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

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May 21, 2018

ABSTRACT

This paper studies the effect of information disclosure on banks' portfolio risk. We cast a simple banking system into a general equilibrium model with trading frictions. We find that the information disclosure lowers the expected risk-adjusted profits for a non-negligible fraction of banks. The magnitude of this effect depends on the structure of the banking system and, alarmingly, it is more pronounced for systemically important institutions. We connect these theoretical findings to the stress test procedure, where bank information is disclosed by the regulator. The 2011 and 2014 stress tests are used in an empirical study to further support our theoretical results.

JEL classification: D50, D80, G21.

Keywords: Information Disclosure, General Equilibrium, Systemic Risk.

Introduction

In the aftermath of the 2008 financial crisis, policymakers were faced with a task of restoring the soundness and safety of financial systems. An extra effort has been made to ensure the stability of financial institutions and to make their balance sheets as transparent as possible.[1] The stress test procedure has been developed as a part of this endeavor, 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] Alternatively, one could view the stress test as a stability analysis of financial institutions in various adverse scenarios.

As a part of the procedure, banks are required to disclose otherwise unavailable information.[3] There is an ongoing debate on whether such information should be disclosed and if so, how detailed it should be. A growing strand of literature, both theoretical and empirical (see Prescott (2008) and Goldstein and Leitner (2017) for theories and Schuermann (2014) for empirical evidence), provides mixed results on the issue. The advantages appear to be clear: information disclosure helps to discipline banks, reduces adverse selection, and leads to more informative prices. One could easily agree that market transparency seems like a desirable feature. However, Goldstein and Leitner (2017) find that during normal times, no disclosure is optimal. They show that during bad times some disclosure is necessary, but too much may destroy risk-sharing. Moreover, Goldstein and Yang (2017) show that disclosing

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[1]Further details can be found in the Dodd-Frank Act and Basel Accords for the US and Europe, respectively.

[2]European Banking Authority (EBA) definition of the stress test's purpose.

[3]From 2011 the stress test procedure is coordinated by the EBA. The scope is to analyze the evolution of banks' capital under both a baseline as well as an adverse scenario over a two-year period. The setup of the two scenarios is provided by the European Commission (baseline) and the European Systemic Risk Board (adverse). The European Central Bank is responsible for interacting with banks during the exercise and for the validation of banks' data and results. Although stress test methodology can differ from one year to another, the basic timeline of the procedure stays the same. In the first step, the EBA announces the new round of stress tests. In the second step, it publishes the methodology and the scenarios that will be used. In the third step, it publishes the final template for the test such that banks can simulate the scenarios themselves. Finally, the EBA reports both results and the micro-data used during the procedure. This last step is what we mean by information disclosure. For details on current methodology see http://www.eba.europa.eu/-/eba-issues-2018-eu-wide-stress-test-methodology-for-discussion.

public information has a potential negative indirect effect of changing price informativeness.

Our main finding indicates that the information disclosure may result in a reduction of risk-adjusted expected profits for a non-negligible fraction of banks in the system. We refer to this change of risk-adjusted expected profits as the *disclosure effect.* Interestingly, in our model, systemically important banks[4] gain the least from the disclosure and bear the highest cost in terms of its volatility. Moreover, their likelihood of experiencing a negative disclosure effect (as a result of new information) is higher.

These results follow from a simple one-period general equilibrium model in which agents (hereafter banks) face trading frictions. Being the main ingredient of our framework, trading frictions can be seen as a network of connections. Bank A is said to be *connected* to bank B if and only if A is not constrained in investing into B's asset. Therefore, the network is simply a way of writing down the portfolio constraints in a systematic way, which allows us to assess the structure of these restrictions.

The simulation exercise suggests that disclosure is beneficial in a sense that an average bank is expected to attain a positive profit. However, there are multiple factors that could possibly tip the scales towards non-disclosure. Firstly, we show that systemically important banks are more likely to be negatively affected by the disclosure. Alarmingly, these are the players that could potentially destabilize the whole system.[5] Secondly, one needs to take into account the network density (the level of banks' interconnectedness) when drawing policy implications. We find that a negative disclosure effect is more likely to be observed in low-density networks.

We further show that these results are robust across different connection structures. The effect is present in simulated homogeneous networks as well as in network structures more similar to the actual financial systems. Moreover, we include an empirical section where

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[4]We focus on the network component of systemic risk where the institutions' positions play a vital role. Throughout the paper, we use the terms *systemic risk* and *network systemic risk* interchangeably.

[5]The literature provides several examples in which systemically important banks can endanger the integrity of the network via contagious defaults (see Allen and Gale (2000) or Elsinger, Lehar, and Summer (2006)).

we test our model predictions using the actual 2011 and 2014 stress tests. Results support our theoretical findings - i.e., banks subjected to a stress test procedure exhibit lower future expected risk-adjusted profits.

Related literature. Our work contributes to a few strands of literature. Broadly, our paper fits within the scope of the literature on public information disclosure. In frictionless markets, more information is always ex-ante better for a decision maker, a result known as Blackwell's Theorem (Blackwell (1951)). However, when operating in an environment with asymmetric information, more information does not necessarily imply an improvement.

The proponents of public information disclosure argue that it disciplines markets, reduces adverse selection, and improves price informativeness (Tarullo (2010), Bernanke (2013)). Diamond (1985) shows that optimal disclosure reduces information asymmetries and enhances trade. Moreover, Korn and Schiller (2003) show that firms lose the ability to misreport under mandatory disclosure. Additionally, Admati and Pfleiderer (2000) demonstrate how correlated firms' values can increase the welfare under mandatory disclosure.

However, there are also arguments why public information disclosure can be harmful. Hirshleifer (1971) shows that releasing information about the future state of the economy destroys ex-ante risk-sharing incentives. Goldstein and Leitner (2017) apply this idea to study the optimal disclosure policy in banking systems. They find that disclosing too much destroys the risk-sharing, but disclosing too little might result in a market breakdown in the time of a crisis. Andolfatto, Berentsen, and Waller (2014) show that it is only optimal to disclose information to prevent agents from its costly acquisition. Alvarez and Barlevy (2015) show in a model of information spillover that the decision to disclose depends on the presence of contagion. Furthermore, Gigler, Kanodia, Sapra, and Venugopalan (2014) show that frequent disclosure requirements may lead to managers' short-termism.

Morris and Shin (2002) provide an argument which is based on the dichotomy between public and private information. If there is no private information, public disclosure is always welfare enhancing. However, in the presence of private information, an increase in public

information precision can be detrimental. If access to the private information is costly, agents have less incentive to obtain it and rely on the - possibly imprecise - public information. In comparison, disclosure in our model is unanticipated. This ensures that the only friction in the agents' decision making is their portfolio constraints.

Prescott (2008) provides an additional argument against information disclosure, namely possible detrimental welfare effects caused by disclosure during bad times. As a result, by disclosing banks' private information, the regulators' ability to obtain such information in the first place is threatened. In comparison, there is no business cycle in our model. **?** show that disclosure can also simply reduce investors' incentives to acquire and trade on private information. Earlier literature also argues that mandatory information disclosure may simply be unnecessary because firms have plenty incentives to disclose information by themselves (see Grossman and Hart (1980), Grossman (1981), and Milgrom (2007)).

This paper adds to the existing literature by showing that the information disclosure may have negative effects even in a simple general equilibrium framework with portfolio constraints. We show the implications of the banking system network structure on the effect of information disclosure. More importantly, our paper shows that systemically important banks are more likely to suffer from disclosure.

Our work is closely linked to many of the papers we have already mentioned. Similarly to Admati and Pfleiderer (2000), our framework is also built around different effects of correlated assets, only we do not focus on a welfare analysis. Unlike Tarullo (2010), Bernanke (2013) or Diamond (1985) who focus on agency problems, our model uses a general equilibrium market mechanism with trading frictions instead. Similarly to Goldstein and Leitner (2017) and Andolfatto et al. (2014), we question the purpose of disclosure. The same goes for Prescott (2008), except instead of incorporating a business cycle into our model, we focus on a market-implied riskiness resulting from a general equilibrium.

Our work also contributes to the literature on financial networks (see e.g. Upper (2011), Poledna, Molina-Borboa, Martnez-Jaramillo, van der Leij, and Thurner (2015), or alterna-

tively Roukny, Battiston, and Stiglitz (2016)). We offer a novel modeling approach based on a simple general equilibrium framework. It has a closed form solution which makes it computationally attractive while being easily implemented by a regulator at the same time. Translating the portfolio constraints into network connections constitutes a new perspective on systemic risk. Empirical works on the subject include Acharya, Pedersen, Philippon, and Richardson (2017a) and Adrian and Brunnermeier (2016).

As suggested by the title, a practical example of information disclosure is the stress testing procedure. We strive to contribute to the debate on its proper design (see Goldstein and Sapra (2014)). Our paper provides a potential channel (trading frictions) to complement the literature on negative effects of information disclosure.

The paper unfolds as follows. Section 1 introduces the theoretical framework. Section 2 describes the simulation exercise. Section 3 presents the main results. Section 4 presents the empirical analysis and Section 5 concludes.

1 The Model

1.1 Two-period Finance Economy with Network Constraints

In order to study the effect of information disclosure we employ a general equilibrium framework in which agents (banks) are treated as portfolio maximizers.[6] The economic environment is a standard one-period (two dates) finance economy, with dates labeled as $t = 0, 1$ and N banks.

At $t = 0$, bank $i \in \{1, ..., N\}$ has an endowment of size 1 as well as access to its own investment opportunity (referred to as an asset or project).[7] The value of this endowment is

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[6]Other papers in the literature address information disclosure in a game-theoretic framework with strategic interactions, see Goldstein and Leitner (2017) for instance. We have settled for a general equilibrium with simulated networks because it provides tractable solutions while not losing the potential applicability to a real-world data. Even though networks in our model are simulated, we still regard our work as a theoretical paper. The main advantage of our approach is that it allows us to study the market effects instead of the player' strategic interactions. The idea behind this framework is that prices are determined in equilibrium and banks' risk-adjusted profits are indirectly affected as a result.

[7]These projects can be seen as a bank's external assets on international markets. Hence the correlation

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. Projects/assets are perfectly divisible into arbitrarily small amounts. Due to a one-to-one relationship, we will further refer to banks and their assets (or projects) interchangeably. The assets' returns, $\mathbb{X}$, are assumed to be jointly normally distributed with mean μ and variance-covariance matrix V. Moreover, each bank has access to an unlimited quantity of risk-free asset that delivers 1 unit of consumption at time $t = 1$ per 1 unit invested at time $t = 0$.

Banks are not allowed to trade freely with each other. We assume that each bank has its own specific set of counterparties available for trading. More precisely, bank i is said to be *connected* to bank j if and only if bank i can purchase asset j. Therefore one can represent the banking system as a network in which nodes correspond to banks and edges stand for trading opportunities. This network is characterized by an *adjacency matrix* G.[8]

Formally the maximization problem of bank i at $t = 0$ is given by:

$$\max_{\{\phi_i, \theta_i\} \in \mathbb{R}^{N+1}} \left\{ \mathbb{E}[\mathbb{Y}_i] - \frac{1}{2} \mathrm{Var}\left[\mathbb{Y}_i\right] \right\}$$

s.t.

$$p_i = p'\phi_i + \theta_i$$

$$\mathbb{Y}_i = \mathbb{X}'\phi_i + \theta_i \tag{1}$$

$$\phi_i \in A_{i1} \times A_{i2} \times \cdots \times A_{iN}$$

$$A_{in} = \begin{cases} \mathbb{R} & \text{if } g_{in} = 1 \\ \{\emptyset\} & \text{if } g_{in} = 0 \end{cases} \quad \forall n \in \{1, \ldots, N\}$$

where $\mathbb{X} = [\mathbb{X}_1, \ldots, \mathbb{X}_N]'$ is a $t = 1$-measurable random vector of assets' returns, $\phi_i =$

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with other banks in the network.

[8]Each element, g_{ij}, 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. Connections need not be symmetric, e.g. i being connected to j does not imply j being connected to i. Also, since we assume that every bank can always decide to hold some fraction of its own asset, self-connections are feasible such that $g_{ii} = 1$ for all 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, $p = [p_1, ..., p_N]'$ is the price vector of risky assets, $\mathbb{Y}_i$ is the value of bank i's portfolio, and g_{ij} is the (i, j) element of the adjacency matrix G. The first constraint is the resource constraint. At time $t = 0$, the market value of bank i's initial endowment is equal to p_i. This represents the wealth that is allocated between 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 two lines restrict banks to invest only into counterparties that they are connected to.

We follow a standard definition of equilibrium:

Definition 1.1. *An equilibrium is characterized by a price vector p^* and allocations $\{\phi_i^*\}_{i=1}^N$ and $\{\theta_i^*\}_{i=1}^N$ such that*

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

(ii) *markets clear*

$$\phi_1^* + \phi_2^* + \cdots + \phi_N^* = \mathbf{1} \tag{2}$$

Under the assumption of jointly normally distributed asset payoffs, the equilibrium price vector and demand functions can be obtained in closed form. Proposition 1.1 presents this result.

Proposition 1.1. *Assume that the vector of asset payoffs, $\mathbb{X}$, is jointly normally distributed with mean μ and variance-covariance matrix Σ, then the demand function for risky assets of bank $i \in \{1, \ldots, N\}$ is given by*

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

where $\lambda_i := [\lambda_{i1}, ..., \lambda_{iN}]' \geq 0$ is the vector of Lagrange multipliers associated with the appropriate network constraints. Given the demand equations in (3), the market clearing condition

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in (2) determines the equilibrium price vector

$$p^* = \mu - \frac{1}{N}\Sigma\mathbf{1} - \frac{1}{N}\sum_{j=1}^{N}\lambda_j. \tag{4}$$

The proof is in Appendix A.

1.2 The Model with Disclosure

In our model, the disclosure mechanism works via the information about the variance-covariance matrix of assets' returns. In the previous section, banks had access to matrix V when making their decisions. In the current section, banks do not observe V. Instead, they form identical beliefs about it, represented by a matrix W. Therefore, W can be seen as a noisy observation of the true variance-covariance matrix V.[9] The matrix V is revealed to banks with zero probability after their initial portfolio choice. This modeling approach of assuming zero probability event builds on Allen and Gale (2000).[10]

At $t = 0$, banks form the optimal portfolios based on the $N \times N$ positive definite matrix W. We denote the vector of allocations of risky assets based on this initial belief by $\{\phi_i(W)\}_{i=1}^{N}$ to stress their dependence on W. If no disclosure takes place, then banks keep these allocations until returns are realized and the model is identical to (1) with $\Sigma = W$.

In the zero probability event (where the true variance-covariance matrix V is revealed) banks can readjust their existing portfolios upon learning new information. In such a case

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[9]Section 2.1 contains detailed information about the banks' belief structure.

[10]In Allen and Gale (2000) a financial contagion is spread in the system after a liquidity shock is realized. Given that the shock is assumed to be a zero probability event, banks do not take it into account when making their decisions at time zero.

bank i solves the following optimization problem:

$$\max_{\{\phi_i(V),\theta_i(V)\}\in\mathbb{R}^{N+1}} \left\{\mathbb{E}[\mathbb{Y}_i] - \frac{1}{2}\mathrm{Var}\,[\mathbb{Y}_i]\right\}$$

$$\text{s.t.}$$

$$p'(V)\phi_i(W) + \theta_i(W) = p'(V)\phi_i(V) + \theta_i(V)$$

$$\mathbb{Y}_i = \mathbb{X}'\phi_i(V) + \theta_i(V) \qquad (5)$$

$$\phi_i(V) \in A_{i1} \times A_{i2} \times \cdots \times A_{iN}$$

$$A_{in} = \begin{cases} \mathbb{R} & \text{if } g_{in} = 1 \\ \{\emptyset\} & \text{if } g_{in} = 0 \end{cases} \qquad \forall n \in \{1,\ldots,N\}.$$

This problem does not introduce any new variables. We merely stress the dependence of ϕ_i, θ_i, and p on either W or V. The difference between the two optimizations lies in the bank's endowment, which is now equal to the market value of its portfolio (see the first constraint in (5)).

Everything else stays the same, including the network constraint. Thus, Proposition 1.1 applies with Σ exchanged for V.

1.3   Discussion of the Main Assumptions

We assume that banks are risk-averse, which is a necessary condition for their interest in diversification. Risk aversion can be seen as a modeling device to capture regulatory requirements (e.g. requiring banks to keep some level of capital according to Basel III). In the literature, it is often assumed that banks are so well diversified that they behave in a risk-neutral fashion. However, this is only true for the marginal investment. In our case, banks' connection constraints create a limit to diversification.[11]

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[11]The banks in our model are not subjected to any explicit regulatory capital requirements. Risk aversion is implicitly capturing such effects as more risk-averse banks would invest a higher fraction of their endowment into the risk-free asset and de facto keep a higher capital buffer. In our model investment in the risk-free asset is basically a cash accumulation. Another option is to include an additional constraint which forces banks to keep a given fraction of safe capital. For example, Efing (2016) includes an explicit regulatory constraint

We assume mean-variance preferences. For any other standard preference structure, we expect to observe qualitatively similar results.[12] Mean-variance preferences allow for the equilibrium price vector and the demand schedules to be obtained in closed form.

We assume that the network of connections is fixed. Preventing banks from changing their respective sets of counterparties can be justified by two arguments. Firstly, undertaking new business relationship might be a long process which is not captured in our one-period model. Secondly, creating new connections might be too costly.

2   Simulation Framework

2.1   The Structure of the Banks' Beliefs

We use the following structure to ensure consistency between beliefs and the true variance-covariance matrix. We assume that the vector of asset payoffs, $\mathbb{X}$, is conditionally normally distributed

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

where μ is the vector of expected payoffs and V the variance-covariance matrix of the assets' payoffs. We keep μ constant and equal across all assets since we want to isolate the effect of disclosure with respect to the uncertainty about the variance/covariance matrix, V.

We sample V from the inverse-Wishart distribution. That is,

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

in a model very similar to ours. Building on his paper and incorporating such additional constraint in our model brings several negative aspects and no qualitatively improvements. First, we would not be able to solve the model in a closed form which is one of the nice features that makes this model computationally feasible. From an economic perspective, a regulatory constraint would definitively affect the initial portfolio allocations. The set of allocations would differ if the constraint is binding for at least one bank. However, the mechanics of the information disclosure would still be in place as banks will try to re-optimize upon receiving new information. Thus results would be affected only quantitatively but not qualitatively. It is worth noting that a regulatory constraint would eliminate our *disclosure effect* only if it completely prevents banks to invest in risky assets. As our model aims at providing qualitative results on the negative effect of information disclosure created by network frictions, we opted to shut down the regulatory constraint channel.

[12]This is due to banks acting as individual (atomistic) optimizers.

where N is the total number of banks in the system, S is an $(N \times N)$ positively definite scale matrix, and $d > N-1$ measures the degrees of freedom. We let banks form their beliefs about the true variance/covariance matrix, V, by estimating the empirical variance/covariance matrix of asset payoffs W.[13]

2.2   Simulation Settings

In order to model a regulator's limited knowledge about the structure of the system, we use a simulation that samples over different random networks. Even though our model is not meant to produce quantitative predictions, it potentially could. Still, the main objective is to obtain qualitative economic insights. Another reason for using simulation methods is to observe the impact of different network structures.

We solve the model from Section 1 with the belief structure described in Section 2.1. Each simulation begins by generating a random network represented by an $N \times N$ adjacency matrix G. The number of banks, N, is set to either 50 or 100, and the number of iterations to 15,000.

Once the network structure is generated, we sample a random positive definite scale matrix S and follow the procedure described in Section 2.1. 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.

2.3   Key Outcome Variable: Risk-Adjusted Expected Profits

We look at changes in risk-adjusted expected profits of banks to analyze the effect of information disclosure on the distribution of risk. The risk-adjusted expected profit of bank i under the no-disclosure scenario is defined by the following ratio

$$\Pi_i^{nd} \stackrel{\text{def}}{=} \frac{(\mu - p^*(W))' \phi_i^*(W) + p_i^*(W)}{\sqrt{\phi_i^{*\prime}(W) V \phi_i^*(W)}} \tag{8}$$

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[13]Each bank uses the same sample, which results in an equal information set.

Under the disclosure scenario, the risk-adjusted expected profit for bank i is given by

$$\Pi_i^d \stackrel{\text{def}}{=} \frac{(\mu - p^*(V))' \phi_i^*(V) + (p^*(V) - p^*(W))' \phi_i^*(W) + p_i^*(W)}{\sqrt{\phi_i^{*\prime}(V) V \phi_i^*(V)}} \tag{9}$$

Equations 8 and 9 can be thought of as pseudo-Sharpe ratios on bank i portfolios.

We define the *disclosure effect*, $\mathcal{DE}_i$, as the percentage change in the risk-adjusted expected profits, which is

$$\mathcal{DE}_i \stackrel{\text{def}}{=} \log \left(\frac{\Pi_i^d}{\Pi_i^{nd}} \right), \tag{10}$$

This quantity allows us to study the effect of information disclosure on the distribution of risk within a banking system. By constructing (8) and (9) as the ratio of expected returns and their standard deviation, we are capturing the Basel III capital adequacy requirements where risk-weighted assets are considered. Therefore, disclosure ought to be considered beneficial when $\mathcal{DE}_i \geq 0$ and detrimental when $\mathcal{DE}_i < 0$.

2.4 Network Structure and the Banks' Systemic Relevance

We consider two types of network structure. The first type is a banking network generated by the Erdős-Rényi (ER) model. In this framework, every bank has the same probability, q, to be connected to any other bank in the network. The resulting structure is therefore homogeneous.

The second type is a core-periphery network structure where the probability of a connection is empirically calibrated (see Puhr, Seliger, and Sigmund (2012) for data and Frey and Hledik (2014) for the calibration method). Our interest in this type of network structure is motivated by its frequent appearance in banking systems.[14] To model this observed heterogeneity of real-world interbank networks, we slightly modify the Erdős-Rényi setting.

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[14]Many empirical papers document that various financial networks take core-periphery structure (see Boss, Elsinger, Summer, and Thurner (2003), Minoiu and Reyes (2013), Fricke and Lux (2014), and Lelyveld and Veld (2014)). Moreover, core-periphery networks often appear as an equilibrium outcome of the network formation process as in Farboodi (2017).

Instead of assuming that each pair of banks forms a connection with the same probability q, we divide banks into two groups (core and periphery). The difference between these two groups lies in their respective probabilities of forming connections with other banks. Any core bank has a high probability of establishing a connection both with other core banks and with other peripherals, while a connection between two peripherals is less likely. The result of this method is a random network with the desired core-periphery structure.

Figure B.1 shows a stylized representation of both types of network structure.

We study the properties of the average disclosure in relation to the characteristics of banking network. In particular, we characterize a network by its density, $D(G)$:

$$D(G) = \frac{1}{N(N-1)} \sum_{i \neq j} g_{ij} \tag{11}$$

where g_{ij} is the the ij-th element of adjacency matrix G such that the numerator corresponds to the number of all actual connections (edges) while the denominator represents all potential connections in the system (excluding self-connections). By such a construction, a complete network has a density of one, while an empty network has zero density.

Moreover, we examine how the bank's position in the network affects its risk-adjusted expected profit. In particular, we look at how the disclosure effect varies across banks of different network-systemic relevance. Usually, one thinks of systemically important institutions as the ones whose failure could endanger the whole system. If such institutions were more prone to suffer from the disclosure, then the stabilizing intention of the information revelation policy could potentially be harmful from the systemic risk perspective. In our model, a simple way to characterize systemic important banks is to consider the ratio of in- and out-degrees of a bank (the ratio of the number of its in-connections and out-connections).[15] Formally, we define the following systemic index for any bank i,

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[15] 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.

$$\mathcal{SI}_i(G) = \frac{\sum_j^N g_{ji}}{\sum_j^N g_{ij}}, \tag{12}$$

The idea behind this index is that a distressed bank with a relatively large *in-degree* (i.e. there is a large number of banks exposed to the asset of this bank) could negatively affect its neighboring banks via contagion.[16] The *in-degree* of the bank is deflated by its *out-degree* because banks with fewer diversification opportunities are expected to be riskier. We would like to emphasize that this index is specifically designed to capture the network-related systemic importance of a bank. According to the Financial Stability Board, it is standard to take into account bank's size, complexity and other factors besides interconnectedness when evaluating its systemic importance.[17] In our model, banks are identical in terms of their other observable characteristics. Therefore we evaluate banks' systemic relevance solely according to their position in the network.

3   Simulation Results

3.1   The Disclosure Effect in Erdős-Rényi Random Networks

Figure B.2 plots the full distribution of the disclosure effect. A non-negligible fraction of the banking system is expected to have its risk-adjusted expected profit decreased (a negative disclosure effect). This implies that there is a considerable part of the system which is expected to suffer as a result of the disclosure. In other words, there is a non-negligible probability that the information disclosure generates a negative effect on a given bank's risk-adjusted performance. This figure also underlines that a bank in a lower density network

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[16]Notice that the index contains self-connections in both the numerator and the denominator. This is a purely technical reason to avoid division by zero.

[17]*Systemically important financial institutions (SIFIs) are financial institutions whose distress or disorderly failure, because of their size, complexity, and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity.* - http://www.fsb.org/what-we-do/policy-development/systematically-important-financial-institutions-sifis/

has a higher likelihood of exhibiting a negative disclosure effect.[18]

[Figure B.2]

Figure B.3 displays the average disclosure effect as a function of the underlying network density. The figure underlines the importance of network characteristics for evaluating the effects of information disclosure. The average disclosure effect exhibits a hump shape with its peak at an intermediate density level and stays above zero throughout, thus, suggesting that disclosure is beneficial in expectation. The same pattern can be observed for the standard deviation of the disclosure effect, resulting in the observed pattern. The important takeaway from this figure is the positive relationship between average disclosure effect and its standard deviation.[19]

[Figure B.3]

The increase in a bank's riskiness could undermine the stability of the bank itself or, in some cases, even the stability of the whole banking system through a contagion effect. Despite the fact that we do not model contagion explicitly, there is a vast literature showing the devastating effects of such an event (see for example Elsinger et al. (2006) or Roukny et al. (2016)). Papers in this strand of literature show how a default of a single institution can cause a large portion of the financial system to become distressed.

The fact that a part of the banking system is expected to become riskier is not surprising. What seems to be more important is the relationship between a bank's disclosure effect and its network systemic importance. In order to get an idea about that, we rank all banks based on the index in equation (12) such that bank 1 has the highest value of $\mathcal{SI}(G)$ and bank 50 has the lowest. Figures B.4a and B.4b plot the average and standard deviation

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[18]Higher density does not necessarily correspond to a higher probability of contagion. For instance, an institution with many equally spread exposures is more likely to withstand a default of one of its counterparties (provided its other debtors stay healthy). This is the old story of diversification applied to network-systemic riskiness, see e.g. Frey and Hledik (2014).

[19]We observe a zero disclosure effect for an empty network with no connections as well as for a full network without any trading frictions as expected from standard theory.

of the disclosure effect based on this ordering. More systemically important banks tend to experience a lower disclosure effect. Moreover, the uncertainty associated with the disclosure, as measured by the standard deviation, is slightly larger for such banks. In order to be more specific, the more systematically important the bank, the higher the likelihood that the disclosure effect will be negative. The effect is opposite for less important banks where the disclosure effect is on average higher.[20]

[Figures B.4a and B.4b]

The intuition behind this result is simple. In our model, information is only valuable to the extent that it allows banks to optimally re-adjust their portfolio holdings. At the same time, systemically relevant banks are at the center of other banks' exposures. This implies that they are the ones least enjoying the benefits of new information while suffering the costs imposed by the other banks' re-adjustments.[21]

3.2   The Disclosure Effect in Core-Periphery Random Networks

In order to verify that our results persist if we move from the basic case of Erdős-Rényi random networks, we calibrate our network structure on the data of Austrian interbank market. Since the network density is given in this case, we can only report the relationship between disclosure effect and network systemic importance.

[Figures B.4c and B.4d]

Figures B.4c and B.4d again show that the most systemically relevant banks are expected to gain the least from the information disclosure.

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[20]Our simulations are qualitatively unchanged for different system dimensions. We have tested the framework on networks of sizes 50 and 100. Increasing the overall dimension of the system improves banks' ability to diversify and therefore decreases the variance of the disclosure effect.

[21]Acharya, Pedersen, Philippon, and Richardson (2017b) argue that banks tend to invest in assets that are heavily correlated with each other, hence increasing their systemic importance. In our model, the assets that are heavily invested in are the ones belonging to heavily connected-to institutions.

The basic intuition behind this result is the same as the one presented for Erdős-Rényi random networks: information is only valuable to the extent that it allows banks to optimally re-adjust their portfolio holdings. In the core-periphery random network, we observe an even stronger negative disclosure effect for systemically relevant banks because of the structural characteristics of this type of network. Here it arises naturally that banks with many in-degree connections have fewer out-degree connections. This furthermore reduces the value of the new information for systemically important banks, as compared to the previous environment with Erdős-Rényi random networks.

4   Empirical Evidence

We provide a simple empirical analysis using the 2011 and 2014 stress tests conducted by the European Banking Authority to support our results.[22] Our theoretical model suggests that being subjected to information disclosure is expected to have an impact on bank's risk-adjusted expected profits.

We develop a simple event study to explore this hypothesis using the following baseline linear model:

$$\Pi_{bct} = \beta \cdot \text{D.Stress Test}_{bct-1} + \gamma \cdot \mathbf{X}_{bct} + a_{ct} + a_b + \epsilon_{bst}, \tag{13}$$

where Π_{bct} is the risk-adjusted expected profit of bank b in country c at time t. D.Stress Test is an indicator variable equal to one if a bank was subjected to a stress test in the previous quarter and zero otherwise. Moreover, our model accounts for time-varying banks' characteristics by including the set of standard controls $\mathbf{X}$ (see Ellul and Yerramilli (2013), Beck, De Jonghe, and Schepens (2013)). It contains the following variables: Tier 1 capital ratio, size as measured by the value of total assets, total gross loans, and total deposits. More details on the definition of all variables can be found in Table 1. Lastly, we take steps to

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[22]We do not account for the stress tests conducted in 2009 and 2010 because the stress testing has been subjected to a significant restructuring by the EBA in 2011.

account for bank-specific time-invariant unobservables and country-specific common trends by including the appropriate fixed effects.

In addition to this baseline scenario, we also consider a specification with further control variables, particularly the Loan Loss Reserve and the ratio of Liquid Assets over Liabilities. These are also described in Table 1. We also use leads of the main explanatory variable (D.Stress Test) to account for a possible systematic difference in the trends of the dependent variable for treated and control group of banks. Moreover, we use lags to account for potential after treatment reversals.

Our interest lies in the parameter β which quantifies the marginal contribution of the stress test participation towards the risk-adjusted expected profits.

We use data from SNL Financial. Our sample in the baseline specification includes 1,818 bank-quarterly observations over the years 2011, 2014, and 2015.[23] Our sample includes 725 unique banks. Table 3 presents summary statistics for the variables used in the empirical analysis. This suggests that we are working with a representative sample. Importantly, as a proxy for the unobservable risk-adjusted expected profits, Π, we use the ratio of net income and risk-weighted assets.

Column (1) in Table 4 shows results from the estimation of the baseline scenario in Equation (13). Columns (2)-(4) add subsequent controls to this specification as well as further differentiation between listed and non-listed banks. Across all these specifications, the point estimate for β is negative and statistically significant. In our model, this inverse relationship would correspond to a negative disclosure effect $\mathcal{DE}$. Since the banks chosen for the stress test are arguably the systemically important ones, it is reasonable to claim that the observed relationship is in line with our theoretical results. This claim is further supported by the slight increase of β when performing a subsample analysis on publicly listed banks in column (2). Columns (3) and (4) serve as a further robustness check of our approach.[24]

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[23]These years correspond to the time when stress tests took place. The first was conducted in the third quarter of 2011, while the second took place in the fourth quarter of 2014 (hence the need for including the year 2015).

[24]Column (3) adds the banks' loan loss reserve and the ratio of their liquid assets over all liabilities. Both

One should not view our estimates as causal, exactly due to the non-random choice of stress tested banks. Hence, we can only argue correlation, not causality.[25] However, Figure B.5 shows no statistical difference in risk-adjusted profits between the two groups of banks (stress-tested and not stress-tested) in the quarter before and the quarter during the stress test. The effect observable in the quarter following the stress test can, therefore, be attributed to whether a bank was part of it or not.

5   Conclusion

In a world without frictions, banks are only subjected to the market risk such that the introduction of new information cannot possibly be detrimental. However, the situation is different if banks are constrained in their trading opportunities. In such a case the new information generates non-hedgeable risk. This additional risk comes from the negative externalities imposed by other banks' portfolio adjustments.

We show that - in such a constrained economy - the disclosure of information results in a reduction of risk-adjusted expected profits for a non-negligible fraction of banks. This effect depends on the structural features of banks' portfolio constraints and is more pronounced for systemically important banks. We observe this result in both the homogeneous and core-periphery systems and we provide empirical evidence supporting these findings.

Altogether, our results suggest that a regulator should carefully consider possible effects of information disclosure via an interbank network channel, especially on systemically important institutions. Using the information on system structure in line with our reasoning may prove beneficial for a policy design. Quantitative results could potentially be obtained

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measure the flexibility of a bank when threatened with a particular type of shock. Column (4) further includes contemporaneous, leading and lagging D.Stress Test variable. The results show statistical significance only in the quarter directly following the stress test exercise.

[25]To pin down the causal effect of disclosure is of great interest in the accounting research. Leuz and Wysocki (2016) review the existing empirical literature and provide avenues for future research. As pointed out in their paper, there is lack of good counterfactuals that would move the field forward and allow to make causal statements on the effect of disclosure. We relate to that literature as our experiment does not provide the ideal research environment to pin down the causal effect of the information disclosure as a consequence of the stress test procedure.

by calibrating our framework to a network structure observed by the regulator.

References

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson, 2017a, Measuring systemic risk, *The Review of Financial Studies* 30, 2–47.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson, 2017b, Measuring systemic risk, *The Review of Financial Studies* 30, 2–47.

Admati, A., and P. Pfleiderer, 2000, Forcing Firms to Talk: Financial Disclosure Regulation and Externalities, *The Review of Financial Studies* 13, 479–519.

Adrian, T., and M. K. Brunnermeier, 2016, CoVaR, *American Economic Review* 106, 1705–41.

Allen, F., and D. Gale, 2000, Financial contagion, *Journal of Political Economy* 108, 1–33.

Alvarez, F., and G. Barlevy, 2015, Mandatory disclosure and financial contagion, *NBER Working Paper No. 21328* .

Andolfatto, D., A. Berentsen, and C. Waller, 2014, Optimal disclosure policy and undue diligence, *Journal of Economic Theory* 149, 128–152.

Beck, Thorsten, Olivier De Jonghe, and Glenn Schepens, 2013, Bank competition and stability: Cross-country heterogeneity, *Journal of Financial Intermediation* 22, 218–244.

Bernanke, B., 2013, Stress testing banks: What have we learned?, *A speech at the Maintaining Financial Stability: Holding a Tiger by the Tail financial markets conference sponsored by the Federal Reserve Bank of Atlanta* .

Blackwell, D., 1951, Comparison of Experiments, *Proceedings of the 2nd Berkeley Symposium on Mathematical Statistics and Probability* 93–102.

Boss, M., H. Elsinger, M. Summer, and S. Thurner, 2003, The Network Topology of the Interbank Market, *Quantitative Finance* 4, 1–8.

Diamond, D. W., 1985, Optimal release of information by firms, *The Journal of Finance* 40, 1071–1094.

Efing, M., 2016, Arbitraging the Basel Securitization Framework: Evidence from German ABS Investment, *Swiss Finance Institute Research Paper* .

Ellul, A., and V. Yerramilli, 2013, Stronger risk controls, lower risk: Evidence from U.S. bank holding companies, *Journal of Finance* 68, 1757–1803.

Elsinger, H., A. Lehar, and M. Summer, 2006, Using market information for banking system risk assessment, *International Journal of Central Banking* 2.

Farboodi, M., 2017, Intermediation and Voluntary Exposure to Counterparty Risk, *Working Paper* 1–66.

Frey, R., and J. Hledik, 2014, Correlation and Contagion as Sources of Systemic Risk, *Working Paper Series* .

Fricke, D., and T. Lux, 2014, Core-periphery structure in the overnight money market: Evidence from the e-mid trading platform, *Computational Economics* 1–37.

Gigler, F., C. Kanodia, H. Sapra, and R. Venugopalan, 2014, How frequent financial reporting can cause managerial short-termism: An analysis of the costs and benefits of increasing reporting frequency, *Journal of Accounting Research* 52, 357–387.

Goldstein, I., and Y. Leitner, 2017, Stress Tests and Information Disclosure, *Working Paper* .

Goldstein, I., and H. Sapra, 2014, Should banks' stress test results be disclosed? an analysis of the cost and benefits, *Foundation and Trends in Finance* 8, 1–54.

Goldstein, I., and L. Yang, 2017, Good disclosure, bad disclosure, *Working Paper* .

Grossman, S., 1981, The Informational Role of Warranties and Private Disclosure about Product Quality, *The Journal of Law and Economics* 24, 461–483.

Grossman, S., and O. Hart, 1980, Takeover bids, the free-rider problem, and the theory of the corporation, *The Bell Journal of Economics* 11, 42–64.

Hirshleifer, J., 1971, The private and social value of information and the reward to inventive activity, *American Economic Review* 61, 561–574.

Korn, E., and U. Schiller, 2003, Voluntary disclosure of nonproprietary information: A complete equilibrium characterization, *Journal of Business Finance and Accounting* 30, 1327–1339.

Lelyveld, I., and D. Veld, 2014, Finding the core: Network structure in interbank markets, *Journal of Banking & Finance* 49, 27 – 40.

Leuz, C., and P. D. Wysocki, 2016, The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research, *Journal of Accounting Research* 54, 525–622.

Milgrom, P., 2007, Good news and bad news : representation theorems and applications, *The Bell Journal of Economics* 12, 380–391.

Minoiu, Camelia, and Javier A. Reyes, 2013, A network analysis of global banking: 19782010, *Journal of Financial Stability* 9, 168 – 184.

Morris, S., and H. S. Shin, 2002, Social value of public information, *American Economic Review* 92, 1521–1534.

Poledna, S., J. Molina-Borboa, S. Martnez-Jaramillo, M. van der Leij, and S. Thurner, 2015, The multi-layer network nature of systemic risk and its implications for the costs of financial crises, *Journal of Financial Stability* 20, 70 – 81.

Prescott, E. S., 2008, Should Bank Supervisors Disclose Information about their Banks, *Economic Quarterly* 94, 1–16.

Puhr, C., R. Seliger, and M. Sigmund, 2012, Contagiousness and vulnerability in the austrian interbank market, *Austrian National Bank Report* .

Roukny, T., S. Battiston, and J. E. Stiglitz, 2016, Interconnectedness as a source of uncertainty in systemic risk, *Journal of Financial Stability* .

Schuermann, Til, 2014, Stress testing banks, *International Journal of Forecasting* 30, 717 – 728.

Tarullo, D., 2010, Lessons from the crisis stress tests, *Remarks Made to the International Research Forum on Monetary Policy, Washington D.C.* .

Upper, C., 2011, Simulation methods to assess the danger of contagion in interbank markets, *Journal of Financial Stability* 7, 111–125.

A   Proofs

Proof of Proposition 1.1. The proof follows immediately by solving the following maximization problem,

$$\max_{\{\phi_i,\theta_i\}\in\mathbb{R}^{N+1}}\left\{\mathbb{E}[\mathbb{Y}_i]-\frac{1}{2}\text{Var}\left[\mathbb{Y}_i\right]\right\}$$

$$\text{s.t.}$$

$$p_i = p'\phi_i + \theta_i$$

$$\mathbb{Y}_i = \mathbb{X}'\phi_i + \theta_i \tag{14}$$

$$\phi_i \in A_{i1} \times A_{i2} \times \cdots \times A_{iN}$$

$$A_i n = \begin{cases} \mathbb{R} & \text{if } g_{in} = 1 \\ \{\emptyset\} & \text{if } g_{in} = 0 \end{cases} \quad \forall n \in \{1,\ldots,N\}$$

After plugging the first two constraints into the objective function we obtain the Lagrangian for bank $i \in \{1,\ldots,N\}$:

$$\mathcal{L} = \mu'\phi_i + p_i - p'\phi_i - \frac{1}{2}\phi'\Sigma\phi_i - \lambda_i'\phi_i, \tag{15}$$

where the last term corresponds to the network constraint.

The first order condition gives bank's i optimal demand for risky assets, ϕ_i^*. That is,

$$\frac{\partial\mathcal{L}}{\partial\phi_i} = 0 \implies \phi_i^* = \Sigma^{-1}\left(\mu - p - \lambda_i\right). \tag{16}$$

The optimal demand for the risk-free asset, θ_i^*, follows from the resource constraint,

$$\theta_i^* = p_i - p'\Sigma^{-1}\left(\mu - p - \lambda_i\right) \tag{17}$$

The equilibrium price vector is obtained by equating the aggregate demand to the aggre-

gate supply of risky projects in the economy, that is

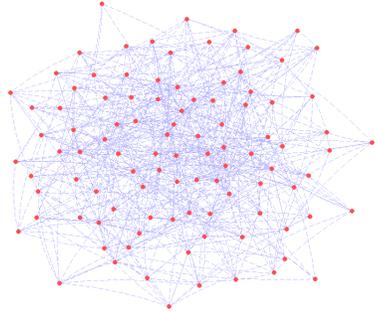$$\phi_1^* + \phi_2^* + \cdots + \phi_N^* = \mathbf{1} \tag{18}$$

substituting the optimal ϕ^* from equation (16) and solving for p yields:

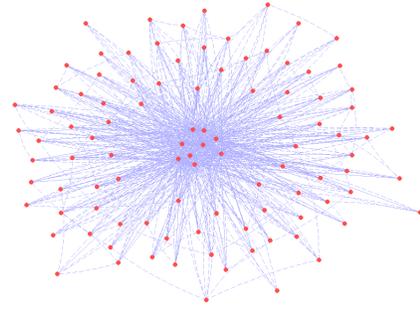$$p^* = \mu - \frac{1}{N}\Sigma\mathbf{1} - \frac{1}{N}\sum_{j=1}^{N}\lambda_j \tag{19}$$
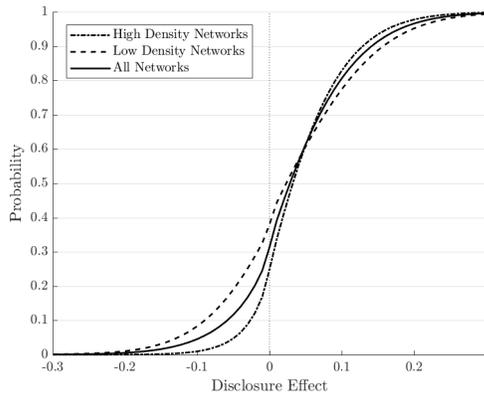
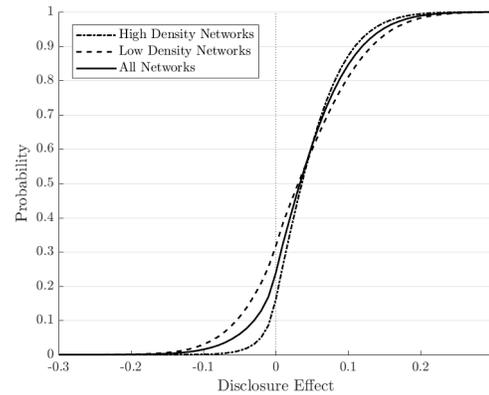This concludes the proof.

$\square$

B Figures

(a) Erdős-Rényi network.

(b) Core-periphery network.

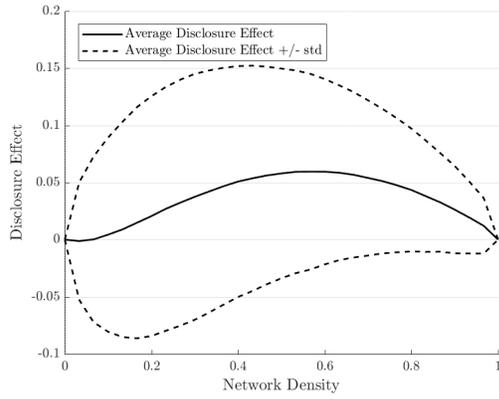**Figure B.1.** One realization of a random network for $N = 100$ banks.
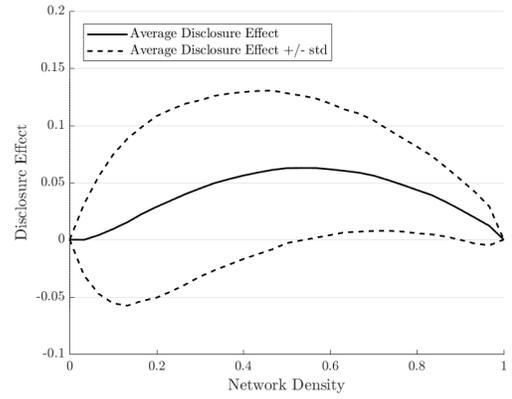

(a) Erdős-Rényi network with N=50 banks.

(b) Erdős-Rényi network with N=100 banks.

Figure B.2. Distribution of Disclosure Effect as a function of network density. This figure plots the cumulative distribution of the average disclosure effect for different network densities. The dashed line corresponds to networks with a density below the median, while the dash-dotted line stands for networks with density above the median. The disclosure effect is measured as a percentage change of the expected risk-adjusted profits with and without disclosure. The simulation comprises $15,000$ iterations and the networks are generated using the Erdős-Rényi model.

(a) Core-Periphery network with N=50 banks.

(b) Core-Periphery network with N=100 banks.

Figure B.3. Disclosure effect +/- one standard deviation as a function of network density. The disclosure effect is measured as a percentage change of the expected risk-adjusted profits with and without disclosure. The simulation comprises 15,000 iterations and the networks are generated using the Erdős-Rényi model.
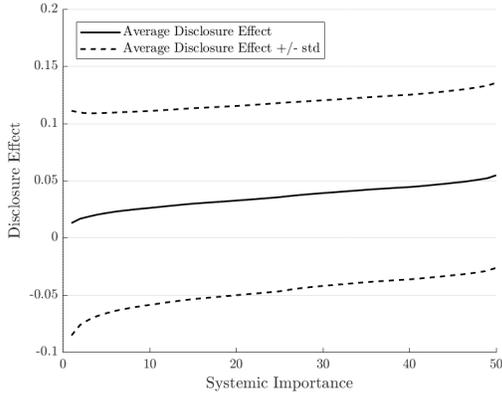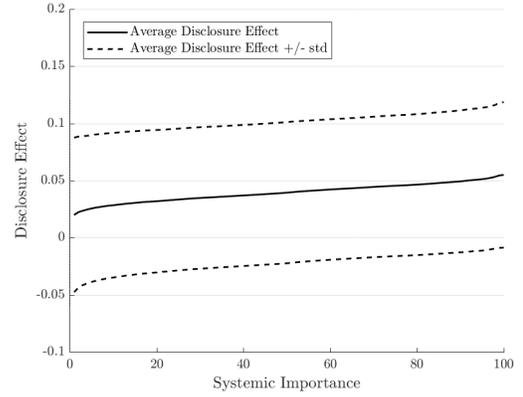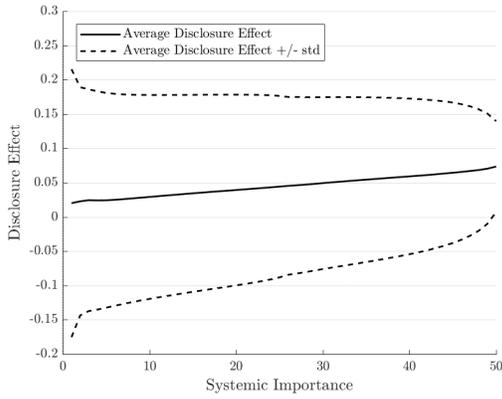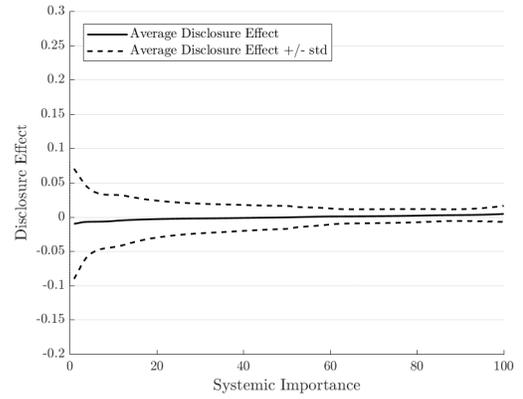
(a) Erdős-Rényi network with N=50 banks.

(b) Erdős-Rényi network with N=100 banks.

(c) Core-Periphery network with N=50 banks.

(d) Core-Periphery network with N=100 banks.

Figure B.4. Disclosure effect as a function of systemic importance. This figure plots the disclosure effect $+/-$ one standard deviation for banks ranked according to the $\mathcal{SI}$ index, which corresponds to the network systemic importance of a bank. The bank ranked $\mathcal{SI} = 1$ is the most systemically relevant, while the bank ranked $\mathcal{SI} = 50$ is the least systemically relevant. The disclosure effect is measured as a percentage change of the expected risk-adjusted profits with and without disclosure. The simulation comprises $15,000$ iterations and the networks are generated using either the Erdős-Rényi model (Figures B.4a, B.4b) or the core-periphery model (Figures B.4c, B.4d).
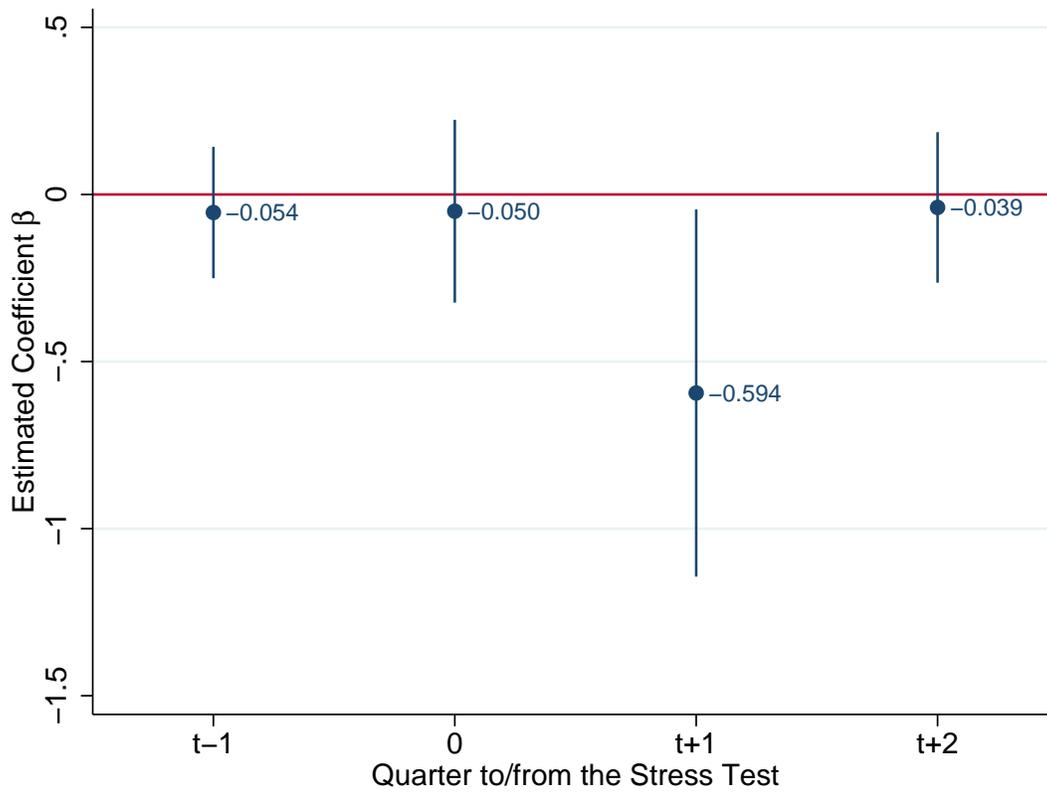
Figure B.5. The coefficient estimate for the contemporaneous, leading and lagged variable D.Stress Test as seen in column (4) of Table 4

C Tables

Table 1. Variable Description

Variable Label	Description
	Panel A: Dependent Variables
Risk-Adj Profit	Ratio between net income and the value of risk-weighted assets.
	Panel B: Explanatory Variables
D.Stress Test	Dummy variable equal to one if a bank is subjected to stress test assessment, and zero otherwise.
Tier 1 Ratio	Ratio between Tier 1 capital, as defined by Basel Accord, and the value of risk-weighted assets.
Size	The natural logarithm of the value of total assets.
Total Gross Loans	The value of total gross loans divided by the value of risk-weighted assets.
Total Deposit	The value of deposits divided by the value of risk-weighted assets.
Liquid Assets/Liabilities (%)	The ratio between liquid assets and total liabilities as defined by SNL Financial.
Loan Loss Reserve	The accounting measure loan loss reserve scaled by the value of risk-weighted assets.

Table 3. Summary Statistics

The table reports the summary statistics of the variables used in the empirical analysis. Data are from SNL Financial covering the years 2011, 2014, and 2015. There are a total of 1,818 bank-quarter observations for a total of 725 unique banks. The dependent variable, Risk-Adj Profit, is computed as the ratio between net income and the value of risk-weighted assets. More details on the computation of covariates can be found in Table 1. All variables are Winsorized at 1% tail.

	Mean	SD	P25	Median	P75
	Dependent Variable				
Risk-Adj Profit	0.17	0.84	0.08	0.25	0.43
	Control Variables				
D.Stress Test	0.04	0.19	0	0	0
Tier 1 Ratio	0.15	0.06	0.11	0.14	0.17
Size	15.41	2.37	13.50	14.95	16.91
Total Gross Loans	1.35	0.69	0.99	1.25	1.53
Total Deposit	1.12	0.52	0.85	1.09	1.33
Loan Loss Reserve	0.04	0.06	0.01	0.03	0.06
Liquid Assets/Liabilities (%)	31.8	20.93	17.32	25.99	41.09

Table 4. Event Study on 2011 and 2014 Stress Test

The table reports the results from estimating Equation (13). The dependent variable is the Risk-Adj Profit for all specifications. It is computed as the ratio between net income and the value of risk-weighted assets. The covariates include: D.Stress Test, Tier 1 Ratio, Size, Total Loans, Total Deposit, Loan Loss Reserve, and Liquid Assets/Liabilities. More details on the definition of variables can be found in Table 1. All variables are Winsorized at 1% tail. Standard errors are robust to heteroscedasticity and clustered at bank level.

	(1)	(2)	(3)	(4)
	Dependent Variable: Risk-Adjusted Profits			
	Baseline	Listed	Robustness	
D.Stress Test$_{t-2}$				-0.039
				(0.121)
D.Stress Test$_{t-1}$	-0.386**	-0.483**	-0.575**	-0.594**
	(0.175)	(0.240)	(0.233)	(0.239)
D.Stress Test$_t$				-0.050
				(0.149)
D.Stress Test$_{t+1}$				-0.054
				(0.122)
Tier 1	5.774***	11.543***	3.681**	3.355
	(1.689)	(4.309)	(1.786)	(2.110)
Bank Size	0.482**	0.589**	0.479**	0.437**
	(0.194)	(0.288)	(0.210)	(0.215)
Total Gross Loans	0.054	-0.306	0.049	0.062
	(0.066)	(0.260)	(0.072)	(0.077)
Total Deposit	0.077	0.241	0.308*	0.359*
	(0.127)	(0.180)	(0.178)	(0.184)
Loan Loss Reserve			-2.485	-2.285
			(3.204)	(3.340)
Liquid Assets/Liabilities (%)			-0.011**	-0.010*
			(0.005)	(0.005)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter by Country FE	Yes	Yes	Yes	Yes
Observations	1,818	1,091	1,031	961
Adjusted R^2	0.751	0.787	0.756	0.764