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Systemic risk and causality dynamics of the world international shipping market

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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.

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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

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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,

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

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]

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

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) $d_{ij} \le d_{ik} + d_{kj}$ [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.

2.2. Granger causality analysis

To investigate the dynamic systemic risk, we must measure both the degree of interconnectedness between the subsectors of the shipping industry and the direction of these relationships [35–37]. To this end, using Granger causality analysis we propose a statistical definition of causality based on the relative forecasting power of two series. Specifically, let R_t^i and R_t^j be two stationary time series, and for simplicity we assume they both have zero mean. We can represent their linear inter-relationships using the model [38,39]

$$R_{t+1}^i = a^i R_t^i + b^{ij} R_t^j + e_{t+1}^i, \tag{3}$$

$$R_{t+1}^j = a^j R_t^j + b^{ji} R_t^i + e_{t+1}^j, \tag{4}$$

where e_{t+1}^i and e_{t+1}^j are two uncorrelated white noise processes. The definition of causality implies that R_t^j causes R_{t+1}^i when b^{ij} is statistically significant from zero. Likewise, R_t^i causes R_{t+1}^j when b^{ji} is statistically significant from zero. When both b^{ij} and b^{ji} are statistically significant from zero, there is a feedback relationship between the two time series. In practice, the causality is based on the F-test where the null hypothesis is defined such that coefficients a^i and a^j are equal to zero.

We analyze the pairwise Granger causality between the t and $t+1$ monthly returns of the shipping physical market and the shipping stock market. We follow the definition of the dynamic causality index (DCI) [40] series,

$$L_{DCI}(t) = \frac{\text{number of causal relationships over a given period}}{\text{total possible number of causal relationships}}. \tag{5}$$

2.3. Brownian distance

Distance correlation is a new approach proposed by Székely and Rizzo to measure statistical interdependence between two random vectors of arbitrary, not necessarily equal dimension [41]. Brownian distance covariance captures the non-linear dependence, which make up deficiency of the classical measure of dependence, such as the Pearson correlation coefficient, that is mainly sensitive to a linear relationship between two variables [41].

According to the basic definition of distance correlation, Brownian covariance $(\upsilon(X, Y))$ between $f_X f_Y$ and $f_{X,Y}$ is obtained as the square root of $\upsilon^2(X, Y) = \|f_{X,Y}(t, s) - f_X(t) f_Y(s)\|^2$ where $\|\cdot\|$ is the joint characteristic function of X and Y. Brownian covariance is based on Brownian motion or Wiener process with an important property that $\upsilon(X, Y) = 0$ if and only if X and Y are independent [42]. The Brownian covariance is equal to the distance covariance. The distance correlation $R(X, Y)$ can be defined from the following expression:

$$R^2 = \begin{cases} \dfrac{\upsilon^2(X, Y)}{\sqrt{\upsilon^2(X)\upsilon^2(Y)}}, & \upsilon^2(X)\upsilon^2(Y) > 0. \\ 0, & \upsilon^2(X)\upsilon^2(Y) = 0. \end{cases} \tag{6}$$

In this paper we utilize Brownian distance correlation between current value of time series Y_t and l lagged value of another time series vector X_{t-l} exploring then the non-linear causality effect. In general, if $R(X_{t-l}, Y_t) \neq 0$ and $l > 0$, then X_{t-l} leads the series Y_t. Additionally, if $R(X_{t-l}, Y_t) \neq 0$, $R(X_t, Y_{t-l}) \neq 0$, and $l > 0$, there is a unidirectional relationship between X and Y.

3. Data

We investigate two datasets. Dataset I comprises the prices of the real shipping market. Dataset II comprises the stock prices of publicly-listed shipping companies. For the shipping market we select 45 monthly price indicator series for the time period from January 2003 to June 2013, provided by world leading shipping database Clarksons. The dataset includes three shipping markets, the new ship market, the second-hand ship sale and purchase market, and the world-wide chartering market. For each market we use price indicators according to ship type, oil tankers, container carriers, and bulk carriers. The New-building ship market price indicators investigated are shown in Table 1. The Secondhand ship market price indicators are shown in Table 2. The freight rates are shown in Table 3.

We also select 40 publicly-listed shipping companies to represent the shipping financial market. The sample includes the oil tanker, container carrier, and bulk carrier industry as well as the ship-building industry. The monthly closing price of each stock is recorded from January 2003 to June 2013, provided by Yahoo Finance.

4. Real shipping market hierarchical structure

In this section, using 45 physical shipping market price indicators, we present the MSTs and the HTs, and investigate the topology and structure of the correlation networks in the shipping market. We find that MSTs and HTs both show

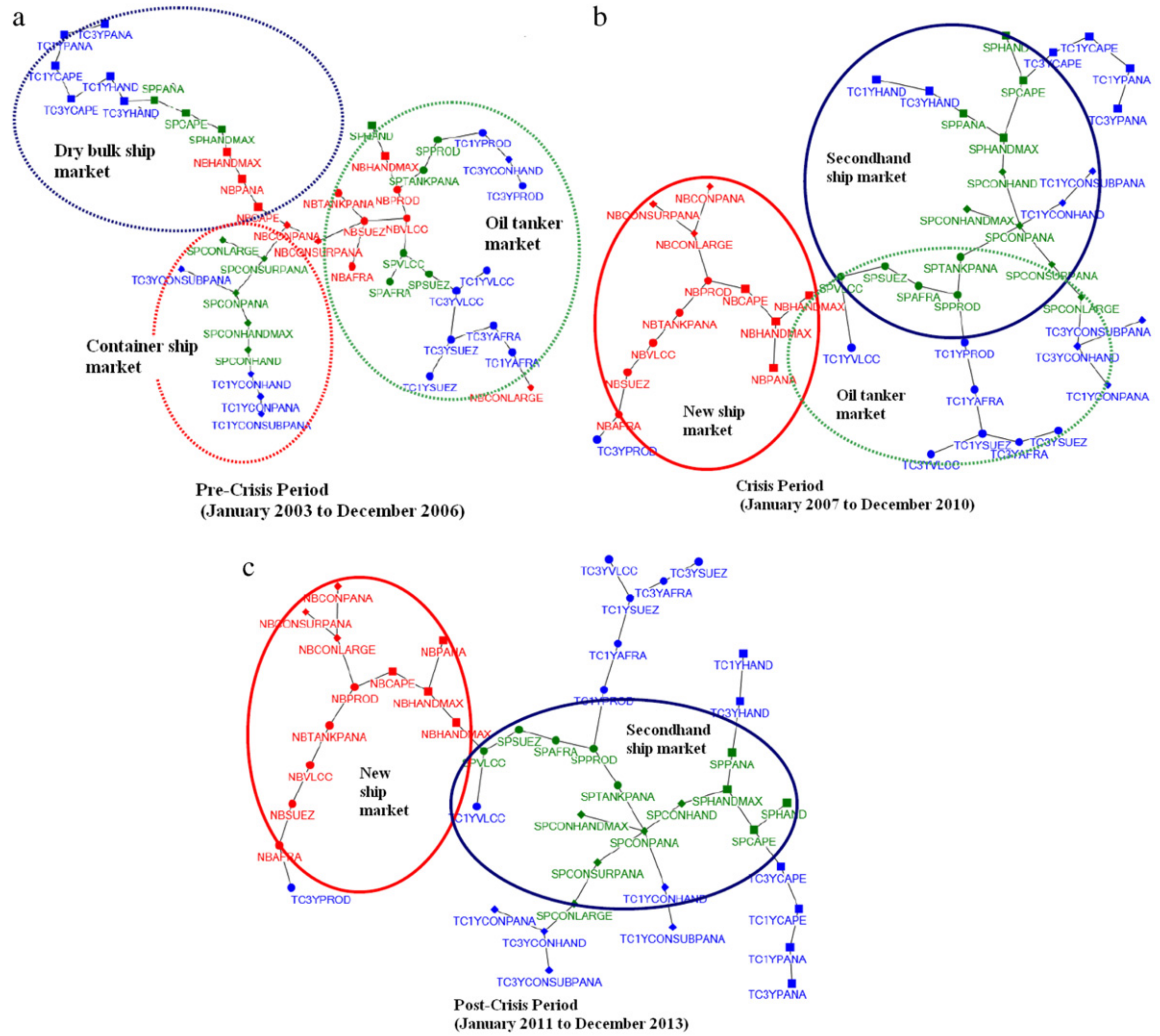

Fig. 1. Minimal spanning tree of the shipping market. Red indicates the new-building ship market, green indicates the second-hand ship sale and purchase market, blue indicates the freight market. Solid cycle represents oil tanker, solid square represents dry bulk ship and solid diamond represents container ship. (a) Pre-Crisis period (January 2003–December 2006). (b) Crisis period (January 2007–December 2010). (c) Post-Crisis period (January 2011–June 2013). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

significantly different structures in three periods: prior to the financial crisis, during the crisis, and after the crisis. Notice that prior to the financial crisis (see Fig. 1(a)), the three groups are easily identified, the container ship market (red dash line circle), dry bulk ship market (blue dash line circle), and oil tanker market (green dash line circle). Inside each group, we find that newly-built prices (red color nodes) are linked only to second-hand prices (green color nodes). Freight rates (blue color nodes) are also linked only to second-hand ship prices. Thus the second-hand ship market acts as a bridge between the new ship market and the freight market. Changes in the freight rates of a ship influence the prices of second-hand ships of the same type but not ships of other types, implying that there are clear boundaries existing between the container, dry bulk, and oil tanker markets.

Using HTs we also find little distance between the second-hand prices and the freight rate of dry bulk carriers during the pre-crisis period, indicating a strong relationship between these two markets in dry bulk transport (the first cluster, the red block in Fig. 2(a)). The second cluster is the second-hand purchase-and-sale market of container ships. This submarket contains all five price indicators and is thus different from other submarkets, the green block in Fig. 2(a). The third cluster, the blue block in Fig. 2(a), is the new ship market of the three major crude oil tanker sizes: VLCC (large), Suezmax (middle-sized), and Aframax (small).

During the crisis period the new ship market tends to link to freight rates, which means that new ship prices are seriously affected by freight rate fluctuations. We also see that the boundaries separating the submarkets based on ship type in the pre-crisis disappear, indicating a high systemic risk throughout the shipping market system. Notice that only freight rate

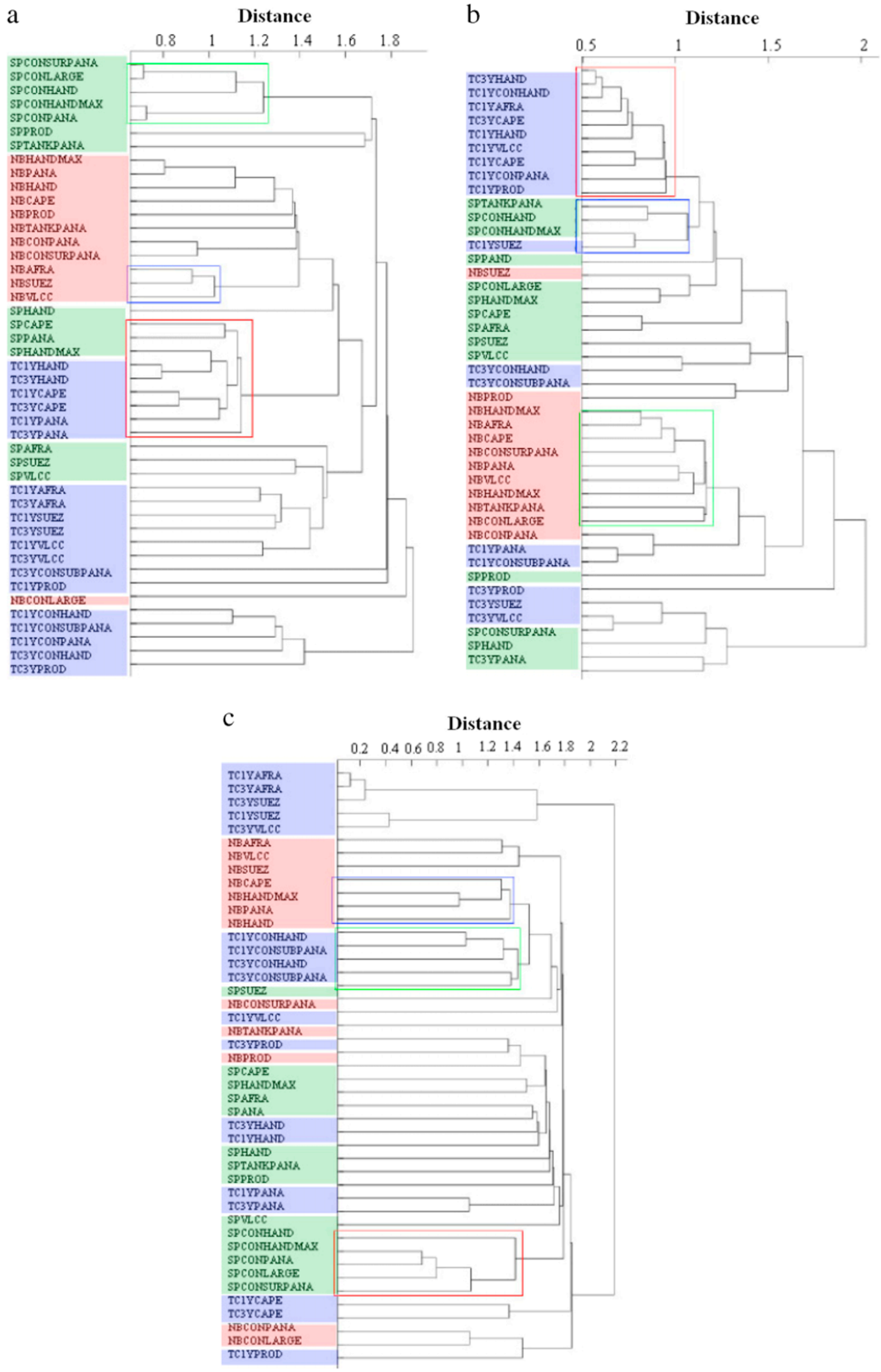

Fig. 2. Hierarchical tree of subdominant ultrametric space. Each text label presents one price indicator. Text label with red bottom color means price indicators belong to the new ship market, green bottom color one means the second-hand ship market, and blue bottom color means the freight market. (a) Pre-Crisis period (January 2003–December 2006). (b) Crisis period (January 2007–December 2010). (c) Post-Crisis period (January 2011–June 2013). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and second-hand ship price indicators of the oil tanker market tend to link to each other (green dash line circle in Fig. 1(b)). Moreover two groups can be easily identified: the new ship market (red solid line circle Fig. 1(b)) and the second-hand ship market (blue solid line circle Fig. 1(b)). Fig. 2(b) shows a structure that differs greatly from that in Fig. 2(a). We see that (i) freight rates for several dry bulk carriers, container ships, and oil tankers are closely correlated and form a tight cluster with shorter distances, indicating that during the crisis period the second-hand ship prices of a certain ship type are determined both by its own supply-and-demand and by freight rates of other ship types (the red block in Fig. 2(b)); (ii) prices of new container carriers, dry bulk carriers, and tankers cross the boundaries previously separating them and move together, which can be found in the green block in Fig. 2(b); and (iii) a third cluster, made up of second-hand container ship prices and second-hand Panamax oil tanker prices, that indicates a close business connection between oil transport and container transport (the blue block in Fig. 2(b)).

In the post-crisis period the shipping market is no longer fragments. Fig. 1(c) shows that the new ship markets form one independent group (red solid line circle), while the freight rate and second-hand ship price indicators tend to split into groups based on the three major ship types, that are oil tanker ship (green dash line circle), dry bulk ship (blue dash line circle) and container ship (red dash line circle). Fig. 2(c) shows that second-hand container ship prices link to form the first cluster (the red block), freight rates of container transport vessels form a second cluster (the green block), and the prices of new crude oil tankers form a third (the blue block). Fig. 1(c) also shows that the boundaries separating submarkets reappear in the post-crisis period.

5. Causality analysis of the shipping industry

5.1. Granger causality analysis

To shed additional light on the structure and dynamics of the shipping industry, we implement Granger causality using the monthly returns of indices of the new ship market, the second-hand ship market, the freight market, and the shipping stock market prices for the pre-crisis, crisis, and post-crisis periods. Fig. 3 shows the linear Granger causality relationships between months t and $t+1$ among the monthly indexes return of (i) the new ship market, (ii) the second-hand ship market, (iii) the freight shipping market, and (iv) shipping stock market prices for three periods, 2003–2006, 2007–2010, and 2011–2013. There are no significant bi-directional causal relationships among the four markets during the pre-crisis period. During the crisis period, however, all four markets become highly linked. During that period bi-directional relationships between the new ship market and the second-hand ship market, as well as between the second-hand ship market and the freight market emerge. All three shipping markets affect the shipping market stock price, and the new ship market influences the freight market. Thus shocks to real shipping markets easily propagate to stock market prices. During the earlier period, 2003–2006, only freight rate fluctuations affect stock market prices. During the post-crisis period, all four markets tend to become distant and there is only one significant bi-directional causal relationship remaining, the one between the second-hand ship market and the freight market. Stock market prices in the post-crisis period are much more independent than during the crisis period, and are influenced only by freight rate fluctuations.

5.2. Brownian distance correlation analysis

Granger causality previously applied shows only linear directional interdependence, and next we further utilize Brownian distance correlation to explore non-linear directional interconnectedness among market sectors. Fig. 4 shows Brownian distance correlation between months t and $t+l$ ($l = 1, 2$, and 3) among the monthly return indexes of (i) the new ship market, (ii) the second-hand ship market, (iii) the freight shipping market, and (iv) shipping stock market prices for three periods, 2003–2006, 2007–2010, and 2011–2013. For the pre-crisis period, the Brownian distance correlation recognizes bi-directional causal relationships between the new ship market and the second-hand ship market. In contrast, Granger causality only shows that the second-hand ship market causes the changes of the new ship market in the same period (see Fig. 4(a)). During the crisis period, the Brownian distance also captures more bi-directional dependent relationships, which are not significant in the Granger causality test. A feedback interdependence relationship can be observed among all four markets. Moreover bi-directional interdependence between the new-building ship market and the second-hand ship market as well as the new-building ship market and the freight market are both significant at time lag $l = 1, 2$ and 3, indicating the strong interaction effect among these markets. Additionally, feedback interdependence between the new-building ship market and the shipping stock market lasts for two time lags ($l = 1$ and 2), but is not significant when $l = 3$. During the post-crisis period, all causality relationships are significant only when the time lag is the one when Brownian distance explores bi-directional causal relationships between the new ship market and the second-hand ship market, which are also not recognized by the Granger causality analysis (see Fig. 4(c)). Brownian distance correlation is a natural extension and generalization of classical Person correlation to measure non-linear association to multivariate dependence. Through preview tests, researchers find that in most cases Brownian distance correlation results show strong significant correlation than Granger causality and Person correlation [43]. So this phenomenon is not unique in the shipping market, but the difference between Brownian distance and classical correlation measurements mainly depends on the market characteristics.

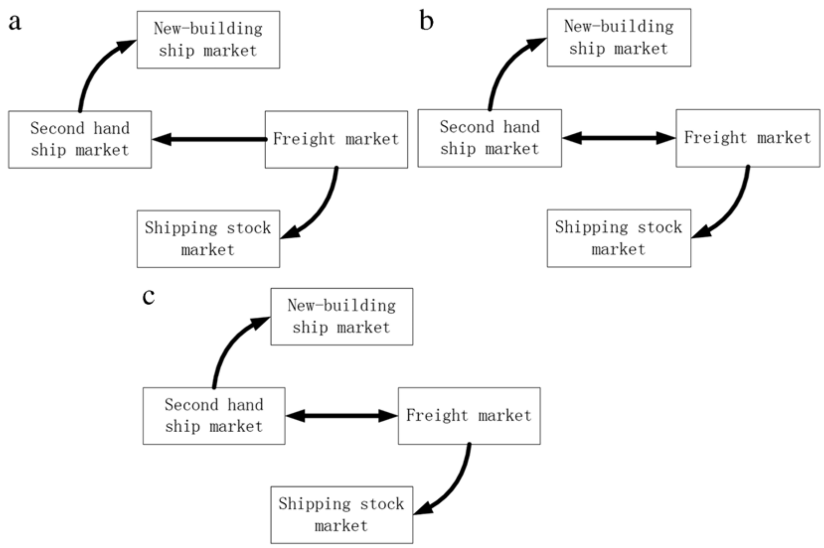

Fig. 3. Granger causality relationships (at the 10% level of statistical significance) among the monthly log returns of the new-building ship market, second ship sale & purchase market, freight market and shipping stock market over three sample periods: (a) prior to crisis (January 2003–December 2006), (b) during crisis (January 2007–December 2010) and (c) post-crisis (January 2011–June 2013) and marks with arrows the relationships that are significant at the 10% level. Single-headed arrows indicate uni-directional causal relationships, and double-headed arrows indicate bi-directional causal relationships.

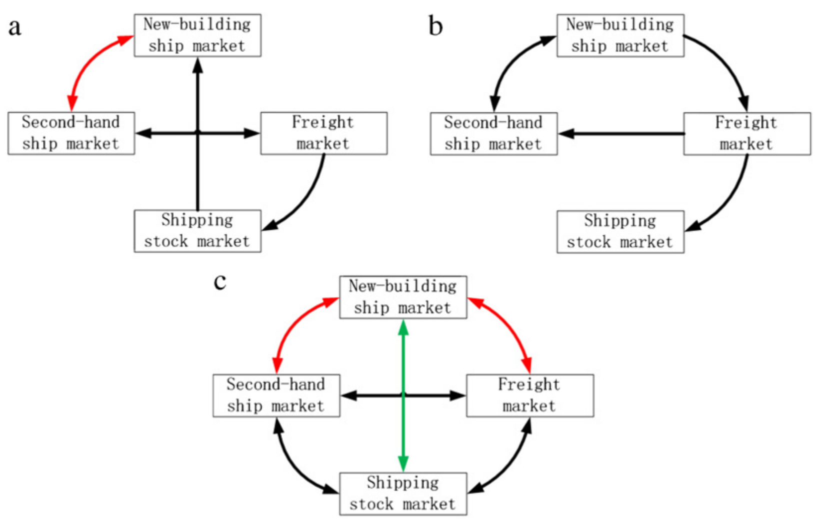

Fig. 4. Brownian distance correlation relationships (at the 10% level of statistical significance) among the monthly log returns of the new-building ship market, second ship sale & purchase market, freight market and shipping stock market over three sample periods: (a) prior to crisis (January 2003–December 2006), (b) during crisis (January 2007–December 2010) and (c) post-crisis (January 2011–June 2013). Single-headed arrows indicate uni-directional causal relationships, and double-headed arrows indicate bi-directional causal relationships. Red arrows indicate that feedback relationships are all significant when time lag $l = 1$, 2 and 3; green arrows indicate that feedback relationships are significant when time lag $l = 1$ and 2; black arrows indicate that feedback relationships are significant when time lag $l = 1$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.3. Dynamic causality index

To fully appreciate the impact of causal relationships in the shipping industry, finally we apply the dynamic causality index (DCI) defined such that an increase in the DCI indicates a higher level of system interconnectedness. We first apply a Granger causality test based on the new ship market containing a total of 12 time series to explore its interdependence with the second-hand ship market, the freight market, and shipping stock market prices. Based on this DCI definition, we use moving 24-month windows of monthly return prices from January 2003 to December 2012. Fig. 5 (a) shows the DCI of

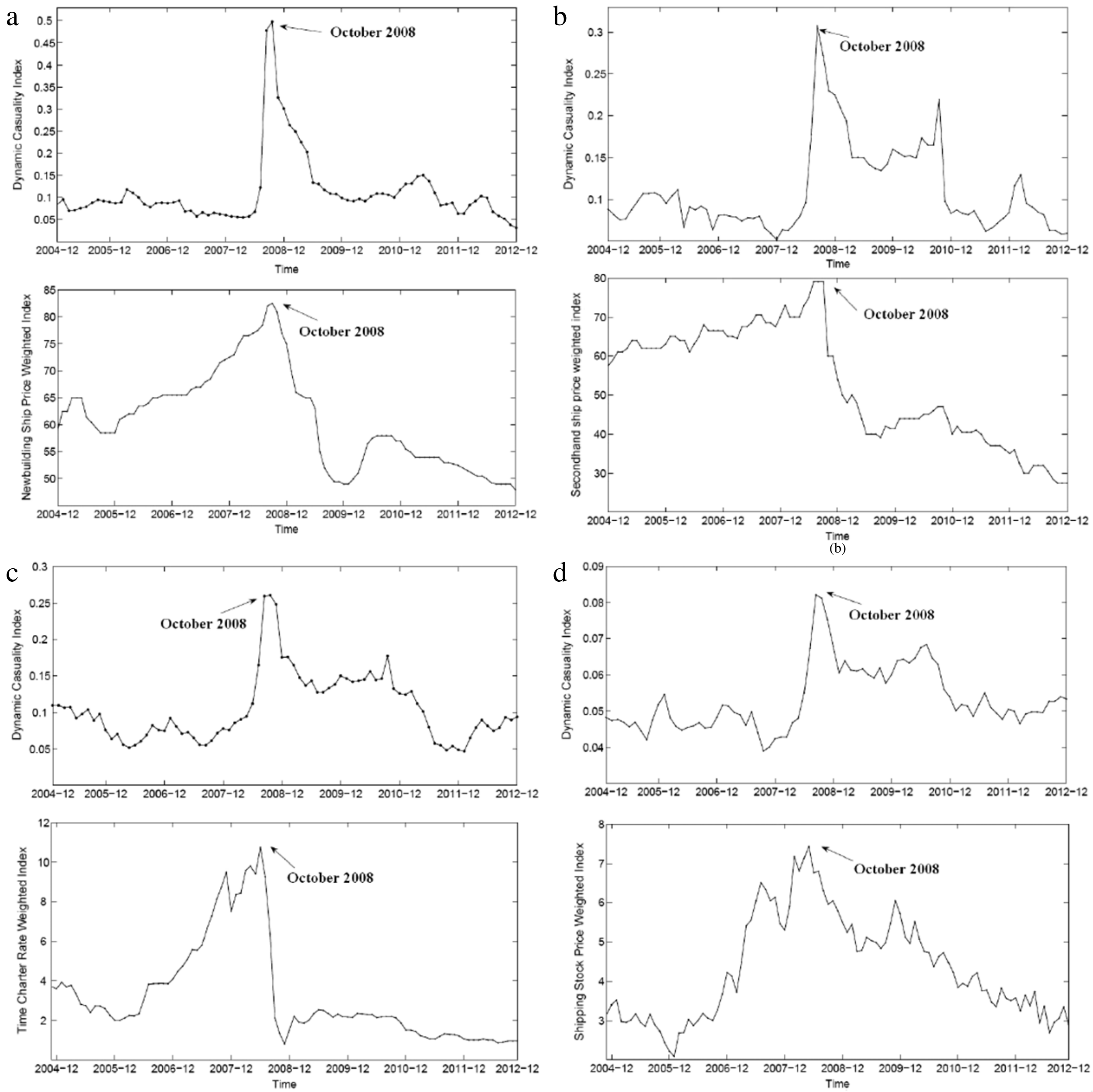

Fig. 5. Contrast of the Dynamic Granger causality index with 24-month moving window and Monthly weighted index of market price according to the capacity ratio of each ship type from December 2004 to December 2012. (a) New-building ship market, (b) second-hand ship market, (c) freight market, (d) shipping stock market.

the new ship monthly market price return versus time and the trend of the new ship weighted index price made up of 12 representative time series according to the capacity market ratio of each ship type during the same time period. The DCI shows a rich dynamic behavior over the entire period from January 2003 to December 2012. During the pre-crisis period, the DCI tends to be stable and only fluctuates from about 0.1 to 0.15. Beginning in June 2008, just prior to the October 2008 crash in new ship prices, the DCI begins to exhibit a sharp increase in the number of causality links. This indicates that the entire system including the real shipping market and the shipping financial market prices has become much more interconnected, a significant systemic risk indicator, especially during the financial crisis of 2008. We further confirm our results by studying the *DCI* of another three markets, that are second-hand ship prices, freight market and shipping stock market, also comparing the trend of *DCI* to real price weighted index within the same time period. Fig. 5(b)–(d) all show the largest *DCI* peak in October 2008 when there is a rapid drop in the real price index. The *DCI* shows itself to be an efficient measure of systemic risk in the shipping industry and can provide a useful early-warning signal that serious market regression will soon occur.

6. Conclusions

We have shown that correlation network and causality analysis can be used to analyze real market price and stock price influences in the shipping industry. We have examined the topology and hierarchical structures of the real shipping market based on correlations in monthly returns. We have also explored the directional relationships between the physical market and the stock market of the shipping industry. In both cases we have compared the results of the pre-crisis, crisis, and post-crisis periods, and we have presented three main conclusions. (I) There are clear boundaries separating container, dry bulk, and oil tanker sectors, and in each sector the new ship market is relatively distant from the second-hand ship and freight markets before and after the financial crisis. During the crisis period, the boundaries separating these three major markets of the shipping industry tend to disappear and the three markets become more closely related to each other. (II) During the crisis period, both Granger-causality connectivity and Brownian distance correlation show that the impact of all three physical shipping markets on other physical shipping markets and on shipping stock market prices become much more substantial. Brownian distance correlation is more powerful to recognize the non-linear causality relationship than Granger-causality analysis. (III) Dynamic Causality Index can be regarded as a useful indicator to measure the dynamic trend of systemic risk level of the market, which provides efficient warning before market downturn.

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Appendix

See Tables 1–3.

Table 1
New-building ship market price indicators.

Price indicator	Code
VLCC Tanker Newbuilding Price	NBVLCC
Suezmax Tanker Newbuilding Price	NBSUEZ
Aframax Tanker Newbuilding Price	NBAFRA
Panamax Tanker Newbuilding Price	NBTANKPANA
Products Tanker Newbuilding Price	NBPROD
Panamax Bulkcarrier Newbuilding Price	NBPANA
Handysize Bulkcarrier Newbuilding Price	NBHAND
Handymax Bulkcarrier Newbuilding Price	NBHANDMAX
Capesize Bulkcarrier Newbuilding Price	NBCAPE
Panamax Containership Newbuilding Price	NBCONPANA
Super Panamax Containership Newbuilding Price	NBCONSURPANA
Large Containership Newbuilding Price	NBCONLARGE

Table 2
Second-hand ship market price indicators.

Price indicator	Code
VlCC Tanker Secondhand ship price	SPVLCC
Suezmax Tanker Secondhand ship price	SPSUEZ
Aframax Tanker Secondhand ship price	SPAFRA
Panamax Tanker Secondhand ship price	SPTANKPANA
Products Tanker Secondhand ship price	SPPROD
Capesize Bulkcarrier Secondhand ship price	SPCAPE
Panamax Bulkcarrier Secondhand ship price	SPPANA
Handymax Bulkcarrier Secondhand ship price	SPHANDMAX
Handysize Bulkcarrier Secondhand ship price	SPHAND
Panamax Containership Secondhand ship Price	SPCONPANA
Super Panamax Containership Secondhand ship Price	SPSURPANA
Large Containership Secondhand ship Price	SPCONLARGE
Handymax Containership Secondhand ship price	SPCONHANDMAX
Handysize Containership Secondhand ship price	SPCONHAND

Table 3
Freight market time charter rate.

Price indicator	Code
VLCC Tanker 1 Year time charter rate	TC1YVLCC
Suezmax Tanker 1 Year time charter rate	TC1YSUEZ
Aframax Tanker 1 Year time charter rate	TC1YAFRA
Panamax Tanker 1 Year time charter rate	TC1YTANKPANA
Products Tanker 1 Year time charter rate	TC1YPROD
Panamax Bulkcarrier 1 Year time charter rate	TC1YPANA
Handysize Bulkcarrier 1 Year time charter rate	TC1YHAND
Capesize Bulkcarrier 1 Year time charter rate	TC1YCAPE
Panamax Containership 1 Year time charter rate	TC1YCONPANA
Super Panamax Containership 1 Year time charter rate	TC1YCONSURPANA
Handysize Containership 1 Year time charter rate	TC1YCONHAND
VLCC Tanker 3 Year time charter rate	TC3YVLCC
Suezmax Tanker 3 Year time charter rate	TC3YSUEZ
Aframax Tanker 3 Year time charter rate	TC3YAFRA
Products Tanker 3 Year time charter rate	TC3YPROD
Panamax Bulkcarrier 3 Year time charter rate	TC3YPANA
Handysize Bulkcarrier 3 Year time charter rate	TC3YHAND
Capesize Bulkcarrier 3 Year time charter rate	TC3YCAPE
Panamax Containership 3 Year time charter rate	TC3YCONPANA
Handysize Containership 3 Year time charter rate	TC3YCONHAND

References

[1] R.N. Mantegna, H.E. Stanley, An Introduction to Econophysics Correlations and Complexity in Finance, Cambridge University Press, Cambridge, UK, 2010.
[2] X. Gabaix, P. Gopikrishnan, V. Plerou, H.E. Stanley, A theory of power-law distributions in financial market fluctuations, Nature 423 (2003) 267.
[3] F. Lillo, J.D. Farmer, R.N. Mantegna, Econophysics: master curve for price-impact function, Nature 421 (2003) 129.
[4] M. Billio, M. Getmansky, A.W. Lo, L. Pelizzon, Econometric measures of connectedness and systemic risk in the finance and insurance sectors, J. Financ. Econ. 104 (2012) 535.
[5] T. Preis, D.Y. Kenett, H.E. Stanley, D. Helbing, E. Ben-Jacob, Quantifying the behavior of stock correlations under market stress, Sci. Rep. 2 (2012) 752.
[6] D. Wang, B. Podobnik, D. Horvatic, H.E. Stanley, Quantifying and modeling long-range cross correlations in multiple time series with applications to world stock indices, Phys. Rev. E. 83 (2011) 046121.
[7] G. Bonanno, F. Lillo, R.N. Mantegna, High-frequency cross-correlation in a set of stocks, Quant. Finance 1 (2001) 96.
[8] A. Utsugi, K. Ino, M. Oshikawa, Random matrix theory analysis of cross correlations in financial markets, Phys. Rev. E. 70 (2004) 026110.
[9] Z. Zheng, K. Yamasaki, J.N. Tenenbaum, H.E. Stanley, Carbon-dioxide emissions trading and hierarchical structure in worldwide finance and commodities markets, Phys. Rev. E. 87 (2013) 012814.
[10] J.P. Bouchaud, M. Potters, Theory of Financial Risk and Derivative Pricing: From Statistical Physics to Risk Management, Cambridge University Press, Cambridge, UK, 2003.
[11] M.J. Mauboussin, Revisiting market efficiency: the stock market as a complex adaptive system, J. Appl. Corp. Financ. 14 (2002) 47.
[12] A. Majdandzic, B. Podobnik, S.V. Buldyrev, D.Y. Kenett, S. Havlin, H.E. Stanley, Spontaneous recovery in dynamical networks, Nat. Phys. 10 (2014) 34.
[13] A. Branch, M. Stopford, Maritime Economics, third ed., Routledge, NY, USA, 2013.
[14] S. Albertijn, W. Bessler, W. Drobetz, Financing shipping companies and shipping operations: a risk-management perspective, J. Appl. Corp. Financ. 23 (2011) 70.
[15] W. Drobetz, T. Richter, M. Wambach, Dynamics of time-varying volatility in the dry bulk and tanker freight markets, Appl. Financ. Econ. 22 (2012) 1367.
[16] M.G. Kavussanos, I.D. Visvikis, Market interactions in returns and volatilities between spot and forward shipping freight markets, J. Bank. Financ. 28 (2004) 2015.
[17] R. Adland, K. Cullinane, The non-linear dynamics of spot freight rates in tanker markets, Transport. Res. E-log. 42 (2006) 211.
[18] J. Tvedt, A new perspective on price dynamics of the dry bulk market, Marit. Pol. Manag. 30 (2003) 221.
[19] R. Adland, H. Jia, Charter market default risk: a conceptual approach, Transport. Res. E-log. 44 (2008) 152.
[20] M. Krafft, International Shipping in Crisis: Background, Framework and Implications, GRNI Press, European Union, 2010.
[21] C.T. Grammenos, A.G. Arkoulis, Macroeconomic factors and international shipping stock returns, Int. J. Marit. Econ. 4 (2002) 81.
[22] A.G. Samitas, D.F. Kenourgios, Impact of mergers and acquisitions on stock returns of tramp shipping firms international, J. Financ. Serv. Manag. 2 (2007) 327.
[23] R.N. Mantegna, Hierarchical structure in financial markets, Eur. Phys. J. B. 11 (1999) 193.
[24] M. Tumminello, F. Lillo, R.N. Mantegna, Kullback–Leibler distance as a measure of the information filtered from multivariate data, Phys. Rev. E. 76 (2007) 031123.
[25] M. Tumminello, F. Lillo, R.N. Mantegna, Correlation, hierarchies, and networks in financial markets, J. Econ. Behav. Organ. 75 (2010) 40.
[26] J.G. Brida, W.A. Risso, Hierarchical structure of the German stock market, Expert. Syst. Appl. 37 (2010) 3846.
[27] J.P. Onnela, A. Chakraborti, K. Kaski, J. Kertesz, A. Kanto, Dynamics of market correlations: taxonomy and portfolio analysis, Phys. Rev. E. 68 (2003) 056110.
[28] D.Y. Kenett, M. Tumminello, A. Madi, G. Gur-Gershgoren, R.N. Mantegna, E. Ben-Jacob, Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market, PLoS ONE 5 (2010) e15032.
[29] R.J. Hill, Comparing price levels across countries using minimum-spanning trees, Rev. Econ. Stat. 81 (1999) 135.
[30] T. Mizuno, H. Takayasu, M. Takayasu, Correlation networks among currencies, Physica A 364 (2005) 336.
[31] C.G. Gilmore, B.M. Lucey, M.W. Boscia, Comovements in government bond markets: a minimum spanning tree analysis, Physica A 389 (2010) 4875.
[32] B.M. Tabak, T.R. Serra, D.O. Cajueiro, Topological properties of commodities networks, Eur. Phys. J. B. 74 (2010) 243.
[33] J.P. Onnela, K. Kaski, J. Kertesz, Clustering and information in correlation based financial networks, Eur. Phys. J. B. 38 (2004) 353.
[34] D.M. Song, M. Tumminello, W.X. Zhou, R.N. Mantegna, Evolution of worldwide stock markets, correlation structure, and correlation-based graphs, Phys. Rev. E. 84 (2011) 026108.
[35] V.V. Acharya, L.H. Pedersen, T. Philippon, M.P. Richardson, Measuring Systemic Risk, New York University Working Paper, 2010.
[36] M. Getmansky, A.W. Lo, I. Makarov, An econometric model of serial correlation and illiquidity in hedge fund returns, J. Financ. Econ. 73 (2004) 529.
[37] D.Y. Kenett, T. Preis, G. Gur-Gershgoren, E. Ben-Jacob, Quantifying meta-correlations in financial markets, Europhys. Lett. 99 (2012) 38001.

[38] Giovanni Bonanno, Nicolas Vandewalle, Rosario N. Mantegna, Taxonomy of stock market indices, Phys. Rev. E. 62 (2000) R7615.
[39] M. Billio, M. Getmansky, A.W. Lo, L. Pelizzon, Econometric measures of connectedness and systemic risk in the finance and insurance sectors, J. Financ. Econ. 104 (2012) 535.
[40] Z. Zheng, B. Podobnik, L. Feng, B. Li, Changes in cross-correlations as an indicator for systemic risk, Sci. Rep. 2 (2012) 00888.
[41] G.J. Székely, M.L. Rizzo, Brownian distance covariance, Ann. Appl. Stat. 3 (2009) 1236.
[42] R. Lyons, Distance covariance in metric spaces, Ann. Probab. 41 (2013) 3284.
[43] C. Hiemstra, J.D. Jones, Testing for linear and nonlinear granger causality in the stock price-volume relation, J. Finance 49 (1994) 1639.