BIG DATA IN FINANCE PROJECT

Submission 2

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Problem Introduction

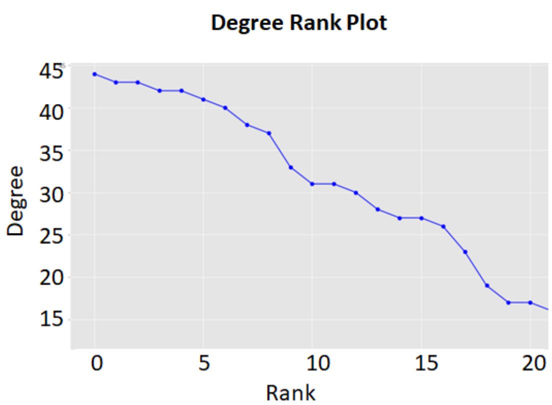
The increasing integration of world economies, which organize in complex multilayer networks of interactions, is one of the critical factors for the global propagation of economic crises (Starnini et al., 2019).

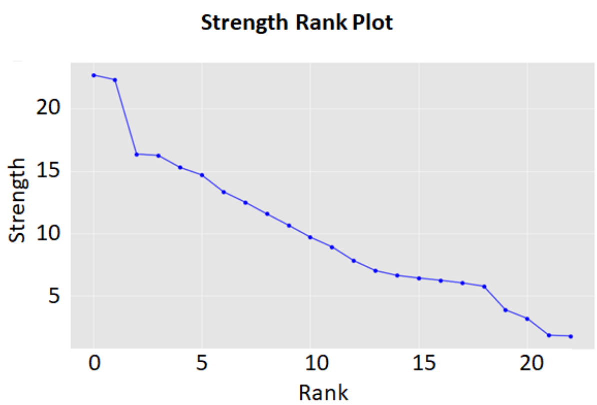
In this project, we aimed to better understand the factors affecting the propagation of risk throughout the global economic system. For our analysis, we represent a subset of the global economic system, spanning 23 economies, as an interdependent complex network, where nodes are individual countries and edges are the trade flows between national economies. We then examined the epidemic spread of crises based on an SIS model, evolving our analysis from a simple model with full homogeneity to a more complex model that introduces heterogeneity on the country level to reflect that certain countries have a higher risk of infection with an economic virus.

The observed dynamic behavior is the result of an interplay between the MMCA framework and the network topology. Therefore, we examine the topological properties of the network before moving on to modelling the epidemic spread of risk by experimenting with the exogenous variables β and μ, which characterize the infectivity rate and recovery rate respectively. We then analyse the obtained experimental results with regards to the global behavior of the system. Specifically, we study how β and μ, as well as the set of initially infected countries affect the speed and reach of the financial crisis. Finally, we draw conclusions about the potential impact of policy initiatives aiming to prevent or mitigate a financial crisis in general and the relevance of interventions in high-impact nations in particular.

Topology

Analysing the underlying network properties is paramount to understand the propagation of risk and financial crises throughout this network. As a proxy for the connectedness of national economies we leverage bilateral trade data from the United Nations Comtrade Database. Defining the edges based on import/export trade volume results in a directed graph with weighted edges, indicating that each country acts as an exporter as well as importer and the trade flows between economies vary significantly.
The resulting network is almost complete, meaning every node is connected with every other node, if represented by unweighted edges. For our analysis, we excluded edges whose strength was in the bottom 30% of the network. We then analysed the global network properties by plotting a degree and strength graph.





We observe that the network does not follow a perfect power law, however, the strength plot clearly indicates the presence of hubs (i.e. US, UK, Germany) that are connected to more nodes and have higher bilateral trade flows, showing the existence of a "rich-gets-richer" effect. As is characteristic for a real network, we observe a low diameter of 2 and a high clustering coefficient of 0.85.

Model explanation

The modeling of financial and economic scenarios using networks has received considerable academic attention. In the following section we outline the Microscopic Markov Chain Approach (MMCA) designed for the spread of epidemics, which we adapt for the modeling of risk propagation in economic networks.

MMCA model for default contagion

The MMCA model was built to cope with the evolution of epidemics, where the states of the agents (nodes) shaping the network were either susceptible or infected. $\tilde{\beta}$ is the infectivity rate for each contact, and $\tilde{\mu}$ is the rate at which an infected individual recovers.

The equation that governs the evolution of the infection process is the following:

$$p_i(t+1) = \big(1 - q_i(t)\big)\big(1 - p_i(t)\big) + (1-\mu)p_i(t) + \mu\big(1 - q_i(t)\big)p_i(t),$$

where $p_i(t)$ is the probability that a given economy is infected by one of the economies it is connected to and $q_i(t) = \prod_{j=1}^{N}\left(1 - \beta w_{ji} p_j(t)\right)$ the likelihood that a given country i is not infected by any of its neighbors.

The right-hand side of the equation represents: $(1 - q_i(t))(1 - p_i(t))$ is the probability that a given node, i is susceptible of entering into default $(1 - p_i(t))$ and it is infected, $(1 - q_i(t))$, by at least one of its neighbors in default. The term $(1 - \mu)p_i(t)$ is the probability that a node i in default does not recover $(1 - \mu)$. Finally, the term $\mu(1 - q_i(t))p_i(t)$ corresponds to the probability that a given node i recovers from default but is re-infected by at least one of its neighbors already in default $(1 - q_i(t))$. (Barja et al., 2019)

Our context

For our analysis we ran a variety of experiments, the two main factors we experimented with were the impact of the origin nation of the crisis and the impact of the exogenous variables β and μ on the propagation of the financial virus. In a first step, the simulations were run with infectivity and recovery rates as exogenous parameters in the range [0, 1] equally applied to the whole network. In an additional step we ran the same simulations on a heterogenous underlying network topology. With the aim of more closely representing the reality of the economic system, we defined a set of countries with a higher risk of infection. For this subset of countries, we applied a multiplier to the β when running the simulations. The affected countries were selected based on the reserves to outstanding debt ratio which serves as a measure of resilience towards crises (Frankel et al.). Countries with the lowest ratio were defined as high risk β were manipulated with different multipliers.

To assess the impact of the origin of the crisis, we initiated the crisis in the three most and three least system relevant countries in the network. We based our selection on the strength ranking of all countries, which indicates the strength of the connections of a specific nation with the rest of the network. Specifically, we identified the United States, United Kingdom and Germany as highly connected countries and Greece, Chile and Finland as the least connected countries. As a baseline for comparison we also initiated the crisis in 3 random countries in the middle of the strength ranking.

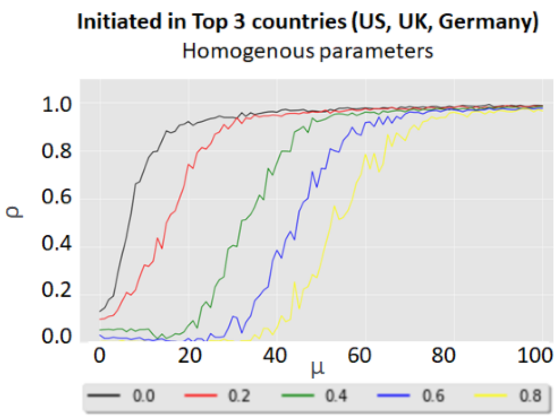
Those three countries were Austria, Italy and Turkey. To assess how changes in the risk profile of specific high leverage nations impact the system, we reran the same analysis with adjusted β for highly vulnerable countries. The selected countries based on reserves to outstanding debt ratio were the Netherlands, Finland, France, Austria, Germany and the United States.

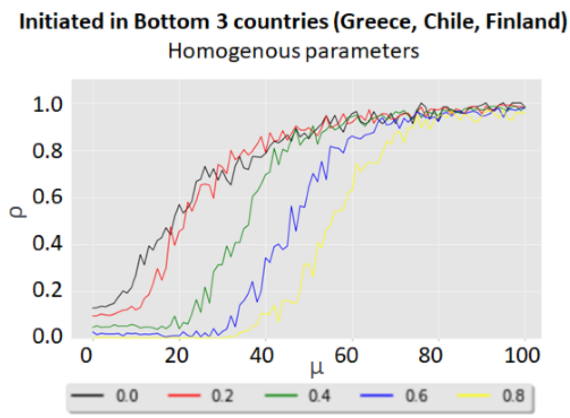
Results

As mentioned above, we performed different simulations of the spread of defaults across the network. In each of the scenarios we observed changes in the intensity and speed of the infection.
The following graphs show how the defaults spread across the network. On the x-axis we have the β-value referring to the infectivity assigned to the network. The y-axis reflects the percentage of the network that has been infected. The lines therefore represent how the overall percentage of the network that is infected changes as the infectivity rate of the network increases. The different colors represent different μ values, indicative of the recovery rate of each node across the network. The higher the μ value, the higher the probability of recovery of the nodes in the network. For each of these scenarios we begin the infection by manually infecting three countries.

Homogeneous Model

To begin our explanation of the results we will analyze a baseline scenario, in which there is no heterogeneity introduced in the model, and we will observe the differences in the way the infection spread across the network based solely on the different countries of origin.



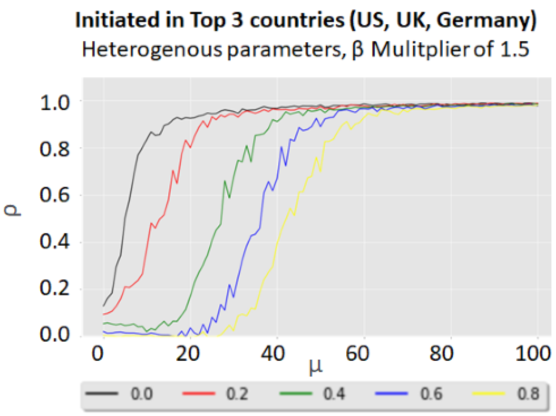


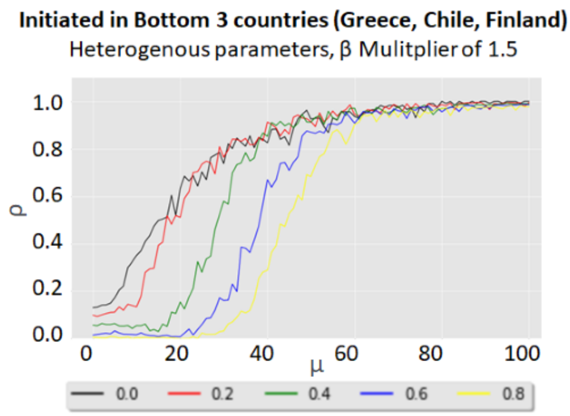
The results show the source of the infection is of high importance relative to the spread of a financial crisis in the homogeneous mode. Comparing the two simulations, we observe that a crisis beginning in the most interconnected countries, namely United States, United Kingdom and Germany, will spread much faster, infecting a large part of the network with relatively low infectivity values compared to an infection starting from the least interconnected countries in the network (Greece, Chile and Finland).

For example, the green line in the graphs represents how the infection would spread across our network if all nodes had a probability of recovery of 40%. In graph 2, we see that the infection would reach 80% of the network with a β value of 0.41 which indicates that to infect 80% of the network the nodes need to have a 41% chance of being infected. In graph 3, we observe that this value increases by about 5 percentage points to reach 0.46. Interestingly enough, if the μ value was equal to 0.2 (red line), the value of β required to infect 80% of the network would respectively be equal to 0.22, 0.24, and 0.32 for an infection originating in the three most connected, three randomly picked, or three least interconnected countries. As expected, the strength degree of the countries from which a financial crisis originates is of great importance to determine how the crisis will spread.

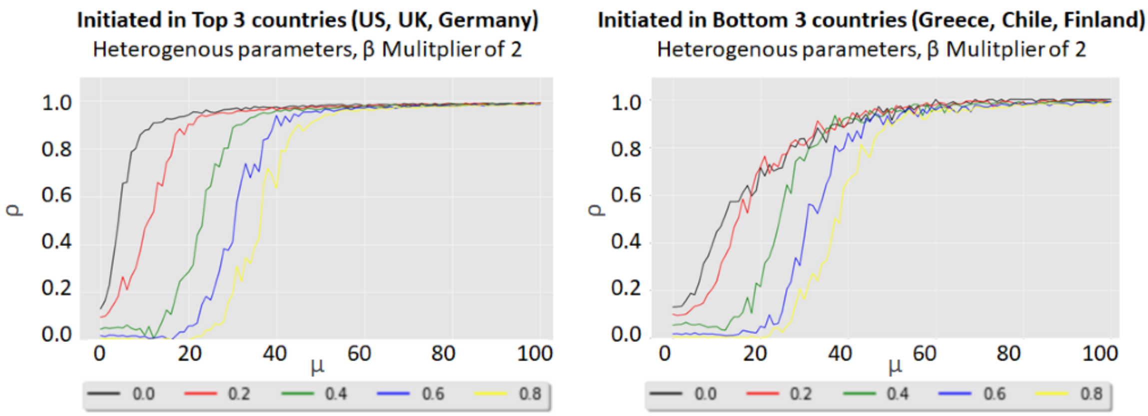
Introducing Heterogeneity

In order to introduce heterogeneity, we created a multiplier of the risk based on economic data. We identified that the levels of reserves of a country are very indicative of the country's ability to sustain such crisis. The theory behind this concept is that reserves are necessary to repay outstanding debt during a crisis, and an absence of liquidity is imposing risk of default. Therefore, we decided to rank the countries in our network based on reserves as a percentage of their outstanding debt. We then performed simulations applying additional risk only to those countries with the lowest reserves as percentage of outstanding debt, to identify changes in the way the crisis spreads.
In our first scenario, we apply a multiplier equal to 1.5.





The results show the effects of introducing heterogeneity in the model. At first glance we can see a relatively strong difference between these graphs and the ones we analyzed previously in the homogeneous model. Comparing to the previous graphs, the values of β necessary for the infection to reach 80% of the network have decreased across the board. The effect is especially pronounced in simulations with a high μ value (yellow line), whose slope increases more. This indicates that higher risk exposure of critical countries might not effectively be countered with higher recovery rates. The charts show that as the level of μ increases, the magnitude of the changes in the β necessary to infect 80% of the network increase as well. This may indicate that as we introduce heterogeneity, the impact of the recovery rate on mitigating the increase in infection decreases.
Increasing the multiplier to 2.0 creates an extreme case in which the countries that are considered to be at risk due to their values of reserves as a percentage of outstanding debt have their infectivity ratios (β) doubled. This scenario continues the trend we have observed when we first introduced heterogeneity.



Ultimately, it should be noticed that two of the countries that are defined as having higher risk of infection due to their reserve/debt ratio are countries that rank within the top three most interconnected countries in the network (United States and Germany). This is important as the impact of the multiplier may be underestimated in the scenario in which we originate the crisis from the aforementioned top-ranking nations. In fact, as we select them to be infected automatically, the effect of the multiplier may be lost. However, the instance in which a highly interconnected country holds very few reserves compared to its outstanding debt is highly interesting, as it may hold a lot of value with regard to the implementation of economic policy to prevent a financial crisis from happening in the first place.

Implications and Conclusions

The models clearly display large differences in the severity of financial crisis dependent on the country of origin for an economic crisis. Understanding what consequences one can expect as a result of an economic crisis is very valuable for politicians and central banks. Politicians and central banks can use models of systemic economic risk to make better decisions about the policies needed to prevent or mitigate future economic crisis.

Not surprisingly, the interconnectedness with the nation of which an economic crisis originates is highly important for the consequences one can expect. Moreover, being ingrained in a larger interconnected network, the size or strength of the originating economy is also very important for the severity of the economic downturn.

Through these results we have observed that adding heterogeneity to the model increases the magnitude of the spread of the crisis across the network, but also decreases the impact of the inherent recovery rate. This may be an interesting topic to further research as it would indicate that higher risk in specific countries may hinder the recovery ability of the network as a whole.

Furthermore, the relationship between the top-ranking countries with regard to their strength in the network, and the low ratio between reserves and outstanding debt provides important insights. In fact, the countries with the highest interconnectivity across the network, are also in part the same countries that have the largest inherent risk on the basis of the reserve to outstanding debt ratio. Due to their strong connection with the entire network they might act as catalysts of a potential crisis.

This information may be valuable when developing policies aiming at preventing the insurgence of a crisis. If countries that are highly interconnected across the network were required to hold a higher percentage of reserves based on their outstanding debt, the risk of a crisis spreading to these countries may be mitigated, which in turn would decrease the impact of the crisis on the network overall.

References

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Barja, A., Martínez, A., Arenas, A. et al. *Assessing the risk of default propagation in interconnected sectoral financial networks*. EPJ Data Sci. 8, 32 (2019). https://doi.org/10.1140/epjds/s13688-019-0211-y

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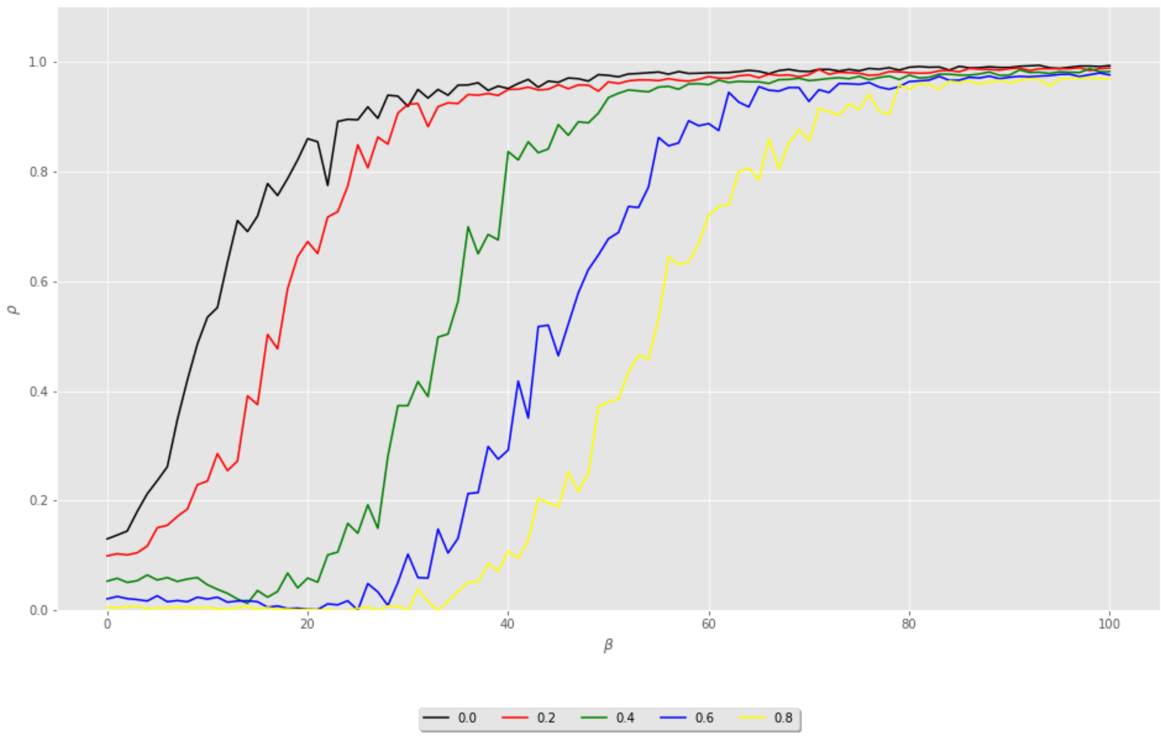
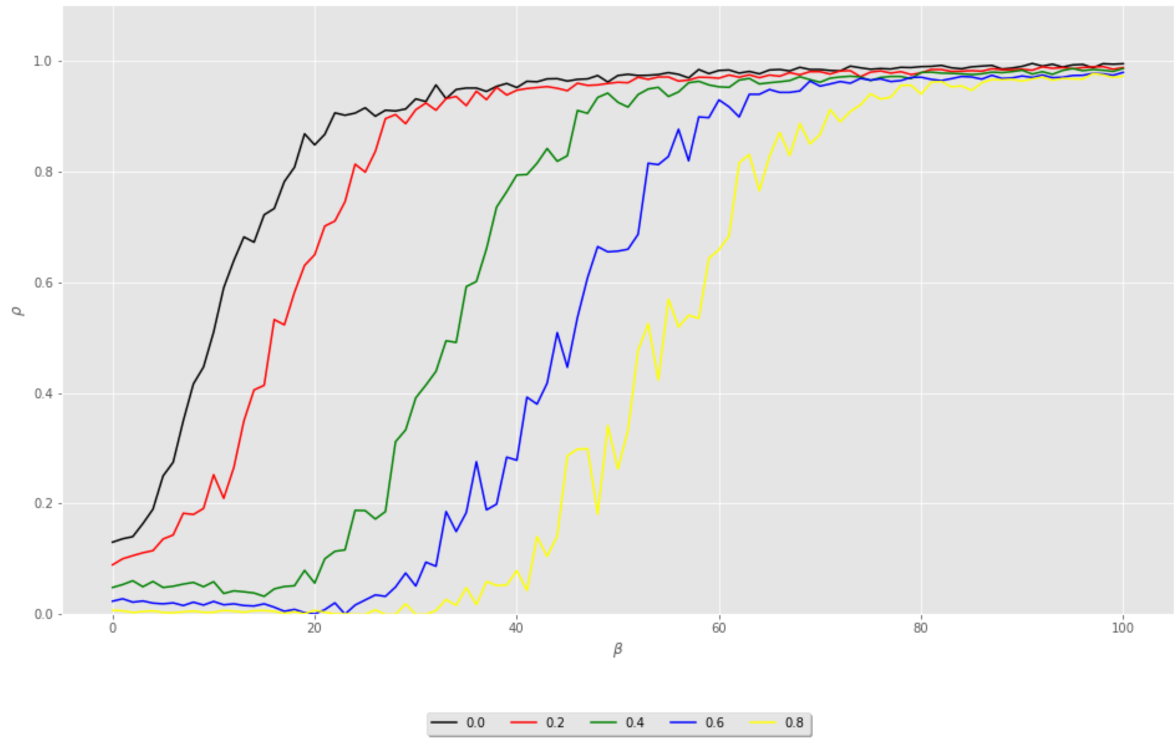
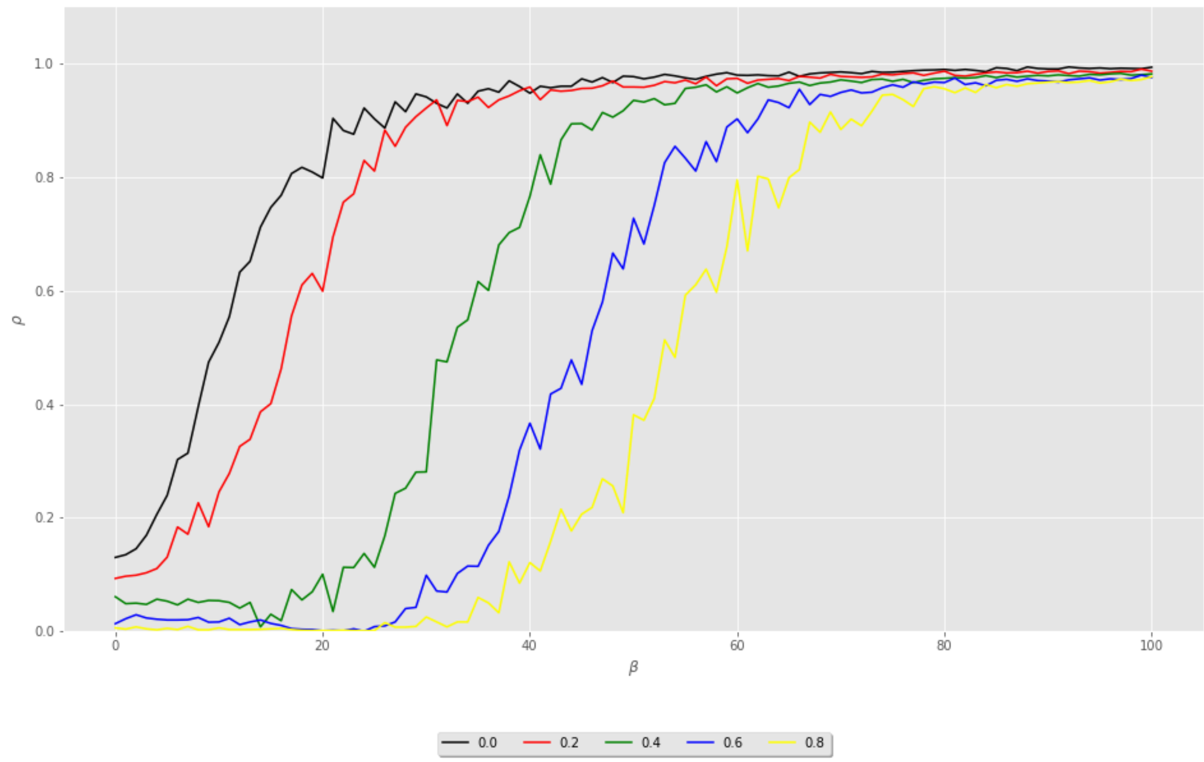
Appendix



Graph 1: Spread of Defaults across the network starting from a random selection of countries in a homogeneous model



Graph 2: Spread of Defaults across the network starting from a random selection of countries after introducing heterogeneity in the model



Graph 3: Spread of Defaults across the network starting from a random selection of countries after increasing heterogeneity in the model

Country Name	Reserves	GDP	Reserves % GDP	Outstanding Debt	Reserves % Debt
Netherlands	13194707105.00	913658000000.00	0.14%	1.3271E+13	0.09943%
Finland	8284157187.00	276743000000.00	0.30%	4.729E+12	0.17518%
France	66103290547.00	2777540000000.00	0.24%	3.0986E+13	0.21333%
Austria	11653251921.00	455286000000.00	0.26%	3.912E+12	0.29788%
Germany	59173100675.00	3947620000000.00	0.15%	1.8734E+13	0.31586%
United States	114757000000.00	20544300000000.00	0.06%	3.5996E+13	0.31880%
Spain	59030411978.00	1419040000000.00	0.42%	1.7566E+13	0.33605%
Canada	83925602808.00	171334170487701.00	0.05%	1.8979E+13	0.44220%
United Kingdom	159872000000.00	2855300000000.00	0.56%	3.6057E+13	0.44339%
Greece	2918421299.00	218032000000.00	0.13%	5.77E+11	0.50579%
Ireland	4975323463.00	382487000000.00	0.13%	9.28E+11	0.53613%
Italy	51330748572.00	2083860000000.00	0.25%	8.516E+12	0.60276%
Australia	51048086920.00	1433900000000.00	0.36%	6.876E+12	0.74241%
Belgium	17486655859.00	542761000000.00	0.32%	2.335E+12	0.74889%
Portugal	9158607287.00	240675000000.00	0.38%	9.56E+11	0.95801%
Sweden	55385715101.00	556086000000.00	1.00%	3.465E+12	1.59843%
Japan	1238940000000.00	4971320000000.00	2.49%	4.3718E+13	2.83394%
Singapore	287466000000.00	364157000000.00	7.89%	5.676E+12	5.06459%
Switzerland	744167000000.00	705140000000.00	10.55%	1.0842E+13	6.86374%
Korea	398780000000.00	1619420000000.00	2.46%	1.978E+12	20.16077%
Chile	39848699140.00	298231000000.00	1.34%	1.42E+11	28.06246%
Turkey	72866830470.00	771350000000.00	0.94%	2.59E+11	28.13391%
India	374425000000.00	2718730000000.00	1.38%	8.56E+11	43.74124%

Table 1: Macroeconomic Data by Country in the Network