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On the topologic structure of economic complex networks: Empirical evidence from large scale payment network of Estonia

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ABSTRACT

This paper presents the first topological analysis of the economic structure of an entire country based on payments data obtained from Swedbank. This data set is exclusive in its kind because around 80% of Estonia's bank transactions are done through Swedbank; hence, the economic structure of the country can be reconstructed. Scale-free networks are commonly observed in a wide array of different contexts such as nature and society. In this paper, the nodes are comprised by customers of the bank (legal entities) and the links are established by payments between these nodes. We study the scaling-free and structural properties of this network. We also describe its topology, components and behaviors. We show that this network shares typical structural characteristics known in other complex networks: degree distributions follow a power law, low clustering coefficient and low average shortest path length. We identify the key nodes of the network and perform simulations of resiliency against random and targeted attacks of the nodes with two different approaches. With this, we find that by identifying and studying the links between the nodes is possible to perform vulnerability analysis of the Estonian economy with respect to economic shocks.

1. Introduction

The network approach applied to financial and economic systems has potential to go further on the frontiers of research; there are two currents of origin: one comes from finances, economics and sociology, and the second one comes from computer science, big data challenges, physics, and complex evolving network studies [1]. Both converge in how node representation is done and how the relationships and interactions across the nodes form, whatsoever the nature of these links are. This is an intuitive path that starts to follow the approach that fusions economy and complex systems studies.

Nowadays, networks are a central concept and they can be: biological, technological, economic, social, cultural, among other types. The physical approach has made significant effort during the recent years around the study of evolution and structure of networks [2–9] while some other works have been dedicated to certain network phenomena and specific properties [10,11].

Since the structure of a network has direct influence on the vulnerability and dynamic behavior of the underlying system, important network properties such as stability and robustness can be understood by analyzing the clustering coefficient, the degree distribution and by determining the

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average shortest path length between nodes in the network [12,13].

In networks, the degree distribution *P(k)* is the probability that a node links to k number of nodes. Complex networks can be separated into two classes based on their degree distributions:

(1) Homogeneous networks are identified by degree distributions that follow an exponential decay. The distribution spikes at an average k and then decays exponentially for large values of k, such as the random graph model [14,15] and the small-world model [4], both leading to an homogeneous network: in which each node has approximately the same number of links k and a normal distribution where the majority of the nodes has an average number of connections, and only some or none of the nodes have only some or lots of connections.

(2) Heterogeneous large networks or scale-free networks, are those for which *P(k)* decays as a power law with a characteristic scale. The degree distribution follows a Pareto form of distribution where many nodes have few links and few nodes have many links, therefore, highly connected nodes are statistically significant in scale-free networks.

Network topology gives a fair basis for investigating money flows of customer driven banking transactions. A few recent papers describe the actual topologies observed in different financial systems [13,16–19]. Other works have focused on shocks and robustness in economic complex networks [20,21–24].

Scale-free networks display a strong tolerance against random removal of nodes [14] whereas exponential networks not (this means an exponential network can break easily into isolated clusters). Scale-free networks are more resistant to random disconnection of nodes because one can eliminate a considerable number of nodes randomly and the network's structure is preserved and will not break into disconnected clusters. However, the error tolerance is acquired at the expense of survival attack capability. When the most connected nodes are targeted, the diameter of a scale-free network increases and the network breaks into isolated clusters. This occurs because when removing these nodes, the damage disturbs the heart of the system, whereas a random attack is most likely not. One way to entangle the interaction of the nodes is by taking a look to the heavy tail effects they produce and see the implications on their robustness. Heavy-tailed distributions are strong against random perturbations but are extremely sensitive to targeted attacks.

Unlike previous studies, we illustrate the topology of an unstudied complex system that can be analyzed as a particular case of a complex network: Estonia's network of payments. We study the full country economic development, found on Swedbank's data as a proxy. The main goal of our analysis is to study the structure of this economic network. Additionally, this data set is unique given the fact that around 80% of Estonia's bank transactions are done through Swedbank, hence it is expected to reproduce fairly well the structure of the Estonian economy.

This paper is organized as follows. In Section 2 we provide the description of the selected data and the methods utilized; Section 3 is devoted to the discussion of the results and Section 4 concludes the study.

2. Materials and methods

2.1. Data

Payment events data from Swedbank AS were used to create the network. Data and information related to identities of the nodes will remain confidential and cannot be disclosed. We believe the utilized data describes fairly well the tendencies of money transactions and is the best possible information available.

The considered dataset corresponds to year 2014. We analyze the network of the payment flows of Swedbank (Estonia), specifically: domestic payments transferred electronically from customer to customer (legal entities). There are 16,613 nodes and 2,617,478 payment transactions in the network. There are 43,375 links if we count them as undirected.

A network (or a graph) is a set of nodes connected by links. The links are the connections between the nodes. In our network, the nodes are the companies and a link is established from one node to another if at least 20 payments were executed, or more than 1000 money units were paid/received per year. When there is a link from a node to itself, it is called a loop. We eliminated loops resulting from parties making money transfers across their own bank accounts.

There are several ways to define the network of payments; in this study we consider three definitions. The first definition is to look at the structure as a weighted graph where the links have certain weights associated to them representing less or higher important relationships with the nodes. Transactions between any two parties add to the associated link weights in terms of value of payments settled. In this representation we built a payment adjacency matrix that represents the whole image of the network and each element represents the overall money flow traded between companies i and j. This non-symmetric matrix represents the weights of the volumes of money exchanged between the companies.

The second definition is to consider an undirected graph, ignoring directions and weights of the payments and considering that two parties are connected if they share at least one payment, then $a^u_{ij} = a^u_{ji}$ and $a^u_{ij} = 1$ if there is a transaction between company i and j or $a^u_{ij} = 0$ if there is no transaction between them. Diagonal elements are equal to 0 and non-diagonal elements are either 0 or 1.

The links can also represent directions on the flow of the relationship. They could be directed or undirected. The third definition is a un-weighted-directed graph where the links follow the flow of money, such that a link is incoming to the receiver and outgoing from the sender of the payment. For this case we have two more matrices, one for the in-degree case and another one for the out-degree case. The choice of the definition of the matrix representation depends on the focus of the analysis.