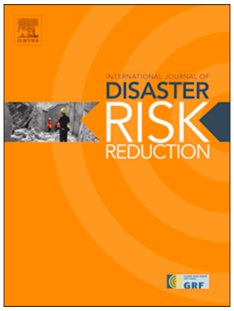

Enhancing Resilience of Systems to Individual and Systemic Risk: Steps toward An Integrative Framework

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Title:

Enhancing Resilience of Systems to Individual and Systemic Risk: Steps toward An Integrative Framework

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Abstract: Individual events can trigger systemic risks in many complex systems, from natural to man-made. Yet, analysts are still usually treating these two types of risks separately. We suggest that, rather, individual risks and systemic risks represent two ends of a continuum and therefore should not be analyzed in isolation, but in an integrative manner. Such a perspective can further be related to the notion of resilience and opens up options for developing an integrated framework for increasing the resilience of systems to both types of risks simultaneously. Systemic risks are sometimes called network risks to emphasize the importance of inter-linkages, while, in contrast, individual risks originate from individual events that directly affect an agent and happen independently from the rest of the system. The two different perspectives on risk have major implications for strategies aiming at increasing resilience, and we, therefore, discuss how such strategies differ between individual risks and systemic risks. In doing so, we suggest that for individual risks, a risk-layering approach can be applied, using probability distributions and their associated measures. Following the risk-layering approach, agents can identify their own tipping points, i.e., the points in their loss distributions at which their operation would fail, and on this basis determine the most appropriate measures for decreasing their risk of such failures. This approach can rely on several well-established market-based instruments, including insurance and portfolio diversification. To deal with systemic risks, these individual tipping points need to be managed in their totality, because system collapses are triggered by individual failures. An additional and complementary approach is to adjust the network structure of the system, which determines how individual failures can cascade and generate systemic risks. Instead of one-size-fits-all rules of thumb, we suggest that the management of systemic risks should be based on a careful examination of a system's risk landscape. Especially a node-criticality approach, which aims to induce a network restructuring based on the differential contributions of nodes to systemic risk may be a promising way forward toward an integrated framework. Hence, we argue that tailor-made transformational approaches are needed, which take into account the specificities of a system's network structure and thereby push it toward safer configurations for both individual risks and systemic risks.

Keywords: Extreme risk, Systemic risk, Resilience, Integration, Risk layering

1. Introduction

Experiences in the past have shown the potential of single events to trigger systemic risks (Massaro et al. 2018). For example, the 2011 Thailand flooding and its consequences for global supply chains (Chongvilaivan 2012; Haraguchi and Lall 2015) have demonstrated the magnitude of potential knock-on effects. Such risks are expected to increase with the growing interconnectedness of economic processes and to be magnified by changes in the intensity and frequency of weather-related extreme events brought about by climate change (Ghil et al. 2011; Field et al. 2012). Along the same line, a review of globally relevant systemic risks by Centeno et al. (2015) found strong indications that individual events, even very localized ones, may cause large repercussions globally. Guidelines for systemic-risk governance recently published by the International Risk Governance Center (Florin et al. 2018) also strongly emphasize how individual failures may trigger systemic risks. Hence, individual and systemic risk are intrinsically interconnected and need to be analyzed together.

In reality, however, they are often treated separately, especially in the context how to enhance resilience. In this paper we suggest a rationale as well as highlight ways forward for developing an integrated analytical framework for increasing a system's resilience to both types of risks. Enormous amount of literature and approaches dealing with each type of risk is available (see the discussion further down below). In our paper, as a starting point, we use a probabilistic risk-perspective as suggested and often employed in disaster risk research, e.g. focusing on the tails of a distribution (Grossi and Kunreuther 2005, SREX 2012, Hinkel et al. 2015; NCC editorial 2016, Abadie et al. 2017). This enables the employment of a risk-layering approach to inform resilience-enhancing strategies that initially focus on individual risk but can further be related to systemic risk and resilience through network restructuring. This is due to the fact that systemic risk originates from interconnectedness of the network underlying a system. The way how a system is defined will be instrumental for the debate and our point of departure for our discussion.

As already indicated above, individual failures may trigger systemic risks. Systemic risk is sometimes called network risk to emphasize the importance of inter-linkages (Helbing 2013). In contrast, individual risks originate from single events that directly affect an agent and unfold in isolation from the rest of the system. While usually treated separately, we first suggest that individual risks and systemic risks may be seen, in fact, as representing the two ends of a continuum and therefore should not be analyzed in isolation, but rather in an integrative manner (Hochrainer-Stigler et al. 2018a). From such a perspective, individual risks describe how an event perturbs a single component in a system and causes a primary failure, whereas systemic risks capture the propensity for cascades of secondary failures to be triggered by such events. The continuum is spanned by the proportion of all failures that are secondary with regard to the system's size, with larger proportions characterizing risk settings at the more systemic end of the spectrum (Figure 1). Quantitative approaches based on so-called copula methods are particularly well suited to this integrative perspective (Hochrainer-Stigler et al. 2018b; Pichler and Pflug 2018). More importantly, such a perspective can further be related to the notion of resilience and opens up options for developing an integrated framework for increasing a system's resilience to both types of risks. For example, to increase resilience to individual risks, e.g., to accidents leading to material losses, modern societies typically rely on some form of diversification, most prominently through insurance

(Geneva Association 2010). By not incurring the total material costs of accidents, insured individuals can recover more quickly. To increase resilience to systemic risks, in contrast, fundamentally different approaches are needed, which may, for instance, imply restructuring a network's connectivity (Gao et al. 2016; Poledna and Thurner 2016), e.g. to decrease the amount of secondary failures.

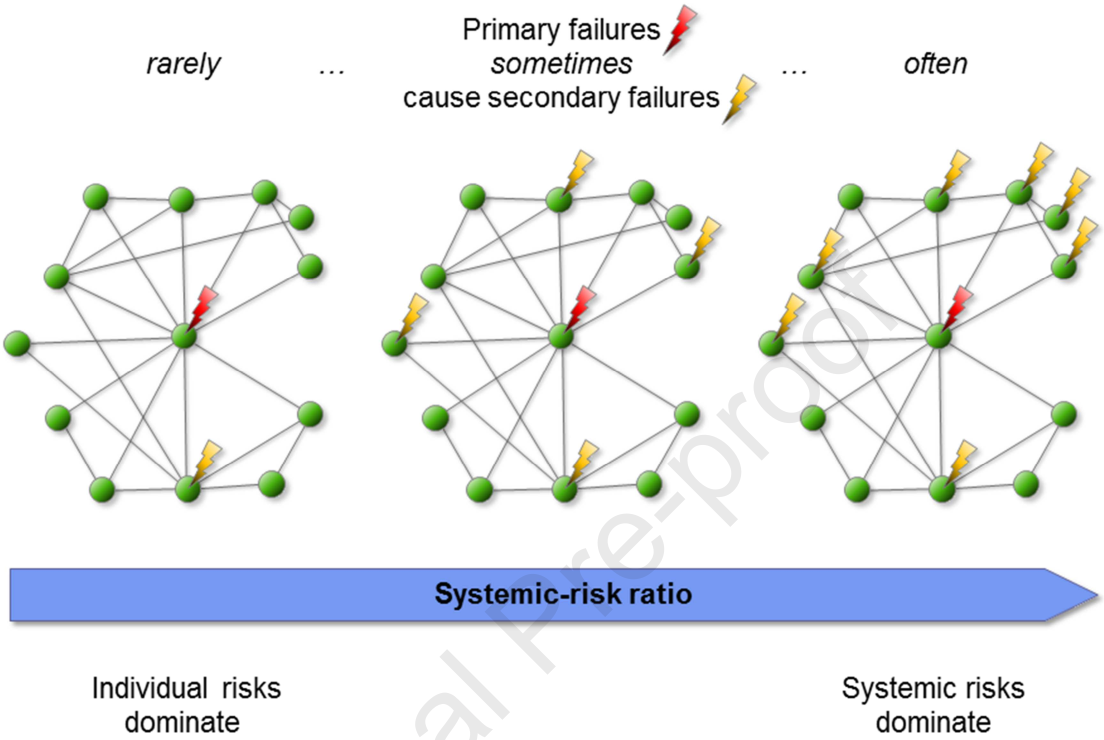

Figure 1. The continuum between individual risks and systemic risks. System components (green circles) are interacting (black lines) in a networked system. Owing to these interactions, primary failures (red flashes) can trigger secondary failures (orange flashes). The systemic-risk ratio (blue arrow) measures the proportion of all failures that are secondary. Accordingly, individual risks dominate on the left-hand side (for systemic-risk ratios close to 0) and systemic risks dominate on the right-hand side (for systemic-risk ratios close to 1).

However, insurance and network restructuring are not the only strategies to increase resilience. Indeed, multiple schools of thought dealing with the concept of resilience are present in the literature (e.g., National Research Council 2012; Ilmola et al. 2013; Keating et al. 2014; Mochizuki et al. 2018). We provide some indicative examples next. Engineering approaches were among the first to introduce the term resilience and to examine a system's resistance to disturbances and the speed at which it returns to equilibrium (reviewed, e.g., by Davoudi, 2012). The current notions of resilience depart from this equilibrium-centric view by embracing complexity, dynamics, interdependencies, and nonlinearities. From a disaster risk reduction perspective, Alexander (2013) discusses the use and meaning of the word resilience and concludes that this concept may be especially helpful to bridge the gap between dynamic and static assessments. In a similar vain, Keating et al. (2014) reviewed different resilience approaches and how they had been used in the past to decrease disaster risks and suggested to embed resilience within a development context. Recently, Tiernan et al. (2019) identified emerging themes for disaster risk reduction in the context of resilience, such as the focus on community engagement. In a more general context, Linkov and Trump (2019) provide a comprehensive discussion of resilience approaches, and Florin et al. (2018) as well as Trump et al. (2018) provide extensive reviews and corresponding literature. While it is not possible to give a comprehensive account of all those discussions and reviews, they indicate that resilience can be seen as an emergent property of a system that can be investigated from various angles, e.g., by analyzing the persistence of critical functions under environmental changes, by identifying thresholds that, when exceeded, precipitate regime shifts, or by investigating the evolution of recovery capacities, to name just a few (Linkov et al. 2016).

Traditionally, when studying large and complex systems, such as ecosystems or economies, scientists often assume their stability, which allows them to focus on smaller components and study them in isolation. A major shift away from this paradigm originated through the work of C.S. Holling, who introduced the concept of resilience in ecology to emphasize the pre-eminence of nonlinearities, unstable dynamics, and interconnectedness, both in theory and observations. In this context, resilience is the “ability to absorb change and disturbance and still maintain the same relationships between populations or state variables” (Holling 1973, p. 14). Insufficiently resilient systems are exposed to knockouts, by which small perturbations trigger lasting system-wide collapses, a phenomenon that we now call systemic risks (Thurner 2018). Based on our integrated systems approach depicted in Figure 1, understanding resilience and systemic risks therefore requires a careful assessment of the dynamic interactions between a system’s components. As will be discussed in Section 2, identifying strategies to increase resilience often depends on how individual and systemic risks are measured. By comparing the most prominent risk measures and how they relate to resilience, we highlight ways forward for developing an integrated framework for increasing a system’s resilience to both types of risks. We use as our starting point the probabilistic risk-perspective, which we then relate to a risk-layer approach for enhancing resilience to individual risks, and which we further connect to the systemic risk approach. To the authors’ best knowledge, integrating risk layering within network restructuring has not yet been suggested to foster resilience to both individual and systemic risks from a probabilistic risk perspective.

Our paper is organized as follows. Section 2 discusses measures of individual risks and systemic risks. Special attention is given to probability-based concepts commonly employed in disaster research, which are particularly appropriate to tackle extreme risks (Field et al. 2012; United Nations Office for Disaster Risk Reduction 2019). Section 3 then proposes an integrated approach based on risk layering and network restructuring. Finally, Section 4 presents an integrative management approach that jointly tackles individual risks and systemic risks.

2. Measures of Individual Risks and Systemic Risks

Any complex system can be seen as a set of interconnected elements. Each one of these elements can be at risk, which we from now on call individual risk. A widely accepted and comprehensive measure of individual risk is the cumulative distribution function (CDF) of losses (Pflug and Römisch 2007). As it is difficult to grasp this entire function at a glance, it can be used to define particular measures that focus on specific aspects of individual risk. For example, disaster risk research usually focuses on the tails of a distribution, or in other words on low-probability high-consequence events. Table 1 shows a selection of measures of individual risks and systemic risks currently used by analysts—for a comprehensive treatment of the former, see Pflug and Roemisch (2007), and of the later, see Bisias et al. (2012), Sum (2016), and Hochrainer-Stigler et al. (2019). For example, for frequent events, the expected loss, the median loss, or the variance of losses may provide the most appropriate summary information. For extreme events, on the other hand, tail measures such as the Value at Risk (VaR) or the Conditional Value at Risk (CoVaR; also called the expected shortfall) are more appropriate. These risk measures are often used to determine risk-management options. For instance, the expectation and the variance of losses can be used for setting up premium payments for insurance schemes or for performing costs-benefit analyses for structural mitigation measures (Shreve and Kelman 2014, Mechler 2016). For example, Hochrainer-Stigler et al. (2019) used these measures to assess investments in structural-flood proofing of low-income, high-risk houses in Uttar Pradesh, India. Applications of the Value at Risk, or of other tail indices, include stress testing, the evaluation the probability of ruin, or the calibration of back-up capital for risk instruments (Embrechts et al. 2012). For example, Abadie et al. (2017) used these measures to determine the acceptable level of risk of low-probability, high-impact coastal floods in cities. Jongman et al. (2014) performed stress tests and used these tail measures to determine the ruin probabilities of the European Union Solidarity Fund due to large scale pan-European floods. Thus, cumulative distribution functions and their characteristics have a wide area of application and play a prominent role in discourses about individual risks, including extremes (SREX 2012, NCC editorial 2016).

Table 1. Selected measures of individual risks and systemic risks.

Individual-risk measure	**Informal explanation**
Cumulative distribution function (CDF)	Measures the probability Prob($X \leq x$) that the random variable X describing losses is less than or equal to a given loss x (Bauer 2011).
Location measure: Expectation E(X)	Measures the average value of the random variable X describing losses over a large number of realizations (Sachs 2012).
Location measure: Median Med(X)	Measures the mid-point between the higher and lower half of the cumulative distribution function of losses (Sachs 2012).
Dispersion measure: Variance Var(X)	Measures how far the values of the random variable X describing losses are spreading from its expectation (Sachs 2012).
Tail measure: Value at risk (VaR)	Measures the value that is at risk in a system at a given quantile level q, i.e., VaR satisfies Prob($X \leq$ VaR) = q (Pflug and Römisch 2007).
Tail measure: Tail index	Measures the rate at which the thickness of the tail of a given cumulative distribution function of losses is decreasing (Embrechts et al. 2012).
Tail measure: Probable maximum loss (PML)	Measures the maximum loss that can occur in a system (Grossi and Kunreuther 2005).

Systemic-risk measure	**Informal explanation**
Systemic expected shortfall (SES)	Measures the propensity for an institution to be undercapitalized when the whole system is undercapitalized (Acharya et al. 2017).
Conditional value at risk (CoVaR)	Measures the value that is at risk in a system at a given quantile level q, conditional on an event stressing a set of institutions, i.e., when X is the negative random variable describing the system-level losses triggered by the event, CoVaR satisfies Prob($X \leq$ CoVaR) = q (Adrian and Brunnermeier 2011).
ΔCoVaR	Measures how the conditional value at risk (CoVaR, see above) changes when the system's "normal" operation becomes further stressed (Adrian and Brunnermeier 2011).
Systemic risk index (SRISK)	Measures the amount of capital an institution would need to raise in order to function normally given an event that stresses a set of institutions (Brownless and Engle 2017).
Distress insurance premium (DIP)	Measures the expected system-level loss given that the loss triggered by an event that stresses a set of institutions exceeds a pre-defined threshold level (Huang, Zhou and Zhu 2012).
Default impact (DI)	Measures the total loss in capital in a system caused by the cascade triggered by the default of an institution, excluding the loss from this initial default (Cont et al. 2010).
DebtRank	Measures the recursively defined impact on a system resulting from an event that stresses an institution, allowing only for impact pathways that do not visit the same institutional links twice (Battiston et al. 2012).
Measures in copula models	Measure the conditional value at risk (CoVaR, see above) given an event that stresses a set of institutions, with institutions having a nonlinear probabilistic dependency structure described by a copula (Kovacevic and Pflug 2015).

Systemic risks result from the interactions of individual risks. Consequently, systemic risks cannot be measured by separately quantifying the contributing parts. Systemic-risk research therefore construes systems as networks of interconnected components and thereby focuses on the interdependencies among individual risks. The way such interlinkages are analyzed may vary markedly between systems of different types, leading to a variety of systemic-risk measures that have been proposed in the literature. In the context of network analyses, the system components forming the studied network are often referred to as nodes. Some systemic-risk measures focus on the influence of a single node on overall systemic risks, which, for instance, may directly be related to its position within the network (e.g., Poledna and Thurner 2016). Other measures, in contrast, capture risks for a system as a whole based on its network structure (e.g., Kharrazi et al. 2016). Many systemic-risk measures have recently been suggested for financial systems, not only driven by the large influence of financial markets on society, but also because of the increasing availability of high-resolution data. One of the most prominent indicators is called DebtRank (Battiston et al. 2012). DebtRank estimates the impact of a node's default on the rest of the network. Inspired by the notion of network centrality, DebtRank recursively evaluates how the financial distresses of nodes impact each other. Accordingly, DebtRank can be considered as an early-warning indicator for a node being too central to fail—an important feature aggravating a node's contribution to systemic risk, in addition to being too big to fail (Poledna and Thurner 2016). As indicated in Table 1, other measures of systemic risk are also available, such as the Systemic Expected Shortfall, which uses pre-defined thresholds—akin to Value at Risk—to quantify a node's anticipated contribution to a systemic crisis (Acharya et al. 2009, Ganin et al. 2017, Massaro et al. 2018). Collecting data and applying such measures are the first steps to the development of strategies aimed at enhancing resilience.

3. Enhancing Resilience: Risk Layering and Network Restructuring

When the cumulative distribution functions of individual risks are known, a so-called risk-layering approach can be applied. This approach aims to identify different risk layers, or risk components, and to determine, separately for each one of them, the most appropriate options for increasing its resilience (Mechler et al. 2014). For example, in the case of natural disasters, such risk layering uses hazard-recurrence data to identify appropriate interventions. The approach relies on the principle that different risk bearers or stakeholders—e.g., in households, businesses, and the public sector—are experiencing different contexts, and each of them should therefore adopt the most appropriate strategy given their own risk exposure, the cost efficiency of the risk-mitigating solutions they can use, and their access to financing instruments. Hence, through risk layering, individual risk measures, such as the ones in Table 1, can directly point to the most appropriate instruments to increase resilience (Figure 2).

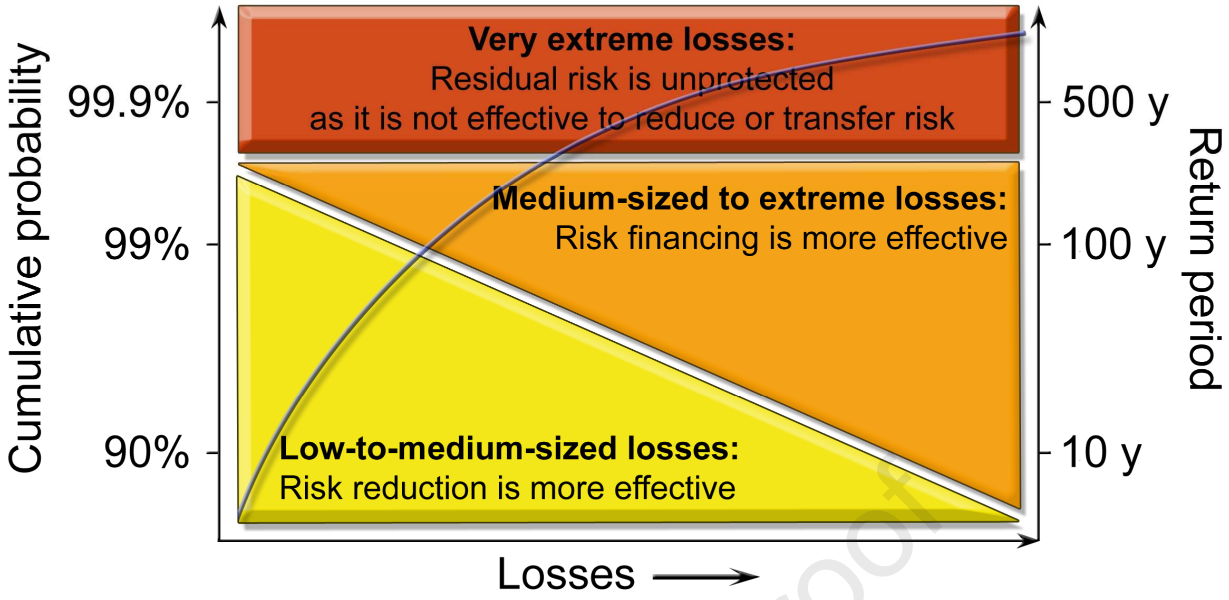

Figure 2. Risk-layering approach for risk reduction and risk financing, based on analyzing a system's cumulative distribution function of losses. Depending on the studied system, the levels of losses (horizontal axis) are associated with the quantiles, or cumulative probabilities, of losses (left-hand vertical axis) according to the cumulative distribution function (blue curve) and with the expected return periods, or waiting times, separating the occurrence of events causing such levels or quantiles of losses (right-hand vertical axis). The transitions between risk reduction being more effective (yellow region), risk financing being more effective (orange region), and residual risk having to remain unprotected (red region) are merely illustrative and, depending on the studied system, can take other, nonlinear shapes. Moving along the cumulative distribution function, the corresponding three intervals—alternatively expressed in terms of the levels, quantiles, or return periods of losses—can be read off. Adapted from Mechler et al. (2014).

For example, for events causing low-to-medium-sized losses that happen relatively frequently, solutions aiming at risk reduction—for instance, by enforcing rules that decrease asset exposure to hazards—typically are more cost-effective than solutions aiming at risk financing. The cost-effectiveness of potential solutions can be assessed using the mean and median of reduced losses, as in cost-benefit analyses (Mechler 2016). Because the costs of risk-reducing solutions often increase disproportionately with the severity of the events, other instruments are needed for larger disasters. Risk-financing instruments may thus become more cost-effective for disasters occurring with lower probability and higher impact that have debilitating consequences (catastrophes), which can be quantified by deviation measures and tail measures (Table 1). Finally, as suggested by the uppermost layer in Figure 2, there is a point above which even financial instruments become too costly. These unmanaged risks are said to be residual and have to be left unprotected. This risk-layering approach is readily extended from financial risks to non-financial risks.

Generally speaking, depending on its own resilience, an agent may or may not be able to cope with a particular event. For example, during a financial crisis, a bank may go bankrupt as a result of large defaults on its loans. A government may not be able to finance all infrastructure losses resulting from a disaster because of budget constraints (Hochrainer-Stigler et al. 2015). A firm may go out of business because of sudden changes in market conditions (Poledna et al. 2018). Following the risk-layering approach, we suggest that agents can identify their own tipping points, i.e., the points in their loss distributions at which they would fail, and on this basis determine the most appropriate measures for decreasing their risk of failing. However, as indicated in Figure 1 to deal with systemic risks, these individual tipping points need to be managed together, because system collapses are triggered by individual failures. In other words, without any individual failure (e.g., disease, default, bankruptcy, stress), no systemic risk can realize. Whether an individual failure occurs, depends on the individual's own resilience, which we suggest can be measured and enhanced using the risk-layering approach. If an individual is at risk, its failure has the potential to trigger systemic risks. How to assess and enhance systemic risk under these circumstances is discussed next.

Systemic risk is generally investigated using complexity theories, within which network analysis plays one but very important role (Thurner 2018). Approaching a system as a network of connected components is particularly useful to analyze systemic risks, as illustrated by Figure 1. It intuitively suggests a complementary approach for dealing with systemic risks, which consist in adjusting the network structure of a system, thereby changing how individual failures cascade and generate systemic risks. Inspired by the management of individual risks, applying some sort of diversification to the network structure is thought to be a promising strategy to reduce systemic risks. This intuition has been tested in various fields, resulting in many new findings on the properties of complex networks, as evidenced, e.g., by the large body of research on the diversity-stability debate in ecology (e.g., McCann 2000).

It turns out, however, that diversification does not necessarily increase resilience. On the one hand, diversification does indeed enable risk sharing and facilitate post-failure recovery, but, on the other hand, it also multiplies the number of contagion pathways that increase systemic risks (Gai and Kapadia 2010; Haldane and May 2011; Allen et al. 2012; Battiston et al. 2012; Amini et al. 2016). In particular, naïve diversification strategies may cause different system components to diversify too similarly: as this may raise systemic risks, diversification strategies have been recommended to aim at diverse diversification (Beale et al. 2011). Similar to diversification, building modularity into a system—i.e., adjusting the degree to which the nodes of a system can be decoupled into relatively weakly connected subsets of nodes—may diminish herding effects (Banerjee 1992; Yang 2013), but in general has equivocal consequences for systemic risks: it often decreases risks for most parts of the system at the expense of the remaining parts—which may, overall, jeopardize the resilience of the system as a whole (May et al. 2008).

These contradicting consequences of well-intentioned interventions correspond to the numerous "system surprises," well known to complex-systems scientists (Meadows 2009). Policies aimed at increasing safety may, in the case of a large event, aggravate losses. For example, such "levee effects" took place in New Orleans before Hurricane Katrina caused disastrous flooding in the city (Kates et al. 2006). More generally, efficiency does not always go hand in hand with resilience, as has been shown for road systems (Hochrainer-Stigler and Pflug 2009; Ganin et al. 2016)—which may imply social dilemmas and generate moral hazards. Focusing on resilience in the short term may also stimulate so-called erosive strategies, which—for instance, by over-exploiting present resources (Heltberg et al. 2012)—lead to medium- and long-term negative impacts on development and well-being (Keating et al. 2014).

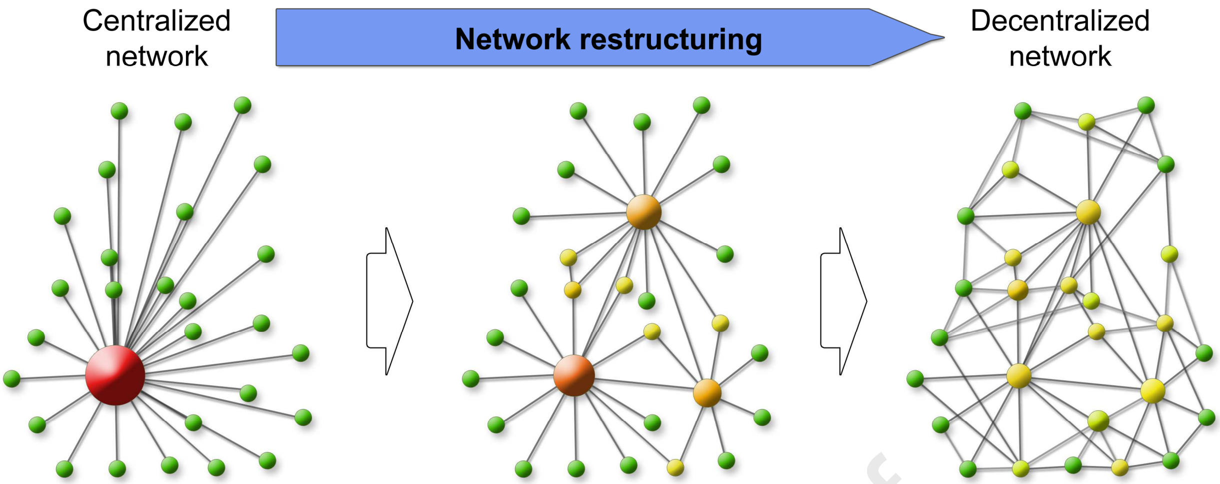

Figure 3. Reduction of systemic risk through network restructuring. System components (colored circles) are interacting (black lines) in networked systems. By reducing the connections of too-interconnected-to-fail system components (red and orange circles), a centralized network becomes decentralized, which in turn mitigates system risk.

Instead of one-size-fits-all rules of thumb, the management of systemic risks should therefore be based on a careful examination of a system's risk landscape. A promising strategy, called the node-criticality approach, is to reshape a system's network topology based on the differential contributions individual nodes make to systemic risks (e.g., Gephart et al. 2016; Colon and Ghil 2017; Colon et al., under review). This proceeds by identifying the nodes that are too big to fail, too interconnected to fail, and other type of so-called keystone nodes, whose failures are expected to trigger large ripple effects or to lead to a systemic breakdown (Paine 1969; see also the critical comments on the keystone concept by Mills et al. 1993). Interventions should then be designed to act on those nodes and reduce their criticality, without simply transferring it to other nodes. A promising application of this approach is that of Poledna and Thurner (2016), who used DebtRank to quantify the marginal contributions of individual liabilities to systemic risks in financial networks and calibrated a tax scheme that can completely eliminate systemic risks (see Figure 3, which conceptually shows the result of such an approach on a network). The resultant systemic-risk tax is a concrete policy that can increase both individual and systemic resilience (e.g., Adrian and Brunnermeier 2008; Cooley et al. 2009; Roukny et al. 2013). In other cases, more broadly-based governance approaches may be necessary (Linkov et al. 2016), which in turn might require changes in human behavior (Massaro et al. 2018) or cultural norms (see, e.g., the current "loss and damage" debate in the climate-change community; Mechler et al. 2018).

4. Integrative Management of Individual and Systemic Risks to Enhance Resilience

Our discussion above has shown that typical strategies aiming at increasing resilience differ between individual risks and systemic risks. For individual risks and under a probabilistic risk perspective, a risk-layering approach can be applied, using cumulative distribution functions and associated measures. This approach can rely on several well-established market-based instruments, including insurance and portfolio diversification. In contrast, the conceptual underpinnings of strategies for mitigating systemic risks are still being consolidated. Diversification is not always possible for reducing systemic risks. Instead, tailor-made transformational approaches are needed, which take into account the specificities of a system's network structure and on this basis push or nudge it toward safer configurations. One example we gave is the node-criticality approach, which aims to induce network restructuring based on the differential contributions of nodes to systemic risks. Individual risks and systemic risks can be seen as the two ends of a continuum (Figure 1) and therefore enhancing individual and system-wide resilience should be managed not in isolation but rather in an integrative manner (Hochrainer-Stigler et al. 2018a). A careful analysis on how system elements are interconnected in the two most extreme cases (Figure 1, no connection or fully connected) provides the basis for such an integration and for decision making.

In line with Pichler and Pflug (2018), we suggest measuring systemic risk in a system by the difference between the level of risk when accounting for nodes' interdependencies and the level of risk in a counterfactual system in which nodes are independent (Figure 1, left hand side). In the context of Figure 1, this means counterfactually disregarding secondary failures, i.e., considering a system with a systemic-risk ratio of 0. Our integrated approach would then proceed by first analyzing individual risks in the counterfactual independent scenario, using the appropriate measures shown in Table 1, and by envisioning mitigating actions, using the risk-layering approach shown in Figure 2. The performance of these actions would set a baseline level of risk reduction. Next, the added risks due to interdependencies would be assessed, using the appropriate measures shown in Table 1, and managed, using the specific strategies for systemic-risk mitigation discussed in Section 3. Doing so, using both the independent scenario (as the first step) and the interdependent scenario (as the second step), one can assess the appropriateness (Linkov and Trump 2019) of each resilience strategy for reducing both types of risks, while explicitly accounting for the inherent tradeoffs (Garnier et al. 2013; López-Espinosa et al. 2013; Yongoua Tchikanda 2017). Such an approach would enable iterations between mitigating both types of risks, which seems most appropriate for systems with high uncertainty, as exist, e.g., in climate-change management (Field et al. 2012) or insurance-system supervision (International Association of Insurance Supervisors 2018). It also clarifies the responsibilities of decision makers within a system, with risk layering being the responsibility of the individual elements while network restructuring being that of system-level decision-makers (e.g., regulators). That way, bottom-up and top-down approaches can be integrated in a seamless fashion. Summarizing our approach we suggest:

(i) **Start with a fully independent network**: Measure individual risk and resilience to determine risk of individual failures. Use the risk-layer approach to design resilience solutions. Individual elements are in charge of implementing them (bottom-up).
(ii) **Consider interdependencies**: Measure how they increase individual risks and evaluate systemic risk. Use network restructuring to design resilience policies to systemic risk, implemented by system-level decision makers (top-down).
(iii) **Integrate both approaches**: Analyze potential trade-offs between individual and system-wide resilience. Design a collaborative and iterative process to coordinate and solve these trade-offs.

It should be noted that this approach is just one possible way, among others, to move forward with the integration of individual-risk and systemic-risk research. As seen in the context of risk management under climate change, multiple approaches can usefully be integrated by using ensembles of models. Furthermore, our quantitative perspective, which is rooted in natural sciences, should be broadened to include social-science aspects. For example, Hochrainer-Stigler et al. (2019) provide new contributions on how this objective can be accomplished by using integrative, adaptive, and iterative approaches based on pluralistic methodologies, which enable processes of continuous learning, reframing, and transformation of systems in efforts to decrease systemic risks. Such and similar methods (see especially Linkov et al. 2016; Renn 2017; Florin et al. 2018) have the potential to bridge the gap between strands of research that currently are still pursued in separation (e.g., extreme-event analyses and systemic-risk analyses). As we have explained here, these strands are essentially connected and need to be approached within an integrated framework to decrease current and emerging risks to complex systems with increased effectiveness and efficiency. As suggest, from a probabilistic risk-perspective, risk layering can beneficially be integrated with network restructuring within a coherent framework to enhance and optimize resilience to both kind of risks.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: