

The Changing International Network of Sovereign Debt and Financial Institutions*

Mardi Dungey, John Harvey and Vladimir Volkov
University of Tasmania, Australia

August 2016

Abstract

We develop a theoretical and empirical framework to model the international connections between financial institutions and sovereign debt markets. By allowing for both good and poor returns on the investments of financial institutions in real economy firms and the potential for haircuts in sovereign debt markets we show how shock transmission and the default probabilities of these entities are affected through a network of these institutions. To model the financial network empirically, directional edges are established via Granger causality tests between CDS spreads, while the weights of the edges are obtained from variance decompositions. The empirical framework nests both tests of contagion and changes in the structure of the network itself. The network is found to be "robust but fragile" meaning that either a large enough single shock, or a number of small contemporaneous shocks can result in the propagation of crises. Between 2003 and 2013 for a global model of 67 financial institutions and 40 sovereigns we show that the completeness of the network changes substantially, reflecting changes in both the number and strengths of the links between them. The resulting changes in the probability of default for sovereigns and institutions demonstrate the fragility of the combined system when under stress from alternative sources.

Keywords: network, sovereign debt, financial institutions, systemic risk, contagion

JEL classification:

*We acknowledge funding from Australian Research Council DP 150101716, and CIFR Grant E102. Part of this paper was completed while Dungey was Hallsworth Fellow at the University of Manchester and she is grateful for their hospitality. Corresponding author: Mardi Dungey, School of Economics and Finance, University of Tasmania, Private Bag 85, Hobart, Tasmania 7001, Australia. E-mail: mardi.dungey@utas.edu.au.

1 Introduction

International connections between banks and sovereign debt markets are complex and important for financial and economic stability. However, the nature of the relationship between them, and the direction of influence remains a matter of debate; see for example the discussion in Reinhart and Rogoff (2009) and Kallestrup et al (2016).¹ Theoretical arguments can be made for poor macroeconomic policy weakening the state of the economy and transferring stress to the banking sector. Alternatively an abrupt interruption of private credit growth may weaken the banking market to the point where it requires government support and in turn undermines the creditworthiness of the sovereign. A spiral of weakening banks and weakening sovereign credit may result where banks have significant holdings of sovereign debt. These network effects can then spillover to the real economy; Carvahaló (2010), Acemoglu et al (2012), Anufriev and Panchenko (2015).

This paper develops a theoretical and empirical framework, which analyzes the network of connections between financial institutions and sovereign debt, and particularly focuses on the evidence for changes in the network structure during periods of market stress. The framework provides a mechanism by which ‘robust-but-fragile’ networks may emerge in the face of an unexpected shock to the system through poor investments and/or poor government policies.

Our theoretical model consists of two sectors: financial institutions (banks) and sovereigns. Banks are engaged in capital lending with each other without a requirement to borrow all available funds. Each bank has an opportunity to invest in the real economy with an uncertain return. Financial institutions which choose to retain (some) funds in the sovereign debt market face the risk of a haircut. In this case, both sectors experience a potential underinvestment problem caused by an influence of an external random shock. The volatility of this shock nonlinearly affects the network, and illustrates how the defaults of a

¹Other relevant literature includes Kalbaska and Gatowski (2012), Alter and Schuler (2012), Ureche-Rangau and Burietz (2013), Bruyckere et al (2013).

financial institution and/or sovereign can potentially increase the probability of other entities defaulting.

By generalizing the results of Acemoglu et al (2015) we show that a default of any of the entities, as a function of the unexpected shock, leads to multiple equilibria defined by a collection of mutually consistent payments between entities. To analyze the continuum of equilibria we show how to assess the sensitivity of the counterparty to default. This quantity measures how defaults of counterparties influence the ability of an entity to meet its obligations.

Given the existence of multiple equilibria, systemic default probabilities occur in different scenarios related to normal or poor investment outcomes. In particular; *Good times*, when both real economy returns are good and there are no sovereign defaults in which case the network is relatively robust; *Poor investment*, when real economy returns are poor but there are no sovereign defaults; *Poor government*, when real economy returns are good but poor government policy leads to sovereign bond haircuts, and *Stress conditions*, where both poor real economy returns and sovereign haircuts place stress on the entity network. The first two cases are consistent with the original Acemoglu et al (2015) analysis. These scenarios permit the identification of the efficient equilibrium, which is the state that minimizes the aggregate loss of all creditors.

Empirically we provide evidence on three specific hypotheses about the changing nature of a global network comprising 67 financial sector institutions and 40 sovereigns via the CDS market over the period of 2003 - 2013. Specifically our framework provides evidence for (i) changes in the strength of links between the nodes in a manner consistent with existing tests of contagion (ii) changes in the number of connections between the nodes, that is the network may become more or less dense, as evidenced in existing network literature and (iii) changes in the completeness of the network weighted by the strength of linkages, allowing us to combine the information on both the existence of linkages and their relative importance. We test for these potential changes in the network from September 15, 2008, consistent with global financial crisis initiated with the collapse of Lehman Brothers, and from April 1, 2010, consistent

with the period of the Greek and subsequent sovereign debt crisis in Europe.

The evidence supports a high degree of completeness in the networks between all entities, consistent with the major role played by common factors in Longstaff et al (2011). The empirical framework is based on a network of vertices assessed by Granger-causality tests, see also Billio et al (2012), Merton et al (2013). Drawing on Diebold and Yilmaz (2009, 2014, 2016) and weighting the existence of linkages by their strength, we show that although the number of links may have been increasing across some crisis periods, such as in Billio et al (2012), once these links are weighted by their strength the completeness of the network falls, see also Atil et al (2016) and Fabozzi et al (2016). Although there may be a net increase in the number of linkages, this represents the removal of a large number of stronger linkages and their replacement with a larger number of weaker linkages, resulting in a different network topology between the periods.

Our approach nests tests for contagion into the systemic risk assessment through the removal and formation of new linkages during periods of financial stress. Contagion is defined as the formation of new linkages, such as new commonalities between formerly unrelated assets, see Bekaert et al (2014), Dungey and Martin (2007), or the breakdown of linkages between counterparties (Gai and Kapadia, 2010), and differences in the transmission mechanisms for tail-shocks such as in Boyson et al (2010), Buseti and Harvey (2011). By using the Granger-causality framework we are also methodologically directly tied to the contagion literature, see Longstaff (2010), Marais and Bates (2006), Sander and Kleimeier (2003).²

The evidence for changes in the network structure around the timing of the global financial crisis supports shifts in the relationships between the financial institutions and sovereign debt markets. One form of shift is consistent with both global flight from markets with heavily increased risk during the crisis –

² Acemoglu et al (2015) use the term contagion to denote the transmission of shocks across their networks based on the known lending relationships between the banks. Their usage is more consistent with the spillovers where spillovers are ex-ante known linkages between nodes; contagion is usually used to refer to transmission of shocks beyond that indicated by the usual linkages. See for an overview Dungey et al (2005).

notably source markets from European sovereigns and US financial institutions – represented by the breakdown of linkages in the network. The other form represents the seeking of new markets consistent with a shift in relative risk/return trade-offs globally – specifically notable increased linkages with Asia and Africa – represented by the formation of new links in the network.

The default probabilities calculated for the network in the different phases of the sample clearly illustrate the difficulties inherent in financial regulation. In the period prior to the Lehman Brothers crisis, default probabilities for all entities are relatively low, a large shock is expected to cause only a small number of defaults, and the sovereign network is unlikely to default at all. The default probability of the combined network moderates the default probability of the financial institutions alone. However, in the crisis periods, the default probability of the combined network is higher than that of the financial network, pointing to the feedback effects between the banks and sovereigns. This risk is highest in the second phase of the sample, equivalent to the GFC period, when it is almost ten-fold that of the pre-crisis period. While default risk reduces in the third phase, during the period for the Greek and European sovereign debt crisis, it does not return to previous levels, a feature particularly evident for sovereigns. An immediate practical outcome of these results is to support the calls for regulators to recognize the need for non-zero risk weightings on sovereign debt in bank capital assessment; see Hannoun (2011), and for evidence on the potential importance of the so-called zero risk practice, Korte and Steffen (2015).

The paper proceeds as follows. Section 2 discusses the theoretical framework for modelling a network between financial institutions (banks), real economy firms and sovereign debt. Section 3 explores the data set used for empirical analysis. The econometric methodology for establishing vertices is outlined in Section 4 and Section 5 presents results for our sample of 107 entities (financial institutions and sovereigns). Section 6 concludes.

2 Theoretical Framework

Papers by Gai & Kapadia (2010) and Acemoglu et al (2015) propose a theoretical framework for modelling the networks between banks and simulate the transmission of shocks through banking networks. We extend the framework of Acemoglu et al (2015) to consider that banking network connections are susceptible to potential default by sovereign debt investment. Acemoglu et al (2015) specifically include the possibility that banks do not take full advantage of all possible borrowing options available within their bank counterparty network and instead ‘hoard funds’ as a form of cash reserve. In particular they identify this component of the bank’s portfolio decision as representing investment in sovereign debt providing a standard riskless return, R , and thus acting as cash in their model. Our extension speaks strongly to the outcomes for banking networks when the certainty of the sovereign debt return is thrown into doubt. Specifically, we show that results in Acemoglu et al (2015) for the stability and fragility of banking networks carry over directly to the extended network between sovereign debt markets and banking. We produce evidence of a network between sovereign debt and financial markets that is highly interconnected, demonstrating a robust-yet-fragile structure, Haldane (2009) . This highly interconnected, robust-yet-fragile network is at risk when exposed to a large enough single shock, or enough close to contemporaneous small shocks.

2.1 The model of banks and sovereigns

Banks are in the business of lending for projects with uncertain returns. As in Diamond (1982) banks cannot fund their lending activities from their own balance sheets and need to engage in inter-bank relationships to fund projects. This creates a network of liabilities between the banks where the vertices are determined by the repayments required between pairs of financial institutions. Banking networks become highly interconnected as an individual bank can hold assets and liabilities with any number of other banks in the network as in Allen and Babus (2009).

Consider a risk-neutral bank, operating in a three period time frame as in Acemoglu et al (2015). Each bank has capital to lend, and a pre-determined

individual credit limit with each other bank in the network (this means that the total available loan to bank i from bank j may not match that available to bank j from bank i). No bank is required to borrow the total credit available, but is required to settle all interbank liabilities at each of $t = 1, 2$.

Each bank has the opportunity in period $t = 0$, to take an investment opportunity in the real economy, z_i , where that investment has an uncertain return in period $t = 1$, but a certain, non-pledgable return at $t = 2$. If the bank needs to redeem its investment at $t = 1$ the fraction of loan it may recover is assumed to be small.

Our extension concerns the funds which the bank chooses not to invest. In Acemoglu et al (2015) these funds, denoted c_i , are considered to be equivalent to a sovereign bond, bearing a certain return, R , with no risk. We extend the analysis to consider the case where not only the investment project has an uncertain payoff, but there is also a risk that the sovereign bond may face a haircut. In this case, in period $t = 1$ the values of returns z_i and c_i are influenced by an external shock u_i , which is a random variable drawn from a given distribution with mean zero and variance one and its standard deviation³ is σ_i . The joint probability distribution $p(u_1, \dots, u_n)$ for n entities⁴ is assumed to be known.

Definition 1 *The network G is the pair (N, E) where N is a set of nodes representing the entities (banks or sovereigns) and a set of edges E represents contracts between two entities going from the lender to the borrower.*

After making its investment decisions in the initial period, at time $t = 1$ the financial institution has to settle its counterparty liabilities with other banks in the network, y_j , and meet its unavoidable contractual obligations, such as wages, and required payments to the investment projects, v . We assume that that v is senior to counterparty payments. The resources available to make

³Acemoglu et al (2014) and Glasserman and Young (2015) imply that shocks have a negative impact on returns. In this paper the shock u_i takes value between -1 and 1, which permits positive shocks.

⁴In the following discussion the term entity means bank (financial institution) or sovereign.

these repayments, α_j , consist of the funds the bank placed in sovereign bond investments, c_j , the uncertain first period returns on the investment project, z_j , and repayments it receives from its counterparties, $\sum_{i \neq j} x_{j,i}$.

Define a default indicator d_j , with $d_j = 1$ if entity j defaults at time $t = 1$ and $d_j = 0$ otherwise. If all entities are assume to default, $x_{j,i}(d_j) = 1, \forall i, j$. An entity j defaults if its assets α_j at time $t = 1$ are smaller than total liabilities $l_j = v_j + y_j$. That is the entity will not be able to meet its first period obligations in the case where

$$\alpha_j = c_j + z_j + \sigma_j u_j + \sum_{i \neq j} x_{j,i} < v_j + y_j. \quad (1)$$

The default condition, defined in equation (1), is expressed as a function of the stochastic shock u_j that impacts both sovereign and bank returns⁵, which permits us to rewrite (1) as

$$u_j > \frac{c_j + z_j + \sum_{i \neq j} x_{j,i} - v_j - y_j}{\sigma_j} = q_j, \quad (2)$$

in which q_j defines the threshold value for the shock u_j . If $u_j > q_j$, the shock causes the default of entity j . In this case the sign and the magnitude of the shock u_j has an impact on probability of default of entity j on their obligations, which potentially increases the probability of other entities defaulting. Moreover, this default probability also depends on the volatility of shock σ_j that nonlinearly affects the network, meaning that it is unlikely to be plausible that an absolute threshold value can be established across multiple markets (for example the banking sectors of individual economies) as the variability of the shocks may well vary across different networks.

Equation (2) can be used to express the default condition of n entities in terms of the default indicators d_j as

$$d_j = 1(u_j - q_j), \quad (3)$$

in which 1 denotes the Heaviside step function, which is equal one if the argument is positive and zero otherwise. A solution of the system (3) is represented

⁵This implication is different from Acemoglu et al (2014) who assume that c_j is certain, which means that risk entirely arises from the uncertainty around z_j .

by a vector $\hat{d} = (d_1, \dots, d_n)$.

Definition 2 *An equilibrium is defined by a vector of default indicators $d = (d_1, \dots, d_n)$ that is a solution of equation (3).*

In general a solution of equation (3) can be represented by multiple equilibria, that have two sources. First, the interdependence of the liabilities of entities might imply more than one vector \hat{d} . Second, there can be multiple values of shocks u_j that solve equation (3). While a typical approach in the literature⁶ is to focus on the best-case equilibria, in which as few entities as possible default, we show in the following section that multiplicity of equilibria can be useful for analyzing different scenarios of the changing international network.

As every counterparty can have only two states (default when $d_j = 1$, or not to default, $d_j = 0$), definition 2 implies that q_j for every entity j can take a finite number of values 2^{n_j} , where n_j is the number of counterparties borrowing from entity j . Given that the shock u_j is a random variable taking values on the interval $[-1, 1]$, it is important to identify conditions under which the value of u_j has an impact on the default of entity j .

Proposition 1 *Under the mapping $\tilde{q}_j = \min\{\max\{q_j, -1\}, 1\}$ the default is a function of shock u_j .*

Proposition 1 implies that when $-1 < q_j < 1$, the shock u_j effects the network G . It is not necessary to constrain the values of q_j . This range is of interest when focusing on default scenarios, which is a primary task of this paper. When values of q_j lies outside the interval $[-1, 1]$, the results become independent of the shock u_j .

2.2 Multiple equilibria

The main task now is to identify how the structure of the network leads to unique or multiple solutions of the system (3). As follows from the default condition (2), a collection of mutually consistent payments between entities at

⁶see e.g. Elliott et al. (2014)

$t = 1$ define the structure of the network, which is also defined by the entity's borrowing counterparties' default state. This setting implies that a shock to an entity might not only lead to that entity's default, but may also initiate a cascade of defaults by spreading to its creditors, which permits financial contagion in the system.

Definition 3 A walk P_{j_1, j_k} is a sequence of entities (j_1, \dots, j_k) such that the pairs $(j_1, j_2), (j_2, j_3), \dots, (j_{k-1}, j_k) \in E$ are edges of the network. A walk is closed if the first and the last institution in the sequence are the same, and open if they are different. The length of the walk P_{j_1, j_k} is given by the number of edges k contained in it. A cycle C_n is a closed walk represented by n entities and $n - 1$ edges.

Following the definition 3, in a network of banks and sovereigns, a cycle is an arrangement of contracts that can be represented by a circle in which an entity j borrows from one neighbor and lends to another neighbor.

Definition 4 Sensitivity of entity j to default of counterparty i is

$$scd_{j,i} = \tilde{q}_j(\mathcal{H}_{i=1}^k) - \tilde{q}_j(\mathcal{H}_{i=0}^k), \forall i \neq j \quad (4)$$

in which $\mathcal{H}_{i=1}^k$ is the realization of defaults of k entities subject to $d_i = 1$.

Entity j may also fail if counterparties fail to pay their debts, providing another source of multiple equilibria. An inability to pay is closely related to the sensitivity of counterparties of entity j , as defined in (4). In particular, the sensitivity of counterparties to default measures how the inability of entity j to meet its obligations influences entity i , which implies that more fragile entities have a higher sensitivity to default. The presence of cycles in the network and the dependencies between liabilities of entities are important conditions for generating multiple equilibria, as formalized in the following proposition.

Proposition 2 Consider the network of n institutions with $x_j^d = \sum_{i \neq j} x_{j,i}^d$, in which $x_{j,i}^d$ is amount of money that institution j recovers from the default of

institution i . Suppose that $x_j^d < 1$, unavoidable contractual obligations $v_j > 0$, and shock variance $\sigma_j > 0$ is finite. Multiple equilibria exist if and only if

- (a) a cycle C_k of contracts along $k \geq 2$ institutions exists;
- (b) for each entity in the cycle C_k the sensitivity to default $scd_{j,i} \neq 0$.

The necessary condition (a) in the proposition 2 relates an existence of multiple equilibria to the structure of the network. In particular, the network contains at least two entities with inter-dependent default conditions. The sufficient condition⁷ (b) specifies how the defaults influence entities belonging to the cycle C_k . If for a given shock u_j the default condition of institution j does not change, given borrowing counterparties of j default or not, there are no multiple equilibria for institution j . Formally it means that the realizations \mathcal{H}_j^k are identical for $j = 1$ and $j = 0$.

An important implication of the proposition 2 is that equilibria in the financial network are defined by default indicators d_j , that are dependent on shocks u_j . In fact, condition (b) implies that there is a large shock u_j^* triggering institutions in the cycle C_k . This finding motivates the necessity of incorporating unexpected shocks in the empirical framework, as proposed in the following section. In particular, variance decompositions are used to capture the impact of shocks on the network, thus relating our methodological framework to the approach of Diebold and Yilmaz (2014). Proposition 2 also suggests that an acyclical network, such as a tree, will have a unique equilibrium for all possible realizations of shocks. Moreover, if nodes of a network are represented by only out-going or incoming links, there is only one equilibria. In other words, if entities either only borrow from or only lend money to their counterparties, a continuum of equilibria does not exist; networks need at least one bivariate linkage in order to generate multiple equilibria in this framework.

Definition 5 Given a distribution $p(u)$, the expected number of defaults is represented by $\sum_{i=1}^n scd_{j,i}^2/n$.

⁷If shock $u_j = 0$ for all institutions, the sufficient condition (b) is similar to the unique payment equilibrium condition of Acemoglu et al (2014), which is $\sum_j (z_j + c_j) \neq nv$. This condition restrict banks to default due to "coordination failures".

As follows from definition 5, the expected number of defaults in the network is defined by sensitivity indicators $scd_{j,i}$ aggregated across all entities. This measure not only depends on the size of the realized shocks u_j , but also on the variance of shocks σ_j and the structure of the network. Moreover, the expected number of defaults measure is closely related to a variance decomposition. This result motivates the proposed econometric framework, which will be discussed in the following sections in more detail.

2.3 Systemic default probability

Given the solution of system (3) and a joint probability density function of shocks $p(u)$, following Roukny et al (2016), a systemic default indicator d^{sys} can be defined as

$$d^{sys} = 1_{\{\sum_j d_j \geq n^*\}}, \quad (5)$$

in which n^* is a threshold that defines how many entities initiate systemic default. For example, if $n = n^*$ systemic default is a situation when all entities can not meet their obligations. If there is a unique equilibrium for the default state d , the systemic default probability can be defined as

$$P^{sys} = \int d^{sys}(u)p(u)du, \quad (6)$$

in which d^{sys} is estimated from equation (5) where d is a solution of equation (3). Note that any possible correlation structure across shocks can be incorporated in $p(u)$.

In the case of multiple equilibria the systemic default probability can not be estimated directly from equation (6) as $d^{sys}(u)$ can take several values. However, for a given shock multiple equilibria can be analyzed according to different scenarios that related to different values of q_j defined in equation (2).

If we imagine that different states of nature are related to each of the project investments, z_j , and the sovereigns, c_j , so that in good (or normal) times the bank and sovereign will achieve the standard returns z_j^+ and c_j^+ respectively and in a poor outcome period they will be subject to the haircut, which let them to

receive z_j^- and c_j^- . In this case there are four separate potential scenarios the entity network may face at $t = 1$ in order to meet its liabilities.

Good times: Investments achieve payoff z_j^+ and there are no haircuts in sovereign debt markets. This is equivalent to the good case in Acemoglu et al (2015). Bank networks should function normally - all sources of income are available to meet liabilities.

$$c_j^+ + z_j^+ + \sum_{i \neq j} x_{j,i} \geq v_j + y_j.$$

Stress: Investments do not perform, providing payoff z_j^- , and there is poor performance in the sovereign debt market requiring haircuts, which provides a sovereign with the negative return c_j^- . An entity's incoming counterparty payments need to exceed outside obligations owing due to the investment, the entity's own outgoing counterparty requirements, the loss from investments and the haircut.

$$\sum_{i \neq j} x_{j,i} > v_j + y_j - c_j^- - z_j^-.$$

Poor investment: Investments do not perform, so the bank receives payoff z_j^- . However, sovereign debt markets are performing normally with no haircuts required, which gives c_j^+ . The bank's bond holdings and incoming counterparty payments need to exceed outside obligations owing, the bank's own outgoing counterparty requirements and the loss due to the poor investment outcome. This is equivalent to the bad case in Acemoglu et al (2015).

$$c_j^+ + \sum_{i \neq j} x_{j,i} > v_j + y_j - z_j^-.$$

Poor government: Investments perform well and provide payoff z_j^+ . However there is poor performance in the sovereign debt market entailing negative returns c_j^- . An entity's income from successful investments and incoming counterparty payments need to exceed outside obligations owing due to the investment, the entity's own outgoing counterparty requirements and the haircut.

$$z_j^+ + \sum_{i \neq j} x_{j,i} > v_j + y_j - c_j^-.$$

These scenarios permit estimating the systemic default probability in the case of multiple equilibria. Consider the set $\Omega \supseteq \{I_i \cup I_g \cup I_s\}$ of all possible solutions of equation (3) for a given shock u , in which I_i is a set of equilibria in the poor investment case, I_g is a similar set for the poor government case, and I_s is assigned to the stress scenario. Moreover, for the set Ω the best equilibrium can be defined as $d^{sys}(u) = \inf_{k \in \Omega} d_k^{sys}(u)$, while the worst equilibria is $d^{\overline{sys}}(u) = \sup_{k \in \Omega} d_k^{sys}(u)$. These definitions select the best (worst) solutions according to smallest (largest) number of defaults in the entity network. The systemic default probability in the worst and best scenarios can be defined respectively as

$$P^{sys} = \int d^{sys}(u)p(u)du. \quad (7)$$

$$P^{\overline{sys}} = \int d^{\overline{sys}}(u)p(u)du. \quad (8)$$

Note that if the maximal and minimal values of $P^{\overline{sys}}$ and P^{sys} are received for indices $k_1, k_2 \in I_i$, the systemic default is caused by poor investments from banks, if $k_1, k_2 \in I_g$, the systemic default is related to an unsuccessful governmental policy⁸. When $k_1 \in I_i \cup I_s$ and $k_2 \in I_g \cup I_s$ mixed strategies from sovereigns and institutions are required to minimize the systemic default probability in the entity network.

Given the systemic default probabilities defined for different scenarios, risk on the systemic default probabilities can be defined as

$$RISK = P^{\overline{sys}} - P^{sys}. \quad (9)$$

Risk measure $RISK$, defined in equation (9), defines the uncertainty of systemic default in the presence on multiple equilibria. Quantity $RISK$ depends on the network structure and the returns of banks z_j^\pm and sovereigns c_j^\pm .

⁸Acharya et al. (2014) investigated how government's bailout triggers credit spreads and found a positive relationship between level of government debts and credit risks.

Definition 6 A couple of equilibria $d^* = \{d^{\overline{sys}}(u), d^{sys}(u)\}$ is efficient if and only if $RISK(d^*)$ is the lower bound across all possible equilibria $d^{sys}(u)$.

Due to the fact that the risk measure $RISK$ depends on the network topology, it can be used to identify efficient equilibria (see Definition 6). For the optimistic scenario, when all entities can meet their liabilities and there are no defaults, there exists a trivial solution of system (3) and $RISK = 0$.

On the other hand, the efficient equilibria is the state that minimizes the aggregate loss of all creditors. In particular, given a realization of shocks u_j , losses of creditors, caused by a default of entity j , are equal to the total liabilities l_j . The expected loss from entity j , EL_j , are computed by aggregating loss over the range of shocks in the case where entity j defaults. The total expected systemic losses are

$$EL^{sys} = \int \sum_j l_j d_j(u) p(u) du. \quad (10)$$

Taking into account that several values of expected loss can exist in the case of multiple equilibria, we may analyze different scenarios. Hence, the risk of expected loss can be defined as a difference between highest and lowest expected losses:

$$REL = EL^{\overline{sys}} - EL^{sys}. \quad (11)$$

The efficient equilibria can be identified by minimizing the risk of expected losses REL for a given probability distribution of shocks $p(u)$.

The proposed framework makes very evident how the combination of events in private investment and sovereign debt markets may contribute to placing extra stress on the banking network. A further complication is that there may be less heterogeneity in the sovereign debt market options available to the banks, than the investments. That is, although the failure of a relatively small investment opportunity can cascade and cause financial stress in the Acemoglu et al (2015) model, there are in practice fewer sovereign bond investment opportunities available for banks. Thus, a haircut in the sovereign debt market is likely to cause a common shock to a number of entities simultaneously, providing a

further means of amplifying a crisis via the network. Moreover, the stochastic shock and its variance are important quantities that impact both sovereign and bank returns, and may cause cascades of defaults in the network. This motivates developing a novel econometric framework presented in Section 4.

3 Data and Summary Statistics

This paper explores connections between sovereigns and institutions and changes to this network structure before and over the global financial, Greek debt and European debt crises. Five year CDS are the most issued and traded in this class of asset, and thus the most liquid (Duca and Peltonen 2013, Pan & Singleton 2008, Kalbaska and Gatkowski 2012); data on these contracts were extracted from Markit over the period January 1, 2003 to November 21, 2013. Over the whole time period there are 2842 end of the day CDS spread prices for each sovereign and institution. The combined dataset contains 40 individual sovereigns and 67 institutions, for a total of 107 potential nodes used in the analysis, which are listed in Tables 1 and 2.

The sample is divided into three separate phases; Phase 1 represents the non-crisis period from January 1, 2003 to September 14, 2008. This is typical of the dating conventions used in the literature to separate the pre-crisis and crisis period; see the review of dates extant in the literature in Dungey et al (2015). Phase 2 represents the period from September 15, 2008 to March 31, 2010, consistent with the global financial crisis (GFC) and period following, where the end of March represents the period prior to which the Greek debt crisis became critical in April 2010. In this way the final period, Phase 3, from April 1, 2010 to November 21, 2013 represents the period of the Greek and European sovereign debt crisis.

The first panel of Table 3 shows summary statistics for Phase 1. Phase 1 is the longest of the three exogenously chosen time periods, containing 1488 observations per entity. Latin America displays a higher mean spread during period 1, while financial institutions and insurance companies exhibit relatively

higher kurtosis than other groups.

The GFC crisis period is the shortest of the sub-sample periods with 403 observations. There is an increase in the mean spreads for most groups of institutions and sovereigns, reflecting the perceived increase of risk during this turbulent period in international debt markets. The financial institution group has the largest mean, standard deviation and kurtosis of all groups during period two.

The third Phase, associated with the Greek debt crisis and subsequent spread to the European debt crisis involves a small drop in spread means for this time period, however the Euro zone group spread means increase from period two, potentially due to the transformation of the Greek debt crisis into the European debt crisis during the third period. Insurance companies and Latin American sovereigns exhibit high levels of kurtosis comparing with other groups.

4 Econometric Framework and Hypotheses

4.1 Establishing network edges via Granger causality

The banks and sovereign debt issuers form the nodes of the network that are linked by edges. We use Granger-causality tests on CDS spreads to establish edges between these nodes. The Granger-causality test approach has a number of advantages in this framework. It is directly comparable with the existing empirical networks of Billio et al (2012) and Merton et al (2013). It establishes directional edges, allowing for an examination of the hypothesis that causation runs from sovereign debt to banking markets. It also maps clearly to the existing empirical frameworks for measuring and testing contagion during financial crises via the formation and breaking of linkages (the overarching framework for this is provided in Dungey et al., 2005).

Consider a standard Granger causality test between Y_1 and Y_2 ,

$$\begin{aligned}
Y_{1,t} &= \phi_{10} + \sum_{i=1}^k \phi_{11,i} Y_{1,t-i} + \sum_{i=1}^k \phi_{12,i} Y_{2,t-i} + \varepsilon_{1,t} \\
Y_{2,t} &= \phi_{20} + \sum_{i=1}^k \phi_{21,i} Y_{1,t-i} + \sum_{i=1}^k \phi_{22,i} Y_{2,t-i} + \varepsilon_{2,t}
\end{aligned}$$

where k is the number of lags and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the disturbance terms.

Equivalently

$$Y_t = \Phi_L Y(L) + \varepsilon_t$$

where $Y_t = [Y_{1,t} \ Y_{2,t}]'$.

The empirical contagion literature typically focusses on changes in the structure of the very shortest period relationships across two periods. Consider for example, the first period interaction matrix estimated for a non-crisis period, denoted Φ_1^{nc} , and a crisis period, denoted Φ_1^{cr} as follows:

$$\begin{aligned}
\Phi_1^{nc} &= \begin{bmatrix} \phi_{11,1}^{nc} & \phi_{12,1}^{nc} \\ \phi_{21,1}^{nc} & \phi_{22,1}^{nc} \end{bmatrix}, \\
\Phi_1^{cr} &= \begin{bmatrix} \phi_{11,1}^{cr} & \phi_{12,1}^{cr} \\ \phi_{21,1}^{cr} & \phi_{22,1}^{cr} \end{bmatrix}.
\end{aligned}$$

Tests for changes in the network finance literature (and related tests for contagion) can be characterized as tests of whether $\phi_{12,k}^{nc} = \phi_{12,k}^{cr}$ and $\phi_{21,k}^{nc} = \phi_{21,k}^{cr}$ for all k .

In this paper the focus is on the formation of new links:

$$\text{new link from } Y_1 \text{ to } Y_2 \quad H_0 : \phi_{21,k}^{j-1} = 0; \phi_{21,k}^j \neq 0 \quad (12)$$

$$\text{new link from } Y_2 \text{ to } Y_1 \quad H_0 : \phi_{12,k}^{j-1} = 0; \phi_{12,k}^j \neq 0 \quad (13)$$

and the breaking of existing links

$$\text{broken link from } Y_1 \text{ to } Y_2 \quad H_0 : \phi_{21,k}^{j-1} \neq 0; \phi_{21,k}^j = 0 \quad (14)$$

$$\text{broken link from } Y_2 \text{ to } Y_1 \quad H_0 : \phi_{12,k}^{j-1} \neq 0; \phi_{12,k}^j = 0 \quad (15)$$

where index j is assigned to the phase, which is non-crisis, the GFC or the European sovereign debt crisis.

Results of the Wald test indicating Granger causality are recorded as binary entries in matrix A as

$$A = [a_{ij}],$$

where,

$$a_{ij} = \begin{cases} 0, & \text{if } Y_i \text{ does not Granger cause } Y_j \\ 1, & \text{if spread } Y_i \text{ Granger causes } Y_j \end{cases}$$

Matrix A is used to construct the directional edges between sovereigns and banks.

The CDS spread data used to motivate the Granger-causality testing is effectively a premium for an insurance policy against the default of a third party. The price of a CDS spread reflects the market's perceived risk of default; favorable news decreases the value of the CDS spread, while unfavorable news increases the value. When a significant Granger-causality link exists from entity i to entity j , this indicates that Y_i has at least one significant lag in predicting the value of Y_j . So the perceived risk of entity i defaulting predicts the perceived risk of default of entity j . The edges of the network constructed from these Granger causality links show the predictors of each node's perceived risk of default.

CDS spreads were found to be non-stationary with a maximum of one unit root according to KPSS and ADF tests. When the series are $I(1)$, Wald test statistics do not follow an asymptotic chi-squared distribution and consequently Todo and Yamamoto's (1995) correction for the Wald statistic distribution was implemented. Bivariate VARs are estimated using five lags, based on AIC information criterion, with the inclusion of an additional lag, accounting for the maximum level of integration found. The standard Wald test is performed using results from the VAR(6), but excluding all associated coefficients and variance covariance estimates of the additional (sixth) lag.

4.2 Network connectedness

Once the linkages between the banks and sovereigns, represented by the matrix A , are established, the strength of these linkages can be quantified assigning weights $W = [w_{ij}]$ to edges of the network⁹. Using as an approximating model VAR from the previous section¹⁰, weights w_{ij} can be obtained from variance decompositions, as proposed by Diebold and Yilmaz (2009). Suppose that j 's contribution to entity i 's H -step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, is

$$\theta_{ij}^g(H) = \frac{V_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h V e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h V B_h' e_j)}, \quad H = 1, 2, 3, \dots,$$

in which V is the variance covariance matrix for the error vector ε_t , V_{jj} is the standard deviation of the error term j and e_i is the selection vector with one as the i th element and zero otherwise. The coefficient matrices B_i obey the recursion $B_i = \Phi_1 B_{i-1} + \Phi_2 B_{i-2} + \dots + \Phi_k B_{i-k}$, with B_0 an $n \times n$ identity matrix and $B_i = 0$ for $i < 0$. Note that the generalized variance decomposition allows for correlated shocks and does not depend on the ordering of the variables.

In the original generalized framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), the variance shares do not necessarily add to 1, that is $\sum_{j=1}^n \theta_{ij}^g(H) \neq 1$. Hence each entry of the generalized variance decomposition matrix is normalized by the row sum as

$$w_{ij} = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^n \theta_{ij}^g(H)}.$$

Now by construction $\sum_{j=1}^n w_{ij} = 1$ and $\sum_{i,j=1}^n w_{ij} = n$.

Given the estimates of the matrix A and the weighting matrix W ¹¹, the structure of the weighted network can be characterized by the matrix

$$\tilde{A} = A \odot W,$$

where \odot is the Hadamard product. The elements of the adjacency matrix \tilde{A} capture connectedness between the banks and sovereigns conditional on the sig-

⁹In this case the network is defined as a weighted directed graph. A weighted financial network was also used by Demirer, Diebold, Liu and Yilmaz (2015) and Glasserman and Young (2015) for modelling connectedness between financial institutions.

¹⁰If yield spread series are cointegrated a respective VECM is used.

¹¹The matrix W is not necessarily symmetric, which is different from the partial correlation network of Anufriev and Panchenko (2015) that is symmetric by construction.

nificant casual linkages between them¹². The network defined by the adjacency matrix \tilde{A} shows the predictors of risk of default subject to a shock captured by the matrix W . Using the entries of the matrix \tilde{A} , system-wide completeness is measured as

$$C = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^n \tilde{a}_{ij}}{\sum_{\substack{i,j=1 \\ i \neq j}}^n w_{ij}}. \quad (16)$$

This measure is used in the following sections to analyze a system-wide connectedness between the financial institutions and sovereigns¹³. The proposed econometric framework permits us to formalize the following empirical hypotheses.

Hypothesis 1 *The strength of links between nodes change during periods of stress. This hypothesis relates to the test of whether new links form or links are removed due to the forces of contagion described in equations (12) to (15).*

Hypothesis 2 *The number of links changes during a period of stress. This test is compatible with the results in papers such as Billio et al (2012) who observe that networks increase in density during stressful periods.*

Hypothesis 3 *The completeness of the weighted network increases during stressful periods. This hypothesis will distinguish the results of the role of both changing numbers and strength of linkages to determine whether networks are in fact more intertwined during periods of stress.*

Formally, we use the results from the Granger Causality tests in each sub-period between each of the nodes to assess whether the strength of the links between nodes has changed. Given the estimates of matrices A and \tilde{A} , hypotheses 1 and 2 can be tested formally applying the statistical test of Mantel (1967).

¹²This approach extends a spillover index of Diebold and Yilmaz (2009). While the spillover index contains all elements of a variance decomposition matrix, here the elements that are not linked causally are equal to zero. The importance of disentangling the network strength from the network structure was also highlighted by Scida (2015) in the different context.

¹³The completeness measure can be computed for sub-networks (e.g. completeness of a specific geographical region) in the same way by summing up the specific elements a_{ij} and w_{ij} .

The null hypothesis is that the networks in the two different phases are identical, which can be tested using the following statistic

$$\tilde{Z} = \sum_{\substack{i,k=1 \\ i \neq k}}^n \tilde{a}_{ik}^j \tilde{a}_{ik}^{j-1} \quad \text{for Hypothesis 1,} \quad (17)$$

$$Z = \sum_{\substack{i,k=1 \\ i \neq k}}^n a_{ik}^j a_{ik}^{j-1} \quad \text{for Hypothesis 2,} \quad (18)$$

in which index $j > 1$ is assigned to the phase. The null distribution of Z or \tilde{Z} is obtained by a finite population approach outlined by Mantel (1967).

5 Results

To illustrate the degree of connectivity in the sovereign debt network, Figure 1 represents the weighted network of significant Granger causality links between pairs of sovereigns in Phase 1. This network is extremely dense, and in fact it is almost impossible to make any meaningful analysis of these results other than confirming the high degree of connectivity in these markets. (Note that these networks include the US as a possible node - to counter the possibility that a common market factor is driving our result we conducted the same analysis using the US returns as a control variate in the Granger causality tests with no discernible difference in the results. Consequently we analyze the specification including the US as a node to provide a comparable analysis for all geographic sources of connectivity.) The high level of connectedness is consistent with the discovery of a major common global factor in CDS spreads in Longstaff et al (2011), Eichengreen et al (2012). Due to the difficulty of analysis of these highly interconnected nodes, we do not present the comparable network for the 67 financial institutions or the combined network between them. In both cases, however the degree of connectivity in the networks is relatively high - where the potential number of links is $40!/38!(=1560)$ in the sovereign bonds network and $67!/65!(=4355)$ links in the financial sector network, and comparably $107!/105!(=11342)$ in the combined network.

We consider first the results for the smaller sovereign debt network, then the banking network and finally the combination of the two. For brevity we record first that in each case Hypotheses 1 and 2 are rejected by the empirical tests at standard significance levels - there is no evidence that the networks are unchanged between the different Phases of the sample period.

5.1 Sovereign debt network

To aid analytical tractability we condense the network shown in Figure 1 to geographical nodes. We nominate six nodes with their constituent members as shown in Table 2.¹⁴

Figure 2 presents the same information as Figure 1 using the geographical regions as nodes and displaying the same high degree of completeness. The width and shade of vertices indicate the strength of link between two nodes representing the proportion of significant linkages amongst the available linkages as explained in Sections 4.1 and 4.2. Figure 2 illustrates the strength of the links involving North America and the Euro Area, while the links to Latin America and Africa are less strong. Arrows on the ends of edges provide evidence on the direction of transmissions - where all the evidence suggests bidirectional linkages.

Connectedness results for the sovereign network in each Phase of the sample are presented in Table 4. In particular, measures of the average strength of the links present for the given network, the number of links present and the corresponding completeness statistic from the weighted network are reported. The sovereigns-only network results are presented in the first panel of Table 4. During Phase 1, 896 of the possible 1560 links are statistically significant with average weight of 0.0297, corresponding to completeness of 72.30%. The completeness rises to 73.41% in Phase 2 as the net number of links increases to 953 at a lower average weight. In this case there are both more linkages in the Phase 2 than Phase 1 and the average weight of the links is decreased,

¹⁴A number of papers consider the detailed relationships for CDS within these regions. For example Fabozzi et al (2016) for the Euro Area.

confirming hypotheses 1 and 2. Table 4 shows that the change in linkages is made up of 342 new connections between the two Phases, and 285 removed connections. On average the removed connections are stronger than the new connections. Here, while the average strength of the new links is weaker relative to the removed links, the number of links increases, which overall increases the completeness of this network consistent with evidence of both contagion as in hypothesis 1 and increased network density in much of the existing literature. However, this turns out to be the exception in our empirical results.

The four panels in Figure 3 represent the changes between the phases of the sample. Figures 3 (a) and (c) represent the changes in links between sovereigns which were removed and formed in the transition between Phase 1, the non-crisis period, and Phase 2, the first stage of the crisis. Figure (a) shows the majority of removed links disconnected the European market as the driving force for default probabilities in other markets, that is the arrows on the vertices predominantly point away from the European node supporting that European conditions were no longer driving the risk assessment of sovereigns in other countries in the second Phase of the crisis. In this sense the role of Europe as a centre of world financial markets was somewhat reduced. There is lesser evidence of disconnections between the geographical nodes which were less involved in this Phase of the crisis, such as Latin America and Africa. Moreover, there is no evidence of a reduction in the number of linkages between the North America sovereigns and those of Asia, Europe, and Latin America.¹⁵

Although in the transition from Phase 1 to Phase 2 we have previously recorded that there is a net gain in completeness and the number and average weight of the links, the location of the formed linkages provide a contrast to the removed links; Latin American sovereigns show evidence of a new role where their risk spreads are influential to others in a way that was not previously evident, with new links formed from Latin America to Asia, Africa, and North America, showing that this region has a growing influence on the global financial

¹⁵For an analysis on decoupling of sovereign CDS markets in a different framework see Dooley and Hutchison (2009).

markets for credit default. The African node also forms new linkages with other nodes, with the exception only of the Euro area. Potentially this emergence of influence from some of the least developed financial regions is evidence of a shift in the entirety of global risk assessment, and potentially represents prior massive underestimation of default risk in the more developed markets.

Figure 3, panels (b) and (d) turn to the issue of changing links between Phase 2 and Phase 3, that is the GFC crisis to the Greek and European sovereign debt crisis. In the move from Phase 2 to Phase 3, Table 4 documents that the number of linkages increases again to 997. However, this is comprised of 354 new links which are on average weaker (0.0207) than the 310 links which were removed (0.0303). The net effect of this is that the completeness of the weighted network of sovereigns declines further between Phases 2 and 3, supporting hypothesis 3. This evidence is consistent with the existing literature on the relatively weak contagion effects in European CDS market in Dungey and Renault (2016) but the increasing density of the network of unweighted links; other papers with consistent results for this market include Atil et al (2016), Fabrozzi et al (2016), and Caporin et al (2014). It is the combination of both strength and number of links which contribute to the fragility of the system. Over these phases there is a net gain of 44 connections – leaving Phase 3 of the sample with 101 more connections than in Phase 1. As noted previously the weighted network figures given in Table 4 show that the removal of weighted linkages was greater than the gain, even though the actual count of linkages increased. This feature explains why the weighted network approach provides a slightly different outcome from existing literature such as Billio et al (2012) where completeness relates to an unweighted network.

Figure 3 (b) shows the removed links between Phase 2 and 3, with very strong evidence that Africa is no longer a leader for Latin American - representing an unpicking of links that were formed between Phase 1 and Phase 2. A similar outcome applies for the European area, where a number of previously existing links to Europe disconnect, as is seen by the existence of vertices with arrows pointing towards both the Euro Area and non-euro Europe sovereign

CDS markets in Figure 3(b). North America takes an opportunity to disconnect somewhat from both Asia and Europe and no longer receives links from Latin America. As follows from Figure 3 (d), Asian markets remain on net more connected in Phase 3 than in Phase 2 (or indeed Phase 1) - there is strong growth in the connections between Asia and the Euro Area, and in the driving effects of North America to Asia and Latin America.

These schematics are very informative in thinking about the changing global financial scenery. Links which break between the two periods (panels (a) and (b) of Figure 3), show that the countries primarily associated with the crisis events of 2008-2013 become more isolated from the global financial network - a large proportion of the broken linkages concern interactions with the US and Euro Area sovereigns. The links which form, depicted in Figure 3 (c) and (d), show new markets becoming more globally important. The rise of Africa and Asia is pronounced. In the fuller exposition of the model which follows, where banking and sovereigns are intertwined the role of financial institutions in seeking new markets becomes apparent in this result¹⁶.

5.2 Financial Institutions network

The 67 financial institutions in our sample are grouped into institutional types, categorized as banks, insurance companies, investment banks, real estate firms and other financial institutions, with the constituents of each group shown in Table 1. The dispersion of these institutions by country is not conducive to undertaking a geographic-institutional breakdown, but given that we are dealing with institutions with sufficient market power to be involved in the CDS market we make the relatively safe assumption that these institutions are globally active investors¹⁷. These institutions may invest in almost any sovereign debt market, may be involved in cross-border counterparty arrangements, and have sophis-

¹⁶The figures for connections which are retained or newly formed between Phase 1 and Phase 3 support the analysis provided and are omitted for brevity. They are available from the authors on request.

¹⁷An analysis of the changing connections between financial institutions in Europe and the US using equity market data may be found in Diebold and Yilmaz (2016) and for global banks in Demirer et al (2015).

ticated currency hedging mechanisms in place. A limitation of our approach is the possibility of home bias or incomplete currency hedging may distort the results.

Table 4 documents that 3750 of the potential 4355 links exist in Phase 1, and this decreases in Phase 2 confirming hypothesis 2. Between Phase 1 and Phase 2, the net reduction in links is due to the loss of 1674 links, overwhelming the formation of the slightly stronger 292 new links. Thus between Phases 1 and 2, the completeness of the weighted network of financial institutions falls from 94.35% to 56.87%. Between Phase 1 and Phase 2, and the further removal of 707 (stronger) links and formation of 1028 (weaker) links between Phase 2 and Phase 3 means that the net gain of 321 links also results in a fall in overall completeness of the weighted network to 26.47%. Overall the network in Phase 3 has 1061 links fewer than in Phase 1, and the average strength of these links has fallen. This important finding confirms the fragility of the financial sector during the GFC, see also Alter and Shuler (2012).

Figure 4 illustrates the location and strength of the newly formed and removed linkages between each Phase. There is a relatively evenly distributed reduction in links between the financial institution nodes between Phase 1 and Phase 2, reflecting the general conditions in the market, rather than a specific institutional type common to the entire global sample. There is a removal of links between banking institutions and real estate, reflecting the unravelling of the strong connections between the real estate markets and the banking sector prior to September 2008, the link which many hold as responsible as the root cause of the crisis via the residential mortgage backed securities market. See also Eichengreen et al (2012) who find spillovers from US to European banks decrease during the GFC period.

However, between Phase 2 and Phase 3 there is clear evidence of disconnection between investment firms and financial companies. Both banks and insurers are the focus of a substantial number of disconnections over the crisis. This may reflect that by this point in the sample new international risk assessments and domestic regulatory environments were put in place to ensure that insurance

companies are also recognized for their potential contribution to systemic risk. The systemic riskiness and regulatory approaches to insurance have been hotly debated; insurers favour the view of self-regulation and insurance as a recipient of shocks from banks, see Cummins and Weiss (2014) for empirical evidence, in contrast to the view from the Financial Stability Board and Acharya et al (2014) that insurers may have an important role to play in propagating systemic risk. Insurers also reduce their linkages with investments companies in both parts of the sample.

As a proportion of the total links, there are relatively few new links forming during Phase 2. As institutions attempt to manage their portfolios, and risk appetite generally decreases, the financial system becomes less interconnected than previously. Regulatory policy may well be a contributing factor here. Regulators around the globe have surveyed financial institutions much more carefully since 2008, and many new bodies have been set up to address particular segments of the financial sector.

5.3 Combined financial institutions and sovereign debt network

The combined financial institutions and sovereign network has potentially 107!/105! (=11342) links. The number of links existing in Phase 1 is 8217, which declines to 6202 in Phase 2 and recovers somewhat to 6943 in Phase 3; see Table 4. The intertwining of these two sectors is relatively complete in the pre-crisis period (at 82.03%) with a high number of linkages, but drops substantially during the crisis samples. In this manner the Phase 1 network is robust in the terms of Gai and Kapadia (2010) and Acemoglu et al (2015), but the crisis periods also reflect the reduction in linkages found in Caporin et al (2014). The numbers of links which change in these networks seems relatively large, but needs to be seen in the context of the total numbers of links; in total 4452 (39.25% of all possible links) were unchanged in the unweighted network during the sample, 3425 (30.20%) links remained present and intact, and 1027 (9.05%) links did not exist at any point in the sample. However, between Phase 1 and Phase 2,

the network lost 3601 links and gained 1586, a net loss of 2015. The average strength of the formed links in the weighted network was 0.0082, weaker than the lost links of 0.0094. In the transition from Phase 2 to Phase 3, a further 1948 links, of average strength 0.0097, were lost and 2689 formed, of average strength 0.0051, a net gain of 741 links which were of lower average strength than those lost, so that overall the number of links in the system fell and in the weighted network completeness also fell.

Not only do the proportions of links change between the phases, supporting hypothesis 2, but the taxonomy of these changes is highly revealing. Categorizing the nodes into geographic sovereign debt markets and financial institution types as used in the analysis of the previous sub-sections, Figure 5 provides the schematic for the links which are broken and formed between Phases 1 and 2, and Phase 2 and 3.

The results show that the CDS premia for financial institutions became disconnected from US and Euro zone sovereign debt CDS premia during the first phase of the crisis; Figure 5(a). The darkest lines are associated with the connections between the US and Euro sovereign nodes. This is particularly pronounced for the real estate and investment sectors. The disconnection from financial companies, and to a slightly lesser extent insurance and banks is evident in the links to Euro Area sovereigns. In the US, however, there is less evidence of disconnection between the CDS premia of the banks and sovereign debt, perhaps speaking to the intimate connection that US sovereign debt has with the balance sheet of banks, the operations of the US Federal Reserve in providing liquidity, and the feedback effects between sovereigns and banks posited in Acharya et al (2014). Relatively few links are formed between Phase 1 and Phase 2, shown in Figure 5 (c). The most pronounced is the new link from Investment markets to Euro, and Latin America to North America and Africa already noted in Section 5.1. There are new formations to Africa from the European companies also, suggesting the rising importance of Africa in global risk determination in this phase.

During Phase 3 of the sample, the links which were established between

North America, Africa and Latin America sovereigns are largely undone as in the analysis of the sovereigns only network, Figure 5(b). There is less evidence of retraction of these links with the financial sector nodes, although the reduction of the financials link, for instance is relatively strong. Newly formed links in this period, shown in Figure 5(d), relate to the Euro zone and North America, particularly reflecting new influences to real estate and financial institutions from North American entities. This likely reflects the increasing evidence at this time of the involvement of key financial institutions from outside Europe in these markets, such as Goldman Sachs and Metlife, as well as the exposure of feedback effects between sovereign debt markets and banks (and by extension the financial sector) as the write-down of assets, increased premia and regulatory focus on the exposure to sovereign debt came under scrutiny.

The combined network is characterized by the highest completeness during the non-crisis Phase 1, mainly originating from the financial institutions. Moreover, the net number of new links is negative for Phases 2 and 3, in contrast to the results reported by Diebold and Yilmaz (2014) who show that system-wide connectedness is significantly higher during the global financial crisis. This difference might be explained by their inclusion in the spill-over index all elements of a variance decomposition matrix, while in this paper the elements that are represented by zero values of a_{ij} are not taken into account. The difference between our work and other existing network papers based on Granger causality is the use of a weighted networks, we reveal that in some cases although the number of unweighted links may increase during crisis, when the links are weighted by their relative strength the completeness of the network falls. Caporin et al (2014) also find a reduction in connectedness in a period equivalent to the third Phase.

5.4 Identifying the financial networks

In the previous discussion it has been found that the sensitivity of sovereigns and banks is a key characteristic for identifying the structure of the network. Following definition 5, the sensitivity of entities defines the expected number

of defaults in the network, which in turn can be used to uncover the network structure. Clearly, the sensitivity of a counterparty to default indicator $scd_{j,i}$ from equation (4) is closely related to an impulse response function. If the direction of shock u is positively correlated with the number of defaults, measured by vector d , impulse responses can be used as empirical measures of $scd_{j,i}$. In this case, the expected number of defaults can be estimated from significant Granger-causality linkages and respective variance decompositions as discussed in Section 4.

The expected number of defaults for the sovereign, financial institutions, and combined networks conditional on the size of the shock u are presented in Figure 6. Figure 6 (a) shows that during Phase 1 the bank and combined networks have similar patterns; a shock of size 3 standard deviations causes more than 2 expected defaults. In the first phase the sovereign network is quite robust and does not default even in the face of the relatively larger shocks. During Phase 2 all three networks become very sensitive to unexpected shocks, i.e. even a shock of size 2 standard deviations stimulates more than 5 entities to default in each of these networks. In the third Phase (European debt crisis) the sovereign network is less resilient to the shock compared with the first phase. The combined network is most fragile of the three examined in crisis phase 3. These results shed light on debate in the literature about whether bank or sovereign default precede each other in an orderly manner - the results of this work suggest that it is the intertwining of these markets which provides increased protection against financial fragility.

The empirical work of this paper provide strong evidence of the changing strength of linkages between nodes in the financial institutions and sovereigns network during periods of stress, consistent with the existence of contagion as in hypothesis 1. The number of nodes changes, increasing the density of the unweighted sovereign network, consistent with findings in the existing literature and supporting hypothesis 2. The completeness of the weighted network, however, decreases in the majority of cases examined here. Between Phase 1 and Phase 2 this reflects the sheer reduction in the number of linkages in the system

in the combined and financial institutions networks, while between Phases 2 and 3 the formed linkages are in the majority but are sufficiently weaker than broken links to result in reduced completeness. Thus our evidence suggests that in these examples completeness has been reduced for all networks examined except the network for sovereigns only between Phase 1 and 2 (where arguably this does not represent crisis conditions for sovereign debt markets). The changing completeness of the institutional, sovereign and combined networks in the different phases represent changes in the structure and combination of what Acemoglu et al (2014) classify as a γ -convex combination of networks.

6 Conclusion

This paper investigates international connections between financial institutions and sovereign debt markets with both a theoretical framework and empirically tractable implementation. We extend the model of Acemoglu et al (2015) which shows how financial institutions facing shocks generated from their real economy firm investments may demonstrate a robust-but-fragile network subject to increased risk of default when faced with either a sufficiently large shock (or with coincidentally contemporaneous small ones). Our innovation is to extend uncertainty around return to the sovereign bond markets as the alternative investment option to the risk modelled for the real economy investments. By including potential haircuts on sovereign debt investment we address the debate on the importance of the links between financial institutions and sovereign debt during crisis conditions.

The results reinforce the ‘robust-but-fragile’ nature of financial institutions networks facing shocks from the real economy and emphasize that haircuts in the sovereign debt market may additionally cause a shock to a number of institutions simultaneously, providing a further means of amplifying uncertainty via the network. This uncertainty implies different scenarios for changes in the financial network: *Good times*, when both real economy returns are good and there are no sovereign defaults in which case the network is relatively robust;

Poor investment, when real economy returns are poor but there are no sovereign defaults, consistent with the potential for stress under the ‘robust-but-fragile’ analysis of Acemoglu et al (2015); *Poor government*, when real economy returns are good but poor government policy leads to sovereign bond haircuts, as these may also lead to financial system fragility, and *Stress conditions*, where both poor real economy returns and sovereign haircuts place stress on the financial network. These scenarios permit identifying the sources of changes of the systemic default probability in the network.

The paper specifically examines the transition of a combined sovereign and financial institutions network for 2003-2014 through three phases. In the transition between Phase 1 representing non-crisis conditions and Phase 2, which corresponds with the sub-prime crisis period, the network shows significant evidence of changing linkages between nodes - with both the removal of existing links and the formation of new ones consistent with the contagion literature. Between Phases 1 and 2 the net number of links falls, so that although on average the number of newly formed links is larger than those which have been removed, the sheer loss of linkages is enough to reduce the completeness of the weighted network falls. Between Phases 2 and 3, corresponding to the European sovereign debt crisis, the number of linkages increases, consistent with the greater density of links observed in much existing work on financial networks during periods of crisis. However, this increase masks changes in the strength of these links. On average the newly formed links are weaker than those which have been removed, resulting in a reduction in the completeness of the weighted network. Unpacking the strength and changing existence of linkages between the nodes reveals that the completeness of the weighted network may fall in a way which is consistent with both the existence of contagion and of increasing numbers of links. It provides confirmatory evidence of the robust but fragile nature of the network during the periods of crisis.

Examining changes in the networks by geographical region and type of institution reveal that during the transition from the pre-crisis Phase 1 to Phase 2 of the global financial crisis, there is a significant removal of links, which mainly

centers around Euro zone, North America, financial institutions, banks and real estate institutions. This is in line with expectations, as the GFC was closely linked to the sub-prime mortgage collapse in the USA. In the transition from Phase 2 to Phase 3, the period of the Greek/European debt crisis, most of the changes in links are centered around the Euro zone. A large number of links are formed from Euro zone to real estate institutions, and to Asian sovereigns.

The next step in this agenda is to test for evidence of key links between the two networks in terms of δ -dependency, Acemoglu et al (2014), which identifies whether there are critical sets of links which influence the financial fragility of the system.

7 Appendix

7.1 Proofs

Proof of Proposition 1 .

This trivially follows from the definition of $\tilde{q}_j: (-\infty, +\infty) \rightarrow [-1, 1]$.

Proof of Proposition 2. **Condition (a)**

Suppose that the network G does not contain any cycles. In this case the set of all nodes is

$$N = \{N_l \cup N_b\}, \tag{19}$$

$$\emptyset = \{N_l \cap N_b\}, \tag{20}$$

in which N_b contains entities that only borrows money from their counterparties and N_l is a set of lenders. If entities from N_b do not lend to anyone, for any realization of shock u there exists a unique threshold value \tilde{q}_j^* for all $j \in N_b$. Therefore, the set N_l contains all creditors of entities from the set N_b . The default conditions for all $i \in N_l$ are determined by the borrowers, and for this reason also unique. This implies that an existence of continuum of equilibria is only possible when there is at least one entity that lends and borrows money simultaneously, which contradicts (20). Hence, multiple equilibria can exist only in the cyclical network.

Condition (b)

Assume that there exists at least one cycle C_k in the network G . It is sufficient to show that for a specific realization of shock u the network G has at least two equilibria. Consider the sensitivity to default measure $scd_{k,k-1}$ defined in (4). If $scd_{k,k-1} \neq 0$ then there exists a non-empty interval

$$[a_i; b_i] = [\min(\tilde{q}_k(d_{k-1} = 0), \tilde{q}_k(d_{k-1} = 1)); \max(\tilde{q}_k(d_{k-1} = 0), \tilde{q}_k(d_{k-1} = 1))],$$

which implies the different values for the default conditions.

Consider two vectors of payments $(\hat{x}_1, \dots, \hat{x}_k)$ and $(\bar{x}_1, \dots, \bar{x}_k)$, that are associated with the threshold values

$$\begin{aligned} \tilde{q}_1(x_1 = \hat{x}_1) &= a_1 \\ &\dots = \\ \tilde{q}_k(x_k = \hat{x}_k) &= a_k \end{aligned}$$

and

$$\begin{aligned} \tilde{q}_1(x_1 = \bar{x}_1) &= b_1 \\ &\dots = \\ \tilde{q}_k(x_k = \bar{x}_k) &= b_k \end{aligned}$$

In this case each of k entities are linked by mutual liabilities. However, in this case shock u_i takes values on the interval $[a_i; b_i]$, which implies two equilibria, \hat{d} and \bar{d} .

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Table 1: Financial institutions grouped by broad type.

Banks	Financials	Insurance
Aust & New Zld Bkg	ACOM CO LTD	ACE Ltd
Amern Express Co	John Deere Cap Corp	Aegon N.V.
Barclays Bk plc	MBIA Inc.	American Intl Gp Inc
BNP Paribas	Natl Rural Utils Coop	Allstate Corp
Cap One Finl Corp	Aiful Corp	Aon Corp
Citigroup Inc	ORIX Corp	Assicurazioni Generali
Ctrywde Home Lns	Gen Elec Cap Corp	CHUBB CORP
Kookmin Bk	Goldman Sachs Gp Inc	CNA Finl Corp
Commerzbank AG	Morgan Stanley	Legal & Gen Gp PLC
Deutsche Bk AG	SEARS ROEBUCK	MBIA Ins Corp
Hana Bank	Toyota Mtr Cr Corp	MetLife Inc
HSBC Bk plc	Swire Pac Ltd	Munich Re
ING Bk N V		Old Mut plc
Korea Dev Bk		Safeco Corp
Merrill Lynch & Co		Mitsui Sumitomo Ins
Mizuho Corporate Bk		Sompo Japan Ins Inc
Macquarie Bk Ltd		HARTFORD FIN INC
Natl Aust Bk Ltd		Loews Corp
Oversea Chinese Bkg		
Rabobank Nederland		
Royal Bk of Scotland		
Resona Bk Ltd		
Societe Generale		
Std Chartered Bk		
Sumitomo Mitsui Bkg		
UBS AG		
Wells Fargo & Co		
Westpac Bkg Corp		
Investment	Real Estate	
Daiwa Secs Gp	EOP Oper Ltd Pship	
Bombardier	Hammerson PLC	
Nomura Secs	Hongkong Ld Co	
	Mitsubishi Estate Co	
	Simon Ppty Gp L P	
	Simon Ppty Gp Inc	

Table 2: Sovereigns grouped by region. Groups are intentionally broad to minimise the total number.

Europe	Asia	Latin America
Bulgaria	Australia	Argentina
Czech Republic	China	Brazil
Denmark	Indonesia	Chile
Norway	Japan	Colombia
Poland	Malaysia	Mexico
Sweden	Philippines	Panama
Russia	South Korea	Peru
Turkey	Thailand	Venezuela
Ukraine	Vietnam	

Africa	Euro Zone	North America
Israel	Belgium	USA
Morocco	Finland	
South Africa	France	
Qatar	Germany	
	Ireland	
	Italy	
	Netherlands	
	Portugal	
	Spain	

Table 3: Summary statistics are reported for all sovereign and financial institution CDS spread data used in this paper.

	Obs.	Mean	Std dev	Skewness	Kurtosis
Phase 1	01/01/2003 - 14/09/2008				
Banks	1488	0.4253	0.6634	6.2252	73.1315
Financials	1488	0.7426	1.4386	9.2843	131.738
Insurance	1488	0.5413	1.1174	10.551	146.240
Investment	1488	1.0126	1.6023	3.5076	19.9933
Real Estate	1488	0.5737	0.5135	2.5807	11.3350
Latin America	1488	3.3274	5.0302	4.3823	24.8403
Asia	1488	1.0935	1.3470	1.4863	4.1704
Euro Zone	1488	0.0698	0.0759	2.8669	11.6775
Europe	1488	0.9062	1.5211	2.8717	13.9841
Africa	1488	0.8038	0.7205	2.5980	11.9358
North America	1488	0.0262	0.0311	2.9249	11.0294
Phase 2	15/09/2008 - 31/03/2010				
Banks	403	1.6490	1.2574	2.1977	8.4938
Financials	403	12.719	32.619	6.6554	58.383
Insurance	403	3.6890	5.1029	2.4613	9.2081
Investment	403	1.9650	1.1711	1.0721	2.8133
Real Estate	403	2.6080	2.4492	1.4525	4.1223
Latin America	403	6.3541	8.8135	2.2891	7.7371
Asia	403	2.0159	1.5864	1.7696	7.0876
Euro Zone	403	0.8250	0.5597	1.5966	6.8034
Europe	403	3.4588	6.4693	3.8884	20.298
Africa	403	1.9245	0.9750	1.3394	4.5551
North America	404	0.4169	0.1834	1.1935	3.9374
Phase 3	01/04/2010 - 21/10/2013				
Banks	951	1.3971	0.6334	1.6584	6.8687
Financials	951	6.3933	10.211	2.0464	5.9045
Insurance	951	1.8314	2.1538	3.7857	20.033
Investment	951	1.4738	1.0772	0.5886	2.2274
Real Estate	951	1.1053	0.4586	0.6091	2.8172
Latin America	951	3.7769	5.6733	3.1106	14.840
Asia	951	1.3284	0.7275	1.6687	6.1909
Euro Zone	951	2.5872	2.5487	1.9267	7.1373
Europe	951	1.6592	1.9220	2.2460	7.9880
Africa	951	1.4990	0.5059	0.5376	2.5000
North America	951	0.3067	0.0801	-0.2616	2.3762

Table 4: This table contains statistics used in the analysis of network structures. The average link strength is estimated from connectedness for each respective network. The number of edges was calculated using bivariate Granger causality tests between network nodes (entities). Completeness is calculated via equation (16).

	Phase 1	Phase 2	Phase 3	Formed		Removed	
				1 to 2	2 to 3	1 to 2	2 to 3
Sovereigns							
Average strength	0.0297	0.0291	0.0216	0.0266	0.0207	0.0456	0.0303
No. of edges	896	953	997	342	354	285	310
Completeness	0.7230	0.7341	0.5711	0.2411	0.1944	0.3526	0.2484
Financials							
Average strength	0.0155	0.0156	0.0064	0.0173	0.0080	0.0138	0.0150
No. of edges	3750	2368	2689	292	1028	1674	707
Completeness	0.9435	0.5687	0.2647	0.0778	0.1264	0.3730	0.1639
Combined							
Average strength	0.0101	0.0094	0.0050	0.0082	0.0051	0.0094	0.0097
No. of edges	8217	6202	6943	1586	2689	3601	1948
Completeness	0.8203	0.5555	0.3302	0.1248	0.1289	0.3365	0.1806

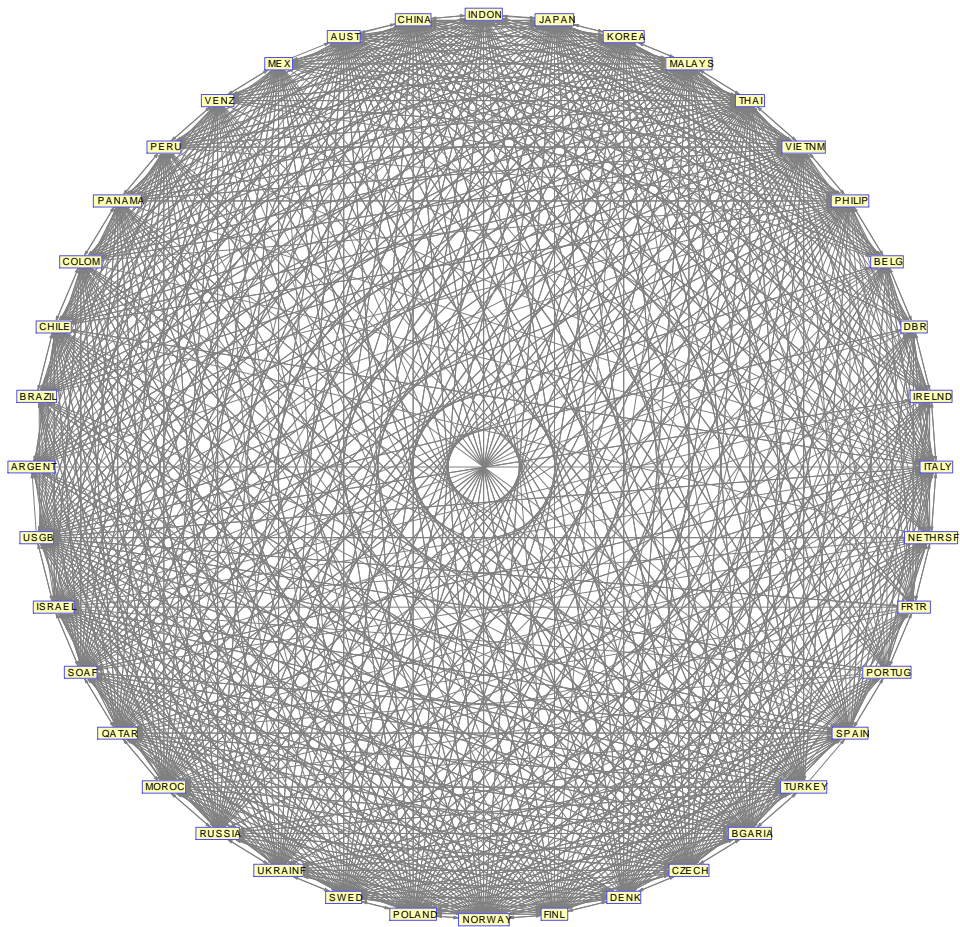


Figure 1: This figure displays the network of sovereigns in Phase 1 (01/01/2003 - 14/09/2008). Edges were calculated with bivariate granger causality testing between sovereigns (nodes). The level of significance is 5%.

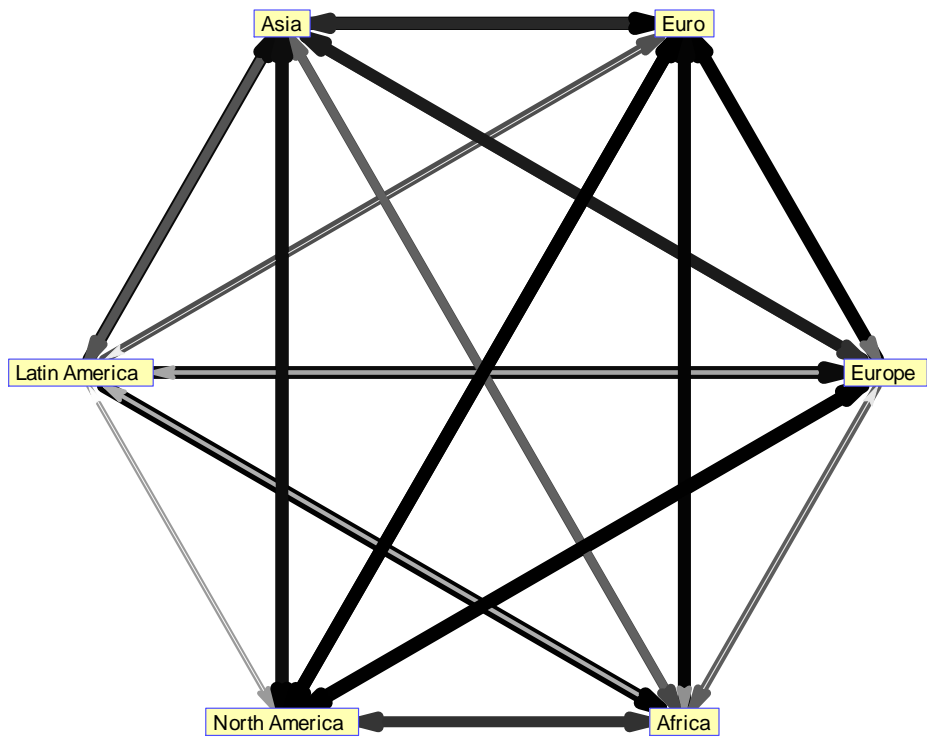


Figure 2: This figure shows a condensed version of the Phase 1 sovereign network from figure 1. The changes are performed by grouping sovereigns/nodes into geographical regions.

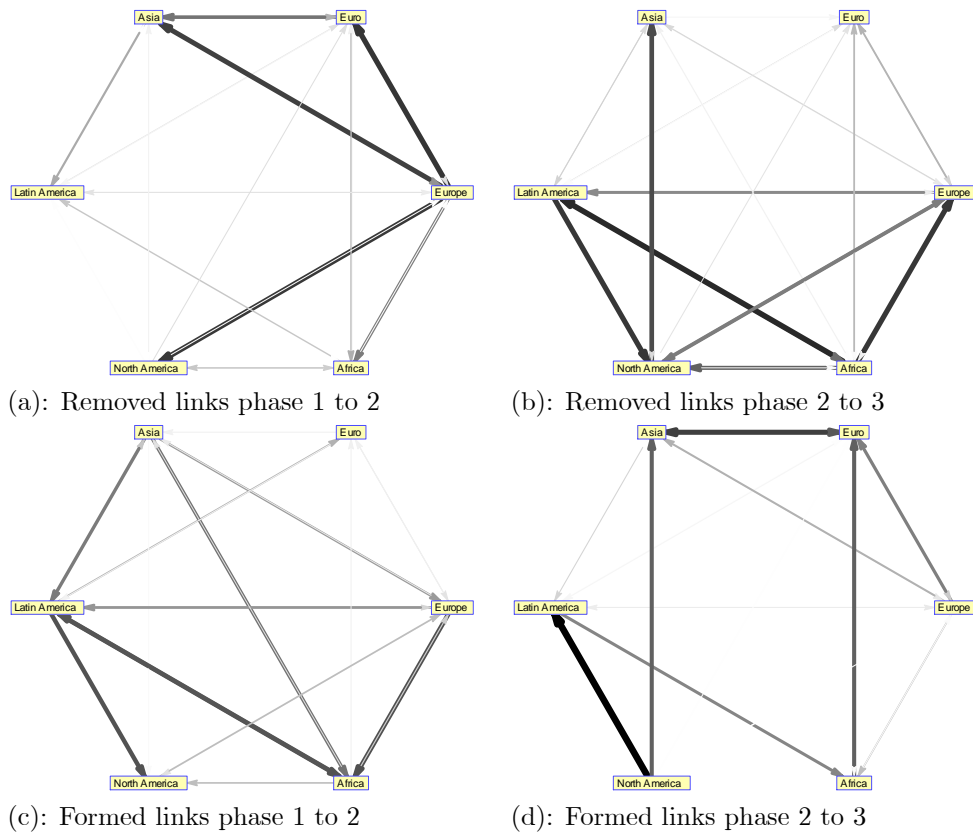


Figure 3: This group of figures shows changes in the sovereign network. Changes to edges connecting nodes are calculated between Phase 1 (01/01/2003 - 14/09/2008), Phase 2 (15/09/2008 - 31/03/2010) and Phase 3 (01/04/2010 - 21/10/2013).

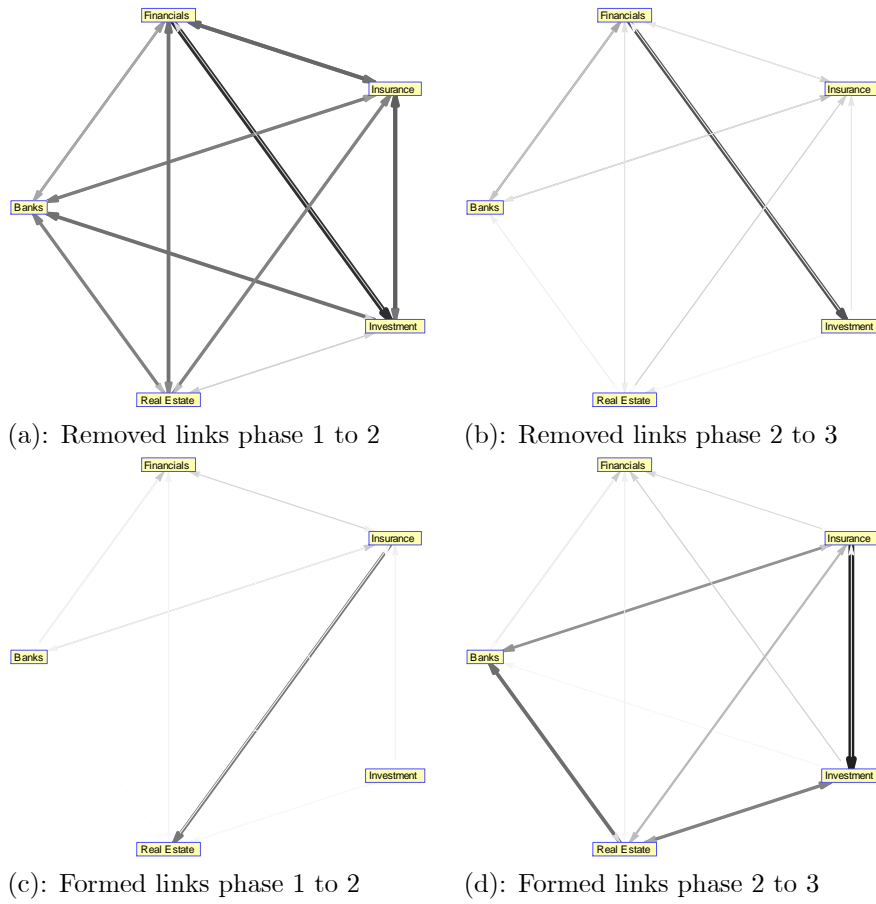
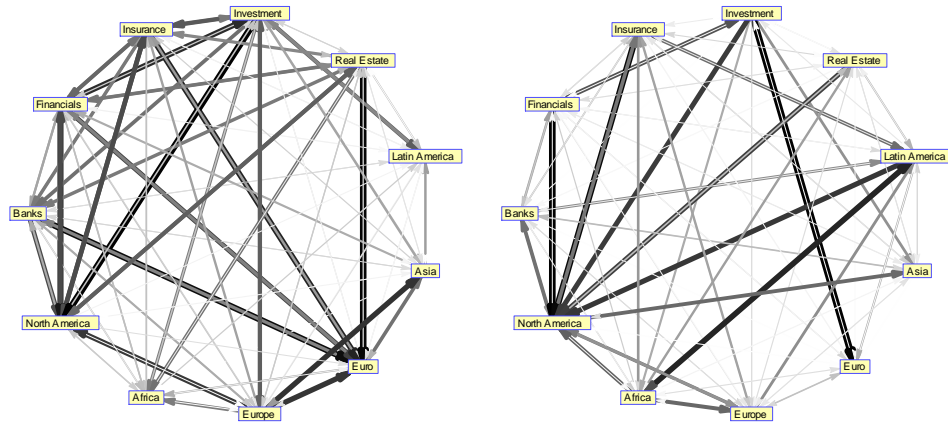
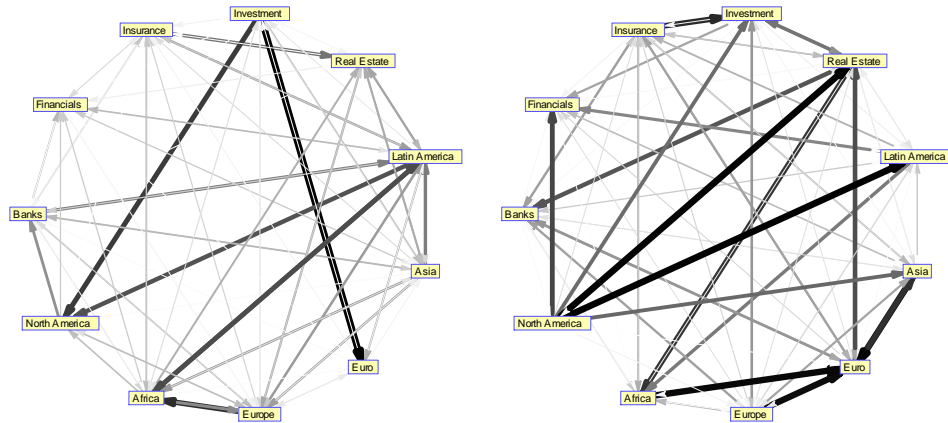


Figure 4: This group of figures displays changes of the financial network between Phase 1 (01/01/2003 - 14/09/2008), Phase 2 (15/09/2008 - 31/03/2010) and Phase 3 (01/04/2010 - 21/10/2013). Changes are calculated using matrix \tilde{A} .



(a): Removed links phase 1 to 2

(b): Removed links phase 2 to 3



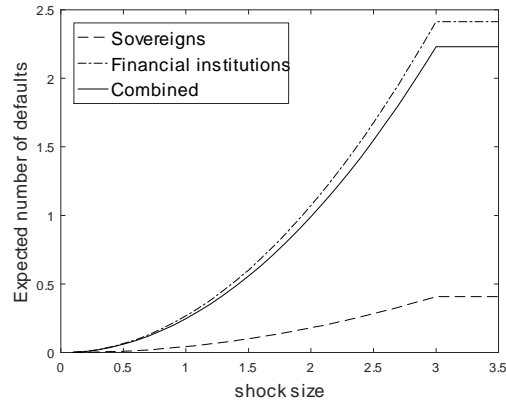
(c): Formed links phase 1 to 2

(d): Formed links phase 2 to 3

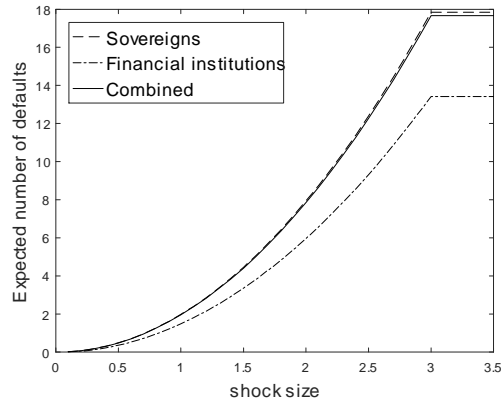
Figure 5: This group of figures displays the combined sovereign and financial network changes. Changes between Phase 1 (01/01/2003 - 14/09/2008), Phase 2 (15/09/2008 - 31/03/2010) and Phase 3 (01/04/2010 - 21/10/2013) are calculated from matrix \hat{A} .

Figure 6: This set of figures show expected number of defaults in the sovereign, financial and combined networks for a shock size by multiple of standard deviations. The logarithm of the CDS spreads is used for calculations.

(a): Phase 1 (01/01/2003 - 14/09/2008)



(b): Phase 2 (15/09/2008 - 31/03/2010)



(c): Phase 3 (01/04/2010 - 21/10/2013)

