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## Economic Modelling

journal homepage: [www.elsevier.com/locate/econmod](http://www.elsevier.com/locate/econmod)RiskRank: Measuring interconnected risk<sup>☆</sup>József Mezei<sup>c</sup>, Peter Sarlin<sup>a,b,\*</sup><sup>a</sup> Department of Economics, Hanken School of Economics, Helsinki, Finland<sup>b</sup> RiskLab Finland at Arcada University of Applied Sciences, Helsinki, Finland<sup>c</sup> School of Business and Management, Lappeenranta University of Technology, Lappeenranta, Finland

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## ABSTRACT

Given the consequences of the recent financial crisis, there is an increased interest in modelling and predicting the behaviour of complex financial systems. As a novel approach to measuring risk in networks, this paper proposes RiskRank as a general-purpose aggregation operator of risk in nodes and links. RiskRank relies on a system represented as a hierarchical network, where node values and linkages represent individual risk levels and interconnectedness, respectively. The measure is used to aggregate risk in the vein of a novel network centrality measure, allowing for the integration of the interrelations of different entities in the network with any other measure of node risk. The use of RiskRank is illustrated through a real-world case on systemic risk in Europe, in which we show that it improves performance in out-of-sample analysis. We provide an estimation of systemic risk from country-level risk indicators and combine it with cross-border linkages to illustrate the practical benefit of the proposed approach. From a policy perspective, our results strengthen the results of previous research and underline the importance of integrating a network perspective in macro-prudential analysis.

## 1. Introduction

The current financial crisis has stimulated an increased interest in modelling and predicting the behaviour of complex financial systems. A large number of this literature has focused on modeling financial systems as networks (e.g., Billio et al. (2012) and Pourkhanali et al. (2016)), while more traditional work on risk measurement focuses on individual entities (or nodes) (e.g., Lo Duca and Peltonen (2013) and Betz et al. (2014)). As a novel approach to measuring risk in networks, this paper proposes RiskRank as a general-purpose aggregation operator of risk in nodes and links. RiskRank relies on a system represented as a hierarchical network, where node values and linkages represent individual risk levels and interconnectedness, respectively. The measure is used to aggregate risk in the vein of a novel network centrality measure, allowing for the integration of the interrelations of

different entities in the network with any other measure of node risk. While the measure lends itself for measuring any interconnected risk, we focus in this paper on the case of systemic financial risk.

The literature on systemic risk measurement has evolved along two dimensions (Borio, 2011): cyclical and cross-sectional systemic risk. These two dimensions accentuate the need for modeling not only individual financial components, be they economies, markets or institutions, but also interconnectedness among them and their system-wide risk contributions (Popescu and Turcu, 2017). To this end, analytical tools and models provide ample means for two types of tasks: (i) early identification of vulnerabilities and risks, and (ii) early assessment of transmission channels of and a system's resilience to shocks. While the first task is usually tackled with early-warning indicators and models to derive a probability of a systemic crisis (e.g., Lo Duca and Peltonen (2013)), macro stress-testing models and

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contagion and spillover models provide means to assess the resilience of the financial system to a wide variety of aggregate shocks (e.g., Castrén et al. (2009)) and cross-sectional transmission of financial instability (e.g., IMF (2009)), respectively. Additionally, a large share of the literature on cross-sectional systemic risk has focused on network-based measures of interconnectedness and connectivity (e.g., Billio et al. (2012), Peltonen et al. (2015) and Minoiu et al. (2015)). The RiskRank measure proposed in this paper aims at measuring both of the two dimensions concurrently. RiskRank provides a centrality measure for networks, but goes beyond link-based centrality by also accounting for materialization probabilities (or node importance) through applying an aggregation procedure combining node values and linkages.

This paper puts forward RiskRank as a measure of interconnected risk. While focusing on systemic risk, the approach is general in nature as it applies to any type of risk that exhibits individual risk levels of components and inter linkages among components. In this paper, we put forward a framework to aggregate risk levels to system-wide vulnerability by also accounting for the size of inter linkages across the components of the system (be they economies, markets or institutions). Hence, this can also be seen as a network-based centrality measure that also accounts for node importance (i.e., risk levels). This provides nothing else than an estimation of the risk associated to a systemic event at all levels of the system, ranging from re-calculated risk at the lowest levels to aggregated risk at the highest level. In this paper, we illustrate the use of RiskRank from country-level early-warning models to connected individual and system-wide risk. While being illustrated with the case of systemic financial risk, RiskRank is applicable for measuring any connected risk.

The rest of the paper is structured as follows. Section 2 discusses systemic risk measurement and introduces aggregation operators and centrality measures, particularly with a view to systemic risk. In Section 3, we motivate and describe the modification of the general form of Choquet integral into the RiskRank measure and discuss its most important features and use scenarios. Section 4 presents the application of the RiskRank to the case of European systemic risk. Finally, we present some conclusions in Section 5.

## 2. Measuring systemic risk: a synthesis

To quantify systemic risk, there is a broad toolbox of models available for measuring and analyzing system-wide threats to financial stability. In the following, we disentangle the topic of systemic risk based on the cyclical and cross-sectional dimensions. While assigning probabilities to events aims at ranking individual risks and vulnerabilities as per intensity (i.e., tasks of early-warning models), assessing the effect of an event complements by modeling transmission channels and quantifying losses given their materialization. This accentuates the need for modeling not only the likelihood of a distress event  $p_i^t$  in time  $t$  for entity  $i$ , but also system-wide importance by accounting for interconnectedness and other types of transmission channels  $m_{ij}^t$  between entities  $i$  and  $j$  at time  $t$ .

This section discusses the literature on systemic risk analysis, particularly the two strands of literature on cyclical and cross-sectional systemic risk. Additionally, we motivate the need for a general-purpose approach for joining the two strands. Furthermore, we discuss the role played by aggregation procedures in systemic risk analysis, and the particular features of existing approaches that can be potentially addressed by the use of aggregation procedures.

### 2.1. Systemic risk models

Broadly speaking, tools and models are generally tasked with early identification of systemic risk and early assessment of systemic risk. Within the cyclical and cross-sectional dimensions, ECB (2010) provides a mapping of tools to the following three forms of systemic risk: (i) early-warning models, (ii) contagion and spillover models, and (iii) macro stress-testing models.

#### 2.1.1. Cyclical systemic risk

The first form of systemic risk focuses on the unraveling of widespread imbalances and is illustrated by a thorough literature on the presence of risks, vulnerabilities and imbalances in banking systems and the overall macro-financial environment prior to historical financial crises. Early and later empirical literature alike have identified common patterns in underlying vulnerabilities preceding financial crises (see, e.g., Reinhart and Rogoff (2008)).

By focusing on the presence of vulnerabilities and imbalances in an economy, early-warning models can be used to derive probabilities of the occurrence of systemic financial crises in the future (e.g., Alessi and Detken (2011) and Lo Duca and Peltonen (2013)). These models use a set of vulnerability and risk indicators to identify whether or not an economy is in a vulnerable state. The outputs of such models mostly take the form of a probability of a crisis within a specific time horizon and are monitored with respect to threshold values. Hence, this provides us a probabilities of crisis  $p_i^t$  in time  $t$  for entity  $i$ , where entities may be economies, markets or institutions, but does not provide information about the potential interrelations and their consequences among individual entities. Typical methods used in early-warning models include logistic models (e.g., Lo Duca and Peltonen (2013)) and machine learning (e.g., Holopainen and Sarlin (2015)).

#### 2.1.2. Cross-sectional systemic risk

The second type of systemic risk refers to two types of models for measuring the cross-sectional dimension. Macro stress-testing models provide means to assess the resilience of the financial system to a wide variety of aggregate shocks, such as economic downturns (e.g., Castrén et al. (2009) and Hirtle et al. (2009)). These models allow policy-makers to assess the consequences of assumed extreme, but plausible, shocks for different entities. The key question of macro stress-testing is to find the balance between plausibility and effect of the stress scenarios such that they are plausible enough to be taken seriously and significant enough to be meaningful (e.g., Alfaro and Drehmann (2009) and Quagliariello (2009)). Contagion and spillover models can be employed to assess how resilient the financial system is to cross-sectional transmission of financial instability (e.g., IMF (2009)). Hence, they attempt to answer the question: With what likelihood, and to what extent, could the failure of one or multiple financial intermediaries cause the failure of other intermediaries? Accordingly, this line of work provides information on system-wide importance by accounting for interconnectedness and other types of transmission channels  $m_{ij}$  between each entity  $i$  and all other entities  $j$ . Yet, this provides little information on the likelihood of individual entities being distressed.

Another type of cross-sectional systemic risk refers to a widespread exogenous aggregate shock that has negative systematic effects on one or many financial intermediaries and markets at the same time. These types of aggregate shocks have empirically been shown to co-occur with financial instabilities (see, e.g., Gorton (1988)). An example of such an event is the collapse of banks during recessions due to the vulnerability to economic downturns. The third form of systemic risk is contagion and spillover, which usually refers to an idiosyncratic problem, be it endogenous or exogenous, that spreads in a sequential fashion in the

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