



Interconnectedness as a source of uncertainty in systemic risk[☆]



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ABSTRACT

Financial networks have shown to be important in understanding systemic events in credit markets. In this paper, we investigate how the structure of those networks can affect the capacity of regulators to assess the level of systemic risk. We introduce a model to compute the individual and systemic probability of default in a system of banks connected in a generic network of credit contracts and exposed to external shocks with a generic correlation structure. Even in the presence of complete knowledge, we identify conditions on the network for the emergence of multiple equilibria. Multiple equilibria give rise to uncertainty in the determination of the default probability. We show how this uncertainty can affect the estimation of systemic risk in terms of expected losses. We further quantify the effects of cyclicality, leverage, volatility and correlations. Our results are relevant to the current policy discussions on new regulatory framework to deal with systemic events of distress as well as on the desirable level of regulatory data disclosure.

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1. Introduction

The emergence of systemic risk in financial networks is receiving increasing attention in the literature (Stiglitz, 2010; Allen and Babus, 2009; Acemoglu et al., 2015a) and among regulators (IMF, 2015; Yellen, 2013). Network effects matter for financial stability because shocks can be amplified along various channels: common funding sources can lead to a spreading of bank runs (e.g.,

Diamond and Dybvig, 2015; Goldstein and Pauzner, 2004); balance sheet interlocks (e.g., loans, repurchasing agreement, derivatives, etc.) can lead to cascades of defaults, (e.g., Allen and Gale, 2000; Eisenberg and Noe, 2001) or propagation of distress (Battiston et al., 2012); exposures to common assets can lead to a spiral of fire sales and deleveraging across banks (e.g., Caballero and Simsek, 2013; Caccioli et al., 2013).

The main focus of the literature has been so far on understanding how the structure of the financial network (along the various aforementioned channels) can mitigate or amplify systemic risk (Elsinger et al., 2006; Gai and Kapadia, 2011; Gai et al., 2011; Georg, 2015; Cont et al., 2013; Roukny et al., 2013; Elliott et al., 2014; Acemoglu et al., 2015b; Glasserman and Young, 2015). Fewer works have been devoted to understanding how the structure of the financial network can instead affect the very ability to assess systemic risk. At the regulatory level, forecasting limitations is a source of uncertainty that, in turn, can make any decision potentially harmful to the system despite the apparent need for action (Bernanke, 2010). At the individual level, uncertainty about cross exposures and losses of counterparties can trigger panic and fire sales even from healthy banks (Caballero and Simsek, 2013; Alvarez and Barlevy, 2014).

In this paper, we develop a model of a financial network that includes an interbank market as well as external assets and external sources of funds. In spirit, our model is closest to Elsinger et al. (2006) and Rogers and Veraart (2013) who build on the framework introduced by Eisenberg and Noe (2001) in which a clearing vector of payments and a recovery rate is determined after the

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maturity of the contracts (i.e., *ex-post*) assuming different levels of liquidation efficiency. Instead, we are here interested in *ex-ante* valuation of contracts in order to determine probabilities of default. Furthermore, as in practice asset liquidation implies lengthy legal settlements, we assume that, in the short run, recovery rates are limited (Cont et al., 2013).

Our first contribution is thus to provide a framework that allows to compute analytically the probability of default of any subset of banks for a generic structure of the interbank network and a generic structure of shocks correlation among external assets. To our knowledge, few works have provided a simple solution to this problem (Gouriéroux et al., 2013; Glasserman and Young, 2015). The simplicity of our result stems from the analysis of the set of default conditions as a system of coupled equations in the space of shocks.

Our second contribution is to show how, even in the case of complete knowledge of the web of contracts and distributions of shocks, multiple equilibria can exist depending on the network structure. Those co-existing equilibria may include the case in which all banks default and the case in which no bank defaults, as well as intermediate cases.¹ More precisely, we show that, under mild conditions on the balance sheets across banks, a sufficient condition for multiple equilibria to exist is that the interbank network architecture exhibits cyclical structures, i.e., at least one closed chain of lending ties. The reason is that a closed chain of lending ties implies a mutual dependence of the interbank asset values.²

A common way to deal with multiple equilibria is to add to the model some mechanism of equilibrium selection, in order to be able to focus only on one equilibrium.³ However, making assumptions on the equilibrium selection process rules out by construction an intrinsic uncertainty that may be valuable to assess. Indeed, both from the point of view of a firm in a network of contracts as well as for the regulator, uncertainty is fundamental for decision making (Caballero and Simsek, 2013; De Grauwe and Ji, 2015). In this paper, our goal is precisely to characterize the uncertainty stemming from equilibrium multiplicity.

Accordingly, our third contribution is the quantification of this uncertainty, that is, the extent of the area of multiplicity of equilibria in the space of the shocks. While the realization of each equilibrium is mathematically consistent with the set of conditions, there might be different mechanisms at work leading the system to one equilibrium rather than another. In fact, each equilibrium is the result of a coordination of actions at the agent level which, in turn, depends on each agent's belief. In this paper, we do not model explicitly the mechanisms that could lead to coordination. We focus instead on the relation between the structure of the financial network and the existence of the multiplicity.⁴

¹ Furthermore, note that, as our model considers secured credit contracts, the mere occurrence of counterparty default is not sufficient to determine subsequent defaults. It also depends on the amount of collateral posted by the borrower, the capacity to recover it after default and the relative exposure of the lender. Hence, the co-existing solutions are also determined by the balance-sheet structure of the markets participants and the relative level of risk exposure of each bilateral contract.

² The existence of multiple equilibria due to mutual dependence between agents also relates to previous work on specific ring structures reported in (see Chapter 7 in Stiglitz and Greenwald, 2003).

³ For example, both in (Rogers and Veraart, 2013) and in (Elliott et al., 2014), the authors rank the equilibria according to a systemic risk criteria (e.g., the number of defaults) and select the first equilibrium.

⁴ There are several mechanisms that could make agents coordinate on socially good or bad equilibria. Such a coordination could be rational, if the equilibrium is consistent with the beliefs, or not. The rational case further includes sunspot equilibria as described in (Stiglitz and Greenwald, 2003). While the mechanisms leading to the good equilibrium can be very simple (i.e., rational incentives for each bank to survive), the bad equilibrium case can result from information asymmetry, interest rate dynamics, and the combination of liquidity hoarding and asset fire sales. In the latter, if agents come to believe that external assets held by their counterparties are

We further quantify how the uncertainty is affected by the network structure and potential correlations across banks' portfolio returns. In particular, we determine the difference between the probability of default in an optimistic scenario (i.e., the equilibrium with the least number of defaulting banks) and in a pessimistic scenario (i.e., the equilibrium with the highest number of defaulting banks) and we introduce a method to measure the cost of equilibrium selection in terms of expected losses. For instance, we show that a market structure in which banks are arranged in a ring of obligations bears less uncertainty than a centralized structure in which one bank lends to and borrows from all others mainly due to an increase of number of cycles in the network. We also find that correlations have an ambiguous effect on uncertainty. Correlations across shocks increase uncertainty when banks balance sheets are homogenous, but decrease uncertainty for certain heterogeneous allocations of assets across banks.

The insights from this work are relevant to three current policy discussions. A first discussion concerns the lack of a satisfactory framework to deal with too-big-to-fail institutions and with systemic events of distress in the financial system (Haldane and May, 2011; BoE, 2013). In this respect, our work makes a contribution to the stream of work aimed at estimating the systemic impact of financial institutions in a network context. A second discussion concerns the level of financial data disclosure on the side of individual institutions that would be desirable for the regulator to properly assess systemic risk (Abbe et al., 2012). Our results show that the knowledge of the structure is crucial to assess systemic risk but that some level of uncertainty is intrinsic to more interconnected systems. A third discussion concerns the role of the regulator (Draghi, 2012; Miller and Zhang, 2014; De Grauwe and Ji, 2015): in the presence of multiple equilibria, the actions of the regulator can affect, voluntarily or not, the equilibrium selection. On the one hand, our model helps to quantify the expected monetary loss due to a mis-assessment of systemic risk. On the other hand, our model also allows to identify when instead the outcomes are very close and, thus, regulatory decisions would have limited impact.

The structure of the paper is as follows. Section 2 describes the model. Section 3 analyses necessary and sufficient conditions for the existence of multiple equilibria. Section 4 shows how to compute default probability in different scenarios and analyses the effect of the structure of the network and the effect of correlations across shocks. Section 5 introduces a method to compute the expected losses. Finally, Section 6 concludes.

2. The model

We consider a financial network with over-the-counter (OTC) credit contracts among n agents or, for simplicity, banks. A similar model can be found in a companion paper (Battiston et al., 2016) where the focus is on quantifying the effects of network configurations and measurement errors in systemic risk evaluations. We distinguish between secured contracts (i.e., banks have to post a collateral in order to receive a loan) within the banking system itself ("interbank") and contracts of banks on securities outside the banking system ("external"). Formally, we define the interbank financial network as a directed graph as follows.

Definition 1. The network or graph G is the pair (n, E) where n is a set of nodes representing the banks and a set of edges E representing directed credit contracts between two banks going from the lender to the borrower.

overpriced they will hoard liquidity and sell assets, thus inducing counterparties to do the same, effectively causing a coordination on socially bad equilibria.

2.1. Timing of the model

The timing of the model is as follows. At time 1, banks raise funds and make investments in external and interbank assets. At time 2, the values of the external assets are shocked and updated. While the shock distribution is known at time 1, shocks are only observed at time 2. At time 2, the interbank contracts mature and their value is also updated depending on the shocks that have occurred. For each bank i , the main quantities are detailed in the following section.

2.2. Balance sheets

Assets and liabilities of bank i on the external markets are denoted as a_i^E and ℓ_i^E . Assets and liabilities of bank i on the interbank credit market are denoted as a_i^B and ℓ_i^B . Additionally, banks also hold other types of assets that they can use as collateral for their interbank liabilities, denoted as a_i^C . Total assets and liabilities are respectively denoted as a_i and ℓ_i . The equity of each bank is denoted by e_i and is defined as the difference between total assets and total liabilities. Fig. 1 illustrates the model in the context of 3 heterogenous banks lending to and borrowing from each other in a circular way: Bank 1 lends a_1^B to Bank 3 while borrowing l_1^B from Bank 2; Bank 2 lends a_2^B to Bank 1 (i.e., $l_1^B = a_2^B$) while borrowing l_2^B from Bank 3; Bank 3 lends a_3^B to Bank 2 (i.e., $l_2^B = a_3^B$) while borrowing l_3^B from Bank 1 (i.e., $l_3^B = a_1^B$). At the same time, the 3 banks invest in some external assets (a_1^E , a_2^E and a_3^E). In the figure, the 3 assets partially overlap with each other. This feature highlights potential correlations in the return of each bank's external investment. Below we detail the different types of assets.

2.2.1. External assets

At time 1, each bank i allocates its external assets in a portfolio of securities on the external markets. Let E_{ik} denote the fraction of i 's external assets invested at time 1 in the security k . The unitary value of the external security k is x_k^E . Without loss of generality: at time 1, $x_k^E(1) = 1$ for all k , while $x_k^E(2)$ is a random variable drawn from a given distribution. At time 2, then the external assets of bank i , is a sum of random variables:

$$a_i^E(2) = a_i^E(1) \sum_k E_{ik} x_k^E(2). \tag{1}$$

For our purposes, it is sufficient to assume that we can express the external assets of bank i as follows:

$$a_i^E(2) = a_i^E(1)(1 + \mu_i + \sigma_i u_i), \tag{2}$$

where u_i is a random variable drawn from a given distribution with zero mean and finite variance, the parameter μ_i is the expected net return of the portfolio and σ_i is a scaling factor of the magnitude of the shocks. We also assume to know the joint probability distribution $p(u_1, \dots, u_n)$. Let us define $e_i(1)$ as the equity of bank i at time 1. It is then convenient to use the parameter $\varepsilon_i = (a_i^E(1)/e_i(1))$ which measures the magnitude, per unit of initial equity of bank i , of the investments of bank i in external assets. We thus obtain:

$$\frac{a_i^E(2)}{e_i(1)} = \varepsilon_i(1 + \mu_i + \sigma_i u_i). \tag{3}$$

2.2.2. Interbank assets

At time 1, each bank i allocates its interbank assets among the other banks, B_{ij} denotes the fraction of i 's interbank assets invested at time 1 in the liability of bank j . Let us define a default indicator $\chi_j(t)$, with $\chi_j(t) = 1$ in case of default of bank j at time t and $\chi_j(t) = 0$ otherwise. The unitary value of the interbank liability of bank j to bank i is $x_{ij}^B(\chi_j(t))$.

If all banks are assumed to not default at time 1, we have without loss of generality: $x_{ij}^B(\chi_j(1)) = 1$ for all i and j . The liabilities of bank j are constant in value from the perspective of bank j , i.e., the debt agreed upon in the contract at time 1. However, from the point of view of counterparties of j , $x_{ij}^B(\chi_j(2)) = 1$ if bank j honors its obligation, $x_{ij}^B(\chi_j(2)) = R_{ij}$ otherwise, where R_{ij} is the recovery rate, i.e., the fraction of assets that the lender i can recover after the default of j . In formulas:

$$x_{ij}^B(\chi_j(2)) = \begin{cases} 1, & \text{if } \chi_j(2) = 0, \\ R_{ij}, & \text{if } \chi_j(2) = 1. \end{cases} \tag{4}$$

Accordingly, at time 2, the interbank assets of bank i , is

$$a_i^B(2) = a_i^B(1) \sum_j B_{ij} x_{ij}^B(\chi_j(2)). \tag{5}$$

Similar to the external assets, we introduce the parameter $\beta_i = a_i^B(1)/e_i(1)$, which measures the magnitude, per unit of initial equity, of i 's investments in interbank assets. We thus obtain:

$$\frac{a_i^B(2)}{e_i(1)} = \beta_i \sum_j B_{ij} x_{ij}^B(\chi_j(2)). \tag{6}$$

2.2.3. Assets used as collateral

Finally, banks hold some assets a_i^C to be used as collateral for their borrowing. For sake of simplicity, we assume that the value of these assets does not change across the two periods (i.e., $a_i^C(2) = a_i^C(1)$). These assets determine the recovery rate for the lender i after a borrower j defaults. Let R_{ij} be the recovery rate, that is the share of the interbank asset from bank i to bank j that is covered by the collateralized asset of bank j (a_j^C) and R_i be the total recovery rate of bank i in the interbank market weighted by the exposure to each counterparty. We thus have $R_{ij} = (a_j^C/a_{ij}^B(2))$ and $R_i = \sum_j B_{ij} R_{ij}$. As $a_{ij}^B = l_{ji}^B$, the total amount of total collateral posted by one bank is given by:

$$a_i^C(2) = \sum_j R_{ji} l_{ij}^B. \tag{7}$$

Similar to the previous cases, we introduce the parameter γ_i , which measures the magnitude, per unit of initial equity, of i 's collateralized assets:

$$\frac{a_i^C(2)}{e_i(1)} = \gamma_i. \tag{8}$$

2.3. Default condition

As it is standard in financial accounting, we consider that an agent i defaults when its equity at time 2 is negative (i.e., $a_i(2) - \ell_i(2) < 0$). Assuming that the funding side remains constant between time 1 and 2 (i.e., no liability shock), we can re-express such condition in equity relative terms, that is, we divide by the value of equity at time 1 using Eqs. (3), (6) and (8). Note that, in equity relative terms, the liability side is equal to the value of the asset side relative to the equity at time 1 minus the equity, we obtain:

$$\varepsilon_i(1 + \mu_i + \sigma_i u_i) + \beta_i \left(\sum_j B_{ij} x_{ij}^B(\chi_j) \right) + \gamma_i - (\varepsilon_i + \beta_i + \gamma_i - 1) < 0. \tag{9}$$

Note that the collateral portion of the balance sheet is removed from the default condition as its value does not change between time 1 and time 2. Nevertheless, the value of the collateralized assets remains captured in the recovery rate as shown in Eq. (4)

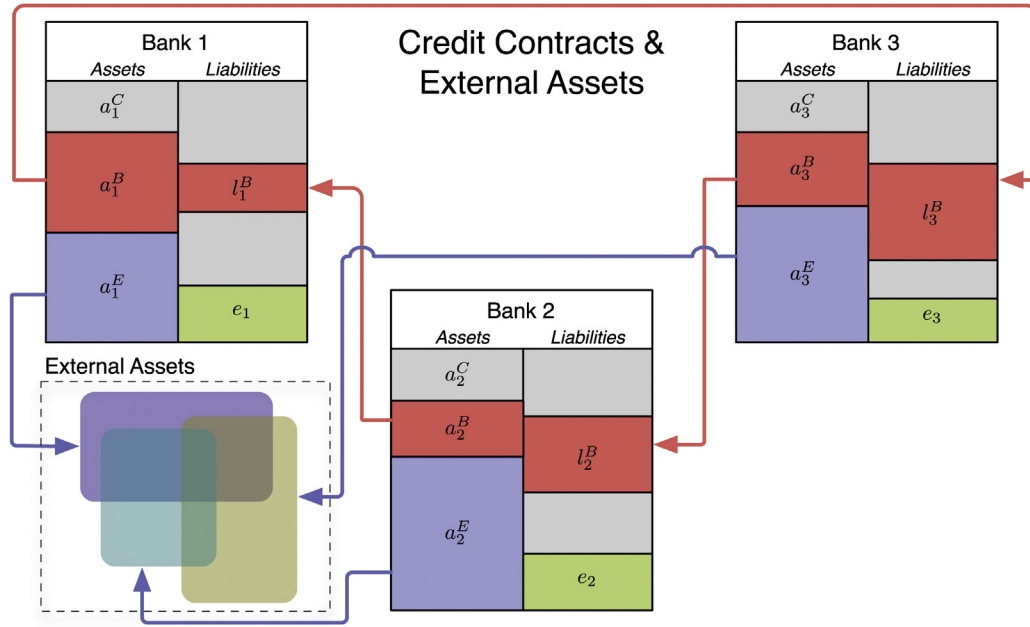


Fig. 1. An illustration of an interbank market of 3 banks lending to and borrowing from each other and investing in external assets (source: Battiston et al., 2016). Each bank is represented by its balance-sheet which is composed of collateral, interbank and external assets and liabilities. The 3 banks are arranged in a circular way, such that Bank 1 borrows from Bank 2 while lending to Bank 3 and Bank 2 borrows from Bank 3. The 3 banks also invest in external assets. The overlap between the external assets highlights potential correlations in the assets' returns.

defining $x_{ij}^B(\chi_j)$. Finally, we express the above condition as a function of the stochastic shock variable on the external assets u_i . We obtain a condition such that if the external shock is below a threshold θ_i , this leads to the default of bank i :

$$u_i < \theta_i = \frac{-\varepsilon_i \mu_i + \beta_i (1 - \sum_j B_{ij} x_{ij}^B(\chi_j)) - 1}{\varepsilon_i \sigma_i}, \tag{10}$$

where θ_i is the threshold value below which u_i would cause the default of i . Notice that we have dropped the time in the notation. Thus, depending on the magnitude and the sign of the shock u_i on each bank, some can default on their obligations, potentially pushing other banks to default.

We can now express the default indicators χ_i of all banks as a system of equations

$$\forall i \quad \chi_i = \Theta(u_i - \theta_i(\chi_1, \dots, \chi_n)), \tag{11}$$

where Θ denotes the step function (or Heaviside function, i.e., equals one if the argument is positive, zero otherwise). A solution of the system above is denoted as χ^* . We define an equilibrium as follows:

Definition 2. An equilibrium is a vector of default indicators $\chi = \{\chi_1, \dots, \chi_n\}$ that is a solution to Eq. (11).

Because Eq. (11) is a system of non-linear equations, in general there can be multiple equilibria. This aspect will be analyzed in Section 3.

2.4. Threshold values

From the above definitions, it follows that the threshold value of every bank i can take a finite amount of different values depending on the identity of i 's counterparties that default at time 2.⁵ Let V_i denote the subset of banks borrowing from bank i and $|V_i|$ the

⁵ Note that, in case of homogeneity, only the number of defaulting counterparties matters and not their identity.

cardinality of such a set. Let Λ_i be the discrete set of all values that θ_i can take, sorted by ascending order, $\Lambda_i = \{\theta_i^1, \dots, \theta_i^{\lambda_i}\}$ with $\theta_i^s \leq \theta_i^t$ if $0 < s \leq t \leq \lambda_i$ and $s, t \in \mathbb{N}$. As every counterparty can have 2 states (i.e., $\chi_j = 1$ or $\chi_j = 0$), we denote the number of values that θ_i can take as λ_i such that:

$$\lambda_i = |\Lambda_i| \leq 2^{|V_i|}. \tag{12}$$

We can characterize the minimum and maximum values that the threshold can take, respectively θ_i^- and θ_i^+ . For convenience, we will refer to those values as θ_i^- and θ_i^+ . Intuitively, the former corresponds to the case where none of the counterparties defaults (i.e., $\chi_j = 0 \forall j \in V_i$) while the latter corresponds to the case where all counterparties default (i.e., $\chi_j = 1 \forall j \in V_i$). From Eq. (10) it follows:

$$\begin{cases} \theta_i^- = \theta_i(\chi_j = 0 \quad \forall j \in V_i) = \frac{-\varepsilon_i \mu_i - 1}{\varepsilon_i \sigma_i}, \\ \theta_i^+ = \theta_i(\chi_j = 1 \quad \forall j \in V_i) = \frac{-\varepsilon_i \mu_i + \beta_i (1 - \sum_j B_{ij} R_{ij}) - 1}{\varepsilon_i \sigma_i} = \theta_i^- + \frac{\beta_i (1 - R_i)}{\varepsilon_i \sigma_i}, \end{cases} \tag{13}$$

where for convenience we denote by $R_i = \sum_j B_{ij} R_{ij}$ the total amount of collateral that bank i recovers from the default of all its counterparties.

The equation above shows that as long as $R_i < 1$ and the parameters $\varepsilon_i, \sigma_i, \beta_i$ are positive, it follows that $\theta_i^- < \theta_i^+$. This reflects the fact that it is easier to default when all counterparties have defaulted than when none has defaulted. Indeed, a larger value of the threshold implies that more shocks will fall below the threshold.

An equivalent way to interpret θ_i^- is to view it as the threshold condition below which a shock would lead bank i to default irrespective of its counterparties' default state (recall that in our model shocks on the external assets can be positive or negative). Indeed, if the shock is below θ_i^- , bank i defaults even if none of its counterparties defaults. Hence, it does not matter whether the bank faces a counterparty default or not, the shock will always lead to the default of bank i . In contrast, θ_i^+ represents the minimal shock needed to

sustain the worse case scenario, i.e., when bank i has lost all its investments in the interbank market, apart from the collateral.

In the remainder of this section, we discuss the parameters' value of interest for our study. We identify conditions under which the value of u_i has an effect on the default of bank i . Let us start with the extreme cases:

- when $\theta_i \leq -1$, In this case, no matter what the value of the shock u_i is, the bank will never default;
- when $\theta_i \geq 1$, In this case, no matter what the value of the shock u_i is, the bank will always default;
- when $-1 < \theta_i < 1$, In this case, the default is a function of the shock u_i . Hence, we are interested in this range of values.

As our study will focus on thresholds whose values belong to the third point, let us analyze what are the underlying parameter conditions for that condition to hold. In order to do so, we can focus on the two extreme thresholds values, θ_i^- and θ_i^+ , as any other $\theta_i \in \Lambda_i$ will be comprised between those two extremes.

For the case of θ_i^- , using Eq. (13) on the above condition, we have:

$$-1 < \theta_i^- < 1 \Leftrightarrow \begin{cases} -\varepsilon_i(\mu_i - \sigma_i) > 1, \\ -\varepsilon_i(\mu_i + \sigma_i) < 1. \end{cases} \quad (14)$$

To interpret the elements $\varepsilon_i(\mu_i - \sigma_i)$ and $\varepsilon_i(\mu_i + \sigma_i)$, recall the expression of the volatility of the external portfolio at time 2 and extract the changes with time 1: $\varepsilon_i(\mu_i + u_i\sigma_i)$. Hence, the two expressions result from the extreme cases where u_i is equal to -1 and 1 , respectively. As we are framing our accounting in terms relative to the equity, we have that the equity is equal to 1. It is thus possible to read the conditions of Eq. (14) as a set of 2 conditions on the effect of the worst shock and best shock. The worst shock, that is, when $u_i = -1$, must yield a return on the external asset that is a loss larger than the equity. The best shock, that is, when $u_i = 1$, must yield a return on the external asset that can be a loss but not larger than the equity.

Similarly, for the case of θ_i^+ , we have:

$$-1 < \theta_i^+ < 1 \Leftrightarrow \begin{cases} -\varepsilon_i(\mu_i + \sigma_i) < 1 - \beta_i(1 - R_i), \\ -\varepsilon_i(\mu_i - \sigma_i) > 1 - \beta_i(1 - R_i). \end{cases} \quad (15)$$

Following the same reasoning as for the interpretation on the conditions for θ_i^- , similar results hold with the subtraction of the element $\beta_i(1 - R_i)$ from the equity. Indeed, this element represents the fraction of assets covered by collateral in terms relative to the equity. Hence, $1 - \beta_i(1 - R_i)$ represents the equity of bank i after all its borrowers have defaulted and all the collateral has been transferred to bank i .

It is clear that all values of θ_i do not have to be constrained between -1 and 1 . Nevertheless, those ranges are the ones of interest when focusing on default scenarios. The above exercise is thus an illustration of how to interpret the conditions under which the network of contracts and the distribution of external shocks will have an effect on the system's equilibrium. For convenience and without loss of generality, we can thus use the following expression:

$$\hat{\theta}_i = \min\{\max\{\theta_i, -1\}, 1\}, \quad (16)$$

where $\hat{\theta}_i$ is the result of a cut-off on both sides of the threshold variable. Indeed, as shown above, when values of θ_i exceed the range $[-1, 1]$, the results become independent of the rest of the system conditions.

3. Multiple equilibria

We now analyze under which conditions the system of equations characterizing the default (i.e., Eq. (11)) leads to multiple equilibria. In particular, we are interested in identifying the conditions on the network structure leading to unique or multiple solutions. Indeed, the structure of the network of contracts enters in the default conditions of Eq. (10) via the matrix B_{ij} of interbank assets. For each bank i , the associated equation has a default threshold θ_i that is a function of the bank's borrowing counterparties' default status. Such subset of banks is, in turn, determined by the network of contracts.

Let us start by defining the notions of walks, paths and simple cycles, that we use to address the multiplicity of equilibria.

Definition 3. A walk W_{i_1, i_k} connecting bank i_1 and i_k is a sequence of banks (i_1, i_2, \dots, i_k) such that the ordered pairs $(i_1 i_2), (i_2 i_3), \dots, (i_{k-1} i_k) \in E$, i.e., are edges in the network. A walk is *closed* if the first and last bank in the sequence are the same, and *open* if they are different. The length of the walk is given by the number of edges it contains, i.e., any walk $W(i_1, i_k)$ has length $k - 1$. A *simple cycle*, denoted by C_n , is a closed walk encompassing n different banks and $n - 1$ edges.

In simple terms, in an interbank financial network, a *cycle* is thus an arrangement of contracts that can be displayed on a circle such that a bank at a position i is borrowing from its left neighbor and lending to its right neighbor. Using this definition, we can now state the necessary and sufficient condition for the system to generate multiple equilibria.

Proposition 1 (Multiple equilibria). *Consider the case of n banks, with: recovery rate $R_i < 1$; interbank leverage $\beta_i > 0$; external leverage ε_i ; shock scale σ_i positive and finite; shock mean μ_i finite. For some realization of u , multiple equilibria exist if and only if there exists a simple cycle C_k of credit contracts along $k \geq 2$ banks, such that for each bank i and its borrowing counterparty $i + 1$ along the cycle C_k , it holds that $\hat{\theta}_i(\chi_1, \dots, \chi_i, 0, \dots, \chi_k) \neq \hat{\theta}_i(\chi_1, \dots, \chi_i, 1, \dots, \chi_k)$*

Proof. See Appendix A. \square

The necessary and sufficient conditions in the proposition above are supported by two related but different aspects. The first is the network structure: there can only be multiple solutions to Eq. (11) if the network contains at least 2 banks whose default condition depend upon each other's default status. More in general, a cycle is a chain of dependencies that goes back to the first node, so that the banks involved in such a structure are indirectly lending from and borrowing to all others. Therefore their default conditions depend on all others' defaults. In contrast, an acyclic structure implies that some banks are not lending to any other. It is thus possible to compute unequivocally the default state of those banks independently of any other bank. Once we know their status, the default status of their lender can be determined unequivocally. The same process is iterated recursively to the lenders of the lenders until a unique vector of all default states is reached (i.e., a unique equilibrium).

The second aspect is related to the dependencies among the default states. If, for a given shock on the external assets, the default condition of bank i does not change whether i 's borrowing counterparties default or not because, for instance, both thresholds are above 1 or below -1 or equal, then there are no multiple equilibria for bank i . Accordingly, the second condition in the above Proposition, states that the default of a borrower of bank i in the cycle must imply a difference on the default condition of bank i . Note that in the Proposition we use the cutoff expression (see Eq. (16)) for the thresholds in order to account for the fact that the interval between the thresholds must intersect the shock domain $[-1, 1]$.

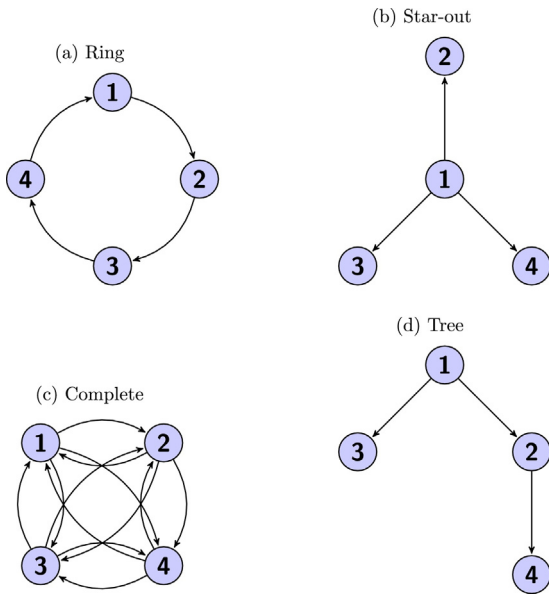


Fig. 2. Example of network structures.

While it might be intuitive to think that the different structure will lead to different profiles of multiplicity in the shock space, Proposition 1 allows to gain precise insights regarding specific structures. To illustrate this point, let us inspect several simple network structures represented in Fig. 2.

For the tree structure, which is acyclical, we can deduce that, for all combinations of shocks, the equilibrium will be unique. The same holds for the star-out structure. On the contrary, the complete and ring structure will display multiple equilibria as long as condition 2 of Proposition 1 holds. From condition 1 in Proposition 1, we can also state a sufficient condition on the interbank market to ensure uniqueness of the equilibrium.

Corollary 1. *An interbank market with no intermediation (i.e., banks only act as borrowers or lenders) always lead to a unique equilibrium for the default state.*

This result is obtained from the fact that, in a directed graph, if the nodes have only out-going or in-coming links, for sure there cannot be a directed cycle. In other words, in a market where banks play only one role (i.e., no intermediaries, only strict borrowers and strict lenders), there are no cyclical interdependencies and thus no multiplicity of equilibria.

4. Probability of default

We now show how our model can be used to compute the individual and systemic probability of default, given a network of contracts and a joint probability density function of shocks on external assets. In order to compute the systemic probability of default, in analogy to the individual default indicator, we define a systemic default indicator χ^{sys} as follows:

$$\chi^{sys} = \prod_i \chi_i. \tag{17}$$

The definition implies that $\chi^{sys} = 1$ only when all banks default, i.e., $\chi_i = 1 \forall i$ and $\chi^{sys} = 0$ otherwise. Note that this definition could be relaxed in order to account for less extreme definitions of systemic default. For example, we could consider as systemic default

a situation in which *at least* more than half of the banks default as follows,

$$\chi^{sys} = \begin{cases} 1 & \text{if } \sum_i \chi_i > \frac{n}{2}, \\ 0 & \text{else.} \end{cases}$$

For the sake of simplicity in the remaining of the paper, we focus on the cases of all banks defaulting (i.e., $\prod_i \chi_i = 1$ for all i). We also show that the results are qualitatively robust to relaxations in the definition of χ^{sys} as long as it is based on the vector of defaults states $\{\chi_i\}$.

Let us consider the case in which Eq. (11) has a unique solution for every combination of shocks. Given the individual and systemic indicators of default, we can compute the individual (resp. systemic) probability of default by integrating the individual (resp. systemic) default indicator across the whole space of shocks, weighted by the joint probability associated with each shock combination according to the following definition.

Definition 4 (Systemic default probability). Consider a market of n banks. The default probability of an individual bank i , P_i , and the systemic default probability P^{sys} for the default states $\{\chi_i\}$ for each u are defined as follows:

$$\forall i \quad P_i = \int_{[-1,1]^n} \chi_i(u) p(u) du, \tag{18}$$

$$P^{sys} = \int_{[-1,1]^n} \chi^{sys}(u) p(u) du, \tag{19}$$

where χ_i is a unique solution of Eq. (11) as a function of u and $p(u)$ denotes the joint probability distribution of the shocks on the external assets of the banks.

The above definition illustrates that, once the default status of all the banks is known for every combination of shocks and that each combination of shocks is associated with a probability, we can compute the probability of default of every bank individually and the probability of systemic default.

In fact, for any given default state χ , we can determine the values of the thresholds $\theta = f(\chi)$. For example, in a market of two banks, we have:

$$(\chi_1, \chi_2) = (1, 1) \text{ iff } u_1 > \theta_1^1(\chi_2 = 1) \text{ and } u_2 > \theta_2^1(\chi_1 = 1).$$

From the values of the thresholds in the space of shocks, we can determine the individual probability of default P_i .

Recall that the space of shocks is weighted by the probability distribution of the shocks, which account for possible correlations. Every default condition holds in a region of the space. As the default information is retrieved by the binary default indicator χ_i summing up the areas where a given condition holds and dividing by the whole area of shocks gives its probability of occurrence.

Notice that by weighting the elements of the shock space by the joint probability distribution of the shocks we account for possible correlations across shocks. Any correlation structure can be embedded in the function $p(u)$.

4.1. Multiple equilibria and probability of default

In the presence of multiple equilibria of the default state χ for a given combination of shocks, the formula of Definition 4 cannot be applied anymore, because, when integrating over the shock space, the integrand can take several values for the same shock.

In order to overcome this problem, we resort to the study of scenarios. Depending on the scenario, for any given shock for which multiple equilibria exist, one equilibrium is selected according to a predefined rule. More precisely, we define the worst and the best

equilibrium as the function that for any given shock u , selects the solution in which the largest (resp. the smallest) number of banks default.

Definition 5. Given the set $\{\chi_k^{sys}(u)\}$ of all the possible solutions for the default conditions of Eq. (11) for any given shock u , the *worst equilibrium* is the function of the shock u : $\chi^{sys+}(u) = \max_k \{\chi_k^{sys}(u)\}$. The *best equilibrium* is the function of the shock u : $\chi^{sys-}(u) = \min_k \{\chi_k^{sys}(u)\}$

In the following we will refer to the best (worst) scenario as the one in which the best (worst) equilibrium is selected. Accordingly, we define as P^+ (respectively P^-) the systemic default probabilities in the two scenarios.

Definition 6. The **systemic default probability** in the worst (+) (“pessimistic”) scenario and best (−) (“optimistic”) is defined as:

$$P^\pm = \int \chi^{sys\pm}(u)p(u) du. \tag{20}$$

We define as **uncertainty on the systemic default probability** the difference between the systemic default probability in the two scenarios:

$$\Delta P = P^+ - P^-. \tag{21}$$

We define as **uncertainty area**, the portion of the shock space in which the worst and the best equilibria are different.

$$\Delta U = \int (\chi^{sys+}(u) - \chi^{sys-}(u)) du. \tag{22}$$

According to the above definitions, ΔU measures the area in the normalized shocks space where multiple equilibria arise, while ΔP measures the difference between the probability of default in a “pessimistic” and in an “optimistic” scenario. Note that the inequality $1 \geq \Delta P = P^+ - P^- \geq 0$, always holds, with $\Delta P = P^+ - P^- > 0$ strictly holding in the case of multiple equilibria.

Intuitively, while ΔU captures the extent of the multiplicity, ΔP captures the impact of the multiplicity on the computation of default probabilities. More in detail, ΔP captures the uncertainty in the assessment of systemic risk, due to the presence of multiple equilibria, as a difference between the probabilities of systemic default in the best and the worst scenario. In other words, ΔP measures the possible misjudgment in assessing systemic risk by relying only on one single scenario (the optimistic or the pessimistic one). In this respect, cases with small ΔP (even in the presence of multiple equilibria) imply less uncertainty and less potential misjudgment than cases with large ΔP .

If the systemic default indicator is defined as equal to one in case a subset of banks default instead of the whole system, the results of this paper remain qualitatively robust. In fact, the insights from Proposition 1 would still hold for the following argument. Recall that in order to compute the probability of a systemic event of k out n banks defaulting we have to impose the default of k banks and measure the area in the shock space where this is a solution of the system. If multiple solutions exist, the default of at least k banks represents the worst scenario (instead of requiring n defaults), while the solution with the least number of defaults represent the best scenario. The conditions for multiplicity are still the same, i.e., that there is at least a cycle of contracts with different values of thresholds for each of the banks along the cycle.

In contrast, quantitatively the result could change with $k < n$. Indeed, everything else the same, it is more probable to have at least k banks out of n defaulting rather than n banks defaulting. In the limit of very large n and very small k (with homogenous banks), the probability of having no bank defaulting or k bank defaulting should be the same and thus $\Delta P \rightarrow 0$. However, the qualitative results of this paper still hold because in the formula for ΔP the worst case

scenario of n banks defaulting includes the case of at least $k < n$ defaulting. In the following, we obtain analytical expressions for this measure and we provide results on how it depends on the network structure and the balance sheet of the banks. To make the presentation more intuitive, we start with a simple example of two banks.

4.2. Example: a market of 2 banks

Let us take a market composed of only 2 banks that lend to and borrow from each other. For the sake of simplicity, let us assume the distribution of shocks to be uniform and uncorrelated. In this simple case, Bank 1 and Bank 2 experience respectively the shocks u_1 and u_2 on their external assets, and their corresponding default state depends on each other’s default state. More precisely, their default condition threshold θ_i can take 2 values. In formulas, we have:

$$\theta_i = \begin{cases} \theta_i^- = \frac{-\varepsilon_i \mu_i - 1}{\varepsilon_i \sigma_i} & \text{if } \chi_j = 0 \quad \forall j, \\ \theta_i^+ = \frac{-\varepsilon_i \mu_i - 1}{\varepsilon_i \sigma_i} + \frac{\beta_i(1 - R_{ij})}{\varepsilon_i \sigma_i} & \text{if } \chi_j = 1 \quad \forall j. \end{cases} \tag{23}$$

The case of 2 banks can be easily illustrated on the 2-dimensional shock space, as shown in Fig. 3 where the market with 2 banks is illustrated in the top of the figure while the bottom part of the figure represents the shock space in which the different equilibrium cases are reported.

Recall that θ_i^- defines the threshold below which the bank defaults unconditionally. In Fig. 3, those thresholds are reported in dotted lines. The case of θ_i^+ defines the threshold below which the bank defaults conditional on the other bank’s default. In Fig. 3, those thresholds are reported in plain lines. The space can be divided into 4 different regions characterized by the ordered pair of default state combinations. Recall that the value of interbank liability of bank j and its default state are related as follows: $x_{ij}^B = 1$ iff $\chi_j = 0$ (no default) and $x_{ij}^B = R_{ij}$ iff $\chi_j = 1$, see Eq. (4). Note that, as banks have only one exposure, we can simplify the expression by $R_i = R_{ij}$. Therefore, we have:

$$(\chi_1, \chi_2) = \begin{cases} (0, 0) & \text{when } u_i > \theta_i^- \quad \forall i; \\ (0, 1) & \text{when } u_1 > \theta_1^+ \text{ and } u_2 < \theta_2^-; \\ (1, 0) & \text{when } u_1 < \theta_1^- \text{ and } u_2 > \theta_2^+; \\ (1, 1) & \text{when } u_i < \theta_i^+ \quad \forall i; \end{cases} \tag{24}$$

Notice that the first and fourth conditions in the list above hold simultaneously for certain values of u_1, u_2 , implying that there is a multiplicity of equilibria. In particular the equilibrium in which both banks default and the one in which no bank defaults coexist in the following region of shocks, indicated in squared purple area in Fig. 3.

$$(0, 0) \text{ AND } (1, 1) \text{ when } \theta_1^- < u_1 < \theta_1^+ \text{ and } \theta_2^- < u_2 < \theta_2^+. \tag{25}$$

Following Eq. (20), and recalling that we have assumed in this example a uniform distribution of shocks in the space $[-1, 1]$ (hence $p(u) = 1$), we can provide the analytical expression of P^+ and P^- . Indeed, the region where the default indicator equals 1 is the region defined by the fourth condition in Eq. (24). We thus obtain:

$$P^+ = \frac{(1 + \hat{\theta}_1^+)(1 + \hat{\theta}_2^+)}{4}, \tag{26}$$

$$P^- = \frac{(1 + \hat{\theta}_1^+)(1 + \hat{\theta}_2^+)}{4} - \frac{(\hat{\theta}_1^+ - \hat{\theta}_1^-)(\hat{\theta}_2^+ - \hat{\theta}_2^-)}{4}, \tag{27}$$

$$\Delta P = \frac{(\hat{\theta}_1^+ - \hat{\theta}_1^-)(\hat{\theta}_2^+ - \hat{\theta}_2^-)}{4}. \tag{28}$$

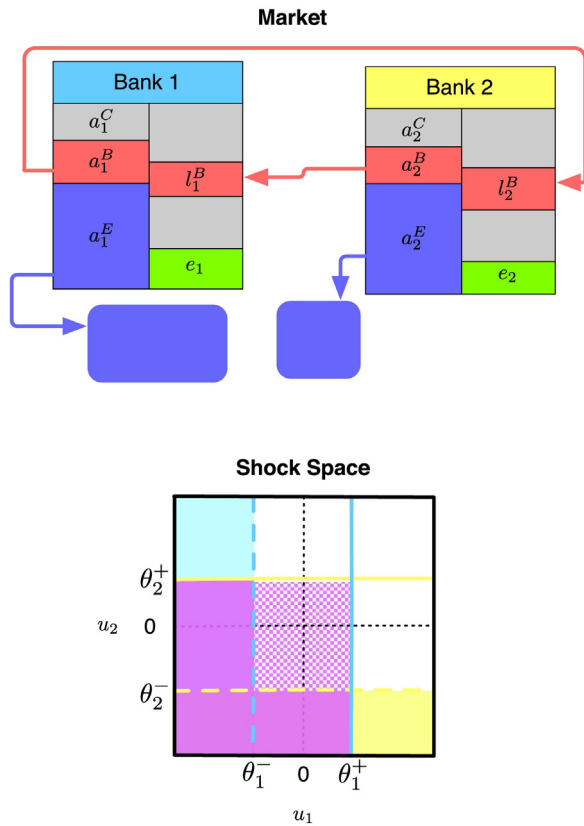


Fig. 3. Simple example of a market of 2 banks lending to and borrowing from each other. The 2 banks also invest in uncorrelated and uniformly distributed external assets. The top figure illustrates the corresponding market of interactions while bottom figure illustrates the shock space and the regions of equilibrium with respect to the combination of states (χ_1, χ_2) . In the shock space, the light blue color is associated with the Bank 1 and the light yellow color is associated with the Bank 2. The white area corresponds to a unique equilibrium where both banks do not default. The light blue area (resp. light yellow area) corresponds to a unique equilibrium where only the Bank 1 (resp. Bank 2) defaults. The plain purple area corresponds to a unique equilibrium where Bank 1 and Bank 2 default. The squared purple corresponds to a case of multiple equilibria: both the equilibrium in which Bank 1 and Bank 2 default and the equilibrium in which Bank 1 and Bank 2 do not default coexist.

Assuming that banks are homogenous and that $\hat{\theta}_i = \theta_i$, we obtain an expression of ΔP as a function of the banks' exposure to the external assets and to the interbank:

$$\Delta P = \frac{(\theta^+ - \theta^-)^2}{4} = \left(\frac{\beta(1 - R)}{2\varepsilon\sigma} \right)^2. \tag{29}$$

Finally, ΔP must be bounded between 0 and 1. We thus have as final expression of the uncertainty in a market of 2 banks:

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \left(\frac{\beta(1 - R)}{2\varepsilon\sigma} \right)^2 \right\} \right\}. \tag{30}$$

Note that, with the uniform distribution of the shocks, the portion of the shock space that is affected by multiple equilibria is simply $\Delta U = \Delta P$.

The above example highlights how mutual interdependencies lead to multiple solutions for the default probability. Moreover, in the homogenous case, the difference between the probability of default in the best and the worse equilibrium as well as the area of the region of multiplicity, increases with the exposure to losses on the interbank market (i.e., measured by the product $\beta_i(1 - R)$). In contrast, they both decrease with the scale of shocks on the external markets (i.e., measured by σ_i). More in general, the result shows that if the recovery rate is equal to one (i.e., the exposure is

completely covered by the collateral) then the difference ΔP is 0 and there is no equilibrium multiplicity. On the other hand, when the recovery rate R is equal to 0, we have $\Delta P = \min\{1, (\beta/2\varepsilon\sigma)^2\}$, i.e., the difference is maximal (a difference of probabilities must have one as its upper bound). The situation $R = 0$ corresponds to the extreme scenario of lending contracts that are fully unsecured.

4.3. A ring market of n banks

We now generalize the results illustrated above to a market of n banks arranged in two types of benchmark structures: a ring and a star. Let us start with the ring structure, defined as follows.

Definition 7. A ring market is a network composed of contracts arranged in one cycle C_n .

In light of the discussion of Proposition 1, in this market there is a closed chain of dependencies from any bank i through the whole set of other $(n - 1)$ banks. For the sake of simplicity, we postpone the analysis of correlation across shocks to Section 4.5 and we assume a uniform distribution of shocks. We can state the following proposition.

Proposition 2 (Effect of multiplicity in a ring market). Consider n banks with interbank credit, arranged in a ring market. Assume: recovery rate $R_i < 1$ and interbank leverage $\beta_i > 0$; external leverage ε_i and shock scale σ_i positive and finite; shock average μ_i finite; the joint probability distribution of shocks $p(u)$ is uniform and with no correlation across shocks. Then:

1. The uncertainty ΔP on the default probabilities in the worst and best scenario, P^+ and P^- increases with the interbank leverage β_i of the banks; it decreases with the fraction of collateral R_i , the external asset leverage ε_i and the variance on the shocks σ_i (where increase and decrease are strict). Its expression reads:

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \prod_{i=1}^n \left(\frac{\hat{\theta}_i^+ - \hat{\theta}_i^-}{2} \right) \right\} \right\}. \tag{31}$$

2. If $\hat{\theta}_i = \theta_i \forall i$, the uncertainty ΔP decreases with the length n of the ring market and its expression reads

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \prod_{i=1}^n \left(\frac{\beta_i(1 - R_i)}{2\varepsilon_i\sigma_i} \right) \right\} \right\}. \tag{32}$$

Proof. See Appendix B. □

The proof is analogous to the computation illustrated above in the example of two banks. Note that the expression of the portion of the shock space subject to multiple equilibria ΔU follows the same equation as in Eq. (31) under the uniform distribution assumption. Hence similar results can be inferred.

The above proposition shows that uncertainty increases with the leverage on the interbank, proportionally to the loss exposure (taking into account the collateral, i.e., with $\beta_i(1 - R_i)$). This result stems from the fact that the probability of default in the optimistic scenario (i.e., selecting the best equilibrium) decreases with respect to the interbank exposure (see proof). This shows that increase in the reliance on the interbank market increases the uncertainty in terms of systemic risk but improves the outcome in case the optimistic scenario is realized.

Moreover, uncertainty decreases with the leverage on the external market and its volatility (i.e., with $\varepsilon_i\sigma_i$). This means that an increase in diversification in a bank's portfolio of external assets increases uncertainty. The result seems counterintuitive but it simply stems from the fact that, in relative terms, the smaller the variance of the shocks on the external assets, the smaller the role of the shocks in determining whether banks default or not and thus

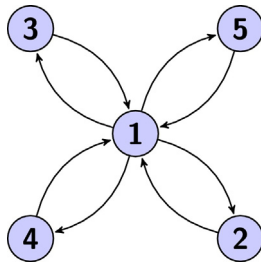


Fig. 4. Star market.

the larger the role played by the interbank assets. In particular, if the variance of the shocks is very small and the interbank assets of banks exceed their equity, then, no matter what is the value of the shocks, in the scenario in which interbank assets are lost, default would occur with probability one.

Finally, the product in the expression of the uncertainty in the above proposition implies that the uncertainty decreases with the length n of the cycle as long as $\beta_i(1 - R_i)/2\varepsilon_i\sigma_i < 1$, which is guaranteed if $\hat{\theta} = \theta$ (see proof). This means that the uncertainty of a ring market decreases exponentially with its size only if the relative weight of the interbank assets over the external assets is small enough.

4.4. A star market of n banks

Let us now move to the case of a star market. In a star market, we have a central counterparty for all the banks in the periphery, both for their borrowing and lending relationships. We illustrate a case of 5 banks in Fig. (4).

Definition 8. A star market is a network composed of one bank in the center, denoted by c , and $n - 1$ banks in the periphery, denoted by the index j . All banks in the periphery only lend to and borrow from the bank at the center.

For sake of simplicity, in the following we assume that the bank at the center lends uniformly across its borrowing counterparties. We thus have that: $B_{cj} = (1/|V_c|)$ where V_c is the set of borrowers of the bank at the center. Note that we now have a system made of multiple cycles. As a result, we have the following proposition.

Proposition 3 (Effect of multiplicity in a star market). Consider n banks with interbank credit arranged as a star network. Assume: recovery rate $R_i < 1$ and interbank leverage $\beta_i > 0$; external leverage ε_i and shock scale σ_i positive and finite; shock average μ_i finite; the joint probability distribution of shocks $p(u)$ is uniform and with no correlation across shocks. Then: The uncertainty ΔP on the default probabilities in the worst and best scenario, P^+ and P^-

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \prod_{i=1}^n \left(\frac{\hat{\theta}_i^+ - \hat{\theta}_i^-}{2} \right) + \frac{(\hat{\theta}_c^+ - \hat{\theta}_c(\sum_j \chi_j = 1)) \prod_{j=1}^{n-1} (1 + \hat{\theta}_j^+)}{2^n} \right\} \right\}. \tag{33}$$

Proof. See Appendix B. □

Where $\hat{\theta}_c(\sum_j \chi_j = 1)$ is the threshold value for the bank at the center to default when only one counterparty has defaulted, that is, when $\sum_j \chi_j = 1$.

Comparing Eq. (33) for the star market with Eq. (31) for the ring market, we observe that the first part of the star market expression is equal to the ring market. In fact, this term comes from the region of overlap between the cases in which all counterparties default and

no one defaults. Such situation is thus similar to the ring case. There are however other equilibria overlap to account for in the case of the star market. Those equilibria correspond to cases where (1) the bank at the center does not default, (2) at least one peripheral bank default and (3) at least one peripheral bank survives. Overall, we thus see that the uncertainty increases when we move from a ring market to a star market mainly due to the increase of cyclicity within the market structure.

4.5. Effect of correlation

We now explore how the uncertainty (i.e., the distance between the best and worse possible probabilities) is affected when we introduce correlations between the shocks on the external assets. In order to illustrate the effect of correlation in the simplest terms, we focus on the case of a ring market structure and we assume a uniform distribution of shocks in $[-1, 1]$. Under the assumption of uniformity, the uncertainty on the default probability coincides with the area of the region of multiplicity. We further consider the case of fully correlated shock and we compare the results with those of uncorrelated shocks from Proposition 2.

Proposition 4 (Effect of correlation). Consider a market of n banks with interbank credit arranged in a ring. Assume: recovery rate $R < 1$ and interbank leverage $\beta_i > 0$; external leverage ε_i and shock variance σ_i positive and finite; shock average μ finite. Shocks are distributed uniformly. Denote by ΔP^U the uncertainty in case of uncorrelated shocks and by ΔP^C the uncertainty in case of fully correlated shocks. Then, the following statements hold.

1. In the case of full shock correlation, the uncertainty on the default probability in the best and worst scenario is:

$$\Delta P^C = \min \left\{ 1, \max \left\{ \frac{\min\{\theta_i^+\} - \max\{\theta_i^-\}}{2}, 0 \right\} \right\}, \tag{34}$$

and if $\min\{\theta_i^+\} \leq \max\{\theta_i^-\}$, there is no uncertainty, $\Delta P^C = 0$.

2. $\Delta P^C > \Delta P^U$ if $\exists k \in N$ s.t. $\min\{\theta_i^+\} = \theta_k^+$ and $\max\{\theta_i^-\} = \theta_k^-$, i.e., complete correlation yields larger uncertainty than no correlation. As a special case, in a ring of identical banks, complete correlation implies larger uncertainty than in the uncorrelated case.
3. $\Delta P^C < \Delta P^U$ if $\sqrt[n]{\min\{\theta_i^+\} - \max\{\theta_i^-\}} < \min\{\theta_i^+ - \theta_i^-\}$, i.e., complete correlation yields smaller uncertainty area than no correlation.
4. $\Delta P^C > \Delta P^U$ if $\sqrt[n]{\min\{\theta_i^+\} - \max\{\theta_i^-\}} > \max\{\theta_i^+ - \theta_i^-\}$, i.e., then complete correlation yields larger uncertainty area than no correlation.

Proof. See Appendix C. □

In the proposition above, the expression of ΔP^C is obtained from a projecting the n -dimensional hypercuboid of the shock space onto its diagonal. Indeed, fully correlated shocks imply that all the shocks hitting all banks have the same value at a time.

From this projection, the determination of the uncertainty depends on the maximal threshold distance (i.e., the distance between the smallest θ_i^+ across all banks i) and the largest θ_i^- (i.e., the smallest maximal and the largest minimal default thresholds across all the banks) in the system.

The first point in the proposition above states that the uncertainty is completely removed if the system has a maximal threshold distance equal to 0, that is, if there is a bank with a maximal default threshold that is smaller than the largest minimal default threshold.

Second, compared to the case of no correlation, full correlation brings in more uncertainty when the two threshold yielding the maximal threshold distance belong to the same bank. This means that there is a bank k for which the interval $[\theta_k^-, \theta_k^+]$ is comprised within the intervals $[\theta_i^-, \theta_i^+]$ of all the other banks. An important

consequence is that in an homogenous ring, full correlation implies more uncertainty than in the uncorrelated case.

Third, correlation also brings more uncertainty when the n th root of the maximal threshold distance is higher than the maximum distance between the 2 extreme thresholds of a single bank in the system. On the contrary, correlation brings less uncertainty when the n -th root of the maximal threshold distance is smaller than the minimum distance between the 2 extreme thresholds of a single bank in the system.

Overall, the above proposition shows that the relationship between correlation and uncertainty is in general non-monotonous.

5. Expected individual and systemic losses

We now provide an extension of our methodology to compute the expected monetary loss in the system resulting from a given configuration of defaults:

Definition 9 (Expected loss). Consider a market of n banks with interbank credit. The expected losses of bank i , $E_i[\text{loss}]$, and the total expected losses $E^{\text{tot}}[\text{loss}]$ are defined as follows:

$$\forall i \quad E_i[\text{loss}] = \int_{[-1,1]^n} e_i(\varepsilon_i + \beta_i - \gamma_i - 1)\chi_i(u)p(u)du, \quad (35)$$

$$E^{\text{tot}}[\text{loss}] = \int_{[-1,1]^n} \sum_i e_i(\varepsilon_i + \beta_i - \gamma_i - 1)\chi_i(u)p(u)du, \quad (36)$$

where χ_i is a solution of Eq. (11) and $p(u)$ denotes the joint probability distribution of the shocks.

Given the individual probabilities of default of each bank, the above definition yields the expected loss that each bank causes to its creditors in case of default. Given a realization of shocks, if bank i defaults, the aggregate amount of money that is lost from its interbank creditors and its external investors is equal to the total liability of bank i , $e_i(\varepsilon_i + \beta_i - 1)$ minus the amount posted as a collateral, $e_i\gamma_i$, i.e., $e_i(\varepsilon_i + \beta_i - \gamma_i - 1)$. Hence, in order to compute the expected loss from bank i , we integrate the aggregated monetary loss over the whole range of shocks accounting for the cases where bank i defaults (i.e., $\chi_i = 1$). For the total expected loss, that is, the total amount of money expected to be lost due to the default of any bank at the system level, we simply aggregate the individual losses for each realization of shocks (i.e., $\sum_i e_i(\varepsilon_i + \beta_i - \gamma_i - 1)\chi_i(u)$) and integrate over the whole range of shocks. Note that in this way, we can simply use the individual default indicator and do not need to identify any systemic default indicator. Hence, in contrast with the computation of the probability of systemic default, the expected total loss quantity E^{sys} is not subject to an arbitrary definition of systemic events (i.e., there is no systemic event indicator akin to χ^{sys} in Eq. (36)).

Similar to the procedure followed for the probabilities of default, if there are multiple equilibria, we consider an optimistic and a pessimistic scenario. In the optimistic (pessimistic) scenario, for any given shock, we choose the equilibrium with the smallest (largest) value of expected losses.

We then define the distance, $\Delta E^{\text{tot}}[\text{loss}]$, between the smallest and largest total expected losses, $E^{-\text{tot}}[\text{loss}]$ and $E^{+\text{tot}}[\text{loss}]$, respectively. This distance measures the impact of multiplicity on the assessment on expected losses and can be interpreted as the monetary cost of uncertainty.

5.1. Example: market of 2 banks.

We illustrate the computation of expected losses with an example of a market of 2 banks lending and borrowing from each

other. For the sake of clarity, let us assume that the distribution of shocks is homogenous and uncorrelated. Let us also define $e_i^* = e_i(\varepsilon_i + \beta_i - \gamma_i - 1)$. Losses occur each time at least one bank defaults. With 2 banks, we have 3 different combinations: bank 1 defaults while bank 2 does not; bank 2 defaults while bank 1 does not; both banks default. We thus have:

$$E^{\text{tot}}[\text{loss}] = e_1^*P(\{\chi_1 = 1, \chi_2 = 0\}) + e_2^*P(\{\chi_2 = 1, \chi_1 = 0\}) + (e_1^* + e_2^*)P(\{\chi_1 = 1, \chi_2 = 1\})$$

The last component of the right hand side bears the multiple equilibria issues defined in the Example 4.2 (i.e., $P(\{\chi_1 = 1, \chi_2 = 1\})$). From Example 4.2 we can derive the expression of highest and lowest total expected losses:

$$E^{+\text{tot}}[\text{loss}] = \frac{e_1^*(1 - \theta_1^+) + e_2^*(1 - \theta_2^+)}{4} + (e_1^* + e_2^*)P^+ = \frac{e_1^*(1 - \theta_1^+) + e_2^*(1 - \theta_2^+) + (e_1^* + e_2^*)(1 + \theta_1^+)(1 + \theta_2^+)}{4}$$

$$E^{-\text{tot}}[\text{loss}] = \frac{e_1^*(1 - \theta_1^+) + e_2^*(1 - \theta_2^+)}{4} + (e_1^* + e_2^*)P^- = \frac{e_1^*(1 - \theta_1^+) + e_2^*(1 - \theta_2^+)}{4} + \frac{(e_1^* + e_2^*)((1 + \theta_1^+)(1 + \theta_2^+) - (\theta_1^+ - \theta_1^-)(\theta_2^+ - \theta_2^-))}{4}$$

Finally, we can identify the effect of equilibrium choice on the expected loss assessment, which we identify by $\Delta E^{\text{tot}}[\text{loss}]$:

$$\Delta E^{\text{tot}}[\text{loss}] = \frac{(e_1^* + e_2^*)((1 + \theta_1^+)(1 + \theta_2^+) - (\theta_1^+ - \theta_1^-)(\theta_2^+ - \theta_2^-))}{4}$$

$$\Delta E^{\text{tot}}[\text{loss}] = (e_1^* + e_2^*)\Delta P$$

If we consider that banks are homogenous and that $\hat{\theta} = \theta$, we obtain:

$$\Delta E^{\text{tot}}[\text{loss}] = 2e(\varepsilon + \beta - \gamma - 1) \left(\frac{\beta(1 - R)}{2\varepsilon\sigma} \right)^2$$

6. Discussion

In this paper, we investigate how the network structure resulting from credit ties among financial agents (i.e., banks) can affect the capacity of a regulator to assess the level of systemic risk. We introduce a model to compute the individual and systemic probability of default in a system of banks connected in a generic interbank network and exposed to shocks with a generic correlation structure. We find that multiple equilibria can exist even in the presence of complete knowledge.

Our main contribution is to show that multiple equilibria can arise from the presence of *closed chains* of debt in the network (i.e., *cycles*). Note that this mechanism differs from the one described in previous works where multiple equilibria result from self-fulfilling expectations (e.g., Diamond and Dybvig, 2015). In its simplest form, our result states that, if the default conditions of a set of banks are mutually dependent along cycles of credit contracts, there exists a range of external shocks such that the equilibrium where all those banks default and the equilibrium where none of them defaults co-exist. More generally, in any network structure the multiplicity of equilibria can arise in the presence of at least one closed chain of lending ties in the market. It is worth noting that, empirically, closed chains of lending ties are ubiquitous in financial markets. Indeed, a large portion of various national interbank markets is

often found to be *strongly connected*, i.e., connected through at least one closed chain (Roukny et al., 2014). Furthermore, the core-periphery structure identified in many cases of inter-bank markets (Fricke and Lux, 2012; Craig and Von Peter, 2014; van Lelyveld et al., 2014) is characterized by an important level of cyclical dependencies between the core-banks (i.e., they form a fully connected network).

The importance of multiple equilibria and the fact that focusing only on the best or the worst equilibrium might be insufficient is witnessed by the growing interest not only in the academic literature but also in policy debates (Draghi, 2012; Miller and Zhang, 2014; De Grauwe and Ji, 2015).

Beyond the mere existence of multiple equilibria, the range of shocks where multiplicity occurs as well as the difference in expected losses across equilibria are also very important. Multiplicity is particularly relevant if both the range of shocks and the gap on the expected losses are large.

In this respect, in this paper we develop an analytical framework to formalize the problem and quantify the gap in relation to the network structure. We quantify this uncertainty by analytically computing the difference between the most extreme scenarios. The *optimistic* scenario is the one where, when multiple equilibria exist, the equilibrium with the minimum number of defaults is selected. Similarly, the *pessimistic* scenario is constructed by selecting the equilibrium with the maximum number of defaults. In addition, we also provide a method to quantify such difference in monetary terms (i.e., expected losses), thus allowing to assess the *cost of uncertainty*.

Furthermore, we investigate how such uncertainty depends on leverage, volatility, interbank market structures and correlation across external shocks. We find that leverage both on the interbank market and the external assets increases uncertainty. Volatility in external assets has ambiguous effects. Correlation across shocks can also have non monotonous effects on uncertainty. However, complete correlation in a set of homogenous banks univocally increases uncertainty with respect to the uncorrelated case. In terms of network structure, we show that the uncertainty decreases with the length of the credit chain. When analyzing a market composed of multiple cycles (i.e., star market), we find that uncertainty increases compared to single-cycle structures.

By design, the model and the analysis could be applied to real data and parameters could be calibrated using information on assets portfolios, credit registers and balance sheets. The model can be used to assess both the level of (individual and systemic) risk and the uncertainty arising from the interconnectedness.

Finally, the work also contributes to several policy related discussions. As it offers a novel way to estimate the systemic impact of financial institutions in a network context, it can bring new insights in the discussion about too-big-to-fail institutions (Haldane and May, 2011; BoE, 2013). By showing how cyclical structures in the network imply more uncertainty over default probability, we also contribute to the discussion on regulatory financial data disclosure (Abbe et al., 2012; Alvarez and Barlevy, 2014).

Appendix A. Proof of Proposition 1

We separate the proof in two parts. In the first we show the necessity of cyclicity in the network of contract and in the second part we show that, once we have a cycle, the sufficient condition to have multiple equilibria is that there is an overlap between the space of default thresholds depending on the counterparties' status in the cycle and the space of shocks.

Necessity. In order to show the necessity of a cycle of contracts with non-empty intervals for the thresholds $\hat{\theta}_i^- < \hat{\theta}_i^+$ of each bank

in the cycle, we show that in absence of cycles there is a unique equilibrium.

Indeed, if the graph of dependencies is an acyclic graph, then we can identify the leaf nodes of the graph (i.e., banks who do not lend to anyone) and recursively the parent nodes of every bank in the interbank network (the creditor of those banks). For every vector of shocks u , the state of default χ of the leafs is uniquely determined. Recursively, the state of all parent nodes is also uniquely determined. Therefore, in order to have multiple solutions, the graph must not be acyclic and thus contain at least one cycle. Further, if $\hat{\theta}_i^- = \hat{\theta}_i^+$ for some i in the cycle, then the volume in the shock space where multiple solution may exist collapses to zero. Notice that only for the nodes in the cycle and those pointing directly or indirectly to the cycle there may be multiple solutions for their default state. All the other nodes, e.g., those that are not part of a cycle or that cannot reach the cycle along a path, will have a unique default state.

Sufficiency. We want to show that the condition in the statement implies that there are at least two coexisting equilibria. Following the assumptions that $R < 1$ and $\beta > 0$, we have that $\theta_i^- < \theta_i^+$ for all $i \in N$. Assume that there is a cycle. If $\hat{\theta}_i(\chi_{i+1} = 0) < \hat{\theta}_i(\chi_{i+1} = 1)$, we have that $\{\theta_i(\chi_{i+1} = 0), \theta_i(\chi_{i+1} = 1)\} \cap [-1, 1] \neq \emptyset$.

Further, the fact that the threshold values are strictly different for every node in the cycle and include some values of the shock domain implies that there is an overlap of the shock spaces associated with the different equilibria. In fact, the following two sets of equilibrium conditions overlap because $\theta_i^- < \theta_i^+$ for all $i \in N$.

$$\begin{aligned}
 (\chi_1, \dots, \chi_m) = (0, \dots, 0) &\Leftrightarrow \begin{cases} u_1 > \theta_1(\chi_2 = 0) = \theta_1^- \\ \vdots \\ u_m > \theta_m(\chi_1 = 0) = \theta_m^- \end{cases} \\
 (\chi_1, \dots, \chi_m) = (1, \dots, 1) &\Leftrightarrow \begin{cases} u_1 < \theta_1(\chi_2 = 1) = \theta_1^+ \\ \vdots \\ u_m < \theta_m(\chi_1 = 1) = \theta_m^+ \end{cases} \quad (A.1)
 \end{aligned}$$

In the system above there are m banks in a cycle, numbered in ascending order along the direction of lending. Bank m lends to bank 1, thus closing the cycle. We thus see that the two equilibria co-exist in the space of shocks defined by $\theta_i^- < u_i < \theta_i^+$.

Appendix B. Proof of Proposition 2 and 3

To compute the distance between the best P^* and worst P^- probabilities of systemic default, stemming from the optimistic and pessimistic scenarios respectively, we introduce a generic methodology that we then apply to the network structure of interest.

The basic idea is to identify the overlapping shock spaces where the equilibrium $\{\chi_i = 1\} \forall i$ is a solution. Indeed, such solution leads to $\chi^{sys} = \prod_i \chi_i = 1$, that is, the identification of systemic default for the computation of the probability of systemic default.

First, we identify the largest portion of shock space where $\{\chi_i = 1\} \forall i$, which we call the *benchmark shock space*. This case corresponds to a situation where, for every bank, the shock is $u_i < \theta_i^+$ because this threshold is the one accounting for the default of all the borrowing counterparties of bank i . In this case, the shock space is thus defined by $\{u_i < \theta_i^+\} \forall i$. Note that, for the rest, all the other default thresholds have a value inferior to θ_i^+ (see Section 2).

Next, we need to find the equilibria with related shock spaces that overlap with the systemic default equilibrium (i.e., $\{u_i < \theta_i^+\} \forall i$). Those equilibria are the equilibria for which the ranges of shocks form a non-empty set of intersection with the systemic default equilibrium shock space. Formally, we need to find the

set of conditions with respect to u_i such that $\{\theta_i^* < \theta_i^+\} \forall i$. There can be several sets of condition (i.e., several equilibria that overlap with the systemic default equilibria). Note that the overlapping equilibria have, within the definition of their shock spaces, conditions different than θ^+ .

Finally, once all the overlapping shock spaces have been identified, we sum the fraction of shock space that overlaps with the systemic default equilibria $\{u_i < \theta_i^+\} \forall i$. This sum determines ΔU . We then use the joint probability distribution of shocks to determine ΔP .

B.1. Application to the ring structure

Without loss of generality and to keep the notation simpler we develop the proof in the case $\hat{\theta}_i = \theta_i$ for all i . We denote by θ_i^- and θ_i^+ the minimum and maximum values that the threshold can take where θ_i^- corresponds to the case in which none of the counterparties default (i.e., $\chi_j = 0 \forall j \in V_i$) while the θ_i^+ corresponds to the case in which all counterparties default (i.e., $\chi_j = 1 \forall j \in V_i$). From Eq. (10) it follows:

$$\begin{cases} \theta_i^- = \frac{-\varepsilon_i \mu_i - 1}{\varepsilon_i \sigma_i}, \\ \theta_i^+ = \frac{-\varepsilon_i \mu_i + \beta_i(1 - \sum_j B_{ij} R_{ij}) - 1}{\varepsilon_i \sigma_i} = \theta_i^- + \frac{\beta_i(1 - R_i)}{\varepsilon_i \sigma_i}, \end{cases} \quad (B.1)$$

where for convenience we denote by $R_i = \sum_j B_{ij} R_{ij}$ the total amount of collateral that bank i recovers from the default of its counterparties.

In a cycle of n agents, each agent has only 2 possible values for the default threshold:

$$\theta_i \in \{\theta_i^- = \theta_i(\chi_{i+1} = 0), \theta_i^+ = (\chi_{i+1} = 1)\}.$$

The equilibria of interest for our purposes are: $\{\chi_i = 1\} \forall i$ occurring in the region of the shock space where $\{u_i < \theta_i^+\} \forall i$; and $\{\chi_i = 0\} \forall i$, occurring in the region of the shock space where $\{u_i > \theta_i^-\} \forall i$.

If and only if the values of θ_i^- and θ_i^+ differ for all i then there is a region where the two equilibria coexist. For each agent, the magnitude of the overlap along the dimension θ_i is then $(\theta_i^+ - \theta_i^-)$. From the expression above it follows that $(\theta_i^+ - \theta_i^-) = \beta_i(1 - R_i)/\varepsilon_i \sigma_i$.

For n agents, we obtain:

$$\Delta U = \frac{\Pi_i(\hat{\theta}_i^+ - \hat{\theta}_i^-)}{2^n}.$$

For the uncertainty, we obtain the following expression:

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \frac{\Pi_i(\hat{P}_i(\hat{\theta}_i^+) - \hat{P}_i(\hat{\theta}_i^-))}{2^n} \right\} \right\},$$

where $\hat{P}_i(u)$ is the cumulative density function obtained from joint probability function $p(u)$ projected on bank i . ΔP is bounded between 0 and 1.

Since we assume a uniform density function it holds $\Delta P = \Delta U$ and we can develop furthermore the expression to highlight the role of the different parameters of the system:

$$\begin{aligned} \Delta P &= \min \left\{ 1, \max \left\{ 0, \frac{\Pi_i(\hat{\theta}_i^+ - \hat{\theta}_i^-)}{2^n} \right\} \right\} \\ &= \min \left\{ 1, \max \left\{ 0, \Pi_i \left(\frac{\beta_i(1 - R_i)}{2\varepsilon_i \sigma_i} \right) \right\} \right\} \end{aligned}$$

As we can directly observe from the expression above, ΔP depends linearly in β , R_i and decreases monotonically with ε and σ for $\varepsilon > 0$ and $\sigma > 0$. Therefore, the increase and decrease in these variables is strict.

B.2. Application to the star structure

We assume $B_{ik} = (1/|V_i|)$. We denote by index c the center agent in the star and j the agents in the periphery. Let us assume that the center agent uniform portfolio such that $B_{ik} = 1/(n - 1)$ and $R_{ij} = R_i/(n - 1)$.

In a star, agents in the periphery only interact with the center agent. They thus have only 2 thresholds:

$$\theta_j \in \{\theta_j^- = \theta_j(\chi_c = 0), \theta_j^+ = (\chi_c = 1)\}.$$

While the agent at the center has n thresholds:

$$\theta_c \in \left\{ \theta_c^-, \theta_c \left(\sum_j \chi_j = 1 \right), \theta_c \left(\sum_j \chi_j = 2 \right), \dots, \theta_c \left(\sum_j \chi_j = n - 2 \right), \theta_c^+ \right\}$$

where $\theta_c(\sum_j \chi_j = k)$ retrieves the threshold for the center agent to default in case k peripheral agents default.

To compute the distance between P^+ and P^- , the equilibrium of interest is $\{\chi_i = 1\} \forall i$ and the benchmark shock space is $\{u_i < \theta_i^+\} \forall i$.

The overlapping equilibria are related to shock spaces where the intersection with the benchmark shock space is non-empty and where $\theta_i < \theta_i^+$ for all i .

For the peripheral agents, the threshold can thus only be $\theta_j = \theta_j^-$.

A first case of overlap is when all shocks are between θ^- and θ^+ (i.e., $\theta_i^- < u_i < \theta_i^+$ for all i). This case is similar to the ring:

$$\frac{\Pi_i(\hat{\theta}_i^+ - \hat{\theta}_i^-)}{2^n}.$$

We use the cumulative density function to obtain the expression in terms of probabilities distance

$$\frac{\Pi_i(\hat{P}_i(\hat{\theta}_i^+) - \hat{P}_i(\hat{\theta}_i^-))}{2^n}.$$

The other cases of overlap can be determined as follows. For each θ_c , all ranges of values for the other shocks are obtained by aggregating the overlapping equilibria. For a given threshold of the center agent $\theta_c^- < \theta_c < \theta_c^+$, the conditions on the periphery agents to default are $\{u_j < \theta_j^+\} \forall j$, which corresponds to share $(1 + \theta_j^+)$ in each periphery agents shock space. The corresponding $(n-1)$ -volume in the hypercubique subspace of all periphery agents is thus equal to $\Pi_j(1 + \hat{\theta}_j^+)$. On the center agent, the segment in the shocks space is equal to the distance between the threshold where all counterparties default θ_c^+ and the threshold where at least one counterparty defaults $\theta_c(\sum_j \chi_j = 1)$. Overall, the fraction of the shocks space is thus:

$$\frac{(\hat{\theta}_c^+ - \hat{\theta}_c(\sum_j \chi_j = 1))\Pi_j(1 + \hat{\theta}_j^+)}{2^n}.$$

Similarly, translating in probabilities distance, we obtain

$$\frac{(\hat{P}_c(\hat{\theta}_c^+) - \hat{P}_c(\hat{\theta}_c(\sum_j \chi_j = 1)))\Pi_j(\hat{P}_j(\hat{\theta}_j^+))}{2^n}.$$

Finally, we sum of the elements and obtain:

$$\rightarrow \Delta U = \frac{\Pi_i(\hat{\theta}_i^+ - \hat{\theta}_i^-)}{2^n} + \frac{(\hat{\theta}_c^+ - \hat{\theta}_c(\sum_j \chi_j = 1))\Pi_j(1 + \hat{\theta}_j^+)}{2^n},$$

Table B.1
Shock space equilibrium conditions for a star market of 3 banks.

Equilibrium	Central	Peripheral 1	Peripheral 2
0 0 0	$u_c > \theta_c^-$	$u_{p1} > \theta_p^-$	$u_{p2} > \theta_p^-$
0 0 1	$u_c > \theta_c^1$	$u_{p1} > \theta_p^-$	$u_{p2} < \theta_p^-$
0 1 0	$u_c > \theta_c^1$	$u_{p1} < \theta_p^-$	$u_{p2} > \theta_p^-$
0 1 1	$u_c > \theta_c^1$	$u_{p1} < \theta_p^-$	$u_{p2} < \theta_p^-$
1 0 0	$u_c < \theta_c^-$	$u_{p1} > \theta_p^+$	$u_{p2} > \theta_p^+$
1 0 1	$u_c < \theta_c^1$	$u_{p1} > \theta_p^+$	$u_{p2} < \theta_p^+$
1 1 0	$u_c < \theta_c^1$	$u_{p1} < \theta_p^+$	$u_{p2} > \theta_p^+$
1 1 1	$u_c < \theta_c^+$	$u_{p1} < \theta_p^+$	$u_{p2} < \theta_p^+$

$$\rightarrow \Delta P = \min \left\{ 1, \max \left\{ 0, \frac{\Pi_i(\hat{P}_i(\hat{\theta}_i^+) - \hat{P}_i(\hat{\theta}_i^-))}{2^n} + \frac{(\hat{P}_c(\hat{\theta}_c^+) - \hat{P}_c(\hat{\theta}_c(\sum_j \chi_j = 1)))\Pi_j(\hat{P}_j(\hat{\theta}_j^+))}{2^n} \right\} \right\}.$$

If we assume a uniform density function and that $\hat{\theta}_i = \theta_i$, we obtain a result equal the ΔU and we can develop furthermore the expression to highlight the role of the different parameter of the system:

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \Pi_i \left(\frac{\beta_i(1 - R_i)}{2\varepsilon_i\sigma_i} \right) + \frac{(\theta_c^+ - \theta_c(\sum_j \chi_j = 1))\Pi_j(1 + \theta_j^+)}{2^n} \right\} \right\}.$$

B.2.1. Example with 3 banks

To illustrate the above case, let us take 3 banks organized in a star-market: one central bank c lending to and borrowing from 2 peripheral banks denoted by p_1 and p_2 . The central agent has 3 thresholds:

$$\theta_c \in \left\{ \theta_c^- = \theta_c \left(\sum_j \chi_j = 0 \right), \theta_c^1 = \theta_c \left(\sum_j \chi_j = 1 \right), \theta_c^+ \right. \\ \left. = \theta_c \left(\sum_j \chi_j = 2 \right) \right\}.$$

The peripheral agents instead have 2 thresholds:

$$\theta_p \in \{ \theta_p^- = \theta_p(\chi_c = 0), \theta_p^+ = \theta_p(\chi_c = 1) \}$$

We can list all the different equilibrium and the related conditions in the shock space. Table B.1 retrieves, for each combination of default states, the corresponding share of shock space.

We are interested in identifying all equilibria for which the conditions that satisfy the systemic default case (i.e., “1 1 1”), that is: $\{u_c < \theta_c^+; u_{p1} < \theta_p^+; u_{p2} < \theta_p^+\}$.

The three first rows of Table B.1 are compatible with these conditions. The corresponding shock spaces are:

- $(\theta_c^+ - \theta_c^-)(\theta_p^+ - \theta_p^-)(\theta_p^+ - \theta_p^-)$.
- $(\theta_c^+ - \theta_c^1)(\theta_p^+ - \theta_p^-)(1 + \theta_p^-)$.
- $(\theta_c^+ - \theta_c^1)(1 + \theta_p^-)(\theta_p^+ - \theta_p^-)$.

When aggregating the three shock space, we see that the conditions for the peripheral agents are complementary (i.e., $\theta_p^+ - \theta_p^- +$

$1 + \theta_p^-$), and obtain the final expression as a share of the total shock space:

$$\Delta U = \frac{(\theta_c^+ - \theta_c^-)(\theta_p^+ - \theta_p^-)^2 + (\theta_c^+ - \theta_c^1)(1 + \theta_p^-)^2}{2^3}.$$

Appendix C. Proof of Proposition 4

In this proof, we analyze a situation where the returns on all banks’ portfolio are completely correlated. Let us start with a case of 2 banks lending and borrowing from each other. From the 2-dimensional representation, a fully correlated situation can be obtained by projecting the results obtained in the Example in Section 4 on the diagonal such that $u_1 = u_2$ for all combinations of shocks. We then need to compute the length of the diagonal that is under the different areas. The fraction of this length on the total lengths of the diagonal will give us the probability value.

$$P^- = \frac{\sqrt{(1 + \max\{\hat{\theta}_i^-\})^2 + (1 + \max\{\hat{\theta}_i^-\})^2}}{2\sqrt{2}} = \frac{|1 + \max\{\hat{\theta}_i^-\}|}{2},$$

$$P^+ = \frac{\sqrt{(1 + \min\{\hat{\theta}_i^+\})^2 + (1 + \min\{\hat{\theta}_i^+\})^2}}{2\sqrt{2}} = \frac{|1 + \min\{\hat{\theta}_i^+\}|}{2},$$

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \frac{1 + \min\{\hat{\theta}_i^+\}}{2} - \frac{1 + \max\{\hat{\theta}_i^-\}}{2} \right. \right. \\ \left. \left. = \frac{\min\{\hat{\theta}_i^+\} - \max\{\hat{\theta}_i^-\}}{2} \right\} \right\}.$$

Note that we can remove the absolute values as $0 \leq 1 + \hat{\theta}_i$. The results are the same when we generalize to a system of n banks arranged in a ring, as shown in what follows:

$$P^- = \frac{\sqrt{\sum_i (1 + \max\{\hat{\theta}_i^-\})^2}}{2\sqrt{n}} = \frac{|1 + \max\{\hat{\theta}_i^-\}|}{2},$$

$$P^+ = \frac{\sqrt{\sum_i (1 + \min\{\hat{\theta}_i^+\})^2}}{2\sqrt{n}} = \frac{|1 + \min\{\hat{\theta}_i^+\}|}{2},$$

$$\Delta P = \min \left\{ 1, \max \left\{ 0, \frac{1 + \min\{\hat{\theta}_i^+\}}{2} - \frac{1 + \max\{\hat{\theta}_i^-\}}{2} \right. \right. \\ \left. \left. = \frac{\min\{\hat{\theta}_i^+\} - \max\{\hat{\theta}_i^-\}}{2} \right\} \right\}.$$

C.1. Comparative statics

We are now interested in comparing the difference of best of worst probability in a ring market where shocks are completely correlated with the case where shocks are completely independent.

Given the expression for the uncorrelated case ($\Delta P^u = ((\hat{\theta}_1^+ - \hat{\theta}_1^-)(\hat{\theta}_2^+ - \hat{\theta}_2^-))/4$) and for the correlated case ($\Delta P^c = ((\min\{\hat{\theta}_i^+\} - \max\{\hat{\theta}_i^-\})/2)$), we can explore how increasing correlation affects the uncertainty area.

Note that in case $\min\{\hat{\theta}_i^+\} \leq \max\{\hat{\theta}_i^-\}$, there is no uncertainty in the correlation.

In case $\min\{\hat{\theta}_i^+\} = \hat{\theta}_1^+$ and $\max\{\hat{\theta}_i^-\} = \hat{\theta}_1^-$: $\Delta P^u = \Delta P^c((\hat{\theta}_2^+ - \hat{\theta}_2^-)/2)$. Given that $-2 \leq \hat{\theta}_2^+ - \hat{\theta}_2^- \leq 2$:

$$\Delta P^u < \Delta P^c.$$

The same stands if $\min\{\hat{\theta}_i^+\} = \hat{\theta}_2^+$ and $\max\{\hat{\theta}_i^-\} = \hat{\theta}_2^-$. In general: $\min\{\hat{\theta}_i^+\}$ and $\max\{\hat{\theta}_i^-\}$ have $i=j$.

In case $\min\{\hat{\theta}_i^+\}$ and $\max\{\hat{\theta}_i^-\}$ have $i \neq j$: Note that:

$$(\hat{\theta}_1^+ - \hat{\theta}_2^-) < (\hat{\theta}_i^+ - \hat{\theta}_i^-) \quad \forall i.$$

We look at the 2 extreme cases:

$$\frac{\min\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}^n}{2^n} < \Delta P^u < \frac{\max\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}^n}{2^n}.$$

For the upperbound, we have that:

$$\Delta P^u < \frac{\max\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}^n}{2^n},$$

if $\sqrt[n]{\min\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}} > \max\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}$, we thus have that:

$$\Delta P^u < \Delta P^c.$$

For the lower bound, we have:

$$\Delta P^u > \frac{\min\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}^n}{2^n},$$

if $\sqrt[n]{\min\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}} < \min\{\hat{\theta}_i^+ - \hat{\theta}_i^-\}$, we thus have that:

$$\Delta P^u > \Delta P^c.$$

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