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Beyond the power law: Uncovering stylized facts in interbank networks

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HIGHLIGHTS

- Interbank measures are heavy-tailed.
- Evidence for power-law behavior in tail is not strong.
- Lognormal and stretched exponentials can fit the entire distributions of the interbank network measures.
- Robust for time-aggregation and distinctive phases.

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ABSTRACT

We use daily data on bilateral interbank exposures and monthly bank balance sheets to study network characteristics of the Russian interbank market over August 1998–October 2004. Specifically, we examine the distributions of (un)directed (un)weighted degree, nodal attributes (bank assets, capital and capital-to-assets ratio) and edge weights (loan size and counterparty exposure). We search for the theoretical distribution that fits the data best and report the "best" fit parameters.

We observe that all studied distributions are heavy tailed. The fat tail typically contains 20% of the data and can be mostly described well by a truncated power law. Also the power law, stretched exponential and log-normal provide reasonably good fits to the tails of the data. In most cases, however, separating the bulk and tail parts of the data is hard, so we proceed to study the full range of the events. We find that the stretched exponential and the log-normal distributions fit the full range of the data best. These conclusions are robust to (1) whether we aggregate the data over a week, month, quarter or year; (2) whether we look at the "growth" versus "maturity" phases of interbank market development; and (3) with minor exceptions, whether we look at the "normal" versus "crisis" operation periods. In line with prior research, we find that the network topology changes greatly as the interbank market moves from a "normal" to a "crisis" operation period.

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1. Introduction

The frequency of an event follows a power law when that frequency varies as a power of some attribute of that event (e.g. its size). Power-law distributions have been claimed to occur in an extraordinarily diverse range of phenomena from the sizes of wars, earthquakes and computer files to the numbers of papers scientists write and citations those papers receive [1]. In economics and finance, power laws have been documented for income and wealth [2], the size of cities and firms, stock market returns, trading volume, international trade, and executive pay [3].

Most relevant to this paper, the tail parts of interbank network characteristics, such as degree distribution, have been shown to follow a power law too (see Ref. [4] for Brazil, [5,6] for Austria, [7] for Japan, and [8] for the commercial banks in the US). This ubiquitous presence of power laws has resulted in an extensive search for universal dynamics that can explain their existence (see Refs. [9,10] for examples of such search in interbank networks).

Recently, however, Clauset et al. [11] (followed by Ref. [12]) call these findings into question. In particular, they criticize the commonly used methods for analyzing power-law data, such as least-squares fitting, which can produce inaccurate estimates of parameters for power-law distributions or provide no indication of whether the data obey a power law at all. Clauset et al. propose a statistical framework for discerning and quantifying power-law behavior in empirical data and apply that framework to twenty-four real-world datasets, each of which has been conjectured to follow a power law. For most datasets they find moderate to weak evidence in favor of power laws.

This debate about the potential of power laws to capture the underlying network dynamics is important for economic policy. For example, during the recent financial crisis, the interbank lending market was one of the most important channels of financial contagion. The malfunctioning of the interconnectivity of the interbank lending network, caused a liquidity drought with consequences reverberating throughout the entire economy. Since then, interbank markets research has proliferated. In those studies one wishes to uncover the network topology of interbank markets, to understand how they function, and how they could catalyze a systemic meltdown [13,14]. Current research on contagion in interbank markets often relies on a scale-free topology to simulate the interbank network [15,16]. This choice likely affects the outcome of conducted stress tests (as is explicitly confirmed by Ref. [16]) and, therefore, the policy implications stemming from them. Yet the evidence supporting this choice is not ironclad. Understanding the properties of the tail is crucial to understand shock propagation in dynamic networks. The authors of Refs. [17,18], among others, find that only a small fraction of possible network structures may spread relatively sizable contagion losses across the system, thus highlighting the non-linear nature of shock propagation effects and stressing that contagion is to a considerable extent a tail risk problem.

This paper contributes to the debate by providing a detailed analysis of the network characteristics of a real interbank network over an extended period of time. We use daily data on bilateral interbank exposures and monthly bank balance sheets to study network characteristics of the Russian interbank market over August 1998–October 2004. Among other things, the analysis allows one to determine the theoretical distributions of connectivity among banks via interbank loans, crucial to assess efficiency and stability of the Russian interbank market. We focus on measures that represent essential input for most of the interbank contagion simulations. Specifically, we examine the distributions of (un)directed (un)weighted degree, nodal attributes (bank assets, capital and capital-to-assets ratio) and edge weights (loan size and counterparty exposure). Using the methodology of Ref. [11] we set up a horse race between the different theoretical distributions to find one that fits the data best. We then study the time evolution of the best-fit parameters.

We observe that all studied distributions are heavy tailed. The fat tail typically contains 20% of the data and can be systematically described by a truncated power law. In most cases, however, separating the bulk and tail parts of the data is hard, so we proceed to study the full range of the events. We find that the stretched exponential and the log-normal distributions fit the full range of the data best. Our conclusions turn out to be robust to whether we aggregate the data over a week, month, quarter or year. Further, we find no qualitative difference between the "growth" and "maturity" phases of interbank market development and little difference between the "crisis" and "non-crisis" periods.

Section 2 describes our data, defines the network measures we study, and summarizes the conclusions from previous studies of those measures. Sections 3 and 4, respectively, describe and illustrate the methodology we use to find the theoretical distribution that fits the data best. Section 5 reports the results. Section 6 concludes.

2. Data and definitions

2.1. Data source

Mobile, a private financial information agency, provided us with two datasets for the period August 1998–October 2004.[1] The information in the datasets is a part of standard disclosure requirements and is supplied to the regulator on a monthly basis. The first dataset, described in Ref. [19], contains monthly bank balances for most Russian banks. From this dataset we take two variables: total assets and capital. The second dataset contains monthly reports "On Interbank Loans and Deposits" (official form's code 0409501) and represents a register of all interbank loans issued in the Russian market. For each loan we know its size, interest rate, issuer, receiver, reporting date and maturity date. On average, about half of the Russian banks are

[1] For more information on the data provider see its website at www.mobile.ru.

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