Bootstrap-based probabilistic analysis of spillover scenarios in economic and financial networks*

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Abstract

We apply techniques from the event probability forecasting literature to the analysis of spillover scenarios in economic and financial networks. A simple spillover scenario is expressed as an inequality constraint with respect to a single spillover measure. More complex spillover scenarios can be defined as combinations of simple scenarios. The scenario probabilities are evaluated using a non-parametric bootstrap. We use our technique to study credit risk transmission among a group of 18 countries over the 2006–2010 period. We show that abrupt changes in the probabilities of "crisis scenarios" accurately map on to key events during the Global Financial Crisis.

JEL classifications: C32; C58; G01.

Keywords: Empirical network model; Non-parametric bootstrap; Credit risk transmission; Probabilistic scenario analysis; Probabilistic classification.

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1 Introduction

In the October 2008 edition of the Global Financial Stability Report, the International Monetary Fund emphasized the role of financial spillovers in the emergence of the Global Financial Crisis (GFC) from the U.S. subprime mortgage crisis. The role of destabilizing spillovers in the global propagation of the GFC has led to increased scrutiny of the nature of financial networks and their potential to act as conduits for shock transmission. As a result, econometric methods for the estimation of empirical network models have gained prominence. However, the development of techniques to interpret the wealth of information embedded in the estimated networks has not advanced at the same rate. Much of the empirical network literature in economics and finance focuses on changes in the aggregate connectedness of networks over time, with little attention paid to other aspects of network topology [see Greenwood-Nimmo et al. (2017) for a related discussion]. Motivated by this gap in the literature, we develop a novel framework for the probabilistic analysis of spillover scenarios, which we define in a flexible manner using inequality constraints applied to one or more edges in an estimated network. Our technique is highly adaptable and can be used to characterize and study a wide variety of events through a probabilistic lens, yielding a straightforward interpretation suitable for use by non-specialists.

Notable contributions to the literature on the estimation of network models have employed Granger causal analysis (e.g., Billio et al., 2012), impulse response analysis (e.g., Alter and Beyer, 2014), and forecast error variance decomposition (Diebold and Yilmaz, 2009, 2014; Buse and Schienle, 2019) based on underlying time series models, typically estimated on a rolling sample basis. The Diebold and Yilmaz (2009, 2014, hereafter DY) approach is arguably the most influential of these techniques, due to its ease of implementation and its straightforward interpretation. Consequently, we adopt the DY approach as the basis on which we build our probabilistic framework.

DY were the first to show that the forecast error variance decomposition (FEVD) of a vector autoregressive (VAR) model can be interpreted as a weighted directed graph. For a K-variable system and for a given forecast horizon, h, the $\{i, j\}$th element of the h-steps-ahead FEVD matrix $\underset{K \times K}{\boldsymbol{d}}$, denoted d_{ij}, captures the proportion of the h-steps-ahead uncertainty associated with variable i that can be attributed to shocks affecting variable j. This represents an easily interpreted measure of the bilateral spillover from variable j to variable i that exhibits two desirable features: (i) it conveys information on the direction of bilateral spillovers; and (ii) it allows one to measure the relative strength of bilateral spillovers.[1] Consequently, the matrix $\boldsymbol{d}$ can be thought of as a spillover matrix. An increase in the average intensity of bilateral spillovers from one sample period to another corresponds to an increase in the aggregate connectedness of the network, with abrupt increases in connectedness often being interpreted in relation to systemic shocks.

A notable limitation of much of the DY literature is its reliance on point estimates of the bilateral spillover effects and associated network statistics, as opposed to interval estimates or more sophisticated forms of probabilistic analysis. Although it is not generally done, it is possible to characterize the distributions of the network statistics proposed by DY. In principle, one could develop asymptotic approximations by building on the results in Lütkepohl (1990). However, given that DY networks are typically estimated over rolling samples using relatively short windows, it is doubtful that a large-sample approximation would be adequate in practice. Consequently, as in Greenwood-Nimmo et al. (2019b), we pursue a computational technique based on a non-parametric bootstrap,

[1] This contrasts with many other popular techniques for network analysis, such as Granger causal network analysis, which measures the direction but not the strength of bilateral spillover effects.

which is well-suited for use with small samples.

Knowledge of the empirical distribution of the estimated spillover effects provides a basis for probabilistic analysis. We show that the empirical joint distribution of the bilateral spillover effects in a DY network can be used to evaluate the probability of a range of spillover scenarios, which are defined via inequality constraints applied to the elements of the spillover matrix, either individually or jointly. This technique has intuitive appeal, because it enables the researcher to specify any set of inequality constraints that define an event of interest. This contrasts with the use of confidence intervals, where inequality constraints are defined through the use of implicit threshold values determined by the choice of significance level [see Garratt et al. (2006) and Greenwood-Nimmo et al. (2012) for a similar discussion in the context of probabilistic scenario forecasting]. Consequently, the probabilistic analysis of spillover scenarios represents a highly adaptable framework with which to study potentially complex events involving many bilateral spillover effects simultaneously. Furthermore, although our technique can accommodate potentially complex events, it retains a simple interpretation in terms of event probabilities. This is an important consideration, because the ease of interpretation of DY networks is among their key attributes.

We demonstrate the utility of our technique with a study of credit risk spillovers over the 2006-2010 period. For this purpose, we adapt the empirical network model of Greenwood-Nimmo, Huang, and Nguyen (2019a, hereafter GHN), which models credit risk spillovers among a group of 18 sovereigns and their respective financial sectors using data on credit default swap (CDS) spreads, while controlling for a range of country-specific and global phenomena. Our choice to work with an existing model rather than building a new model is motivated by two considerations. First, it allows us to focus on our primary contribution, which is not model-building per se but the development of a new technique to interpret the output from sophisticated network models. Second, it provides us with a natural point of comparison against which to highlight the value added by our new analytical framework.

Due to the high-dimensional nature of their underlying VAR model, GHN estimate its parameters over rolling samples using the Least Absolute Shrinkage and Selection Operator (LASSO) of Tibshirani (1996) and then use the resulting sparse VAR parameter matrices as inputs in the construction of the DY network. We follow a similar approach but we replace the LASSO with the adaptive LASSO (ALASSO) of Zou (2006). This substitution is motivated by the fact that it is considerably easier to bootstrap the ALASSO than the LASSO (Chatterjee and Lahiri, 2010, 2011). The ease of implementation of the bootstrap is an important consideration, because bootstrapping a model of this size estimated over rolling samples using a LASSO-type shrinkage and selection estimator is highly computationally demanding.

Our analysis centers on the interaction between financial sector credit risk and sovereign credit risk, focusing in particular on two phenomena documented by Acharya, Drechsler, and Schnabl (2014, hereafter ADS). First, ADS show that the financial sector bailouts in Europe in the last half of 2008 entailed a massive transfer of private sector credit risk onto sovereigns. As a result, sovereign credit risk increases relative to financial sector credit risk following a bailout. GHN show that the credit risk transfer described above manifests as a sustained reduction in the net spillover from the financial sector to the sovereign in the GHN model.

Second, ADS find that financial sector bailouts can generate comovements between sovereign and financial sector credit risk. Prior to the bailouts, there is no systematic comovement between sovereign and financial credit spreads. At the time of the bailouts in 2008, credit risk was transferred from the financial sector onto the sovereign, resulting in a negative comovement between the two; financial sector credit spreads fell, while sovereign credit spreads rose. However, shortly after the bailouts, sovereign risk and financial sector risk began to increase in a mutually reinforcing manner due to the emergence of an adverse feedback effect.[2] The strength of the financial–sovereign feedback effect can be captured in the GHN model by the total bidirectional spillover between sovereign and financial sector credit risk for each country.

GHN analyze both of these phenomena using point estimates of the spillover effects obtained from their model. This yields a simple narrative but does not convey information on the degree of uncertainty surrounding key findings, nor does it provide a firm foundation for the consideration of joint events involving multiple spillover effects at once. This is precisely the issue that our probabilistic framework is designed to resolve. The GHN model provides an ideal platform for the application of our technique, because the stylized facts documented by ADS that it is designed to capture are easily translated into spillover scenarios using inequality constraints applied to the elements of the spillover matrix. For example, to evaluate the probability that the net credit risk spillover from the ith financial sector to the ith sovereign falls during the period of the financial sector bailouts, one can compute the empirical probability of an inequality of the form $\mathcal{N}_{i,\text{pre-bailout}} > \mathcal{N}_{i,\text{bailout}}$, where $\mathcal{N}_{\text{i,pre-bailout}}$ and $\mathcal{N}_{\text{i,bailout}}$ denote the net financial–sovereign spillover in country i in the pre-bailout and bailout subsamples, respectively. Proceeding in this way, we find a high probability of net credit risk transfer from the financial sector onto the sovereign

[2]Specifically, the increase in sovereign risk brought about by the bailout causes the sovereign's fiscal position to deteriorate, which, in turn, reduces the future value of its guarantee of the financial sector, while simultaneously reducing the value of the financial sector's holdings of domestic sovereign debt. This combination of factors leads to a resurgence of financial sector risk, which raises the likelihood that further action will be required on the part of the sovereign, further raising sovereign risk and so on.

in most European countries during the bailout period and a similarly high probability of increased financial–sovereign feedback in the post-bailout period.

The use of discrete subsample periods to compute event probabilities relating to the ADS stylized facts in the manner described above is susceptible to criticisms regarding the choice of subsample periods and a lack of detail regarding the timing of changes in spillover activity. To address these limitations, we devise and implement a three-way probabilistic classification of the crisis-hit countries in our sample on a rolling-sample basis. Our classification first involves identifying periods of 'normal' financial–sovereign feedback, which we define as feedback not exceeding a threshold determined by the analysis of pre-GFC levels of feedback. Next, for periods in which financial–sovereign feedback exceeds normal levels, we further separate periods of bank-led and sovereign-led feedback based on the sign of the net credit risk spillover between the sovereign and the local financial sector. Our classification scheme provides a vivid and timely characterization of the nature of financial-sovereign feedback among the crisis-hit countries in our sample, including the GIIPS (Greece, Ireland, Italy, Portugal, and Spain), as well as the non-GIIPS countries that experienced a banking crisis in 2008-2009 according to the analysis of Laeven and Valencia (2013). For example, we show that the impairment or failure of a major bank typically leads to an abrupt increase in the probability of bank-led feedback in its home country, while the financial sector bailouts in 2008 precede a marked increase in the probability of sovereign-led feedback in many countries. This exercise offers an elegant demonstration of the value of probabilistic analysis of DY networks—it allows one to distill the wealth of information that they contain in an accessible manner that is readily tailored to the application at hand.

This paper proceeds as follows. In Section 2, we review the DY framework for network analysis and show how it can be extended through the application of bootstrap techniques to allow for the probabilistic analysis of spillover scenarios. In Section 3, we introduce the GHN model of the global credit risk network, which forms the basis for our empirical analysis. Our results are presented and discussed in Section 4. We conclude in Section 5.

2 A probabilistic framework for network analysis

2.1 The Diebold–Yilmaz framework for network analysis

Our technique takes the DY framework for network analysis as its foundation. In the DY framework, a pth order reduced form VAR model of the following form is used to approximate the dynamics of a $K \times 1$ vector of endogenous variables, $\boldsymbol{z}_t$:

$$\boldsymbol{z}_t = \boldsymbol{a} + \sum_{\ell=1}^{p} \boldsymbol{C}_\ell \boldsymbol{z}_{t-\ell} + \boldsymbol{u}_t, \tag{1}$$

where time periods are indexed by $t = 1, 2, \ldots, T$, $\boldsymbol{a}$ is a vector of intercepts, $\boldsymbol{C}_\ell$ is the ℓ-th autoregressive parameter matrix and $\boldsymbol{u}_t$ is a vector of zero-mean residuals with a positive-definite covariance matrix, $\boldsymbol{\Omega}$. Studies have used a variety of estimators to fit the approximating model in equation (1). Many papers focusing on relatively small models, including Diebold and Yilmaz (2009, 2014), have used traditional estimators such as ordinary least squares (OLS). In larger systems and/or when estimation is based on a small sample, a number of techniques for dimension reduction have been used, including elastic net regularization and the estimators that it nests (e.g., Demirer et al., 2018; GHN), as well as global VAR (e.g., Greenwood-Nimmo et al., 2019b).

For now, the choice of estimator is not important—it is sufficient to assume that one has obtained consistent estimates of the parameters of equation (1). With these estimates in hand, one is free to compute the h-steps-ahead $K \times K$ FEVD matrix, the $\{i, j\}$th element of which measures the proportion of the h-steps-ahead forecast error variance associated with the ith variable that is due to shocks associated with the jth variable. The computation of variance decompositions can be problematic in the context of reduced form VAR models such as equation (1), in which the residuals are cross-sectionally correlated. As a result of this correlation, the sum of the variance shares attributed to each variable in the system may exceed one. DY propose two solutions to this issue: (i) consider a large number of orthogonalized forecast error variance decompositions (OVDs) obtained using arbitrary Cholesky factorizations; and (ii) use the generalized forecast error variance decomposition (GVD) of Pesaran and Shin (1998) and then apply a subsequent row-sum normalization to obtain a representation in which the variance shares attributed to each variable in the system sum to one. The latter option has emerged as the norm in the literature and it is this avenue that we pursue. The h-steps-ahead GVD is defined as follows:

$$\theta_{i \leftarrow j}^{(h)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{R}_\ell \boldsymbol{\Omega} \boldsymbol{e}_j \right)^2}{\sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{R}_\ell \boldsymbol{\Omega} \boldsymbol{R}_\ell' \boldsymbol{e}_i \right)} \qquad i, j = 1, 2, \ldots, K, \tag{2}$$

where σ_{jj} is the standard deviation of the residuals from the jth equation in the VAR, $\boldsymbol{e}_i = \left(\underset{1 \times i-1}{\mathbf{0}'}, 1, \underset{1 \times K-i}{\mathbf{0}'} \right)$ and $\boldsymbol{R}_i$ is the ith parameter matrix of the moving average representation of equation (1), which is obtained recursively as $\boldsymbol{R}_i = \boldsymbol{C}_1 \boldsymbol{R}_{i-1} + \boldsymbol{C}_2 \boldsymbol{R}_{i-2} + \ldots$, where $\boldsymbol{R}_0 = \boldsymbol{I}_K$ and $\boldsymbol{R}_j = \mathbf{0}_K$ for $j < 0$, where $\boldsymbol{I}_K$ and $\mathbf{0}_K$ denote the $K \times K$ identity and zero matrices, respectively. The row-sum normalization applied by DY is as follows:

$$d_{i \leftarrow j}^{(h)} = \theta_{i \leftarrow j}^{(h)} / \sum_{j=1}^{K} \theta_{i \leftarrow j}^{(h)}, \tag{3}$$

which ensures that $\sum_{j=1}^{K} d_{i \leftarrow j}^{(h)} = 1$ for $i = 1, 2, \ldots, K$.

For a given forecast horizon, DY demonstrate that the matrix of normalized GVDs can be interpreted as a weighted directed network capturing the pairwise relations among the elements of $\boldsymbol{z}_t$. Values on the prime diagonal of the normalized GVD matrix represent unilateral spillovers, or "loops", while the bilateral spillover from entity j to entity i occupies the $\{i, j\}$th position. The net spillover from entity j to entity i is defined as $\mathcal{N}^{(h)}_{i\leftarrow j} = d^{(h)}_{i\leftarrow j} - d^{(h)}_{j\leftarrow i}$, while the total bidirectional feedback effect between entities i and j is defined as $\mathcal{T}^{(h)}_{i\leftrightarrow j} = d^{(h)}_{i\leftarrow j} + d^{(h)}_{j\leftarrow i}$. Lastly, the proportion of the systemwide h-steps-ahead forecast error variance due to bilateral spillovers is a natural measure of aggregate spillover activity and is referred to as the spillover index, $S^{(h)}$.

DY describe the network evaluated over the full estimation sample as an unconditional network, in the sense that it conveys information on the average topology of the network under scrutiny. To obtain conditional estimates, DY apply a rolling-sample estimation framework. If the maximum available sample size is T and the size of the rolling window is w, then one can obtain $T - w + 1$ time-varying estimates of the network structure. In this way, it is possible to track changes in the topology of the network over time.

2.2 Probabilistic analysis of spillover scenarios

The large majority of studies of DY networks analyze point estimates of aggregate spillover indices and/or point estimates of pairwise spillover effects (e.g., Diebold and Yilmaz, 2009, 2014; Demirer et al., 2018; GHN). The virtue of this approach is its simplicity and ease of interpretation. The drawback is that the joint evolution of multiple spillover effects is often not explored in depth, despite the fact that it would allow one to extract more information from the estimated network. In addition, the typical reliance on point estimates prevents authors from conveying the degree of uncertainty surrounding the estimated spillover effects and their dynamic evolution. Our principal innovation is to propose a framework that tackles both of these issues simultaneously via the probabilistic analysis of spillover scenarios, defined in relation to the joint evolution of a potentially large number of individual spillover effects. Furthermore, because our approach yields an estimate of the probability of the occurrence of a scenario, it does not sacrifice the ease of interpretation that is a key feature of the DY literature.

The logic of our approach is to generate a set of $b = 1, 2, \ldots, B$ bootstrap samples using the estimated approximating VAR model, re-estimate the approximating model on each bootstrap sample, and construct the corresponding DY network for each bootstrap sample. It is then possible to evaluate the probability of the occurrence of any scenario defined in relation to the elements of the normalized GVD matrix by simply counting the proportion of bootstrap samples in which that scenario comes to pass. This approach has several desirable features, notably that it does not require knowledge of the asymptotic distribution of the spillover statistics, it is suitable for use in small samples or in a rolling regression setting where the rolling window is small and it is sufficiently flexible to accommodate a wide variety of spillover scenarios.

Our technique proceeds in three stages, as follows:

1. The Estimation Stage

(a) Estimate the approximating model (1) over rolling samples of length w time periods.

(b) For each rolling sample, $r = 1, 2, \ldots, R$, store the VAR residuals, $\widehat{\boldsymbol{u}}_t^{(r)}$, and the VAR parameters, $\widehat{\boldsymbol{\alpha}}^{(r)}$ and $\widehat{\boldsymbol{C}}_\ell^{(r)}$, $\ell = 1, 2, \ldots, p^{(r)}$.

2. The Bootstrap Stage

(a) For the rth rolling sample, generate $b = 1, 2, \ldots, B$ bootstrap samples of length w, denoted $\boldsymbol{z}_t^{(r,b)}$:

$$\boldsymbol{z}_t^{(r,b)} = \widehat{\boldsymbol{a}}^{(r)} + \sum_{\ell=1}^{p^{(r)}} \widehat{\boldsymbol{C}}_\ell^{(r)} \boldsymbol{z}_{t-\ell}^{(r,b)} + \widetilde{\boldsymbol{u}}_t^{(r,b)}. \tag{4}$$

For this purpose, we take the $p^{(r)}$ initial values of $\boldsymbol{z}_t^{(r)}$ as given and we obtain resampled residuals, $\widetilde{\boldsymbol{u}}_t^{(r,b)}$, in line with the moving-block bootstrap routine proposed by Brüggemann et al. (2016). We select this bootstrap algorithm because it accounts for conditional heteroskedasticity, an issue that is likely to be important in many economic and financial network models.

(b) Having obtained the set of B bootstrap samples, equation (1) is re-estimated B times to obtain new parameter estimates, $\widehat{\boldsymbol{a}}^{(r,b)}$, $\widehat{\boldsymbol{C}}_\ell^{(r,b)}$, $\ell = 1, 2, \ldots, p^{(r)}$ and $\widehat{\boldsymbol{\Omega}}^{(r,b)}$.[3]

(c) For each bootstrap replication, compute and save the h-steps-ahead normalized GVD matrix, $\left\{ d_{i \leftarrow j}^{(r,b,h)} \right\}_{i,j=1}^{K}$.

(d) Repeat steps 2(a) to 2(c) for every rolling sample, $r = 1, 2, \ldots, R$.

3. The Probabilistic Analysis Stage

(a) Conduct probabilistic analysis of any desired spillover event by counting the proportion of the B bootstrap samples in which that event occurs. To illustrate, consider the following examples:

(i) The level of the $\{i, j\}$th spillover effect at horizon h is less than an arbitrary threshold, c_1, i.e., $d_{i \leftarrow j}^{(r,h)} < c_1$, for any $i, j = 1, 2, \ldots, K$. The probability

[3] In practice, it is necessary to inspect the eigenvalues of the companion matrix of the VAR model in each bootstrap sample to ensure that it is dynamically stable. If the stability condition is violated in a given bootstrap sample, that sample is discarded and a new bootstrap sample generated.

that this event occurs in the rth rolling sample is given by:

$$\Pr\left(d_{i\leftarrow j}^{(r,h)} < c_1\right) = \frac{1}{B}\sum_{b=1}^{B}\mathcal{I}\left(c_1 - d_{i\leftarrow j}^{(r,b,h)}\right),$$

where $\mathcal{I}(\zeta)$ is a Heaviside function equal to one if $\zeta > 0$ and zero otherwise.

(ii) The $\{i,j\}$th spillover effect in rolling sample r exceeds its bootstrap mean value in the previous rolling sample by less than an arbitrary threshold, c_2, i.e., $\left(d_{i\leftarrow j}^{(r,h)} - \overline{d}_{i\leftarrow j}^{(r-1,h)}\right) < c_2$, for any $i,j = 1,2,\ldots,K$. The probability that this event occurs in the rth rolling sample is simply:

$$\Pr\left(\left[d_{i\leftarrow j}^{(r,h)} - \overline{d}_{i\leftarrow j}^{(r-1,h)}\right] < c_2\right) = \frac{1}{B}\sum_{b=1}^{B}\mathcal{I}\left(c_2 - \left[d_{i\leftarrow j}^{(r,b,h)} - \overline{d}_{i\leftarrow j}^{(r-1,h)}\right]\right).$$

(iii) The joint event that the level of the $\{i,j\}$th spillover effect is less than an arbitrary threshold, c_1, and that the $\{i,j\}$th spillover effect in rolling sample r exceeds its bootstrap mean value in the previous rolling sample by less than an arbitrary threshold, c_2, for any $i,j = 1,2,\ldots,K$. The joint probability can be computed as follows:

$$\begin{aligned}\Pr&\left(d_{i\leftarrow j}^{(r,h)} < c_1 \cap \left[d_{i\leftarrow j}^{(r,h)} - \overline{d}_{i\leftarrow j}^{(r-1,h)}\right] < c_2\right)\\ &= \frac{1}{B}\sum_{b=1}^{B}\left\{\mathcal{I}\left(c_1 - d_{i\leftarrow j}^{(r,b,h)}\right)\mathcal{I}\left(c_2 - \left[d_{i\leftarrow j}^{(r,b,h)} - \overline{d}_{i\leftarrow j}^{(r-1,h)}\right]\right)\right\}.\end{aligned}$$

Although the illustrations above are simple, they are sufficient to highlight the flexibility of our technique. Our approach can be used to evaluate the probability of spillover scenarios defined as combinations of an arbitrarily large number of simple events, which are defined in a very flexible manner as inequalities.

3 A model of credit risk transmission

We apply our technique to the credit risk network model of GHN. We use this model to examine credit risk transmission among the following $N = 18$ countries indexed by $i = 1, 2, \ldots, N$: Austria, Australia, Belgium, China, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, Russia, Spain, Sweden, the United Kingdom and the United States.

The GHN model is estimated over a sample of 2,495 trading days from 1/3/2006 to 7/27/2015. However, unlike GHN who analyze both the GFC and the European debt crisis, our focus is exclusively on the GFC. Consequently, we truncate the dataset at 3/31/2010, shortly before the first Greek sovereign bailout. This results in a sample size of $T = 1,107$ trading days indexed by $t = 1, 2, \ldots, T$ and a commensurate reduction in the number of rolling samples under analysis. Reducing the number of rolling samples sharpens the focus of our analysis and also moderates the computational burden that we face. Note that the GHN model is large and computationally demanding in its own right and we add another layer of computational effort through the application of bootstrap methods.

The GHN dataset contains both country-specific data and a set of global controls, as discussed below.

3.1 Country-specific data

Macroeconomic and financial conditions in the ith country are summarized by the following $k \times 1$ vector of country-specific variables:

$$\boldsymbol{x}_{it} = \left(\Delta g_{it}, \Delta b_{it}, \Delta s_{it}, \Delta \ln\left(q_{it}\right)\right)', \tag{5}$$

where 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, each of which is defined below.

3.1.1 Sovereign credit spread

Sovereign credit risk is measured using five-year CDS spreads obtained from Markit. As shown by Blanco et al. (2005), Longstaff et al. (2011), and Gyntelberg et al. (2018), among others, CDS spreads may provide a more precise measure of credit risk than bond yield spreads, because the CDS market is typically more liquid than the equivalent sovereign bond market and is widely believed to be the leading forum for credit risk price discovery. Following the CDS market conventions documented by Bai and Wei (2017), USD-denominated CDS are used in all cases except for the U.S., where euro-denominated CDS data are used instead.

3.1.2 Financial sector credit spread

Building on ADS, GHN construct a synthetic sector-wide CDS spread computed as an equally-weighted average of the CDS spreads for selected major financial institutions (banks and insurers) domiciled in the ith country. In order to be included, firms must generally satisfy the following criteria: (i) they have USD-denominated five-year CDS data provided by Markit covering at least 10% of the trading days in GHN's sample period and that satisfies the CDS market conventions laid out by Bai and Wei (2017); (ii) they are listed as financial firms by Markit; (iii) they are listed as either banking or insurance firms by Bureau van Dijk; (iv) they are reported as operating in the ith country by Markit; and (v) they have total assets of USD 10 billion or more in at least one year of the GHN sample period.[4]

[4] GHN depart from these selection criteria in some cases. For example, a small number of firms that do not appear in Bureau van Dijk's Osiris database but that played an important regional or global role

3.1.3 Term spread

Information on domestic macroeconomic conditions in the ith country is conveyed by the term spread, which is computed as the spread between the 10-year and the 90-day government bond yields. The term spread captures the slope of the yield curve and, as such, it summarizes a wealth of information relating to output growth and inflation expectations, monetary policy, and macroeconomic fundamentals.

3.1.4 Broad stock index

The performance of a broad local stock index is used to convey additional information on domestic economic performance, as well as conditions in the domestic financial markets.

3.2 Global controls

In addition to the country-specific data described above, the dataset also contains the following $k^* \times 1$ vector of global controls:

$$\boldsymbol{x}_t^* = \left(\Delta l_t^{US}, \Delta l_t^{EU}, \Delta v_t^{TY}, \Delta v_t^{EQ}\right)' \tag{6}$$

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.

in the GFC (e.g., Fortis) are manually included. In such cases, asset data are gathered directly from the firms' published financial reports. Similarly, there are three notable cases in which firms without publicly traded equity are included in the sample. First, in Austria, Raiffeisen Zentralbank is included to ensure that the CDS index is not based on a single firm. Second, in China, data for four large state-sponsored banks are used due to the lack of CDS data for private Chinese banks. Finally, rather than simply dropping failed banks from the sample, CDS data for several institutions that became state-owned as a result of the crisis are used. Note also that GHN experiment with the use of asset-weighted indices, as well as equally-weighted indices and find that the correlation between the two is very high, typically exceeding 0.9. Consequently, the simpler approach is adopted in deference to the principle of parsimony. See the Online Appendix to GHN for a comprehensive discussion of the properties and construction of the financial sector credit spreads.

3.2.1 Funding liquidity

The TED spread is the spread between the 90-day USD LIBOR and the 90-day U.S. Treasury yield. The Euribor-DE TBill spread can be thought of as a European counterpart of the TED spread and is defined as the spread between the 90-day Euribor and the 90-day German T-bill yield. The TED spread and the Euribor-DE TBill spread vary with the level of counterparty risk in the banking sector and are therefore indicative of the conditions under which funding liquidity can be accessed (e.g., Greenwood-Nimmo et al., 2016; Pelizzon et al., 2016).

3.2.2 Investor risk appetite

The variance risk premium (VRP) is a popular indicator of investor risk appetite. Following Bollerslev et al. (2009), we define the VRP as the difference between the implied variance and a forecast of the realized variance at the one-month horizon. Under this definition, the VRP is typically positive, with higher values indicating a higher price of hedging against volatility risk and a correspondingly lower risk appetite. GHN consider two different methods of constructing the VRP: the original martingale method proposed by Bollerslev et al. (2009) and a subsequent method in which an auxiliary regression model is used to forecast the realized variance. We adopt the latter option, using the same augmented version of Corsi's (2009) heterogeneous autoregressive volatility forecasting model employed by Bekaert and Hoerova (2014). We compute the equity VRP as $v_t^{EQ} = VIX_t^2 - E\left[RV_{t+1}^{(22)}\right]$, where VIX_t^2 denotes the de-annualized squared VIX and $RV_t^{(22)}$ denotes the realized variance for the S&P 500 measured over the next 22 trading days as the sum of squared five-minute intraday returns. Meanwhile, the Treasury VRP is computed as $v_t^{TY} = TYVIX_t^2 - E\left[TYRV_{t+1}^{(22)}\right]$, where TYVIX is the de-annualized squared TYVIX Treasury volatility index and $TYRV_t^{(22)}$ is the realized variance of the U.S. 10-year Treasury measured over the next 22 trading days. Including both the equity and Treasury VRPs in the model provides valuable information about the risk appetite of both equity and fixed income investors.

3.3 Properties of the data

Table 1 provides a variety of basic summary statistics for the dataset. Additional information including time series plots of the data, pairwise correlations, and unit root test statistics can be found in the Data Supplement to GHN. GHN demonstrate that each of the series used in estimation is stationary with modest autocorrelation. The credit spreads display widespread positive cross-sectional correlation both within variable groups (e.g., $\mathrm{corr}(\Delta g_{it}, \Delta g_{jt}) > 0$ in general for $i \neq j$) and between groups (e.g., $\mathrm{corr}(\Delta g_{it}, \Delta b_{jt}) > 0$ in general both for $i = j$ and $i \neq j$). Inspection of the credit and term spreads in Table 1 reveals that the sample countries can be naturally partitioned into a high volatility group (the GIIPS and Russia) and a low volatility group (the remainder).

— Insert Table 1 here —

3.4 The estimation strategy

The approximating model is a VAR in $\boldsymbol{z}_t = (\boldsymbol{x}'_{1t}, \ldots, \boldsymbol{x}'_{Nt}, \boldsymbol{x}^{*\prime}_t)'$, where $\boldsymbol{z}_t$ is of dimension 76×1. Given the high-dimensional nature of the model, we follow GHN and estimate the VAR model in equation (1) on an equation-by-equation basis using a shrinkage and selection estimator.[5] The main results in GHN are obtained from a VAR(1) model

[5] As noted by Song and Bickel (2011) and Furman (2014), shrinkage and selection estimation of a VAR model of the form of equation (1) on an equation-by-equation basis is beneficial, because the degree of penalization is chosen optimally for each equation rather than globally for the system as a whole. This ensures that differences in the degree of sparsity between equations can be captured.

estimated by LASSO, an approach introduced to the financial connectedness literature by Demirer et al. (2018).[6] We follow in the same vein, although we substitute the LASSO for the ALASSO of Zou (2006) for reasons that we discuss below. Assuming a first order VAR and abstracting from deterministic terms, the ALASSO solves the following minimization problem for the ith equation in the system:

$$\widehat{\boldsymbol{C}}_i = \arg\min_{C} \left(\sum_{t=1}^{T} \left(z_{it} - \sum_{j=1}^{K} c_{ij} z_{ij,t-1} \right)^2 + \lambda_i \sum_{j=1}^{K} \hat{w}_{ij} \left| c_{ij} \right| \right), \tag{7}$$

where $\boldsymbol{C}_i$ denotes the ith row of the VAR(1) parameter matrix, $\boldsymbol{C}$, c_{ij} is the $\{i,j\}$th element of $\boldsymbol{C}$, $\lambda_i > 0$ is the LASSO penalty parameter for the ith equation and where the coefficient-specific ALASSO weights are defined as $\hat{w}_{ij} = 1/\left|\tilde{c}_{ij}\right|^{\gamma}$, with $\gamma > 0$ and where $\tilde{c}_{ij}$ is a $\sqrt{T}$-consistent estimator of c_{ij}. We compute $\tilde{c}_{ij}$ by ridge regression, as it accounts for the cross-sectional correlation in the data better than common alternative methods such as OLS.

The reason that we adopt the ALASSO instead of the LASSO is that it is simpler to bootstrap. The challenges involved in bootstrapping the LASSO are well-documented. For example, Chatterjee and Lahiri (2010) show that the common residual bootstrap estimator converges to a random probability measure if one or more of the unknown regression parameters is zero. The underlying problem is that the formulation of standard bootstrap procedures fails to accurately reproduce the signs of the zero elements of the parameter matrix. Chatterjee and Lahiri (2011) note that this issue may be overcome by the introduction of a thresholding step, whereby values close to zero are replaced with zero. However, Chatterjee and Lahiri (2011) show that this issue does not affect the

[6] Support for the use of a first order model in every rolling sample is provided by the Schwarz information criterion and reflects the low level of autocorrelation in the data.

ALASSO estimator, as the ALASSO penalty term already incorporates a soft-thresholding step for the zero components of the parameter matrix. As a result, simple bootstrapping procedures can provide a valid approximation to the distribution of the ALASSO estimator. For example, under mild regularity conditions, Chatterjee and Lahiri demonstrate the in-probability convergence of the residual bootstrap estimator and show that confidence sets obtained via the residual bootstrap attain the nominal coverage probability, as desired. The authors' numerical study of the finite sample properties of the ALASSO residual bootstrap procedure also indicate that it "performs exceedingly well in estimating the true variance of the ALASSO estimator" and that the coverage probability of the bootstrap confidence intervals is "very close to the nominal coverage probability" (p. 620).[7]

Zou (2006) notes that both the exponent, γ, and the penalty parameter, λ_i, may be tuned by two-dimensional cross-validation. However, the computational burden of tuning both parameters in this way is unmanageable in our case, because our probabilistic analysis involves a bootstrap procedure conducted on a rolling-sample basis. To illustrate the computational intensity of this approach, suppose that we set the length of the rolling window to $w = 150$ trading days and that we work with 1,000 bootstrap samples. In this case, we must estimate and bootstrap 76 equations by ALASSO for each of $T - w + 1 = 958$

[7] As financial data of the type that we study is known to exhibit heteroskedasticity, we employ the heteroskedasticity-robust moving block bootstrap of Brüggemann et al. (2016) instead of the simple residual bootstrap. Because of the soft-thresholding inherent to the ALASSO penalty term, the issue of reproducing the sparsity of the regression parameter matrix that would be encountered with the LASSO will not arise in this case. However, because the theoretical properties of the Brüggemann et al. bootstrap procedure have not been explored in the ALASSO context to our knowledge, we conducted a comparison against the residual bootstrap, the properties of which are known in the ALASSO context. Specifically, we compared the empirical distributions of the aggregate financial-to-sovereign and sovereign-to-financial spillover effects obtained from both procedures over rolling samples of length $w = 150$ trading days. The bootstrap means are very similar in both cases, although the Brüggemann et al. bootstrap yields slightly wider confidence intervals at the time of the GFC. We interpret our findings as evidence that the Brüggemann et al. bootstrap procedure: (i) performs comparably to the residual bootstrap in terms of the bootstrap mean; and (ii) may have an advantage over the residual bootstrap in terms of capturing uncertainty. Further details of this comparison are available from the authors upon request.

rolling samples, which entails the estimation of 72,880,808 equations. This is a highly computationally demanding problem, even for known values of γ and λ_i. In practice, tuning one parameter by cross validation is feasible given the computing resources at our disposal but tuning both parameters is not. We adopt a pragmatic solution whereby, for the ith equation in each rolling sample, we select the value of λ_i that minimizes the mean squared error (MSE) from a fine grid of 100 points by five-fold cross validation for a fixed value of γ.[8] To evaluate the effect of the choice of γ, we consider three values: $\gamma \in \{0.5, 1.0, 2.0\}$. This is the same array of candidate values originally used by Zou (2006). As demonstrated in Section 4, our estimation results are relatively insensitive to the value of γ, so our discussion is based on results obtained using $\gamma = 1$ without loss of generality.

4 Empirical analysis

4.1 Selection of modeling options

Before we proceed with our empirical analysis, our first task is to determine the appropriate length for the rolling window, w, as well as an appropriate value of the forecast horizon, h. GHN consider values in the range $w \in \{200, 250, 300\}$ and $h \in \{5, 10, 15\}$ trading days and demonstrate the robustness of their estimation results across all possible combinations. Given that, unlike GHN, we only work with a shrinkage and selection estimator and do not consider simpler estimators such as OLS, it is feasible for us to work with shorter window lengths. For this reason, we consider values in the range $w \in \{150, 200, 250, 300\}$ and $h \in \{5, 10, 15\}$ trading days. Using too narrow (wide) a

[8] We estimate the model using the MATLAB implementation of `glmnet` by Jerome Friedman, Trevor Hastie, Rob Tibshirani, Noah Simon, and Junyang Qian (see https://web.stanford.edu/~hastie/glmnet_matlab/).

window may increase (decrease) the timeliness of changes in the rolling sample spillover measures but is also likely to decrease (increase) the precision of the estimates.

To investigate the degree of sensitivity of the estimated network to the choice of w and h, we compute the pairwise common-sample correlation among point estimates of the spillover index generated under all possible combinations of w and h. In addition, we allow the ALASSO exponent, γ, to vary in the set $\{0.5, 1.0, 2.0\}$, while the LASSO penalty parameter for the ith equation, λ_i, is selected by five-fold cross validation. Consequently, we evaluate the similarity of the point estimate of the spillover index generated under $4 \times 3 \times 3 = 36$ different settings of the model. The results are summarized in the form of a heatmap in Figure 1. Different settings of the model are labeled A-AJ, with the details of each setting provided in the notes to the figure. The correlations across model settings are strongly positive, with the lowest (highest) correlation being 0.83 (0.99), a mean (median) correlation of 0.93 (0.94), and a standard deviation of 0.048 across all pairwise combinations. Careful inspection of the figure reveals a faint block structure, which indicates that, for any given rolling window length, variations in the forecast horizon and/or the ALASSO exponent have very little effect on the dynamics of the spillover index. Consequently, the most important choice is the rolling window length. We select $w = 150$ trading days to achieve the greatest timeliness in our analysis. In addition, we set $h = 5$ and $\gamma = 1$ without loss of generality.

— Insert Figure 1 here —

4.2 The sovereign–financial nexus

To develop relevant spillover scenarios regarding the evolution of the sovereign–financial credit risk nexus during the GFC, we take inspiration from both the theoretical and empirical results presented by ADS in their analysis of bank bailouts and sovereign credit risk in Europe. The interplay of two different spillover measures plays a central role in the analysis, so we introduce simplifying notation for them. The first is the net spillover from the ith financial sector to the ith sovereign, which we denote $\mathcal{N}_{g_i \leftarrow b_i}$. The second is the total bidirectional spillover between the ith sovereign and the ith financial sector, which we denote $\mathcal{T}_{g_i \leftrightarrow b_i}$. With this notation in hand, consider the following two phenomena:

(i) ADS show that financial sector bailouts entail a transfer of private sector credit risk onto sovereigns. The immediate effect of this risk transfer is to increase sovereign credit risk relative to financial sector credit risk. GHN show that this manifests as a sustained reduction in the net spillover from the ith financial sector to the ith sovereign, $\mathcal{N}_{g_i \leftarrow b_i}$.

(ii) ADS describe the emergence of an adverse feedback effect between sovereign and financial sector credit risk in the wake of the financial sector bailouts. The increase in sovereign risk brought about by a sovereign's intervention in the financial sector causes the sovereign's fiscal position to deteriorate. This, in turn, reduces the future value of the sovereign's guarantee of the financial sector, while simultaneously reducing the value of the financial sector's holdings of domestic sovereign debt. These factors fuel a resurgence of financial sector risk, raising the likelihood that further action will be required on the part of the sovereign, further raising sovereign risk and so on. The strength of the feedback loop between the sovereign and the financial sector can naturally be captured by the total bidirectional spillover between the ith sovereign and the ith financial sector, $\mathcal{T}_{g_i \leftrightarrow b_i}$.

In keeping with the European focus of ADS, in Figure 2, we illustrate the evolution of both $\mathcal{N}_{g_i \leftarrow b_i}$ and $\mathcal{T}_{g_i \leftrightarrow b_i}$ for a selection of European countries over the period 7/31/2006 (the end date of our first rolling sample) until 3/31/2010, shortly before the first Greek sovereign bailout. The four countries that we focus on for this exercise are Ireland (the motivating case study used by ADS), the U.K. (due to its large financial services sector and its position outside the eurozone), Germany (representing the eurozone core), and Spain (representing the eurozone periphery). In each case, we report the bootstrap mean of the spillover measure, as well as the associated 90% bootstrap confidence interval. For reference, the bailout period considered by ADS (9/26/2008 to 10/21/2008) is shaded. The horizontal dashed line shown in panels (b), (d), (f), and (h) is a common threshold value defined in Subsection 4.5.

— Insert Figure 2 here —

First, note that the width of the bootstrap confidence intervals in Figure 2—and, therefore, the degree of uncertainty surrounding the estimated spillover effects—changes considerably across rolling samples and across countries. Knowledge of this time and cross-sectional variation enriches one's ability to interpret changes in spillover activity relative to the case where the analysis is based only on point estimates, as in GHN. This simple observation offers a clear insight into the value of characterizing the empirical distribution of the spillover effects.

At the start of our sample, the net financial–sovereign spillover is close to zero in all four countries (the 90% bootstrap interval includes zero for most rolling samples over this period for Ireland, the U.K., and Spain) and the financial–sovereign feedback effect is relatively weak. This is a period of economic growth and high investor risk appetite, where concerns around credit risk are not widespread. However, as the subprime crisis develops in 2007 and the GFC breaks, the net financial–sovereign spillover increases in all four countries, reaching positive and statistically significant values. This intensification of the net credit risk transmission from the financial sector onto the sovereign reflects growing concerns over credit risk in the financial sector and the implications this may have for the sovereign in the event that a bailout is needed. The financial–sovereign feedback effect also intensifies over this period, as financial instability weighs on the macroeconomic outlook, weakening the sovereign's fiscal position.

The credit risk transfer brought about by the financial sector bailouts in late-2008 has a profound effect on the credit risk network, leading to reductions in the strength of the net financial–sovereign spillover in all four countries.[9] In Germany and Spain and, to a lesser extent, in the U.K., the financial sector bailouts exert a stabilizing influence on the credit risk network, with the financial–sovereign feedback effect weakening in the short-run. However, after a brief respite, the adverse feedback loop described by ADS takes effect in these three countries and $\mathcal{T}_{g_i \leftrightarrow b_i}$ starts to strengthen. Ireland exhibits different behavior. Ireland announced a wide-ranging financial sector guarantee on 9/30/2008, before any of the other countries in Figure 2. The financial–sovereign feedback effect intensifies markedly following this announcement, only weakening once other countries adopted similar bailout measures.

4.3 Probabilistic scenario analysis over the ADS bailout period

Our analysis of Figure 2 reveals that the interaction of the net financial–sovereign spillover effect and the financial–sovereign feedback effect is important in the analysis of financial sector bailouts. However, the graphical presentation of these two spillover effects in Figure 2 only allows us to evaluate them individually, not jointly. Probabilistic event analysis offers an elegant solution, as it provides a means to concisely summarize

[9] This effect is sufficiently strong that the sign of the bootstrap mean of the financial–sovereign spillover effect becomes negative in all four cases, although the bootstrap interval includes zero in each case.

changes in spillover activity either individually or jointly that focuses explicitly on events of interest. Consider the following simple events for the ith country:

A $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < \overline{\mathcal{N}}^{\text{pre-bailout}}_{g_i \leftarrow b_i}$

The net financial–sovereign spillover effect becomes less positive/more negative over the bailout period, where the bar symbol denotes the average over bootstrap samples.

B $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < 0$

The sovereign is the net source of credit risk with respect to the domestic financial sector after the bailout period.

C $\mathcal{T}^{\text{post-bailout}}_{g_i \leftrightarrow b_i} < \overline{\mathcal{T}}^{\text{pre-bailout}}_{g_i \leftrightarrow b_i}$

The financial–sovereign feedback effect weakens over the bailout period.

Now, consider the following joint events:

$A \cap C$ $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < \overline{\mathcal{N}}^{\text{pre-bailout}}_{g_i \leftarrow b_i}$ and $\mathcal{T}^{\text{post-bailout}}_{g_i \leftrightarrow b_i} < \overline{\mathcal{T}}^{\text{pre-bailout}}_{g_i \leftrightarrow b_i}$

The net financial–sovereign spillover effect becomes less positive/more negative and financial–sovereign feedback weakens over the bailout period.

$B \cap C$ $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < 0$ and $\mathcal{T}^{\text{post-bailout}}_{g_i \leftrightarrow b_i} < \overline{\mathcal{T}}^{\text{pre-bailout}}_{g_i \leftrightarrow b_i}$

The sovereign is the net source of credit risk with respect to the domestic financial sector after the bailout period and financial–sovereign feedback weakens over the bailout period.

$A \cap B$ $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < \overline{\mathcal{N}}^{\text{pre-bailout}}_{g_i \leftarrow b_i}$ and $\mathcal{N}^{\text{post-bailout}}_{g_i \leftarrow b_i} < 0$

The net financial–sovereign spillover effect becomes less positive/more negative over the bailout period and the sovereign is the net source of credit risk with respect to the domestic financial sector after the bailout period.

The events above are defined such that they correspond to key aspects of the mechanism described by ADS and analyzed by GHN. We deliberately define the events in a simple way, so that the link between the interval estimates reported in Figure 2 and the event probabilities is easily appreciated. This helps to develop intuition for our probabilistic approach. Our goal in this exercise is to compute the probability of each event occurring over the bailout period identified by ADS. To do so, we need to compare the values of the spillover measures relevant to each event immediately prior to the bailout period and immediately after the bailout period. Given that disaggregate spillover measures display some day-to-day variation, particularly where estimation proceeds via a shrinkage and selection estimator that may select different explanatory variables from one rolling sample to the next, we must define the pre-bailout and post-bailout periods with care. To ensure that this day-to-day variation does not dominate our analysis, it is wise to avoid making comparisons of spillover measures between two individual rolling samples. Rather, we measure average spillover activity in the pre-bailout period using the average value of the bootstrap mean of each spillover measure over the five trading days immediately prior to the ADS bailout period. Meanwhile, we measure spillover activity in the post-bailout period by pooling the values obtained in the five trading days immediately after the ADS bailout period. Because we focus on the ADS bailout period, which relates to bank bailouts in Europe, our analysis below focuses on the European countries—we report event probabilities for non-European countries for completeness but we do not discuss them in the text.

The estimated probability of each event is recorded in Table 2. First consider event A. With the exception of Norway, which did not experience a systemic banking crisis during the GFC according to Laeven and Valencia (2013), the probability that the net financial–sovereign spillover effect falls over the bailout period is substantial for all of the European countries, ranging from 35.0% in Sweden to 98.8% in France and Ireland. This reflects a shift in the balance of credit risk transmission between the sovereign and the domestic financial sector due to the absorption of financial sector credit risk by the sovereign.

— Insert Table 2 here —

Although the net financial–sovereign spillover effect falls in most European countries, the probability that the sovereign is the net source of credit risk with respect to the domestic financial sector immediately after the ADS bailout period is generally low (event B). The exceptions are Greece (99.3%), Ireland (78.7%), and Portugal (99.1%), each of which experienced a sovereign debt crisis. In addition, in most of the European countries, we observe a high probability that the financial–sovereign feedback effect weakens over the bailout period (event C). Ireland is the main exception to this rule, as it was the first European country to announce a bailout program and so the relation between sovereign and financial sector credit risk in Ireland evolves differently to that of the other countries in our sample (see Figure 2).

Moving on to the joint events, with the exception of Ireland and Norway that exhibit distinct behavior, as described above, $\Pr(A \cap C)$ is non-negligible for most European countries, which suggests that the bailout programs implemented by most European countries may have contributed to reducing financial–sovereign feedback by transferring private sector credit risk onto the sovereign. In general, however, both $\Pr(B \cap C)$ and $\Pr(A \cap B)$ are low throughout Europe, indicating that the risk transfer onto the sovereign at this time was not so large as to make it the net source of credit risk in most countries. It is notable that all of the European countries for which we record high probabilities of the joint events $B \cap C$ and/or $A \cap B$ would go on to experience sovereign debt crises.

4.4 Probabilistic scenario analysis over the ADS feedback period

ADS document the emergence of an adverse feedback loop between sovereign credit risk and financial sector credit risk in the period after the 2008 financial sector bailouts. For this "feedback period", we consider the following simple events:

D $\mathcal{T}^{\text{feedback}}_{g_i \leftrightarrow b_i} > \overline{\mathcal{T}}^{\text{post-bailout}}_{g_i \leftrightarrow b_i}$

Bidirectional financial–sovereign feedback rises.

E $d^{\text{feedback}}_{g_i \leftarrow b_i} > \overline{d}^{\text{post-bailout}}_{g_i \leftarrow b_i}$

The spillover from the domestic financial sector to the sovereign intensifies.

F $d^{\text{feedback}}_{b_i \leftarrow g_i} > \overline{d}^{\text{post-bailout}}_{b_i \leftarrow g_i}$

The spillover from the sovereign to the domestic financial sector intensifies.

G $\mathcal{N}^{\text{feedback}}_{g_i \leftarrow b_i} < 0$

The sovereign is the net source of risk with respect to the domestic financial sector.

The joint events of interest are as follows:

$E \cap F$ $d^{\text{feedback}}_{g_i \leftarrow b_i} > \overline{d}^{\text{post-bailout}}_{g_i \leftarrow b_i}$ and $d^{\text{feedback}}_{b_i \leftarrow g_i} > \overline{d}^{\text{post-bailout}}_{b_i \leftarrow g_i}$

The spillovers in both directions between the financial sector and the sovereign rise.

$D \cap G$ $\mathcal{T}^{\text{feedback}}_{g_i \leftrightarrow b_i} > \overline{\mathcal{T}}^{\text{post-bailout}}_{g_i \leftrightarrow b_i}$ and $\mathcal{N}^{\text{feedback}}_{g_i \leftarrow b_i} < 0$

Financial–sovereign feedback rises and the sovereign is the net source of risk with respect to the domestic financial sector.

$D \cap \bar{G}$ $\mathcal{T}^{\text{feedback}}_{g_i \leftrightarrow b_i} > \overline{\mathcal{T}}^{\text{post-bailout}}_{g_i \leftrightarrow b_i}$ and $\mathcal{N}^{\text{feedback}}_{g_i \leftarrow b_i} > 0$

Financial–sovereign feedback rises and the financial sector is the net source of risk with respect to the sovereign.

To compute the event probabilities, we measure average post-bailout spillover activity by taking the average value of the bootstrap mean of a given spillover effect over the five trading days immediately after the ADS bailout period. To measure spillover activity after the financial–sovereign feedback has taken effect, we pool values of the spillover effect over the last five trading days in our sample in March 2010, shortly before the first Greek sovereign bailout. The event probabilities are reported in Table 3. As in Subsection 4.3, although we tabulate event probabilities for all countries, our discussion focuses on European countries only, because this exercise is based on the dates of the European bank bailouts.

— Insert Table 3 here —

We observe a high probability of an intensification of financial–sovereign feedback in most European countries (event D). The notable exception is Ireland, where the feedback effect intensifies earlier than in any other country, perhaps due to the fact that Ireland was the first country to implement bailout measures for its financial sector (see Figure 2(d)). The probabilities of events E and F suggest that the intensification in financial–sovereign feedback was bidirectional in most countries. This is clearly reflected in the high reported probabilities of the joint event $E \cap F$ for most countries. However, in Austria and Belgium, the evidence of increased spillovers from the sovereign onto the financial sector is stronger than the evidence of increased spillovers from the financial sector onto the sovereign and the joint probability is relatively low for both countries.

Finally, we observe a relatively high probability that the sovereign is the net source of credit risk with respect to the domestic financial sector (event G) as of March 2010 in most countries, with four Northern European economies (Germany, France, the Netherlands, and Norway) being the most notable exceptions.

The last two joint events offer an interesting opportunity for the classification of the countries in our sample. The joint event $D \cap G$ captures the case where there is an intensification of financial–sovereign feedback and the sovereign is the net source of credit risk with respect to the domestic financial sector. This can be viewed as a case of sovereign-led feedback. By analogy, the joint event $D \cap \overline{G}$ captures bank-led feedback. Our results indicate that, on average over the period October 2008 to March 2010, Belgium, Greece, Portugal, Spain, and the UK exhibit sovereign-led feedback, while France, Germany, Italy, and the Netherlands display bank-led feedback. Of course, this classification is limited by the fact that it relies on the comparison of specific points in time and it only conveys information on the average behavior of each country. In the next section, we address both of these limitations.

4.5 Probabilistic classification

In Table 4, we propose a rolling sample three-way classification scheme based on the values of $\mathcal{N}_{g_i \leftarrow b_i}$ and $\mathcal{T}_{g_i \leftrightarrow b_i}$. We use the sign of $\mathcal{N}_{g_i \leftarrow b_i}$ to determine whether the financial sector or the sovereign is the dominant source of risk in the ith country and the level of $\mathcal{T}_{g_i \leftrightarrow b_i}$ relative to a common threshold, c, to determine whether or not the financial–sovereign feedback effect exceeds "normal" levels. Our intention is to set the threshold at a level that separates rolling samples in which the ADS adverse feedback loop operates from rolling samples characterized by normal feedback. To ascertain what level of feedback is normal, we study the pooled empirical distribution of the sovereign–financial feedback effect across countries over the R' rolling samples ending prior to 2007.[10] As our focus in this exercise is on countries that experienced a crisis during our sample period, we limit our attention to: (i) the GIIPS, all of which would go on to experience sovereign debt crises in the wake of the GFC; and (ii) non-GIIPS countries that experienced a banking crisis during the GFC according to the classification of Laeven and Valencia (2013).[11] First, we pool the values of $\mathcal{T}^{(r,b)}_{g_i \leftrightarrow b_i}$ for all crisis-hit countries obtained from all R' rolling samples and all B bootstrap iterations. We then set c equal to the 90$^{\text{th}}$ percentile of this pooled empirical distribution. For reference, the resulting threshold value is reported relative to the total feedback effect over rolling samples for Ireland, the U.K., Germany, and Spain in the four panels on the right side of Figure 2. With the threshold set in this way, we interpret the three quadrants of Table 4 as follows:

(i) Normal feedback region. Financial–sovereign feedback is at normal pre-crisis levels.

(ii) Bank-led feedback. Strong feedback is driven by the financial sector.

(iii) Sovereign-led feedback. Strong feedback is driven by the sovereign.

— Insert Table 4 here —

Figure 3 reports the results of our classification for the GIIPS countries. To assist the reader, several important events are marked by vertical lines in each panel of the figure (see the notes to the figure and Table 5 for details). A characteristic that distinguishes the GIIPS economies is the relatively high probability of bank-led feedback in the period

[10] Due to a spike in sovereign–financial feedback in Greece in late 2006, we limit our attention to rolling samples ending prior to September 2006 in the Greek case.

[11] Laeven and Valencia (2013) identify a banking crisis if two conditions are met: (i) there is significant evidence of financial distress in the banking system, including events such as bank runs and/or bank liquidations; and (ii) at least three from a list of six policy measures are taken in response to losses in the banking system, such as bank nationalizations, asset purchases, and the extension of guarantees.

prior to Bear Stearns' revelation of the insolvency of two hedge funds in July 2007. This finding may reflect low real interest rates in these countries in the period prior to the GFC, which fueled rapid credit growth and may have led to the inflation of asset bubbles (Feldstein, 2012).

— Insert Figure 3 here —

It is interesting to note the singular behavior of Greece among the cohort of GIIPS countries. Where we find a low probability of normal feedback in the other GIIPS countries over 2008–2009, for Greece, we estimate a high probability of normal feedback over this period. This may appear surprising, given that Greece would subsequently experience a severe sovereign debt crisis. However, the comparison between Greece and Ireland helps to provide insight on this phenomenon, as it reveals that the Greek financial sector bailout program in 2008–2009 was comparatively small. Over these two years, the European Commission State Aid Scoreboard reveals that the Greek government funded bank recapitalizations totaling EUR 3.8 billion, extended guarantees covering EUR 1.5 billion of liabilities, and undertook other liquidity measures worth EUR 4.8 billion.[12] By comparison, Ireland, a country with less than half of the population of Greece and roughly three-quarters of its GDP in 2008, funded recapitalizations worth EUR 11 billion and guaranteed liabilities totaling EUR 284.3 billion. Relative to Ireland, the fiscal burden of the financial sector bailout program in Greece was not excessive over 2008 and much of 2009 and this is reflected in Figure 3(a). This analysis also implies that the fiscal burden of the Greek financial sector bailouts is insufficient on its own to account for the abrupt surge in the probability of sovereign-led feedback in the final weeks of 2009. Rather, this regime change can be attributed to the revelation of inaccuracies in the Greek economic

[12]See http://ec.europa.eu/competition/state_aid/scoreboard/index_en.html.

data and aligns very closely with the downgrade of Greek sovereign debt by Fitch. Unable to raise funds on the financial markets, an acute sovereign debt crisis rapidly developed and the government was obliged to access external bailout funds in May 2010.

In Ireland, meanwhile, we observe a rapid transition from the normal feedback regime to the bank-led feedback regime starting in early-2008, at the time of the global stock market retrenchment. We estimate the probability of bank-led feedback at more than 80% at the time of the failure of Lehman Brothers. Shortly after this, the introduction of a massive bank bailout program in Ireland coincides with an abrupt surge in the probability of sovereign-led feedback. Interestingly, we find this effect to be relatively short-lived, with the probability of a return to normal levels of feedback rising in late-2008 and into early-2009. Concerns over the sustainability of Irish sovereign debt create a resurgence of sovereign-led feedback in mid-2009, exacerbated by news of the inaccuracies in Greek macroeconomic data. With the agreement of a bailout of the Irish sovereign by the Troika in late-2009, Ireland returns to the normal feedback regime with probability close to 1.

The probabilistic classifications for Italy, Portugal, and Spain show several similarities. In each case, a high probability of bank-led feedback characterizes the months leading up to the financial sector bailouts. The announcement of bailout measures leads to an increase in the probability of normal feedback that is relatively modest and short-lived in both Italy and Portugal but that occurs on a relatively sustained basis and with high probability in Spain. In late-2008 for Portugal and in early-2009 for Italy and Spain, we observe a high probability of sovereign-led feedback. The abrupt shift from normal feedback to sovereign-led feedback in Spain at this time can be attributed to the decision to rescue regional saving banks at end of March 2009, which transferred a substantial amount of private credit risk onto the sovereign. Both Italy and Portugal return to the bank-led feedback regime in 2009, while Spain remains in the sovereign-led feedback regime until late-2009, when the probability of normal feedback rises. However, we find that the sovereign-led feedback regime is reinstated in Spain in early-2010 and also emerges with high probability in Portugal at this time, as the deepening of the Greek sovereign debt crisis raises concerns over the fiscal sustainability of other heavily indebted European sovereigns.

Figure 4 reports our three-way classification for the group of non-GIIPS countries that experienced a systemic banking crisis during our sample period according to the classification of Laeven and Valencia (2013). This group consists of Austria, Belgium, Germany, the Netherlands, the U.K., and the U.S.[13]

— Insert Figure 4 here —

A common pattern characterizes the behavior of the European countries in Figure 4. They all experience a non-negligible probability of bank-led feedback in 2007 and/or 2008. Over this period, several high profile bank failures and/or mergers in Europe contribute to the development of bank-led feedback. For example, the distressed sale of the German bank Sachsen Landesbank in August 2007 coincides with a marked increase in the probability of bank-led feedback in Germany. Likewise, the nationalization of British bank Northern Rock in February 2008 leads to a brief increase in the probability of bank-led feedback in the U.K.

The probability of sovereign-led feedback increases markedly in all of the European countries in Figure 4 in 2009-2010. This is consistent with the emergence of a feedback

[13]Given that our selection of a threshold is based on the separation between normal financial–sovereign feedback prior to a crisis and elevated financial–sovereign feedback during a crisis, we limit our attention to countries where Laeven and Valencia (2013) report strong evidence of a banking crisis at the time of the GFC. This leads to the exclusion of Russia, France, and Sweden, each of which the authors classify as a borderline case, which implies that the evidence of a banking crisis at this time is inconclusive.

loop in the months following the enactment of financial sector bailout measures in these countries, as described by ADS. In Germany and the Netherlands, the financial sector becomes the main driver of the financial–sovereign feedback effect in late-2009. In the U.K., the economy remains in a high-feedback regime until the end of our sample, but the dominant source of the feedback is unclear and alternates over time. Meanwhile, in Austria, and also in Belgium to a lesser degree, the probability of sovereign-led feedback is non-negligible in the last part of our sample period.[14]

The U.S. behaves slightly differently to the European countries in Figure 4. The probability of normal feedback in the U.S. remains comparatively high throughout most of our sample period. The probability of bank-led feedback exhibits several discrete jumps at the time of key events, notably the stock market downturn in January 2008 and the failure of Lehman Brothers in September 2008. However, episodes of bank-led feedback are generally short-lived, a finding that may reflect the large borrowing capacity of the U.S. sovereign, which is typically buoyed up during crises by a surge in safe haven demand for U.S. government debt. Nonetheless, it is interesting to see a gradual upward drift in the probability of sovereign-led feedback in the U.S. starting in 2009. This finding can be understood in relation to the rapid growth of the U.S. federal budget deficit, which rose from USD 0.459 trillion in 2008 to USD 1.413 trillion in 2009. This rapid expansion of public debt prompted acute concerns over the sustainability of U.S. finances at this time and would go on to provoke several disputes over revisions to the U.S. debt ceiling in subsequent years.

[14] Given the strong linkage between the Belgian and Dutch financial sectors, the reader may be surprised to see stronger evidence of feedback in the Netherlands than Belgium, given that it was Belgium that narrowly avoided default in 2011 through the issuance of Staatsbons. However, the size of the financial sector is an important driver of fiscal costs that consist primarily of bank recapitalizations and asset purchases. Laeven and Valencia (2013) show that the fiscal costs relative to both GDP and financial system assets were just 6% for Belgium compared to 12% in the Netherlands, which has a larger financial sector.

5 Conclusion

In this paper, we develop a probabilistic framework for the analysis of spillover scenarios in economic and financial networks. We take the popular DY framework for network analysis as our starting point and develop a bootstrap-based procedure to estimate the probability of spillover scenarios defined in terms of inequality constraints applied to the elements of the spillover matrix, either individually or jointly. The result is a powerful and highly adaptable framework for the analysis of empirical network models that offers new opportunities to tease out and interpret the wealth of information embedded in the estimated network.

We apply our technique to the analysis of credit risk spillovers in a set of 18 countries over the 2006-2010 period using a slightly adapted version of the empirical network model developed by GHN. Our analysis is complementary to that of GHN in the sense that we place several of the authors' findings based on point estimates on a firm probabilistic footing. Our work also goes considerably beyond that of GHN, in the sense that we offer a formal treatment of the joint evolution of selected spillover measures to extract and exploit more of the information contained in the estimated network.

We show that the stylized facts put forth by ADS are reflected with high probability in the estimated credit risk network. Notably, we find a high probability of credit risk transfer from the financial sector onto the sovereign during the period of the financial sector bailouts in Europe in 2008 and a high probability of elevated bidirectional feedback between the financial sector and the sovereign in the months after the bailouts. In addition, we develop and implement a novel three-way probabilistic classification scheme that we use to weigh the evidence that a given country experiences normal levels of financial–sovereign feedback, bank-led feedback or sovereign-led feedback. By applying our classification scheme over rolling samples, we obtain a vivid and timely characterization of the nature of financial-sovereign feedback among the crisis-hit countries in our sample over the period of the GFC.

Our technique represents a valuable addition to the DY literature, as it places the analysis of DY networks on a foundation that provides a robust basis for statistical inference, while simultaneously easing the task of processing the information embedded in the estimated network. This offers benefits for academic researchers, policymakers, and practitioners alike, because the connectedness of financial networks is widely agreed to have important implications for investor risk management and for the design and conduct of financial regulation and stabilization policy.

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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: Event probabilities over the ADS bailout period

	$\Pr(A)$	$\Pr(B)$	$\Pr(C)$	$\Pr(A \cap C)$	$\Pr(B \cap C)$	$\Pr(A \cap B)$
European Countries						
AT	0.768	0.027	0.430	0.360	0.014	0.027
BE	0.657	0.242	0.940	0.647	0.242	0.238
FR	0.988	0.000	0.996	0.986	0.000	0.000
DE	0.985	0.287	0.994	0.980	0.286	0.287
GR	0.464	0.993	0.523	0.138	0.521	0.464
IE	0.988	0.787	0.014	0.013	0.003	0.787
IT	0.701	0.029	0.999	0.701	0.029	0.029
NL	0.825	0.070	0.710	0.647	0.053	0.069
PT	0.662	0.911	0.540	0.331	0.489	0.660
ES	0.794	0.300	0.985	0.789	0.300	0.296
SE	0.350	0.057	0.890	0.343	0.057	0.053
UK	0.787	0.130	0.642	0.625	0.102	0.130
NO	0.073	0.078	0.499	0.038	0.032	0.054
Non-European Countries						
AU	0.712	0.000	0.915	0.709	0.000	0.000
CN	0.018	0.956	0.435	0.003	0.417	0.018
JP	0.494	0.064	0.630	0.340	0.038	0.060
RU	0.403	1.000	0.013	0.000	0.013	0.403
US	0.174	0.000	0.050	0.048	0.000	0.000

Table 3: Event probabilities for the ADS feedback period

	$\Pr(D)$	$\Pr(E)$	$\Pr(F)$	$\Pr(G)$	$\Pr(E \cap F)$	$\Pr(D \cap G)$	$\Pr(D \cap \bar{G})$
European Countries							
AT	0.405	0.049	0.860	1.000	0.049	0.405	0.000
BE	0.721	0.266	0.978	0.999	0.266	0.720	0.001
FR	0.877	0.749	0.960	0.002	0.739	0.002	0.875
DE	1.000	1.000	0.999	0.014	0.999	0.014	0.986
GR	1.000	1.000	1.000	1.000	1.000	1.000	0.000
IE	0.000	0.000	0.000	0.982	0.000	0.000	0.000
IT	0.994	0.961	0.999	0.303	0.960	0.301	0.693
NL	0.975	0.906	0.986	0.042	0.897	0.041	0.934
PT	0.823	0.596	0.870	0.969	0.576	0.795	0.028
ES	0.991	0.939	0.999	0.960	0.939	0.951	0.040
SE	0.430	0.301	0.637	0.637	0.290	0.300	0.130
UK	1.000	0.991	1.000	0.952	0.991	0.952	0.048
NO	0.322	0.293	0.445	0.083	0.217	0.047	0.275
Non-European Countries							
AU	0.999	0.977	1.000	0.387	0.977	0.387	0.612
CN	1.000	1.000	1.000	0.911	1.000	0.911	0.089
JP	0.632	0.175	0.907	1.000	0.175	0.632	0.000
RU	0.000	0.000	0.000	1.000	0.000	0.000	0.000
US	0.075	0.002	0.931	0.995	0.002	0.074	0.001

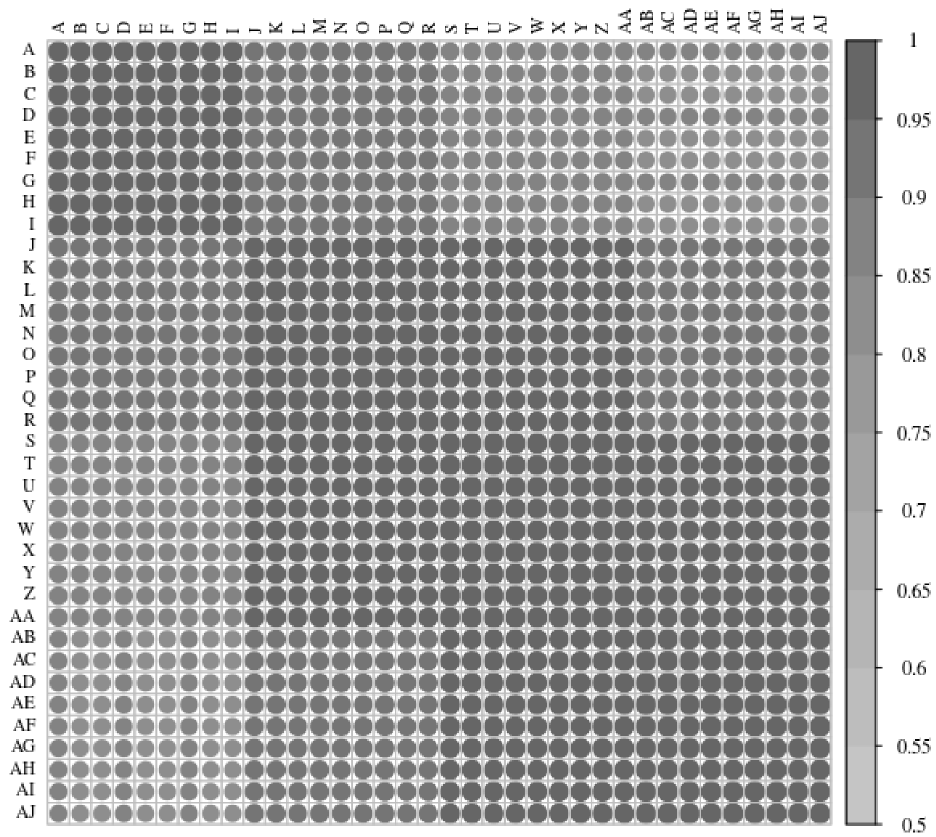
Table 4: Classification of financial–sovereign spillovers

	$\mathcal{T}_{g_i \leftrightarrow b_i} \leq c$	$\mathcal{T}_{g_i \leftrightarrow b_i} > c$
$\mathcal{N}_{g_i \leftarrow b_i} > 0$	Normal feedback	Bank-led feedback
$\mathcal{N}_{g_i \leftarrow b_i} \leq 0$		Sovereign-led feedback

Table 5: Timing and description of additional country-specific events

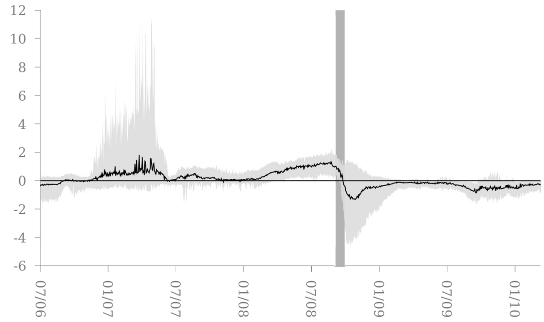
Country	No.	Date	Event
Austria	9	11/3/2008	Austrian bank Kommunalkredit is nationalized.
	10	12/15/2008	Hypo Group Alpe Adria receives state aid of EUR 900 million.
	11	4/20/2009	Finance minister explains higher deficits before parliament.
Benelux	9	3/31/2009	Fortis reveals a loss of EUR 28 billion.
	10	11/17/2009	Fortis reports a third-quarter profit.
Germany	9	8/28/2007	Sachsen Landesbank faces collapse.
	10	1/8/2009	Commerzbank is to be partly nationalized.
	11	3/27/2009	Commerzbank warns that its 2009 earnings will be badly affected.
Greece	9	12/8/2009	Fitch downgrades Greeces's credit rating from A- to BBB+.
Ireland	9	12/15/2008	Irish government provides EUR 10 billion to recapitalize listed banks.
	10	10/02/2009	Ireland's ratification of the Treaty of Lisbon.
	11	11/28/2009	Agreement of Irish sovereign bailout with the Troika.
Italy	9	2/25/2009	Finance Ministry approves a plan to strengthen bank's capital reserves.
	10	4/16/2009	Fitch downgrades Unicredit SpA from A+ to A, with a negative outlook.
Portugal	9	1/21/2009	S&P cuts Portugal's long-term rating from AA- to A+.
	10	2/18/2009	Millennium BCP announces that it may issue up to EUR 1.2 billion of non-dilutive financial debt instruments.
Spain	9	3/30/2009	Spain's decision to rescue a regional savings bank sends Spanish financial stocks lower.
	10	12/9/2009	S&P cuts Spain's credit outlook to negative from stable.
U.K.	9	2/18/2008	Nationalization of Northern Rock.
	10	1/11/2009	The U.K. economy contracts by 1.5% in 2008Q4, its worst performance in twenty-eight years.
	11	5/21/2009	S&P downgrades its view of the U.K. to negative.
U.S.	9	2/7/2007	HSBC announces losses linked to U.S. subprime mortgages.
	10	5/27/2009	The number of problem U.S. banks jumps by 40% to a fifteen-year high in the first three months of 2009.
	11	8/25/2009	The White House and Congress warn that the U.S. budget deficit will reach almost USD 1.6 trillion in 2009.
	12	12/24/2009	The Treasury Department removes the cap on the amount of preferred stock that the Treasury may purchase in Fannie Mae and Freddie Mac.

Figure 1: Correlation heatmap showing the sensitivity of the spillover index to w, h, and γ

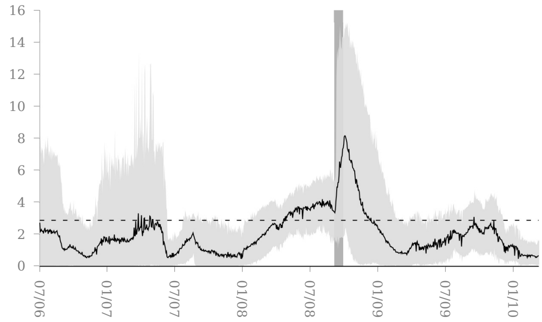


NOTES: The 36 possible combinations of w, h and γ are denoted by letters A—AJ as follows: (A) $w = 150$, $h = 5$, and $\gamma = 0.5$; (B) $w = 150$, $h = 5$, and $\gamma = 1.0$; (C) $w = 150$, $h = 5$, and $\gamma = 2.0$; (D) $w = 150$, $h = 10$, and $\gamma = 0.5$; (E) $w = 150$, $h = 10$, and $\gamma = 1.0$; (F) $w = 150$, $h = 10$, and $\gamma = 2.0$; (G) $w = 150$, $h = 15$, and $\gamma = 0.5$; (H) $w = 150$, $h = 15$, and $\gamma = 1.0$; (I) $w = 150$, $h = 15$, and $\gamma = 2.0$; (J) $w = 200$, $h = 5$, and $\gamma = 0.5$; (K) $w = 200$, $h = 5$, and $\gamma = 1.0$; (L) $w = 200$, $h = 5$, and $\gamma = 2.0$; (M) $w = 200$, $h = 10$, and $\gamma = 0.5$; (N) $w = 200$, $h = 10$, and $\gamma = 1.0$; (O) $w = 200$, $h = 10$, and $\gamma = 2.0$; (P) $w = 200$, $h = 15$, and $\gamma = 0.5$; (Q) $w = 200$, $h = 15$, and $\gamma = 1.0$; (R) $w = 200$, $h = 15$, and $\gamma = 2.0$; (S) $w = 250$, $h = 5$, and $\gamma = 0.5$; (T) $w = 250$, $h = 5$, and $\gamma = 1.0$; (U) $w = 250$, $h = 5$, and $\gamma = 2.0$; (V) $w = 250$, $h = 10$, and $\gamma = 0.5$; (W) $w = 250$, $h = 10$, and $\gamma = 1.0$; (X) $w = 250$, $h = 10$, and $\gamma = 2.0$; (Y) $w = 250$, $h = 15$, and $\gamma = 0.5$; (Z) $w = 250$, $h = 15$, and $\gamma = 1.0$; (AA) $w = 250$, $h = 15$, and $\gamma = 2.0$; (AB) $w = 300$, $h = 5$, and $\gamma = 0.5$; (AC) $w = 300$, $h = 5$, and $\gamma = 1.0$; (AD) $w = 300$, $h = 5$, and $\gamma = 2.0$; (AE) $w = 300$, $h = 10$, and $\gamma = 0.5$; (AF) $w = 300$, $h = 10$, and $\gamma = 1.0$; (AG) $w = 300$, $h = 10$, and $\gamma = 2.0$; (AH) $w = 300$, $h = 15$, and $\gamma = 0.5$; (AI) $w = 300$, $h = 15$, and $\gamma = 1.0$; (AJ) $w = 300$, $h = 15$, and $\gamma = 2.0$. The figure reports the pairwise common-sample correlation among the spillover index obtained under each combination of parameters. The depth of shading and the size of the circle within each cell reflects the strength of the correlation. Given that all of the reported correlations are strongly positive, we restrict the scale of the figure to lie in the interval $[0.5, 1.0]$.

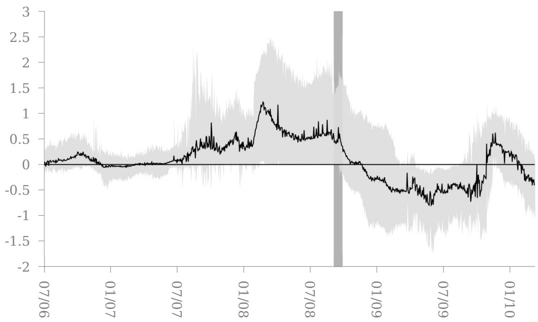
Figure 2: Net and total financial–sovereign spillovers for selected countries



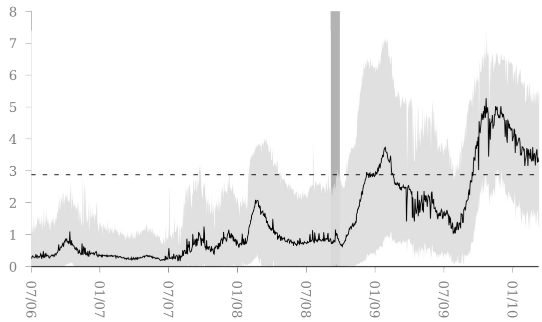
(a) Ireland Net Financial–Sovereign Spillover



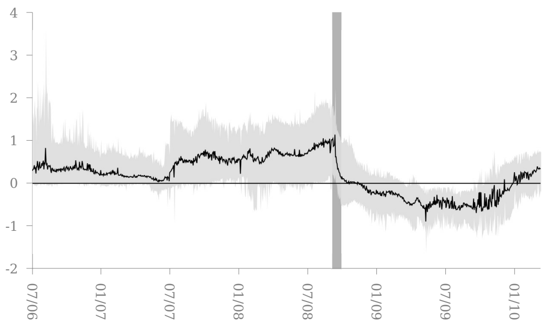
(b) Ireland Financial–Sovereign Feedback Effect



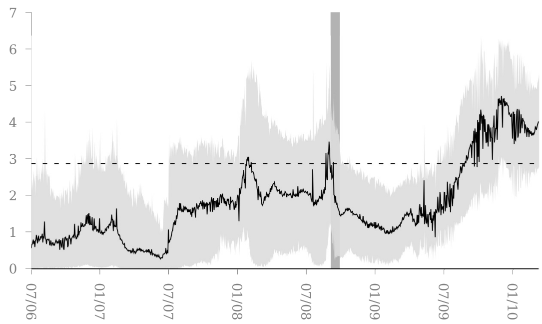
(c) U.K. Net Financial–Sovereign Spillover



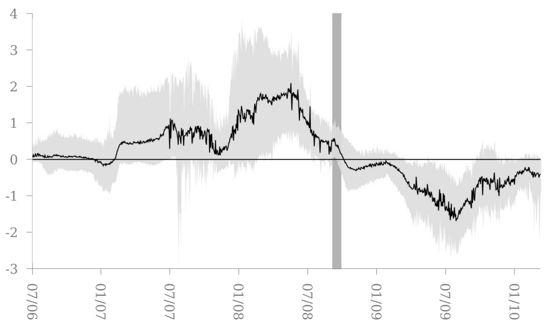
(d) U.K. Financial–Sovereign Feedback Effect



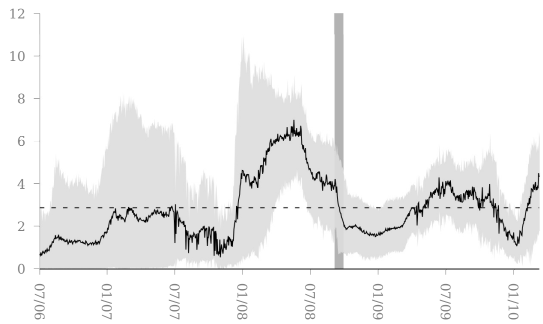
(e) Germany Net Financial–Sovereign Spillover



(f) Germany Financial–Sovereign Feedback Effect



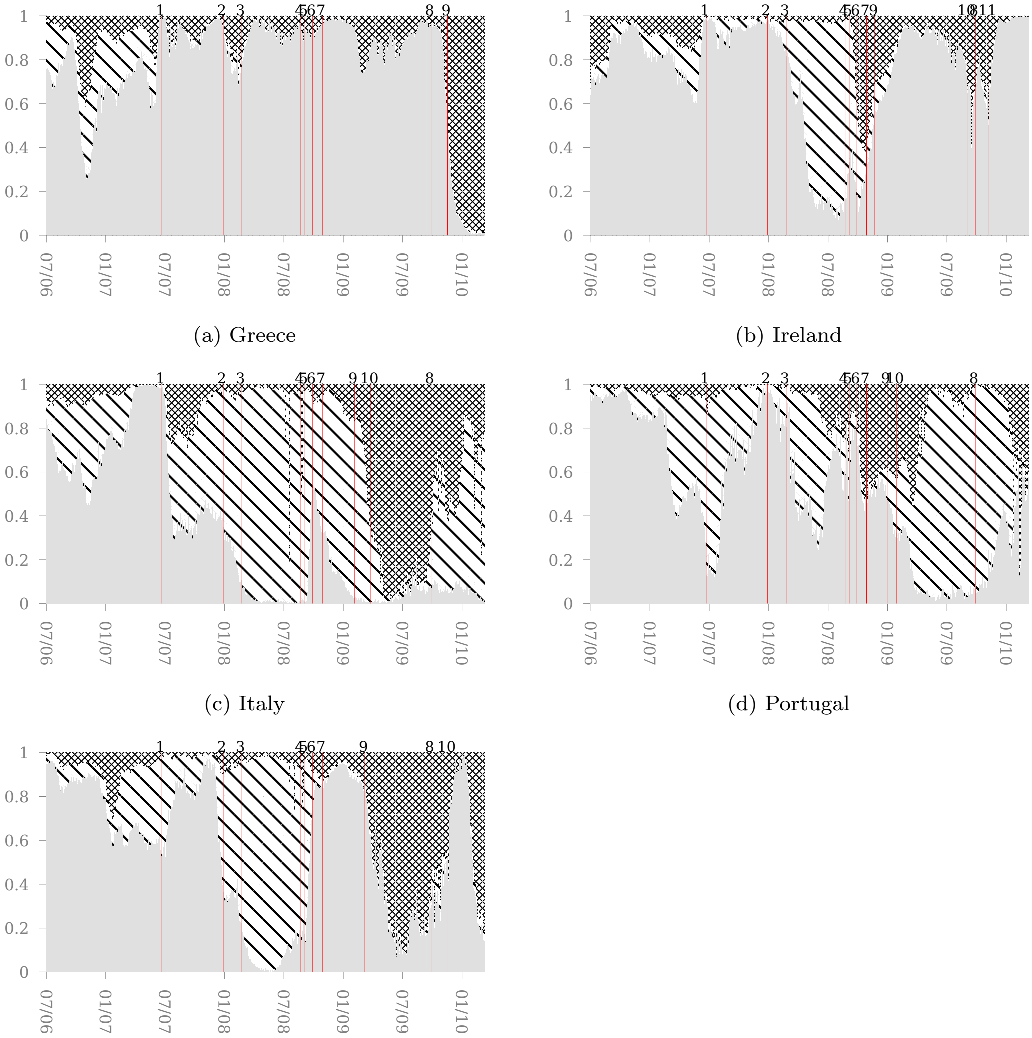
(g) Spain Net Financial–Sovereign Spillover



(h) Spain Financial–Sovereign Feedback Effect

NOTES: The figure reports the bootstrap mean values of the net financial–sovereign spillover effect ($\mathcal{N}_{g_i \leftarrow b_i}$) and the total financial–sovereign feedback effect ($\mathcal{T}_{g_i \leftrightarrow b_i}$) as well as the corresponding 90% bootstrap confidence intervals for a selection of countries. Results are reported for 958 rolling samples, starting with the first rolling sample that ends on 7/31/2006 and finishing with the rolling sample that ends on 3/31/2010, shortly before the first Greek sovereign bailout. Both the net and total spillovers are measured in percent. The dashed horizontal line in panels (b), (d), (f) and (h) shows the value of the common threshold, c, introduced in Subsection 4.5. The dates recorded on the horizontal axis show the final trading day of the rolling samples in MM/YY format. The results are based on 1,000 iterations of the heteroscedasticity-robust block bootstrap routine proposed by Brüggemann et al. (2016). The shaded vertical area depicts the bailout period considered by ADS (9/26/2008 to 10/21/2008).

Figure 3: Three-way probabilistic classification, GIIPS countries



(a) Greece

(b) Ireland

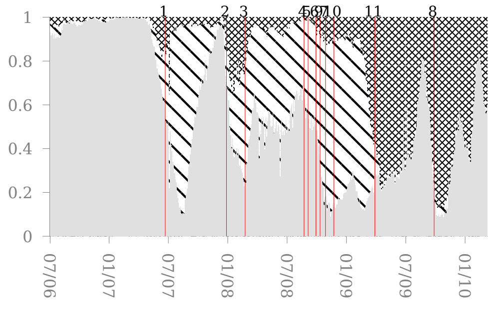
(c) Italy

(d) Portugal

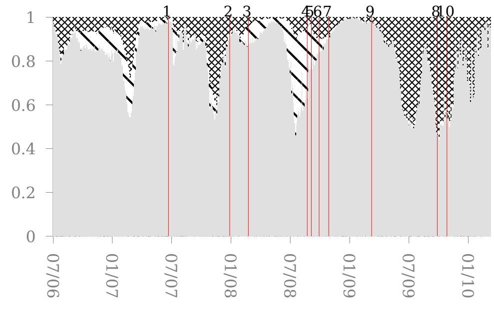
(e) Spain

Notes: The figure reports the probability of each of the three scenarios defined in Table 4. Gray shading denotes normal feedback, the striped region denotes bank-led feedback and the cross-hatched region denotes sovereign-led feedback. Results are reported for 848 rolling samples, starting with the rolling sample that ends on 1/1/2007 and finishing with the rolling sample that ends on 3/31/2010, shortly before the first Greek sovereign bailout. The dates recorded on the horizontal axis show the final trading day of the rolling samples in MM/YY format. The results are based on 1,000 iterations of the heteroscedasticity-robust block bootstrap routine proposed by Brüggemann et al. (2016). The following events are marked: 1—Bear Stearns announces the insolvency of two hedge funds (7/17/2007); 2—Global stock market collapse (1/21/2008); 3—Bear Stearns is sold to JP Morgan (3/16/2008); 4—Lehman Brothers fails (9/15/2008); 5—the start of the ADS bailout period (9/26/2008); 6—the end of the ADS bailout period (10/21/2008); 7—Global stock market collapse (11/19/2008); and 8—Greece reveals that its fiscal situation is worse than was previously thought (10/19/2009). Further country-specific events listed in Table 5.

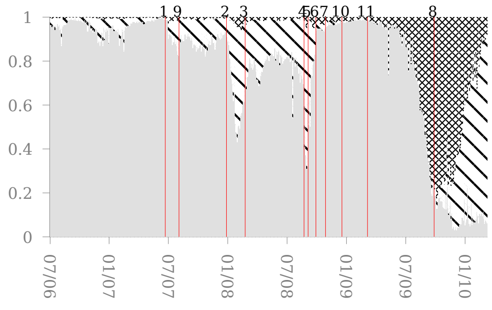
Figure 4: Three-way probabilistic classification, crisis countries



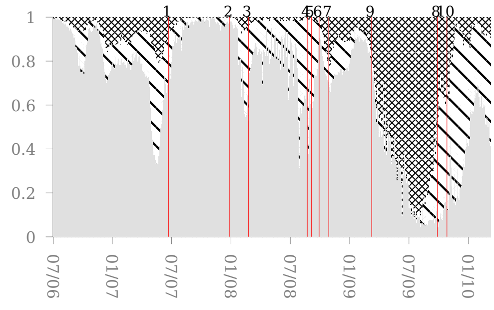
(a) Austria



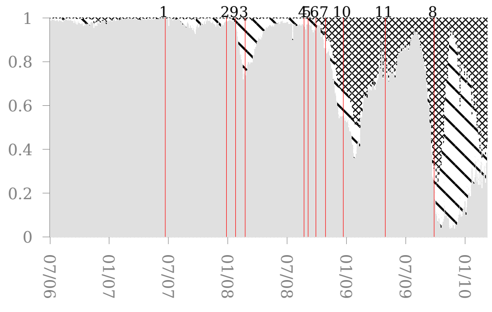
(b) Belgium



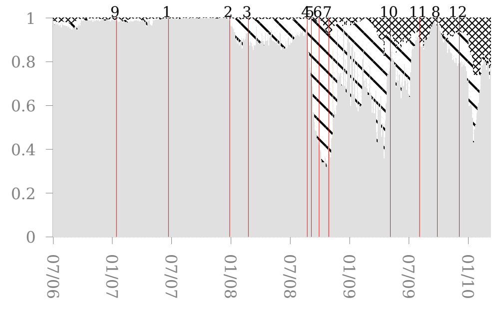
(c) Germany



(d) Netherlands



(e) U.K.



(f) U.S.

NOTES: The figure reports the probability of each of the three scenarios defined in Table 4. Gray shading denotes normal feedback, the striped region denotes bank-led feedback and the cross-hatched region denotes sovereign-led feedback. Results are reported for 848 rolling samples, starting with the rolling sample that ends on 1/1/2007 and finishing with the rolling sample that ends on 3/31/2010, shortly before the first Greek sovereign bailout. The dates recorded on the horizontal axis show the final trading day of the rolling samples in MM/YY format. The results are based on 1,000 iterations of the heteroskedasticity-robust block bootstrap routine proposed by Brüggemann et al. (2016). The following events are marked: 1—Bear Stearns announces the insolvency of two hedge funds (7/17/2007); 2—Global stock market collapse (1/21/2008); 3—Bear Stearns is sold to JP Morgan (3/16/2008); 4—Lehman Brothers fails (9/15/2008); 5—the start of the ADS bailout period (9/26/2008); 6—the end of the ADS bailout period (10/21/2008); 7—Global stock market collapse (11/19/2008); and 8—Greece reveals that its fiscal situation is worse than was previously thought (10/19/2009). Further country-specific events listed in Table 5.