Negative Effects of Information Disclosure: The Dark Side of Stress Test

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ABSTRACT

We analyze the effect of information disclosure, such as for the stress test, on banks' portfolio risk in a general equilibrium framework. Using simulations in a network model, we show how this effect depends on the structure of the system. We find that the disclosure is expected to increase portfolio risk for a non-negligible fraction of banks in the network. Alarmingly, this effect is more pronounced for systemically important banks. Additionally, we find that the effect of network density on bank's risk-adjusted expected profit is twofold: while banks in the systems of lower densities are expected to gain more from the disclosure, these are also the systems with larger uncertainty about the outcome.

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I. Introduction

In the aftermath of the 2008 financial crisis, policymakers were heavily trying to send signals of soundness and safety of their financial system. An extra effort has been made to regulate banks' activities, to evaluate their stability, and to make their balance sheets as transparent as possible to the market participants[1]. The Stress Test exercise is one of the recently introduced tools aiming at *"assessing the resilience of financial institutions to adverse market developments, as well as to contribute to the overall assessment of systemic risk in the EU financial system"*.[2] This procedure has been adopted in both the European and American banking system with similar methodologies and information disclosure policies. Relative to the latter, the regulator mandates the disclosure of detailed data about banks on both the results of the tests and the balance sheet information that has been provided for the simulation exercise.

There is an ongoing debate on whether such information should be disclosed and on how detailed this information should be. The regulator's attitude towards information disclosure seems to be mostly positive, viewing the disclosure as something that cannot cause harm to the system. There is a growing literature providing both theoretical and empirical evidence on this issue (see Prescott (2008) and Goldstein and Leitner (2015) for theories and Schuermann (2013) for empirical evidence). The results are mostly mixed. On the one hand, the advantages appear to be clear: information disclosure helps to discipline banks, reduces adverse selection, and leads to more informative prices. Plus, one can easily agree that market transparency seems a desirable feature. On the other hand, there are subtle disadvantages which are less evident and that the regulator needs to be aware of.

In the wake of this debate, this paper addresses the following questions: how does public information disclosure affect banks' portfolio risk? How does this effect depend on the underlying network structure of the system and a position of individual banks within the network? In order to answer these questions, we develop a general equilibrium model of the interbank market.

We find that the information disclosure results in a reduction of risk-adjusted expected profits for a non-negligible fraction of banks in the system (hereafter, we refer to changes in banks' risk-adjusted expected profits as the disclosure effect). Moreover, this decline is even more profound for systemically important banks - banks located in the center of the network (i.e. core banks in the sense of core-periphery structure).

We argue that public information disclosure may have undesirable consequences even if only network frictions are considered and no strategic interaction between agents takes place. In our model, as a result of the disclosure, a bank can become riskier through re-adjustments in portfolios of other banks (negative externalities) - a general equilibrium effect. Our simulation exercise shows that the structural features of networks have a first-order importance for evaluating the effects of the new information into the economy.

Our analysis considers two types of network structures: homogeneous and inhomogeneous (also

[1]See the Basel requirements for further details.

[2]European Banking Authority (EBA) definition of the stress test's purpose. More details can be found on their website: www.eba.europa.eu

known as core-periphery or star-like) networks. Both of them are characterized by a slightly different random pattern in the banks' connections. The former is a classical way of modeling homogeneous random networks, whereas the latter displays a structure with few banks acting as hubs for all other banks in the system - just like in the empirically observed financial networks. We further look at differences in macro characteristics within the same network class; for example, we consider networks with different densities which measures the level of connectivity in a system. Here, the density of a given network is defined as the ratio of the number of all existing connections in the system over the number of all possible connections. By construction, this quantity takes values between zero and one.[3]

We show that, within the class of random networks, the effect of the different densities is two-fold. On the one hand, we observe that for lower-density networks the disclosure produces on average a positive effect on the banks' risk-adjusted expected profits. On the other hand, such effect is quite volatile for the same class of networks. The simulation statistics show that although such systems on average produce a positive effect, it is relatively small compared to its volatility. The opposite is true for networks with higher density. In such systems, effects are very predictable but also rather small. Further investigation on the distribution of the disclosure effect reveals that a bank in a low-density network is more likely to be negatively affected by the disclosure of information compared to the same bank in a high-density network. Another equivalent interpretation for this finding is that in low-density networks the fraction of banks which are expected to have a negative disclosure effect is larger compared to the one in the high-density networks.

These findings suggest that the regulator faces a trade-off when deciding to disclose sensitive information in a system with network frictions. The disclosure of new information appears to be more beneficial in less dense networks. However, in a such networks, the regulator pays the cost in terms of volatility of this effect (e.g. ex-ante uncertainty) and in terms of the fraction of banks who bear the risk of a negative disclosure effect. This trade-off also applies to high-density networks. In this case the positive disclosure effect is very small, but the fraction of banks who are expected to get worse is significant. Although outside of this analysis, it is worth mentioning that we do not consider uncertainty related to the knowledge about the network structure and its related density. This could potentially increase the expected costs of the information disclosure. In the real world, the network is usually not perfectly observable.

One additional important point of our analysis concerns the identity of the banks who are negatively affected by the new information. We show that systemically more relevant banks, on average, are the ones who gain the least from the disclosure and bear the highest cost in terms of the volatility of such effect. Moreover, further investigation show that the likelihood of experiencing a negative disclosure effect as result of new information available is higher for more systemically

[3] A complete network has density of measure one because every bank is connected (or simply can trade) with every other bank, while a disconnected network has density of measure zero because it is a set of singletons. These two limiting cases are important benchmarks. The theory tells us that in both limiting cases the disclosure of new information has no effect on the risk-adjusted profits of the banks given that markets are complete and the network constraint vanishes.

relevant banks. All the results are similar, even stronger, when the network considered is a core-periphery.

The intuition behind this result lies in the heterogeneity of the values attached to new information by different banks. In general, the banks exposed to a large number of other banks are the ones gaining the most from the disclosure. The reason is because they can use it to optimally re-adjust their portfolio. On the contrary, the least exposed banks have no use for this new information and suffer externalities generated by other banks' re-adjustments. The characteristic of a systemically relevant bank is indeed the one of being attractive for other banks but at the same time, in relative terms, less exposed to others. This mechanism delivers the aforementioned result.

The model developed to obtain these results is a two-period finance economy with banks acting as portfolio-maximizers. There are N banks which are born with an initial endowment - project - of size N. Banks operate in an exogenously given network structure, meaning they can only invest in projects of banks to which they have connections to. They can also invest in a risk-free asset which can be interpreted as a money market. Thus, banks allocate their initial endowment between risky assets - the projects of banks they are connected to - and the money market.

It is understood that if one considers a frictionless market with this type of preferences, then every bank holds the same portfolio, namely the market portfolio. The banking market is far from being frictionless. In this model, we focus on how the disclosure effect varies with the degree of network incompleteness. An incomplete network occurs when some banks are unable to invest in some projects. Given their trading constraints, banks' choice boils down to setting the optimal exposures towards their own project, the other accessible banks' projects and the storage technology. This is exactly why an incomplete network gives rise to heterogeneity among banks.

In order to incorporate the information disclosure, we model each bank with initial identical beliefs about the distribution of project payoffs (included its own project). Then the information disclosure may take place before the uncertainty is revealed - that is banks may learn the true distribution of project payoffs. If this happens, banks are free to re-optimize their portfolio holdings. We study the effects of such information disclosure on banks' risk-adjusted profits. The model delivers a close form solution for all the important quantities, that is portfolio holdings (risky and risk-free projects) and market prices.

Related literature. The negative effect of information disclosure has been analyzed in the literature quite extensively. There is a very long strand of literature on the effects and incentives behind the information disclosure.

Initially it was argued that mandatory information disclosure may simply be unnecessary because firms have plenty incentives to disclose information by themselves (e.g. Grossman and Hart (1980), Grossman (1981), and Milgrom (2007)). However, a number of reasons in favor for voluntary disclosure was offered later. For example, if the mandatory disclosure can be beneficial when firms have the possibility to misrepresent (Korn and Schiller (2003)) or when firms have correlated returns, they might end up disclosing too little (Admati and Pfleiderer (2000)).

Positive effects of information disclosure seem to be intuitive: disclosure helps to discipline banks, reduces adverse selection and leads to more efficient/informative prices. However, this intuition does not always apply - more information is not always better. For example, a result that goes back to Hirshleifer (1971), known as Hirshleifer effect, shows that an early release of information about the future state of the economy is welfare detrimental as it destroys risk-sharing incentives. Goldstein and Leitner (2015) apply this idea to study the optimal disclosure policy in banking systems. They find that disclosing too little might result in a market breakdown (especially in the time of a crisis) but disclosing too much destroys the risk-sharing opportunities via the Hirshleifer effect.

By disclosing bank's private information, the regulator risks losing the ability to obtain such information in the first place (see Prescott (2008)). Disclosure can also simply reduce the incentives of private investors to acquire information and trade on it (Bond and Goldstein (2014)).

Why would more information be detrimental? Without strategic interaction and frictionless markets, more information is always ex-ante better for a decision maker (see Blackwell's Theorem in Blackwell (1951)). When operating in the asymmetric information environment with strategic interactions, more information does not necessarily means an improvement.

This paper adds to the existing literature by showing that the disclosure of information may have negative effects even in a simple general equilibrium framework with constraints imposed by the exogenous network structure in the economy. The theoretical model fits very well if one considers the banking system as the reference economy and the disclosure of information that takes place subsequently the stress test mandated by the banking authorities. Firstly, we contribute to the literature by showing the dependence between the effect of information disclosure and the network structure. More importantly, our paper shows that the negative effect coming from the information disclosure is more severe for those banks considered systemically important.

The paper unfolds as follow. Section II introduce the theoretical framework and show its solution. Section III describes the simulation exercise and reports its result. Section IV concludes.

II. The Model

A. Two-period Finance Economy with Network Constraints

In order to study the effect of public information disclosure we employ a general equilibrium framework in which agents (banks) are treated as portfolio maximizers. The whole exercise is studied with N banks in a standard two-period economy in which periods are labeled as $t = 0, 1$.

At t=0, bank $i \in \mathcal{B} = \{1, ..., N\}$ has an endowment of size[4] N as well as access to its own investment opportunity (referred to as an asset or project). The value of this endowment is a $(t = 1)$-measurable random variable and can generally be interpreted as bank i's project. The access to their respective projects is then traded among banks for the purpose of diversification and risk-adjusted profit maximization. Due to a one-to-one relationship, we will further refer to banks

[4] The choice of having an initial endowment equal to N is convenient in terms of numerics. It can be replaced by any other positive constant without the loss of generality.

and their assets (or projects) interchangeably.

Crucially, banks are not allowed to trade arbitrarily. An exogenous network structure is assumed, such that the set of counterparties available for trading is fixed for each bank in the system. More precisely, bank i is said to be *connected* to bank j if and only if bank i can purchase asset j. In such setting, both directed and undirected network structures are possible: the connection of bank i to bank j does not necessarily imply the connection of bank j to bank i and vice versa. Also, since we assume that every bank can always decide to hold some fraction of its own asset, the self-connection of bank i to itself is present in all considered network structures.

Banks choose their asset portfolios at $t = 0$ conditional on the network structure. Apart from being able to invest in a restricted set of risky assets (projects of banks it is connected to), bank i also has access to a risk-free asset that always delivers 1\$ at time $t = 1$ per 1\$ invested at time $t = 0$.

Formally the maximization problem of bank i is given by

$$\begin{aligned} \max_{\{\phi_i,\theta_i\}\in\mathbb{R}^{N+1}} \quad & \left\{\mathbb{E}[\mathbb{Y}_i] - \frac{1}{2}\mathrm{Var}\left[\mathbb{Y}_i\right]\right\} \\ \text{s.t.} & \\ Np_i &= p'\phi_i + \theta_i \\ \mathbb{Y}_i &= \mathbb{X}'\phi_i + \theta_i \\ \phi_i &\in NC_i \end{aligned} \tag{1}$$

where $\mathbb{X} = [\mathbb{X}_1, \dots, \mathbb{X}_N]'$ is a $t = 1$-measurable random vector of assets returns, $\phi_i = [\phi_{i1}, ..., \phi_{iN}]'$ is a vector of bank i portfolio exposures, θ_i is bank i's holding of the risk-free asset, $p = [p_1, ..., p_2]'$ is the price vector of risky assets, and Y_i is the value of bank i's portfolio. The first constraint is the resource constraint at $t = 0$: the market value of the initial endowment is equal to Np_i and it is allocated between the risky assets (having value $p'\phi_i$) and the risk-free asset (having value θ_i). The second constraint says that the value of the bank i's portfolio at time $t = 1$ is the sum of payoffs from the risky asset holdings $\mathbb{X}'\phi_i$ and the risk free-rate θ_i. Finally, the last constraint (NC_i is short for "network constraint of bank i") is defined as follows: $NC_i = A_1 \times A_2 \times \ldots \times A_N$ where $A_j = \mathbb{R}$ if i is connected to j and $A_j = \{0\}$ otherwise. Therefore, if bank i is not connected to bank j, NC_i implies that $\phi_{ij} = 0$.

The equilibrium is defined as follows:

Definition II.1: *The equilibrium of the two-period finance economy with network constraints is given by the equilibrium price vector p^* and the equilibrium allocations $\{\phi_i\}_{i=1}^N$ and $\{\theta_i\}_{i=1}^N$ such that*

(i) every bank $i \in \{1, ..., N\}$ solves maximization problem in (1) *taking prices as given*

(ii) markets clear

$$\sum_{i=1}^{N} \phi\left(p^*\right)_i = N \tag{2}$$

Assuming that the vector of asset payoffs is jointly normally distributed one can derive the equilibrium price vector and the demand functions in closed form. The following proposition presents this result.

Proposition II.1: *Assume that the vector of asset payoffs is jointly normally distributed with mean* μ *and variance-covariance matrix* Σ

$$\mathbb{X} \sim \mathcal{N}_N(\mu, \Sigma)$$

then the demand function of bank i *for risky assets is given by*

$$\phi_i(p) = \Sigma^{-1}(\mu - p - \lambda_i) \tag{3}$$

where $\lambda_i := [\lambda_{i1}, ..., \lambda_{iN}]' \geq 0$ *is the vector of Lagrange multipliers associated with the network constraint* NC_i*. Given the demand equations in* (3) *and the market clearing condition in* (2)*, the equilibrium price vector is given by*

$$p^* = \mu - \Sigma\mathbf{1} - \frac{1}{N}\sum_{i=1}^{N}\lambda_i \tag{4}$$

where $\mathbf{1}$ *denotes a column vector of ones.*

B. *The Model with Disclosure*

In order to introduce disclosure to our setup, we assume that at $t = 0$, banks form the optimal portfolios based on the belief about the distribution of asset payoffs. In particular, banks are assumed to believe that the variance-covariance matrix of asset payoffs is given by an $N \times N$ positive definite matrix W (For more information about the belief structure and consistency, refer to Section III.A). We denote the vector of optimal portfolios based on this initial belief by $\{\phi_i(W)\}_{i=1}^{N}$ to stress their dependence on W.

Between $t = 0$, when $\{\phi_i(W)\}_{i=1}^{N}$ are formed, and $t = 1$, when uncertainty is realized, a public disclosure may take place. By public disclosure we mean that all banks learn the true variance-covariance matrix V. If no disclosure takes place then the model is identical to the model described in the previous subsection in which $\Sigma = W$. However, if the disclosure does take place then the banks will re-optimize their portfolios based on the additional information.

Formally, upon learning new information (the true variance-covariance matrix V) a bank i solves the following optimization problem

$$\max_{\{\phi(V)_i,\theta(V)_i\}\in\mathbb{R}^{N+1}} \left\{\mathbb{E}[\mathbb{Y}_i] - \frac{1}{2}\text{Var}\left[\mathbb{Y}_i\right]\right\}$$
$$\text{s.t.}$$
$$p'(V)\phi_i(W) + \theta_i(W) = p'(V)\phi_i(V) + \theta_i(V) \tag{5}$$
$$\mathbb{Y}_i = \mathbb{X}'(V)\phi_i(V) + \theta_i(V)$$
$$\phi_i(V) \in NC_i$$

where $\phi_i(W)$ is the bank i's initial portfolio vector (the one that was computed based on W), $\phi_i(V)$ is the bank i's new (readjusted) portfolio vector, $\theta_i(W)$ is bank i's initial holding of the risk-free asset and $\theta_i(V)$ is bank i's readjusted holding of the risk-free asset. Finally $p(W)$ and $p(V)$ are respectively the initial prices and the prices formed as a result of the readjustment in asset holdings. In other words, the prices in $p(V)$ represent the true market value of banks' assets. The first constraint in (5) is the resource limitation upon learning the new information: the bank i's endowment, which is equal to the new valuation of the initial portfolio plus the initial holding of the risk-free asset, is allocated between the readjusted holdings of risky assets $p'(V)\phi_i(V)$ and the risk-free asset $\theta_i(V)$. The second constraint says that the value of the bank i's portfolio is the sum of payoffs from risky asset holdings $\mathbb{X}'(V)\phi_i(V)$ and risk free-rate $\theta_i(V)$. Finally, the last constraint is the network constrain as defined in the problem (1).

Given the mean-variance preferences the optimal solution of the problem in equation (5) is identical to the problem in equation (1), when $\Sigma = V$, and thus, proposition II.1 applies.

III. Simulation

A. The Structure of the Beliefs about the Variance-Covariance Matrix V

Let us start by describing the implementation of the banks' beliefs for the purpose of a simulation. In the previous section, we have explained how the disclosure is modeled: banks have a belief about the distribution of asset returns, captured by the variance-covariance matrix W, and between $t = 0$ and $t = 1$, they may or may not learn the true variance-covariance matrix V depending on whether information was disclosed.

The aim is to construct beliefs - W - which are consistent with respect to the true information contained in V. There is nothing easier than finding a pair W and V for which the result of the disclosure is always detrimental for the banking system. However, such result can be easily dismissed on the ground of W and V being inconsistent if, say, W is too "different" from V. One could go on and simply say that it is very unlikely that an agent would form a belief W that is so much different from the true value V. This aspect would considerably affect the conclusions drawn from the simulation exercise.

Therefore, in order to guarantee consistency between the belief and the true value of the variance-covariance matrix, we use the following belief structure. We assume that the vector of asset payoffs, $\mathbb{X}$, is conditionally normally distributed

$$\mathbb{X}|\mathbb{V}, \mu \sim \mathcal{N}_n(\mu, \mathbb{V}) \tag{6}$$

where μ is the vector of expected payoffs and $\mathbb{V}$ the variance-covariance matrix of the assets' payoffs. We assume that the true variance-covariance matrix is a random matrix sampled from the inverse-Wishart distribution. That is,

$$\mathbb{V} \sim \mathcal{W}_n^{-1}(S, d) \tag{7}$$

where S is an $(N \times N)$ positively definite scale matrix and $d > N - 1$ measures the degree of freedom.

Given equations (6) and (7) the marginal distribution of $\mathbb{X}$ is a multivariate Student t-distribution

$$\mathbb{X} \sim t_{d-n+1}(\mu, S) \tag{8}$$

and the variance of $\mathbb{X}$ is then given by

$$\mathrm{Var}(\mathbb{X}) = \frac{1}{d-n-1} S. \tag{9}$$

The following proposition summarizes the belief structure of the model

Proposition III.1: *Suppose that the conditional distribution of asset returns is given by equation* (6) *and that the distribution of the true variance-covariance matrix of asset returns is given by equation* (7)*, then all banks form a Bayesian belief about the true variance-covariance matrix and this belief is given by equation* (9)

The parameter d from the inverted Wishart distribution captures the precision of banks' belief about the true variance-covariance matrix: as d increases banks have beliefs which are "closer" to the true value. One interpretation of this setting is that the disclosure of information allows banks to improve their estimates of the true variance-covariance matrix. The parameter d could be also used to evaluate the disclosure of information at different levels of accuracy. This is strongly related to the Stress Test procedure in the banking system with subsequent disclosure of the results. The policy of the EBA is to release all the information that have been provided by the banks for the test.

B. Simulation Settings

To study the effect of information disclosure on individual banks as well as the banking system as a whole, we employ a Monte Carlo simulation. It allows us to quantify the likelihood of the detrimental effect of information disclosure as well as its magnitude. However, it is important to understand that this model is not meant to produce quantitative predictions. Instead, it should be thought of as a qualitative model where interesting economic intuition can be observed. Nevertheless, the output of our model is quantifiable, simply because we want to find out how big is the set of parameters for which a particular effect takes place. For instance, we could construct a simple example - a set of model parameters - in which the effect of information disclosure results in a strong increase in riskiness of the banking system. However, the mere possibility of the construction of such an example does not tell us how likely it is. It is a priori not impossible that the set of parameters for which the example goes through is of measure zero. This is why we believe it is important to quantify the likelihood of the information disclosure effect and its corresponding magnitudes, even if our model produces strictly qualitative results.

Another reason for using simulation methods is to observe how the network structure influences the effect of information disclosure.

Let us explain the mechanism of our simulation routine. We solve the model from Section II with the belief structure described in Section III.A 10000 times. The number of banks, N, is set to 50 (we did some robustness checks for different values of N as well) and the parameter d is equal to 100. The choice of d is purposely high such that to obtain beliefs, W, very close to the true value V. We know from Section III.A that the parameter needs to satisfy $d > N - 1$. Each simulation begins by generating a random network represented by an $N \times N$ adjacency matrix G. Each element of G is either 0 or 1, that is, $g_{ij} \in \{0, 1\}$. If $g_{ij} = 1$ then bank i is connected to bank j, otherwise it is not. Remember that connections need not be symmetric, e.g. i being connected to j does not imply j being connected to i. Also note that $g_{ii} = 1$ for all i since every bank is by definition connected to itself.

Once the network structure is generated, we sample a random positive definite scale matrix S, which is used to compute banks' belief about the variance-covariance matrix of the asset payoffs as in equation 9, which we denote by W. Afterwards, the true value of the variance covariance matrix is sampled according to equation 7. Again, we denote the realization of the true variance-covariance matrix by V.

Having generated both V and W we proceed to solve the model under both scenarios (with and without information disclosure). Allocations and prices are recorded under both scenarios.

C. Risk-Adjusted Expected Profits and Leverage

In order to analyze the changes in the distribution of risk brought by information disclosure we look at the changes in risk adjusted expected profits of banks. The risk-adjusted expected profit of bank i under no-disclosure scenario is defined as

$$\Pi_i^{nd} = \frac{(\mu - p\,(W))'\phi_i(W) + p_i(W)}{\sqrt{\phi_i'(W)V\phi_i(W)}} \tag{10}$$

Analogically, in the case of disclosure:

$$\Pi_i^d = \frac{(\mu - p(V))'\phi_i(V) + (p(V) - p(W))'\,\phi_i(W) + Np_i(W)}{\sqrt{\phi_i'(V)V\phi_i(V)}} \tag{11}$$

Equations 10 and 11 can be though of as pseudo Sharpe ratios on bank i portfolios. Finally, to quantify the effect of information disclosure on the distribution of risk within the banking system, we use a percentage change in the risk adjusted expected profit of bank i:

$$\mathcal{DE}_i := \log\left(\frac{\Pi_i^d}{\Pi_i^{nd}}\right), \tag{12}$$

which refers to what we call the *disclosure effect*.

Apart from studying the effect of information disclosure on the risk-adjusted expected profits, we also consider the effect on bank leverage. We define bank's leverage as debt over equity. Thus the leverage of bank i under no disclosure is given by

$$L_i(W) = \frac{\mathbb{I}_{\{\theta_i(W)<0\}}|\theta_i(W)| + \sum_j \mathbb{I}_{\{\phi_{ij}(W)<0\}}|p_j(W)\phi_{ij}(W)|}{Np_i(W)} \tag{13}$$

whereas the same quantity under disclosure takes the following form:

$$L_i(V) = \frac{\mathbb{I}_{\{\theta_i(V)<0\}}|\theta_i(V)| + \sum_j \mathbb{I}_{\{\phi_{ij}(V)<0\}}|p_j(V)\phi_{ij}(V)|}{p'(V)\phi_i(W) + \theta_i(W)} \tag{14}$$

The average leverage ratio is then defined as

$$L(M) := \frac{1}{N}\sum_i L_i(M), \quad \text{for} \quad M \in \{W, V\} \tag{15}$$

which refers to what we call the *leverage effect*. In order to asses the effect of information disclosure on the average leverage as well as the leverage of individual banks, we compute the percentage change in these measures.

D. Results for Random Networks

D.1. The Disclosure Effect

First of our results shows the average disclosure effect, as defined in equation (12) depends closely on the network structure. One of the simplest ways to quantify a network is by its density. In our setting the density of a network represented by an $N \times N$ adjacency matrix G, $D(G)$, is defined as follows

$$D(G) = \frac{1}{N(N-1)}\sum_{i\neq j} g_{ij} \tag{16}$$

where the numerator is the number of all existing connections and the denominator represents all possible connections (excluding self-connections). A complete network has a density equal to one, while an empty network has a density of zero. We create $k = 0, \ldots, 20$ groups of networks with different densities. This implies that each group k contains networks covering 5% of the density space. We next present the results for the disclosure effect as function of these k groups of densities.

Figure 1 displays the average disclosure effect as well as its volatility as a function of the network density.[5] The figure shows that the network structure is relevant for the disclosure effect. The average disclosure effect peaks at the density of about 0.35 with the value of approximately 7.7% and is in general tilted, in terms of its magnitude, towards left. However, not only does the mean of the disclosure effect vary with network density, but so does its volatility. The effect of information disclosure on bank's risk-adjusted expected profit is most uncertain at network density of about 0.15 with the value of the standard deviation of 14%.

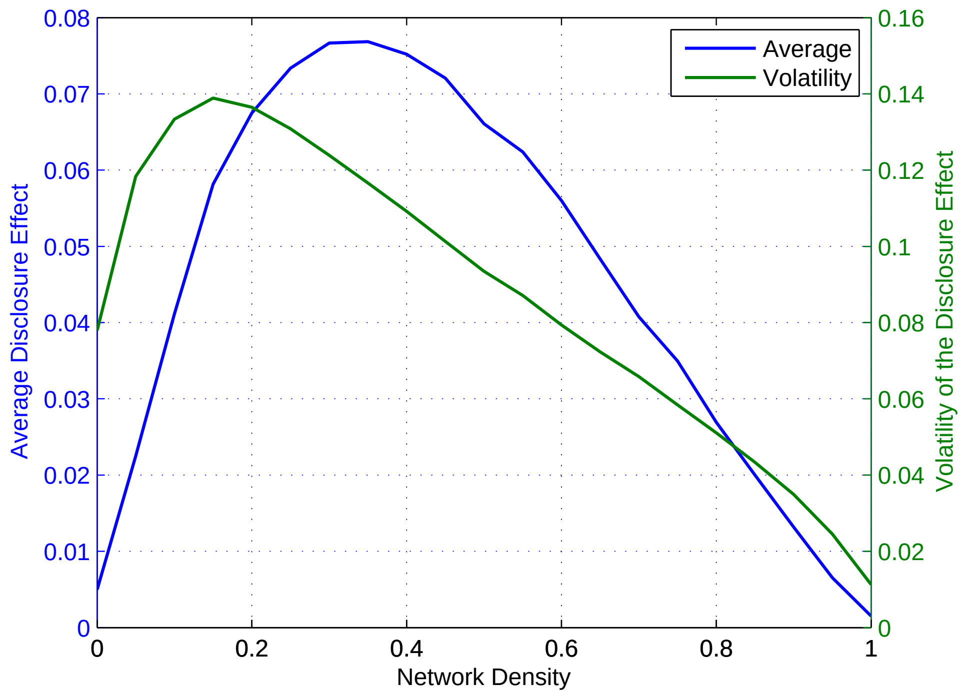

Figure 1. This figures plots the average and volatility of the *disclosure effect* for different classes of network density. Th simulation comprises 10000 iterations, $k = 0, \ldots, 20$, $d = 100$, and $N = 50$.

It is true that on the one hand, relatively sparse networks are subject to a significant expected disclosure effect. Yet at the same time, this is exactly the class of networks where the uncertainty of this effect is greater as well. In order to make a reasonable comparison, we examine the ratio of mean to volatility of the disclosure effect in Figure 2. As we can see, such "risk-adjusted" disclosure effect reaches the maximum for a density around 0.5.

The fact that a part of the banking system is expected to become riskier deserves special attention as it could have potentially severe repercussions. Suppose there is a bank with an already high risk exposure. Once the disclosure takes place, there is a strictly positive probability that

[5] A small caveat on the pictures reporting results as function of the network density. The theory says that for complete and empty networks the disclosure effect is zero. For computational reason we discretized the space of densities by creating $k = 0, \ldots, 20$ groups of densities. This means that in the group of $k = 0$ there are networks with densities $0 \leq D(G) < 0.05$. The discretization causes the two aforementioned limiting cases to have a disclosure effect different from zero.

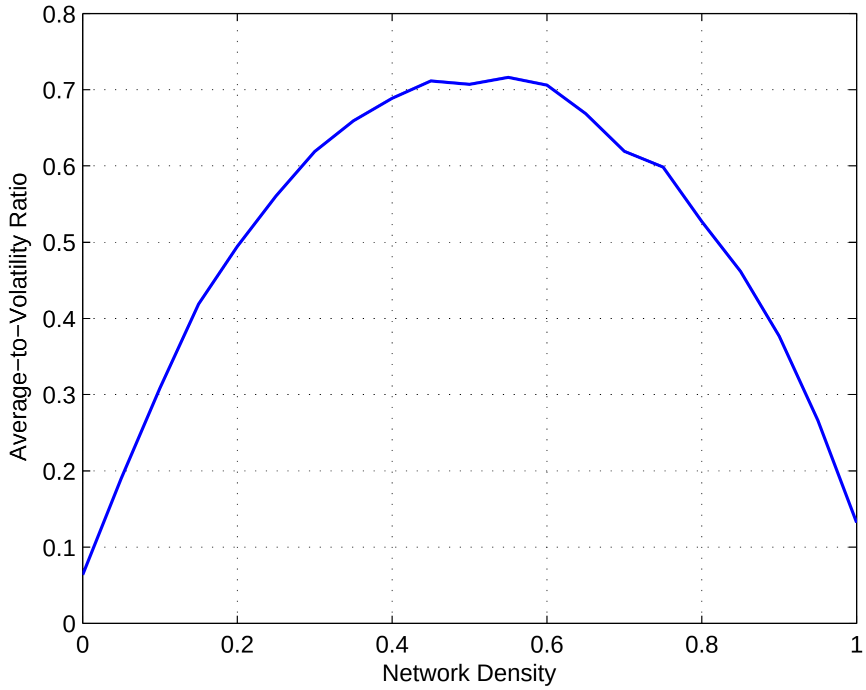

Figure 2. This figures plots the average-to-volatility ratio of the *disclosure effect* for different classes of network density. Th simulation comprises 10000 iterations,$k = 0, \ldots, 20$, $d = 100$, and $N = 50$.

this bank will turn even riskier. The increase in the bank's riskiness could then undermine the stability of the bank or even the banking system as a whole: there could be a bank run and/or should this bank fail it could affect others through the contagion effect. Despite the fact that we do not model contagion explicitly, there is a vast literature showing how devastating can be such an event (see Hledik and Frey (2014)). Papers in this strand of literature show how a default of a single institution can cause a large portion of the financial system to be in distress.

Next, we analyze how the distribution of the disclosure effect varies with the density of the network. Figure 3 presents the distribution of disclosure effect for different levels of network density. The strong relation between disclosure effect and network density is clear already by simply eye-balling the figure. For lower values of network density a large negative values of the disclosure effect are much more likely than for the medium densities and these are even less likely for the high densities. To be more precise, the probability that bank's risk-adjusted expected profit goes down by more than 20% is 0.1 if the network is sparse (low density), about 0.05 for networks of average density, and virtually zero in nearly complete networks. Figure 4, with only two groups of densities: LOW and HIGH, delivers the same intuition with a better graphical support.

We also examine how bank's position within the network affects the disclosure-induced change in its risk-adjusted expected profit. It is especially interesting to know how the disclosure effect varies with the systemic importance of a given bank. A systemically important bank is generally

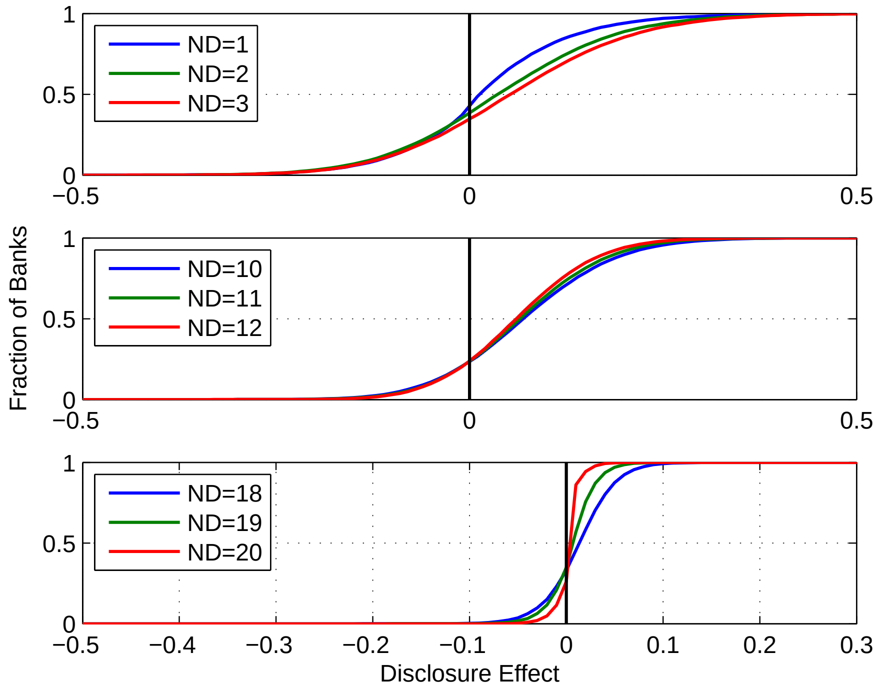

Figure 3. Distribution of the fraction of banks with respect to the disclosure effect for different classes of network density. The simulation comprises 10000 iterations, $k = 0, \ldots, 20$, $d = 100$, and $N = 50$

defined as a bank whose failure could endanger the whole banking system. If such institutions were more prone to suffer from the disclosure, the stabilizing intention of the information revelation policy could potentially turn out to be harmful in terms of systemic risk.

One simple way to characterize systemic importance of a bank in our model is to consider the ratio of in- and out-degrees[6] of a bank. Formally, we define systemic index a bank i as follows

$$\mathcal{SI}_i(G) = \frac{\sum_j^N g_{ji}}{\sum_j^N g_{ij}}, \tag{17}$$

notice that the index contains self-connections in both the numerator and the denominator. This is done for convenience such that to avoid situation of division by zero.

The idea behind this index is that a bank with a relatively large in-degree (i.e. there is a large number of banks exposed to the asset of this bank) being distressed (e.g. a drop in the expected payoff of its asset) could negatively affect its neighboring banks via contagion. The in-degree of the bank is deflated by its out-degree because a bank which is exposed less to assets of other banks is more likely to fail if its own asset deteriorates - such a bank is relatively more exposed to its own

[6]A degree is a graph-theoretic concept that characterizes the number of links of a given node in the graph. In our context, an in-degree of bank i refers to the number of banks that can invest into bank i's project, whereas the out-degree of bank i is the number of projects it can invest into itself.

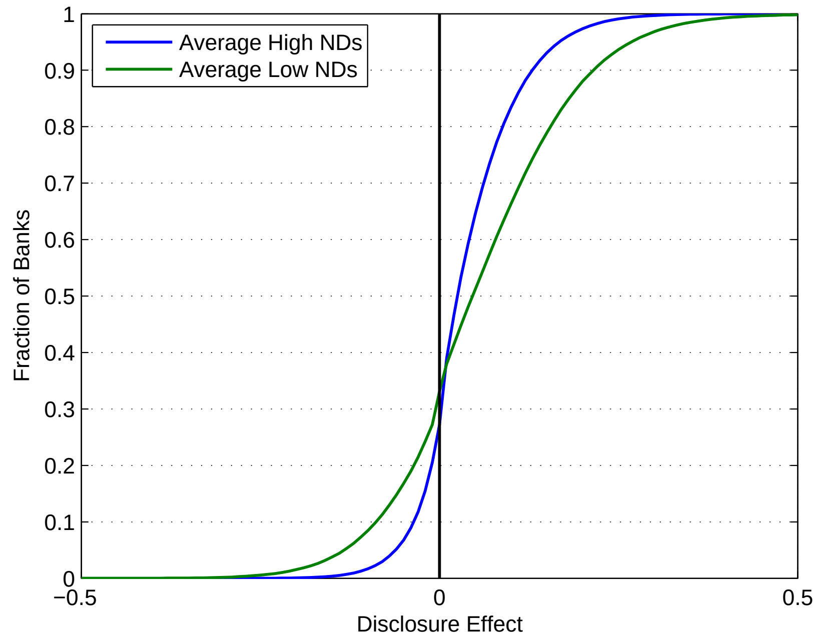

Figure 4. Distribution of the fraction of banks with respect to the disclosure effect for the average across LOW and HIGH classes of network density. The simulation comprises 10000 iterations, $k = 0, \ldots, 20$, $d = 100$, and $N = 50$.

risky asset, that is subject to more idiosyncratic risk. It is important to note that if one thinks of the core-periphery network structure, then banks within the core will have large values of the index in equation 17.

In our simulation exercise we rank all banks based on the index in equation (17) such that bank 1 has the highest value of the index and bank 50 the lowest. Figure 5 presents the average disclosure effect as well as its volatility for each bank in the system ranked according to the $\mathcal{SI}_i(G)$ index. It is apparent from the figure that systemically more important banks tend to experience a smaller disclosure effect, less than 5% for the first 10 banks. Moreover, the uncertainty associated with the disclosure is larger for the such important banks, more than 10% for the first 10 banks. In order to be more specific, within one standard deviation, the disclosure effect can be negative for the most systemically important bank within the banking system. This does not happen for the least important bank, the effect stays positive. Figure 6 depicts the ratio of the average disclosure effect and its volatility. The figure is meant to stress the lower efficacy of the disclosure for systemically more important banks in our model.

Additionally to studying how the first and second moments of the disclosure effect vary with the systemic importance of banks we also analyze disclosure effect distribution for the banks of different systemic importance. Figure 7 presents the distribution functions of the disclosure effect for banks of different systemic importance. We create 5 groups of banks (each contains 10 banks) ordered based on systemic relevance.

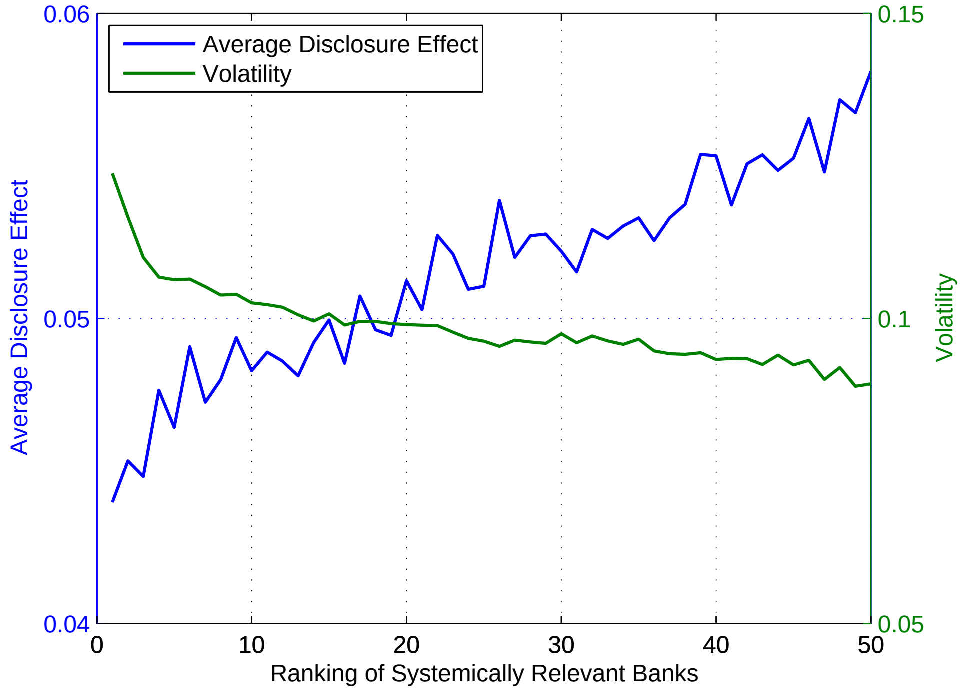

Figure 5. Average and Volatility of the *disclosure effect* for all the banks ranked according to the $\mathcal{SI}$ index. Bank 1 has the highest $\mathcal{SI}$, while bank 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

The figure makes it clear that there is almost no difference between the distribution functions on the positive part of the support - the distributions of the positive disclosure effects are virtually the same regardless of the systemic importance. On the contrary, for negative support the disclosure effect distribution of less systemically important banks "dominates" more systemically important ones. That is to say, the same minimum level of negative disclosure is more likely for the systemically more important banks than systemically less important ones.

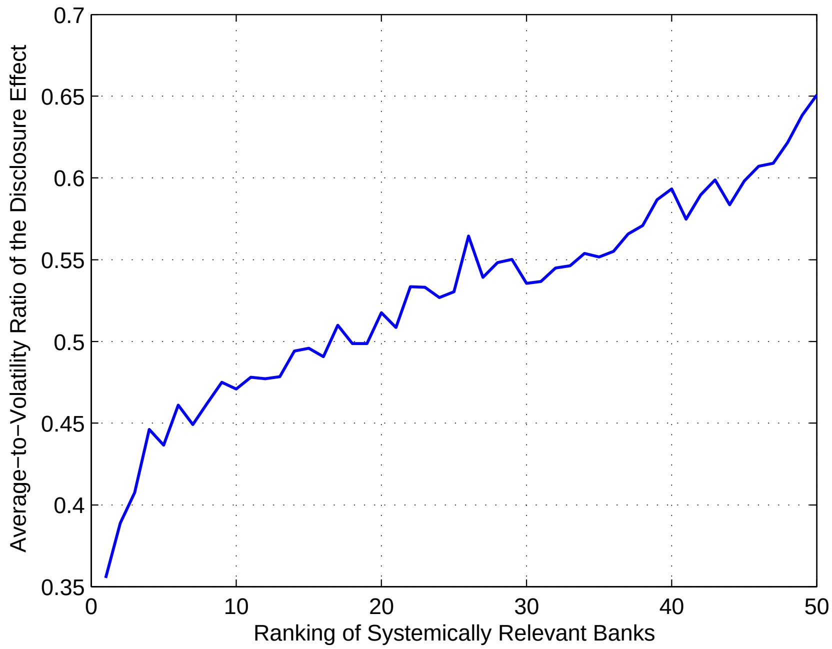

Figure 6. Average-to-volatility ratio of the *disclosure effect* for all the banks ranked according to the $\mathcal{SI}$ index. Bank ranked 1 has the highest $\mathcal{SI}$, while bank ranked 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

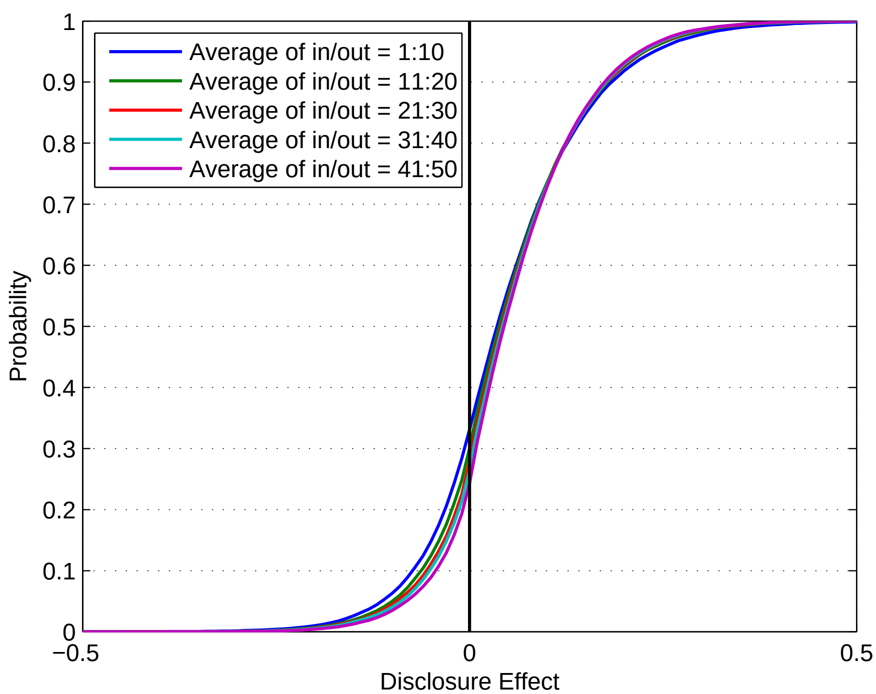

Figure 7. Cumulative distribution of the average of the *disclosure effect* within groups of banks ranked according to the $\mathcal{SI}$ index . Bank 1 has the highest $\mathcal{SI}$, while bank 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

The intuition behind this result is simple. In this model, information is valuable to the extent that allows banks to optimally re-adjust their portfolios holdings. The main feature of the systemically relevant banks is to be not very exposed to others but being at the center of other banks' exposure. This implies that, at the margin, they are the least enjoying the benefits of new information, but suffering the costs imposed by the other banks' re-adjustment.

E. Results for Core-Periphery Random Networks

We now turn our attention to a special type of random networks - core-periphery - also known as star-like networks. Figure 8 presents a schematic depiction of the network exhibiting star-like structure. There are 3 banks (banks 1,2, and 3) which are located in the center of the star and to which we shall refer to as stars. There are also 8 banks (banks from 4 to 11) located on the periphery of the star. The banks inside the core are characterized by a large in-degree - many banks have exposures towards them - and a high degree of interconnectedness among each other. Banks from the periphery are in contrast characterized by a very small in-degree and a low degree of interconnectedness among each other. The periphery banks are mostly exposed to the banks inside the core.

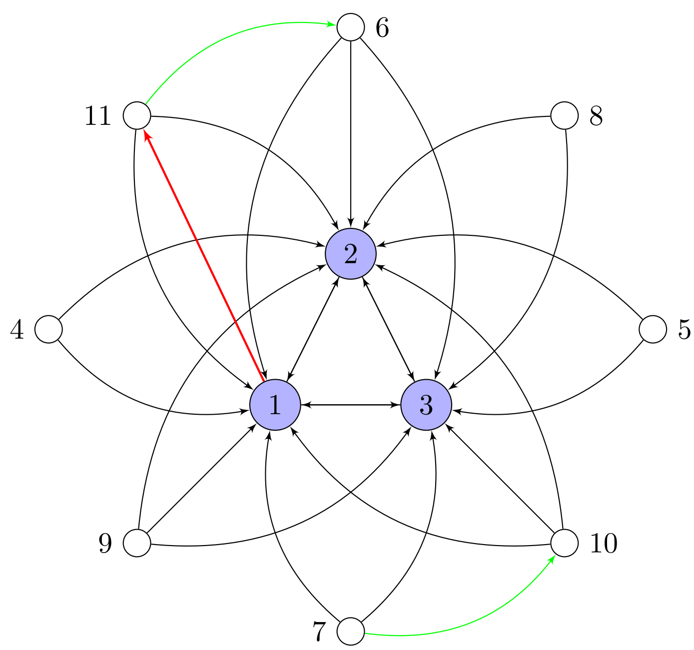

Figure 8. Schematic depiction of a Core-Periphery Network with 3 banks in the core and 8 banks in the periphery. Core banks are characterized by a large in-degree and high level of interconnectedness, whereas periphery is characterized by smaller in-degrees and very low level of interconnectedness.

Our interest in this type of network structure is motivated by its frequent appearance in banking systems. Many empirical papers document that various financial networks take star-like structure (see Boss, Elsinger, Summer, and Thurner (2003), Camelia and Reyes (2011), Fricke and Lux (2014), and Lelyveld and Veld (2012)). Moreover, star-like networks often appear as an equilibrium outcome of the network formation process as in Maryam (2015). Given this special status of star-like networks we believe it is important to study the disclosure effect of information in this type of networks.

In general, the systemic importance of the core banks is apparent. If the asset of such a bank deteriorates, banks exposed to it would be negatively affected. The larger is the number of such institutions, the larger is the fraction of the system which becomes contaminated. The analysis that follows mirrors the one conducted for random networks. Specifically, we focus on showing the how the disclosure effect impact the systemically relevant banks in the network. We repeated the same simulation procedure as explained in Section III.B, with the only difference that the exogenous networks simulated have the structure as the one in Figure 8.

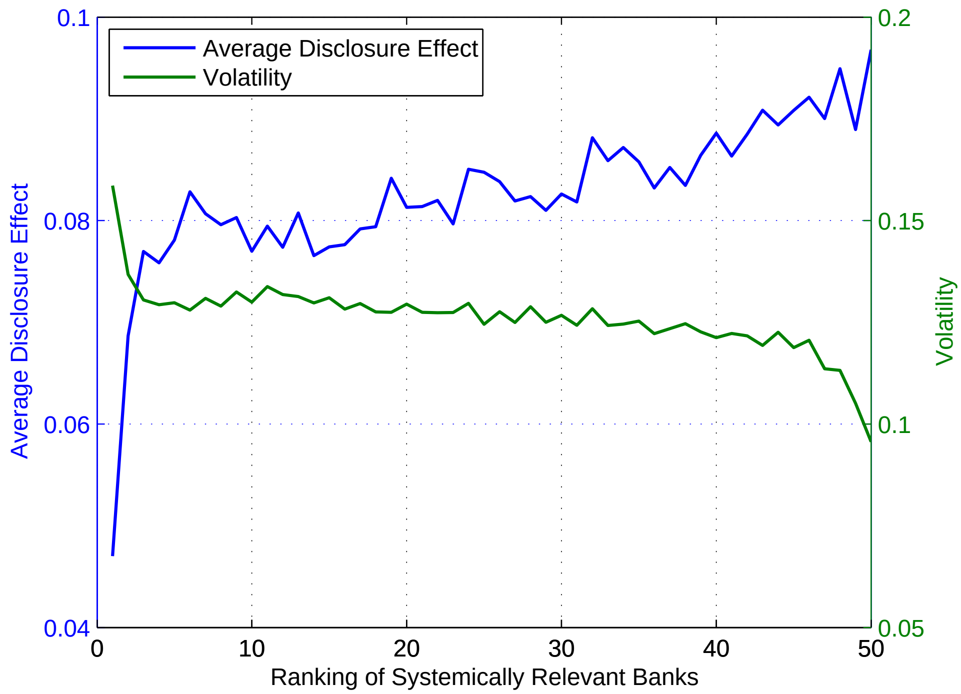

Figure 9. Average and Volatility of the *disclosure effect* for all the banks ranked according to the $\mathcal{SI}$ index. Bank ranked 1 has the highest $\mathcal{SI}$, while bank ranked 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

The results found for random networks are even stronger when the exogenous network has a star-like shape. Figure 9 clearly show that the most important bank has the lowest advantage in terms of changes in risk-adjusted expected profits, yet it bears the higher volatility of such changes. The average disclosure effect for this bank lies below the 5%, with a standard deviation of this effect above 15%. Form the figure is clear that the trend of the average disclosure effect is upward sloping while its volatility is downward sloping when moving form relevant to less relevant banks, as it has been shown for random networks. This shows that the disclosure effect is robust across network structure and alarmingly it suggests that the relevant banks are bearing the cost in terms of riskiness of their portfolios. Figure 10 displays the ratio between the average disclosure effect and its volatility. This is meant to stress the difference between the effect on more relevant banks and less relevant ones from a systemic view point.

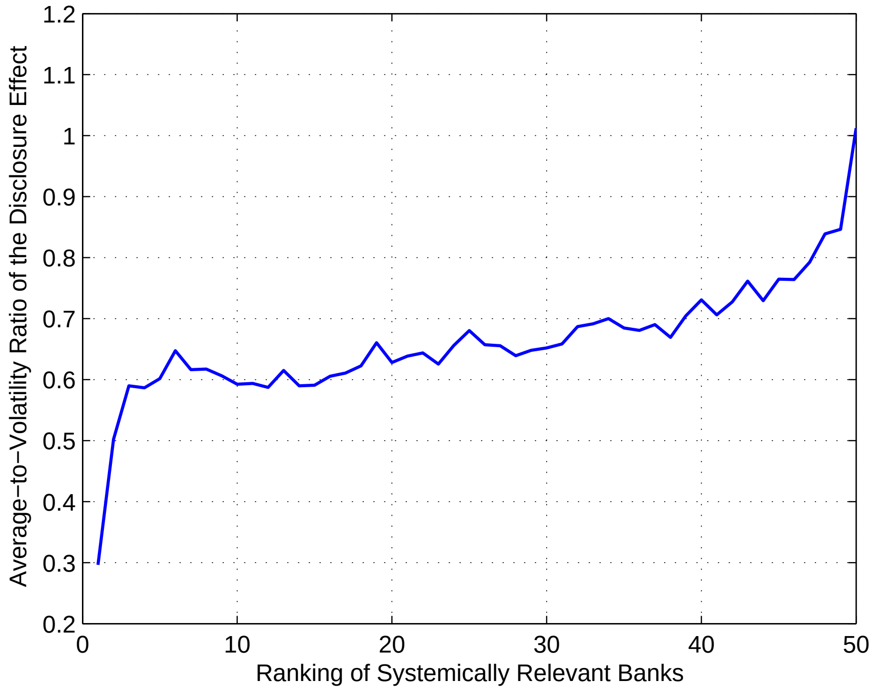

Figure 10. Ratio between the average and the volatility of the *disclosure effect* for all the banks ranked according to the $\mathcal{SI}$ index. Bank ranked 1 has the highest $\mathcal{SI}$, while bank ranked 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

As before we present evidence on distribution of the disclosure effect for the banks of different systemic importance. Figure 11 presents the distribution functions of the disclosure effect for banks of different systemic importance. We create 5 groups of banks (each contains 10 banks) ordered based on systemic relevance.

We observe that there is almost no difference between the distribution functions on the positive part of the support - the distributions of the positive disclosure effects are virtually the same regardless of the systemic importance. On the contrary, for negative support the disclosure effect distribution of less systemically important banks "dominates" more systemically important ones. That is to say, the same minimum level of negative disclosure is more likely for the systemically more important banks than systemically less important ones.

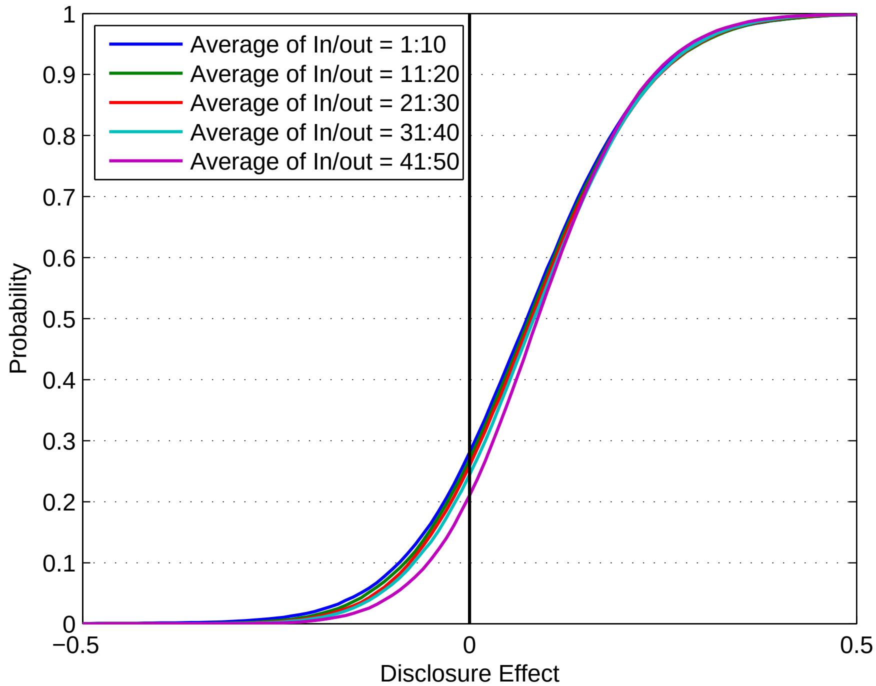

Figure 11. Cumulative distribution of the average of the *disclosure effect* within groups of banks ranked according to the $\mathcal{SI}$ index. Bank ranked 1 has the highest $\mathcal{SI}$, while bank ranked 50 has the lowest one. The simulation comprises 10000 iterations, $d = 100$, $N = 50$.

The intuition behind this result for star-like network is the same presented for random networks. The effect is actually stronger for star-like networks. The reason is because, given the nature of the network structure, naturally arise banks which have a very high in-degree and a very low out-degree. This implies that for these banks the valuation of new information is, on average, even lower with respect to banks in a random network.

IV. Conclusion

This paper studies the effects of the information disclosure on banks' portfolio risk. We do so by developing a general equilibrium framework in which banks face exogenous network constraints.

We show that the disclosure of information results in a reduction of risk-adjusted expected profits for a non-negligible fraction of banks in the system. Moreover, this negative effect is even more profound for systemically important banks - banks located in the center of the network. Our simulation exercise shows that the structural features of networks have a first-order importance when evaluating the effects of the injection of sensitive information into the economy.

Additionally, we present evidence that the negative effect for systemically relevant banks in star-like networks is even more severe compared to the same effect for relevant banks in random networks. This finding is extremely important in relation to real world applications. As we already discussed, several empirical papers document that financial networks take a star-like structure. Our finding plus the empirical evidence on the shape of the network suggest that we should dig more into details about the overall effect of the information disclosure and make sure neither to harm individual banks (especially relevant ones) nor the system as whole.

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Appendix A. Proofs

[TO BE EDITED]