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JEL classifications: F34, G01, G15

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Credit Risk Spillovers, Systemic Importance and Vulnerability in Financial Networks*

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1 Introduction

Why does the downgrade of a European country not only raise the CDS spreads of that specific sovereign but also those of other Eurozone member states (Arezki et al. (2011))? More generally, how does the change in the creditworthiness of a financial institution or state impact its creditors′ solvency?

This paper addresses such questions, investigating how a financial event that originates in one specific country can spread beyond its borders, infecting other states like an epidemic. I model default as a process - a multi-stage disease. Each credit-rating corresponds to an infection phase, during which default happens and therefore contagion is transmitted with a certain probability (Section 2). The model is general and could be applied not only to sovereigns, but to any financial institutions such as banks, firms, etc. interlinked by mutual financial liabilities. However, given data availability and recent events, I illustrate its workings in the context of the European sovereign debt crisis. The seventeen member states are the nodes in the network, and the weighted directed edges between them measure cross-country investment flows (Fig.1).

My goal is to develop indicators of node importance and vulnerability by investigating how the exogenous change in the creditworthiness of one of the financial network members impacts the creditworthiness of all the other ones (Section 3). Firstly, I derive some analytical indices from the early time properties of the model, then I employ computer simulations to measure systemic

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importance and vulnerability. Both indicators are systemic in the sense that they not only capture the immediate effect of the "exogenous risk that hits the system" (such as an aggregate exogenous shock or an idiosyncratic shock to one of the nodes in the network), but also the "endogenous risk generated by the system itself" (Zigrand (2014)). The system here is the network and the aim is to find indicators that will take into account how the structure of the links shapes and propagates an initial exogenous shock. I also extend the model to analyse how the same feedback mechanisms that generate endogenous risk, could set off a process of positive contagion, reversing negative market sentiments (Section 4).

This paper can be related to the existing vast literature on financial contagion. At the two extremes, contagion is classified as *pure* - when a herd of investors drives apparently healthy and unrelated economies towards sunspot equilibria - or *fundamentals-based* (Masson (1999)). In reality however, spillovers are complex and encompass both features: they spread through real or financial channels, while still retaining some randomness driven by market sentiments. I try to capture this duality by on the one hand considering a financial network of cross-country investment flows, while on the other hand making downgrades happen stochastically. Indeed, the probability that an agent transmits the "default disease" to its network neighbours depends on both: its actual credit rating (an agent with a lower credit-rating, i.e. in a more advanced infection phase, transmits the negative contagion at a higher rate) and the interaction intensities (a stronger mutual relation increases the transmission probability).[2]

One of the first models studying financial contagion on networks is Allen & Gale (2000). The authors extend Diamond & Dybvig (1983) to a four banks system, showing how the completeness and distribution of interconnections determine the extent of spillovers following a bank-specific shock. With evenly allocated deposits, contagion may be completely avoided, whereas in an incomplete system, a cascade of failures might emerge. Allen & Babus (2009) give an overview of some recent developments in this field. Espinosa-Vega & Sole (2011) build an interbank exposure model, simulating credit and liquidity shocks. Their algorithm starts with the default of a country′s banking system shifting the balance sheets of yet solvent banks and triggering new failures. In a similar spirit, Elliott et al. (2014) construct a theoretical model in which the market values of organisations are interdependent through the network of cross-holdings. The default of an organisation (bank or country) changes the values of all the other ones inducing those, whose new values fall below certain specified "bankruptcy thresholds", to fail as well. The contagion process continues until either the algorithm converges with no new failures, or no solvent organisation remains.

One of the main criticisms of such studies has been their limited scope given the "extremely rare" nature of "contagious *failures*" (Upper (2006)). Here, instead of analysing how financial contagion results from the *initial default* of a bank or country, I model the *default process* itself, and investigate how financial contagion can be triggered by simple *changes in the creditworthiness* of one of the network members.

The credit-rating determination of a bank (Bissoondoyal-Bheenick & Treepongkaruna (2009)) or a sovereign (Melliosa & Paget-Blanc (2006), Afonso (2003), Cheung (1996)) have been traditionally studied using econometric ordered-response models with creditworthiness as the latent variable. The problem with this approach is that it completely ignores the possibility of credit risk spillovers between financial entities. Unfortunately, once we model agents′ interactions explicitly

[2] For a discussion of the relative importance of trade linkages versus macroeconomic similarities in currency crises, see Eichengreen et al. (1996). Gerlach & Smets (1995), Corsetti et al. (1999), and Pesenti & Tille (2000) present theoretical models of contagious transmission with applications to the Asian currency crisis and the ERM turmoil.

through a network, and admit that their creditworthiness levels are interrelated and determined simultaneously, this econometric framework can no longer be used because of endogeneity.

I propose a different approach to studying creditworthiness and credit risk spillovers that takes inspiration from the epidemiology literature. Indeed, the highly interconnected and complex nature of the global financial system has spurred researchers to draw interesting and original parallels between financial networks, ecosystems (May et al. (2008)), epidemiology, and even engineering (Haldane (2009)). Demiris et al. (2014) explore financial contagion in the context of a Susceptible-Infected-Recovered (SIR) model, emphasising its advantages over more conventional modelling approaches. In particular, the SIR framework allows them to model explicitly the country-interdependencies that are essential to the propagation of a crisis, measure crisis severity by a threshold parameter instead of composite macroeconomic indicators as in Kaminsky & Reinhart (1998), and evaluate potential policy interventions.

Beside these theoretical advances, an increased interest in complexity economics and agent-based modelling have recently re-emphasized the usefulness of computer simulations in understanding complex systems (Farmer & Foley (2009)). For instance, Caporale et al. (2008) develop a multinomial model using time series data on stock returns during the East Asian crisis (1997), and thereby disentangle potentially destabilizing connections that could signal the inception of a contagion process. Gai et al. (2011) experiment with different parameter configurations, studying how complexity and concentration affect the resilience of a financial system. I follow this trend and use computer simulations not only to derive indicators of systemic importance and vulnerability, but also to incorporate positive contagion, thereby making the model more complex, interesting, and realistic.

2 Credit Risk Spillovers

2.1 The determinants of creditworthiness

Consider a network with $n \in \mathbb{N}$ nodes. As an illustration, Figure 1 depicts the network of the seventeen Eurozone member states. Since the ultimate goal is to study credit risk spillovers, the links between nodes should reflect the intensity of potential contagion flows. Fig.1 looks at the 2011 cross-border *Total Portfolio Investment* (TPI) flows. The data is available from the IMF (Consolidated Portfolio Investment Survey). TPI flows are reported on an annual basis and include long & short term equities and debt-securities. I transform the data into investment shares since absolute values of investment flows vary with the overall size of the economy and need to be normalised. Formally, I define the weighted, directed link from j to i (v_{ij}) as the proportion of country i's total investment flowing into j. Intuitively, the arcs follow contagion flows so that the larger v_{ij}, the more significant the direct potential spillover from j's downgrade onto i's creditworthiness. In Fig.1, nodes are coloured and weighted by their average degrees $\frac{1}{2}\left\{\sum_i v_{ij} + \sum_j v_{ij}\right\}$.

Investment shares v_{ij} can be summarized in an $n \times n$ adjacency matrix $\mathbf{V}$ (Table 1). Note that $v_{ii} = 0$ (foreign investment only) and row i gives the distribution of country i's TPI across other Eurozone member states. For instance, Austria invests 21.46% into Germany and only 0.64% into Greece. Rows do not sum up to 100% because countries also invest in non-EZ states. In general, $v_{ij} \neq v_{ji}$, e.g. Italy invests 26.22% into Luxembourg, while Luxembourg only invests 4.64% into Italy.

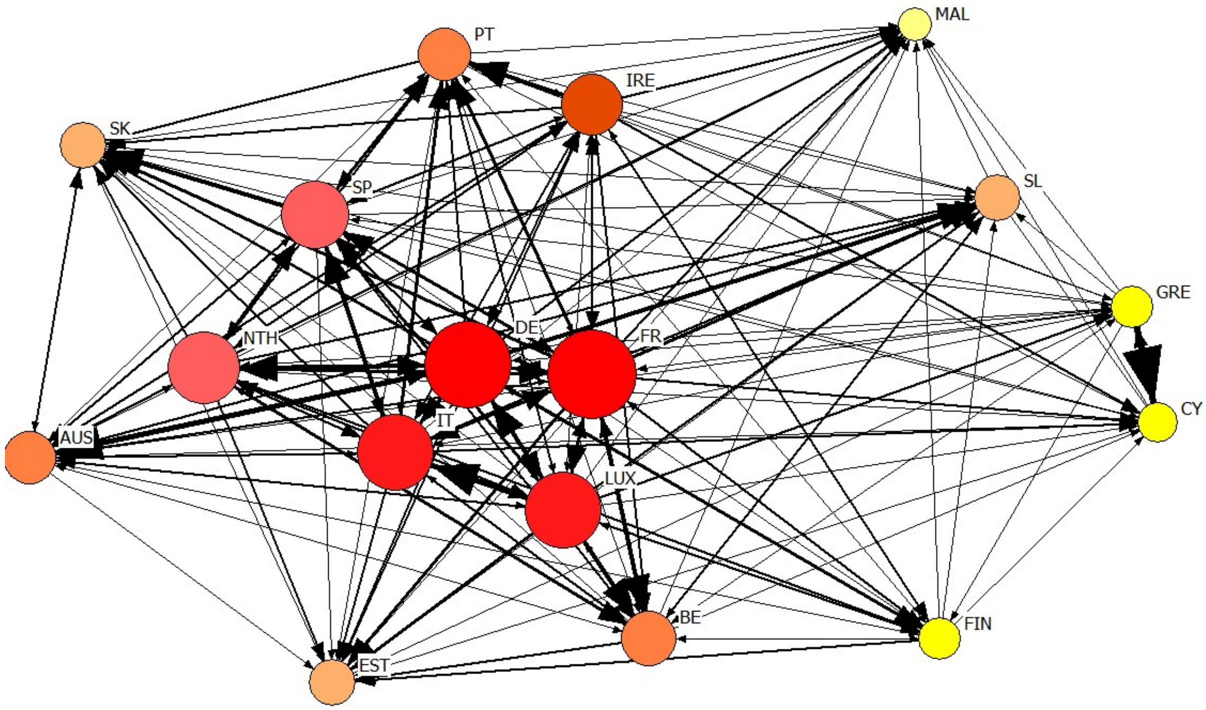

Figure 1: Eurozone network, 2011 Total Portfolio Investment (TPI) shares

Table 1: Adjacency matrix, 2011 Total Portfolio Investment (TPI) shares (percentages)

	AUS	BE	CY	EST	FIN	FR	DE	GRE	IRE	IT	LUX	MAL	NTH	PT	SK	SL	SP
AUS	0	1.319	0.140	0.023	1.368	8.524	21.456	0.638	3.705	7.398	8.434	0.010	7.327	0.525	0.790	0.710	3.538
BE	2.265	0	0.032	0.002	0.838	18.459	6.689	0.455	5.700	4.845	19.111	0.006	14.661	0.730	0.195	0.226	5.172
CY	0.496	1.838	0	0	0.411	4.291	2.372	27.833	3.708	3.448	2.419	0	2.121	0.300	0.003	0.112	0.924
EST	3.113	3.352	0.311	0	7.328	14.679	7.328	0.096	6.346	7.807	11.997	0.024	8.357	0.431	0.455	0.216	1.461
FIN	1.425	0.668	0.036	0.094	0	8.007	10.144	0.291	5.159	2.243	8.755	0	5.742	0.398	0.022	0.079	2.156
FR	3.072	4.340	0.012	0.001	0.678	0	11.303	0.587	4.138	10.761	6.104	0.038	11.883	1.381	0.039	0.104	8.281
DE	3.865	1.415	0.042	0.002	1.053	12.668	0	0.516	5.263	7.299	16.218	0.004	9.968	0.935	0.180	0.127	6.878
GRE	0.929	0.330	3.393	0	0.052	3.284	2.727	0	2.394	1.857	7.902	0	2.242	0.296	0	0	0.641
IRE	0.358	0.544	0.009	0.008	0.594	5.374	7.174	0.144	0	5.724	2.248	0.011	3.820	2.633	0.017	0.009	2.031
IT	1.719	0.810	0.007	0	0.328	13.094	10.381	0.430	8.634	0	26.215	0.022	6.483	0.690	0.035	0.116	4.505
LUX	1.036	1.792	0.045	0.009	0.648	9.750	12.381	0.103	2.711	4.635	0	0.019	5.164	0.264	0.019	0.023	2.299
MAL	1.939	1.011	0.107	0	0.308	3.942	5.765	0.950	5.191	2.309	2.720	0	4.851	1.134	0.175	0.942	2.677
NTH	2.255	1.673	0.015	0.002	1.181	11.271	15.964	0.228	3.445	3.487	5.355	0.004	0	0.807	0.037	0.024	3.920
PT	1.372	1.762	0	0	0.416	9.599	5.298	1.327	20.645	9.603	6.566	0	7.113	0	0.050	0.028	11.795
SK	5.286	1.173	0.527	0	2.431	9.394	4.222	1.154	8.663	7.995	2.864	0	6.088	4.343	0	2.444	15.855
SL	6.269	3.923	0.040	0.015	0.805	13.337	18.605	2.721	2.348	8.654	4.082	0	7.023	0.953	1.227	0	2.259
SP	1.678	2.054	0	0	0.358	13.227	8.685	0.872	6.806	15.753	9.975	0	9.567	3.933	0	0	0

Source: Coordinated Portfolio Investment Survey (CPIS), IMF

cf. Table 8: Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment, http://cpis.imf.org/

The adjacency matrix is obtained by dividing the original entries in the CPIS matrix by the total value of investment for each country.

Let the creditworthiness of each node at time t - y^*_{it}- be described by:

$$y^*_{it} = \mathbf{x}'_{\mathbf{it}}\boldsymbol{\beta} + \omega \sum_j v_{ij} y^*_{jt} \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of parameters, and $\mathbf{x_{it}}$ - a vector of economic indicators that include variables like debt ratios, growth and inflation rates, default history, etc. in the case of sovereigns. If banks were considered instead, $\mathbf{x_{it}}$ would include variables like asset quality, liquidity risk, capital adequacy, operating performance, etc. The parameter ω captures how changes in i's debtors' creditworthiness will affect its own creditworthiness given i's portfolio allocation $\sum_j v_{ij}$. The model could be made more general by allowing all parameters to depend on i, reflecting the fact that different characteristics do not necessarily have the same importance in determining the creditworthiness of two different financial entities. However, this would make the model more complex, and I shall leave this extension to future research.

Even though in practice many credit-rating agencies have been recently accused of assigning credit-ratings that do not reflect the true creditworthiness of a bank or sovereign, theoretically we can assume that there exists a direct mapping from creditworthiness to credit-ratings. Credit-ratings are ordinal qualitative variables often designated by alphabetical letters. Standard & Poor's ratings for example range from AAA (no default risk) to C - the worst possible rating before the restricted default D. Suppose there are k possible ratings in total (the actual number varies from agency to agency). I translate credit-ratings to a numerical scale with the highest possible rating denoted as k and the lowest possible one as 0. Financial institution i is downgraded as its creditworthiness y^*_{it} , defined by eq.1, drops below certain thresholds α:

$$cr_{it} = \begin{cases} k & \text{if } y^*_{it} > \alpha_k \\ k-1 & \text{if } \alpha_{k-1} < y^*_{it} \leq \alpha_k \\ \vdots & \\ 0 & \text{if } y^*_{it} \leq \alpha_1 \end{cases}$$

where cr_{it} is i's credit-rating at time t.

As mentioned in the introduction, eq.1 cannot be estimated econometrically through an ordered-response model because the sum $\sum_j v_{ij} y^*_{jt}$ - which in the context of the illustrative Eurozone network can be interpreted as country i's creditworthiness-adjusted portfolio investment - is unobservable. Since in practice credit-ratings are only an imperfect measure of the underlying creditworthiness, replacing y^*_{jt} by j's observed credit-rating at time t in eq.1 could make things even worse because of the second important problem: endogeneity. Indeed, the whole idea of this paper is to argue that y^*_{it} and y^*_{jt}will be determined simultaneously if v_{ij} and v_{ji} are non-zero.

To identify credit risk spillovers, I therefore take inspiration from the epidemiology literature and model the default process as a multi-stage disease with each credit-rating corresponding to a new infection phase.

2.2 The Default Process

2.2.1 From the "Susceptible - Infected" (SI) model to the "Solvent-Default"(SD) one

The SI model was initially developed to analyse human disease spreading on contact networks (Kermack & McKendrick (1932)). Although the process of infection is much more complex than this two-states model, it remains a "useful simplification" to the extent that it captures the contagion dynamics "happening at the level of networks" (Newman (2012)).

At any point in time, an individual is either susceptible or infected. Suppose that you are susceptible - which happens with probability s_i. To catch the disease, one of your neighbours must already be infected - the probability of this event is d_j. Since this infected neighbour transmits the disease at rate δ, the probability that you become infected at any point in time is:

$$\frac{dd_i}{dt} = \delta \sum_j v_{ij} \{s_i d_j\} \tag{2}$$

where the accolades on the right-hand side take into account the correlations (joint probabilities) for nodes i and j to have the specified states, e.g. $\{s_i d_j\}$ is the "average probability that i is susceptible and j is infected at the same time" (Newman (2012)). Interaction intensities v_{ij} play a crucial role in eq.2. Two individuals, interacting with exactly the same people, could have completely different infection probabilities if the first person's contacts mainly include already contaminated individuals, whereas the second one is more interlinked with still healthy people.

Translating the SI framework into a "Solvent-Default" (SD) one is rather trivial. We can simply think of the interaction intensity v_{ij} as the strength of the potential contagion flow from j to i. For instance, in the Eurozone network illustrated in Fig.1, the v_{ij}'s will be the TPI shares. Eq.2 implies that two countries, Z and W, investing in exactly the same sovereigns with the only difference that $\sum_j v_{Zj}$ puts relatively higher weights on countries with larger d_j than $\sum_j v_{Wj}$, would have very different default probabilities. In particular, Z's default probability would be larger than W's. Notice that this discrepancy would occur not because of a difference in d_j, but as a consequence of different TPI shares' distributions.

Unfortunately, this simple SD framework is inappropriate for the investigation of *credit risk spillovers,* because it only models two states: Solvent and Default. In reality, a solvent financial institution does not suddenly declare bankruptcy; it undergoes a process of rating downgrades, which I model as a multi-stage disease.

2.2.2 Default as a multi-stage disease

Modeling default as a multi-stage disease makes the previous framework more complex, but allows financial institutions to differ in *how* solvent they are.

It might be insightful to think about each credit-rating downgrade as marking the beginning of a new infection phase. Let $\theta(cr_{it}) \in [0;1]$ be the rate at which institution i with credit-rating cr_{it} transmits the "default disease" to its creditors. An institution with lower creditworthiness, i.e. in a more advanced infection phase, is more likely to default itself. It should therefore be more virulent and transmit the default contagion at a higher rate, i.e. $\theta(cr_{it})$ must be decreasing in cr_{it}.

For simplicity, suppose there are only four possible credit-ratings ($k = 4$): A, B, C, and D. Let a_{it}, b_{it}, c_{it} and d_{it} denote the probabilities that institution i has rating A, B, C, or D respectively at time t. Clearly:

$$a_{it} + b_{it} + c_{it} + d_{it} = 1$$

because an institution must be rated at any point in time.

Further, let the transmission rates be: $\theta(A) = 0$ and $\theta(cr) \in (0; 1]$ for any $cr \neq A$.

Given the network of n financial institutions or states, i can be downgraded from A to B for two reasons. Firstly, as a result of a credit risk spillover from one of its debtors. For this, i must start with rating A which happens with probability a_{it}. Moreover, one of its debtors must have rating $cr_{jt} \in \{B,\ C,\ D\}$ - which happens with probabilities $z_{jt} = \{b_{jt},\ c_{jt},\ d_{jt}\}$ respectively - and transmit the contagion at rate $\theta(cr_{jt})$. Secondly, i could also be downgraded because of an exogenous deterioration in one of its characteristics x_{it}. The following differential equation describes the probability that i loses credit-rating A:

$$\frac{da_i}{dt} = -\omega \sum_j v_{ij} \{a_{it} z_{jt}\} \theta(cr_{jt}) + \beta^A \frac{dx_i}{dt} \tag{3}$$

Similarly, the probability that i has rating B increases in i's probability of being downgraded from A to B, but decreases in i's probability of being downgraded from B to C:

$$\frac{db_i}{dt} = \omega \sum_j v_{ij} \{a_{it} z_{jt}\} \theta(cr_{jt}) - \omega \sum_j v_{ij} \{b_{it} z_{jt}\} \theta(cr_{jt}) + \beta^B \frac{dx_i}{dt} \tag{4}$$

The differential equation for rating C is described in a similar way:

$$\frac{dc_i}{dt} = \omega \sum_j v_{ij} \{b_{it} z_{jt}\} \theta(cr_{jt}) - \omega \sum_j v_{ij} \{c_{it} z_{jt}\} \theta(cr_{jt}) + \beta^C \frac{dx_i}{dt} \tag{5}$$

Finally, the last downgrade from C to D corresponds to the default after which the country exits the system:

$$\frac{dd_i}{dt} = \omega \sum_j v_{ij} \{c_{it} z_{jt}\} \theta(cr_{jt}) + \beta^D \frac{dx_i}{dt} \tag{6}$$

where the parameter on the exogenous shock β is allowed to depend on the credit rating under consideration.

There is one important difference between this extended SD model and the existing multi-stage disease ones from the epidemiology literature. In the latter, "the only stochastic step [...] is transmission of the disease" (Jaquet & Pechal (2009)) - i.e. once an individual becomes infected, she will traverse all the disease stages deterministically until reaching the final phase (e.g. becoming resistant) - whereas in the multi-stage SD model, progression towards the next infection phase still depends on contact with already contaminated units. [3][4]

[3] Note that the infection phases of the node's debtors do not have to be "more advanced" than its own contamination phase in order to make him progress to the next infection stage. Consider the following example: country X currently has rating B and has only two debtors: countries Y and Z, both with ratings A, i.e. in "less advanced" infection phases than itself. If country Y is downgraded from A to B, this will increase the probability of country X being downgraded to C, i.e. there will still be a credit-risk spillover despite the fact that country Y was initially less infected than country X.

[4] Aside from the economic content of this paper, there is a need to properly understand the dynamics and phase diagrams of a multi-stage epidemic model in which progression to the next infection phase depends on interaction with other contaminated people. Although such a model could not be applied in common epidemic

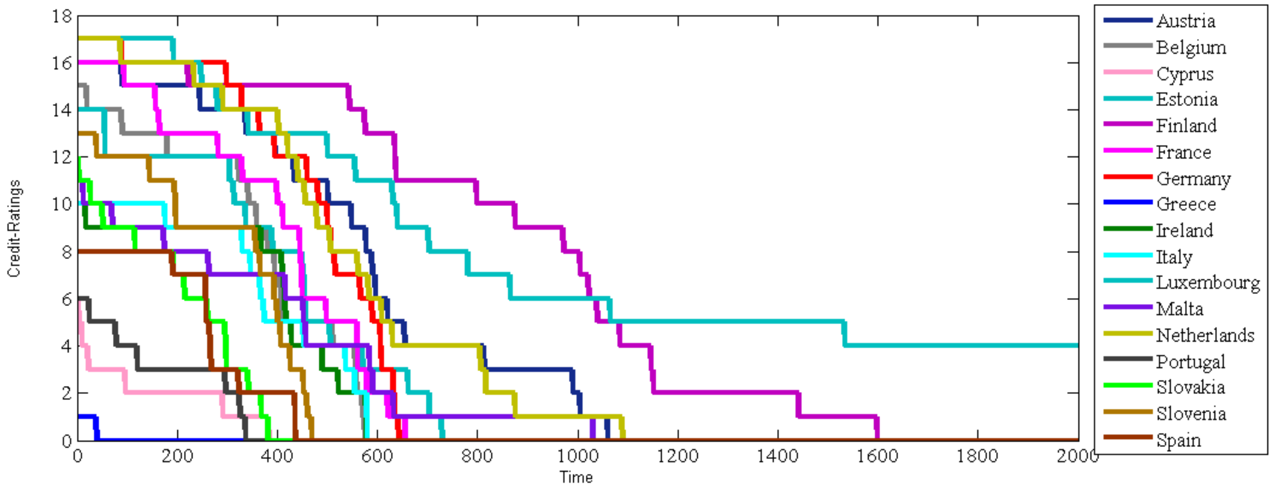

Figure 2: Given the initial vector of ratings (2012 Q4), this experiment simulates the contagion process showing the evolutions of the ratings for each country.

2.3 Computer Simulations

The model presented in the previous section has no closed form solution. To analyse it, I have written a graph-based computer algorithm whose main component is a function called *spillovers*. This function takes as arguments an adjacency matrix $\mathbf{V}$, a transmission-rates vector $\boldsymbol{\theta}$, and the vector of initial ratings rat_0. Firstly, it associates to each country i a transmission rate $\theta(cr_i)$ that depends on its rating. After computing country-specific downgrade probabilities using eq.7, some countries are stochastically downgraded:

$$\mathbf{Pr}(i\ downgraded) = \omega \sum_j v_{ij}\theta(cr_j) \tag{7}$$

Here, $\omega \in \mathbb{R}^+$ captures the overall spillovers' magnitude (the "severity" of the disease) and allows to change the speed of the simulations without altering downgrade rankings.

Spillovers' output is a new vector of ratings: rat_1. The *contagion* function recalls *spillovers* until all countries default - which happens at time T_d - using the *spillovers'* previous ratings output vector as the new input at each iteration step, and producing a matrix with columns: rat_0, rat_1, rat_2, ..., rat_{T_d}. Technically, one country usually remains solvent. Since the simulation stops when all but one country default, this solvent country also defaults at T_d.

Fig.2 illustrates the computer simulation on the Eurozone TPI network with the fourth quarter 2012 S&P's credit ratings as rat_0. I only use the first seventeen S&P's ratings, grouping together

settings such as the transmission of a viral infection, it could be very useful in understanding contagious mental illnesses. For instance, Joiner & Katz (1999) investigate 40 studies conducted between 1976-1997 "that examined the relationship between two non-genetically related individuals' levels of depression or negative mood", and find evidence of significant contagion for all the 12 studies that analysed syndromal *depression spillovers* between "college roommates, dating couples, young spouses, elderly spouses, and relatives." Interestingly, they also find that only 13 of the 28 studies dealing with *negative mood*, report significant spillovers, concluding that "depressive symptoms are [...] more contagious than negative mood." This agrees with the framework used in this paper, whereby more advanced infection phases are presented as more virulent. Hence, the model analysed in section 2 could help understand the transition from a moderate state of depression or even a simple negative mood to more severe phases.

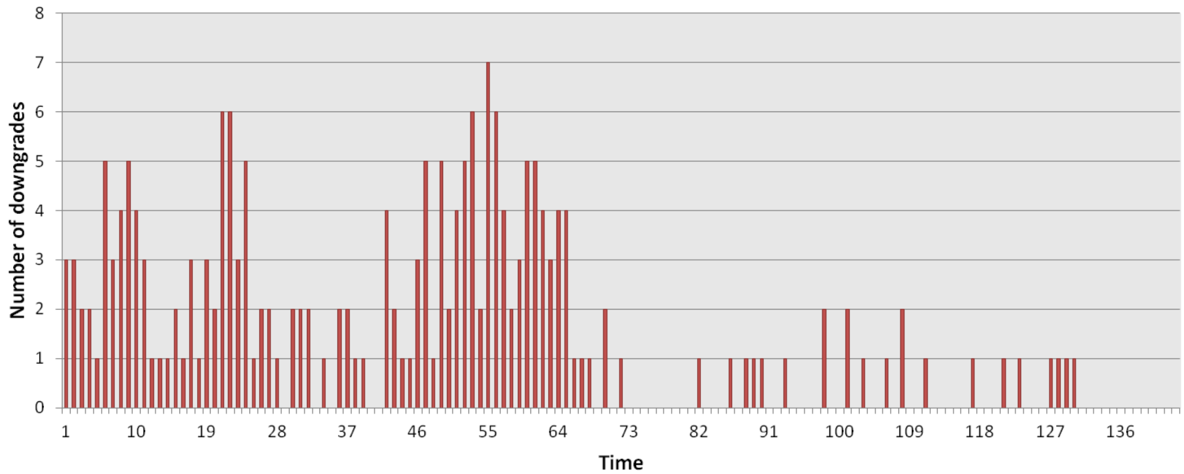

Figure 3: Given the initial vector of ratings (2012 Q4), this experiment simulates the contagion process recording the number of downgrades each period.

ratings below or equal to CCC, and translating them into a numerical scale with the highest rating defined as $AAA = 17$ and the lowest as $CCC = 1$. In this simulation, $\omega = 1$ and $\boldsymbol{\theta}$ is reported in the first column of Table 5 below.

As expected, Greece, Portugal and Cyprus are the first sovereigns to default, whereas the Netherlands, Finland, and Luxembourg are the last ones. Note that "Time" here has no specific length and should simply be interpreted as regular time-intervals. The total number of time-intervals depends on the values of $\boldsymbol{\theta}$ and ω. In particular, setting a higher ω speeds up the overall contagion process, whereas a smaller ω gives a more precise ranking of country default times.

Fig.2 also illustrates an interesting network phenomenon inherent to epidemics - the "tipping point" (Gladwell (2000)). The main idea is that changes often happen very quickly and unexpectedly as some threshold is reached. Here "threshold" may be interpreted as a country-specific exposure level after which its default process gains momentum. As an example, consider the evolution of Germany's credit-rating (red). It remains above AA (15) for almost 400 periods, then suddenly plummets to CCC (1) in less than 300 time-intervals. At the network level, such tipping points lead to contagion waves and clustering of default times. In fig.2, three main default clusters occur around $t = 400$ (Portugal, Cyprus, Slovakia, Spain, and Slovenia), $t = 600$ (Belgium, Italy, Ireland, France, and Germany), and soon after $t = 1,200$ (Malta, Austria, The Netherlands).

To investigate this issue further, I increase the spillovers' magnitude to $\omega = 10$, and record the number of downgrades over time for a particular *contagion* realisation. Fig.3 shows the emergence of contagion waves. They happen as a set of countries becomes increasingly virulent and starts transmitting downgrade spillovers at a faster pace. With each iteration of the *spillovers* function, downgrade probabilities increase for all countries, making them more likely to reach their "thresholds". This process continues until some sovereigns start defaulting. At this point, downgrade probabilities drop and the contagion process slows down because the set of highly virulent countries leaves the system. However, since downgrade probabilities for the remaining countries are still positive, a new wave eventually emerges. In practice, this experiment suggests that in order to lower the downgrade probabilities of still relatively healthy member-states and limit spillovers, the set of most virulent countries should leave the system.

While further investigation of tipping points and contagion waves is an important direction for future research, the next step and main goal of this paper is to use the model and the computer algorithm presented in this section to derive indicators of node/country importance and vulnerability.

3 Systemic Importance and Vulnerability

3.1 Early-time properties: some analytical results

Consider again the model from subsection 2.2.2 and suppose that all n financial institutions start with the best possible credit-rating A, i.e. $a_{i0} = 1$ for any i. Now, let one of the institutions be exogenously downgraded. Afterwards, in order to disentangle credit risk spillovers from exogenous economic fundamentals' deterioration, set $\frac{dx_i}{dt} = 0$ for any i and t.

Which institutions are most likely to be downgraded from A in this early period? To answer this question, note that since $c_{it} = 0$, $d_{it} = 0$, and $a_{it} + b_{it} = 1$ for any i, one only needs to focus on eq.4 which can be rewritten as:

$$\frac{db_i}{dt} = \omega \sum_j v_{ij} b_{jt} \theta(B)$$

because $a_{it} \to 1$ and $\theta(A) = 0$. In matrix notation:

$$\frac{d\mathbf{b}}{dt} = \omega\theta(B)\mathbf{V}\mathbf{b}$$

which is a system of differential equations that has a solution of the following form:

$$\mathbf{b}(t) = \sum_{r=1}^{n} u_r(0) \exp(\omega\theta(B)\kappa_r t)\mu_{\mathbf{r}}$$

where κ_r's and $\mu_{\mathbf{r}}$'s are respectively the eigenvalues and eigenvectors of the matrix $\mathbf{V}$ and $u_r(0)$'s are some constants. Let κ_1 and $\mu_{\mathbf{1}}$ denote the largest eigenvalue and its associated eigenvector respectively:

$$\mathbf{b}(t) \sim \exp(\omega\theta(B)\kappa_1 t)\mu_{\mathbf{1}} \tag{8}$$

Hence, thinking of $\mathbf{b}(t)$ as an indicator of *early-time vulnerability*, eq.8 shows that it will be directly proportional to $\mathbf{V}'$*s right* leading eigenvector $\boldsymbol{\kappa_1}$. In the network literature, this metric is called ***(right)* eigenvector centrality** (Newman (2012)).

A closely-related indicator can be constructed to gauge *early-time importance*. The trick here consists in taking the transpose of the adjacency matrix: $\mathbf{W} = \mathbf{V^T}$ so that $w_{ij} = v_{ij}^T = v_{ji}$. Now row i of $\mathbf{W}$ gives the distribution of all network members' investment shares into i. Let $\sigma(t)$ denote the vector of *early-time importance*. I want an indicator that ranks higher those countries, whose major creditors are themselves more important. The differential equation of the form:

$$\frac{d\sigma_i}{dt} = \eta \sum_j v_{ji}\sigma_{jt}$$

shows that the importance of node i is indeed increasing in the importance of its creditors σ_{jt} and the proportion that they invest into i : v_{ji}. Rewriting in matrix notation and performing the same exercise as above one gets:

$$\sigma(t) \sim \exp(\eta\lambda_1 t)\pi_{\mathbf{1}}$$

where λ_1 and $\pi_{\mathbf{1}}$ are the leading *left* eigenvalue and eigenvector of the matrix $\mathbf{V}$. Hence the vector of early-time importance will be proportional to the ***left* eigenvector centrality**.

3.2 Late-time properties: systemic indicators

One of the main goals of this paper is to measure *systemic* importance and vulnerability. To build indicators that take into account every possible feedback mechanism generated by the network structure, I need to switch from the early-time when the contagion process just sets off, to the time when the countries have traversed their default processes almost completely.

Conceptually, the experiment remains the same: all n institutions start with the best possible credit-rating A, and one of the institutions is exogenously downgraded. Nevertheless, the key difference is that instead of asking which institutions are most likely to be downgraded to rating B first, I now ask how long will it take for institution i to default? How does this time compare to the time needed for other institutions to default? What if I pick and downgrade another institution first?

A bit of imagination leads to define the following two possible indicators of systemic importance:

- *All-default time:* T_d^i gives the time when all of the nodes in the network default after the initial exogenous downgrade of node i.
- *First-default time:* F_d^i gives the time of the first default in the network after the initial exogenous downgrade of node i.

Intuitively, the initial downgrade of a systemically more important country should lead to quicker First- and All- default times (smaller F_d^i and T_d^i).

In the same spirit, the default time of node i after the initial downgrade of node j - V_i^j - identifies i's systemic vulnerability to j. If i is more vulnerable to l than to h, we should observe: $V_i^l < V_i^h$. A summary indicator is i's average *systemic vulnerability*:

$$Vul_i = \frac{1}{n}\sum_j V_i^j$$

3.3 Application to the Eurozone Sovereign debt crisis

To see how these different analytical and simulation-based indicators relate to each other, tables 2 and 3 report the computed rankings and indicators for all 17 member-states using the TPI shares as the adjacency matrix (Table 1). Countries are arranged according to All-default (Td) and Vulnerability (Vul) rankings respectively.

Germany alternates with France in the role of the most systemically important Eurozone country depending on the indicator used. Although Luxembourg is a small country, it is consistently ranked second/third because other EZ members invest substantial shares into it: between 2.4% (Cyprus) and 26.2% (Italy). Remarkably, many countries (e.g. the Netherlands, Italy, Ireland, Spain) keep exactly the same positions in all importance rankings. In terms of vulnerability, the picture is less clear-cut. Slovenia and Slovakia are ranked highest by different indicators. Greece

Table 2: Systemic Importance

	Rankings			Indices		
	LeftEig	Fd	Td	LeftEig	Fd	Td
Germany	1	2	1	0.469	17.535	26.652
France	3	1	2	0.456	17.527	26.792
Luxembourg	2	3	3	0.465	17.555	26.799
Netherlands	4	4	4	0.353	17.961	27.197
Italy	5	5	5	0.320	18.019	27.431
Ireland	6	6	6	0.233	18.319	27.577
Spain	7	7	7	0.225	18.543	28.109
Austria	8	8	8	0.102	20.548	29.987
Belgium	9	9	9	0.090	21.085	30.776
Portugal	10	10	10	0.058	22.250	31.840
Greece	12	11	11	0.022	22.767	33.724
Finland	11	12	12	0.036	24.862	34.559
Cyprus	15	13	13	0.003	35.323	46.868
Slovenia	13	14	14	0.005	43.168	53.474
Slovakia	14	15	15	0.004	47.989	58.222
Estonia	17	16	16	0.000	369.900	379.521
Malta	16	17	17	0.001	429.148	438.018

Note: LeftEig = Left eigenvector centrality, Fd = First default time, Td = All default time

Table 3: Systemic Vulnerability

	Rankings		Indices	
	RightEig	Vul	RightEig	Vul
Slovakia	3	1	0.308	70.149
Slovenia	1	2	0.310	70.238
Estonia	5	3	0.288	70.352
Belgium	2	4	0.309	70.432
Spain	4	5	0.296	70.496
Portugal	6	6	0.287	70.518
Austria	7	7	0.274	70.549
France	9	8	0.265	70.637
Germany	10	9	0.262	70.652
Italy	8	10	0.273	70.667
Netherlands	11	11	0.213	71.136
Cyprus	15	12	0.135	71.293
Finland	12	13	0.178	72.106
Luxembourg	13	14	0.178	72.198
Malta	14	15	0.136	74.018
Ireland	16	16	0.135	75.959
Greece	17	17	0.093	77.599

Note: RightEig = Right eigenvector centrality, Vul = Average vulnerability

Table 4: Robustness simulations

	Simulation 2 (different θ)						Simulation 3 (different ω)					
	Fd2		Td2		Vul2		Fd3		Td3		Vul3	
	Index	R	Index	R	Index	R	Index	R	Index	R	Index	R
Austria	74.290	8	86.760	8	617.601	7	27.339	8	56.691	8	128.670	8
Belgium	81.050	9	94.200	9	617.332	3	28.277	9	57.834	9	127.504	1
Cyprus	232.962	13	253.988	13	618.879	12	62.441	13	90.615	13	132.343	11
Estonia	4231.200	16	4243.600	16	617.475	5	714.407	16	744.862	16	127.866	4
Finland	126.770	12	139.011	12	620.943	14	36.237	11	65.681	12	134.305	13
France	39.512	2	50.385	2	617.674	8	20.961	1	50.164	1	129.066	10
Germany	39.140	1	49.989	1	617.777	9	21.018	3	50.758	2	128.825	9
Greece	83.683	10	104.333	10	624.523	17	37.772	12	64.946	11	150.784	16
Ireland	49.159	6	62.703	6	622.238	16	22.818	6	52.158	6	151.436	17
Italy	44.847	5	57.869	5	617.872	10	22.062	5	51.954	4	128.310	7
Luxembourg	39.627	3	50.399	3	619.867	13	20.974	2	51.633	3	138.959	14
Malta	4525.400	17	4537.400	17	621.473	15	879.368	17	909.022	17	139.594	15
Netherlands	43.846	4	56.643	4	618.813	11	21.790	4	52.097	5	132.440	12
Portugal	93.860	11	107.579	11	617.499	6	30.652	10	59.459	10	127.976	5
Slovakia	364.315	15	377.453	15	616.502	1	83.556	15	115.409	15	127.579	2
Slovenia	301.904	14	315.323	14	616.656	2	74.789	14	106.016	14	127.666	3
Spain	51.559	7	64.515	7	617.398	4	23.247	7	52.769	7	127.978	6

Note: R = Ranking

is ranked lowest probably because most of its investment flows into the UK with only 26.1% remaining in the EZ. The interpretation of all the results is necessarily limited and future research should test the model on a larger dataset.

To check whether these results depend on the specific values assumed for $\boldsymbol{\theta}$ and ω in the computer simulations, table 4 contains the results from two additional simulations: with a different $\boldsymbol{\theta}$ (simulation 2), and a different ω (simulation 3). I arrange countries alphabetically and report all three simulation-based indicators. The parametrization of all simulations is summarized in table 5.

Rankings remain almost identical. Indeed as table 6 shows, the ranking correlations of *All-default times*, *First-default times*, and *Vulnerability* indicators across all three simulations are almost perfect.

Table 6 also sheds more light on the relationships between different indicators. There is significant positive correlation *within* the two sets of importance and vulnerability rankings, but negative correlation *between* them (bottom-left part). The positive within correlation suggests that the indicators capture indeed the same node characteristic (either importance or vulnerability). The difference in rankings reflects the presence of endogenous risk generated by the network structure itself. The negative between correlation shows that the sets of most important and most vulnerable countries do not overlap. Such a situation may lead to moral hazard problems if the most systemically important players do not bear the full network costs of idiosyncratic shocks affecting them, i.e. they do not internalize the negative externality generated on the most vulnerable countries, and take on more risks than would be socially desirable.

Table 5: Simulations parametrization

	Simulation 1	Simulation 2	Simulation 3	Positive contagion
Shock ω	100	100	50	
No. simulations	10,000	10,000	10,000	
Credit-rating	Transmission rates			
CCC	0.2958	0.1372	0.2958	0
B-	0.1479	0.1143	0.1479	0.0007
B	0.0986	0.1067	0.0986	0.0027
B+	0.0739	0.0991	0.0739	0.0060
BB-	0.0592	0.0915	0.0592	0.0107
BB	0.0493	0.0838	0.0493	0.0167
BB+	0.0423	0.0762	0.0423	0.0241
BBB-	0.0370	0.0686	0.0370	0.0328
BBB	0.0329	0.0610	0.0329	0.0428
BBB+	0.0296	0.0457	0.0296	0.0541
A-	0.0269	0.0381	0.0269	0.0668
A	0.0246	0.0305	0.0246	0.0809
A+	0.0227	0.0229	0.0227	0.0963
AA-	0.0211	0.0152	0.0211	0.1130
AA	0.0197	0.0076	0.0197	0.1310
AA+	0.0185	0.0015	0.0185	0.1504
AAA	0	0	0	0.1711

Note: For Malta and Estonia the no. of simulations is 1,000

Table 6: Ranking correlations for Importance and Vulnerability indicators

	LEig	Fd1	Td1	Fd2	Td2	Fd3	Td3	REig	Vul1	Vul2	Vul3
LEig	1										
Fd1	0.980	1									
Td1	0.985	0.998	1								
Fd2	0.980	0.995	0.998	1							
Td2	0.980	0.995	0.998	1	1						
Fd3	0.980	0.995	0.990	0.985	0.985	1					
Td3	0.978	0.998	0.995	0.993	0.993	0.993	1				
REig	-0.115	-0.157	-0.159	-0.186	-0.186	-0.152	-0.149	1			
Vul1	-0.199	-0.213	-0.216	-0.243	-0.243	-0.216	-0.211	0.961	1		
Vul2	-0.132	-0.152	-0.154	-0.181	-0.181	-0.154	-0.149	0.968	0.990	1	
Vul3	-0.208	-0.223	-0.221	-0.248	-0.248	-0.228	-0.211	0.953	0.961	0.961	1

4 Positive Contagion

"We spoke a lot about contagion when things go poorly but I believe there is a positive contagion when things go well. "

Mario Draghi, summer 2012

4.1 A world of two contagions

In the model analysed up to now, the only possible transition for countries was downwards. For instance, in the simple model with only four ratings from subsection 2.2.2, I had:

$$A \to B \to C \to D$$

In reality however, countries can also be upgraded; and as Draghi's quotation suggests, the sign of contagion is probably determined on a daily basis by market news and sentiments. An announcement like the "Draghi Put" or a successful summit might lead to a round of positive contagion, whereas a failed government bonds auction or the publication of exorbitant youth unemployment rates may induce negative contagion. In this more realistic world of two contagions - positive and negative - the transition pattern becomes:

$$A \leftrightarrows B \leftrightarrows C \to D$$

Akin to negative credit spillovers, positive ones occur if institution/sovereign i's initial upgrade leads to an increase in the upgrade probabilities of its creditors. This section extends the basic default model with only four credit ratings to allow for this possibility.

For simplicity, I ignore the exogenous factors that could lead to upgrades and downgrades and concentrate on credit changes that happen because of credit spillovers. Let $\xi(cr_{it}) \in [0;1]$ be the rate at which institution i with credit-rating cr_{it} transmits a positive spillover to its creditors. In this case, the positive transmission rates vector $\boldsymbol{\xi}$ shall be increasing in cr, reflecting the fact that it becomes easier for an institution to transmit positive spillovers as its rating rises. Since a defaulted organisation cannot transmit positive spillovers, I further simplify the vector as: $\xi(D) = 0$, and $\xi(cr) \in (0;1]$ for any $cr \neq D$.

For institution i to be upgraded from B to A thanks to a positive credit spillover from one of its debtors j, it must itself have rating B at the outset - which happens with probability b_{it}, one of its debtors must have rating $cr_{jt} \in \{A,\ B,\ C\}$ - which happens with probabilities $\psi_{jt} = \{a_{jt},\ b_{jt},\ c_{jt}\}$ respectively - and transmit the positive spillover at rate $\xi(cr_{jt})$.

In a world of two contagions, the differential equation that describes the probability that i has rating A at any point in time is therefore:

$$\frac{da_i}{dt} = -\omega \sum_j v_{ij} \{a_{it} z_{jt}\} \, \theta(cr_{jt}) + \phi \sum_j v_{ij} \{b_{it} \psi_{jt}\} \, \xi(cr_{jt}) \tag{9}$$

where $\phi \in \mathbb{R}^+$ captures the magnitude of the positive spillovers. Here I assume that both contagions propagate through the same network - the network of investment shares with adjacency matrix $\mathbf{V}$. A more complex and realistic model would allow positive and negative contagions to spread through multiple and/or different networks.

Similarly, the probability that i has rating B increases in i's probability of being downgraded from A to B, decreases in i's probability of being downgraded from B to C, decreases in i's probability of being upgraded from B to A, and increases in i's probability of being upgraded from C to B.

$$\frac{db_i}{dt} = \omega \sum_j v_{ij} \left\{a_{it} z_{jt}\right\} \theta(cr_{jt}) - \omega \sum_j v_{ij} \left\{b_{it} z_{jt}\right\} \theta(cr_{jt}) - \phi \sum_j v_{ij} \left\{b_{it} \psi_{jt}\right\} \xi(cr_{jt}) + \phi \sum_j v_{ij} \left\{c_{it} \psi_{jt}\right\} \xi(cr_{jt}) \tag{10}$$

Since once defaulted, an institution can no longer be upgraded, the probability that i has rating C increases in i's probability of being downgraded from B to C, decreases in i's probability of being downgraded from C to D, and decreases in i's probability of being upgraded from C to B:

$$\frac{dc_i}{dt} = \omega \sum_j v_{ij} \left\{b_{it} z_{jt}\right\} \theta(cr_{jt}) - \omega \sum_j v_{ij} \left\{c_{it} z_{jt}\right\} \theta(cr_{jt}) - \phi \sum_j v_{ij} \left\{c_{it} \psi_{jt}\right\} \xi(cr_{jt}) \tag{11}$$

Finally, the probability of defaulting remains as before:

$$\frac{dd_i}{dt} = \omega \sum_j v_{ij} \left\{c_{it} z_{jt}\right\} \theta(cr_{jt}) \tag{12}$$

Note that this is a more general version of the model presented in subsection 2.2.2 where ϕ - the magnitude of positive spillovers - was equal to zero, i.e. the positive contagion channel was shut down.[5]

4.2 Can positive contagion save the Eurozone?

"Where's your positive contagion now, Mr. Draghi?"

J. Warner, *The Telegraph* (05/02/2013)

To analyse this more complex model through computer simulations I define:

$$\mathbf{Pr}(i\ upgraded) = \phi \sum_j v_{ij} \xi(cr_j) \tag{13}$$

The new extended *spillovers'* function in the computer algorithm, now associates to each country i two transmission rates $\theta(cr_i)$ and $\xi(cr_i)$. After computing country-specific downgrade and upgrade probabilities using equations 7 and 13, some countries are stochastically downgraded and upgraded producing a new vector of ratings.

Whether positive contagion ultimately dominates its negative counterpart will depend both on the transmission rates vectors $\boldsymbol{\xi}$ and $\boldsymbol{\theta}$, and the respective spillover magnitudes ω and ϕ. While

[5]Following my discussion in footnote 4 about how this multi-stage epidemic model might be used in the context of contagious mental illnesses, note that this extended version with both positive and negative contagions could allow researchers to investigate in a more systematic way "how depressed people's well-being is enhanced or eroded by positive and negative social interactions."(Kashdan & Steger (2009)) Different networks, reflecting the type and intensity of the interaction between people, could be used to propagate the latter.

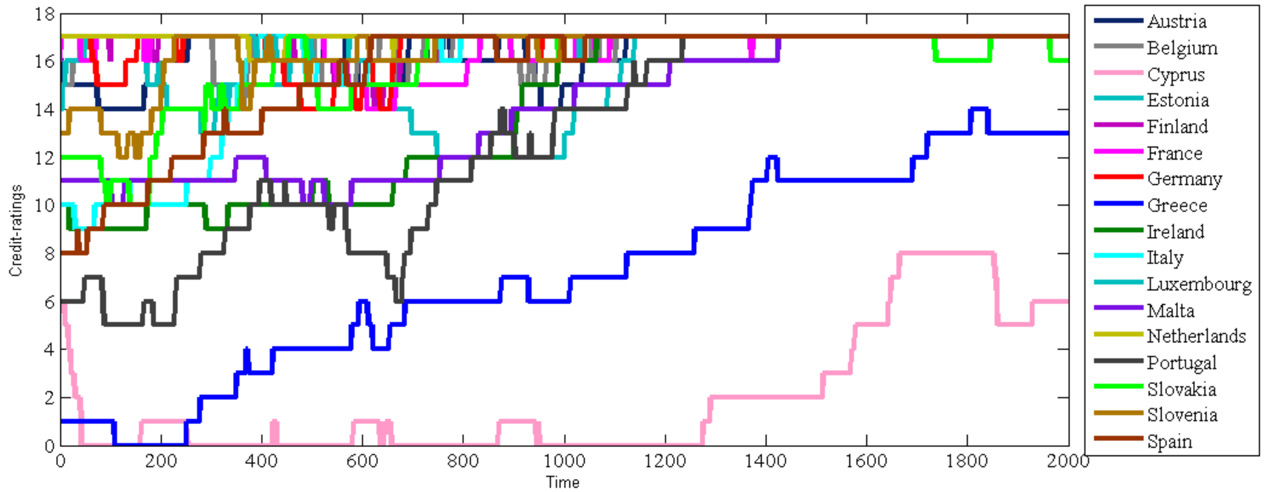

Figure 4: $\omega = 1$; $\phi = 0.3$

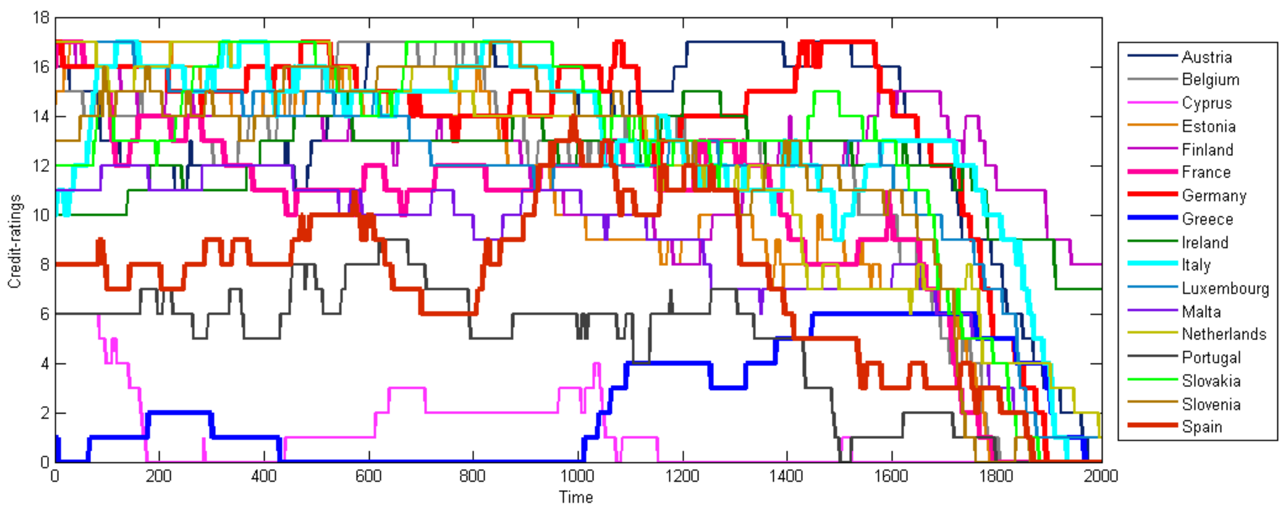

Figure 5: $\omega = 1$; $\phi = 0.2$

future research shall investigate this important issue in a more details, figures 4 and 5 illustrate how, for given $\boldsymbol{\xi}$, $\boldsymbol{\theta}$ and ω, lowering the positive contagion magnitude ϕ from 0.3 to 0.2 changes the scenario from one where most of the countries finish with rating AAA, to a more morose one, with complex spillover dynamics.[6]

This suggests that unless Mr. Draghi manages to make "things go well [enough]", we will have difficulty in noticing positive contagion.

[6] The positive transmission-rates vector used is reported in Table 5.

5 Conclusion and Future Research

> *"The deadliest aspect of the Eurozone crisis is the tripwire linking the riskiness of banks and governments."*
>
> Acharya et al. (2010)

Most of the literature on financial contagion in networks has concentrated on analysing how an initial default of a bank or country triggers a cascade of further failures. The Eurozone sovereign debt crisis however has demonstrated that although *defaults* are likely to be prevented, *credit-rating downgrades* occur rather often. Since credit-ratings are one of the key drivers of investment decisions, a model explaining credit risk spillovers could help understand the observed reallocation of investors' portfolios in response to changes in the creditworthiness of interlinked countries or banks. To identify such credit risk spillovers, this paper models the process of default as a multi-stage disease with each credit-rating corresponding to a different infection phase. I use the model to develop indicators of systemic importance and vulnerability by investigating how the initial exogenous change in the creditworthiness of one of the members of the financial network impacts the creditworthiness of all the other ones.

The illustration of the model in the context of the Eurozone sovereign debt crisis yields interesting and intuitive results. For example, I find that France and Germany occupy the highest positions in the systemic importance hierarchy. However, the interpretation of all the results is necessarily limited by the small dataset. Future research should include more countries and test the model on interbank data, as well as investigate more carefully such phenomena as tipping points and contagion waves. The above quote from Acharya et al. (2010) implies that governments and banks are closely interlinked. Hence further research should not only analyse the networks of banks and governments separately, but also investigate how an initial shock in one of the networks could potentially engender contagion in the other one, or even change its structure.

The literature has focused almost exclusively on negative contagion. However, policymakers seem to be aware that the same endogenous feedback mechanisms that yield negative financial contagion, could in principle be used to activate positive spillovers and shift investors' sentiments. Unfortunately, the extension of the model to include such positive spillovers shows that even though positive contagion could be an attractive solution to the Eurozone sovereign debt crisis, the main policy question remains how to generate it permanently, halting its negative counterpart. Another task for further research is therefore to examine how the ratio of positive to negative spillover magnitudes determines the overall sign of contagion.

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