INFORMS Tutorials in Operations Research

Systemic Risk, Policies, and Data Needs

Agostino Capponi

To cite this entry: Agostino Capponi. Systemic Risk, Policies, and Data Needs. *In* INFORMS Tutorials in Operations Research. Published online: 04 Nov 2016; 185-206.
https://doi.org/10.1287/educ.2016.0156

CORRECTED VERSION OF RECORD; SEE LAST PAGE OF ARTICLE
TUTORIALS IN OPERATIONS RESEARCH
INFORMS 2016

 | ISBN 978-0-9843378-9-7
http://dx.doi.org/10.1287/educ.2016.0156

Systemic Risk, Policies, and Data Needs

Agostino Capponi
Industrial Engineering and Operations Research Department, Columbia University, New York, New York, 10027, ac3827@columbia.edu

Abstract The study of financial system stability is of fundamental importance in modern economies. The failure or distress experienced by systemically important financial institutions can have contagious effects on the rest of the financial system. This may, in turn, result in deteriorating macroeconomic conditions and price instability, with negative consequences and spillover effects to other sectors of the real economy. This tutorial surveys the different approaches to systemic risk modeling put forward by the academic and practitioner literature. We review the methodologies, with a focus on the relevant economic forces in play and the mechanisms leading to systemic instabilities. We discuss macroprudential, monetary, and resolution policies targeting financial stability. We report the supervisory authorities of the different financial institutions, as well as the current barriers to data sharing.

Keywords systemic risk; policies; contagion risk; networks; centralized trading; data

1. Introduction

The global interconnectedness of today's financial systems, and the numerous channels along which distress can propagate and affect other economic sectors, has been a subject of considerable investigation. Early studies on network resilience and systemic risk were conducted before the great recession (Allen and Gale [11], Eisenberg and Noe [52]), but research efforts have greatly intensified after it. The credit quality deteriorations and default events experienced by investment banks and mono-line insurances starting from the year 2007 have highlighted the fragility of the financial system, as well as the critical role played by the complex network of contractual dependencies.

There are two main forms of linkages arising between financial institutions. The first is via counterparty risk (Battiston et al. [18], Capponi [28], Eisenberg and Noe [52], Glasserman and Young [66]) and comes from the fact that institutions share risk through derivatives trading and interbank loans, thus incurring losses if their trading counterparties fail or enter into a distressed state. Under certain circumstances, counterparty-related losses may lead to the insolvency of creditors who were relying on these payments to fulfill their obligations. A second form of contagion propagation is via common balance sheet holdings. In this case, the forced sale of illiquid assets done by institutions that need to meet redemption requests or satisfy regulatory requirements may depress prices if their selling pressure cannot be adequately satisfied by unconstrained buyers. These price drops may, in turn, cause troubles to institutions holding the same assets on their balance sheets, leading to liquidity spirals and generating fire-sale externalities (Brunnermeier and Pedersen [27], Capponi and Larsson [30], Shleifer and Vishny [84, 83]).

This tutorial surveys the models proposed in the literature to measure systemic risk. Those include bottom-up approaches, whose aim is to model the direct interaction between banks as well as the interconnectdness of their balance sheets, and top-down approaches, whose goal is to quantify the contribution to the overall system distress caused by each institution, typically achieved via the specification of a risk measure (Acharya et al. [4], Adrian and

Brunnermeier [6], Brownlees and Engle [25]). We survey both the underlying models and mathematical techniques that have been used for quantifying negative externalities caused by financial instability, and empirical literature on systemic risk measurements. We discuss preventive and resolution policies, designed to enhance the resilience of the whole financial system and minimize the inefficiencies arising when assets of defaulted institutions need to be liquidated. Those include macroprudential policies targeting financial stability, monetary policies aimed at preserving price stability, structural policies imposing constraints on the network infrastructure, and policies targeting the resolution of bank failures. We also highlight the key elements of policies aimed at categorizing systemically important financial institutions. An impediment to systemic risk analysis is the lack of a comprehensive data set for the analysis of macrofinancial linkages. We dedicate one section to describe the relation between regulatory authorities and supervised financial institutions. This provides guidance on which regulatory authorities are responsible for collecting data sources related to the different financial institutions, and it hence facilitates the task of researchers and specialists relying on these data for systemic risk analysis.

The present tutorial complements the existing surveys on the subject. These include the excellent survey by Bisias et al. [23], whose primary focus is on the collection of systemic risk measures proposed in the literature, including those based on macroeconomic factors, network and illiquidity measures, and stress testing. Another recent survey on the field has been written by Benoit et al. [19] and is focused primarily on systemic risk measures and their empirical evaluations. We also refer to Staum [85] for an early survey on systemic risk models but centered primarily on the network of counterparty relationships.

The rest of the chapter is organized as follows. Section 2 discusses the approaches to systemic risk modeling. Section 3 discusses policies. Section 4 discusses the dependence of financial institutions on their supervisory authorities and barriers to systemic risk data. Section 5 concludes.

2. Systemic Risk Modeling

This section provides a categorization of systemic risk models into two groups, referred to as bottom-up and top-down models.

2.1. Bottom-Up Models

The current literature has put forward two main bottom-up approaches to systemic risk modeling. The first approach is based on a network representation of the financial system in which institutions are connected via direct counterparty exposures. The vast majority of the literature takes the network of interbank relations as given (see Sections 2.1.1 and 2.1.3), while a more recent branch studies the formation of this network (see Section 2.1.2). The second approach models the interdependence of balance sheet holdings of financial institutions, which take losses when asset prices are hit by liquidity shocks (see Section 2.1.5). These two approaches have also been combined to produce hybrid models (see Section 2.1.6). Another class of models is designed to analyze spreading of contagion via informational effects (see Section 2.1.4), triggered by loss of confidence in the banks' performance.

2.1.1. Financial Networks. The network model provides a convenient representation of bilateral exposures arising from contractual obligations between counterparties, and it allows for analysis of the propagation of contagion effects within the network. The inability of an institution to fulfill its liabilities may induce distress on its creditors in the network, which rely on these payments to meet their own liability obligations. This risk is usually referred to as counterparty risk (see Capponi [28] for a survey) and has been at the heart of losses and credit quality deteriorations experienced by monoline insurers and investment banks during the great recession. The seminal paper by Allen and Gale [11] models contagion risk using equilibrium theory. They connect the network structure to the fragility of the financial system. They also analyze the role of the central bank in avoiding systemic crisis. Their model of payment flows allows capturing propagation of financial crises in an environment where both liquidity and solvency shocks affect financial intermediaries. Several follow-up studies have been conducted to analyze the systemic consequences of initial shocks arising in a particular area of the network.

We next describe the basic setup of a static financial network consisting of n nodes, representing financial institutions, and position ourselves in an ex post economic scenario, i.e., where asset shocks have already occurred. Let $L \in \mathbb{R}^{n\times n}_{\geq 0}$ be the *interbank liability matrix* with $l_{i,j}$ denoting the amount of liabilities owed by i to j, and let $c \in \mathbb{R}^n_{\geq 0}$ be the vector of (non-interbank) assets. Throughout the section, all vectors are considered to be row vectors. The component c_i can be interpreted as the total value of mortgage, real estate, and corporate bond asset holdings of bank i after the occurrence of market shocks. Denote the total liability vector by $\ell \in \mathbb{R}^n_{\geq 0}$, where $\ell_i := \sum_{j=1}^n l_{i,j}$ is the total amount of obligations that bank i has toward the rest of the network (we assume $l_{i,i} = 0$). Let $\theta_i \in [0,1]$ be the fraction of liabilities that bank i is able to repay. If bank i is solvent, then it is able to repay liabilities in full, and $\theta_i = 1$; otherwise, it will only be able to partially repay its liabilities, and $\theta_i < 1$. The total asset value of bank i is given by $\sum_{j=1}^n \theta_j l_{j,i} + c_i$. If it is less than bank i's total liabilities, bank i defaults. Such a default may be directly caused by asset shocks; i.e., in the absence of all other defaults, $\sum_{j=1}^n l_{j,i} + c_i < \ell_i$. In this case, the default is *fundamental*, or it may be triggered by the reduced payments received by other banks in the network, in which case we refer to the default as *contagious*.

Eisenberg and Noe [52] develop an elegant framework, in which interbanking liabilities are cleared consistently with the laws of bankruptcy to endogenously determine the recovery rate, θ_i, for each bank i. Concretely, denote by

$$\pi_{i,j} := \begin{cases} \dfrac{l_{i,j}}{\ell_i} & \text{if } \ell_i > 0, \\ 0 & \text{if } \ell_i = 0, \end{cases}$$

the proportion of liabilities owed by i to j. The payments made by the nodes in the network when the interbank liabilities are cleared are denoted by p^* and are a solution to the system of fixed point equations,

$$p^* = \ell \wedge (p^*\Pi + c), \tag{1}$$

where $x \wedge y = (\min\{x_1, y_1\}, \ldots, \min\{x_n, y_n\})$ for $x, y \in \mathbb{R}^n$. In this model, $\theta_i = p_i^*/\ell_i$ for $i = 1, \ldots, n$. Eisenberg and Noe [52] provide conditions guaranteeing the uniqueness of the fixed point (a sufficient condition is that the vector of non-interbank 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

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

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 that default in step k. Equivalently, the ith diagonal entry of $\Lambda(p^k)$ is defined by

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

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 $k = 2, 3, \ldots$, the payment vector p^k is determined via an iterative procedure consisting of repeatedly solving the following fixed point equation:

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

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

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

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

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

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 the default of institution 3 in the second step, while institution 4 remains solvent in all steps.

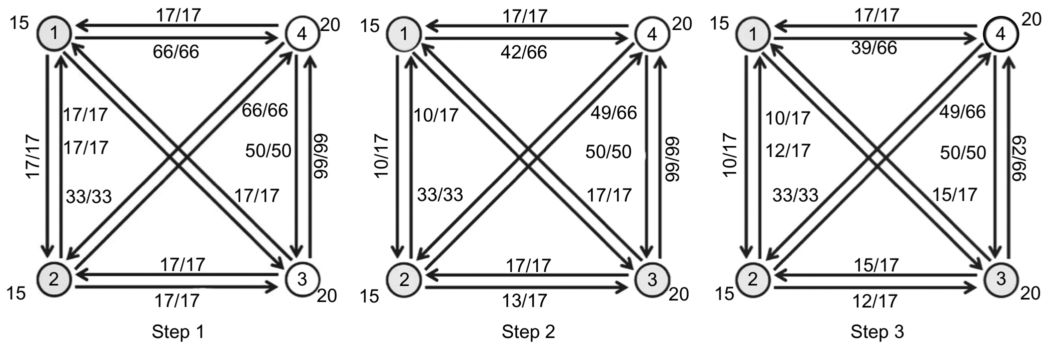
Rogers and Veraart [82] and Glasserman and Young [66] enrich the Eisenberg–Noe framework by adding bankruptcy costs. The model introduced by Rogers and Veraart [82] captures the loss from assets liquidation arising at default. They use two constants, $\alpha, \beta \in (0, 1]$, to represent the recovery rate of non-interbank and interbank assets at default, respectively. 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 are 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:

$$p_i^* = \begin{cases} \ell_i & \text{if } \ell_i \le \displaystyle\sum_{j=1}^{n} p_j^* \pi_{j,i} + c_i, \\[2ex] \beta \displaystyle\sum_{j=1}^{n} p_j^* \pi_{j,i} + \alpha c_i & \text{else,} \end{cases}$$

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.



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, 93, 170)
Defaulted institution	1, 2	1, 2, 3	1, 2, 3

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 [66], and it 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

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

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

We next discuss the dependence of systemic risk on the network topology. This has been investigated in the works of Amini et al. [13], Acemoglu et al. [1], Battiston et al. [18], Capponi et al. [31], and Elliott et al. [54], which are surveyed next. Amini et al. [13] provide analytical results on the connection between network structure and stability in large networks. Their criterion only depends on the exposure-to-capital ratios. In their model, contagion of losses occurs along the (sub)network of contagious links defined as exposures whose ratio to capital exceeds a given threshold. Capponi et al. [31] analyze the conditions under which the 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. Conversely, 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 distribute 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. [54] 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 levels (very low or very high) of integration and diversification, the risk of far-reaching cascades of financial failures is the lowest. Acemoglu et al. [1] 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 perform worse than any δ-connected financial network (see Definition 5 in Acemoglu et al. [1] for the definition of δ-connected). The findings of Acemoglu et al. also provide analytical support for the "robust-yet-fragile" property of highly interconnected financial networks observed by Gai and Kapadia [62] through numerical simulations.

Battiston et al. [18] 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. [12] 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 et al. [55] develop an empirical analysis of the Eisenberg–Noe model using data from the Austrian banking system. They find that correlation in banks' asset portfolios is the main source of systemic risk. Their analysis separates fundamental defaults from contagious defaults, the latter being defaults that would have been avoided if all banks were repaying their obligations in full. Angelini et al. [15] provide an early study of systemic risk for the Italian interbank system. Cont et al. [41] show how defaults transmit through the payment system and originate systemic crisis using data from the Brazilian interbank system. Craig and Von Peter [42] develop an empirical analysis using bilateral interbank data from German banks covering the period 1999–2007 and find that the matrix of interbank liabilities exhibits a core–periphery structure. The core banks are large financial institutions, while periphery banks are small institutions that act as net lenders. Cocco et al. [39] find that small banks tend to act mostly as lenders, while large banks tend to provide interbank intermediation services (see also Table 5 therein).

2.1.2. Endogenous Financial Networks. The vast majority of models proposed in the literature take the financial network as given. Understanding the formation mechanisms plays, however, an important role for the analysis of causes and consequences of systemic failures. This, in turn, contributes to inform the development of regulatory policies targeting the resilience of the financial system.

Literature on endogenous network formulation is still in its infancy. One of the early works in this direction is by Farboodi [56], who designs an endogenous model of financial intermediation, where profit-maximizing institutions decide to strategically borrow and lend. In her network model, the endogenously emerging borrowing/lending interbank activities resemble a core–periphery network. She shows that banks who make risky investments voluntarily expose themselves to excessive counterparty risk, while banks who mainly provide funding establish connections with a small number of counterparties in the network. Acemoglu et al. [2] also study the endogenous formation of financial networks. In their model, banks borrow from and lend to each other in order to finance risky investments. Each bank realizes gains from trading but is also exposed to the default risk of its borrower. They show that, in equilibrium, each bank charges its borrowers an interest that is increasing in their risk-taking behavior.

The findings of Acemoglu et al. [2] indicate that in the presence of counterparty risk, the networks that emerge in equilibrium are not compatible with the incentives of a social planner. This compatibility of incentives is studied by Elliott and Hazell [53]. In their model, banks decide on their bilateral exposures so as to maximize shareholder value. A critical finding of their paper is that socially efficient networks are typically unstable. Their model predicts that the social planner, who aims at maximizing the sum of shareholder and debt-holder value, redistributes surplus from the shareholders of healthy companies to debt holders of distressed organizations. As a result, his incentives are compatible with debt holders but not aligned with those of shareholders. This leads them to trade in a manner that diverts the network away from a socially efficient structure. The efficiency and stability of a financial network is also studied by Gofman [68]. His model assumes that each bank has preferential trading partners to whom it is tied by long-term relationships, and he uses it to compute the optimal trading decisions of banks and their efficient allocations. He also calibrates the model using characteristics of the fed funds market.

2.1.3. Mean Field Models of Systemic Risk. A recent branch of the literature has put forward models of the mean field type to capture the dynamics of systemic stability. Different 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, on common exposure to systematic factors (macroeconomic indicators such as gross domestic product (GDP) growth, stock index performance, etc.), and on an interaction term that captures the pattern and strength of the 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 [59] 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 [60] 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 to 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 [60], Bo and Capponi [24] 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 they are modeled through a compound Poisson process. This leads to two sources of interbanking correlation: (1) mean field interaction, as in Fouque and Sun [60], 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 they use it to construct the law of large number approximations for systemic indicators, such as the average distance to default, and the total volume of interbanking activities. Garnier et al. [64] consider a model of interacting agents who can be either in a normal or in a 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. [80] 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 behavioral rules and cannot strategically influence the evolution of the network. Such an assumption has been relaxed in the work of Carmona et al. [34], who extend the model proposed in Fouque and Sun [60] by allowing the bank to control its borrowing/lending rate from/to a central bank at a quadratic cost decided by the regulator. This results in a game played by the banks that control the intensity of borrowing/lending activities and the central bank that 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.

2.1.4. Bank Runs. An important transmission mechanism of distress in financial networks comes from bank runs. Banks transform short-term deposits into long-term investments. If bank customers experience a liquidity shock and wish to withdraw their deposits early, then the bank is forced to liquidate long-term assets to cover short-term liabilities. Other depositors may in turn withdraw their deposits as they believe that the bank may become insolvent, hence triggering a funding run. Depositors are likely to recover less than the promised amount. The banks may be forced to fire-sale their long-term securities, which may in turn affect macroeconomic conditions (for instance, causing a surge in interest rates).

The pioneering model of bank runs has been proposed by Diamond and Dybvig [46] and is able to capture features such as loss of investors' confidence observed during the recent crisis. As investors began to fear that the underlying assets might be riskier than anticipated, they refused to renew funding, hence decreasing dramatically the money flow through this market. Freixas et al. [61] extend their model and assume that the triggering liquidation shock is not a liquidity shock but rather driven by movements of deposits across regions, justified by the fact that depositors have asymmetric payments needs. Gorton [69] analyzes the impact of incomplete information on depositors' runs. He shows that only rational and efficient depositor runs occur under complete information. If depositors are incompletely informed on the state of bank investments, they may panic after observing a noisy signal and withdraw their deposits as they expect capital losses.

In recent years, the bank run models have been extended to deal with multiple banks. Chen [35] develops a multiperiod model in which consumers select in period 0 the depository institutions, and these banks invest the funds in long-term projects with random return. In each period, depositors learn about liquidity shocks as well as their banks' long-term investment outcome and decide whether or not to withdraw their deposits. As a consequence, a subset of these banks may be run and triggered to failure. This information is then used in a Bayesian fashion to update the likelihood that investment projects of surviving banks succeed in later periods. Chen [35] shows that even if depositors choose the Pareto-dominant equilibrium, there exists a critical number of early failures above which a run on the remaining banks is always triggered. Iyer and Puria [73] identify factors responsible for contagion effects of bank runs and analyze microlevel data to empirically identify factors affecting the propensity of depositors to run.

2.1.5. Fire-Sale Spillovers. Institutions that happen to have holdings of common assets on their balance sheets may experience financial distress, even if they do not have mutual counterparty exposures. The massive liquidation procedure carried out by an institution may depress asset prices and, in turn, prompt financial distress at other institutions holding the same assets on their balance sheets. This can create self-reinforcing or spiral effects, leading to distortion of prices away from their fundamental values. These liquidations may be driven by the need of maintaining regulatory requirements (e.g., capital-to-asset or reserve-to-deposit ratio kept above a certain threshold) or of raising sufficient liquidity to fulfil outstanding obligations. Glasserman and Young [66] demonstrate that contagion effects coming from direct counterparty exposures may not be as strong as fire sales and other related mechanisms in determining losses. Cont and Wagalath [40] develop a model capturing endogenous risk resulting from fire sales in a multi-asset setting.

Adrian et al. [10] and Greenlaw et al. [70] provide empirical evidence that financial institutions actively manage their balance sheets and quickly take actions to respond to changes in 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. [20] find that the targeted leverage is well below the regulatory minimum. Moreover, larger banks tend to set a higher target, a finding that is consistent with the view that they engage in riskier investments and hence need a larger amount of funding capital. These findings are also confirmed by the empirical analysis of Gropp and Heider [72]. Memmel and Raupach [76] analyze a sample of large, publicly traded banks in 16 countries, and they conclude that banks have stable capital structures fixed at levels that 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. [71], who study the first-order effects of fire sales, and Capponi and Larsson [30], 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 $\mathbf{S}_t$, 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,and 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-sale externalities and a key quantity to characterize asset price dynamics. Indeed,

$$\frac{\Delta P_t}{P_t} = (\mathbf{I} - \mathbf{S}_t)^{-1}[\text{aggregate shock}] = [\mathbf{I} + \mathbf{S}_t + \mathbf{S}_t^2 + \mathbf{S}_t^3 + \cdots][\text{aggregate shock}]; \tag{4}$$

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 [48] 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 [87] 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. Wagner shows 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. [37] analyze the propagation mechanism of shocks in a network of firms holding common assets under general portfolio choices.

As discussed by Duffie [49], 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. Department of the Treasury'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 [46] 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 [3]).

2.1.6. Hybrid Models. This section analyzes a class of network models in which the value of non-interbank assets is not kept fixed at its book value. Rather, an exogenous rule for the price impact generated by the sale of illiquid assets is postulated. When an insolvent bank is unable to fulfill outstanding obligations using the available cash, it sells its illiquid assets so to raise sufficient liquidity. This may depress asset prices and trigger default events of institutions, which become insolvent as a result of the reduced price of their illiquid assets. Hence, such an extended model includes two source of correlation, the first via the network structure and the second via common asset holdings. For this reason, it can be thought of as a hybrid of the models presented in Sections 2.1.1 and 2.1.5.

The main contribution in this direction is by Cifuentes et al. [38], who extend the Eisenberg–Noe framework to account for the price impact generated by asset liquidation. In their model, the non-interbank asset held by institution i consists of liquid and illiquid assets, denoted by ϕ_i and e_i, respectively. The liquid asset has a constant unit price, while the illiquid asset has current price v. The system of fixed point equations that need to be satisfied by a clearing payment vector is given by

$$p_i^* = \min\left\{\ell_i, \sum_{j=1}^{n} p_j^* \pi_{j,i} + \phi_i + v e_i\right\}, \quad i = 1, \ldots, n. \tag{5}$$

The change in price of the illiquid asset is driven by the fact that each institution is required to maintain a minimum capital ratio r. When an institution violates this constraint, it would need to reduce its balance sheet size. This is implemented by selling its liquid assets first and then illiquid assets. The number of units of the illiquid asset sold by institution i is determined by

$$s_i = \min\left\{e_i, \frac{\sum_{j=1}^{n} p_j^* \pi_{j,i} + v e_i - (\sum_{j=1}^{n} p_j^* \pi_{j,i} + v e_i - p_i^*)/r}{v}\right\}. \tag{6}$$

In the above expression, the numerator represents the difference between the total asset value held by i after selling its liquid assets and the total asset value it would need to hold to satisfy the capital adequacy requirement. The price of the illiquid assets is determined by an inverse demand function $d^{-1}(\cdot)$, which takes as an input the number of units of the illiquid asset sold; i.e.,

$$v = d^{-1}\left(\sum_{i=1}^{n} s_i\right). \tag{7}$$

An equilibrium is the triple (p, s, v) solving Equations (5)–(7). A comprehensive model of an interbank network, integrating direct counterparty contagion, bankruptcy costs, fire sales, and balance sheet cross-holdings has been recently proposed by Weber and Awiszus [88].

2.2. Top-Down Models

The top-down approach uses systemic risk measures to quantify the level of distress in the economy and the contributions to it made by each market participant. Rather than modeling the interaction between the components of the system and providing a microscopic description of the channels of distress propagation, they aim at measuring the overall distress of the system and then attributing it to its individual components. These measures are usually designed to capture tail comovements of firms' balance sheets as well as the resulting negative spillovers to the real economy. The risk is then allocated across the various financial institutions according to certain axioms, which reflect the contribution of each institution to the aggregate risk.

Key contributions in this direction include the CoVaR measure by Adrian and Brunnermeier [6], 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 [6] employ quantile regression methods to estimate it and use weekly equity returns data of publicly traded financial institutions. Acharya et al. [4] 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 [25] 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. [22]. They develop an econometric study in a financial business consisting of hedge funds, banks, broker-dealers, and insurance companies; they 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 [47] 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 U.S. financial institutions and analyze its evolution during the financial crisis. Demirer et al. [45] 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. [65]. They perform an empirical analysis of 20 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 [26] measure the total systemic risk by determining the total costs borne 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 a higher weight to losses occurring in states of the world in which the overall economy is depressed.

Biagini et al. [21] study systemic risk measures using multidimensional sets of acceptance describing desirable states of the system. Feinstein et al. [58] develop a a related analysis and define systemic risk as the set of allocations of additional capital that leads to acceptable financial outcomes. Armenti et al. [17] define the concept of multivariate shortfall risk and then discuss how this is allocated to each individual risk factor. An axiomatic foundation that includes many statistical risk measures proposed in the literature as special cases is provided by Chen et al. [36].

3. Policies

Concerns about the onset and propagation of systemic risk have prompted regulatory authorities to design preventive and resolution policies. Policies of the preventive type include structural policies targeting the balance sheet management of financial institutions, as well the trading network infrastructure. Policies of the resolution type include plans for orderly liquidation in the event of failure or contingency plans for preserving the function of critical operations in times of stress. We discuss preventive policies in Section 3.1 and resolution policies in Section 3.2.

3.1. Preventive Policies

We describe capital structure policies in Section 3.1.1, monetary policies in Section 3.1.2, and network infrastructure policies in Section 3.1.3.

3.1.1. Macroprudential Policies. The objective of macroprudential policies is to enhance the resilience of financial institutions so as to prevent and mitigate the negative externalities generated when financial institutions enter into distress. This is achieved by disciplining them via the imposition of ex ante measures targeting balance sheet growth. The U.S. regulatory capital rules require institutions to satisfy minimum leverage ratio requirements, where the leverage is defined as the ratio between core capital (common stocks and retained earnings) and the total value of consolidated assets. These measures of leverage ratios do not distinguish across exposure types, hence applying the same capital requirement to all assets. Although it can be argued that the imposition of capital requirements may have the unintended consequence of reducing lending and the overall economic activity, it is shown in Admati et al. [5] that this is likely to result in reduced social costs. Banks are instead forced to make better lending decisions, and more specifically, they have smaller incentives to engage in excessively risky activities. Moreover, Admati et al. argue that the response of highly levered banks to increased capital requirements is not to restrict loans, especially if they are adequately capitalized. Additional equity gives them the ability to provide money-like securities, which are considered less risky by investors.

An important policy proposed in response to the great depression was the conservation and countercyclical capital buffer policy. This was designed to ensure that banks build up capital buffers during periods of booms and use them in periods of distress when losses are likely to be generated. The countercyclical nature guarantees that, in downturns, the risk that the supply of credit is constrained by regulatory capital requirements is reduced. This, in turn, contributes to improved performance of the real economy while avoiding additional credit losses in the banking system.

During the financial crisis, the imposition of regulatory capital requirements amplified the credit cycle. In the good times when risks were deemed to be low, capital requirements were also low, stimulating the easing of lending conditions and favoring credit expansion. In the distressed periods, however, the riskiness of bank assets rose, forcing the build-up of capital at a time when increasing capital levels was costly. In these cases, capital regulation contributed to increased pressure on banks' balance sheets, which resulted in negative externalities.

Domestic authorities are required to monitor credit growth and decide whether such growth is excessive and likely to trigger the build-up of systemic risk. The measure for credit growth is chosen to be the credit-to-GDP ratio, which is expected to oscillate around a stable equilibrium value and to deviate from it only in situations of instability. The capital conservation buffer, set at 2.5%, ensures that banks accumulate capital buffers above the minimum requirements outside periods of distress. The countercyclical capital buffer is then triggered in periods of high credit growth as a precaution against losses arising during periods of downturns.

Despite being adequately capitalized, in the great recession, banks experienced difficulties because they did not prudently manage their liquidity. Prior to the crisis, funding was cheap and readily available. The deterioration of market conditions made it evident how quickly liquidity can evaporate and be replaced by a long-standing regime of illiquidity. To ensure a more resilient banking sector during these distressed situations, the Basel Committee put forward the liquidity coverage ratio (LCR) policy as one of the key reforms. The objective is to promote the short-term resilience of the liquidity risk profile of banks. This is achieved by ensuring that banks have an adequate stock of high-quality liquid assets that can be readily converted into cash to meet their liquidity needs over a 30-day liquidity stress scenario. Under these conditions, the banking sector has a higher ability to absorb shocks during distressed situations, and this contributes to reduce the risk of spillovers from the financial sector to the real economy.

Other prudential policies are the establishment of minimum margin requirements for securities financing transactions. These are effectively collateralized loans, including repurchase agreements activities in which investors temporarily post an asset as collateral in exchange for cash (repo financing), or vice versa (security lending activity as in the case of short-selling). An important consequence of this policy is that excess leverage in the financial system is prevented and demand of the financed assets is reduced.

There is, at present, scarce literature on macroprudential policies. Angeloni and Faia [16] construct a macroeconomic model for risky banks and analyze the effect of bank capital regulation. Their analysis suggests that the introduction of anticyclical capital requirements can be beneficial for financial stability. Crowe et al. [44] and Lim et al. [74] discuss policies imposing a cap on the loan-to-value ratio in anticipation of future real estate booms and busts. These caps are expected to dampen the build-up of systemic risk in the residential mortgage market and indirectly in the banking system.

3.1.2. Monetary Policies. This section discusses monetary policies put forward by the Federal Reserve to mitigate the threats to financial stability arising from the realization of adverse outcomes. Different from macroprudential policies, these are not too concerned with the solvency of financial institutions but rather focus on pursuing price stability over some target horizon.

These policies prescribe reserve requirements, i.e., funds that commercial banks must hold in deposits at the Federal Reserve against certain types of liabilities. The Federal Reserve decides the minimum ratio of liabilities for which reserves are required and the interest rates that these depository institutions receive for the required reserves.

The Federal Reserve also provides liquidity assistance to commercial banks in times of need, hence helping to stop or dampen the fall in asset prices caused by fire sales. This is implemented through the discount window lending. This provision of funds also offsets the arrest in banks' funding, which is likely to occur during these periods.

The Federal Reserve can also provide forward guidance by signaling variations in the federal funds rate, i.e., the rate at which commercial banks are allowed to borrow. For instance, by signaling a future increase in this rate, it would condition monetary tightening in the economy. This would reduce the excess leverage taken by financial institutions by reducing credit demand as a result of the higher rate charged on borrowing transactions.

Although monetary policies contribute to financial stability, they may have conflicting objectives with other policies. For instance, Adrian et al. [8] show that most of the monetary tightening cycles are followed by recessions or by increases in the unemployment rate. They also link reduced economic activity to the 10Y-3M Treasury spread. They show that when this spread is low, the activity of the banks that provide long-term loans to investors and fund them via short-term debt becomes less profitable and hence may lead to a reduction of credit supply in the economy.

Moreover, different from macroprudential policies, monetary policies cannot target specific asset classes but rather the macroeconomy as a whole. In this respect, they apply to both the banking and non-banking sectors in contrast to macroprudential policies, which typically apply to banking institutions. Moreover, monetary policies are faster to implement once they are designed as opposed to macroprudential policies, which typically have implementation lags.

Important contributions to the literature on monetary policies include Farhi et al. [57], who provide a mechanism of how liquidity requirements impact interest rates on private markets and characterize the optimal liquidity adequacy requirement under a general specification of shocks. Adrian et al. [9] show that looser requirements on monetary policies lead institutions to take excessive leverage and influence risk premia. We also refer to Adrian and Liang [7] for more institutional details and a thorough literature review of monetary policies.

3.1.3. Network Infrastructure Policies. Structural policies on trading networks aim at reducing the catastrophic consequences coming from excess exposure to systemically important institutions or at mitigating losses resulting from counterparty contagion in derivatives trading.

Policy proposals by the Basel Committee aim at limiting the size of gross exposures to individual counterparties. The proposed framework, referred to as the large exposures framework, is expected to be fully implemented by January 1, 2019. It is designed to protect banks from contagion losses generated by the sudden default of a group of connected counterparties. The set of acceptable exposures is computed in such a way that the maximum possible loss incurred by a bank as a result of contagion effects would not induce its own default. These large exposure limits directly contribute to reduce the systemwide contagion risk. A recent study by Capponi et al. [31] constructs an analytical framework in which a concentration of interbank exposures is quantified by applying the majorization order to the network matrix of liabilities. The conclusion of the study supports the imposition of policies targeting exposures concentration limits to individual institutions in highly capitalized banking systems.

The most significant policy regulating financial trading in over-the-counter markets is the move to a centralized trading structure. This policy requires that standardized contracts are traded via a central entity, the clearinghouse, which is responsible for setting collateral requirements to trading parties so as to reduce contagion effects arising from counterparty failures. Such a policy has been mandated by the European Market Infrastructure Regulation (EMIR) and the Dodd–Frank Wall Street Reform and Consumer Protection Act in the United States.

Central clearing changes the distribution of risk in derivatives trades. In a traditional over-the-counter transaction, each counterparty is exposed to the default risk of the other, i.e., to the possibility that it stops fulfilling its obligations at some time during the life of the contract (for instance, it no longer pays the spread premium in a credit default swap transaction or the LIBOR (London Interbank Offered Rate) floating rates in an interest rate swap transaction). When trades are cleared, the original counterparties novate the trade to the central clearinghouse; i.e., the central counterparty (CCP) becomes the buyer to the original seller and the seller to the original buyer. If the buyer or seller defaults, the CCP is responsible for reimbursing the surviving parties of the losses generated by the defaulting parties. To satisfy its obligations, the CCP has access to a default waterfall management structure—namely, a variety of financial resources including collateral posted by those who clear contracts with it and financial commitments made by its members and owners.

We next survey the main contributions to the literature on central clearing and refer to Pirrong [79] for a good overview. Duffie and Zhu [51] provide a theoretical analysis of the impact on aggregate collateral generated by the introduction of a centrally cleared network structure. They show that the netting efficiency is maximized if there is a single CCP that jointly clears various classes of derivatives, while there can be a loss of netting efficiency with a resulting increase in counterparty risk if clearing is fragmented; i.e., each clearinghouse only clears a specific class of derivatives. Cont et al. [41] perform a similar analysis but focus more on the role of heterogeneity in exposures, and they show that under these circumstances, the gain from multilateral netting in a CCP is the dominant force; for instance, adding a CCP clearing credit default swap when there already exists a CCP for interest rate derivatives is likely to decrease the overall exposure.

Besides the counterparty risk, other types of risks have been investigated by recent literature. These risks are related to the quality of posted collateral, concentration in traded positions and asset values, and distribution of collateral resources among members. Mancini et al. [75] provide an empirical analysis of the centrally cleared euro market and find that high-quality collateral behaves as a shock absorber, stabilizing the market. Glasserman et al. [67] analyze hidden illiquidity effects in the case of multiple central counterparties and identify potential "race to the bottom" phenomena in collateral levels. Menkveld [77] analyzes the social cost of crowded trades in a centralized clearing setting. Capponi et al. [32] show that, while hedging risk through a central clearinghouse is desirable at an individual level, it may lead to excessive concentration in asset value of member banks.

3.2. Resolution Policies

This section is centered on resolution policies, both for the network of bilateral contractual exposures and for the centralized network of derivatives trading.

The Dodd–Frank Wall Street Reform and Consumer Protection Act (DFA) provides liquidation authority to the Federal Deposit Insurance Corporation (FDIC). The FDIC can utilize several methods to resolve a failing bank, including open bank assistance, conservatorship, purchase and assumption, insured deposit transfer, and a deposit payoff (see also Ragalevsky and Ricardi [81] for details). In practice, the FDIC used Purchase and Assumption (P&A) transactions to resolve most of the bank failures since it became effective on December 19, 1991. P&A transactions 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. [33] 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 [29] develop a multiperiod 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 a subject of high debate. As also argued by Duffie [50], 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. 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 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 the MIT Center for Finance and Policy report prepared by Criscitello [43] for a detailed description of the contest, and we provide here a brief summary of distinguishing characteristics of systemic importance proposed by respondents.

An effective measure of systemic importance is a score that accounts for both 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 as a result of the unavailability of the institution's functions during the resolution period. Regulators would need to carefully specify relevant stressed scenarios and parameters that 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 fragmentation of the available data and often by the unavailability of specific data sets. To the best of my 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. Although 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 data set. We also refer to Murphy [78] 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 that are considered 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 the liquidation of trading positions during emergency situations. CFTC publishes weekly interest rates swap reports. The swaps market data included in this publication are produced by entities such as the Bank for International Settlements (BIS), 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.
- *Consumer Financial Protection Bureau* (*CFPB*): It regulates non-bank mortgage-related firms, private student lenders, and consumer businesses of banks whose asset size exceeds $10 billion.

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 collection and analysis of financial data. The Office of Financial Research collects counterparty network data that can be used for the monitoring and analysis of systemic risk. These include over-the-counter (OTC) credit default swap data, bilateral money-fund exposures, loan syndication networks, bilateral and triparty repo, historical bank clearing networks, and BIS data on cross-border interbank claims.

Another important data provider is the Depository Trust and Clearing Corporation (DTCC), one of the world's largest securities depositories and providers of electronic record-keeping 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.[1] Similarly, the VLab directed by Robert Engle provides free access to end-of-day SRISK measures.

There are, unfortunately, data sources that 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 are not available. The absence of such a data set prohibits a full-fledged assessment of contagion effects arising from counterparty contagion in the network. To compensate for the absence of this data set, researchers have developed statistical methods for estimating the interbank liability matrix using balance sheet data. Contributions in this direction include Upper and Worms [86], 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. [14], who propose the

[1] We refer the reader to http://scholar.princeton.edu/markus/publications/covar for the code reproducing the CoVaR measures.

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 [63] 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 shaping the future of the banking industry and to informing the design of regulations. We have discussed policies targeting the prevention and mitigation of systemic risk, as well as of default resolution. Being that systemic risk is tightly linked to financial stability and regulations, we have described 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 from more empirical studies targeting systemic risk measurements as well as the effectiveness of policies. The findings of this research can be expected to play a major role in the validation/refinement of existing models, as well as 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 and information sharing, and it also requires a close interaction of academia and regulatory authorities worldwide.

Acknowledgments

Research supported by a grant from the Global Risk Institute.

References

[1] D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review* 105(2):564–608, 2015.

[2] D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi. Systemic risk in endogenous financial networks. Columbia Business School Research Paper 15-17, Columbia University, New York, 2015.

[3] V. Acharya and T. Yorulmazer. Too many to fail—An analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation* 16(1):1–31, 2007.

[4] V. Acharya, R. Engle, and M. Richardson. Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review* 102(3):59–64, 2012.

[5] A. Admati, P. DeMarzo, M. Hellwig, and P. Pfeiderer. Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not expensive. MPI Collective Goods Preprint (2010/42), Max Planck Institute for Research on Collective Goods, Bonn, Germany, 2011.

[6] T. Adrian and M. K. Brunnermeier. CoVaR. *American Economic Review* 106(7):1705-1741, 2016.

[7] T. Adrian and N. Liang. Monetary policy, financial conditions, and financial stability. Federal Reserve Bank of New York Staff Report 690, Federal Reserve Bank of New York, New York, 2014.

[8] T. Adrian, A. Estrella, and H. S. Shin. Monetary cycles, financial cycles, and the business cycle. Federal Reserve Bank of New York Staff Report (421, Federal Reserve Bank of New York, New York, 2010.

[9] T. Adrian, E. Etula, and T. Muir. Financial intermediaries and the cross-section of asset returns. *Journal of Finance* 69(6):2557–2596, 2014.

[10] T. Adrian, H. S. Shin. Liquidity and financial contagion. *Banque de France Financial Stability Review* (11):1–7, 2008.

[11] F. Allen and D. Gale. Financial contagion. *Journal of Political Economy* 108(1):1–33, 2000.

[12] H. Amini, R. Cont, and A. Minca. Stress testing the resilience of financial networks. *International Journal of Theoretical and Applied Finance* 15(1):1250006, 2012.

[13] H. Amini, R. Cont, and A. Minca. Resilience to contagion in financial networks. *Mathematical Finance*, 26(2):329-365, 2016.

[14] K. Anand, B. Craig, and G. von Peter. Fill in the blanks: Network structure and interbank contagion. *Quantitative Finance* 15(4):625-636, 2016.

[15] P. Angelini, G. Maresca, and D. Russo. Systemic risk in the netting system. *Journal of Banking and Finance* 20(5):853–868, 1996.

[16] I. Angeloni and E. Faia. Lending relationships in the interbank market. *Journal of Monetary Economics* 60(3):311–324, 2013.

[17] Y. Armenti, S. Crepey, S. Drapeau, and A. Papapantoleon. Multivariate shortfall risk allocation. Preprint arXiv:1507.05351, http://arxiv.org/abs/1507.05351, 2015.

[18] S. Battiston, D. D. Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz. Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control* 36(8):1121–1141, 2012.

[19] S. Benoit, J.-E. Colliard, C. Hurlin, and C. Perignon. Where the risks lie: A survey on systemic risk. Working paper, University of Paris–Dauphine and HEC Paris, Paris, 2015.

[20] A. N. Berger, R. DeYoung, M. J. Flannery, D. Lee, and Ö. Öztekin. How do large banking organizations manage their capital ratios? *Journal of Financial Services Research* 34(2–3): 123–149, 2008.

[21] F. Biagini, J.-P. Fouque, M. Frittelli, and T. Meyer-Brandis. A unified approach to systemic risk measures via acceptance sets. Preprint arXiv:1503.06354, https://arxiv.org/abs/1503.06354, 2015.

[22] M. Billio, M. Getmansky, A. W. Lo, and L. Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104(3):535–559, 2012.

[23] D. Bisias, M. Flood, A. Lo, and S. Valavanis. A survey of systemic risk analytics. Working Paper N.0001, Office of Financial Research, U.S. Department of the Treasury, Washington, DC, 2012.

[24] L. Bo and A. Capponi. Stability in a model of inter-bank lending. *SIAM Journal on Financial Mathematics* 6(1):386–424, 2015.

[25] C. T. Brownlees and R. F. Engle. SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, Forthcoming, 2015.

[26] M. K. Brunnermeier and P. Cheridito. Measuring and allocating systemic risk. Working paper, Princeton University, Princeton, NJ, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2372472, 2014.

[27] M. Brunnermeier and L. Pedersen. Deciphering the liquidity and credit crunch 2007–2008. *Review of Financial Studies* 22(6):2201–2238, 2009.

[28] A. Capponi. Pricing and mitigation of counterparty credit exposures. J.-P. Fouque and J. A. Langsam, eds. *Handbook on Systemic Risk*. Cambridge University Press, Cambridge, UK, 485–511, 2013.

[29] A. Capponi and P.-C. Chen. Systemic risk mitigation in financial networks. *Journal of Economic Dynamics and Control* 58(September):152–166, 2015.

[30] A. Capponi and M. Larsson. Price contagion through balance sheet linkages. *Review of Asset Pricing Studies* 5(2):227–253, 2015.

[31] A. Capponi, P.-C. Chen, and D. D. Yao. Liability concentration and losses in financial networks. *Operations Research*, ePub ahead of print November 17, http://dx.doi.org/10.1287/opre.2015.1402, 2015.

[32] A. Capponi, W. A. Cheng, and S. Rajan. Asset value dynamics in centrally cleared networks. Working paper, Columbia University, New York, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2542684, 2015.

[33] A. Capponi, J. M. Dooley, M. V. Oet, and S. J. Ong. Capital and resolution policies: The US interbank market. *Journal of Financial Stability*, ePub ahead of print May 6, http://dx.doi.org/10.1016/j.jfs.2016.04.010, 2016.

[34] R. Carmona, J.-P. Fouque, and L.-H. Sun. Mean field games and systemic risk. *Communications in Mathematical Sciences* 13(4):911–933, 2015.

[35] Y. Chen. Banking panics: The role of the first-come, first-served rule and information externalities. *Journal of Political Economy* 107(5):946–968, 1999.

[36] C. Chen, G. Iyengar, and C. C. Moallemi. An axiomatic approach to systemic risk. *Management Science* 59(6):1373–1388, 2013.

[37] C. Chen, G. Iyengar, and C. C. Moallemi. Asset-based contagion models for systemic risk. Working paper, Columbia University, New York, 2015.

[38] R. Cifuentes, G. Ferrucci, and H. S. Shin. Liquidity risk and contagion. *Journal of the European Economic Association* 3(2–3):556–566, 2005.

[39] J. F. Cocco, F. J. Gomes, and N. C. Martins. Lending relationships in the interbank market. *Journal of Financial Intermediation* 18(1):24–48, 2009.

[40] R. Cont and L. Wagalath. Running for the exit: Distressed selling and endogenous correlation in financial markets. *Mathematical Finance* 23(4):718-741, 2013

[41] R. Cont, E. Santos, and A. Moussa. Network structure and systemic risk in banking systems. J.-P. Fouque and J. A. Langsam, eds. *Handbook on Systemic Risk*. Cambridge University Press, Cambridge, UK, 327–368, 2013.

[42] B. Craig and G. Von Peter. Interbank tiering and money center banks. *Journal of Financial Intermediation* 23(3):322–347, 2014.

[43] D. Criscitello. Crowd-sourcing a better definition of a SIFI. Report, MIT Center for Finance and Policy, Massachusetts Institue of Technology, Cambridge. http://cfpweb.mit.edu/wp-content/uploads/2016/04/SIFI-brief-final-2.pdf, 2016.

[44] C. Crowe, G. DellAriccia, D. Igan, and P. Rabanal. How to deal with real estate booms: Lessons from country experiences. *Journal of Financial Stability* 9(3):300–319, 2013.

[45] M. Demirer, F. X. Diebold, L. Liu, and K. Yilmaz. Estimating global bank network connectedness. PIER Working Paper 15-025, Penn Institute for Economic Research, Philadelphia, 2015.

[46] D. W. Diamond and P. H. Dybvig. Bank runs, deposit insurance, and liquidity. *Journal of Political Economy* 91(3):401–419, 1983.

[47] F. X. Diebold and K. Yılmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182(1):119–134, 2014.

[48] F. Duarte and T. M. Eisenbach. Fire-sale spillovers and systemic risk. Federal Reserve Bank of New York Staff Report 645, Federal Reserve Bank of New York, New York, 2015.

[49] D. Duffie. The failure mechanics of dealer banks. *Journal of Economic Perspectives* 24(1):51–72, 2010.

[50] D. Duffie. Resolution of failing central counterparties. K. E. Scott, T. H. Jackson, and J. B. Taylor, eds. *Making Failure Feasible: How Bankruptcy Reform Can End "Too Big to Fail."* Hoover Institution Press, Stanford, CA, 87-109, 2015.

[51] D. Duffie and H. Zhu. Does a central clearing counterparty reduce counterparty risk? *Review of Asset Pricing Studies* 1(1):74–95, 2011.

[52] L. Eisenberg and T. H. Noe. Systemic risk in financial systems. *Management Science* 47(2):236–249, 2001.

[53] M. Elliott and J. Hazell. Endogenous financial networks: Efficient modularity and why shareholders prevent it. Working paper, California Institute of Technology, Pasadena, 2016.

[54] M. Elliott, B. Golub, and M. O. Jackson. Financial networks and contagion. *American Economic Review* 104(10):3115–3153, 2014.

[55] H. Elsinger, A. Lehar, and M. Summer. Risk assessment for banking systems. *Management Science* 52(9):1301–1314, 2006.

[56] M. Farboodi. Intermediation and voluntary exposure to counterparty risk. Working paper, Booth School of Business, University of Chicago, Chicago, 2014.

[57] E. Farhi, M. Golosov, and A. Tsyvinski. A theory of liquidity and regulation of financial intermediation. *Review of Economic Studies* 76(3):973–992, 2009.

[58] Z. Feinstein, B. Rudloff, and S. Weber. Measures of systemic risk. Preprint arXiv:1502.07961, https://arxiv.org/abs/1502.07961, 2015.

[59] J.-P. Fouque and T. Ichiba. Stability in a model of interbank lending. *SIAM Journal on Financial Mathematics* 4(1):784–803, 2013.

[60] J.-P. Fouque and L. Sun. Systemic risk illustrated. J.-P. Fouque and J. A. Langsam, eds. *Handbook on Systemic Risk*. Cambridge University Press, Cambridge, UK, 444–452, 2013.

[61] X. Freixas, B. Parigi, and J.-C. Rochet. Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking* 32(3, Part 2):611–638, 2016.

[62] P. Gai and S. Kapadia. Contagion in financial networks. *Proceedings of the Royal Society A* 466(2120):2401–2423, 2010.

[63] A. Gandy and L. A. Veraart. A Bayesian methodology for systemic risk assessment in financial networks. Working paper, London School of Economics, London, 2015.

[64] J. Garnier, G. Papanicolaou, and T.-W. Yang. Large deviations for a mean field model of systemic risk. *SIAM Journal on Financial Mathematics* 4(1):151–184, 2013.

[65] S. Giglio, B. Kelly, and S. Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics* 119(3):457–471, 2016.

[66] P. Glasserman and H. P. Young. How likely is contagion in financial networks? *Journal of Banking and Finance* 50(January):383–399, 2015.

[67] P. Glasserman, C. C. Moallemi, and K. Yuan. Hidden illiquidity with multiple central counterparties. *Operations Research*, ePub ahead of print December 16, http://dx.doi.org/10.1287/opre.2015.1420, 2015.

[68] M. Gofman. Efficiency and stability of a financial architecture with too interconnected to fail institutions. *Journal of Financial Economics*, 2014.

[69] G. Gorton. Bank suspension of convertibility. *Journal of Monetary Economics* 15(2):177–193, 1985.

[70] D. Greenlaw, J. Hatzius, A. K. Kashyap, and H. S. Shin. Leveraged losses: Lessons from the mortgage market meltdown. *Proceedings of the US Monetary Policy Forum*, Initiative on Global Markets, Chicago, 7–59, 2008.

[71] R. Greenwood, A. Landier, and D. Thesmar. Vulnerable banks. *Journal of Financial Economics* 115(3):471–485, 2015.

[72] R. Gropp and F. Heider. The determinants of bank capital structure. *Review of Finance* 14(4):587–622, 2010.

[73] R. Iyer and M. Puria. Understanding bank runs: The importance of depositor-bank relationships and networks. *American Economic Review* 102(4):1414–1445, 2012.

[74] C. H. Lim, A. Costa, F. Columba, P. Kongsamut, A. Otani, M. Saiyid, T. Wezel, and X. Wu. Macroprudential policy: What instruments and how to use them? Lessons from country experiences. IMF Working Paper WP/11/238, International Monetary Fund, Washington, DC, 2011.

[75] L. Mancini, A. Ranaldo, and J. Wrampelmeyer. The euro interbank repo market. *Review of Financial Studies* 29(7):1747–1779, 2016.

[76] C. Memmel and P. Raupach. How do banks adjust their capital ratios? *Journal of Financial Intermediation* 19(4):509–528, 2010.

[77] A. J. Menkveld. Systemic risk in central clearing: Should crowded trades be avoided? Working paper, VU Amsterdam, 2015.

[78] E. V. Murphy. Who regulates whom and how? An overview of U.S. financial regulatory policy for banking and securities markets. CRS Report R43087, Congressional Research Service, Washington, DC, 2015.

[79] C. Pirrong. The economics of central clearing: Theory and practice. ISDA Discussion Paper 1, International Swaps and Derivatives Association, New York, 2011.

[80] P. D. Pra, W. J. Runggaldier, E. Sartori, and M. Tolotti. Large portfolio losses: A dynamic contagion model. *Annals of Applied Probability* 19(1):347–394, 2009.

[81] S. V. Ragalevsky and S. J. Ricardi. Anatomy of a bank failure. *Banking Law Journal* 126(December):867–902, 2009.

[82] L. C. Rogers and L. A. Veraart. Failure and rescue in an interbank network. *Management Science* 59(4):882–898, 2013.

[83] A. Shleifer and R. Vishny. Fire sales in finance and macroeconomics. *Journal of Economic Perspectives* 25(1):29–48, 2011.

[84] A. Shleifer and R. W. Vishny. Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47(4):1343–1366, 1992.

[85] J. C. Staum. Counterparty contagion in context: Contributions to systemic risk. J.-P Fouque and J. A. Langsam, eds. *Handbook on Systemic Risk*. Cambridge University Press, Cambridge, UK, 512–544, 2013.

[86] C. Upper and A. Worms. Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review* 48(4):827–849, 2004.

[87] W. Wagner. Systemic liquidation risk and the diversity-diversification trade-off. *Journal of Finance* 66(4):1141–1175, 2011.

[88] S. Weber and K. Awiszus. The joint impact of bankruptcy costs, fire sales and cross-holdings on systemic risk in financial networks. Working paper, Leibniz Universität Hannover, Hannover, Germany, 2016.

CORRECTION

In this chapter, "Systemic Risk, Policies, and Data Needs" by Agostino Capponi (first published in *Tutorials in Operations Research*, pp. 185–206, November 13, 2016, DOI:10.1287/educ.2016.0156lop), an acknowledgment has been added in the online version.