Physica A 415 (2014) 43–53

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Systemic risk and causality dynamics of the world international shipping market

Xin Zhang [a,*], Boris Podobnik [b,c,d,e], Dror Y. Kenett [b], H. Eugene Stanley [b]

[a] College of Transport and Communication, Shanghai Maritime University, Shanghai 201306, China
[b] Center for Polymer Studies and Department of Physics, Boston University, Boston, MA 02215, United States
[c] Faculty of Civil Engineering, University of Rijeka, 51000 Rijeka, Croatia
[d] Zagreb School of Economics and Management, 10000 Zagreb, Croatia
[e] Faculty of Economics, 1000 Ljubljana, Slovenia

HIGHLIGHTS

- We study the temporal correlation networks of the world shipping market over time.
- We model the systemic risk level of the shipping market based on the Dynamic Causality Index.
- We explore directional connections between the shipping market and the financial market.
- Different market sectors tend to link and comove closely during financial crisis.
- The Dynamic Causality Index can provide efficient warning before market downturn.

ARTICLE INFO

Article history:
Received 10 July 2014
Received in revised form 22 July 2014
Available online 2 August 2014

Keywords:
Complex networks
Systemic risk
Correlation networks
Brownian distance
Granger causality test

ABSTRACT

Various studies have reported that many economic systems have been exhibiting an increase in the correlation between different market sectors, a factor that exacerbates the level of systemic risk. We measure this systemic risk of three major world shipping markets, (i) the new ship market, (ii) the second-hand ship market, and (iii) the freight market, as well as the shipping stock market. Based on correlation networks during three time periods, that prior to the financial crisis, during the crisis, and after the crisis, minimal spanning trees (MSTs) and hierarchical trees (HTs) both exhibit complex dynamics, i.e., different market sectors tend to be more closely linked during financial crisis. Brownian distance correlation and Granger causality test both can be used to explore the directional interconnectedness of market sectors, while Brownian distance correlation captures more dependent relationships, which are not observed in the Granger causality test. These two measures can also identify and quantify market regression periods, implying that they contain predictive power for the current crisis.

1. Introduction

It is widely acknowledged that economic systems are highly complex. In recent years they have become a subject of much interest among both economists and physicists [1–12]. Because the international shipping industry facilitates 90% of world trade and is a key factor in global economic development [13] it is a major topic for economic theory. The shipping industry

* Corresponding author.
E-mail addresses: zhangxin@shmtu.edu.cn, sivaxin@bu.edu (X. Zhang).

http://dx.doi.org/10.1016/j.physa.2014.07.068
0378-4371/

is tightly linked to the world economy and to the international trade business cycle; thus it enjoyed a long prosperous period with growing trade at the international level until the financial crisis in 2008. Since then the shipping industry has faced idle capacity, huge losses, and risk of bankruptcy [14]. The shipping industry is also dynamic and volatile. The Baltic capsize index (*BCI*), which measures the volatility in shipping markets, is significantly higher (≈79%) than the average volatility in commodity markets (≈50%) and equity markets (e.g., S&P500 ≈ 20%) [15]. This extremely high risk is not only due to volatility in global economic cycles, but also is highly influenced by intrinsic characteristics of the shipping industry itself. The shipping industry comprises several separate but closely connected markets including the new ship, the second-hand ship, and the freight markets. Each of these markets comprises several tightly integrated sub-sectors according to ship type: oil tanker, dry bulk carrier, and container carrier. Oil tanker is designed for the bulk transport of oil and tankers are generally categorized by size from smallest to largest, e.g., Panamax, Aframax, Suezmax, VLCC and UVLCC. Dry bulk carrier is mainly used to transport dry bulk cargo, such as iron ore, grain and coal. Similar to oil tanker dry bulk ship also can be classified by size into Handysize, Handymax, Panamax, Super-Panamax and VLOC. Dry bulk shipping provides an economical and convenient way to transport three major raw materials to support the world industry. Container shipping provide transportation of containerized goods over sea via regular linear services. According to ship size, container vessel from smallest size to largest one also includes Handymax, Panamax, Post-Panamax and Large Container Vessel.

Despite the economic importance of the shipping industry, there are surprisingly few studies about shipping industry risk. Studies of systemic risk in the shipping industry tend to fall into three categories. The first category uses a linear or non-linear stochastic model and focuses on freight rate returns and the volatility of some specific submarkets in the shipping industry [16–18]. The second category focuses on asset bubbles caused by the supercycle of the shipping industry and determines how much asset values in the second-hand market deviate from underlying fundamentals [19,20]. The third category identifies factors affecting the performance of shipping industry stocks in order to understand the linkage between the real shipping market and financial markets [21,22]. Most previous studies focus on individual segments of the shipping industry and not the industry as a whole. Thus these studies ignore the interactions among different market sectors that are likely to compound systemic risk.

In this paper we use the correlation-based network and the causality measures to examine the structure and dynamics of the shipping industry. We begin our analysis by using the minimal spanning tree (MST) and the hierarchical tree (HT) to examine the topology of correlation networks among different submarkets and ship types of the shipping industry during the pre-crisis, crisis, and post-crisis periods. Then we use a causality analysis based on Granger-causality and Brownian distance correlation to explore the directional connections between the physical market and the financial market of the shipping industry before, during, and after the financial crisis.

2. Methods

2.1. Network topology

Using the minimal spanning tree (MST) and hierarchical tree (HT), we study the structure and dynamics of the shipping industry and explore the hierarchical structure of various time series. Hierarchical structure methods have been introduced in finance to ascertain the structure of asset price influences within a market [23–28], but application of this method is not limited to financial markets, and we extend the method to time series in other economic systems [29–32].

The minimal spanning tree (MST) is a graph of a set of elements in the node arrangement in a given metric space, e.g., an ultrametric space [23]. In the MST the taxonomy displays meaningful clusters, and it reduces the noise in a historical correlation matrix [33].

A hierarchical tree is an important tool for data clustering. It partitions a dataset into subsets (clusters) such that the data in each subset share some common traits—often similarity or proximity at some defined distance. In our case, the construction of an ultrametric hierarchical tree structure allows us to determine the hierarchical structure of a network [34].

Both MST and HT require that a metric distance be defined. Because the definition of correlation does not fulfill the three axioms that define a metric, Mantegna [23] introduced a definition of distance,

$$\rho_{ij} = \frac{\langle Y_i Y_j \rangle - \langle Y_i \rangle \langle Y_j \rangle}{\sqrt{(\langle Y_i^2 - \langle Y_i^2 \rangle \rangle)(\langle Y_j^2 - \langle Y_j^2 \rangle \rangle)}}, \tag{1}$$

where $\langle \cdots \rangle$ denotes the mean. For each time series vector, we calculate the monthly return, defined as the change of logarithmic price of time series $Y_i(t) = \log(P_t) - \log(P_{t-1})$ and P_t is the value of a time series at time t. Here we use the absolute value of the Pearson correlation coefficient to define the distance between two time series as [9]

$$d_{ij} = \sqrt{2(1 - |\rho_{ij}|)}. \tag{2}$$

The distance d_{ij} fulfills the three axioms of a metric: (i) $d_{ij} = 0$ if and only if $i = j$, (ii) $d_{ij} = d_{ji}$, and (iii) $d_{ij} \leq d_{ik} + d_{kj}$ [9]. We then use the distance matrix d_{ij} to determine the minimal spanning tree (MST). An MST is defined as the set of $n - 1$ links that connects a set of elements across the smallest possible total distance. The determination of the hierarchical tree of a subdominant ultrametric is thus completely controlled by the ultrametric distance matrix.