgian war.

To test whether the cross-country heterogeneity evident in Figure 6 and Table 3 reflects variations in country-specific fundamentals, we estimate a panel regression model in which the net credit risk spillover between the financial sector and the sovereign is regressed on a set of macroeconomic fundamentals, while controlling for country and time fixed effects. Furthermore, to study regional effects, we estimate the model for all countries in our sample and then separately for three groups: (i) the GIIPS; (ii) the other European countries; and (iii) the non-European countries. Our explanatory variables are similar to those used by Beirne and Fratzscher (2013) in their study of the drivers of sovereign risk. Our explanatory variables include the growth rate of GDP, the government debt-to-GDP ratio, the current account balance expressed relative to GDP and the cyclically-adjusted budget balance expressed relative to potential GDP. Each of these series is sampled quarterly apart from the budget balance and a subset of the data for the Russian current account balance, which are reported annually and which we interpolate to quarterly frequency. We construct corresponding quarterly series of the net financial–sovereign spillover measure using the value from the last trading day in each quarter.⁹ Data on the explanatory variables is from the Bank for International Settlements, the Federal Reserve Economic Data Service, the International Monetary Fund and the Organisation for Economic Cooperation and Development.

The estimation results are reported in Table 4. For the panel consisting of all eighteen countries, we observe a positive and statistically significant relation between net financial–sovereign credit risk transmission and the budget balance, and a statistically significant negative relation between net financial–sovereign credit risk transmission and the debt-to-GDP ratio. Recall that the more negative the net financial–sovereign spillover, the stronger the net credit risk transmission from the sovereign to the financial sector. Consequently, our results reveal that the net credit risk transmission from the sovereign

⁹We considered various methods to transform the net financial–sovereign spillover measure from daily frequency to quarterly frequency, including using a period average. Our principal results are unaffected by these definitional changes. Full details are available upon request.

to the local financial sector is stronger among countries with higher the debt-to-GDP ratios and weaker structural budget balances. This suggests that the net spillover from the sovereign onto the financial sector is stronger for countries that are under fiscal stress and have a limited capacity for further borrowing.

— Insert Table 4 here —

Comparing the estimation results obtained from the full panel of eighteen countries with the results obtained from the GIIPS panel, the panel of non-GIIPS European countries and the non-European panel leads to an interesting finding. The coefficient estimates for the GIIPS panel share the same sign and pattern of significance as those from the full panel but their magnitude is larger. The coefficient on the debt-to-GDP ratio is also statistically significant and negative in the non-European panel, although the structural budget balance is not significant in this case. By contrast, in the panel of non-GIIPS European countries, neither the structural budget balance nor the debt-to-GDP ratio is statistically significant. The heightened sensitivity of financial–sovereign spillover activity to fundamentals in the GIIPS when compared to other European countries offers a partial explanation of why the GIIPS suffered debt crises while other European countries with similarly weak fundamentals in the pre-crisis period did not.

4.4 Sovereign bailouts and the alleviation of sovereign risk

Our results above provide a number of insights into the emergence of the debt crisis among the GIIPS. As the crisis deepened, sovereign bailouts were extended to four of the five GIIPS. Two questions naturally arise in light of our preceding analysis. First, did the sovereign bailouts weaken the [ADS](#) feedback mechanism that played such an important role in exacerbating sovereign risk among the GIIPS? Second, in light of policymakers’ concerns over contagion (e.g., [Constâncio, 2012](#)), did the sovereign bailouts reduce outward spillovers from the bailed-out sovereigns to foreign sovereigns and to foreign financial institutions?

In [Figure 7](#) and [Table 5](#), we summarize the effects of the sovereign bailouts on a selection of four spillover measures: (i) the spillover from the local financial sector onto

the target sovereign (i.e., the sovereign receiving the bailout); (ii) the spillover from the target sovereign onto its domestic financial sector; (iii) the average spillover from the target sovereign onto the financial sectors of other countries; and (iv) the average spillover from the target sovereign onto all foreign sovereigns. Figure 7 places each bailout in its temporal context by reporting the evolution of these four spillover measures over a six month period, with the timing of additional relevant events not related to the sovereign bailouts, such as Mario Draghi’s “whatever it takes” speech of July 2012, marked by vertical lines. In this case, we observe some sensitivity to the choice of window and horizon. This is particularly apparent for Spain and Portugal, although the intervals mostly indicate uncertainty regarding the level of the spillover measures rather than their trajectory. We find that there is still only modest sensitivity to the exclusion of Greece from the sample. In contrast to Figure 7, Table 5 reports the average of each spillover measure in the five days prior to the bailout (denoted “before”), the average spillover in the five days following the bailout (“after”) and the difference between the two (“change”).

— Insert Figure 7 and Table 5 here —

Figure 7 is laid out as a grid with five rows (one for each bailout episode) and four columns (one for each of the four different spillover measures under scrutiny). Focusing on the two left columns of Figure 7, we find that the sovereign bailouts were associated with a reduction in the spillovers acting in at least one direction between the target sovereign and its local financial sector. The Irish and Spanish bailouts in particular lead to swift and pronounced reductions in the spillovers running in both directions between the sovereign and the local financial sector. The same is true of the second Greek bailout, although the effect is relatively muted and is obscured to a large extent by the marked reduction in spillovers relating to the Greek sovereign, which starts at the time of the half-trillion euro LRTD in December 2011 and which sees Greek credit risk spillovers approach zero by the time of the Greek debt swap agreement in March 2012.¹⁰ Meanwhile, the Portuguese

¹⁰Recall that we substitute the Greek sovereign bond yield spread in place of the Greek sovereign CDS spread from 2/15/2012 to 6/6/2013. It is possible that this change in the definition of the Greek sovereign credit spread contributes to the weak spillover effects for the Greek sovereign at this time. However, the switch occurs too late (mid February 2012) to explain the profound reduction in Greek spillovers,

bailout dampens the credit risk spillover from the Portuguese sovereign to its financial sector, while the first Greek bailout weakens spillovers from the Greek financial sector onto the sovereign.

The same pattern documented above can be seen in Table 5. Negative values under the heading “Change” in the table indicate a reduction in spillover intensity. Focusing on columns one and two, we observe a reduction in spillover intensity in eight out of ten cases. Overall, our results suggest that sovereign bailouts can be effective in disrupting the adverse feedback between sovereign risk and the credit risk of the domestic financial sector that is central to the ADS mechanism.

The previous result is important as it implies that sovereign bailouts improve financial stability within the target country. A natural question, however, is whether the sovereign bailouts affect credit risk transmission from the target sovereign to foreign sovereigns and foreign financial institutions. In this case, the bailout episodes can be readily classified into two groups. The Irish, Portuguese and Spanish bailouts all reduce international credit risk transmission from the target sovereign. The evidence for the two Greek bailouts is much weaker: the first Greek bailout weakens outward spillovers to foreign sovereigns but not to foreign financial institutions, while the second Greek bailout has almost no effect on international spillovers originating from Greece (see Figure 7 and columns three and four of Table 5).

A notable difference between the Greek bailouts and the Irish, Portuguese and Spanish bailouts is the fiscal position of the target sovereign in the period leading up to the bailouts. Columns five and six of Table 5 report the values of debt-to-GDP ratio and the structural budget balance for each sovereign in the quarter immediately prior to the bailouts. As an aid to visualization, the two variables are also shown as a scatter plot in Figure 8. At the time of its first bailout, the fiscal position of Greece was considerably worse than that of Ireland, Portugal or Spain at the time of their bailouts, with a debt-to-GDP ratio roughly one-third higher than its nearest competitor (Portugal) and a structural budget deficit roughly twice as large as any of the other countries when

which starts two months earlier. Furthermore, it is plausible that the Greek sovereign decoupled from the system to a large degree as a result of its partial default in March 2012, which triggered payments on Greek sovereign CDS contracts and ended a prolonged period of uncertainty surrounding Greece’s negotiations with its creditors.

expressed relative to potential GDP. By the time of the second Greek bailout, austerity measures had reduced the structural deficit appreciably (from -17.0% to -8.4% in 22 months) but the debt-to-GDP ratio had risen markedly (from 130.8% of GDP to 172.0%). This pattern draws attention to a conflict within the fiscal policy measures associated with the GIIPS bailouts. Aside from eroding the value of its debt through inflation or through strategic manipulation of the exchange rate, a country can reduce its debt-to-GDP ratio either by paying down its debt or by increasing its growth rate (or both). The emphasis during the GIIPS bailouts was on fiscal consolidation which, all else equal, may have reduced the government debt stock. However, fiscal retrenchment is contractionary and the reduction in GDP may more than offset any reduction in the debt stock, resulting in further deterioration of the debt-to-GDP ratio, as in the case of Greece. Overall, although the sparsity of observations precludes a strong interpretation, our results indicate that the efficacy of a sovereign bailout will be diminished if the fiscal fundamentals of the target country are “too weak” to start with, particularly if the terms of the bailout mandate rapid fiscal retrenchment.

— Insert Figure 8 here —

5 Concluding remarks

The financial sector bailouts of 2008 played a key role in the management of systemic risk at the height of the GFC. However, [Acharya et al. \(2014\)](#) characterize these bailouts as a pyrrhic victory, as they transformed the relation between financial sector risk and sovereign risk, leading to the emergence of a self-referential feedback loop that contributed to the sovereign debt crisis in Europe.

We develop an empirical model of the global credit risk network to examine the interaction of financial sector credit risk and sovereign credit risk, both within and between countries. We focus on a sample of eighteen major countries over the period from 2006 to 2015. We use the five-year sovereign CDS spread to measure the credit risk associated with the debt issued by each sovereign. We construct a bespoke financial sector credit risk index for each country as an equally-weighted average of the five-year

CDS spreads for a group of large locally-domiciled financial institutions. We control for a range of country-specific and global factors to ensure that our model delivers accurate estimates of the intensity of bilateral credit risk spillovers, without simply picking up comovements induced by exposure to common shocks. To this end, our model includes: (i) the daily stock market return and the sovereign term spread for each country to control for domestic macrofinancial conditions; (ii) the TED spread and an appropriate European counterpart to control for variations in liquidity; and (iii) the equity and Treasury variance risk premia to account for variations in risk appetite of equity and fixed income investors.

In contrast to the majority of network studies of credit risk spillovers, our primary focus is on cross-country heterogeneity as opposed to systemwide aggregate measures of spillover intensity. We show that the feedback loop described by [Acharya et al. \(2014\)](#) gives rise to cyclical behavior in the net credit risk spillover between the financial sector and the sovereign. Initially a net source of credit risk, the financial sector becomes a net recipient after the 2008 financial sector bailouts in many countries. We estimate auxiliary panel data models to demonstrate that the cross-sectional variation in the behavior of the net financial–sovereign credit risk spillover can be well-explained at quarterly frequency by differences in fiscal fundamentals across countries. Our results indicate that the degree of net credit risk transmission from the sovereign to the financial sector is positively related to a country’s debt-to-GDP ratio and negatively related to its structural budget balance.

We also use our model to examine the sovereign bailouts extended to Greece, Ireland, Portugal and Spain between April 2010 and June 2012. We show that these bailouts contributed to the restoration of financial stability by disrupting the [Acharya et al. \(2014\)](#) feedback loop in the target country (i.e., the country receiving the bailout). Depending on the initial fiscal condition of the target sovereign, we find that sovereign bailouts can dampen credit risk transmission from the target sovereign to foreign financial institutions and to foreign sovereigns, thereby mitigating the systemic impacts of debt crises.

Our results indicate that the bailouts to Greece were less successful than the other sovereign bailouts in our sample. We argue that this is because the initial fiscal position of Greece was considerably worse than that of Ireland, Portugal or Spain. Furthermore, the austerity measures undertaken in Greece reduced the structural deficit but failed to

reduce the debt-to-GDP ratio due to their contractionary influence on economic activity. This suggests that the efficacy of a sovereign bailout may be diminished if the fiscal fundamentals of the target country are “too weak” to start with, particularly if the terms of the bailout agreement mandate rapid and contractionary fiscal retrenchment.

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Table 1: Descriptive statistics

	Sovereign CDS			Financial CDS			Term Spreads			Equity Returns		
	Mean	Median	StDev	Mean	Median	StDev	Mean	Median	StDev	Mean	Median	StDev
Austria	0.010	0.000	3.458	0.057	0.000	5.397	0.006	-0.040	6.105	-1.624	0.000	168.385
Belgium	0.015	0.000	4.546	0.026	0.000	7.120	0.007	0.000	5.756	0.141	1.457	131.417
France	0.012	0.000	2.989	0.023	-0.008	4.669	0.012	0.000	6.188	0.143	2.247	147.917
Germany	0.005	0.000	1.562	0.025	-0.021	4.061	-0.003	-0.020	5.816	2.835	6.822	141.833
Greece	0.828	0.001	259.544	0.702	0.000	100.312	0.254	0.000	87.361	-6.111	0.000	208.765
Ireland	0.019	0.000	10.824	0.070	0.000	48.045	0.022	0.000	20.519	-0.614	0.257	157.101
Italy	0.043	0.000	8.350	0.047	-0.014	7.144	0.030	-0.200	10.467	-1.825	0.000	163.984
Netherlands	0.007	0.000	1.917	0.045	0.000	5.225	0.006	0.000	6.070	0.357	2.664	138.766
Norway	0.005	0.000	1.149	0.030	0.000	2.740	-0.028	-0.120	9.428	1.278	3.263	172.970
Portugal	0.066	0.000	15.999	0.095	-0.006	14.595	0.054	0.000	29.503	-1.666	0.612	131.862
Spain	0.037	0.000	8.301	0.047	-0.004	8.136	0.041	0.000	11.240	0.131	4.484	156.507
Sweden	0.006	0.000	1.723	0.020	0.000	2.648	-0.019	-0.100	7.961	1.986	1.654	145.941
U.K.	0.007	0.000	1.941	0.028	-0.010	5.027	0.073	-0.050	6.219	0.587	0.202	122.826
Australia	0.013	0.000	2.189	0.032	-0.016	5.132	0.043	0.000	6.354	0.641	0.205	114.379
China	0.033	-0.007	4.202	0.041	-0.008	5.887	-0.039	0.000	6.574	4.658	2.485	170.626
Japan	0.015	0.000	2.270	0.020	-0.030	3.596	-0.042	0.000	2.455	-0.029	0.000	143.616
Russia	0.112	-0.018	14.484	0.176	-0.079	28.870	-0.032	0.000	38.845	1.802	0.000	219.923
U.S.	0.006	0.000	1.303	0.028	-0.056	9.359	0.075	0.000	7.264	2.023	4.291	129.068

NOTES: Descriptive statistics are reported for the first difference of the sovereign CDS spread, the first difference of the financial sector CDS spread, the first difference of the sovereign term spread and the daily log-return on the equity index. All values are reported in basis points.

Table 2: Ranking the Models by One-Step Ahead Predictive Accuracy

	Rank by Predictive Accuracy				Cumulative RRMSFE
	First	Second	Third	Top Three	
Shrinkage and selection					
LASSO VAR	0.220	0.100	0.091	0.411	1.000
Elastic Net VAR, $\alpha = 0.25$	0.168	0.127	0.159	0.454	0.993
Elastic Net VAR, $\alpha = 0.75$	0.097	0.180	0.233	0.510	0.992
Elastic Net VAR, $\alpha = 0.50$	0.052	0.224	0.245	0.521	0.992
Cross-section aggregation					
GVAR, financial weights	0.141	0.079	0.082	0.302	1.086
GVAR, PPP-GDP weights	0.127	0.109	0.089	0.324	1.076
GVAR, trade weights	0.116	0.088	0.067	0.271	1.136
Shrinkage only					
Ridge VAR	0.044	0.046	0.016	0.107	1.422
No shrinkage or selection					
Simple VAR	0.035	0.048	0.017	0.100	1.436

NOTES: The columns labeled “First”, “Second” and “Third” under the “Rank by Predictive Accuracy” heading report the proportion of rolling samples in which each model is ranked first, second and third according to their one-step-ahead RMSFE. The column labeled “Top Three” under the “Rank by Predictive Accuracy” heading reports the proportion of rolling samples in which each model is ranked among the top three. The cumulative relative RMSFE (RRMSFE) is calculated over all rolling samples using the LASSO as the benchmark.

Table 3: Intensity of the [ADS](#) cycle among the European countries

	Peak	Trough	Amplitude	Net < 0
Portugal	3.913	-8.310	12.224	0.626
Spain	2.415	-7.389	9.804	0.704
Greece	4.196	-5.001	9.198	0.772
Ireland	2.026	-6.435	8.461	0.809
Italy	2.015	-4.719	6.734	0.282
France	3.227	-1.903	5.130	0.051
Belgium	1.617	-3.327	4.944	0.737
Austria	3.526	-1.134	4.660	0.492
Sweden	2.767	-1.808	4.575	0.484
Norway	3.528	-0.769	4.297	0.397
Netherlands	2.347	-1.210	3.557	0.725
Germany	2.310	-0.986	3.295	0.289
U.K.	1.892	-1.207	3.098	0.171

NOTES: “Peak” and “Trough” values are the maximum and minimum values of the net financial–sovereign credit risk spillovers in each country, respectively. “Amplitude” is defined as peak minus trough. Finally, “Net < 0” is the proportion of sample observations in which the net spillover from the i th financial sector to the i th sovereign is negative. The table contains results from the European countries ranked in descending order of “Amplitude”.

Table 4: Dependence of net financial–sovereign credit risk transmission on macroeconomic fundamentals

	All Countries		GIIPS		Other European		Non-European	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Current Account Balance	0.000	0.017	0.028	0.024	-0.026	0.023	0.028	0.055
Structural Budget Balance	0.077 ***	0.020	0.103 ***	0.030	-0.005	0.026	0.087	0.065
Debt to GDP Ratio	-0.017 ***	0.003	-0.019 ***	0.004	0.003	0.004	-0.025 **	0.012
GDP Growth	0.026	0.016	-0.013	0.018	0.052 **	0.021	0.051	0.054
Countries	18		5		8		5	
Observations	630		175		280		175	
Adjusted R ²	0.528		0.439		0.517		0.508	

NOTES: The table contains results for panel regression models with both country and time fixed effects. The dependent variable is the net spillover from the i th financial sector to the j th sovereign. Inference is based on heteroscedasticity-robust standard errors. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Due to the limited cross-sectional dimension of the dataset, we do not report cluster-robust standard errors, although they are available on request. The statistical significance of our principal findings is retained if we use standard errors clustered at the country level.

Table 5: Network effects of the sovereign bailouts

	1	2	3	4	5	6
	Local fin. sector to the target sovereign	Target sovereign local fin. sector to the	Target sovereign foreign fin. sector to the	Target sovereign to the foreign sovs.	Government Debt/GDP (%)	Structural Balance (%)
1 st Greek Bailout, 4/23/2010	Before After Change	5.528 5.449 -0.079	0.982 1.299 0.316	2.529 2.245 -0.284	130.8	-17.0
Irish Bailout, 11/22/2010	Before After Change	4.123 4.058 -0.064	1.589 1.462 -0.127	2.264 2.118 -0.146	83.3	-8.9
Portuguese Bailout, 4/6/2011	Before After Change	3.567 3.053 -0.514	1.737 1.676 -0.061	2.644 2.568 -0.076	97.4	-7.6
2 nd Greek Bailout, 2/21/2012	Before After Change	0.725 0.352 -0.373	0.110 0.114 0.004	0.098 0.103 0.005	172.0	-8.4
Spanish Bailout, 6/25/2012	Before After Change	2.716 2.627 -0.089	1.656 1.592 -0.065	2.298 2.230 -0.068	73.5	-6.5

NOTES: The four spillover measures reported in the table correspond to the columns of Figure 7. "Before" denotes the average value of the spillover measure in the five trading days prior to the sovereign bailout. "After" denotes the average value of the spillover measure in the five trading days following the sovereign bailout. "Change" is defined as "After" minus "Before". Values of government debt relative to GDP and structural budget balance are for the quarter prior to the bailout.

Figure 1: The Greek sovereign CDS and bond yield spreads

NOTES: The black line in panel (a) shows the incomplete Greek five-year sovereign CDS spread plotted on the left axis, while the gray line shows the bond yield spread on the right axis. Panel (b) shows the merged series used in estimation, with the original CDS spread shown in black and the imputed data shown in gray. The unit of measurement is basis points in all cases.

Figure 2: Comovement of the sovereign and financial sector credit spreads

Figure 3: Model evaluation using the relative RMSFE

NOTES: The figure presents frequency plots for $1 + \ln(r_{js})$ over all 2,246 rolling samples, where r_{js} is the relative RMSFE of the j th model in the s th rolling sample using the LASSO as the benchmark. If $1 + \ln(r_{js}) < 1$ (> 1) then the j th model outperforms (is outperformed by) the benchmark model in the s th rolling sample.

Figure 4: Topology of the sovereign–financial network

(a) At the start of the sample, prior to the GFC
(250 trading day sample ending 12/18/2006)

(b) At the time of the Portuguese Request for Aid
(250 trading day sample ending 4/6/2011)

NOTES: The (i, j) th edge shows the total spillover from the j th sovereign and the j th financial sector to the i th sovereign and the i th financial sector. The size of the i th node is proportional to the sum of spillovers between the i th sovereign and the i th financial sector, including “loops” (spillovers from a node onto itself). The layout of the nodes in both figures is identical and is based on the Fruchterman-Reingold force-directed algorithm applied to the Portuguese bailout sample. The strength of the spillover effects is represented by the thickness of the edges. The Portuguese node is shaded gray to draw attention to the role of Portugal within the network.

Figure 5: Aggregate credit risk transfer between sovereigns and the financial sector

(a) Average credit risk spillover between national financial sectors

(b) Average credit risk spillover between sovereigns

(c) Net credit risk spillover from the global financial sector to all sovereigns

NOTES: The fine black line shows the named spillover measure computed using a rolling sample of $w = 250$ days with the forecast horizon set at $h = 10$ days. The heavy black line is a smoothed version computed using a centered 21-day moving average. The gray band shows the extent of variation of the smoothed spillover measure as we vary $w \in \{200, 250, 300\}$ and $h \in \{5, 10, 15\}$. The dashed line shows the smoothed spillover measure when Greece is excluded from the model. The following events are shown by vertical lines/shading: the financial sector bailouts over the period 9/7/2008 to 10/21/2008 (FIN); the first Greek bailout request on 4/23/2010 (GR1); the Irish bailout request on 22-Nov-2010 (IE); the Portuguese bailout request on 06-Apr-2011 (PT); the second Greek bailout request on 2/21/2012 (GR2); the Greek debt swap agreement on 3/9/2012 (DS); and the Spanish bailout request on 6/25/2012 (ES). For the financial sector bailouts, the dark vertical shading denotes the bailout period used by ADS (9/26/2008 to 10/21/2008) while the lighter shaded region includes several prior bailouts in the U.S. over the period 9/7/2008 to 9/25/2008. The unit of measurement is percent.

Figure 6: Net spillovers from the domestic financial sector to the sovereign

NOTES: The fine black line shows the named spillover measure computed using a rolling sample of $w = 250$ days with the forecast horizon set at $h = 10$ days. The heavy black line is a smoothed version of the net spillover computed using a centered 21-day moving average. The gray band shows the extent of variation of the smoothed net spillover as we vary $w \in \{200, 250, 300\}$ and $h \in \{5, 10, 15\}$. The dashed line shows the smoothed net spillover when Greece is excluded from the model. The dark vertical shading denotes the bailout period used by ADS while the lighter shaded region includes several prior bailouts in the U.S. The vertical lines in the panels for Greece, Ireland, Portugal and Spain show the sovereign bailouts marked in Figure 5, as well as the debt swap agreement in the case of Greece. The unit of measurement is percent.

Figure 7: Sovereign bailouts and GIIPS credit risk spillovers

NOTES: The fine black line shows the named spillover measure computed using a rolling sample of $w = 250$ days with the forecast horizon set at $h = 10$ days. The heavy black line is a smoothed version computed using a centered 21-day moving average. The gray band shows the extent of variation of the smoothed spillover measure as we vary $w \in \{200, 250, 300\}$ and $h \in \{5, 10, 15\}$. The dashed line shows the smoothed spillover measure when Greece is excluded from the model. Heavy vertical lines mark the date at which each sovereign requested aid (detailed in the notes to Figure 5). Fine vertical lines mark other events which are likely to influence the credit risk network. For the first Greek bailout, the additional event is the first trading day after the European Financial Stability Facility was agreed (5/10/2010). For the second Greek bailout, the additional events are the two LTROs on 12/21/2011 and 2/29/2012 and the debt swap agreement of 3/9/2012. For the Spanish bailout, the additional events are the government intervention in Bankia on 5/10/2012 and Mario Draghi's "whatever it takes" speech on 7/26/2012. The unit of measurement is percent.

Figure 8: Fiscal position of the target sovereigns prior to the sovereign bailouts

NOTES: For each of the five sovereign bailouts that we study, the figure shows the government debt-to-GDP ratio and the structural budget deficit relative to potential GDP in the quarter immediately prior to the bailout. Both values are expressed in percent.

Appendix: Specification of the GVAR model

Recall that we observe the $k \times 1$ vector $\mathbf{x}_{it} = (\Delta g_{it}, \Delta b_{it}, \Delta s_{it}, \Delta \ln(q_{it}))'$ for the i th country in the system. To develop the GVAR, one must construct a corresponding vector of foreign variables, $\mathbf{x}_{it}^*$, defined as a weighted average of the domestic variables for countries $j = 1, 2, \dots, N$, $j \neq i$. First, define $\mathbf{x}_t = (\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, \dots, \mathbf{x}'_{Nt})'$, which is of dimension $Nk \times 1$. For the i th economy, the $k \times 1$ vector of foreign variables is defined as follows:

$$\mathbf{x}_{it}^* \equiv (\Delta g_{it}^*, \Delta b_{it}^*, \Delta s_{it}^*, \Delta \ln(q_{it}^*))' = \mathbf{W}_i' \mathbf{x}_t, \quad (\text{A.1})$$

where $\mathbf{W}_i$ is a $k \times Nk$ matrix of country-specific weights with the following structure:

$$\mathbf{W}_i = (\underbrace{\mathbf{W}_{i1}}_{k \times k}, \dots, \underbrace{\mathbf{W}_{ii-1}}_{k \times k}, \underbrace{\mathbf{0}}_{k \times k}, \underbrace{\mathbf{W}_{ii+1}}_{k \times k}, \dots, \underbrace{\mathbf{W}_{iN}}_{k \times k}),$$

where the diagonal elements of $\mathbf{W}_{ij}$ contain the weight of country j from the perspective of country i and the off-diagonal elements are all zero. We follow the norm in the GVAR literature and treat the weights as time-invariant to avoid introducing additional uncertainty into the estimation.

To construct the GVAR, we first estimate a VARX model for each economy in the system, as well as a marginal VAR model for the vector of global controls, $\mathbf{x}_t^{**}$. These are then stacked to form the GVAR. The i th country-specific VARX model is given by:

$$\mathbf{x}_{it} = \boldsymbol{\alpha}_i + \sum_{l=1}^{p_i} \boldsymbol{\Phi}_{il} \mathbf{x}_{i,t-l} + \boldsymbol{\Lambda}_{i0} \mathbf{x}_{it}^* + \sum_{l=1}^{q_i} \boldsymbol{\Lambda}_{il} \mathbf{x}_{i,t-l}^* + \mathbf{D}_{i0} \mathbf{x}_t^{**} + \sum_{l=1}^{s_i} \mathbf{D}_{il} \mathbf{x}_{t-l}^{**} + \boldsymbol{\epsilon}_{it}, \quad (\text{A.2})$$

where $\boldsymbol{\alpha}_i$ is a $k \times 1$ vector of intercepts, the $\boldsymbol{\Phi}_{il}$'s, $\boldsymbol{\Lambda}_{i0}$ and the $\boldsymbol{\Lambda}_{il}$'s are $k \times k$ parameter matrices, $\mathbf{D}_{i0}$ and the $\mathbf{D}_{il}$'s are $k \times k^{**}$ parameter matrices and $\boldsymbol{\epsilon}_{it} \sim iid(\mathbf{0}, \boldsymbol{\Sigma}_{ii})$ are the regression residuals, where $\boldsymbol{\Sigma}_{ii}$ is positive definite. The marginal VAR model for $\mathbf{x}_t^{**}$ is specified as follows:

$$\mathbf{x}_t^{**} = \boldsymbol{\alpha}_m + \sum_{l=1}^{p_m} \boldsymbol{\Phi}_{ml} \mathbf{x}_{t-l}^{**} + \boldsymbol{\epsilon}_{mt}, \quad (\text{A.3})$$

where $\boldsymbol{\alpha}_m$ is an $k^{**} \times 1$ vector of intercepts, $\boldsymbol{\Phi}_{ml}$ is a $k^{**} \times k^{**}$ matrix of autoregressive parameters and the residuals, $\boldsymbol{\epsilon}_{mt} \sim iid(\mathbf{0}, \boldsymbol{\Sigma}_{mm})$, are serially uncorrelated with covariance matrix $\boldsymbol{\Sigma}_{mm}$. The lag orders $\{p_i, q_i, s_i, p_m\}$ can be selected by minimisation of an information criterion as usual (we use the Schwarz Information Criterion).

We now define $\mathbf{y}_{it} = (\mathbf{x}'_{it}, \mathbf{x}_{it}^{*'}, \mathbf{x}_t^{**'})'$ such that equation (A.2) can be written compactly as:

$$\mathbf{B}_{i0}\mathbf{y}_{it} = \boldsymbol{\alpha}_i + \sum_{l=1}^P \mathbf{B}_{il}\mathbf{y}_{i,t-l} + \boldsymbol{\epsilon}_{it}, \quad (\text{A.4})$$

where $\mathbf{B}_{i0} = (\mathbf{I}_k, -\boldsymbol{\Lambda}_{i0}, -\mathbf{D}_{i0})$ and $\mathbf{B}_{il} = (\boldsymbol{\Phi}_{il}, \boldsymbol{\Lambda}_{il}, \mathbf{D}_{il})$, where $\mathbf{I}_k$ is the $k \times k$ identity matrix.¹¹ Next, by defining the $2k \times Nk$ transformation matrix $\widetilde{\mathbf{W}}_i = (\mathbf{E}'_i, \mathbf{W}'_i)'$, where $\mathbf{W}_i$ is the country-specific weight matrix and $\mathbf{E}_i$ is a selection vector defined such that $\mathbf{E}_i\mathbf{x}_t = \mathbf{x}_{it}$, we can write $(\mathbf{x}'_{it}, \mathbf{x}_{it}^{*'})' = \widetilde{\mathbf{W}}_i\mathbf{x}_t$. We can now define the $K \times 1$ vector $\mathbf{z}_t = (\mathbf{x}'_t, \mathbf{x}_t^{*'})'$, which contains every variable in the GVAR system such that:

$$\mathbf{y}_{it} = \begin{pmatrix} \widetilde{\mathbf{W}}_i\mathbf{x}_t \\ \mathbf{x}_t^{**} \end{pmatrix} = \begin{pmatrix} \widetilde{\mathbf{W}}_i & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{x}_t \\ \mathbf{x}_t^{**} \end{pmatrix} = \mathbf{L}_i\mathbf{z}_t, \quad (\text{A.5})$$

$$\mathbf{x}_t^{**} = \begin{pmatrix} \mathbf{0} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{x}_t \\ \mathbf{x}_t^{**} \end{pmatrix} = \mathbf{L}_m\mathbf{z}_t. \quad (\text{A.6})$$

With these transformations in hand, equations (A.4) and (A.3) can be re-written in terms of $\mathbf{z}_t$ and then stacked to form the following system of globally endogenous variables:

$$\mathbf{G}_0\mathbf{z}_t = \boldsymbol{\alpha} + \sum_{l=1}^P \mathbf{G}_l\mathbf{z}_{t-l} + \boldsymbol{\epsilon}_t, \quad (\text{A.7})$$

where $\mathbf{G}_0 = (\mathbf{B}_{10}\mathbf{L}_1, \dots, \mathbf{B}_{N0}\mathbf{L}_N, \mathbf{L}_m)'$ and $\mathbf{G}_l = (\mathbf{B}_{1l}\mathbf{L}_1, \dots, \mathbf{B}_{Nl}\mathbf{L}_N, \boldsymbol{\Phi}_{ml}\mathbf{L}_m)'$ for $l = 1, 2, \dots, P$. Assuming $\mathbf{G}_0$ is invertible, the final reduced form GVAR model is:

$$\mathbf{z}_t = \mathbf{a} + \sum_{l=1}^P \mathbf{C}_l\mathbf{z}_{t-l} + \mathbf{v}_t, \quad (\text{A.8})$$

where $\mathbf{a} = \mathbf{G}_0^{-1}\boldsymbol{\alpha}$, $\mathbf{C}_l = \mathbf{G}_0^{-1}\mathbf{G}_l$ and $\mathbf{v}_t = \mathbf{G}_0^{-1}\boldsymbol{\epsilon}_t$.

¹¹To simplify the notation, note that the lag order in equation (A.4) is defined as $P = \max\{p_i, q_i, s_i, p_m\}$ and that $\boldsymbol{\Phi}_{il} = \mathbf{0}_{k \times k} \forall l > p_i$, $\boldsymbol{\Lambda}_{il} = \mathbf{0}_{k \times k} \forall l > q_i$, $\mathbf{D}_{il} = \mathbf{0}_{k \times k^{**}} \forall l > s_i$ and $\boldsymbol{\Phi}_{ml} = \mathbf{0}_{k^{**} \times k^{**}} \forall l > p_m$, where $\mathbf{0}$ is the null matrix.