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Computing systemic risk using multiple behavioral and keystone networks: The emergence of a crisis in primate societies and banks[☆]

Hsieh Fushing[a,*], Òscar Jordà[b,c,*], Brianne Beisner[d], Brenda McCowan[d]

[a] Department of Statistics, University of California, Davis, United States

[b] Federal Reserve Bank of San Francisco, United States

[c] Department of Economics, University of California, Davis, United States

[d] International Institute for Human-Animal Networks, Department of Population Health & Reproduction, School of Veterinary Medicine, California National Primate Research Center, University of California, Davis, United States

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ABSTRACT

What do the behavior of monkeys in captivity and the financial system have in common? The nodes in such social systems relate to each other through multiple and keystone networks, not just one network. Each network in the system has its own topology, and the interactions among the system's networks change over time. In such systems, the lead into a crisis appears to be characterized by a decoupling of the networks from the keystone network. This decoupling can also be seen in the crumbling of the keystone's power structure toward a more horizontal hierarchy. This paper develops nonparametric methods for describing the joint model of the latent architecture of interconnected networks in order to describe this process of decoupling, and hence provide an early warning system of an impending crisis.

1. Introduction

Humanity is becoming increasingly interconnected. This interconnectivity has clear benefits, such as food security, technological innovation, and rapid information exchange. However, an increased connectivity can introduce vulnerabilities of its own—a common feature of complex systems. These vulnerabilities are such that they can sometimes threaten the integrity of the entire network directly. Examples include catastrophic failures, such as stock market crashes; the rapid propagation and dissemination of adverse entities, such as disease outbreaks or internet viruses; and the concentration of key resources around central hubs or clusters, such as oil in OPEC countries, or rare earth minerals in China. This paper introduces nonparametric methods for detecting the build-up of these vulnerabilities empirically. The objective is to provide an early warning system that can be used to prevent a crisis from breaking out.

Social network analysis has become a natural tool for modeling a variety of complex dynamic systems (see, e.g., the special issue on "Complex Systems Networks" in Science, 2009). Although there is no generally accepted definition, it seems fair to say that a system is complex when there are emergent phenomena that are the spontaneous outcome of the interactions of many constituent elements (see for example Amaral & Barthelémy, 2003; Amaral & Ottino, 2004; Barabási, 2005). Network theory is designed to

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* Corresponding authors.
E-mail addresses: fhsieh@ucdavis.edu (H. Fushing), Oscar.Jorda@sf.frb.org (Ò. Jordà).

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reveal the hidden architecture of complex systems (Simon, 1962) and the candidate sources of a network's instability. When paired with computational statistics, this theory can be used to detect the early formation of network vulnerabilities empirically. Ultimately, the objective is not only to identify these network vulnerabilities and prevent them from materializing, but also to design more resilient structures that maximize social welfare and minimize the costs of increased connectivity. Therefore, the concept of a network's *resilience* has received a considerable amount of attention and is related to the literature on *percolation* in complex directed networks (see e.g. Boguñá & Serrano, 2005; Dorogovtsev & Mendes, 2001; Newman, Strogatz, & Watts, 2001; and Schwartz, Cohen, ben Avraham, Barabási, & Havlin, 2002).

The recent Global Financial Crisis laid bare some of these vulnerabilities, and in its aftermath, considerable research effort has been dedicated to understanding its causes. Research focusing on network theory has appeared particularly promising (see for example Haldane & May, 2011; and May & Arinaminpathy, 2010). Initially, financial crises were characterized as being the result of exogenous shocks that propagate through a static network. More recently, the literature has evolved to incorporate endogenous tuning factors that allow for richer and more realistic dynamics of network propagation (see for example Arinaminpathy, Kapadia, & May, 2012).

The structures of the social systems that we investigate are characterized by nodes that relate to each other through multiple networks. Each network has its own topology, and the networks are related to each other in varying degrees. Moreover, we distinguish between the *keystone* network and the subsidiary networks. The keystone network is most closely associated with the hierarchy prevailing among the nodes in the social system.

It is important to recognize that a network's topology is often endogenous, and, as a consequence, is dynamic rather than static. The connections across networks are dynamic as well. Importantly, a network's global characteristics can be very sensitive to local perturbations, especially in directed networks. A theoretical model of a social system with these characteristics is difficult to construct. In this paper, we argue that certain features of social systems can be determined using data-driven, nonparametric-based methods—a natural complement to existing methods which are based on a more structural approach.

One basic assumption of our analysis is that information is available to all nodes in a social system equally. One important reason to entertain such an assumption is in order to give more weight to endogenous mechanisms that generate phase transition dynamics. Assuming that nodes have a heterogeneous access to information tends to place more weight on exogenous factors as an explanation for phase transition dynamics, thus inherently explaining these transition dynamics outside the system.

The assumption that information is available to all nodes equally is certainly justifiable in the context of the two systems investigated here. However, although we assume that all nodes have an equal access to information, we allow the nodes to have heterogeneous information processing capabilities. This heterogeneity leads to the formation of asymmetric and diverse hierarchical structures, and this diversity in turn becomes an endogenous source of tension and a natural source of instability.

The non-parametric methods that we discuss are applied to a primate social system (a large captive group of rhesus macaques), which are observed under both stable and unstable states or phases. This set-up has many points of commonality with the architecture of a banking system. We argue that the mechanics of systemic risk propagation in a monkey social system which is on the brink of *social collapse* are comparable to those in a banking system on the brink of a *financial crisis*.

Admittedly, comparing rhesus macaques to a financial system is unconventional. However, we believe that readers will find this comparison compelling. The fundamental mechanisms underlying the instabilities in these two systems are, in fact, quite similar. Small-scale models of social systems can be quite effective when thinking about models which are applicable to larger human systems (in both scope and scale). Our methods show one approach that could be scaled up in order to model the vulnerabilities of the financial system.

2. Systemic risk propagation: When multilayered networks decouple under primary network collapse

The broad outline of the methods that we describe below can be sketched in a few sentences. We assume that the nodes in the system under consideration all have an equal access to information. However, we also assume that the nodes each have different information processing abilities. This way of introducing heterogeneity is computationally convenient and leads to the endogenous formation of a power structure within the system. The nodes are related to each other in a variety of different ways. Each results in a different network within the system. In normal times, the hierarchical structure of the system results in a natural pattern of network interactions. However, a degradation of the power structure results in a degradation of the relationships across networks, or decoupling. During a crisis, the power structure collapses and the system's networks decouple. The endogenous dynamics of the system in the aftermath of the crisis are quite different from those before the crisis strikes. However, it is difficult to predict when a crisis will arise based solely on observations of the behaviors of the individual networks in the system in isolation. Instead, we argue that one can detect when a crisis is likely to set in by modeling the evolution of the degree of decoupling across the system's networks.

Consider two features of a dynamic system which are relevant for our analysis: (1) the *power structure* of the primary network; and (2) the assumption of *global collection of local* (GCL) information. The power structure characterizes the major flow of information through network connectivity characteristics. It is determined endogenously as the system evolves over time. The GCL information assumption means that each node in the system has an equal access to information that may be local to any given node. The heterogeneity in node-specific information processing abilities leads to the formation of vertical hierarchies within the system—a power structure.