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Centre for Advanced Spatial Analysis University College London 1 - 19 Torrington Place Gower St London WC1E 7HB
Tel: +44 (0)20 7679 1782 casa@ucl.ac.uk www.casa.ucl.ac.uk

Cooperation in container shipping: A small world network of agreements

Simone CASCHILI[1 2], Francesca Romana MEDDA[2], Francesco PAROLA[3], Claudio FERRARI[4]

[1]Centre for Advanced Spatial Analysis, University College London

[2]UCL QASER Lab, University College London, Faculty of Engineering

[3]Business Administration Department, University of Naples "Parthenope"

[4]Department of Economics and Quantitative Methods, University of Genoa

Abstract: The recent economic downturn has increased the need for cooperation among carriers in the container shipping industry. We introduce in this work a network analysis to investigate the topology and hierarchical structure of inter-carrier relationships. Our dataset is comprised of 65 carriers that provide 604 container services. Main findings indicate that the Cooperative Container Network (CCN) belongs to the family of small world networks. We demonstrate that when we increase the value of the connectivity among carriers, the handled capacity increases linearly, whereas the clustering coefficient decreases linearly. We then show how the economic success of a container carrier is often based on cooperation but also on its strategic dominant positioning within the container market.

Keywords: container shipping lines; cooperative agreements; small world networks; complex network analysis.

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1 Introduction

The container shipping industry, as in many other service industries, has increasingly introduced cooperative schemes into its organisation, thus resulting in a growing market concentration (Lorange, 2001); for instance, five major ocean carriers (Maersk, MSC, CMA CGM, Evergreen Line and APL) operate about 50% of the cellular fleet. Cooperative schemes in container carrier shipping are often implemented through the deployment of mega-vessels in order to attain economies of scale. The introduction of mega-vessels, although achieving competitive advantage in service production and cost reduction per slot (Imai et al., 2006; Drewry, 2005), also imposes significant pressure on shipping lines, which are often forced to operate at the break-even point. Nevertheless, cooperative schemes have been useful in order to decrease economic and financial risk and to geographically widen the services (Ferrari et al., 2008; Evangelista and Morvillo, 2000).

Cooperative schemes based on operating agreements had already been developed by the 1960s but only by the mid-1990s did the major ocean carriers decide to establish more formal contractual agreements (Rimmer, 1998). Having said that, we can identify two major cooperative agreements in container shipping: consortia and strategic alliances. Consortia are cooperative agreements focused on a single maritime service in which various members of the consortium share transport capacity. There are numerous consortia in operation on both major and secondary routes. Whereas strategic alliances are agreements where carriers manage several joint shipping services worldwide; by so doing, the members of the alliance also share investment risks (Brooks et al., 1993). Nowadays there are three active strategic alliances, i.e., Gran Alliance, New World Alliance and CKYH Alliance, which involve one tenth of the leading carriers. As observed by Frémont and Soppé (2004), Asian carriers generally prefer long-term and comprehensive cooperation in the form of strategic alliances; this is due to their weak maritime service network that is scarcely diversified and focuses mostly on Far-East trade. Moreover, in order to achieve competitive advantage (Panayides and Cullinane, 2002), established alliances can certainly be viewed as a growth-oriented strategy, as opposed to acquisitions (Alix et al., 1999). An element in common between both consortia and strategic alliances is the agreement to share on-board slots, which can be either slot-charter (S-C) or vessel-sharing (V-S) agreements. Through S-C agreements a carrier books a certain number of slots on the vessels operated by a partner without deploying any (owned) ship. Conversely, through a V-S agreement each carrier deploys its own fleet and allows other partners to place a number of slots at their disposal. In our context S-C and V-S agreements are the most common ways to rationalise operational costs.

Cooperative container schemes have until recently proven to be very unstable agreements, and this intrinsic instability may be attributed to an inadequate organisational and contractual structure in the maritime industry, as well as to opportunistic behaviour of members of cooperative schemes (Hoetker and Mellewigt, 2009; Midoro and Pitto, 2000; Hamel et al., 1989). As a result, the container shipping industry has shown a growing need for stable agreements and flexible operations, and thereby developed cooperation through "elementary units" (Hoetker and Mellewigt, 2009). Even leading carriers that had

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been traditionally averse to cooperation (CMA-CGM, China Shipping, Evergreen Line, etc.) have joined with competitors in cooperative schemes.

The recent economic downturn has induced a collapse of freight rates and cargo flows and increased the need for cooperation among carriers. As result of the progressive diffusion of cooperative scheme, carriers have been able to survive in an unstable and shaken market environment. In fact, ocean carriers can now cooperate with a large variety of players across numerous maritime services without necessarily binding to a specific partner for an extended period. Within this context, the present study introduces a network model to highlight the role of cooperative schemes within the container shipping industry and focuses on different carriers' strategies. The choice of the network approach is made in order to develop an analysis of cooperation agreements from a topological network perspective; this innovative approach allows us to examine cooperative relationships among carriers and detect patterns that emerge from the formation of strategic agreements.

The paper is structured as follows. In section 2 we briefly review complex network applications followed by Section 3, where we describe the dataset and discuss the network modelling applied to container service lines. In sections 4 and 5 we discuss the results from a topological analysis of the cooperative container network. Finally, in section 6 we review our main contributions relative to cooperation in the container shipping industry.

2 Network theory analysis in inter-firm cooperation modelling

In the maritime literature, and in particular in container shipping analysis, little attention has been paid to network theory. A few studies focus on worldwide movements of cargo disaggregated at port level (Ducruet and Notteboom, 2010; Koluza et al., 2010; Bergantino and Veenstra, 2002), and other studies account for sub-networks of the global cargo network (Ducruet et al., 2010; Cisic et al., 2007; McCalla et al., 2005; Helmick, 1994). However, network theory has a long tradition in other fields with roots in the work of Euler (1736), and extended by the works of Solomanov (1951) and Erdos and Renyi (1960) on random graphs. One of the most interesting advances in network theory was proposed by Watts and Strogatz (1998), where they introduce a network class entitled *small world.* Small world networks, different from regular and random networks, are characterised by high local connectivity and small topological distance between each pair of nodes, thus allowing for ease of diffusion of information among the nodes. Several case studies (Barthélemy, 2010; Boccaletti et al., 2006; Newman, 2003) have proven that small world networks are able to capture properties of real systems that neither regular nor random networks are able to explain. Another furtherance of network theory was proposed by Barabási and Albert (1999), who introduced a new paradigm for the growth of networks based on the economic catch phrase "*The rich get richer*." These types of networks, which are represented by the Internet, the World Wide Web, the international airline network, cross-collaboration in science, and many others, all belong to the class of scale-free networks (Boccaletti et al., 2006; Newman, 2003; Albert and Barabási, 2002). Both concepts of small world and scale-free networks will be at the basis of our analysis.

From the point of view of inter-firm cooperation, network theory has been applied extensively in the literature (Souma et al., 2004, 2003; Ebers, 2002;). A number of studies examine the relationships among firms as networks (Zaheer and Bell, 2005; Baum et al., 2000), the characterisation of network topology (Dittrich et al., 2007; Goerzen and

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Beamish, 2005), the nature of alliance relationships (Gimeno, 2004; Stuart et al., 1999), the shared features among firms (Gulati and Higgins, 2003; Stuart et al., 1999), and the composition of partners in the network (Koza and Lewin, 1999; Saxton, 1997). Other works investigate the alliance structures through network modelling in order to describe firms' revenue growth and market share and profitability (Rothaermel, 2001; Ahuja, 2000; Baum et al., 2000; Rowley et al., 2000; Sydow and Windeler, 1998).

Despite the myriad analyses of network theory in various contexts, the maritime industry literature has thus far not utilised the network modelling approach to study inter-firm cooperation. However, some studies (Ducruet et al., 2010; Cisic et al., 2007; McCalla et al., 2005; Helmick, 1994) do use the network approach to investigate container shipping patterns. More recently, Gelareh et al. (2010) and Meng and Wang (2011) in their work on hub-and-spoke systems, both introduce network analysis to examine container shipping operations. In the next sections we introduce our data and describe how we build our cooperative network model in order to better understand the nature of relationships among carriers.

3 Data description and modelling

In this study, based on the total volume of container handled capacity, we select the 25 major ocean carriers from a sample that covers around 85% of the overall cellular fleet. Data have been extrapolated from Containerisation International and refer to January 2010. For each container service we record the service frequency, the existence of V-S and S-C agreements and fleet capacity (in Twenty-Foot Equivalent Unit - TEU) deployed by one or more carriers on the same service. The dataset comprises a subset of 604 container services that can be separated in two categories: services managed by single carriers (205) and services managed by multiple carriers (399). We also calculate the Weekly Container Transport Capacity (WCTC) deployed by each carrier per container service, as defined by Frémont and Soppé (2004).

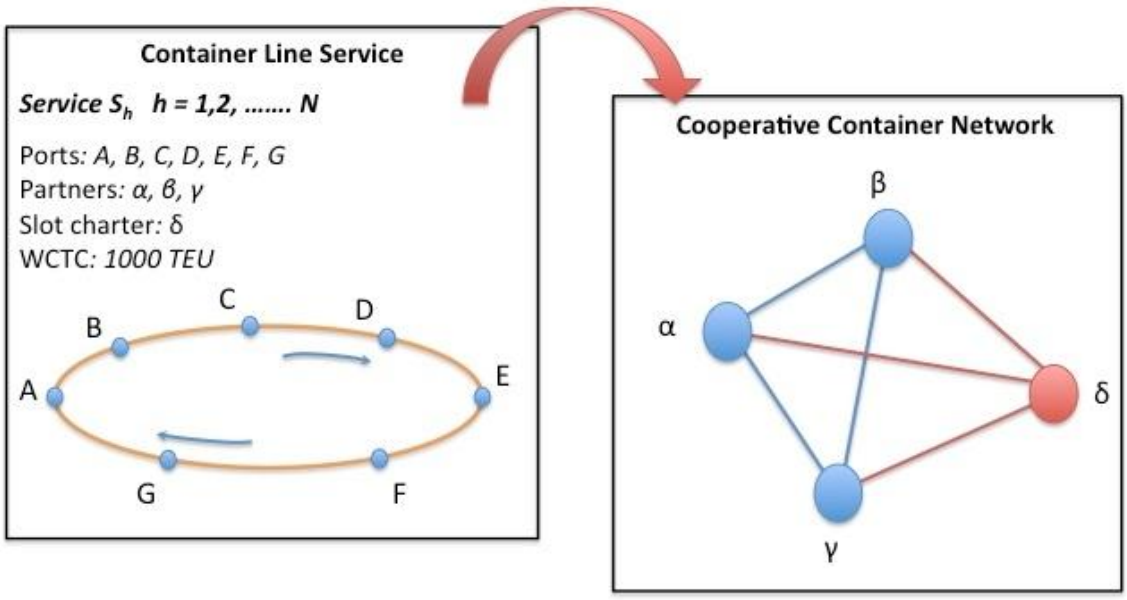

Figure 1. Schema of the construction process of the Cooperative Container Network. Blue links represent V-S relationships and red indicates S-C relationships.

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For each service the carriers cooperate in accordance with the two aforementioned agreements: the V-S agreement, used in all services, and the S-C agreement, used in 41% of the services. A simplified representation of container cooperation schemes is given in Figure 1, where carriers α, ß, and γ operate the container line S among ports A, B, C, D, E, F and G with a certain WCTC. We also consider one slot-charter carrier δ, in container line S, which does not use its fleet to provide the service, but instead rents container slots from carriers α, ß, and γ (vessel sharing).

The two fundamental types of agreements (V-S and S-C) yield two possible mutual interactions between pairs of carriers in our network modelling:

a) The V-S agreement generates a link between carriers (α, ß, and γ partners in Figure 1) whereby they share their own slot capacity with each other;

b) The S-C agreement determines a link between carriers whereby one of them deploys its fleet (α, ß, and γ) and the other player (δ slot charter in Figure 1) charters container slots.

Thus, in the container industry these agreements create a series of complex interrelated cooperative economic relationships, which are of primary interest in this study.

The Containerisation International dataset allows us to construct the Cooperative Container Network (CCN). In this network each node corresponds to a carrier and the links represent cooperation between carriers (as described above in points a and b); the total vessel capacity available for each service S (Q^{S}_{WCTC}) is expressed in WCTC. The CCN is identified by an indirect graph G (N, L) identified by two sets: N is the set of nodes, $N \equiv \{n_1, n_2, \ldots n_N\}$, and L is the set of links, $L \equiv \{l_{p1}, l_{p2}, \ldots, l_{pn}, l_{sc1}, l_{sc2}, \ldots l_{scn}\}$. L is the union of two subsets ($L \equiv L_p \cup L_{sc}$), where L_p is the subset of links with a prevalence of V-S agreements between two carriers (nodes), and L_{sc} is the subset of links with a prevalence of S-C agreements.

In our modelling we assume that our network is represented by a NxN adjacency matrix A, whose off-diagonal entries a_{ij} are equal to 1 when we have one or more shared services between companies i and j ($i \neq j$ or $j \neq i$), and equal 0 otherwise. Diagonal elements a_{ii} are set equal to 0 because there is no intra-firm relationship in our modelling. It is worth noticing that since we have constructed an indirect graph, the adjacency matrix is symmetric. We extend the topological representation provided by the adjacency matrix by constructing the weighted adjacency matrix W, whose off-diagonal elements w_{ij} are the sum of the services' capacities Q^{S}_{WCTC} shared by carriers i and j. The weighted matrix W provides us with a richer description of the CCN, as it considers the topology along with quantitative information on the market share between pairs of carriers.

In Table 1 we rank the ten links with the highest. The German carrier Hapag-Lloyd, belonging to the Grand Alliance, is the European carrier most largely involved in cooperative schemes. The Asian players clearly dominate and are the most significant cooperative carriers within the strategic alliances.

Table 1. Ranking of the leading cooperation agreements in the CCN

Rank	Link	w_{ij}
1	Hapag-Lloyd AG– Orient Overseas Container Line Ltd	93,240
2	Cosco Container Lines Ltd- Hanjin Shipping Co Ltd	91,299
3	Hapag-Lloyd AG- NYK Line	90,175
4	NYK Line- Orient Overseas Container Line Ltd	86,225

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5	Hanjin Shipping Co Ltd- Kawasaki Kisen Kaisha Ltd	73,929
6	Cosco Container Lines Ltd- Kawasaki Kisen Kaisha Ltd	68,134
7	Cosco Container Lines Ltd- Yang Ming Marine TC	67,251
8	Hanjin Shipping Co Ltd- Yang Ming Marine TC	65,516
9	Kawasaki Kisen Kaisha Ltd - Yang Ming Marine TC	65,261
10	APL Ltd - Hyundai Merchant Marine Co Ltd	63,557

CKYH Alliance: Cosco Container Lines Ltd, Kawasaki Kisen Kaisha Ltd, Yang Ming Marine TC, Hanjin Shipping Co Ltd.
Grand Alliance: Hapag-Lloyd AG, Orient Overseas Container Line Ltd, NYK Line.
New World Alliance: APL Ltd, Hyundai Merchant Marine Co Ltd, Mitsui OSK Lines.

The top part of Figure 2 displays the networks of the cooperative agreements: V-S agreements on the left and S-C agreements on the right. The network of V-S agreements is composed of 53 carriers (nodes) and 180 cooperative relationships (links), and the network of S-C agreements has 57 carriers (nodes) and 142 cooperative relationships (links).

The bottom part of Figure 2 displays the complete CCN, which is composed of N=65 carriers (nodes) and K=287 cooperative relationships (links). The size and colour of each node is drawn as a function of the number of connections; blue links represent a prevalence of V-S agreements and grey links represent a majority of S-C agreements. The width of each link is proportional to the number of agreements between two carriers. The node is represented in red and their diameter is proportional to the number of connections.

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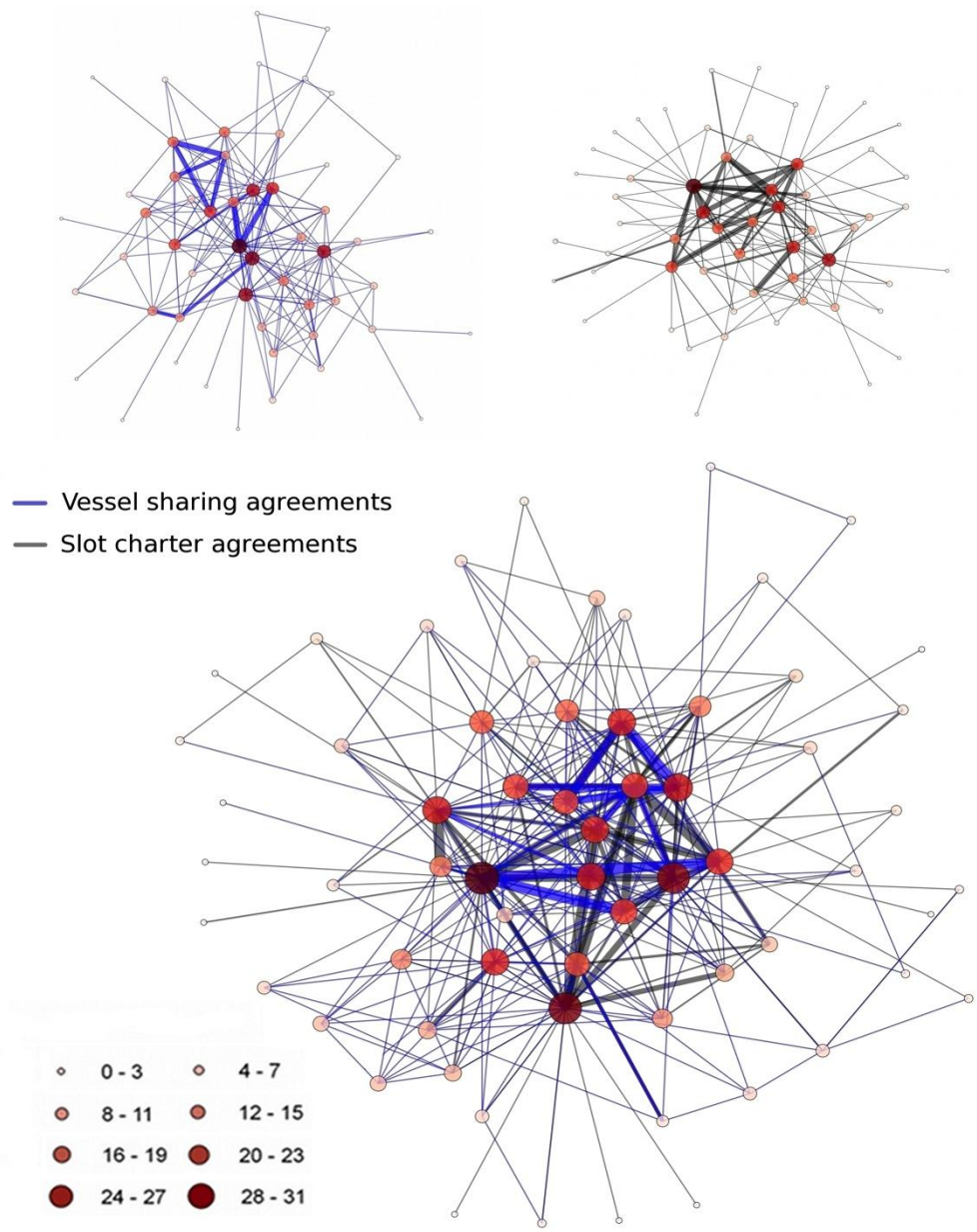

Figure 2. Visualisation of the CCN

The CCN network is sparse because its density is equal to 0.086*; it has a relatively small average shortest path (2.2) and the value of maximum shortest path in the graph is 5 links to connect the most remote nodes.

In the next sections we examine the CCN from a different perspective. We conduct a network analysis in order to characterise the topological structure of the container shipping industry when it is conceived as a system (the CCN in our case study). The challenge here is to verify the assumption that agreements between carriers are not set according to random choice but rather follow specific patterns which emerge from carrier cooperation.

* The density is calculated as the ratio between number of links and maximum number of links for the case of a complete graph with the same number of nodes.

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4 Topological structure of the Cooperative Container Network (CCN)

We examine in this section the characteristics of the Cooperative Container Network (CCN) by measuring the overall network structure and identifying the carriers (nodes) that play a relevant role in terms of cooperation. In so doing, we aim to verify if highly connected carriers play leading roles in the organisation of the container strategic agreements and in the management of the lines.

Our first step is to ascertain the level of connectivity (degree k) for each carrier i, represented by the following expression:

$$k_i = \sum_{j \in n(i)} a_{ij} \qquad (1)$$

where V(i) is the set of topological neighbours of carrier i, i.e., the carrier (nodes) directly connected to i; and a_{ij} is the element of the adjacency matrix A. In our set degree k ranges between 1 and 31. The average degree k is equal to 8.8.

We now define the complementary cumulative probability distribution of degree k (Figure 3), which provides us with a first proxy indication of the regimes of cooperation in the container shipping market. In our case the distributions indicate two different regimes: a power law in the first part and an exponential regime in the final part of the tail of the distribution. These two regimes are clearly depicted in the log-log scatter plot (black dots in Figure 3).

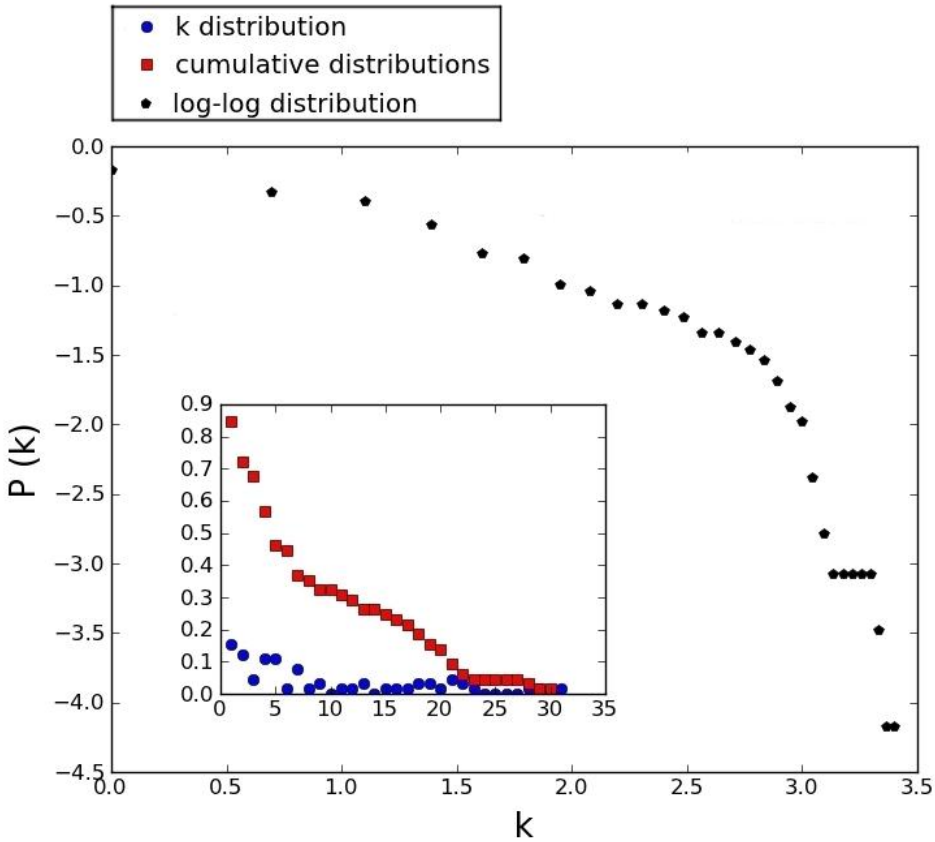

Figure 3. Probability distributions of degree k for the CCN. The probability distribution is shown in blue dots while we can observe in red and black dots the cumulative distributions in lin-lin and log-log scale, respectively.

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The two regimes may be the result of the level of interaction between carriers, that is, a high level of interaction determines a power law regime which then decays to an exponential regime where we observe weaker interaction and therefore cooperation between carriers. Nonetheless, we need to notice that, due to the small number of observations, we may be unable to analyse the complete behaviour of the carriers' cooperation.

In Table 2 we rank the ten most connected carriers in the CCN. Four carriers (CMA-CGM, Evergreen, China Shipping Container and Hamburg S. D-G K.G.) are not members of the three major alliances (CKYH Alliance, Grand Alliance and New World Alliance). For instance, CMA-CGM ranks second with a degree k of 29 and has the highest volume of container handled capacity in the set of Table 2[†]. This is an interesting result because it shows how carriers that are not members of strategic alliances are nevertheless highly cooperative.

Table 2. Ranking of carriers in CCN by their degree k, percentage of TEU shipped in cooperation and total container handled capacity (TEU) with the ranking position, in brackets, according to Containerisation International (February 2011).

Rank	Shipping Companies	Degree K	% WCTC in cooperation	Volume of container handled capacity (TEU)
1	Hapag-Lloyd AG	31	91.73%	564,916 (8)
2	CMA CGM SA	29	81.89%	1,041,429 (4)
2	Mitsui OSK L. Ltd	28	87.74%	369,095 (13)
3	Cosco Container L. Ltd	23	63.07%	571,102 (7)
4	Evergreen L.	22	53.22%	579,735 (5)
5	China Shipping Container L. Co Ltd	22	92.95%	471,534 (9)
6	APL Co Pte Ltd	21	73.84%	579,274 (6)
7	Hanjin Shipping Co Ltd	21	80.93%	463,952 (10)
8	Hamburg S. D-G KG	21	83.85%	329,949 (16)
9	NYK Container L.	20	91.10%	354,629 (14)
10	Orient Overseas Container L. Ltd	19	90.10%	377,684 (12)

We next examine the relationship between the network connectivity and commercial capacity of each carrier (Figure 4).

[†] CMA-CGM also ranks fourth place in the total world container handled capacity.

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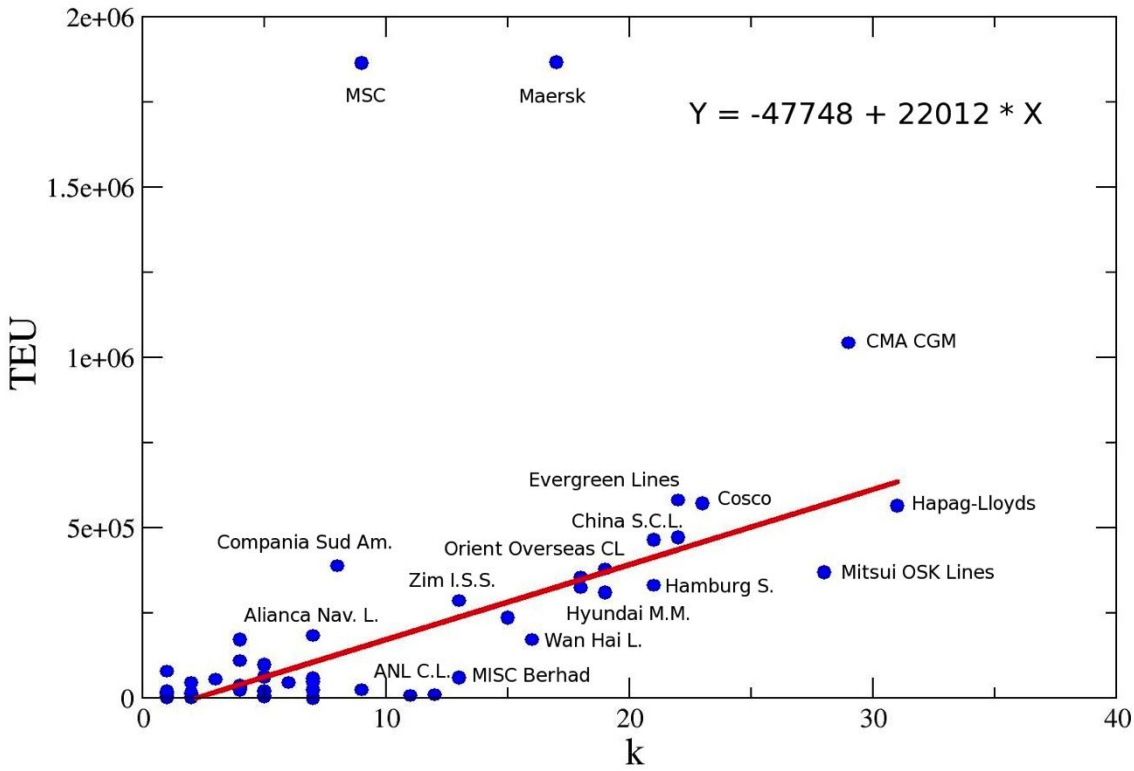

Figure 4. Relationship between degree k and volume of container handled capacity in TEU (February 2011). The linear regression has a correlation coefficient of 0.86, but does not include the two outside players (Mediterranean Shipping Co SA and Maersk Line).

We observe a strong correlation between degree k (i.e., number of agreements) and volume of container handled capacity of each carrier represented by the linear regression (red line in Figure 4). Carriers with low cooperation are clustered at low levels of TEU handled. Another concentration is observed around the degree of connectivity equal to 20, thus highlighting two carrier trends. The first trend is that the majority of carriers in our set have a small TEU handled capacity and thus have limited cooperation. On the other hand, a second trend is depicted around degree k 20, where the connectivity allows for carriers to reach economies of scale. In other words, we can summarise our results by observing that, for a carrier to obtain economies of scale in its operation, it needs to have a level of cooperation around degree k 20. However, two observations in the uppermost part of Figure 4 do not follow the linear regression; these are the mega-carriers Mediterranean Shipping Co SA (k = 9) and Maersk Line (k = 17). Such an industrial strategy shows that high volumes of container handled capacity (high level of market share) may correspond to independent carrier behaviour.

In light of the analysis thus far, cooperation among carriers in container shipping creates a network of relationships whose structure appears to belong to the class of small world networks, because the typical shortest path (2.2) scales as the logarithm of the number of nodes in the network (65). The partial power law regime reinforces this finding, although the CCN cannot be ascribed to the class of scale-free networks. We will compare these results with a cluster analysis in the next section, which is intended to highlight the tendency of nodes to cluster together, which in turn, is another common property of small world networks.

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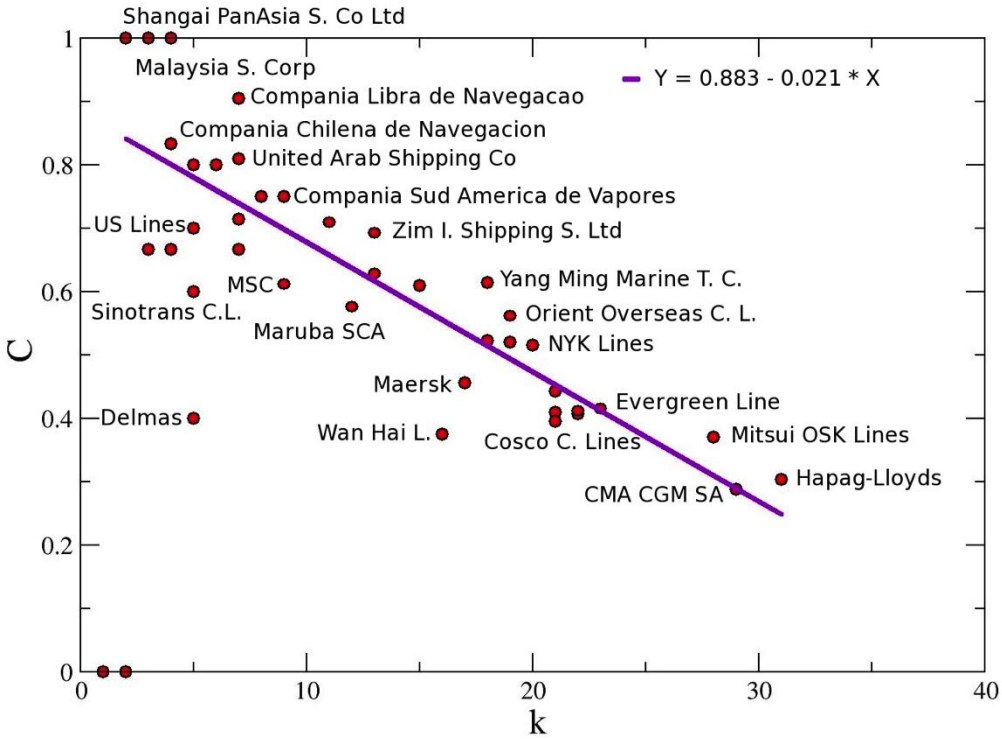
5 Local Cooperation in the CCN

If degree k represents global connectivity in a network, in order to verify whether the CCN is a small world network we need to calculate the local connectivity, i.e., the clustering coefficient, since small world networks are characterised by high local connectivity. The clustering coefficient for node i is defined as the number of closed paths of length two normalised by the maximum possible number of paths of length two[‡]. In the literature we can identify at least four different mathematical expressions for the clustering coefficient (Saramäki et al., 2007). In this study we adopt the following definition:

$$C(i) = \frac{2E(i)}{k_i(k_i - 1)} \tag{2}$$

where E(i) is the number of links between the closest nodes (paths) of node i and $k_i(k_i - 1)/2$ is the maximum number of possible inter-connections among the neighbours of node i (closed paths). For this formulation clustering coefficient C ranges between 0 and 1. We observe values of C close to 1 for carrier i when its first neighbours (i.e., carriers with direct cooperation in the CCN) show mutually high inter-connections; otherwise we have values close to 0.

In Figure 5 we plot the values of degree k versus clustering coefficient C for each carrier. The trend is well approximated by a linear decay law (correlation coefficient r = 0.81). The regression excludes the nodes with clustering coefficient equal to zero.



[‡] A path is a walk that connects two or more nodes. The path is closed (also called cycle) if the start and end node of a walk coincide.

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Figure 5. Scatter plot of degree k versus clustering coefficient C. For ease of reading, we plot the names for a selected subset of carriers.

The results obtained relating to degree k with clustering coefficient C are in line with the results obtained in the previous section. Also in this case we observe two main concentrations of the data. One first concentration for low values of degree k and high clustering coefficient C implies that carriers with few cooperative links and thus also a low level of TEU handled capacity, tend in general to link with each other. The second concentration is detected around the value of degree k equal to 20. In this case we can extrapolate a general behaviour of the carriers: as k increases, carriers tend to establish a dominant position by not allowing other carriers connected with them to cooperate with each other. The implication here is that dominant carriers tend to apply the strategy of 'divide and conquer' by controlling the level of cooperation among its partners. This is the case with carriers such as Cosco Containers Lines, Evergreen Line and NYK Lines. The case of Maersk shows us that the level of connectivity 20 (degree k) is perhaps the optimum level of cooperation needed in order to maintain market share and to be a dominant player. On the other hand, MSC establishes its dominant position in the market by being considerably independent. In fact, only 19% of its TEU handled capacity is shipped in cooperation. In Figure 6 we depict the sub networks of some characteristic carriers in the CCN. As the clustering coefficient increases (from the bottom to the top), the links are more equally distributed among the carriers.

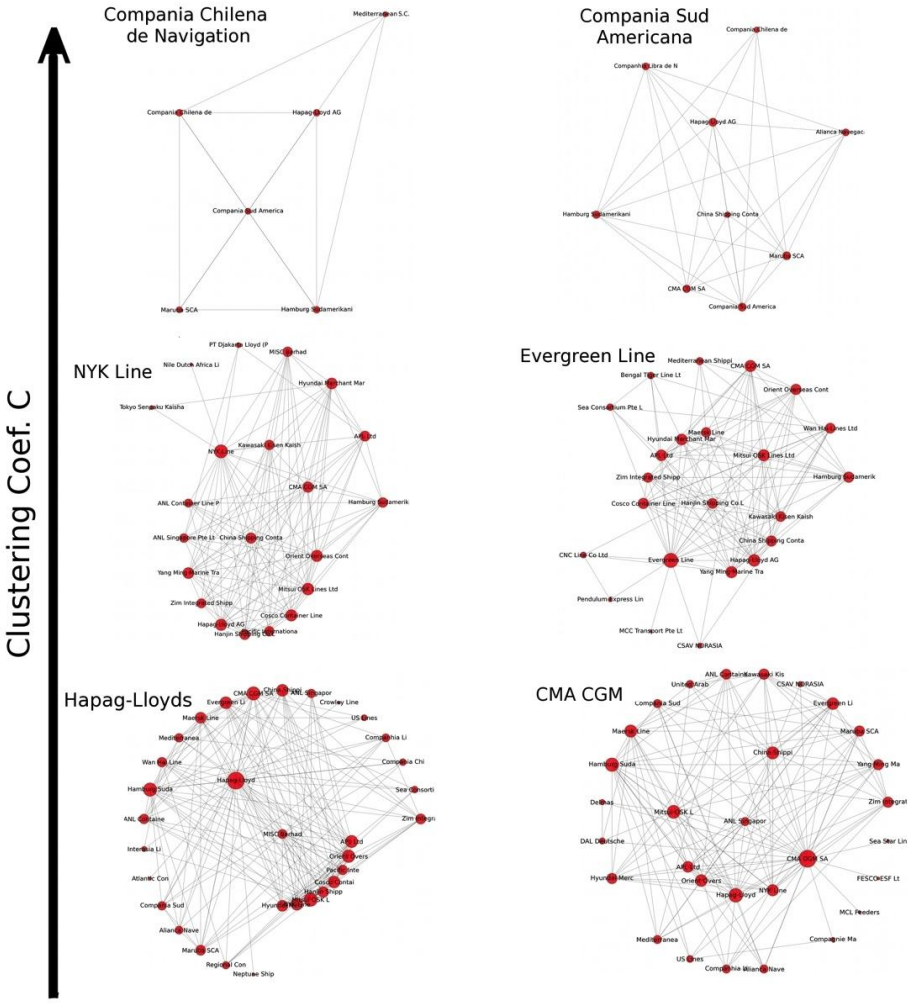

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Figure 6. Representation of sub networks of some characteristic carriers in the CCN

In order to characterise the global behaviour of the CCN, we have considered an averaged measure of the clustering coefficient C(i) for all carriers with a given degree k value. The spectrum of the clustering coefficient versus degree k, yields the following mathematical expression:

$$C(k) = \frac{1}{NP(k)} \sum_{i/k_i=k} C(i) \qquad (3)$$

where NP(k) is total number of nodes of degree k. When we observe Figure 7, we can notice that it refers to the latter spectrum and reveals an exponential downward sloping trend of C(k) over the whole range of degree values (correlation coefficient r = 0.92).

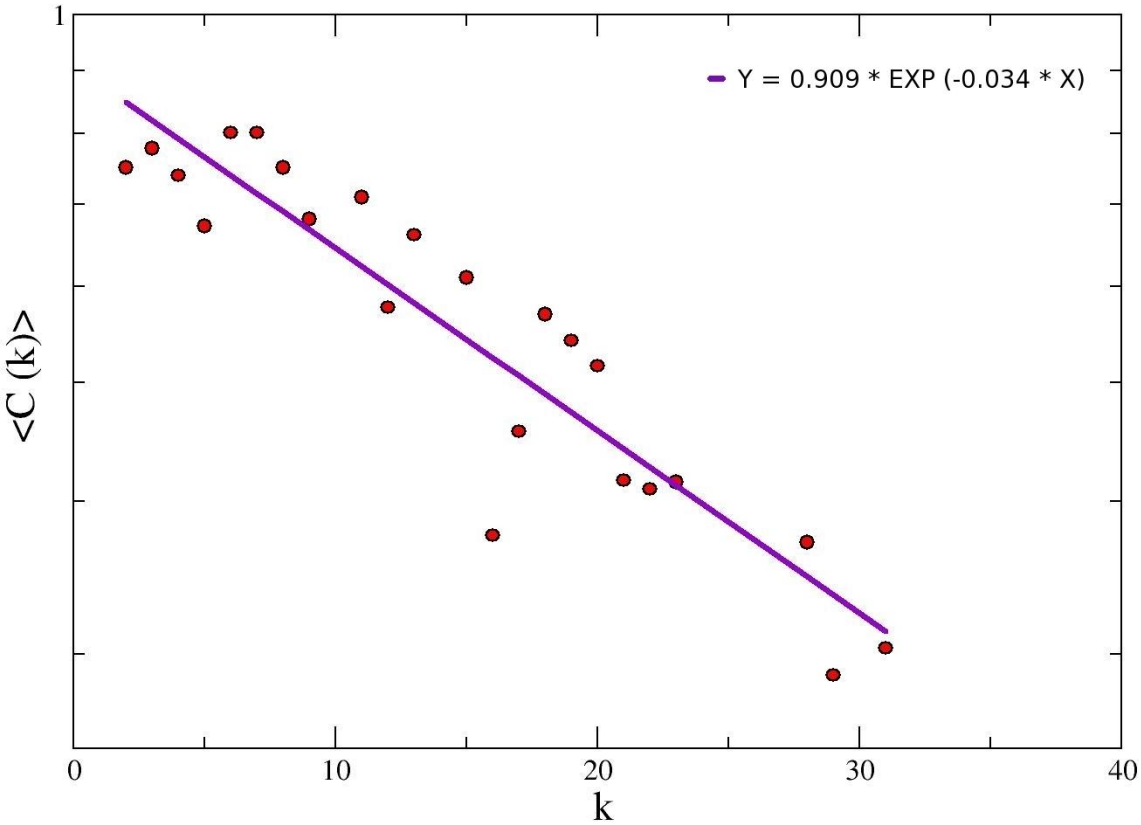

Figure 7. Lin-log scatter plot of the average clustering coefficient C(k) versus degree k for the CCN.

Figure 7 confirms our previous analysis. On average, when small carriers are disconnected from the dominant carrier they tend to form highly-connected clusters, while dominant carriers tend to play the leading role with their commercial partners.

We can conclude by observing that the CCN is very similar to a small world network because its average clustering coefficient is equal to < C(i) > = 0.55, a very high value, which is higher than the case of a random graph with the same number of nodes (< C_{rand} (i) > = 0.1).

We are not able to state definitively that CCN is a small world network as the average shortest path is similar to the case of a random network. This result is probably due to the small number of nodes in our network which produces similar results in both cases: random and small world networks. In appendix 1 we have also developed a community detection analysis over the CCN to provide a detailed picture of the membership of

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families of carriers (clusters) created by cooperative agreements in the container shipping industry. Although interesting as a descriptive tool, the community detection analysis does not allow us to reach conclusive results.

5 Conclusion

The dramatic economic downturn, occurring in 2008, has prompted carriers to increasingly seek cooperative schemes for their operations. In a mature and highly competitive market like container shipping, cooperation, has strategic value because it allows for the reduction of investment in assets and the increase of load factor aggregating demand flows.

In this work we have accounted for the cooperative container network (CCN) comprised by carriers that provide regular services in container shipping. The CCN represents a sample of 604 container services distributed worldwide and involves 65 carriers. Cooperation among carriers in shipping services creates a system of relationships whose structure appears to belong to the class of small world networks with high levels of local interconnectivity. We have shown that no random patterns emerge from cooperation among container carriers, thereby indicating the presence of consistent rules in their mutually cooperative relationships.

We have demonstrated that CCN follows two major patterns. Carriers with small handled capacity have few cooperative links with other carriers, and also when linked, they are often related in their service operations with carriers sharing similar characteristics. As we increase the value of degree k, i.e., the connectivity, the handled capacity increases linearly, whereas the clustering coefficient decreases linearly. We have shown that, by reaching a value of connectivity around 20, carriers tend to have dominant strategies. These carriers allow for cooperation with other carriers but nevertheless try to impose their role as controller of the cooperation agreement within the container service operations. Our findings therefore reach interesting implications for the development of the container shipping industry, since we have shown how the economic success of a container carrier is indeed based on cooperation, but when a container carrier increases its handled capacity it tends to achieve a certain level of connection where the carrier can impose its dominant position within the market.

A logical next step would be to thoroughly investigate the cooperative patterns discussed in the present paper by seeking more quantitative and empirical results, and demonstrating the drivers of various forms of agreements and criteria for partner selection. In particular, future research examine the impacts of the maritime network structure, in terms of hub and spoke solutions and geographical diversification, on the cooperative attitude of different players. By so doing, it would become possible to measure the level of investment risk that may affect cooperation schemes in the container shipping industry.

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6 References

Ahuja, G., 2000. Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly* 45(3), 425–455.

Alix, Y., Slack, B. Comtois, C., 1999. Alliance or acquisition? Strategies for growth in the container shipping industry, the case of CP ships. *Journal of Transport Geography* 7, 203–208.

Albert, R., Barabási, A.L., 2002. Statistical mechanics of complex networks. *Rev. Mod. Phys.* 74, Pages 47–92.

Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. *Science* 286, 509–512.

Barthélemy, M., 2011. Spatial Networks. *Physics Reports* 499, 1–101.

Baum, J.A.C., Calabrese, T., Silverman, B.S., 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal* 21, 267–294.

Bergantino, A.S., Veenstra, A.W., 2002. Interconnection and co-ordination: an application of network theory to liner shipping. *International Journal of Maritime Economics* 4, 231–248.

Blondel, V.D., Guillaume, J., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 10, 1742−5468.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., Hwang, D.U., 2006. Complex networks: structure and dynamics. *Physics Reports* 424, 175–308.

Brooks, M.R., Blunden, R.G., Bidgood, C.I., 1993. Strategic alliances in the global container transport industry. In: Rerck, R. (Ed.), Multinational Strategic Alliances, 221-250. International Business Press, London.

Cisic, D., Komadina, P., Hlaca, B., 2007. Network analysis applied to Mediterranean liner transport system. Proceedings of the International Association of Maritime Economists Conference, Athens, Greece, July 4-6.

Clauset, A., Newman, M.E.J., Moore, C., 2004. Finding community structure in very large networks. *Physical Review E* 70, 066111-066117.

Dittrich, K., Duysters, G., de Man, A.P., 2007. Strategic repositioning by means of alliance networks: The case of IBM. *Research Policy* 36(10), 1496-1511.

Drewry Shipping Consultants, 2005, Ship Operating Costs - Annual Market Review and Forecast, June, London, UK.

Ducruet, C., Notteboom, T., 2010. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. *GaWC Research Bulletin* 364.

Ducruet, C., Lee, S.W., AKY, N.G., 2010. Centrality and vulnerability in liner shipping networks: revisiting the Northeast Asian port hierarchy. *Maritime Policy and Management* 37(1), 17–36.

Ebers, M., 2002. Explaining inter-organizational network formation. In: Ebers, M., (Ed.), The formation of inter-organizational networks, Oxford University Press, Oxford, UK, pp. 3–40.

Erdos, P., Renyi, A., 1960. On the evolution of random graphs, Publications of the Mathematical Institute of the Hungarian Academy of Sciences 12, 17–61.

Euler, L., 1736. Solutio problematis ad geometriam situs pertinentis. *Commentarii Academiae Scientiarum Imperialis Petropolitanae* 8, 128–140.

Evangelista, P., Morvillo, A., 2000. Cooperative strategies in international and Italian liner shipping. *International Journal of Maritime Economics* 2, 1–16.

Ferrari, C., Parola, F., Benacchio, M., 2008. Network economies in liner shipping: the

Simone Caschili and Francesca Romana Medda acknowledge the financial support of the Engineering and Physical Sciences Research Council (EPSRC) under the grant ENFOLD-ing - Explaining, Modelling, and Forecasting Global Dynamics, reference EP/H02185X/1.

role of the home markets. *Maritime Policy & Management* 35(2), 127–143.
Frémont, A., Soppé, M., 2004. Les stratégies des armateurs de lignes régulières en matière de dessertes maritimes. *Belgéo* 4, 391–406.
Gelareh, S., Nickel, S., Pisinger, D., 2010. Liner shipping hub network design in a competitive environment. *Transportation Research Part E* 46(6), 991–1004.
Gimeno, J., 2004. Competition within and between networks: the contingent effect of competitive embeddedness on alliance formation. *The Academy of Management Journal* 47(6), 820–842.
Goerzen, A., Beamish, P.W., 2005. The effect of alliance network diversity on multinational enterprise performance. *Strategic Management Journal* 26(4), 333–354.
Gulati, R., Higgins, M.C., 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal* 24(2), 127–144.
Hamel, G., Doz, Y.L., Prahalad, C.K., 1989. Collaborate with your competitors - and win. *Harvard Business Review* 67(1), 133–139.
Helmick, J.S., 1994. Concentration and connectivity in the North Atlantic liner port network, 1970-1990. University of Miami, Miami, USA.
Hoetker, G., Mellewigt, T., 2009. Choice and performance of governance mechanisms: matching alliance governance to asset type. *Strategic Management Journal* 30(10), 1025–1044.
Hubert, L., Arabie, P., 1985. Comparing partitions. *Journal of Classification* 2, 193–218
Imai, A., Nishimura, E., Papadimitriou, S., Liu, M., 2006. The economic viability of container mega-ships. *Transportation Research Part E* 42, 21–41.
Koluza, P., Kolzsch, A., Gastner, M.T., Blasius, B., 2010. The complex network of global cargo ship movements. *J. R. Soc. Interface* 7, 1093–1103.
Koza, M.P., Lewin, A.Y., 1999. The coevolution of network alliances: a longitudinal analysis of an international professional service network. *Organization Science* 10(5), 638–653.
Lorange, P., 2001. Strategic re-thinking in shipping companies. *Maritime Policy & Management* 28(1), 23–32.
McCalla, R., Slack, B., Comtois, C., 2005. The Caribbean basin: adjusting to global trends in containerization. *Maritime Policy & Management* 32(3), 245–261.
Meng, Q., Wang, S., 2011. Liner shipping service network design with empty container repositioning. *Transportation Research Part E: Logistics and Transportation Review* 47(5), 695–708.
Midoro, R., Pitto, A., 2000. A critical evaluation of strategic alliances in liner shipping. *Maritime Policy & Management* 27(1), 31–40.
Newman, M.E.J., 2006. Finding community structure in networks using the eigenvectors of matrices, arXiv:physics/0605087v3
Newman, M.E.J., Girvan M., 2004. Finding and evaluating community structure in networks. *Physical Review E* 69, 026113-026128.
Newman, M.E.J., 2003. The structure and function of complex networks. *SIAM Review* 45, 167–256.
Panayides, P.M., Cullinane, K., 2002. Competitive advantage in liner shipping: a review and research agenda. *International Journal of Maritime Economics* 4, 189–209.
Pons, P., Latapy M., 2006. Computing communities in large networks using random walks. *Journal of Graph Algorithms and Applications* 10(2), 191–218.
Reichardt, J., Bornholdt, S., 2006. Statistical mechanics of community detection. *Physical Review E* 74, 016110-016124.

Simone Caschili and Francesca Romana Medda acknowledge the financial support of the Engineering and Physical Sciences Research Council (EPSRC) under the grant ENFOLD-ing - Explaining, Modelling, and Forecasting Global Dynamics, reference EP/H02185X/1.

Rimmer, P.J., 1998. Ocean liner shipping services: corporate restructuring and port selection/competition. *Asia Pacific Viewpoint* 39(2), 193–208.

Rothaermel, F.T., 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal* 22, 687–699.

Rowley, T., Behrens, D., Krackhardt, D., 2000. Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal* 21, 369–386.

Saramäki, J,, Kivelä,M., Onnela, J.P., Kaski, K., Kertész, J., 2007. Generalizations of the clustering coefficient to weighted complex networks. *Physical Review E* 75, 027105-027109.

Saxton, T., 1997. The effects of partner and relationship characteristics on alliance outcomes. *Academy of Management Journal* 40(2), 443–461.

Solomonov, R., 1951. Rapport A: Connectivity of random nets. *Bulletin of Mathematical Biophysics* 13, 107–117.

Souma, W., Fujiwara, Y., Aoyama, H., 2004. Random matrix approach to shareholding networks. *Physica A* 344(1-2), 73–76.

Souma, W., Fujiwara, Y., Aoyama, H., 2003. Complex Networks and Economics. *Physica A* 324, 396–401.

Stuart, T.E., Hoang, H., Hybels, R., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* 44, 315–349.

Sydow, J., Windeler, A., 1998. Organizing and evaluating interfirm networks: a structurationist perspective on network processes and effectiveness. *Organization Science* 9(3), 265–284.

Watts, D., Strogatz, S.H., 1998. Collective dynamics of 'small-world' networks. *Nature* 393, 440–442.

Zaheer, A., Bell, G.G., 2005. Benefiting from network position: firm capabilities, structural holes, and performance. *Strategic Management Journal* 26(9), 809–826.

Simone Caschili and Francesca Romana Medda acknowledge the financial support of the Engineering and Physical Sciences Research Council (EPSRC) under the grant ENFOLD-ing - Explaining, Modelling, and Forecasting Global Dynamics, reference EP/H02185X/1.

APPENDIX

We propose the application of a network community detection analysis in order to identify how the carriers cluster together in the container shipping industry.

In this study we present the results of the application of the Spinglass method (Reichardt and Bornholdt, 2006). We have also tested a number of other methods (Table 3), but we propose the partition provided by the Spinglass algorithm which offers the highest value of modularity Q (Newman and Girvan, 2004) among the methods tested. The modularity Q provides a measure to discern if a partition is valid to unfold the community structure in a network.

Table 3. List of community detection methods applied to identify clusters in the CCN.

Method	Modularity Q	# Communities	Reference
Community Spinglass	0.28	5	Reichardt and Bornholdt, 2006
Fast Greedy	0.26	4	Clauset et al., 2004
Eigenvector naive	0.23	8	Newman, 2006
Lauvain	0.22	7	Blondel et al., 2008
Leading Eigen Vector	0.22	9	Newman, 2006
Walktrap	0.21	4	Pons and Latapy, 2006

The six methods tested provide us with partitions of similar values of modularity Q, unless the number of clusters provided by each method ranges between 4 and 9. In order to evaluate how similar these partitions look, we propose the application of a quantitative index, the Adjusted Rand Index (ARI) proposed by Hubert and Arabie (1985). The ARI compares two partitions **T** and **W** of the same data set**.** The first partition **T** is used as a reference partition. Classes in partition **W** are in turn evaluated according to the following formulation:

$$ARI = \frac{\binom{n}{2}(a+d) - \left[(a+b)(a+c)+(c+d)(b+d)\right]}{\binom{n}{2}^2 - \left[(a+b)(a+c)+(c+d)(b+d)\right]} \qquad (4)$$

Where:

a is the number of pairs of elements that belong to the same class both in **T** and **W**.

b is the number of pairs of elements that belong to the same class in **T** and to different clusters in **W**.

c is the number of pairs of elements that belong to different classes in **T** and to the same cluster in **W** .

d is the number of pairs of elements that belong to different classes both in **T** and **W**.

n is the number of elements of the partitions.

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The ARI ranges between 0 and 1 (perfect similarity). Table 4 shows the level of similarity of the partitions provided by the six methods of community detection. We order the table in order to have a comparative analysis from the best method (as proved by the modularity function Q) to the lower value. A high level of agreement can be detected among all the partitions (Table 4) thus confirming that, apart from small variations, the partition provided by the Spinglass method is reliable.

Table 4. Similarity matrix of the Adjusted Rand Index values between the community detection methods tested on the CCN.

	Community Spinglass	**Fast Greedy**	**Eigen Vector naive**	**Lauvain**	**Leading Eigen Vector**	**Walktrap**
Community Spinglass	-	0.90	0.83	0.72	0.81	0.65
Fast Greedy	-	-	0.82	0.66	0.76	0.61
Eigen Vector naive	-	-	-	0.71	0.85	0.61
Lauvain	-	-	-	-	0.79	0.56
Leading Eigen Vector					-	0.58

Table 5. List of cluster carrier membership provided by the Spinglass method.

Community	Members
1	Mitsui OSK Lines Ltd (28); DAL Deutsche Afrika-Linien GmbH & Co (5); Delmas (5); Interasia Lines Ltd (4); Safmarine Container Lines NV (4); Nile Dutch Africa Line (2); OT Africa Line (2)
2	Cosco Container Lines Ltd (23); Hanjin Shipping Co Ltd (21); Hamburg Sudamerikanische Dampfschifffahrts-Gesellschaft KG (21); Hyundai Merchant Marine Co Ltd (19); Kawasaki Kisen Kaisha Ltd (18); Yang Ming Marine Transport Corp (18); Pacific International Lines Pte Ltd (15); MISC Berhad (13); Zim Integrated Shipping Services Ltd (13); Advance Container Lines (Pte) Ltd (7); Heung-A Shipping Co Ltd (5); Shipping Corp of India Ltd (4); Korea Marine Transport Co Ltd (3); Tokyo Senpaku Kaisha (3); Malaysia Shipping Corp Sdn Bhd (2); PDZ Lines (2); Gemadept Corp (1)
3	Hapag-Lloyd AG (31): CMA CGM SA (29); NYK Line (20); Maersk Line (17); Maruba SCA (12); ANL Container Line Pty Ltd (11); Mediterranean Shipping Co SA (9); Compania Sud Americana de Vapores (8); Alianca Navegacao e Logistica Ltda & Cia (7); Companhia Libra de Navegacao (7); United Arab Shipping Co (SAG) (7); Compania Chilena de Navegacion Interoceanica SA (5); US Lines (5); Compagnie Maritime Marfret (2); Atlantic Container Line AB (1); Crowley Liner Services (1); FESCO ESF Ltd (1); MCL Feeders Ltd (1); Neptune Shipping Line (1); Polynesia Line Ltd (1); Sea Star Line LLC (1)
4	China Shipping Container Lines Co Ltd (22); Sinotrans Container Lines Co Ltd (5); CSAV NORASIA (4); Gold Star Line Ltd (4); Shanghai PanAsia Shipping Co Ltd (2)

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5	Evergreen Line (22); APL Ltd (21); Orient Overseas Container Line Ltd (19); Wan Hai Lines Ltd (16); ANL Singapore Pte Ltd (9); Regional Container Lines Public Co Ltd (7); Sea Consortium Pte Ltd (6); Bengal Tiger Line Ltd (5); CNC Line Co Ltd (4); SITC Container Lines Co Ltd (4); PT Djakarta Lloyd (Persero) (3); Pendulum Express Lines (2); Sinokor Merchant Marine Co Ltd (2); Hub Shipping Sdn Bhd (4); MCC Transport Pte Ltd (4)

By comparing the Spinglass partitioning (Table 5) with the results proposed in Table 2, as well as the composition of official alliances, we can notice that community 2 comprises all members of the CKYH alliance. The membership of this cluster appears to be quite heterogeneous, as it is composed of 17 carriers with an average degree k of 11 (standard deviation of 7.9). The other carriers are minor companies, as they do not belong to the first 15 companies in terms of shipped freight volumes. The members of the other official alliances, i.e., Grand Alliance and New World Alliance, are spread over the other clusters.

Table 6. List of community detection methods applied to identify clusters in the CCN.

Cluster	Firms	<k>	STDEV	List of leading nodes in the cluster
1	7	7.1	9.2	Mitsui OSK Lines Ltd (28); DAL Deutsche Afrika-Linien GmbH & Co (5); Delmas (5)
2	17	11	7.9	Cosco Container Lines Ltd (23); Hanjin Shipping Co Ltd (21); Hamburg Sud. Dampf. KG (21)
3	21	8.5	9.1	Hapag-Lloyd AG (31); (5); CMA CGM SA (29); NYK Line (21)
4	5	7.4	8.2	China Shipping Container Lines Co Ltd (22); Sinotras Container Lines Co Ltd (5); CSAV NOROSIA (4)
5	13	11.2	7.7	Evergreen (22); APL Ltd (21); Orient Overseas Container Line Ltd (19)

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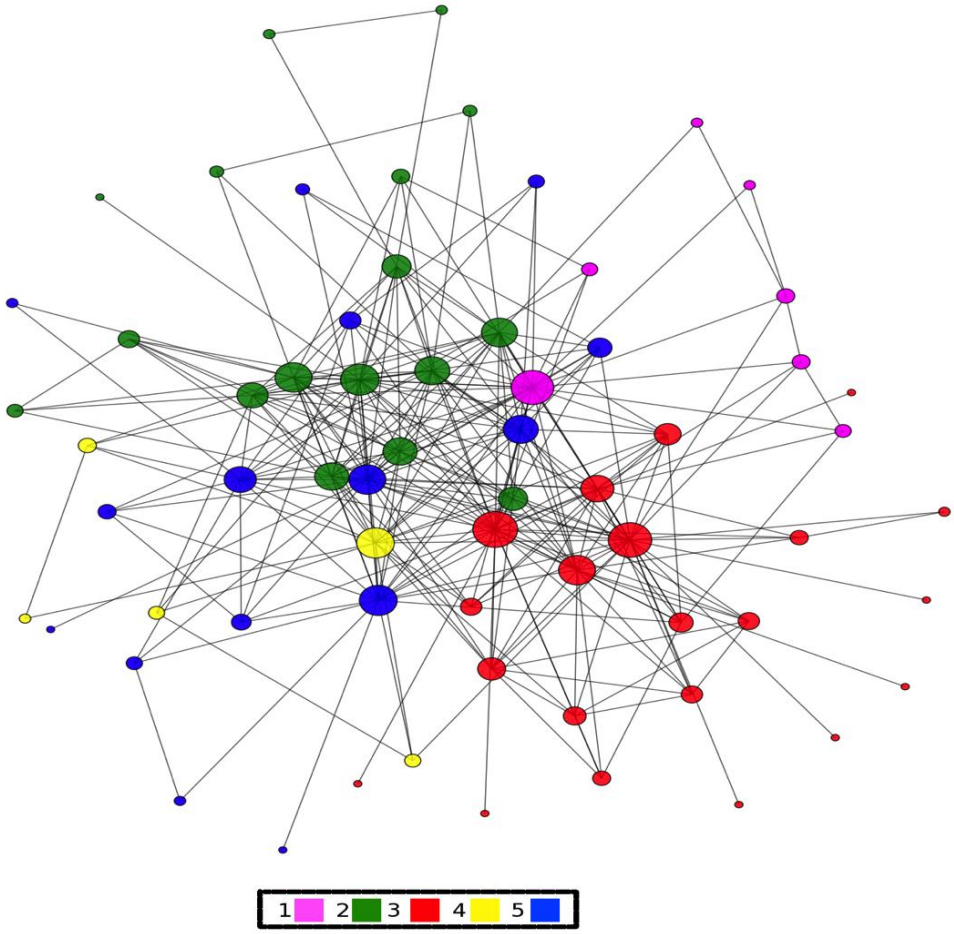

Figure 8. A visualisation of the CCN and the partitions detected by the Spinglass algorithm.

In order to clarify the relationships between the network structure and the cluster organisation of carriers, Table 6 shows some statistics on the average degree and standard deviation of the carriers belonging to each cluster, and the list of the three leading carriers in terms of network connections. Most clusters show similar values of average degree k and standard deviation. There are a few leaders in each group (dominant carriers) while weakly connected carriers compose the remainder of the clusters' population (high values of standard deviation). Finally, Figure 8 depicts the cluster membership of the carriers in our sample as provided by the Community Spinglass method. The size of each node is drawn as a function of the number of connections, while the colours correspond to node membership in the five clusters.

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