where $x \wedge y = (\min\{x_1, y_1\}, \dots, \min\{x_n, y_n\})$ for $x, y \in \mathbb{R}^n$. In this model, $\theta_i = \frac{p_i^*}{\ell_i}$ for $i = 1, \dots, n$. Eisenberg and Noe (2001) provide conditions guaranteeing the uniqueness of the fixed point (a sufficient condition is that the vector of noninterbank assets is strictly positive in all entries). Moreover, they characterize the fixed point in terms of the solution of a linear programming problem given by

$$\begin{aligned} \max_{p} \quad & f(p) \\ \text{s.t.} \quad & p \le p\Pi + c \\ & p \in [0, \ell] \end{aligned}$$

where f is a component-wise strictly increasing function with respect to the vector p. They also provide an algorithm, referred to as the *fictitious default algorithm*, to identify the sequence of defaulted institutions and illustrate how contagion propagates through the financial network. To be more specific, in each step k we use p^k to denote the payments made by all institutions and let $\Lambda(p^k)$ be the $n \times n$ diagonal matrix indicating the institutions which default in step k. Equivalently, the i-th diagonal entry of $\Lambda(p^k)$ is defined by

$$\Lambda_{i,i}(p^k) := \begin{cases} 1 & \text{if } \left(p^k\Pi + c\right)_i < \ell_i \\ 0 & \text{else} \end{cases}.$$

This indicates that when the total asset value of institution i (including interbank and non-interbank assets) is smaller than its total liabilities, institution i would not repay its liabilities in full and default. Set $p^1 := \ell$. For $k = 2, 3 \dots$, the payment vector p^k is determined via an iterative procedure consisting in repeatedly solving the following fixed point equation:

$$p^k = \underbrace{\left[\left[p^k\Lambda(p^{k-1}) + \ell(I - \Lambda(p^{k-1}))\right]\Pi + c\right]\Lambda(p^{k-1})}_{\substack{\text{payments made by} \\ \text{the defaulted institutions} \\ \text{in step } k-1}} + \underbrace{\ell\left(I - \Lambda(p^{k-1})\right)}_{\substack{\text{payments made by} \\ \text{the solvent institutions} \\ \text{in step } k-1}}.$$

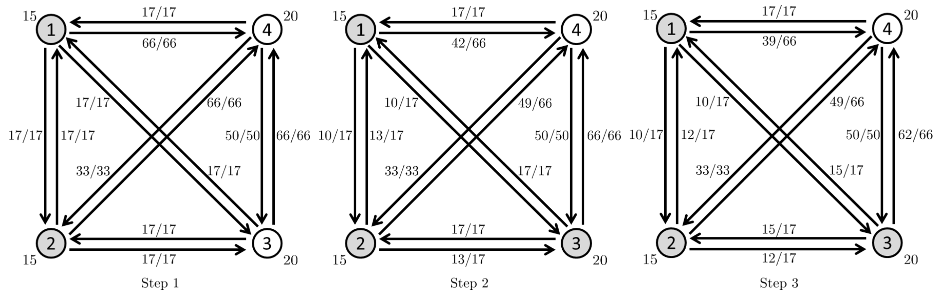
If $\Lambda(p^k) = \Lambda(p^{k-1})$, then the algorithm stops and $p^* = p^k$. Eisenberg and Noe take the number of steps needed for institution i to default as a measure of the institution i's exposure to the systemic risk, i.e. institution i is more fragile than j if the number of steps before i defaults is smaller than the number of steps before j defaults.

Example 1. *We apply the fictitious default algorithm to the network in Figure 1. In step 1,* $p^1 = \ell$ *and*

$$p^1\Pi + c = \begin{pmatrix} 100 & 100 & 100 & 100 \end{pmatrix} \begin{pmatrix} 0 & 0.17 & 0.17 & 0.66 \\ 0.17 & 0 & 0.17 & 0.66 \\ 0.17 & 0.17 & 0 & 0.66 \\ 0.17 & 0.33 & 0.50 & 0 \end{pmatrix} + \begin{pmatrix} 15 & 15 & 20 & 20 \end{pmatrix} = \begin{pmatrix} 66 & 82 & 104 & 218 \end{pmatrix}.$$

This indicates that bank 1 *and* 2 *default as the payments made by them are smaller than their outstanding liabilities (see the network on left in Figure 1); hence,*

$$\Lambda(p^1) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$



Step(k)	1	2	3
p^k	(100, 100, 100, 100)	(62, 75, 100, 100)	(59, 73, 92, 100)
$p^k\Pi + c$	(66, 82, 104, 218)	(62, 75, 93, 177)	(59, 73, 92, 170)
Defaulted Institution	1,2	1,2,3	1,2,3

Figure 1: The steps of the fictitious default algorithm on a financial network in which $\ell = (100, 100, 100, 100)$ and $c = (15, 15, 20, 20)$. The ratio x/y placed on the edge directed from i to j in step k means that the liabilities of institution i to j is y, while the payment made by i to j is x in step k.

Then, in step 2, we obtain $p^2 = (62, 75, 100, 100)$ *by solving the following equation*

$$p^2 = \left[\left[p^2\Lambda(p^1) + \ell(I - \Lambda(p^1))\right]\Pi + c\right]\Lambda(p^1) + \ell\left(I - \Lambda(p^2)\right).$$

Next, using p^2*, we can construct* $\Lambda(p^2)$ *and solve the fixed point equation to derive* p^3 *in step 3. Since* $\Lambda(p^2) = \Lambda(p^3)$*, the algorithm terminates at* $k = 3$*. Figure 1 illustrates the propagation of contagion through a financial network of four institutions using the fictitious default algorithm. Both institutions 1 and 2 default in step 1. This triggers default of institution 3 in the second step, while institution 4 remains solvent in all steps.*

Rogers and Veraart (2013) and Glasserman and Young (2015) enrich the Eisenberg-Noe framework by adding bankruptcy costs. The model introduced by Rogers and Veraart (2013) captures the loss from assets liquidation arising at default. They use two constants $\alpha, \beta \in (0, 1]$ to represent, respectively, the recovery rate of non-interbank and interbank assets at default. When an institution i defaults, the recovery value of its assets is given by

$$\beta \sum_{j=1}^{n} p_j^* \pi_{j,i} + \alpha c_i.$$

This is also the value of the assets i that is distributed to the creditors of i on a pro-rata basis. Hence, the clearing payment vector is the solution to the following modified system of fixed point equations

$$p_i^* = \begin{cases} \ell_i & \text{if } \ell_i \le \sum_{j=1}^n p_j^* \pi_{j,i} + c_i \\ \beta \sum_{j=1}^n p_j^* \pi_{j,i} + \alpha c_i & \text{else,} \end{cases}$$

for $i = 1, \ldots, n$. Under this setting, the uniqueness of a solution to the above system of equations is no longer guaranteed. An alternative approach for modeling bankruptcy costs has been proposed by Glasserman and Young (2015), and captures the fact that large shortfalls are more costly than small shortfalls. Concretely, when an institution i defaults its assets are reduced by the amount

$$\gamma\left[\ell_i - \left(\sum_{j=1}^{n} p_j^* \pi_{j,i} + c_i\right)\right].$$

The above term in square brackets is the shortfall of node i at default. Multiplying this quantity by the factor γ gives the bankruptcy costs incurred by node i at default. After accounting for these deadweight losses, the assets of node i are distributed proportionally to its creditors. Hence, the clearing payment vector is a solution to the system of fixed point equations given by

$$p^* = \left([\ell \wedge (p^*\Pi + c)] - \gamma\, [\ell - (p^*\Pi + c)]^+ \right)^+ , \tag{2}$$

where for any vector $x \in \mathbb{R}^n$, $x^+ = (\max\{x_1, 0\}, \max\{x_2, 0\}, \dots, \max\{x_n, 0\})$.

We next discuss the dependence of systemic risk on the network topology. This has been investigated in the works of Acemoglu et al. (2015a), Battiston et al. (2012), Capponi et al. (2016a), and Elliott et al. (2014), which are survey next. Capponi et al. (2016a) analyze the conditions under which concentration of interbanking liabilities is more likely to affect systemic losses. They find that if the system is highly capitalized (banks with large outstanding liabilities also have high equity value), a more diversified lending structure is able to reduce systemic risk across multiple dimensions (largest loss, total loss, etc...). The intuition is as follows. Larger losses are incurred by banks with smaller equity. When interbank liabilities are more evenly distributed against their counterparties, larger payments are directed to banks with lower equity, making them less likely to default. Vice versa, when the system is lowly capitalized (the banks with higher equity value also have smaller liabilities), a more diversified lending structure is not desired. In this case, larger losses are incurred by banks with higher outstanding liabilities. When banks distributes their loans to a larger number of counterparties, a bank with larger liabilities is more likely to receive smaller payments; thus, it becomes more fragile and can potentially generate larger losses.

Elliott et al. (2014) study the impact of diversification and integration of a financial network. Integration refers to the level of exposure of institutions to each other through cross-holdings. Diversification refers to how spread-out the cross-holdings are, i.e whether a typical organization is held by many others or just a few. They find that at extreme (very low or very high) levels of integration and diversification, the risk of far-reaching cascades of financial failures is the lowest. Acemoglu et al. (2015a) analyze the sensitivity of different network topologies to shocks in asset value. Their findings indicate that if the magnitude of the shock is small, a more concentrated financial system such a ring network, is more likely to spread contagion failures relative to a more diversified network, such as the complete network. Under the latter network structure, contagion risk is shared among a larger number of counterparties and hence the network can better absorb a negative shock spread. If the magnitude of the shock is too high, however, they show that both ring and complete networks performs worse than any δ-connected financial network (see Definition 5 in Acemoglu et al. (2015a) for the definition of δ-connected). The findings of Acemoglu et al. also provide an analytical support for the "robust-yet-fragile" property of highly interconnected financial networks observed by Gai and Kapadia (2010) through numerical simulations.

Battiston et al. (2012) show that in presence of a financial accelerator (the impact of a shock to the economy is amplified by worsening financial market conditions), there exists a threshold of risk diversification (the degree of connectivity of the credit network) below which higher diversification lowers the probability of a systemic failure. When the risk diversification is higher than this threshold, further increases make the financial system more unstable. This indicates that neither ring nor complete networks are the most stable configurations, but rather the preferred network structure has an intermediate degree of network connectivity. Amini et al. (2012), consider a large financial network and derive asymptotic results for the size of contagion, showing that connectivity is a key determinant of network instability.

We conclude the section with a discussion of empirical studies of interbank networks. Elsinger

A recent branch of the literature has put forward models of the mean-field type to capture the dynamics of systemic stability. Differently from endogenous interbank network models, they assume that the matrix of interbank borrowing/lending activities is exogenously specified. The dynamics of banks' asset values depends on stochastic idiosyncratic events, such as inflow/outflow of consumers' deposits, common exposure to systematic factors (macro-economic indicators such as GDP growth, stock index performance, etc...), and on an interaction term which captures the pattern and strength of interaction with the other banks in the system. Such an interaction occurs through the empirical distribution of the system's states, typically corresponding to the banks' asset values.

We next survey the main contributions in this area. Fouque and Ichiba (2013) develop a banking model, in which the monetary reserves of the banks are described by a system of diffusion processes interacting through their drifts. They define the default of a bank as the event that the value of its reserves reaches zero. They study how individual growth rates and lending preferences of banks affect default events and network stability. They also provide an interacting particle system algorithm to compute the probability of a systemic event, defined as the simultaneous occurrence of many defaults. Fouque and Sun (2013) consider a simplified version of the model, in which the borrowing rates of banks are proportional to the differences in log-monetary reserves. This results in a system of Ornstein-Uhlenbeck diffusion processes, each reverting toward the ensemble average of monetary reserves. Under these assumptions, they characterize the mean field limit of the system and compute the probability that the ensemble average reaches the default level. Building on Fouque and Sun (2013), Bo and Capponi (2015) develop a mean field model of interbanking borrowing and lending activities. In their model, each bank interacts with other counterparties in the network via exogenously specified lending preferences, and is exposed to risk coming from inflows or outflows of customer deposits, as well as to sudden shocks affecting the level of its monetary reserves. These shocks can be interpreted as positive or negative announcements regarding the overall banking sector, and are modeled through a compound Poisson process. This leads to two sources of interbanking correlation: (1) mean field interaction as in Fouque and Sun (2013), and (2) exposure to systematic factors affecting the overall banking sector. They provide an explicit characterization of the limit process associated with the sequence of empirical measures driven by the interacting system of jump diffusions, and use it to construct law of large number approximations for systemic indicators, such the average distance to default, and the total volume of interbanking activities. Garnier et al. (2013) consider a model of interacting agents, who can be either in a normal or failed state. The agents tend to be near the normal state, but they can be pulled away from it toward the failed state by external destabilizing forces. They also allow agents to cooperate in order to achieve stability. Pra et al. (2009) consider a mean-field interaction model to analyze financial contagion in large networks of firms exposed to credit risk, and characterize the entire portfolio loss distribution.

The above discussed studies assume that network agents follow prescribed behaviorial rules, and cannot strategically influence the evolution of the network. Such an assumption has been relaxed in the work of Carmona et al. (2015), who extend the model proposed in Fouque and Sun (2013) by allowing the bank to control its borrowing/lending rate from/to a central bank at a quadratic cost decided by the regulator. This result in a game played by the banks who control the intensity of borrowing/lending activities and the central bank who decides the cost of these transactions. They provide an explicit solution for the Nash equilibria of the game when finitely many players are involved and also consider the mean-field game in the asymptotic case of infinitely many banks.

asset prices. Their analysis indicates that commercial banks and broker dealers actively track their leverage ratios, or exhibit procyclical leverage, expanding their balance sheets during periods of booms and contracting them during periods of busts. Berger et al. (2008) find that the targeted leverage is well below the regulatory minimum. Moreover, larger banks tend to set a higher target, a finding which is consistent with the view that they engage in more risky investments and hence need larger amount of funding capital. These findings are also confirmed by the empirical analysis of Gropp and Heider (2010). Memmel and Raupach (2010) analyze a sample of large, publicly traded banks in sixteen countries, and conclude that banks have stable capital structures fixed at levels which are specific to the individual bank. In addition, banks' target leverage/capital ratio is time invariant and bank specific.

These empirical findings have driven the design of models aimed at capturing the systemic implications of these actions. Noticeable contributions in this direction include Greenwood et al. (2015) who study the first order effects of fire-sales, and Capponi and Larsson (2015) who analyze the pecuniary externalities resulting from the target leverage mechanism. They show that higher order effects caused by repeated rounds of deleveraging can be substantial during fire-sales. They introduce the systemicness matrix $\boldsymbol{S}_t$ defined by

$$S_t^{k\ell} = \sum_{i=1}^{N} \alpha_t^{ki} \frac{\lambda_i A_t^{\ell i}}{\gamma_k A_t^{k,\,\mathrm{nb}}}, \tag{3}$$

where α_t^{ki} is the proportion of bank's i value allocated to asset class k, γ_k is the elasticity of the nonbanking demand for asset k, measuring the change in demand per change in the unit price of the asset. The quantity λ_i is the leverage (debt to equity ratio) targeted by bank i, $A_t^{\ell i}$ is market value of asset class ℓ for bank i, and $A_t^{k,\,\mathrm{nb}}$ is the market value of asset class k for the nonbanking sector. The systemicness matrix is a determinant of systemic linkages and fire-sales externalities and a key quantity to characterize asset price dynamics. Indeed,

$$\frac{\Delta P_t}{P_t} = (\boldsymbol{I} - \boldsymbol{S}_t)^{-1} \left[\text{aggregate shock}\right] = \left[\boldsymbol{I} + \boldsymbol{S}_t + \boldsymbol{S}_t^2 + \boldsymbol{S}_t^3 + \ldots\right] \left[\text{aggregate shock}\right], \tag{4}$$

i.e. an initial aggregate shock is amplified through multiple rounds of leverage targeting activity conducted by banks. A related study by Duarte and Eisenbach (2015) defines a measure of systemic risk generated by fire-sale externalities in a similar way to the above systemicness matrix. They decompose systemic risk into three main components, size, leverage and illiquidity concentration, and develop an empirical analysis to assess the contribution of each of these components to systemic risk. Wagner (2011) develops an equilibrium model to analyze the trade-off between diversification in asset holdings at the individual bank level, and diversity in asset compositions across banks. They show that the risk of joint liquidations may have important implications for the choices of banks' portfolios as well as for asset prices. Chen et al. (2014) analyze the propagation mechanism of shocks in a network of firms holding common assets under general portfolio choices.

As discussed by Duffie (2010), the risk of fire sales in the recent financial crisis was mitigated by the intervention of the lender-of-last-resort, and by injection of capital into dealer banks, such as those of the Bank of England and the U.S. Treasury Department's "Troubled Asset Relief Program" (TARP). These funding vehicles are costly to taxpayers and may lead to excessive risk taking by large dealers who know that they will be bailed out if the market moves unfavorably against them. Moral hazard problems arising in this context have been thoroughly investigated (see, for instance, the model of Diamond and Dybvig (1983) and follow-up studies). Banks may find it optimal to invest in highly correlated assets in anticipation of a bailout triggered by the occurrence of many simultaneous failures (Acharya and Yorulmazer (2007)).

Key contributions in this direction include the CoVar measure by Adrian and Brunnermeier (2016), which relates the systemic risk contribution of an individual entity to the value of risk of the overall system, conditioned on the institution being in a distressed state. The main idea is that the distribution of asset values of the financial system should depend on the financial health of the individual institutions as well as on their effects on each other. Hence, if an institution experiences distress, the distribution of asset values of the system will also change. CoVar estimates the size of the tail of the distribution of asset values and how it changes. Adrian and Brunnermeier (2016) employ quantile regression methods to estimate it, and use weekly equity returns data of publicly traded financial institutions. Acharya et al. (2012) propose the systemic expected shortfall index to measure the expected amount of undercapitalization of a bank under the occurrence of a systemic event making the overall financial system undercapitalized. Their proposed risk measure increases with the leverage and size of the institution. A related systemic index, SRISK, has been introduced by Brownlees and Engle (2015) to measure, ex-ante, the expected capital shortfall experienced by a firm under a prolonged period of market distress. As for the systemic expected shortfall, SRISK depends on the size, leverage and risk of the firm. Firms with the highest SRISK are deemed to be the largest contributors to the undercapitalization of the financial system in times of distress. They interpret SRISK as the total amount of capital that the government needs to bail out the financial system in distressed situations. Brownlees and Engle show that an increase in SRISK generates negative externalities on the real economy, in that it predicts future declines in industrial production and increases in the unemployment rate.

Systemic risk in a global economy consisting of a heterogeneous set of market participants has been studied by Billio et al. (2012). They develop an econometric study in a financial business consisting of hedge funds, banks, broker-dealers and insurance companies, and find that the linkages between these four sectors exhibit dynamic patterns. They find that the interconnectedness increased dramatically during the financial crisis, hence increasing the channels for shocks propagation. Most recently, networks of systemic dependencies have been constructed using the variance of stock returns of contributing institutions. Diebold and Yılmaz (2014) decompose the variance of stock returns of each financial institution into different portions, each contributed by any other institution in the network. They use this decomposition to construct the bank stock return volatility network of major US financial institutions, and analyze its evolution during the financial crisis. Demirer et al. (2015) apply the same technique to construct the stock return volatility network of financial institutions in G7 sovereigns as well as those of Spain, Greece and Australia. They find that connectedness is highly dependent on location, and it exhibits a sharp increase during the crisis. The significant power prediction power of the equity volatility of financial institutions has been empirically studied by Giglio et al. (2016). They perform an empirical analysis of twenty systemic risk measures and show that, except for equity volatility, most of them fail to capture the large negative downturns observed during the financial crisis.

Other studies have proposed measures of systemic risk at a more theoretical level. Brunnermeier and Cheridito (2014) measure the total systemic risk by determining the total costs born by the society, in terms of bailout assistance or government loan, and then allocate it to the institutions based on their marginal contributions. Their proposed SystRisk measure grows superlinearly with the exposures of financial institutions. Their measure may be interpreted in terms of preferences of a risk-averse investor, as it gives higher weight to losses occurring in states of the world in which the overall economy is depressed.

Biagini et al. (2015) study systemic risk measures using multi-dimensional sets of acceptance describing desirable states of the system. Feinstein et al. (2015) develop a a related analysis, and

auction the assets and deposits of a failed institution to a group of eligible bidders. The FDIC incurs a loss on assets given by the difference between the book value of a failed bank's assets and the market value at which they are sold. The Resolution Trust Company (RTC), a special and temporary government entity tasked with resolving insolvent thrifts during the savings and loans crisis, proposed the branch breakup to improve upon P&A transactions. This approach conducts auctions on a bank's branches individually to increase auction competition by allowing more participants. Capponi et al. (2016b) provide a study on the efficiency of the branch-breakup resolution strategy and its mitigation effect, as the fraction of assets resolved through auctions and auction competitiveness increase. Capponi and Chen (2015) develop a multi-period version of the Eisenberg-Noe model, and analyze the systemic risk mitigating effects of various policies of liquidity assistance.

Resolution policies of failing central counterparties are currently subject of high debate. As also argued by Duffie (2015), the failure of a major CCP may have catastrophic consequences if the resolution procedures are not well designed. The failure of a systemically important clearing member can have strong contagion effects as it can cause the central clearing counterparty to fail to meet its obligations to other systemically important clearing members. Fire sales of collateral levels may be observed as a result of this failure, which contribute to increase market volatility. This can result in the discontinuity of the clearing service and the necessity of other members to migrate their positions to a different clearinghouse, or of the clearinghouse to return any remaining assets to its clearing members. There have been, so far, two proposed strategies for central clearing resolution. The first, called "variation margin gains haircutting", postulates that the CCP accumulates cash by reducing the variation margin payments that it would have made to the clearing members, while still collecting in full the margin payments owed by the clearing members. The second, referred to as a "tear-up", claims that the CCP cancels its outstanding notional derivatives positions with some clearing members.

3.3 Systemically Important Financial Institution (SIFI) Policies

This section discusses strategies to designate institutions as systemically important. These have been proposed by researchers in response to the contest launched by the MIT Center for Finance and Policy and the Harvard Crowd Innovation Laboratory. We also refer to MIT Center for Finance and Policy (2016) for a detailed description of the contest, and provide here a brief summary of distinguishing characteristics of systemic importance proposed by respondents.

An effective measure of systemic importance is a score which accounts both for the credit quality of the financial institution and its interconnectedness. Other important criteria are leverage, balance sheet fragility, and market significance. Moreover, systemically important institutions can be characterized by high values of the following measures: 1) cash obligations during resolution (COR); and 2) operational cash throughput (OCT). COR measures the amount of capital a hypothetical resolution authority needs to quarantine the institution's failure from creating losses to other parties by paying the institution's obligations during resolution. OCT measures the amount of financing that is lost due to the unavailability of the institution's functions during the resolution period. Regulators would need to carefully specify relevant stressed scenarios and parameters which can be used to simulate COR and OCT distributions. A systemically important financial institution should also have high vulnerability to failures or disruptions in the financial system, and be strongly connected to other entities in the financial system.

4 Data Repository and Supervisory Authorities

The analysis of systemic risk is severely undermined by the the fragmentation of the available data, and often by the unavailability of specific datasets. To the best of the author's knowledge, there is presently no comprehensive document indicating which data are held by which supervisory institutions. In this section, we provide an overview of the main financial regulators in the United States, as well as of the institutions that are regulated by them. Despite this does not provide a complete map between data sources and supervisory institution, it indicates which regulatory authorities are most likely to collect a specific dataset. We also refer to Murphy (2015) for an in-depth discussion

- Federal Reserve (FED). It regulates bank holding, securities holding, loan holding companies, and any firm designated as systemically important by the Financial Stability Oversight Council. The FED also acts as a lender of last resort to member banks through the discount window and can inject liquidity to the financial system in usual circumstances. It can also shut down firms that are deemed to pose serious threats to financial stability.
- Office of Comptroller of Currency. It regulates national banks and federally charted thrift institutions, i.e. targeting consumers rather than businesses. It publishes quarterly reports on bank trading and derivatives activities, based on information provided by all insured U.S. commercial banks, savings associations and trust companies.
- Federal Deposit Insurance Corporation (FDIC). It is responsible for the oversight of federally insured depository institutions, including commercial banks and thrift banks that are not members of the Federal Reserve System. The FDIC has the authority to use the deposit insurance funds to assist depository institutions, including the provision of debt guarantees.
- Securities and Exchange Commission (SEC). It oversees security exchanges, brokers, dealers, clearing agencies, mutual funds and hedge funds with high asset value. It also regulates security based swap (SBS) dealers and SBS execution facilities. SEC is also empowered with the right to suspend trading strategies which are consider to pose systemic threats.
- Commodity Futures Trading Commission (CFTC). It regulates futures exchanges, commodity trading advisors, swap dealers and execution facilities, and clearinghouses. They may decide to order liquidation of trading positions during emergency situations. CFTC publishes weekly interest rates swap reports. The swaps market data included in this publication is produced by entities, such as the Bank for International Settlements, International Swaps and Derivatives Association, and the Office of the Comptroller of the Currency.
- Federal Housing Finance Agency (FHFA). It supervises federal housing agencies such as Fannie Mae, and Freddie Mac, as well as the Federal Home Loan Banks.
- Bureau of Consumer and Financial Protection. It regulates nonbank mortgage-related firms, private student lenders, and consumer businesses of banks whose asset size exceeds \$10 billion in assets.

Several efforts promoting data sharing, retrieval, and distribution have been initiated. These include the G20 Data Gaps Initiative, which recommends the collection of consistent bank level data for enhancing existing sets of aggregate statistics, and the Office of Financial Research, established as a department within the Treasury and tasked with the the collection and analysis of financial data. The Office of Financial Research collects counterparty networks data which can be used for monitoring and analysis of systemic risk. These include over-the-counter credit default swaps data, bilateral money-fund exposures, loan syndication networks, bilateral and tri-party repo, historical bank clearing networks and BIS data on cross-border interbank claims.

Another important data provider is the Depository Trust & Clearing Corporation, one of the world's largest securities depositories and providing electronic recordkeeping of security balances as well as clearing services. DTCC provides global trade repository services for OTC derivatives in multiple asset classes, starting with credit derivatives in 2006. DTCC's Trade Information Warehouse holds 98% of all credit derivative transactions, while the DTCC Derivatives Repository operates the trade reporting repository for OTC equity derivatives transactions. Empirical estimates of systemic risk measures can also been freely assessed. For instance, CoVar measures of dealers operating in the financial markets can be produced using the code made available at the authors' websites. Similarly, the VLab directed by Robert Engle provides free access to end-of-day SRISK measures.

There are, unfortunately, data sources which are either not collected or not released for research purposes, as well as methodologies designed for systemic risk management, whose details are not fully revealed. For instance, data on the full network of pairwise liability exposures between financial institutions is not available. The absence of such a dataset prohibits a full-fledged assessment of contagion effects arising from counterparty contagion in the network. To compensate for the absence of this dataset, researchers have developed statistical methods for estimating the interbank liability matrix using balance sheet data. Contributions in this direction include Upper and Worms (2004) who estimate the German interbank network by minimizing the relative entropy with respect to a matrix in which the interbank exposures are assumed independent, and Anand et al. (2014) who propose the minimum density method to minimize the total number of interbanking links, consistently with the observed total volume of interbank assets and liabilities. Gandy and Veraart (2015) develop a Bayesian framework, based on Markov-chain Monte-Carlo methods, to estimate the distribution of bilateral exposures conditional on observed balance sheet data.

Systemic risk analysis of centrally cleared networks requires information about positions held by clearing members as well as levels of collateral posted. The rule used by major clearinghouses to determine initial margin requirements is not made publicly available. Rather, the only accessible information includes end-of-day posted margins data. Higher transparency regarding the determination of collateral requirements would make it possible to perform studies regarding the implication of central clearing on collateral demand, compare existing with alternative margining rules, and inform the development of safe and financially stable clearinghouse.

5 Concluding Remarks

This tutorial has described the main modeling approaches and techniques for systemic risk analysis. This constitutes a topic of active research interest, which is contributing to shape the future of the banking industry and to inform the design of regulations. We have discussed policies targeting prevention and mitigation of systemic risk, as well as of default resolution. Being systemic risk tightly linked to financial stability and regulations, we have described which are the main regulatory bodies and what their supervisory responsibilities are. Going forward, we believe that research efforts should continue to be directed toward the understanding of mechanisms leading to the formation, preservation, and propagation of systemic risk. The research field would greatly benefit by more empirical studies targeting systemic risk measurements as well as the effectiveness of policies. The findings of this research are expected to play a major role in the validation/refinement of existing models, and the development of novel frameworks capturing the salient features of financial distress and instability. Clearly, the outcome of these efforts is tied to the quality and completeness of the available data set, information sharing, and also requires a close interaction of academia and regulatory authorities worldwide.

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