Bank Systemic Importance and Fragility of Financial Networks

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We propose a dynamic model for systemic risk using a bipartite network of banks and assets in which the nodes and links may vary over time. We apply the model to the European sovereign debt crisis and observe that the results closely match real-world events (e.g. the high risk of Greek sovereign bonds and the distress of Greek banks). The model can be used as a complement to existing stress tests, incorporating the systemic risk contribution of banks and assets in time-dependent networks. In addition, the model provides a simple way of assessing the stability of a system by using the ratio of the log returns of sovereign bonds and the stocks of major sovereign debt holders as a stability indicator. We also propose a *systemic importance ranking*, BankRank, for the financial institutions analyzed in this study to assess the contribution of individual banks to the overall systemic risk.

Keywords: Financial Crisis; Stress Test; Systemic Risk; Linear Response; Phase Transition; Bipartite Network

Classification: D85, G01, G23, N24

1. Introduction

Recent financial crises have motivated the scientific community to seek new interdisciplinary approaches to modeling the dynamics of global economic systems. The seminal papers by Allen and Gale (2000, 2007) sparked a number of empirical studies to estimate the risk of contagion in financial systems: Wells (2002) focused on the UK interbank market, Upper and Worms (2004) considered bilateral exposures in the German interbank market, and Elsinger *et al.* (2006) analyzed a data set of all Austrian banks, to name a few. Nier *et al.* (2007) and Cifuentes *et al.* (2005a) turned their attention to the impact of leverage and liquidity risk on contagion.

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While many of the existing economic models include noise and fluctuations, they assume a representative economic agent or use market data to infer interdependencies. (Adrian and Brunnermeier, 2016) analyze the exposure of financial institutions to common macro-factors, using quantile-regression, to infer the systemic risk impact banks have on each other. (Acharya *et al.*, 2017) follow a similar approach to estimate the contribution of individual banks to systemic risk. In these approaches, the detailed structure of the underlying economic network is generally not taken into account.

Schweitzer *et al.* (2009) argued, as the Global Financial Crisis unfolded, that a new approach was needed. Economists have recently expanded traditional econometrics modeling with increased attention to two factors: (i) the structure of economic networks and (ii) their dynamics. One example of this approach is the work of Battiston *et al.* (2012c). The authors study the 2008 banking crisis and use network analysis to develop a measure of bank importance. By defining a dynamic centrality measure in the interbank lending network, called DebtRank, they show that the banks that need to be rescued are the ones that are more 'central' in terms of their DebtRank. Identifying the critical nodes in the network is highly important since recent work has shown that nodes with higher centrality have the potential for triggering cascading failures (Watts, 2002; Buldyrev *et al.*, 2010; Levy-Carciente *et al.*, 2015; Li *et al.*, 2014).

This paper is motivated by the European sovereign debt crisis that began in 2011 with the divergence of the yield on Greek sovereign debt compared to the yield on debt of other European nations and led to a bailout of the Greek government (Lane, 2012). The nature of the sovereign debt crisis and resulting network behavior that we analyze differs from the US banking crisis. Here we focus on the funds that several eurozone countries – Greece, Italy, Ireland, Portugal, and Spain (GIIPS) – had borrowed from the banking system by issuing of Government bonds. When these governments faced fiscal difficulties, the banks holding their sovereign debt faced a dilemma: should they divest some of their holdings at reduced values or should they wait out the crisis? The bank/sovereign-debt network that we analyze in this study is a bipartite network. In contrast to studies that focus on interbank lending, like (Battiston *et al.*, 2012c; Glasserman and Young, 2015; Constantin *et al.*, 2018), our work explores the systemic risk impact of portfolio overlap. The similarity of banks' assets holding as a channel of contagion has recently experienced increased attention Cifuentes *et al.* (2005b); Caccioli *et al.* (2014); Tasca *et al.* (2017). To this end, DebtRank has also been used to study bipartite networks, e.g. to describe the lending relationships between banks and firms in Japan (Aoyama *et al.*, 2013). That study, however, does not take into account that link weights exhibit a dynamic behavior.

We propose a dynamic network model for assessing the vulnerability of the financial system to economic shocks. We construct a network of the largest institutional holders of sovereign debt in the five troubled countries (Greece, Italy, Ireland, Portugal, and Spain) during the European sovereign debt crisis of 2010-2012. We also study the potency of individual banks to propagate systemic risk throughout the bank network. To this end, we propose a measure for bank systemic importance, *BankRank*, to identify how the linkages of banks within the financial network contribute to the overall network losses in bank assets.

From our model simulations we can determine whether the network is in a stable state in which shocks do not cause major losses, or in an unstable state in which devastating damages occur. Fitting the parameters of the model to the eurozone crisis data, our results show that, pre-crisis, the system was mostly in a stable regime, and that during the crisis it transitioned into an unstable regime. The numerical solutions produced by our model match closely the actual timeline of events of the crisis. We also find that, while the largest sovereign debtholders are usually more important, in the unstable regime smaller holders also exhibit systemic importance.

This suggests that our model may be a useful tool for simulating the response dynamics of shared portfolio networks. We stipulate that our model can improve the ability to estimate the vulnerability of banks and assets to shocks.

We use a snapshot of the GIIPS sovereign debt holders network from the end of 2011 to focus on a simplified version of the network structure. Based on our analysis we observe that:

1. When we model the system's response to an individual bank experiencing a shock, our analysis is in accordance with real-world results, e.g. in our simulations, Greek debt is clearly the most vulnerable.

2. The dynamics arising from our model produces different outcomes for the system depending on the values of the parameters.

In order to determine which banks play a systemically dominant role in this bipartite network, we adjust the equity of each bank until it goes bankrupt and then quantify the impact (the BankRank) of the bank's failure on the system. We simulate the dynamics for different parameter values and observe that the system exhibits at least two equilibria; in one, the system suffers mild monetary damage, while in the other, the monetary damage is quite significant and devastating.

In addition to the work of Battiston *et al.* (2012c), this paper also builds on Huang *et al.* (2013) and Caccioli *et al.* (2014), studying the cascading failures in a bipartite network of banks and assets in which risk propagates among banks through overlapping portfolios. We improve upon these models by taking into account the dynamic lending conditions that exist in real-world financial systems. Other models use simulated networks similar to real systems (Hałaj and Kok, 2013) or allow dynamic behavior of the nodes but not the links (Battiston *et al.*, 2012b). In Hałaj and Kok (2015) and Kok and Montagna (2016), dynamic behavior occurs when a financial network attempts to optimize 'risk adjusted' assets. Our approach expands upon these earlier models; by introducing only two parameters, we enable all network variables to be dynamic.

The rest of this paper is organized as follows. In section 2, we describe the data that we use to construct the bipartite network. We also introduce the model and its dynamics. In section 3, we explain the estimation of parameters in our model from the European sovereign debt crisis data. We further present results from our simulations of different initial shocks, and we address the role of the network and its structure. In section 4, we analyze the relationship between BankRank and systemic risk, and in section 5, we offer our concluding remarks.

2. Bipartite network model and data description

We develop a general dynamic model for a network with banks in one layer and assets in the other. Then we estimate the parameters in our model with data from the European sovereign debt crisis.

2.1. Bipartite network model description

We use a bipartite network as shown in figure 1 for our model. On one side, we have a set of bonds, or assets, $\mathcal{A}$, which we label using Greek indices. In the following, we use the terms 'bond' and 'asset' interchangeably. On the other side, we have a set of banks $\mathcal{B}$, which we label using Roman indices. When a bank owns an asset, a link between the respective bank i and asset μ is formed. The weight of the link indicates the quantity of asset μ that bank i owns.

Each bank is characterized by its equity $E_{i,t}$ and its holdings from the set of assets $A_{i\mu,t}$, which change over time and generally differ from bank to bank. At any given time t, bond μ can be bought or sold for a price $p_{\mu,t}$. This price depends on the supply and demand for this asset. Without loss of generality, all bonds start trading at par, which implies $p_{\mu,0} = 1$.

Our model allows us to describe how each of the variables $E_{i,t}$, $A_{i\mu,t}$, and $p_{\mu,t}$ evolve over time. A key feature of our model is the time-dependence of the links $A_{i\mu}$, introducing dynamics into our network.

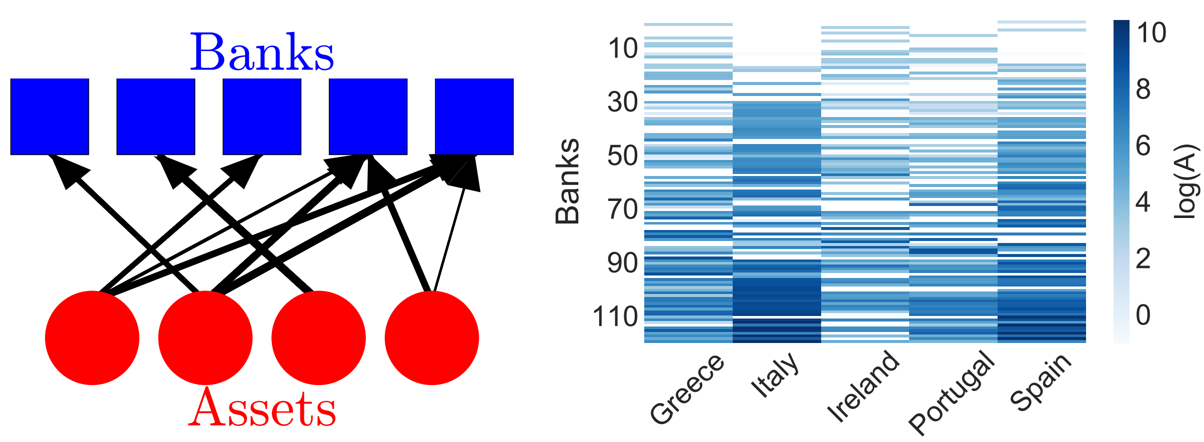

Figure 1: (Left) A sketch of the network of banks vs assets as a directed and weighted bipartite graph. The thickness of the lines represents sovereign debt holding weights. The network is characterized by its weighted adjacency matrix A. The entries $A_{i\mu}$ describe the number of bonds μ held by bank i. (Right) Amount of banks' holdings in GIIPS sovereign debt expressed in units of millions of euros. The vertical axis denotes different banks (121 of them), and they are ordered in terms of their total exposures to GIIPS debt (higher exposure is at the bottom of the plot). Because holdings differ by orders of magnitude, we have plotted $\log A$ here.

2.1.1. Notations and definitions

The equity E_i of a bank i is

$$E_i = \max\left\{ \sum_{\mu\in\mathcal{A}} A_{i\mu} p_\mu + c_i \,,\; 0 \right\}. \tag{1}$$

Here p_μ is the price of asset μ as a percentage of its original price. If the assets are bonds, this corresponds to the percentage of their par value. c_i denotes the liquid capital of the bank. These parameters evolve in time. We use the maximum function to denote that a bank's equity is nonnegative; if the equity of bank drops below zero in our model, it defaults. We further introduce the market value of the bond portfolio held by bank i, $V_i \equiv \sum_{\mu\in\mathcal{A}} A_{i\mu} p_\mu$, and the par amount of bond μ outstanding, $A_\mu \equiv \sum_{i\in\mathcal{B}} A_{i\mu}$.

2.1.2. The time evolution of bank portfolios and asset prices

While the liquid capital of the bank is subject to change for a myriad of reasons, we focus on the impact of sales and purchases of assets from set $\mathcal{A}$. For that reason, we separate out the change due to portfolio transactions from other sources of change in liquid capital:

$$\Delta c_{i,t} = -\sum_{\mu\in\mathcal{A}} (\Delta A_{i\mu,t}) p_{\mu,t} + \Delta S_{i,t}, \tag{2}$$

where the minus sign indicates that a sale of assets implies $\Delta A_{i\mu} < 0$, and the transaction should increase the liquid capital on the balance sheet of bank i. ΔS_i encompasses the impact due to other sources of capital changes.

Due to regulatory constraints, the bank is concerned how changes in liquid capital affect its equity. A sale of an asset, as described in equation (2), does not decrease the bank's equity because the reduction in assets corresponds to a commensurate increase in the cash position. ΔS_i, however, describes the net impact of other factors on liquid capital, and therefore, it has an impact on the bank's equity. A change in the prices of bonds from the set of assets $\mathcal{A}$ also changes the bank's equity, as shown in equation (3):

$$\Delta E_{i,t} = \Delta S_{i,t} + \sum_{\mu\in\mathcal{A}} A_{i\mu,t} \Delta p_{\mu,t} \tag{3}$$

If a bank's equity shrinks, it may need to consider selling assets, possibly at depressed prices, while, if the equity increases, the bank may expand its holdings.

In our model, the bank bases the decision to buy or sell assets on how much to its equity:

$$\Delta A_{i\mu,t+\tau} = \beta \frac{\Delta E_{i,t}}{E_{i,t}} A_{i\mu,t}. \tag{4}$$

We introduce β to model the bank's urgency to purchase or sell assets. The larger the β is, the more assets the bank trades as a response to a change in portfolio value. In the case of asset sales, β can be regarded as a 'panic factor' as it accelerates the selling pressure on the assets. Our model assumes that the bank acts after a response time τ after the change in its equity position.

When banks trade, they have an impact on asset prices. We assume that the price changes are related to the following: firstly, the quantity of assets sold as a fraction of total assets held by other institutions in the set of banks $\mathcal{B}$; secondly, the market sensitivity to sales or market liquidity. The price impact of asset sales is not immediate in our model; instead, we account for a short market response time τ:[1]

$$\Delta p_{\mu,t+\tau} = \alpha \, \frac{\Delta A_{\mu,t}}{A_{\mu,t}} \, p_{\mu,t}, \tag{5}$$

where α is the market sensitivity. The fraction of sales ($\Delta A/A$) required to reduce the price by one unit ($\Delta p/p$) is equal to $1/\alpha$. Therefore, this parameter can also be understood as the inverse of market liquidity or market depth. We choose the same 'inverse market depth' for all bonds in $\mathcal{A}$. All essential variables of our model are summarized in table 1.

Table 1: Notation

$A_{i\mu,t}$	Holdings of bank i in asset μ at time t
$p_{\mu,t}$	Normalized price of asset μ at time t; $p_{\mu,0} = 1$
$E_{i,t}$	Equity of bank i at time t.
α	Inverse market depth factor of price to a sale.
β	Banks' panic factor.

Up until this point, we have considered discrete time steps. In the following, we assume that the time lags are small and convert equations (3) to (5) to second order differential equations. To this end, we transform $\Delta F \to \mathrm{d}F/\mathrm{d}t$ and expand the resulting equations to second order in time.[2] For brevity, we define $\partial_t \equiv \frac{\mathrm{d}}{\mathrm{d}t}$. Then we obtain the following system of equations:

$$\left(\tau\partial_t^2 + \partial_t\right) A_{i\mu}(t) = \beta \, \frac{\partial_t E_i(t)}{E_i(t)} \, A_{i\mu}(t) \tag{6}$$

$$\left(\tau\partial_t^2 + \partial_t\right) p_\mu(t) = \alpha \, \frac{\partial_t A_\mu(t)}{A_\mu(t)} \, p_\mu(t) \tag{7}$$

$$\partial_t E_i(t) = f_i(t) + \sum_{\mu\in\mathcal{A}} A_{i\mu}(t) \, \partial_t p_\mu(t). \tag{8}$$

where $f_i(t) = \mathrm{d}S_i/\mathrm{d}t$ is the impact of external influences, τ is the time-scale in which banks and markets respond to change. Without such a time lag, equations (6) through (8) would merely relate the first-order time derivatives of A, p, E to each other. However, the order in which we update the variables matters, and most of the nontrivial dynamic behavior follows from the time lag between updates to asset holdings and asset prices.

The $f_i(t)$ denotes changes to the liquid capital and the bank's equity from other sources than the changes of bank's portfolio of assets $\mathcal{A}$. We assume that a shock to the system comes in the form of $f_i(t) = sE_i\delta(t)$, where $\delta(t)$ is the Dirac delta function. Such a shock instantaneously changes the equity of a bank i by a fraction s of its equity and leaves all other banks unaffected, $f_j = 0$ for $j \neq i$. Inserting $f_i(t)$ into equation (6), we can find the initial condition for $A_{i\mu}$ through integration:

$$\partial_t A_{i\mu}(0) = \beta A_{i\mu}(0) \ln(1+s). \tag{9}$$

Since the other banks are initially unaffected by this shock, their holdings are not modified. This implies $\partial_t A_{j\mu}(0) = 0$ for $j \neq i$. Additionally, the $f_i(t)$ that we are using implies that the initial equity of bank i changes to $(1+s)E_i(0)$. If $s < 0$, then the bank experiences a deterioration of its

[1] We are assuming that the response time of the market and of the response time of the banks are identical. We have performed our analysis allowing for differences in response time, and we found that the stability of the system is not affected by the different response times.

[2] If the time lags are small, we can expand the equations with τ to $\frac{\mathrm{d}F(t+\tau)}{\mathrm{d}t} \approx \frac{\mathrm{d}}{\mathrm{d}t}\left(F(t) + \tau\frac{\mathrm{d}F}{\mathrm{d}t}\right) = \frac{\mathrm{d}F}{\mathrm{d}t} + \tau\frac{\mathrm{d}^2F}{\mathrm{d}t^2}$

equity value. Naturally, asset prices can not be negative, implying $p_\mu(t) \geq 0$. Our model does not allow short sales, hence $A_{i\mu}(t) \geq 0$. Lastly, the bank's equity cannot fall below zero, which means $E_i(t) \geq 0$, as described in equation (1).

In the following section, we describe how we build the bank-asset bipartite network from empirical data and we also set the initial conditions.

2.2. Data and bank network construction

Governments borrow money by issuing sovereign bonds that trade in a secondary market, similar to the stock market. For a more detailed description of bond characteristics relevant to our model, see (Battiston *et al.*, 2012a). Market supply and demand determine the value of the bonds. The value of sovereign bonds is greater when countries are economically and politically stable. If, however, the country becomes troubled and the market perceives that the government may not be able to pay back the debt, the price of the sovereign bonds can crash, which was the case for Greece.

In this study, we analyze data covering 136 banks, investment funds, and insurance companies, which represent the largest institutional holders of GIIPS sovereign debt in 2011. (Hereafter, for simplicity, we use the term 'banks' to refer to all these financial institutions.) Table 2 shows the percentages of the sovereign bonds issued by each GIIPS country owned by these banks. Since our model requires knowledge of the equity of each bank, we reduce our data set to the 121 banks for which we could obtain this information. By the end of 2011, two important Greek banks – the National Bank of Greece and Piraeus Bank – had negative equity. Because our model only considers banks that can execute trades based on positive equity, we also eliminate these two banks from our analysis. Figure 1 shows a graphic representation of the resulting weighted adjacency matrix of the network.

Table 2: Total amount of exposure of the banks in our data set to the sovereign debt of the GIIPS countries

	Greece	Italy	Portugal	Spain	Ireland
Total (bnEu)	96.90	420.55	48.93	333.46	32.60
% in banks	35.37	25.62	38.04	48.12	36.39

2.2.1. Assumptions and simplifications of the GIIPS network

The following key assumptions and specifications differentiate our model from other banking system or dynamic network models:

1. The banks do not *exclusively* trade with each other. They may trade with an external entity, which may be the ECB or other, smaller investors.[3]

2. When there is no change in equity, price of the sovereign bonds, or bond holdings, there is no intrinsic dynamic activity in our financial network.

[3]This is appropriate in the case of GIIPS sovereign debt because, in addition to the ECB (which buys some of the bonds if there is a need to stabilize the system), a large number of investors hold this debt. This is important to keep in mind because in most problems associated with banking or financial networks, agents are assumed to be trading only with each other.

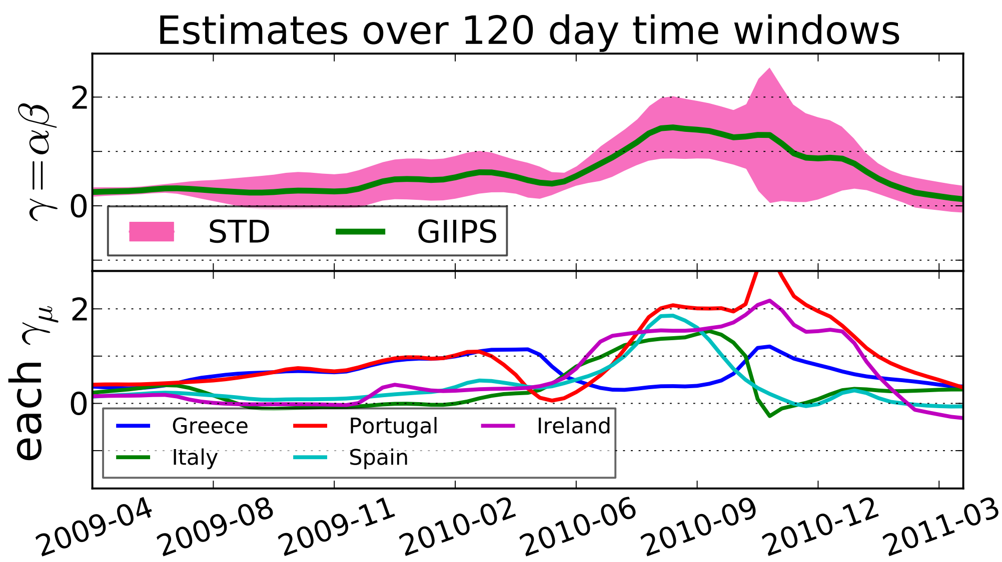

Figure 2: Estimates of $\gamma = \alpha\beta$ over 120-day periods. Top: the solid line is the average of γ calculated for the GIIPS countries, and the shaded purple region is the error-bars based on the standard deviations. Bottom: Calculation of γ_μ for individual countries. The fact that the values for different countries are close to each other is a sign that our assumption of 'herding' (i.e. same α and β for all GIIPS) is justified and that our model is applicable here. As can be seen, before the height of the crisis $0 < |\gamma| < 1$, and then it gradually increases. At the height of the crisis $1 < \gamma < 2$. After the crisis, we see γ decrease again to $\gamma < 1$. Later we show that at $\gamma < 1$ the system rolls into a new equilibrium, but when $\gamma > 1$, asset prices crash. Also note the time-line of bailouts: Greek bailouts were approved in April and September 2010, and the Irish bailout was approved in October 2010. This might explain part of the movements in γ in the bottom plot.

3. The model describes the short-term responses of the system and disregards slow, long-term driving forces of the market.

4. Agents in the system (institutional holders of sovereign debt) follow other agents' actions leading to the so-called 'herding effect'. This is why we assume the free parameters are the same for all agents.

3. Application to the European sovereign debt crisis

We apply our model to the GIIPS data, and before starting the simulations of equations (6) through (8), we estimate the values of our parameters for the case of the GIIPS sovereign debt crisis.

3.1. Estimating values of $\gamma = \alpha\beta$

We use approximate versions of the differential equations (6) to (8) in order to estimate $\gamma = \alpha\beta$. The distribution of asset holdings is roughly log-normal; as a result, a large portion of each GIIPS country's debt is held by only a few banks. Therefore, we can use the equity of the dominant holders of the debt μ and accomplish a good estimate of γ. We denote this set of dominant holders $\mathcal{B}_{\mathrm{Dom}}$. In our estimation, we use the top holders for each country for which we could obtain their stock prices from Yahoo Finance:

- Greece: NBG, EUROB.AT, TPEIR.AT, ATE.AT
- Italy: ISP.MI, UCG.MI, BMPS.MI, BNP.PA
- Ireland: BIR.F, AIB.MU, BEN

- Portugal: BCP.LS, BPI.LS, SAN

- Spain: BBVA, SAN

Combined, these banks hold 45% of Greek, 41% of Italian, 48% of Irish, 29% of Portuguese and 31% of Spanish debt in our data.

We further estimate that the response time τ is at most on the order of several days. Therefore, we calculate $\gamma = \alpha\beta$ over a period of four months to allow the system to reach its new final state. From equation (4) we have

$$\frac{\Delta A_\mu}{A_\mu} \approx \beta \sum_{i \in \mathcal{B}_{\text{Dom}}} \frac{\Delta E_i}{E_i} \frac{A_{i\mu}}{A_\mu} \tag{10}$$

where the $A_{i\mu}/A_\mu$ factor ensures that we have a weighted average of returns $\Delta E_i/E_i$ based on how large banks' holdings are. Since we are performing our estimation for the dominant holders, for consistency we compute $A_\mu = \sum_{i \in \text{Dom}} A_{i\mu}$. Using this approximation, we can relate the first two equations,

$$\frac{\Delta p_\mu}{p_\mu} \approx \alpha \frac{\Delta A_\mu}{A_\mu} \approx \alpha\beta \sum_{i \in \mathcal{B}_{\text{Dom}}} \frac{\Delta E_i}{E_i} \frac{A_{i\mu}}{A_\mu}. \tag{11}$$

Therefore, we can approximate γ as

$$\gamma \approx \frac{\Delta p_\mu / p_\mu}{\sum_{i \in \mathcal{B}_{\text{Dom}}} \frac{A_{i\mu}}{A_\mu} \Delta E_i / E_i}. \tag{12}$$

We evaluate γ for each country μ. Similar values of γ across different μ may indicate a 'herding effect'. This both supports our model and suggests that it is applicable to this problem. We evaluate γ for the time period between early 2009, just before the beginning of the European sovereign debt crisis, and early 2011, when most government bailouts had either been scheduled or completed.

For the return of bond prices $\Delta p_\mu/p_\mu$, we make use of the the average yield of 10-year bonds for the GIIPS countries which we obtained from Bloomberg. This average yield is inversely proportional to the price of a newly issued 10-year sovereign bond. The equity of the banks is mostly comprised of the shareholders' equity, or common stock. We use the stock price changes of the dominant sovereign debt holders to estimate $\Delta E_i/E_i$. For this approximation we use the following formula:

$$\frac{\Delta E_i}{E_i} = \frac{E_i(t_f) - E_i(t_i)}{(E_i(t_f) + E_i(t_i)/2}$$

where $E_i(t_i)$ is the stock price at the beginning of the period and $E_i(t_f)$ at its end.

For the banks, we use the 'adjusted close' stock prices, thus we use the market value of the equity as a proxy for the changes in the equity of banks. Many of the major movements (or slope changes) in each country's γ values seem to coincide with bailout payment dates (See figure 2 caption).

Figure 2 shows the average γ values during this period with standard deviation error-bars. The bottom of the figure shows the individual values of γ for individual country. The graphs illustrate that before the crisis $0 < |\gamma| < 1$, but at the height of the crisis $\gamma > 1$. More detailed analysis of our model reveals that $\gamma > 1$ is an unstable phase in which a negative shock to the equity of any bank causes most asset prices to fall dramatically to almost zero. Similarly, a positive shock causes the formation of bubbles. When $0 < \gamma < 1$, on the other hand, after a shock the system smoothly transitions into a new equilibrium and, although some banks may fail, no asset prices fall to zero.

3.2. Simulations

We find that when values of α and β are small, e.g. $|\alpha\beta| < 1$, shocking any of the banks in the network results in the same final state (see figure 8). The final state does not depend on which bank is shocked; it only depends on α and β. This state is a new stable equilibrium. If we shock the system a second time the prices do not change significantly (i.e. less than 0.1%). Figures 3 and 4 show samples of the time evolution of the asset prices and the equity of the banks that incurred the largest losses, for $\alpha = \beta = 0.6$ in figure 3 and $\alpha = \beta = 1.5$ in figure 4.

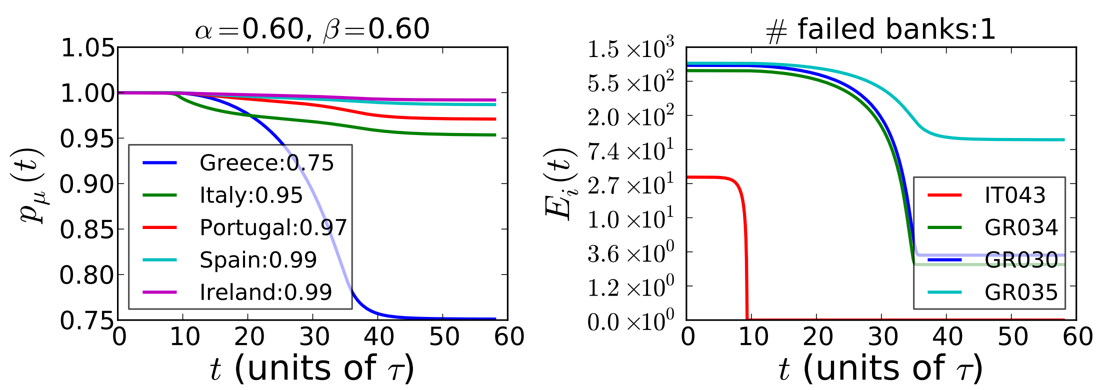

Figure 3: Shocking 'Bank of America' with $\alpha = \beta = 0.6$. Left: Asset prices over time. Greek debt incurs the greatest losses, falling to 75% of its original value. The legend shows the final prices. Right: Equity of the four most vulnerable banks. Three major Greek banks incur large losses, and one Italian bank is predicted to fail. IT043 is Banco Popolare, which has very small equity but large Italian debt holdings. The other three are Agricultural Bank of Greece, EFG Eurobank Ergasias, and T.T. Hellenic Postbank S.A., all among the top holders of Greek sovereign debt.

Three of the four most vulnerable banks in our simulation are holders of Greek sovereign debt. Note that the loss prediction produced by the model is based solely on the network of banks holding GIIPS sovereign debt. In this simulation, Greek debt is the asset that has highest losses, followed by Portugal.[4]

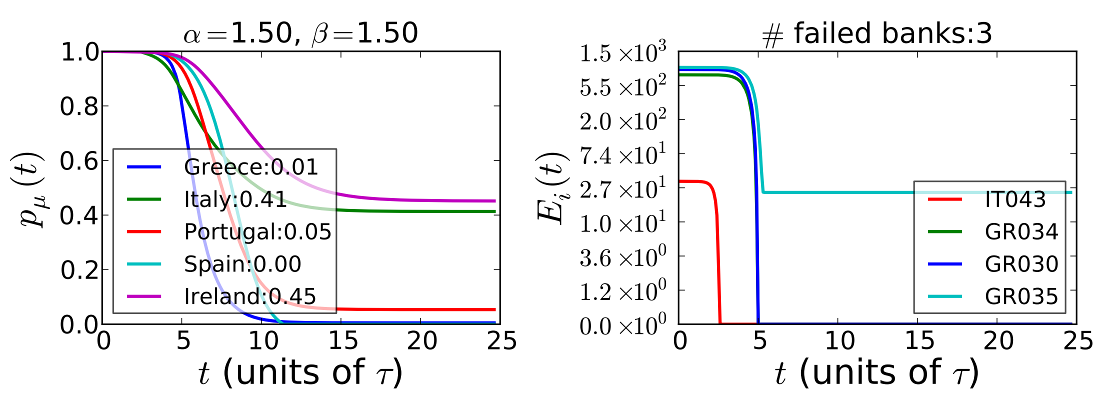

Figure 4: Simulation for larger values of α and β (values in legends are final price ratios $p_\mu(t_f)$). This time, in addition to Greek debt, Spanish and Portuguese debt show the next highest level of deterioration. The same four banks are the most vulnerable and this time two more of them fail. At $\alpha = \beta = 1.5$ the damages are much more severe than at $\alpha = \beta = 0.6$.

[4]Real world data indicates that Ireland's loss was as severe as Portugal's

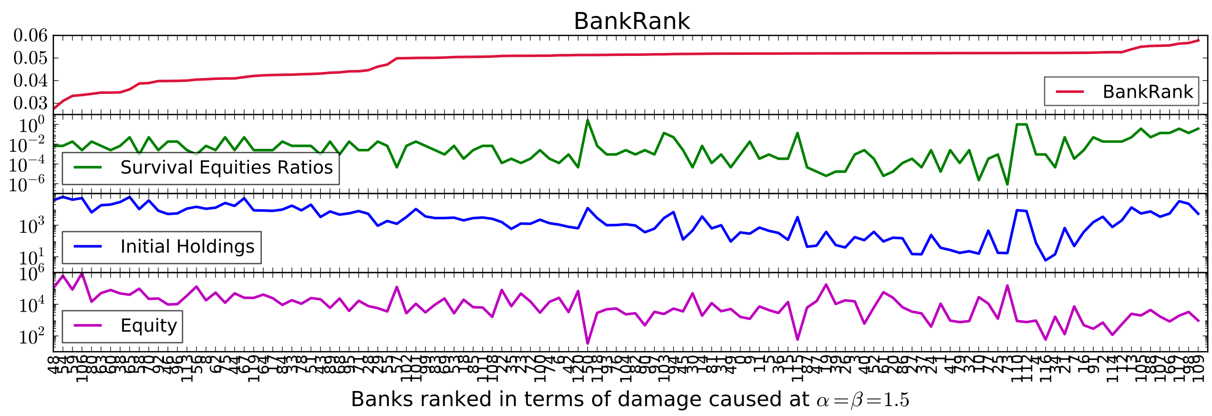

Figure 5: We rank the banks in terms of the effect of their failure on the system. Accordingly, the top plot shows the ratio of final total GIIPS holdings in the system to the initial total GIIPS holdings. The BankRank tells us how much monetary damage the failure of one bank would cause. The second plot shows the survival equity ratio $E^*/\tilde{E}$, the third is the initial holdings, and the fourth shows the initial equity, all sorted in terms of BankRank at $\alpha = \beta = 1.5$. As we see, none of these three variables correlates highly with BankRank. The ranking changes for different values of α and β.

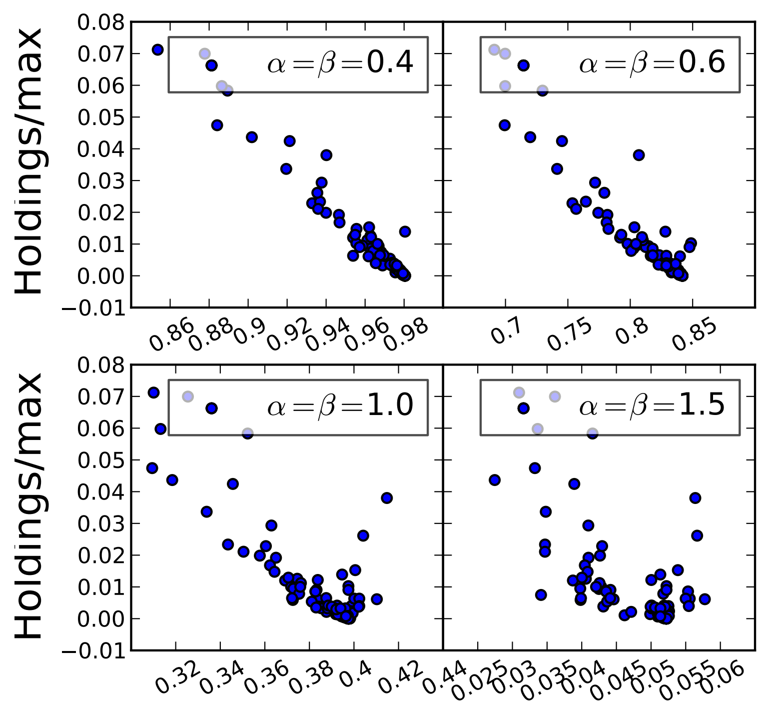

Figure 6: Scatter plot of the holdings divided by maximum holding (Holdings/max) versus BankRank at four different values of $\alpha = \beta = [0.4, 0.6, 1, 1.5]$. As we see, increasing $\alpha\beta$ decreases the correlation between BankRank and initial holdings. BankRank at $\gamma = \alpha\beta < 1$ is strongly negatively correlated with the holdings. But at $\gamma = \alpha\beta > 1$, BankRank deviates significantly from the holdings. In the unstable regime $\gamma > 1$ it is no longer true that only the largest holders have the highest systemic importance.

The new equilibrium depends on α and β. From the real world data in figure 2 we see that before the onset of the crisis $\alpha\beta < 1$. Therefore, as a result of a shock, the system attains a new equilibrium near the initial conditions (similar to figure 3). At the height of the crisis, however, when $\gamma = \alpha\beta \approx 2$, even a small shock may have a devastating effect and precipitate a crisis (as in figure 4). Although many banks incur significant losses when α and β values are at their highest, the same four banks are severely distressed in both regimes $\alpha = \beta = 0.6$ and $\alpha = \beta = 1.5$.

3.3. Testing the role of the network

To test the network importance, we examine the effect of rewiring the links between the banks and sovereign debt. Our goal is to determine to what extent the dynamics of the system is caused by the network structure. We do not change the value of the total GIIPS sovereign debt held by the banks. We only rewire the links in the network, changing the amount of debt held by each bank and the countries to which each bank lends money. Starting with $A_{i\mu}$, we take random permutations of index i so that the banks' sovereign debt holdings debt change randomly. Interestingly, such a rewiring significantly changes the damages suffered by GIIPS bonds, with Greece, for example, no longer being the most vulnerable.

This shows that in our model, while the quantitative behavior of the system only depends on α and β, the final sovereign debt values and bank solvency depend strongly on the network structure.

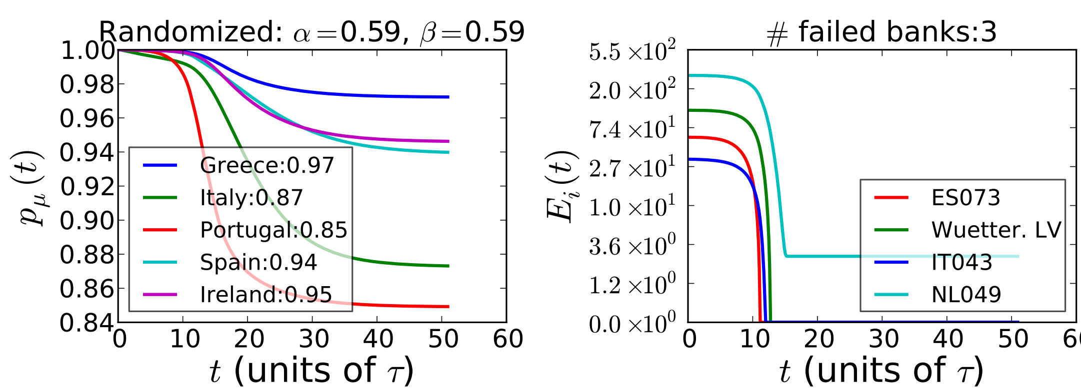

Figure 7: Randomizing which bank lends to which country, while keeping total debt constant for each country. The results differ dramatically from the real world data used in figure 3. In this example Portuguese and Italian sovereign debts experience largest losses, while Greek debt is the least vulnerable. Other random realizations yield different results.

Figure 7 shows an example of network randomization and how dramatically the final results differ. The randomized network demonstrates two important features of the model: (i) system dynamics are strongly affected by network structure, i.e. knowing such global variables as the equity and exposure of individual banks is not sufficient, and (ii) real-world data seems to indicate that the structure of the network of lenders to Greece affected the Greek sovereign bond values. This suggests that our model may be useful as a stress testing tool for banking networks or any network of investors with shared portfolios.

4. Systemic risk and BankRank

We find that a bank can cause a large amount of systemic damage when its equity level is at the bare minimum necessary to survive a shock. Banks with very low equity fail rapidly, no longer trade, and thus no longer transmit damage to the system. Banks with enough equity to survive for a significant period of time, on the other hand, continue to transmit damage into the system and thus cause more damage than extremely weak banks. Based on this observation we rank the banks using a 'survival equity ratio', i.e. the fraction of actual equity a bank needs in order to survive once a shock enters the system through other banks. The total damage done to the system varies significantly from bank to bank. To rank the systemic importance of each bank we measure the effect that each bank failure has on the system. Since normally no banks other than the four mentioned above fail, we slightly modify the data to change the equity levels for these four banks. The steps that we take in obtaining the BankRank of each bank are as follows:

1. We increase the equity of the four failing banks to $\tilde{E}_i(0) = \sum_{\mu \in \mathcal{A}} A_{i\mu}(0) p_\mu(0)$ to keep them from failing and significantly damaging the system, and $\tilde{E}_i = E_i$ for non-failing banks. Doing so makes the system resilient to shocks when $\gamma = \alpha\beta < 1$, and the decrease in prices falls below 1% (the system reaches a stable phase). In the unstable regime, where $\gamma > 1$ the system still incurs significant losses.

2. To assess the systemic importance of bank i, we run separate simulations with initial conditions changed to $\tilde{E}_i(0)$ until we find the value of E_i^* such that for $\tilde{E}_i > E_i^*$ the bank doesn't fail while for $\tilde{E}_i < E_i^*$ the bank fails. We call this E_i^*/E_i the 'survival equity ratio'. Note that for any i the shock is done to the same bank j ($i \neq j$), selected from the banks in the system. Also, note that the behavior of the system doesn't depend on j (see figure 8). However, the small variation in sovereign debt values and consequently, the variations in the $A_{i\mu}(t_f)$ can be used to construct BankRank and find that different banks have different level of influence.

3. We calculate the total GIIPS final holdings $\sum_k (A \cdot p)_k$. We define 'BankRank' of bank i to be the ratio of the final holdings to initial holdings when$\tilde{E}_i = E_i^*$. BankRank of i is equal to the amount of monetary damage exerted on the financial system if bank i fails: The smaller the value of R_i, the greater the systemic importance of bank i.

$$\text{BankRank of } i : R_i = \left. \frac{\sum_j (A \cdot p)_j(t_f)}{\sum_j (A \cdot p)_j(0)} \right|_{\tilde{E}_i = E_i^*} . \tag{13}$$

In figure 5 on top we show the BankRank in the unstable regime at $\alpha = \beta = 1.5$ and how it compares to the initial holdings, minimum ratio of equity required for survival E_i^*/E_i, and initial equities. We observe some correlation between BankRank and each of these variables. The best correlations are between BankRank and initial holdings. On the bottom of figure 5 we show the correlations of the initial holdings with BankRank. In the stable regime where $\alpha\beta < 1$ the holdings correlate well with BankRank, while in the unstable regime $\alpha\beta > 1$ the correlation becomes much weaker. Thus, while in the stable regime sovereign debt holdings almost completely determine the

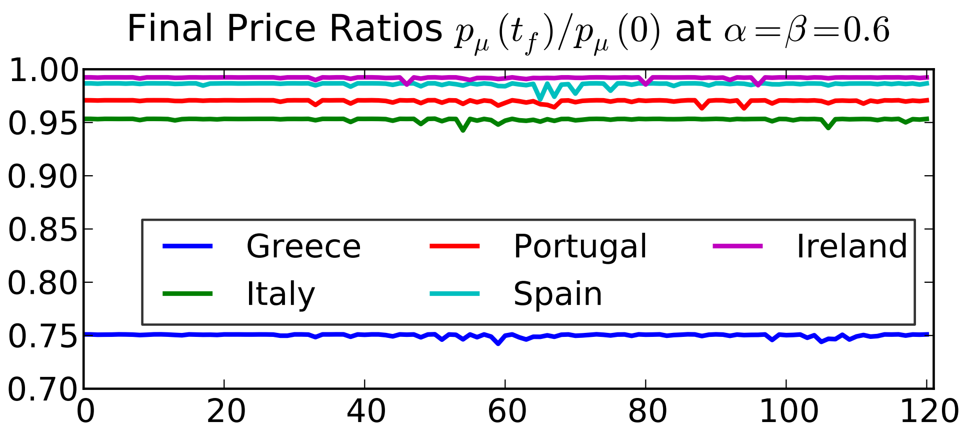

Figure 8: Shocking different banks at $\alpha = \beta = 0.6$. The final prices of the GIIPS sovereign debts are similar to the original prices.

systemic importance of a bank, in the unstable regime this is no longer the case and many small holders might have high systemic importance.

One can also rank the banks in terms of their stability from their 'survival equity ratio', E_i^*/E_i. This ratio can serve as a stress-test for individual banks. The smaller the ratio, the more stable the bank.

5. Conclusion

We study the systemic importance of large institutional holders of GIIPS sovereign debt. Our methodology (i) can be used to model 'systemic risk propagation' through a bipartite network of banks and assets, i.e. it can serve as a 'systemic stress testing' tool for complex financial systems, and (ii) it can be used to identify the 'state' of a financial network, i.e. whether a it is in a 'stable' or an 'unstable' phase – which may lead to a crisis. The prediction of the stability of the GIIPS holders network seems to match well the time-line of the European sovereign debt crisis. We also propose a simple, dynamic 'systemic risk measurement', which we call BankRank, which measures the amount of damage that the bank network suffers from a failure of a particular bank. We find that, while in the stable state, BankRank has significant correlation with GIIPS sovereign debt holdings, while in the unstable state BankRank doesn't correlate well with initial holdings or equity of banks. This shows that simple measures such as initial size of the bank or distribution of bank assets cannot determine the systemic importance of banks. Our method improves the measurement of systemic risk in bank network by investigating the significance of the network structure and proposing that the relations among banks through shared portfolios are central to assessing the risk of the banking system.

We suggest that our model could be useful as a monitoring and simulation tool that allows policy makers to identify systemically important financial institutions and to assess systemic risk build-up in the financial network.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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A. Largest institutional holders of the GIIPS countries' sovereign debt

List of 136 banks, insurance companies, and funds that are largest holders of GIIPS sovereign debt is given in 3.

xName	Code Name	Holdings	Equity	Greece	Italy	Portugal	Spain	Ireland
GESPASTOR	Gespastor	3.5e+02	1.6e+03	0	0	0	3.5e+02	0
M&G	M&G	37	1.1e+04	0	0	37	0	0
UNION INVESTMENT	Union Inv.	3.4e+03	7e+02	1.6e+02	2e+03	77	1e+03	1.5e+02
ATTICA BANK	Attica	1.8e+02	1.5e+04	1.8e+02	0	0	0	0
MILANO ASSICURAZIONI	Milano Assic.	74	9.3e+02	23	0	0.71	49	2.1
GROUPAMA	Groupama	4.4e+02	4.3e+03	0	4.2e+02	19	0	0
AEGON NV	Aegon	1.1e+03	2.6e+04	2	65	9	9.8e+02	26
RIVERSOURCE	River Source	48	7.4e+03	48	0	0	0	0
AVIVA PLC	Aviva	1.1e+04	1.8e+04	1.5e+02	8.4e+03	2.3e+02	1.4e+03	7.2e+02
EMPORIKI BANK	Emporiki	2.9e+02	1.2e+03	2.9e+02	0	0	0	0
MELLON GLOBAL	Mellon	16	2.8e+04	0	0	0	0	16
DAIWA	Daiwa	7.1e+02	7.3e+03	0	5e+02	0	2e+02	0
FIDEURAM	Fideuram	2e+03	5.5e+02	0	2e+03	0	0	0
UNIPOL	Unipol	1.3e+04	2.5e+03	26	1.2e+04	1.5e+02	1.1e+03	2.4e+02
WGZ BANK AG WESTDT. GENO.	DE029	3.6e+03	1.9e+03	3.2e+02	1.4e+03	4.6e+02	1.2e+03	2.2e+02
JYSKE BANK	DK009	1.2e+02	1.4e+04	64	0	19	15	22
OESTERREICHISCHE VOLKSBANK AG	AT003	3.7e+02	4.8e+02	1.1e+02	1.5e+02	29	66	13
CAIXA PORTUGAL	Caixa (PT)	8.1e+03	2.4e+04	35	4.6e+02	30	7.5e+03	44
BLACKROCK	Blackrock	2e+03	2e+04	1.2e+02	1.1e+03	29	7.1e+02	30
BANK OF AMERICA	BofA	3.8e+02	1.8e+05	13	2.5e+02	5.4	83	29
NORDEA BANK AB (PUBL)	SE084	1.6e+02	2.6e+04	0	97	0	64	1.4
CAJA DE AHORROS Y M.P.	ES077	1.5e+03	-	0	0	0	1.5e+03	0
SELLA GESTIONI	Sella	6.6e+02	1.3e+02	0	6.6e+02	0	0	0
MITSUBISHI UFJ	Mitsubishi	1.6e+03	8.1e+04	0	9.2e+02	71	5.2e+02	62
UBS	UBS	1.3e+03	4.8e+04	53	6.8e+02	55	4.4e+02	42
OPPENHEIMER	Oppenheimer	2.4e+02	3.8e+02	15	0	0	2.2e+02	0
VONTOBEL	Vontobel	18	1.2e+03	18	0	0	0	0
NOMURA	Nomura	39	1.8e+04	0	0	20	0	19
MACKENZIE	MacKenzie	15	3.4e+03	15	0	0	0	0
AGEAS	Ageas	5.3e+03	7.8e+03	6.4e+02	2e+03	1e+03	1.1e+03	5.1e+02
DEUTSCHE POSTBANK	De.Postbank	9.2e+02	5.7e+03	9.2e+02	0	0	0	0
MORGAN STANLEY	Morgan Sta.	4.6e+02	5e+04	0	4.6e+02	0	0	0
HELVETIA HOLDING	Helvetia	1e+03	3.6e+03	7.6	7.2e+02	18	2.4e+02	15
HWANG-DBS	Hwang	23	8.7e+02	23	0	0	0	0
ASSICURAZIONI GENERALI	Generali	1.7e+04	1.8e+04	1.3e+03	5.4e+03	3.1e+03	5.7e+03	1.7e+03
AMLIN PLC	Amlin	15	1.6e+03	0	0	0	15	0
SWISS LIFE HOLDING	Swiss Life	5.9e+02	7.5e+03	30	1.7e+02	77	1.8e+02	1.3e+02
PHOENIX GROUP	Phoenix	3.2e+02	2.8e+03	0	2.3e+02	11	76	2.2
PRICE T ROWE	PT Rowe	15	2.6e+03	0	0	0	0	15
AXA	Axa	2.9e+04	4.9e+04	7.6e+02	1.7e+04	1.5e+03	9.4e+03	7.5e+02
TOKIO MARINE	Tokio Marine	56	1e+04	0	0	30	0	26
ROTHSCHILD	Rothschild	1.1e+02	6e+02	61	0	52	0	0
TT ELTA AEDAK	TT Elta Aedak	27	9.3e+02	27	0	0	0	0
BALOISE	Baloise	7.9e+02	3.2e+03	84	2.7e+02	98	2.3e+02	1.1e+02
NATIXIS	Netaxis	3.3e+03	2.1e+04	4.3e+02	1.3e+03	3.9e+02	8.6e+02	3.9e+02
CREDIT AGRICOLE	FR014	1.7e+04	4.9e+04	6.6e+02	1.1e+04	1.2e+03	3.9e+03	1.6e+02
JULIUS BAER	Jul. Baer	1.2e+02	3.5e+03	68	0	0	0	57
FRANKLIN TEMPLETON	Franklin Temp.	5.1e+03	9.7e+03	0	0	0	0	5.1e+03
NOVA LJUBLJANSKA BANKA	SI057	1.7e+02	-	20	96	15	26	15
STATE STREET	State St.	51	1.6e+04	0	0	27	0	24
ALLIANZ	Allianz	3.8e+04	1e+05	6.2e+02	2.9e+04	7.5e+02	7.1e+03	4.9e+02
VIENNA INSURANCE	Vienna	93	5e+03	21	13	0	7	52
BANCO POPOLARE - S.C.	IT043	1.2e+04	33	87	1.2e+04	0	2e+02	0
COMMERZBANK AG	DE018	2e+04	2.5e+04	3.1e+03	1.2e+04	9.9e+02	4e+03	32
LEGAL & GENERAL	L&G	3.8e+02	6.3e+03	1.1	3.3e+02	6.6	35	4.4
EFFIBANK	ES063	3e+03	2.7e+03	37	0	16	2.9e+03	0
INTESA SANPAOLO S.P.A	IT040	6.2e+04	6.4e+05	6.2e+02	6e+04	73	8.1e+02	1.1e+02
IRISH LIFE AND PERMANENT	IE039	1.9e+03	3.5e+03	0	0	0	0	1.9e+03
HSBC HOLDINGS PLC	GB089	1.5e+04	1.3e+05	1.3e+03	9.9e+03	1e+03	2e+03	2.9e+02
DANSKE BANK	DK008	1.2e+03	1.3e+05	1	5.8e+02	1.1e+02	1.2e+02	4.1e+02
ROYAL BANK OF SCOTLAND	GB088	1e+04	9.6e+04	1.2e+03	7e+03	2.9e+02	1.5e+03	4.5e+02
BNP PARIBAS	FR013	4.1e+04	8.6e+04	5.2e+03	2.8e+04	2.3e+03	5e+03	6.3e+02
BARCLAYS PLC	GB090	2e+04	8e+04	1.9e+02	9.4e+03	1.4e+03	8.8e+03	5.3e+02
LLOYDS BANKING GROUP PLC	GB091	94	5.8e+04	0	32	0	62	0
DEUTSCHE BANK AG	DE017	1.3e+04	5.5e+04	1.8e+03	7.7e+03	1.8e+02	2.6e+03	5.3e+02
SOCIETE GENERALE	FR016	1.8e+04	5.1e+04	2.8e+03	8.8e+03	9e+02	4.8e+03	9.8e+02
BPCE	FR015	8.5e+03	4.1e+04	1.3e+03	5.4e+03	3.5e+02	1e+03	3.4e+02
BBVA	ES060	6.1e+04	4e+04	1.3e+02	4.2e+03	6.6e+02	5.6e+04	0
BANK OF VALLETTA (BOV)	MT046	24	-	10	3.9	2.8	0	7
BANCO BPI, SA	PT056	5.5e+03	8.2e+02	3.2e+02	9.7e+02	3.9e+03	0	2.8e+02
BANCO SANTANDER S.A.	ES059	5.1e+04	2.6e+04	1.8e+02	7.2e+02	3.7e+03	4.6e+04	0
CAIXA DE AFORROS DE GALICIA,	ES067	4.7e+03	2.3e+04	0.0022	1.6e+02	1.3e+02	4.4e+03	0
CAIXA D'ESTALVIS DE CATALUNYA	ES066	2.8e+03	2.3e+04	0	0	0	2.8e+03	0
CAJA DE AHORROS Y PENSIONES	ES062	3.7e+04	2.2e+04	0	1.3e+03	26	3.5e+04	0
KBC BANK	BE005	7.9e+03	1.7e+04	4.4e+02	5.6e+03	1.6e+02	1.4e+03	2.7e+02
ERSTE BANK GROUP (EBG)	AT001	1.2e+03	1.5e+04	3.5e+02	6e+02	1e+02	1.4e+02	40
JP MORGAN	JPM	17	1.5e+05	0	0	17	0	0
BAYERISCHE LANDESBANK	DE021	1.3e+03	1.4e+04	1.5e+02	5.1e+02	1.1e-05	6.6e+02	20
BFA-BANKIA	ES061	2.5e+04	1.2e+04	55	0	0	2.5e+04	0
SNS BANK NV	NL050	1e+03	5.4e+03	47	7.6e+02	0	57	1.6e+02
RAIFFEISEN BANK (RBI)	AT002	4.6e+02	1.1e+04	1.7	4.5e+02	2.1	3.5	0.00016
DZ BANK AG DT.	DE020	8.7e+03	1.1e+04	7.3e+02	2.7e+03	1e+03	4.2e+03	51
F VAN LANSCHOT	Lanschot	18	7.4e+02	0	0	0	0	18
ALLIED IRISH BANKS PLC	IE037	6.5e+03	1.4e+04	40	8.2e+02	2.4e+02	3.3e+02	5e+03
SKANDINAVISKA ENSKILDA BANKEN	SE085	6.3e+02	1.2e+04	1.2e+02	2.9e+02	1.3e+02	86	0
IBERCAJA	Ibercaja	9.6e+02	2.7e+03	0	0	0	9.6e+02	0
LANDESBANK BADEN-WURT...	DE019	2.8e+03	9.5e+03	7.8e+02	1.4e+03	95	5.4e+02	0
BANCO POPULAR ESPANOL, S.A.	ES064	9.7e+03	9.1e+03	0	2.1e+02	6.4e+02	8.9e+03	0
CAJA ESP. DE INVER. SALAMANCA	ES070	7.6e+03	-	0	0	27	7.6e+03	0
NORDDEUTSCHE LANDESBANK	DE022	2.8e+03	6.5e+03	1.5e+02	1.9e+03	2.6e+02	5e+02	41
BANCA MARCH, S.A.	ES079	1.5e+02	6.5e+03	0	0	0	1.5e+02	0
OP-POHJOLA GROUP	FI012	43	6.2e+03	3.1	0.36	0.00093	0.07	40
BANCO COMERCIAL PORTUGUES,	PT054	7.4e+03	4.4e+03	7.3e+02	50	6.5e+03	0	2.1e+02
BANCO DE SABADELL, S.A.	ES065	7.4e+03	5.9e+03	0	0	91	7.3e+03	38
HYPO REAL ESTATE HOLDING AG,	DE023	1.1e+04	-	0	7.1e+03	4.9e+02	3.4e+03	44

Continued on next page

xName	Code Name	Holdings	Equity	Greece	Italy	Portugal	Spain	Ireland
FRANKLIN ADVISERS INC	Franklin Adv.	3.6e+02	4.7e+02	0	0	0	0	3.6e+02
ABN AMRO BANK NV	NL049	1.5e+03	2.8e+02	0	1.3e+03	0	1.1e+02	1.3e+02
MUENCHENER RV	Munich RV	8.2e+03	2.3e+04	5.8e+02	3.6e+03	4.2e+02	1.9e+03	1.8e+03
HSH NORDBANK AG, HAMBURG	DE025	1e+03	4.8e+03	1e+02	6.6e+02	62	1.8e+02	0
GRUPO BANCA CIVICA	ES071	4.8e+03	-	5.4	0	0	4.7e+03	0
CAIXA GERAL DE DEPOSITOS, SA	PT053	6.8e+03	5.3e+03	51	0	6.5e+03	2e+02	23
CAJA DE AHORROS DEL MEDITER...	ES083	5.6e+03	3.8e+03	0	20	4.8	5.6e+03	15
GRUPO BMN	ES068	3.7e+03	-	0	0	88	3.6e+03	0
BANK OF IRELAND	IE038	5.6e+03	1e+04	0	30	0	0	5.6e+03
DEKABANK	DE028	6e+02	3.3e+03	87	2.7e+02	32	1.8e+02	30
DEXIA	BE004	2.3e+04	3.3e+03	3.5e+03	1.6e+04	1.9e+03	1.5e+03	0.34
GRUPO BBK	ES075	3.1e+03	-	0	0	3	3.1e+03	4
BANKINTER, S.A.	ES069	3.6e+03	3.1e+03	0	1.2	0	3.6e+03	0
WESTLB AG, DUSSELDORF	DE024	2.2e+03	3e+03	3.4e+02	1.1e+03	0	7.5e+02	35
UNIONE DI BANCHE ITALIANE SCPA	IT044	1.1e+04	1.1e+04	25	1.1e+04	0	0	0
CAJA DE AHORROS Y M.P.	ES072	3.3e+03	2.7e+03	0	3.8e+02	0	2.9e+03	0
CAIXA D'ESTALVIS UNIO DE CAIXES	ES076	2.6e+03	-	0	11	0	2.6e+03	13
BANK OF CYPRUS PUBLIC CO	CY007	2.8e+03	2.4e+03	2.4e+03	36	0	58	3.2e+02
LANDESBANK BERLIN AG	DE027	1.1e+03	2.3e+03	4.5e+02	3.3e+02	0	3.7e+02	0.075
ALPHA BANK	GR032	5.5e+03	2e+03	5.5e+03	0	0	0	0
UNICREDIT S.P.A	IT041	5.2e+04	9.3e+05	6.7e+02	4.9e+04	94	1.9e+03	58
MARFIN POPULAR BANK PUBLIC CO	CY006	3.4e+03	1.7e+03	3.4e+03	0	0	0	39
BANCO PASTOR, S.A.	ES074	2.6e+03	1.6e+03	41	1e+02	1.2e+02	2.3e+03	0
GRUPO CAJA3	ES078	1.5e+03	-	0	0	0	1.5e+03	8.4
TT HELLENIC POSTBANK S.A.	GR035	5.3e+03	9.3e+02	5.3e+03	0	0	0	0
EFG EUROBANK ERGASIAS S.A.	GR030	8.9e+03	8.8e+02	8.8e+03	1e+02	0	0	0
ESPIRITO SANTO GROUP,	PT055	3.1e+03	6.2e+03	3.1e+02	0	2.7e+03	55	0
AGRICULTURAL BANK OF GREECE	GR034	7.9e+03	7.5e+02	7.9e+03	0	0	0	0
CAJA DE AHORROS DE VITORIA	ES080	6e+02	-	0	0	0	6e+02	0
ING BANK NV	NL047	1.1e+04	3.5e+04	7.5e+02	7.7e+03	7.6e+02	1.9e+03	92
RABOBANK NEDERLAND	NL048	1.1e+03	-	3.8e+02	4.4e+02	82	1.6e+02	60
WUERTTEMBERGISCHE LV	Wuetter. LV	7.7e+02	1.2e+02	85	4.5e+02	52	1.8e+02	8
NYKREDIT	DK011	1.1e+02	-	22	88	0	0	0
MONTE DE PIEDAD Y CAJA	ES073	3.3e+03	58	6	3.1e+02	0	2.9e+03	0
CAJA DE AHORROS Y M.P.	ES081	6	58	0	0	0	6	0
BANCA MONTE DEI PASCHI DI	IT042	3.3e+04	1.9e+03	8.1	3.2e+04	2e+02	2.8e+02	0
COLONYA - CAIXA D'ESTALVIS DE	ES082	26	-	0	0	0	26	0
BANQUE ET CAISSE D'EPARGNE DE	LU045	2.8e+03	2.9e+03	85	2.4e+03	1.8e+02	1.7e+02	0
PIRAEUS BANK GROUP	GR033	8.2e+03	-1.9e+03	8.2e+03	0	0	0	0
NATIONAL BANK OF GREECE	GR031	1.9e+04	-4.3e+03	1.9e+04	0	0	0	18
ZURICH FINANCIAL	Zurich	8.7e+03	2.5e+04	0	4.2e+03	3.7e+02	3.7e+03	3.7e+02
MITSUI	Mitsui	6.4e+02	6.9e+04	0	3.7e+02	25	1.7e+02	76

Table 3: GIIPS sovereign debt data used in the analysis. All numbers are in million Euros. Our data is based on two sources: 1) The EBA 2011 stress test data, which only includes European banks and funds (the 'Code Name' for these banks is in the form CC123, where the two letters define the country of the bank and the three subsequent numbers stand for the bank code); 2) A list of top 50 global banks, insurance companies and funds with largest exposures to GIIPS debt by end of 2011 provided by S. Battiston (These banks have a name as their 'Code Name'). The list was consolidated by the authors of this manuscript.