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Capacity management by global shipping alliances: findings from a game experiment

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Abstract :

The present article uses game experiments to understand the dynamics of oligopolistic competition in liner shipping markets. We show how a limited number of carriers, interacting over time, acting independently or grouped into global shipping alliances, are able to effectively and jointly reduce excess capacity. A serious game (called TRALIN) has been designed to this end, mimicking the global liner shipping market where four to five global shipping alliances compete on a set of 12 routes, connecting four ports of call for a few sequential voyages. Carriers are initially subject to low profits due to over-capacity and have to anticipate competitor capacity decisions and vessel deployment simultaneously. Results from 18 experimental games with 4644 decisions were collected and statistically analysed to confirm the main tenets of oligopoly theory and to highlight the existence of a learning effect from successive interactions (rounds in games). Our results suggest that a 'coordinated' reduction in capacity is more likely to occur when the number of competitors is limited, but even more when excessive capacity is high, urging the need for cooperation; a learning effect amongst market participants is detected over time. Serious games are flexible tools for improving our understanding of competition, the organization of liner shipping networks, and the role played by global shipping alliances. This tool may help practitioners to understand how over-capacity is evolving within the competitive process, and what factors may influence it. Although voluntarily made simplistic for the purpose of experiments, our design allows one to focus on the main tenets of oligopoly theory as applied to shipping markets.

Keywords : Oligopoly, Directed networks, Serious game, Shipping, Global shipping alliances, Capacity management

1. Introduction

Over 80 per cent of global merchandise trade is carried by sea and the container liner shipping segment is the most dynamic market with an increase from 30 million TEUs (Twenty-feet equivalent units) in 1990 to 160 million TEUs in 2018 (UNCTAD 2019). Container shipping or liner services provides port-to-port transport of containers and follow a predetermined fixed schedule and transit time (Plum et al. 2014). To provide such services, shipping lines have to take many decisions (Christiansen et al. 2004) that can be strategic (design, fleet size and mix decisions), tactical (fleet deployment of vessels to routes) or operational (cargo booking decisions).

The existence of excessive competition and capacity mean that the provision of regular services has always been challenging for liner shipping companies (Davies 1983, 1990; Davis et al., 1995; Devanney et al. 1975; Haralambides 2007; Cariou 2011). As far back as 1909, the first maritime conference gave the possibility for shipowners to set collectively prices and capacity. As Reported by the Royal Commission on Shipping Rings "…this system is an inevitable and desirable corollary of the development of scheduled liner services…and capacity pools would thus represent a way of achieving efficiency…" (Davies 1981, Graham 1998). The main argument that exempted conferences and later on consortium (1965) and strategic alliances (1994) from antitrust legislation lied in the industry's high fixed costs. In simple terms, once the ship or a liner service is set to sail under a predetermined schedule, its costs become fixed, i.e. independent of whether the ship will leave port full or empty. Under such conditions, and without an agreement on price or capacity, liners would be tempted to undercut prices to the level of marginal costs. Such pricing could obviously not ensure any sustainable service in the long run, something that in the end would be detrimental for the shippers themselves and international trade (Cariou and Haralambides 1999).

Since then, anti-trust authorities gave market participants the possibility to coordinate on capacity through maritime conferences, consortia and strategic alliances (Merk, 2018). During the last decade, a new wave of consolidation took place through Mergers and Acquisition (M&A) and Strategic Alliances. As noted by Rau et al. (2017), in their attempt to safeguard profitability in a market characterized by overcapacity and eroding margins, the main answer from container shipping industry participants has been to develop larger cooperation.

In 2015, the three largest liner shipping companies (Chen et al. 2017) had a share of almost 35 percent of the world's total ocean shipping capacity, with around 20 other companies sharing most of the remaining capacity (UNCTAD 2015). In 2020, strategic alliances (SA) are so important that the top eight container lines that account for 90 percent of global container shipping markets are all operating within one of the three main SAs (Merk, 2018).

The market consolidation opens the door to strategic behaviors. This has led to a renewal in literature of research that uses game theory to liner shipping strategies (Wang et al. 2014; Chen et al., 2016; Rau et al. 2017; Liu and Wang 2019; Choi et al. 2020). Another approach that is available to explore complex economic systems relies on the use of serious games and laboratory experiments, but has not yet been applied to better understand the dynamics of liner shipping competition.

This approach which has increased in popularity for teaching and testing the main insights of oligopolistic theories (Hazlett 1997; Emerson and Taylor 2004; Brauer and Delemeester 2001; Lean et al. 2006; Durham, McKinnon and Schulman 2007; Tsigaris 2008; Ritterfeld et al. 2009; Grant et al. 2016; Han & Ryan 2017; Ng 2019; Davis 2019; Race 2020) can be particularly interesting to study network industries (Harker and Freisz 1986; Rauch and Casella 2001; Nagurney et al. 2002 and 2014; Pal and Scrimitore 2016; Bimpikis et al. 2019). In this research, we propose the use of a game experiment to understand the decision-making process in liner shipping, where the market is characterized by a limited number of players (4 or 5 strategic alliances) who are competing on interconnected markets and face a problem of over-capacity. In particular, the decisions toward the management of capacities are observed through a repeated game experiment. The game aims at illustrating how companies competing on twelve different markets to maximize their profits, learned throughout time from their interactions and solve complex overcapacity and coordination problems.

We therefore design our experiment to mimic the prevailing situation in liner shipping markets over the last decade, where 3 to 5 main strategic alliances compete on a worldwide scale to provide liner shipping services (Figure 1).

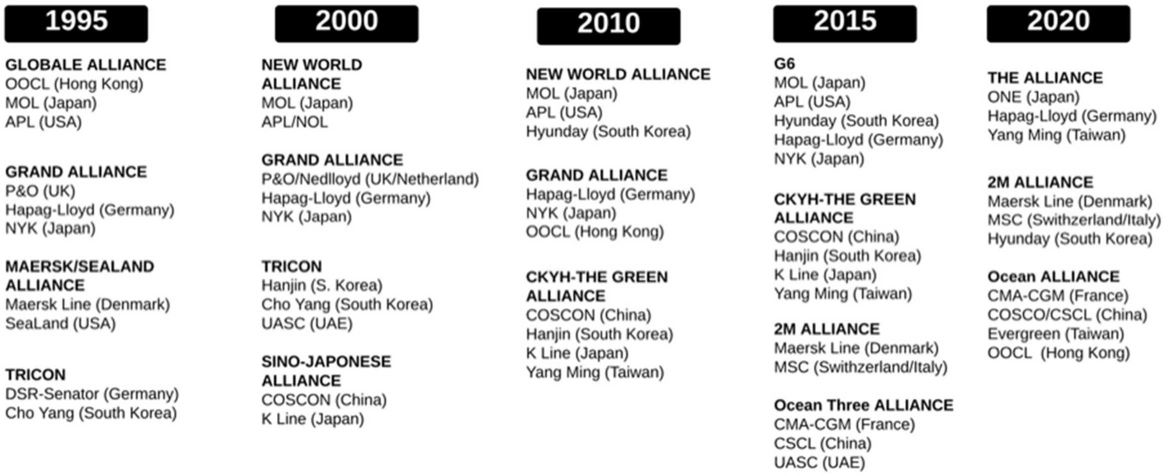


Figure 1. Strategic Alliances since 1995

Source: Authors from Ghorbani et al. (2019)

The game was implemented through 18 experiments that were played for the last 10 years by 88 teams made of undergraduate and postgraduate students that were following shipping and supply chains programs in various academic institutions located in France, Sweden, China, Vietnam and Ivory Coast. The experiments bring some insights for practitioners and policy makers. For practitioners, the game shows how individual companies adjust their strategies over time, a result that could be used to identify the behavior of potential partners which is a critical success factor of SAs (BCG 2014). For policy makers, the experiment shows how the level of concentration in liner shipping that restricts to 3-4 main players gives market players the possibility to better control over-capacity and therefore market prices even without the need for additional consolidation and how overcapacity creates powerful incentives to further cooperate.

The paper is organized as follows. Section 2 is a literature review on liner shipping market competition dynamic and Section 3 presents our hypothesis, the rule of the game and the model. Section 4 discusses the data collected through the game, our econometric strategy and the main findings. Finally, Section 5 are our conclusions.

2. Literature review

The liner shipping market has always been subject to a high degree of concentration (Cariou 2001; Fusillo, 2006). Consolidation has now reached unprecedent level of concentration. Some trade lanes are close to tight oligopoly (Sys 2009). As mentioned by Rau et al. (2017), this process culminated in the potential control of 72 percent of global shipping capacity by three large alliances (P3, G6, and CKYHE), until the Chinese Ministry of Commerce stepped into and prohibit the formation of the P3 alliance between Maersk, MSC, and CMA-CGM (Alphaliner, 2017). This triggered a reconfiguration of strategic alliances, that were initially created in September 1994 with the three alliances representing nowadays 80% of overall container trade and operating around 95% of the total ship capacity on East-West trade lanes market in 2019 (Merk, 2018).

Market concentration in liner shipping is justified by many reasons. Through internal (M&A) or external growth (Strategic Alliances), shipping companies achieve financial, economic, strategic, marketing, and operational savings (Song and Panayides 2002). In particular, sharing services and the investment in larger vessels generate economies of scale, which are the first drivers to reduce operating costs per unit of transportation (Cullinane and Khanna 2000). Due to important capital costs and avoidable vessel fixed costs, the marginal cost curve face discontinuities that affect the whole market equilibrium, especially when the shippers' demand for cargo freight is price-inelastic (Sjöström 1989, Pirrong 1992).

The collaboration on capacity between carriers is also motivated by the well-known empty core problem (Telser 1978, Sjostrom 1989, 1992, Pirrong 1992). If the demand curve does not meet the supply curve at the ship optimal size, i.e. at full load capacity, there is no stable equilibrium of the market price, as in the Edgeworth duopoly model's with bounded capacity. This issue can be evidenced by the conditions on net surplus and addressed by pooling the freight capacity among competitors, raising antitrust concerns (Sjöström 1989, Dong et al. 2011). The volatility of freight rates induced by the specific conditions of maritime transport used to be dealt with by authorized cartels called maritime conferences which existed for more than a century in Europe and the USA, before that this exemption to antitrust laws was repealed in the 1990s in the USA and 2000s in Europe (Sjöström 1989, Global Insight 2005) and replaced by slot-sharing and vessel-sharing agreements within consortia or global alliances (Song et al. 2002, Panayides and Wiedmer 2011, Hirata 2017).

Economies of scope that arise from connecting cross-ocean lines with feeder routes (Mitsuhashi and Greve, 2009; Panayides and Wiedmer, 2011; Caschili *et al,* 2014; Cruijssen *et al,* 2007) are another driver for the increase in the size of firms and for external collaboration. Agarwal (2007) identified capital intensity, larger ships, low product differentiation, high frequency of service due to just-in-time production, increasing global reach as additional drivers. Caschili et al. (2014) found that large economic agents tend to partner with small local industry participants to better serve markets. Small- and medium-sized industry participants tend to look for similar partners in order to benefit from a lower cost position. Midoro and Pitto (2000) assessed alliance stability and argued that alliance formation had so far been a very unstable, repeated process.

The main counterbalancing argument that plays against consolidation is the fact that large firms may use their market power to restrict competition and exert power over service providers such as ports, terminal and inland operators or feeder companies (Merk 2018). As mentioned by Cariou (2002), if the rationale for creating alliances is mostly related to economies of scale (larger vessels) and operational synergies (better allocation of vessels), horizontal and vertical market controls are also critical as larger firms usually go in-hand with market power. This idea is also mentioned by Rau et al. (2017), who developed a cooperative game with five strategic alliances and show that the most determining factor of profitability is the competitive intensity. The idea of competitive intensity is also mentioned by Wang et al. (2014) who conducted an analytical study on competition for two liner shipping companies. By comparing the equilibrium solutions under different scenarios, they found that the Stackelberg equilibrium is a dominating strategy in liner shipping and is more socially desirable for consumers. As compared with Nash game, the price competition gives more payoffs for both players. However, the authors conclude that a generalization of their findings to a more realistic configuration (more than two players and mixed behaviors including both cooperation and competition) remains difficult.

Chen et al. (2016) considered a model where carriers loaded two different types of shipment and needed to decide on the optimal pricing scheme. The authors highlighted that the market sensitivity to price and competition significantly affected the optimal price. Choi et al. (2020) found that the equilibrium price increases with risk attitude and concluded that studying competition games with other decisions, such as the cargo capacity and service quality might be of great interest.

Our contribution to the literature is to investigate some of the pending research questions on the dynamics of competition in liner shipping markets by using an experimental game. Our contribution is built upon findings from network economics (Rauch and Casella 2001, Nagurney et al. 2002, Nagurney et al. 2014) that since the seminal work of Harker and Freisz (1986) or Marcotte (1987), have showed how network structure is essential to understand the market outcome (Bimpikis et al. 2019) when firms are connected to several markets (Fig. 2).

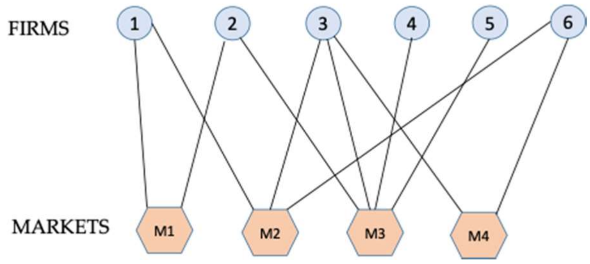


Figure 2. Oligopoly competition in a bipartite graph

In this framework and under certain conditions, a unique Nash equilibrium solution can be obtained (Bimpikis 2019) and the changes in the competition structure (new connection, new market, merging firms…) affect welfare conditions. This setting is relevant for liner shipping as markets which are physically related in time and space meaning for instance, that once a vessel arrives in a port after a first voyage, the number of available sub-markets is then restricted. This introduces both a limitation to the level of substitutability of services through the transmission constraints, and a certain inertia of behaviors, well reflected in the fixed schedule of liner carriers. It also creates conditions either for market power if a position can be hold for some sub-markets in the network (Lee *et al.* 2012) and to hierarchical interactions (Lee et al. 2012, Ducruet and Notteboom 2012).

Next section presents the hypotheses that will be tested through our experiment, the rules of the game and the experimental design.

3. The experimental game: hypotheses, rules and design

3.1 *Hypotheses*

A game experiment has to be built to reflect specific hypothesis (García Gallego 1998, Dobrescu et al. 2015, Han and Ryan 2017, Rau et al. 2017, Davis 2019, Rumeser and Emsley 2019) and we were interested by two main hypotheses related to the dynamics of competition in liner shipping:

- First, in line with one of the main findings of game theory, individual players should have an interest to play Nash strategies over a finite number of rounds (voyages) of a repeated game (Rapoport 1989). We then expected that players would try to increase their profit by deploying more capacity (number of ships) on a route following a classical result of oligopoly theory (Cowling and Waterson 1976, Clarke and Davies 1982). Consequently, a positive relationship should exist between individual profits by trade line and the firm's market share. Expectedly, such a relationship should be affected by the level of concentration as fewer competitors increases individual profit (Orzen 2008, Merikas et al. 2014), as well as demand conditions (intercept and slope of the demand curve).

- Second, a learning effect in a situation of repeated game should take place and may be used to reduce market over-capacity (Wang et al. 2014, Rau and Spinler 2016). This should be particularly prevalent in network and transport markets as non-cooperation can be very detrimental for firms' profitability (Panayides and Wiedmer 2011, Nagurney and Li 2014, Pal and Scrimitore 2016). As sub-markets (routes) are interconnected through the overarching network structure of the global market, the self-limitation of capacity would benefit to all players and lead to higher profit in the long run (Lee et al. 2012, Merk 2018). We then hypothesize that the overall capacity (number of ships) matters more than the market structure (concentration) in the cooperative behavior of firms. Such behavior can be revealed by the overall reduction of the fleet and by increasing average profits.

In order to test these hypotheses, we developed an educational serious game (Lean et al. 2006, Han and Ryan 2017, Race 2020) mimicking oligopolistic competition within a directed network shipping market.

3.2 *Rules of the game*

The game can be played remotely by several players or teams of players. TRALIN rules are few and simple (see Appendix A2). Several (four or five, preferably) Strategic Alliances compete across twelve maritime directed routes between four Atlantic ports (Rotterdam, Dakar, São Paulo/Santos, and New York; Figure 3). Each of the twelve routes has its own fixed cargo demand (from 12,000 to 45,000 TEU per trip) and an inverse demand function that determine prices (or freight rates; see Appendix A2) as a function of deployed capacity.

Figure 3. The twelve transatlantic routes linking four ports in the directed network market

At the beginning of the game, each company is given the same number of containerships (can be 15 or 20) with the same size (maximum 5,000 TEU each) and each player must deploy vessels on the different routes (e.g. 3 vessels from Rotterdam to New York, 1 vessel from Dakar to Santos, etc.). Each player' objective is to maximize their cumulated individual profit over the number of voyages (known or unknown at the beginning of the session and indicated by the instructor).

The decision on the vessels' deployment is based on prior information given on demand and on costs. Costs are made of time charter costs and fuel costs (assumed to be fixed for each voyage of a given duration in days) and variable costs (unit cost per TEU that changes with the number of containers loaded). The profit function is then defined as follows:

$$\pi_{ijk} = (p_{jk} - c).TEU_{ijk} - n_{ijk}.[TT.(BP.F + TC)] \quad (1)$$

where π_{ijk} is firm *i*'s profit on route *j* for voyage *k*, P_{jk} is the common freight rate on route *j* for voyage *k*, TEU_{ijk} is the number of containers (*TEU* = Twenty-Feet Equivalent Units) carried by firm i on route j for voyage k, c is the unitary variable cost per carried container (logistics and handling costs), n_{ijk} is the number of ships required to carry TEU_{ijk}, i.e. $n_{ijk} = \left\lceil \frac{TEU_{ijk}}{s} \right\rceil$, smallest multiple (sup integer) of the ship size s, *TT* is the transit time, *BP* is the fuel price, *F* is the fuel consumed per day and *TC* is the Time Charter (vessel) cost per day.

By convention, each voyage lasts 15 days whatever the route, and the fuel consumption per day is identical (we assume a similar speed for each origin-destination). We are conscious that this might be seen as unrealistic because speed and fuel consumption appear as major factors of competitiveness for carriers, but this strong assumption allows players to focus their decisions on the mere network-level resource allocation problem. In other experiments, this homogeneity of competitors and market conditions could be relaxed to see how some more complex information and resources can be dealt with by agents.

Fixed values were also set for several vessel parameters and economic variables (*c, BP, F, TC; see in Appendix A2*). The number of loaded TEUs and freight rates depend on a fixed cargo demand, but also on the route demand function and the aggregate capacity supplied by all companies:

$$p_{jk} = a_j - b_j.\sum_{i=1}^{n} CAP_{ijk} = a_j - b_j.\sum_{i=1}^{n} s.n_{ijk} \tag{2}$$

Where CAP_{ijk} is the vessel capacity in TEUs deployed by firm i (with $i=1,\ldots,n$) on route *j* for voyage *k*. This functional specification, although not conventional (it should be TEU_{ijk} instead of CAP_{ijk}) is meant to capture the market mechanism of variable freight rates. Because the shippers demand for cargo transport is fixed, freight rates would also be fixed otherwise. Let's assume that the cargo demand for a particular route is *12,000 TEUs* and the demand function for this route is *P = 1200 – 0.02.CAP*. If two companies decide to allocate one vessel each on this route, the supply capacity would be *10,000* TEUs, i.e. less than demand, and vessels would operate at full capacity utilization (100%) for a freight rate of *$1000* per *TEU* (*=1,200 – 0.02×10,000*). In this case, the remaining 2,000 TEUs of cargo demand would not be satisfied. The demand rejection is not intentional from players but may occur if the aggregate capacity deployed by all players on a route does not cover the cargo demand. Suppose now that four companies decide to deploy one vessel each on this route (i.e. total = 20,000 *TEU*), they would share equally the cargo demand between the deployed vessels (3,000 *TEU* each, whatever the owner), the freight rate would decrease to $800 and the loading rate per vessel would be falling down to 60%.

In other words, in a situation of market overcapacity on a given route and voyage, the freight rate decreases with capacity and the service cost increases due to lower utilization rate. Consequently, firms' margins and profits are decreasing. After each voyage, all players receive information on the level of freight rates and loading rates per route, as well as on the current and cumulative profit of each firm and the current location of vessels in the various ports of call. After the first voyage and for every following round, participants can purchase or sell vessels at a fixed price equivalent to the product of the transit time by the time charter rate (i.e. 540,000 USD when selling to or buying from a third party (bank or central agency[1]).

The winner is the company with the largest cumulated profit over the whole game session. According to the time spent by (or left to) players to choose their strategy for each voyage, the

[1] In future developments of the game, we could imagine that players bargain and trade their ships instead of this central agency.

length of the game may vary from a few hours (three or four) to a full training day or more if a second session is organized.

3.3. Experimental design

In the experiment, students are placed in a position to take decisions about resource (ship) allocation in a virtual shipping network market. In a classroom, four or five strategic alliances made up with five or four students each, compete on a schematic transatlantic shipping market. Each SA receives fifteen or twenty containerships when starting the game and must allocate them on the twelve different routes, bearing in mind that there will be several voyages (rounds of the game, whose number is not told to students) and that vessels will have to depart from the port where they called in at the previous round (for the first round, the choice is then fully open).

Once all players have decided, the competition process can begin. Freight rates and loading rates are automatically calculated by the computer and the profit levels by route and by player are also publicized. Players can then adjust their initial strategy for the second voyage (round) to re-direct the vessels to the most profitable lanes if they can do so from the arrival ports, and by investing in new capacity or by selling ships if they think that the range of routes (three possible routes by port) is hampered by overcapacity. Once the choices are made for the second voyage, the competitive process sets new market prices, loading rates by route and profits by player (current and cumulated). Players receive the information and make decisions for the third voyage (round), and so on and so forth until the 8th and last round or when the instructor decides to stop the game session.

Four treatments were proposed for the experimental games and aimed to measure whether or not, with repeated interactions over space and then time, a learning effect allowed to deal with the overcapacity problem. There were two initial configurations w.r.t market concentration and two configurations w.r.t initial over-capacity[2].

- P4 (higher concentration) with four players in the experiment.
- P5 (lower concentration) with five players in the experiment.
- C1 (lower capacity) with fifteen ships per player at the beginning of the experiment.
- C2 (higher capacity) with twenty ships per player at the beginning of the experiment.

In all cases, the experimental sessions corresponded to a non-cooperative strategic framework, where the participants were not allowed to exchange information and to create tacit collusion. Through these various configurations, we investigated first how individual profit increases with the market share (capacity) on a trade line. Secondly, we tested whether the initial over-capacity matters more than concentration in the outcomes of this non-cooperative game and on the learning effect.

4. Data, models and findings

4.1.Data

The 18 experiments took place between April 2013 and January 2020 in France (Nantes, Bordeaux and Marseilles), Vietnam (Hô Chi Minh City), China (Shanghai), Ivory Coast (Abidjan) and Sweden (Malmö). The participants were students involved in Master or Bachelor

[2] The initial total capacity supply usually reached between 320,000 and 500,000 TEUs (4 or 5 companies x 15 or 20 containerships x 5,000 TEUs per vessel), when the aggregate cargo demand for the whole network is only 243,000 TEUs, meaning that the required carrying capacity (50 ships) is by far exceeded.

programs. The initial dataset includes 4,824 observations in overall across 12 variables: 88 teams (firms) are made up with 3 to 6 students each, and the games are with a duration from 3 to 8 voyages (Table 1). We only considered the first 5 voyages because only one session had more rounds, restricting the number of observations to 4,644.

Table 1. Data from TRALIN sessions

	Mean	*St.-dev.*	*Min*	*Max*	*Median*
Profits (in million USD)	0.41	1.45	-7.59	10.24	0.06
Vessels (by route and by firm)	1.31	1.02	0.00	8.00	1.00
Freight rate (‘000 USD×TEU^{-1})	0.79	0.19	0.10	1.35	0.80
Loading rate (%)	0.66	0.20	0.25	1.00	0.60
Cargo by route (in ‘000 TEUs)	20.25	11.44	12.00	45.00	15.00
Session (game)	9.99	5.12	1.00	18.00	10.00
Firm (team)	46.39	25.07	1.00	88.00	47.00
Route (12 connected lanes)	6.50	3.45	1.00	12.00	6.50
Voyage (round)	2.91	1.32	1.00	8.00	3.00
Admin (0=instructor 1, 1=instr. 2)	0.69	0.46	0.00	1.00	1.00
Team (0=4 players; 1=5 players)	0.92	0.27	0.00	1.00	1.00
Capa (0=15 ships; 1=20 ships)	0.64	0.48	0.00	1.00	1.00

Six sessions were organized by the first co-author and twelve by the second co-author. The number of teams per session varies from four (two sessions) to five (other sessions). For the purpose of the experiment, seven sessions were selected with an initial allocation of 15 ships per team at the beginning of the game (C1) and 11 sessions with 20 ships (C2).

Each player/company decided on the number of vessels deployed by route at the beginning of each round (or voyage). Profits by route and voyage varied between -7.59 to 10.24 million US$, whereas the average profit was $0.41 m and the median profit was $0.06 m, meaning a skewed distribution with a long right tail. Low profits might be explained by low freight rates which is determined by the demand function for each route. The average freight rate was $790 per TEU with a standard deviation of $190 and it fluctuated between $100 and $1,350, thus showing a high variability. The loading rate was even more volatile and moved from 25% and 100%, with a standard deviation of 20%.

4.2. Econometric strategy

Our first objective was to confirm that firms increase their profits by playing Nash on every route representing a sub-market. As a result, individual profits should be positively correlated with the number of deployed vessels, which can be seen as a proxy of a firm’s market share. However, profits may turn to be smaller or even negative if other players selected the same strategy on the same routes. Cargo demand being unequally distributed along the network market, the market size had then to be taken into consideration. Our second objective is to measure the learning effect happening throughout the experiment, i.e. an increase in average profits over time that result from the collective reduction in capacity. The voyage variable should therefore be found positively linked with profit for all players.

Strategic alliances may deploy vessels on the same route over time and we used dummy variables to account for several fixed effects affecting the relationship between the main variables. We started with a simple OLS regression to have a first insight on the relationship between firm i’s profit on route j for voyage k (π_{ijk}) and the number of vessels (X_{ijk}):

$$\pi_{ijk} = \alpha + \beta X_{ijk} + \varepsilon_{ijk} \quad (3)$$

Then a more comprehensive OLS model was tested with the following independent variables explaining the individual profit: number of vessels, freight rate, capacity utilization (loading rates) and cargo demand:

$$\pi_{ijk} = \alpha + \beta X_{ijk} + \gamma Y_{jk} + \delta Z_j + \varepsilon_{ijk} \quad (4)$$

Where Y_{jk} captures those variables varying across routes and voyages only (freight rate, capacity utilization), variables varying across routes only (cargo demand Z_j), $\alpha, \beta, \gamma, \delta$ being parameters, and ε_{ijk} the error term. Finally, fixed effects were introduced step by step to account for the learning effect of voyages, the role of capacity and the number of competitors, as well as the unobserved heterogeneity of firms, as the ability of some teams to adopt a more successful strategy (firm's management effect), whatever the routes and session legs.

$$\pi_{ijk} = \alpha + \beta X_{ijk} + \gamma Y_{jk} + \delta Z_j + \theta_k + \mu_i + \varepsilon_{ijk} \quad (5)$$

This model was developed across the four treatments (P4, P5, C1, C2) to test for differences in the slopes of models linking profits and the number of ships (market share) mainly. The models were compared by ANOVA and other statistical tests (Wilcoxon and Krukal-Wallis tests).

4.3 Results

The correlation matrix is displayed in Figure 4. As expected, profits are not significantly and positively correlated with the number of vessels but they are correlated with the loading and freight rates (correlation matrix and significance probabilities are reported in Appendix A1).

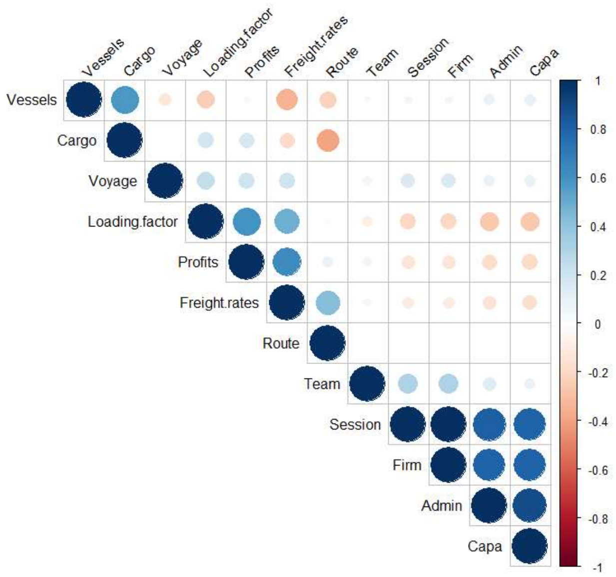


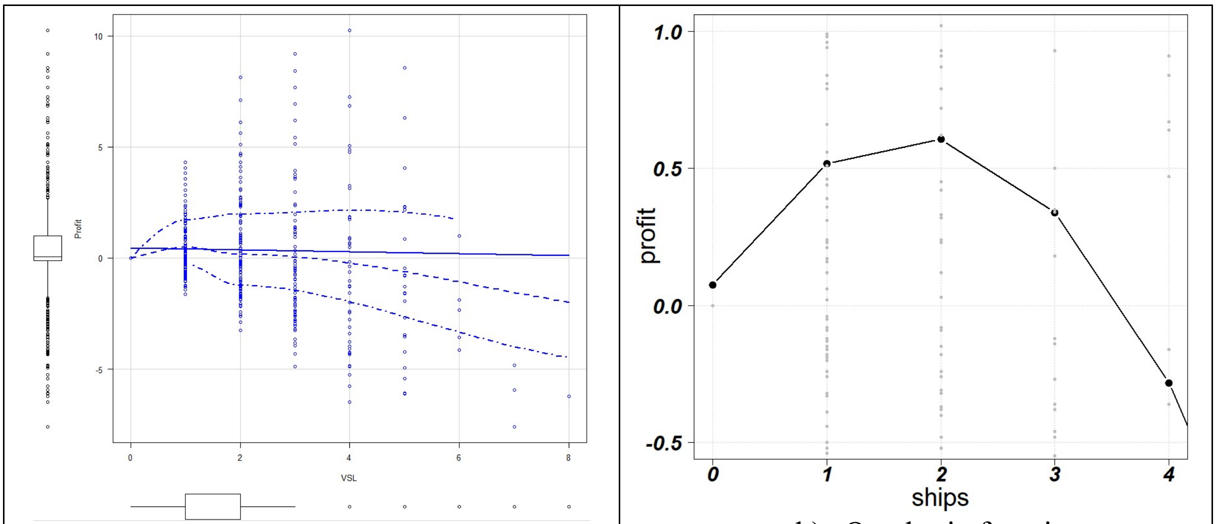
Figure 4. Correlation matrix plot

(Blue is for positive correlations, red for negative ones. The intensity of colors and size of circles are proportional to the correlation coefficients; data can be found in Appendix A1; R-library corrplot)

Variables other than profits were poorly correlated between each other, except for freight and loading rates and for the number of vessels and cargo demand which may result in a possible multicollinearity. Players were expected to allocate more vessels onto the routes whose demand for freight is higher. The positive correlations between the session number, the firm ID, admin and Capa were statistical artefacts and should not be considered because these variables were simply ordered by an increasing number.

4.3.1 The relation between individual profit and capacity for all sessions

The relationship between the level of individual firm's profit and the number of ships deployed on a route is reported in Figure 5. A simple OLS model (Fig. 5a) confirms that the relationship between profit and the number of ships is poorly linear, if existing at all (R^2 = 0.0007). A quadratic term is therefore introduced in the model to provide a better fit (R^2=0.05; Fig. 5b). On average, profit by route increases up to the second ship deployed by a firm, and then decreases beyond that figure, even resulting in negative profits when on average, a fourth vessel is deployed on a route.



a) Simple OLS model
b) Quadratic function

Figure 5(a-b). Profit as simple OLS and quadratic function of the number of ships
(we used the R-package Car with the scatterplot function for the OLS simple model, including a nonparametric-regression loess smooth, the smooth conditional spread and a regression line + boxplots in the margins)

Our econometric results are displayed in Table 2, including previous quadratic regression. The first model corresponds to Eq. (4) stresses that all independent variables are significant at the conventional 1% significance level. As expected from oligopoly theory, individual profit was found positively related to market size (cargo demand). A rise of cargo demand by 1,000 TEUs would result in a $15,000 increase in profit.

Table 2. Econometric results

	(1) OLS	(2a) FE	(2b) FE	(2c) FE
Intercept	-5.980***	-6.023***	-5.887***	-5.760***
	(-50.683)	(-50.138)	(-48.665)	(-28.195)
Vessel	1.202***	1.202***	1.208***	1.207***
	(25.656)	(25.623)	(25.831)	(24.588)
Vessel²	-0.251***	-0.251***	-0.253***	-0.253***
	(-18.411)	(-18.340)	(-18.550)	(-18.435)
Freight rate	4.064***	4.042***	4.028***	4.032***
	(41.667)	(41.509)	(41.437)	(41.954)
Loading rate	3.014***	2.991***	2.900***	2.930***
	(35.386)	(35.219)	(34.288)	(33.177)
Cargo Demand	0.015***	0.015***	0.015***	0.016***
	(9.245)	(9.127)	(9.284)	(9.243)
Voyage FE	NO	YES	YES	YES
Voyage 1		REF	REF	REF
Voyage 2		0.087**	0.092**	0.089**
		(2.417)	(2.555)	(2.488)

Voyage 3		0.105***	0.112***	0.108***
		(2.797)	(2.981)	(2.886)
Voyage 4		0.121***	0.142***	0.143***
		(3.164)	(3.673)	(3.663)
Voyage 5		0.076***	0.114**	0.107**
		(1.657)	(2.244)	(2.235)
Capa2 (REF=Capa1)	NO	NO	-0.132***	-0.171
			(-4.705)	(-0.967)
Firm FE	NO	NO	NO	YES
Adjusted R^2	0.66	0.66	0.66	0.67
Nb of obs.	4644	4644	4644	4644
Residual SE	0.843	0.842	0.840	0.834

Note: Ordinary Least Squares (OLS), Fixed-Effect (FE) estimates. t-values in parentheses are calculated with robust standard-errors. *Significance level at 10%. ** Significance level at 5%. *** Significance level at 1%.

A key variable to explain profitability is the loading rate that affects the extent of economies of scale (Cullinane and Khanna 2000, Stopford 2009, p. 223). This was confirmed by the highly significant and positive influence of loading rates on profit in all models that included this variable. The freight rate played also a significant role. Any increase in market price by $100 per TEU would result in a $400,000 rise of profits. Furthermore, when the dummy variable Capa reflecting the initial over-capacity at the beginning of the experiment was considered (model 2b), individual profit reduced with the degree of over-capacity (see next sub-section). The concentration variable (number of teams) was not statistically significant and the firm fixed-effect accounting for unobserved heterogeneity (model 2c) increased the model fit (for max. adj. R^2 and Min RSE value). Finally, we checked a potential endogeneity between profit and the number of vessels and for the correlation between the residuals and the vessel variable. The null hypothesis was rejected for every model, showing no endogeneity problem[3].

4.3.2 The overall learning effect and the prevailing role of over-capacity

As explained earlier, one of the main hypotheses related to our experiment is the existence of a learning effect over time. To identify and measure such an effect, we first estimated a naive regression of profits to the voyage rank to measure the mean profit for each round. On average, firms have gradually increased their profits along with the rank of voyages, starting with a negative payoff (-$58,370) for the first voyage, to nearly $811,460 on average for the fifth one (Fig. 6a). The FE models [eq. (2a) to (2c)] confirm a significant and positive influence of the voyage rank on profits. When controlling for other variables, profits were still significantly enhancing from voyage 1 to voyage 4, before slightly declining for the fifth round (see the parameters of the variable Voyage in models 2a-c). This result would mean that there is an overall learning effect out of the game through a collective effort to reduce capacity which was illustrated (Fig. 6b) by the decline in the aggregate number of vessels over time.

[3] It was not possible to test for random effects in the model because of the non-panel structure of data. It could be done at the cost of dramatic reduction in the number of observations, by pooling the firm's decisions for all routes. This was also tested but did not provide any interesting additional knowledge for this study.

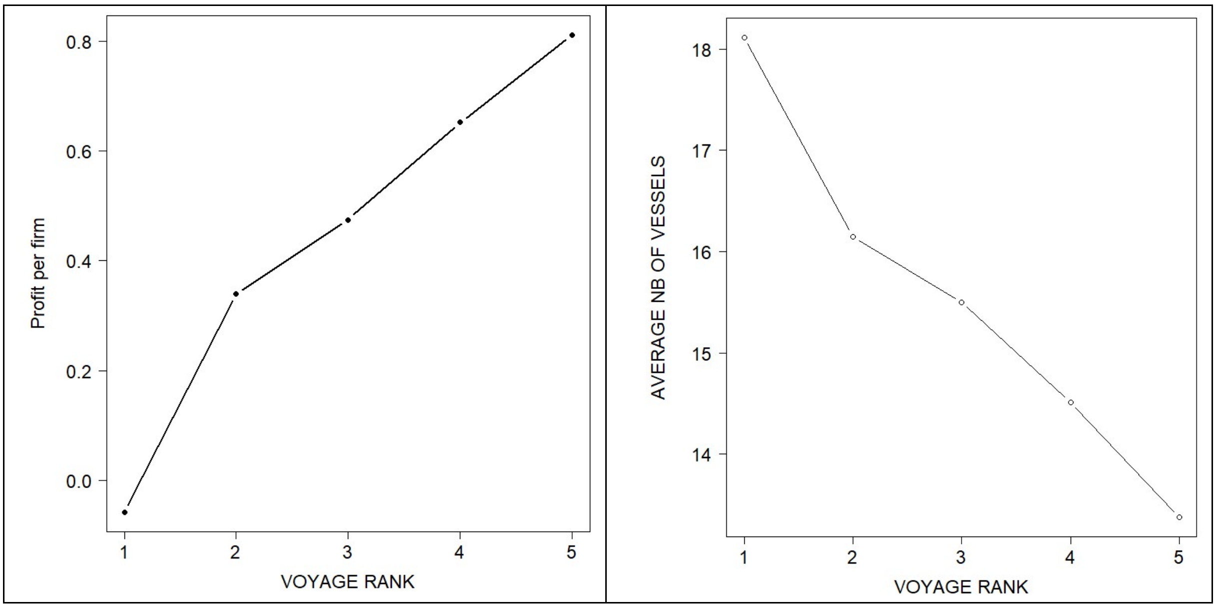


Figure 6(a-b). Average profit /number of ships per firm and by voyage

Table 3 presents the evolution of the aggregate number of vessels by session, knowing that 39% of the sessions started with 15 vessels and 61% with 20. Session 3 had four players only, each one receiving 16 vessels at the beginning of the game. Out of the 18 sessions, only session 4 shows an increasing number of vessels after three rounds, but all others ended with a reduction. in the fleet (Table 3). Most players understood the common problem of over-capacity and decided to sell off vessels, even though they could earn more by keeping their own vessels in a pure non-cooperative strategy. Fig. 6b depicts this individual reduction of fleet throughout time, passing from 18 to 13 ships per carrier on average between the first and fifth leg.

Table 3. Aggregate number of vessels by session

Voyage	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	75	75	64	75	75	75	80	100	75	100	100	100	100	100	100	100	100	100
2	75	61	64	71	70	68	79	76	70	95	88	90	94	92	77	79	77	95
3	73	62	60	78	69	68	81	75	69	93	83	82	82	78	78	75	74	84
4		64	48		71	62	76	75	69	57	80	83	82	75	74	66	70	80
5					64	74					82	83		68	56	40	59	76
6						74												
7						63												
8						60												

The differences in the four treatments (P4, P5, C1, C2) introduced in section 3.3 were investigated to separate the role of concentration (number of players with P4 and P5) from that of capacity (over-capacity with C1 and C2). Although the number of sessions was not evenly balanced between the treatments (in particular concerning the number of players), the sub-samples were large enough to come out with significant results. The most interesting result is reported in Fig. 7.

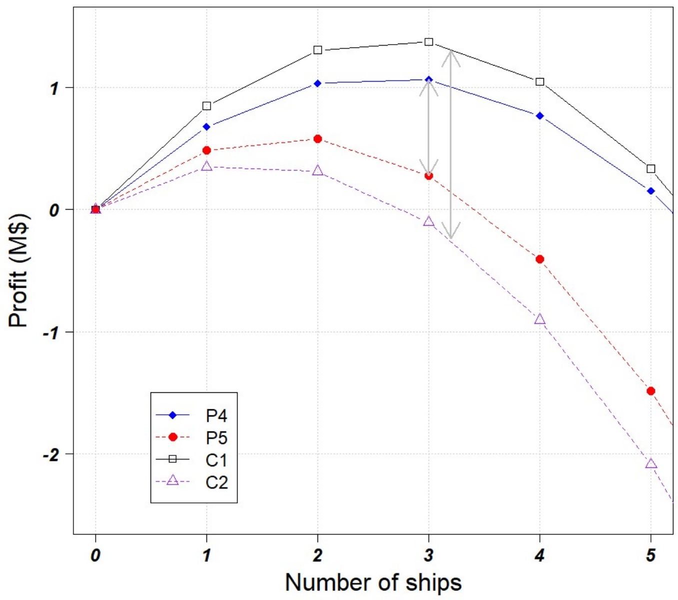


Figure 7. The 4 treatments of the profit/number of ships relation with quadratic-fit

For each treatment, a similar pattern existed with a non-linear relationship between profit and capacity with a positive slope bending down towards negative profits when additional ships were included. Profits decrease much more rapidly when the number of players or when the initial fleet per player was high. Moreover, the voyage fixed effect was not found significant for P4 and C1, contrary to P5 and C2 where profits increased up to the fourth voyage. Under the pressure of competition and mostly when a large over-capacity existed, firms were downsizing their fleet more effectively.

Interestingly, the gap in profit between low and high capacity treatments proved to be larger than the gap for treatments with a low and high level of concentration (see arrows in Fig. 7), showing that the size of the fleet with regard to the cargo demand could matter more than the number of competitors. Table 4 highlights the differences of average profit and number of ships between the various treatments.

Table 4. Mean values under the 4 Treatments

Concentration	**High (P4)**	**Low (P5)**	***t-test***	***Wilcoxon W test***	***Kruskal-Wallis χ^2 test***
Profits (m$)	0.72	0.37	3.89***	926208***	18.65***
Nb of ships	1.44	1.31	2.25**	868752**	4.63**
Capacity	***Low (C1)***	***High (C2)***			
Profits (m$)	0.77	0.20	12.48***	2994753***	152.62***
Nb of ships	1.18	1.39	-6.76	2131520***	63.52***

*Significance level at 10%. ** Significance level at 5%. *** Significance level at 1%.

The pairwise t-test and Wilcoxon rank sum test of equal means between treatments led to reject the null hypothesis in all cases, except the t-test comparing the mean number of ships between low and high capacity levels. However, because the ship variable was not normally distributed, the non-parametric Wilcoxon and Kruskal-Wallis tests were preferred and both concluded to significant differences between the sub-sample values. The quadratic models of the relation between profit and number of ships (Eq. (3) in Table 2) in the whole sample *vs* treatments was also tested using ANOVA, firstly pairwise and then altogether, and confirmed the previous results: the Fisher tests rejected the single-sloped model to select the models having different parameters for the concentration and capacity groups[4].

Table 5. Mean values of profit and fleet by route along voyages under the 4 Treatments

Profit (m$)	***V1***	***V2***	***V3***	***V4***	***V5***
P4	0.634	0.316	0.722	1.194	-
P5	-0.128	0.342	0.450	0.590	0.811
C1	0.708	0.723	0.795	0.898	0.711
C2	-0.541	0.097	0.272	0.543	0.840
Nb of ships					
P4	1.50	1.49	1.47	1.29	-
P5	1.51	1.33	1.27	1.20	1.11
C1	1.26	1.17	1.17	1.09	1.15
C2	1.67	1.45	1.37	1.26	1.10

The plots comparing the evolution of profits and of vessels by voyage between the four treatments (see Appendix A3) stress the reluctance of players to reduce their fleet when the concentration was higher (hence less competition) or when over-capacity was limited. In both cases, profits were found fairly stable. When competition (P5) or initial over-capacity (C2) increased, players were rapidly reducing their fleet, an effort that was benefitting to all. Table 5 shows that average profit by route increased throughout the sessions for all treatments, but the C2 gain was by far the largest (+$1.4m between V1 and V5 against +$0.9m for P5). The average reduction of fleet size by route was also more important for C2 (-34% between V1 and V5, against -14% for P4, -26% for P5, and -9% for C1).

4.3.3. Discussion of results

We showed through our experiments that individual firm's (or alliance's) profit relied on the firm's market share and rivals' reaction (like a classical conjectural variation), but that the payoff was also affected by market conditions (intercept and slope of the demand curve as a proxy of more or less elastic demand, market size measured by the cargo demand, freight rate, loading factor).

Knowing the fixed cargo demand by route, participants are in a better position to calculate the overall capacity required for the network, hence their own fleet size in overall and by route. Despite this advantage, the average capacity and profit by route and by voyage achieved through the experiments were still far from what could have resulted from operating a unique company. The optimal capacity by route was simply obtained by dividing the cargo demand of each route by the ship size to find the optimal number of required vessels (Fig. 8). From this number, end-to-end lines could be operated when the front hauls is equivalent to the back haul for a route, or combined lines (e.g. pendulum or triangular) could also be scheduled by adjusting the capacity to the traffic flows (e.g. 3 ships between Santos, Dakar and Rotterdam).

[4] Capacity model vs simple quadratic model: F=91.504*** (Prob<0.01), Concentration model vs simple quadratic model: F=10.741*** (Prob<0.01), the 3 models (Capacity, Concentration, single-sloped Quadratic) altogether: F=11.842*** (Prob<0.01).

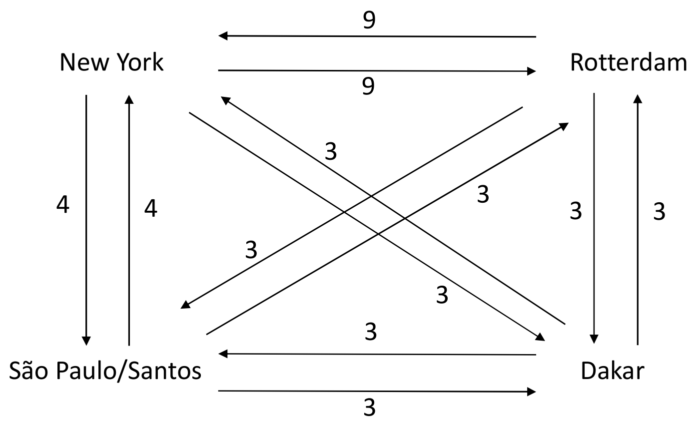


Figure 8. Optimal allocation of ships with fixed cargo demand

A global capacity-sharing agreement would have reduced the total fleet from 75 or 100 initially down to 50 ships. Adjusting the capacity by route in end-to-end trips would have left only nine containerships between New York and Rotterdam (eastbound and westbound) to carry the 45,000 TEU cargo, three ships in both ways between Dakar and Rotterdam for the 12,000 TEUs, etc. In overall, profits by firm, by voyage and by route would have reached \$1.69m for a single company instead of the \$0.41m payoff (i.e. 24% of the maximum profit) achieved on average in the TRALIN sessions.

Our results also revealed a learning effect across the experiments which induced an overall reduction in the fleet over time (i.e. voyages), even though not all players were contributing equally to the joint effort. This is usually observed in repeated games with infinite horizon, but we may consider that a directed network market fosters cooperation and trust to cope with irregular demand and prices. Burt (2001) reported that "trust is twice created by repeated interaction, from the past and from the future. From the past, repeated experience is improved knowledge of the person. Cooperation in today's game is a signal of future cooperation" (Burt 2001, in Rauch and Casella, p. 32). In our overall sample, the aggregate capacity decreased by 26% on average between the first and fifth voyage, ending up with a \$0.81m profit by firm and by route (i.e. 48% of the optimum with a single Grand alliance). Building trust in directed network markets is particularly demanding because it does not only require to select an optimal number of vessels on the whole network, but also to solve coordination problems and organize efficient allocation on every directed sub-market in a consistent way (Nagurney et al. 2002, Lee et al. 2012, Bimpikis et al. 2019).

5. Conclusion

Our main objective through the design and implementation of an experimental game was to show the dual role of concentration and fleet capacity on the willingness of firms to cooperate and to manage capacity. Both tendencies (concentration and increasing capacity) play a significant role on liner shipping markets. In the real world, the number of strategic alliances has been decreasing and M&A movements between global ocean carriers have strongly consolidated the whole liner shipping industry over the past decades (Cariou 2002, Hirata 2017, Merikas et al. 2014, Chen et al. 2017, ITF 2018).

Despite the higher concentration (e.g. fewer SAs), the investment in larger ships to gain from economies of scale tends to maintain a high degree of overcapacity over time, hence lower freight rate levels. Our experimental game results revealed that the initial size of global carriers influenced the cooperative behaviors to a greater extent than concentration, although the latter may also affect negatively the willingness to cooperate. Starting with a large over-capacity tended to increase the common perception of the urgent need to downsize the fleet for all firms. Adding an extra carrier (or extra alliance) would also incentivize the shipping companies to reduce their freight capacities.

A serious game like TRALIN, by its simplicity, appears as a flexible multi-layered tool to support conceptual thinking and conduct experiments about competitive and cooperative behaviors in shipping markets. As understanding the dynamics of oligopoly competition in directed network markets remain challenging, the network structure addresses communication transaction cost issues within the linkages between buyers and sellers (Rauch and Casella 2001). The network structure may also respond to positive externalities created by consumers, where the interest to join a network increases with its size and the number of participants (Pal and Scrimitore 2016). A network can finally describe the multi-market nature of competition (Harker and Freisz 1986, Bimpikis et al. 2019), as for liner shipping. In such a case, when markets within a directed network of trade lanes is combined with a capacity constraint, a potential mismatch between the regular and fixed capacity of ships and the cargo demand for freight creates empty core problems and volatile prices (Telser 1978, Sjöström 1989, Dong et al. 2011, Lee et al. 2012).

Our experiment took place in a dense network by construction because of a low number of nodes and edges. It would be interesting to expand the network (more ports and routes) with a same number of participants and similar capacity, to see how it could affect the network competitive outcomes. Tacit and legal cooperative behaviors through coalitions and alliances would also bring interesting inputs to the shipping literature on the basis of this experimental framework. We hope that this contribution has shown how a simple and flexible tool like the serious game TRALIN may be used by scholars to create an interactive environment enhancing the cognitive abilities of students to understand a complex problem (Dobrescu et al. 2015, Han and Ryan 2017, Davis 2019, Race 2020), but also to researchers in order to develop experimental sessions improving the knowledge of oligopolistic behaviors in directed networks under capacity constraints.

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APPENDIX

A1. Correlation matrix and significance probabilities

	Session	Firm	Route	Voyage	Ship	Profit	FR	Load	Cargo	Team	Capa
Session	1.00										
Firm	1.00	1.00									
Route	0.00	0.00	1.00								
Voyage	0.15	0.15	0.00	1.00							
Ship	0.05	0.05	-0.23	-0.12	1.00						
Profit	-0.14	-0.14	0.09	0.19	-0.03	1.00					
Fr. rate	-0.11	-0.11	0.43	0.19	-0.35	0.63	1.00				
Load.	-0.20	-0.20	-0.03	0.23	-0.24	0.60	0.48	1.00			
Cargo	0.00	0.00	-0.39	0.00	0.57	0.18	-0.18	0.19	1.00		
Team	0.30	0.30	0.00	0.06	-0.04	-0.07	-0.06	-0.08	0.00	1.00	
Capa	0.81	0.80	0.00	0.10	0.10	-0.19	-0.16	-0.27	0.00	0.09	1.00
Prob.											
Session											
Firm	0.00										
Route	0.56	0.56									
Voyage	0.82	0.82	0.93								
Ship	0.87	0.87	0.03	0.17							
Profit	0.00	0.00	0.64	0.53	0.27						
FR	0.04	0.04	0.04	0.42	0.01	0.00					
Load.	0.01	0.01	0.86	0.34	0.16	0.00	0.00				
Cargo	0.46	0.46	0.00	0.47	0.00	0.87	0.15	0.80			
Team	0.19	0.19	0.71	0.76	0.80	0.13	0.25	0.19	0.56		
Capa	0.00	0.00	0.57	0.74	0.70	0.00	0.03	0.00	0.55	0.42	

Results obtained with R-packages corrplot and Hmisc.

A2) Rules of the TRALIN game

Nota Bene: *The online version of TRALIN is in progress and only available in a beta version. Any scholar who would wish to participate to this testing phase should write to nicolas.gruyer@economics-games.com and ask for an access link which will be made available on simple request.*

Rules: You operate a liner shipping company with 15 x 5,000 TEU containerships. Five liner companies are competing on the transatlantic market (12 routes). When starting the game, your company must allocate its 15 vessels on the 12 routes *j* connecting New York, Rotterdam, Dakar and Santos, the port of São Paulo. To do this, you must fill in the Table crossing the Departure ports in columns with the Arrival ports in rows, and indicate for each cell representing a route the number of vessels you want to operate. A maximum of eight sequential voyages of 15 days each (Transit Time, TT) are undertaken. Each round, the team has to decide on:

1. Next port of call for each vessel (with 3 possible choices)
2. To sell (or not) some of your vessels (except for first round)
3. To purchase (or not) additional vessels (except for first round)

The optimal choice is on profit maximization (Total revenue – Total Cost), owing that for each vessel, the profit function is:

$$\pi_{ijk} = (p_{jk} - c).TEU_{ijk} - n_{ijk}.[TT.(BP.F + TC)]$$

where π_{ijk} is the profit of company i on route j for voyage k, P_{jk} is the freight rate on route j for voyage k, TEU_{ijk} is the number of containers carried by company i on route j for voyage k, c is the unit cost per carried container (set at \$200), n_{ijk} is the number of containerships required to carry TEU_{ijk}, TT is the transit time (15 days per voyage whatever the route), BP is the bunker price (fixed at \$600 per tonne), F is the fuel consumed per day (100 tonnes) and TC is the Time Charter (vessel) cost per day (set at \$36 000 per day).

The quantity carried by a company for a voyage (TEU_{ijk}) depends on the demand on each route and the total capacity supplied by all competitors. Two situations are possible:

1. If the aggregate capacity supplied on a route (CAP_j) is smaller than the cargo demand, each vessel will be fully loaded. Any cargo demand above the supplied capacity is not satisfied.
2. If the aggregate capacity supplied on a route (CAP_j) is greater than demand, the cargo is equally shared between all vessels deployed on the route. For instance, if the demand on a route is 9,000 TEUs and three 5,000 TEU containerships are deployed (CAP_j = 15,000 TEUs), each vessel carries 3 000 TEUs, hence a loading rate of 60% (=3000/5000) for every vessel.

The price on a specific route (P_j) in USD/TEU is a function of the total capacity supply and the loading rate depends on both cargo demand and freight supply.

ROUTES j		**Freight rate (USD per tonne)**	**Cargo demand (TEUs)**
A1	New York → Rotterdam	*P = 1300 – 0.01.CAP*	*45,000*
A2	New York → Santos	*P = 1200 – 0.02.CAP*	*15,000*
A3	New York → Dakar	*P = 900 – 0.01.CAP*	*15,000*
B1	Rotterdam → New York	*P = 1400 – 0.01.CAP*	*45,000*
B2	Rotterdam → Dakar	*P = 1200 – 0.02.CAP*	*12,000*
B3	Rotterdam → Santos	*P = 1200 – 0.01.CAP*	*15,000*
C1	Dakar → Rotterdam	*P = 1000 – 0.01.CAP*	*12,000*
C2	Dakar → Santos	*P = 1000 – 0.01.CAP*	*15,000*
C3	Dakar → New York	*P = 1200 – 0.01.CAP*	*12,000*
D1	Santos → Dakar	*P = 1100 – 0.01.CAP*	*15,000*
D2	Santos → New York	*P = 1300 – 0.02.CAP*	*22,000*
D3	Santos → Rotterdam	*P = 1400 – 0.01.CAP*	*20,000*

If a vessel is sold to the banker, the fixed resale price is equivalent to the TC rate per day (\$36,000) x Transit Time (15 days) = \$540,000. The same rate is applied if a vessel is purchased.

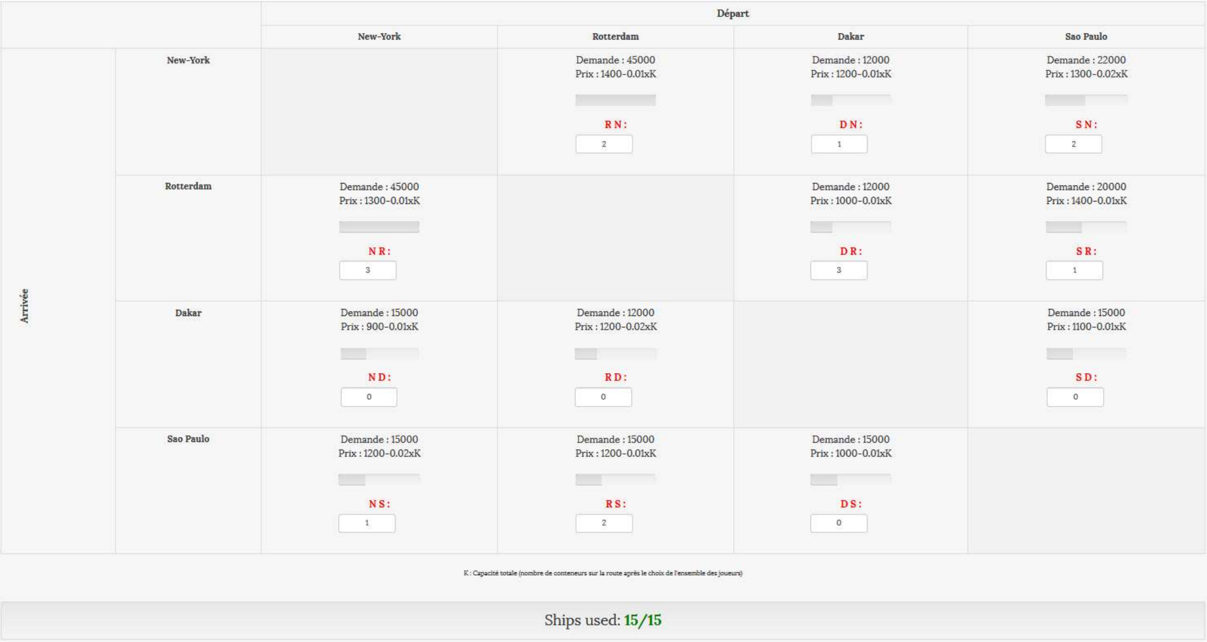
The winner of the game is the company with the highest cumulated gains after 8 rounds/voyages or when the instructor decides to stop the game. The companies have to deploy the 15 vessels on the 12 routes during the first round (V1). For the following rounds (V2 to V8), the vessels must be deployed from their last port of call. The choice of operate, sell or purchase vessels is open after the first voyage and at every following voyage.

After each round, each competitor will be given information about:

1. Current and cumulated profit for all companies
2. The loading rate on each route

3. The freight rate on each route.

The results after each voyage can only be publicized when all the teams have entered their vessel allocation along the different routes. The game is non cooperative, meaning that firms are not allowed to communicate. If the instructor decides so, mergers or alliances can be allowed after a few rounds or in a second session of the game, to see how the overall competition is affected. The parameters of the cost and demand functions can be shifted in the course of the game (e.g. increase in bunker cost) if the instructor wants to.



		Départ			
		New-York	Rotterdam	Dakar	Sao Paulo
Arrivée	New-York		Demande : 45000 Prix : 1400-0.01xK RN: 2	Demande : 12000 Prix : 1200-0.01xK DN: 1	Demande : 22000 Prix : 1300-0.02xK SN: 2
	Rotterdam	Demande : 45000 Prix : 1300-0.01xK NR: 3		Demande : 12000 Prix : 1000-0.01xK DR: 3	Demande : 20000 Prix : 1400-0.01xK SR: 1
	Dakar	Demande : 15000 Prix : 900-0.01xK ND: 0	Demande : 12000 Prix : 1200-0.02xK RD: 0		Demande : 15000 Prix : 1100-0.01xK SD: 0
	Sao Paulo	Demande : 15000 Prix : 1200-0.02xK NS: 1	Demande : 15000 Prix : 1200-0.01xK RS: 2	Demande : 15000 Prix : 1000-0.01xK DS: 0	

K : Capacité totale (nombre de conteneurs sur la route après le choix de l'ensemble des joueurs)

Ships used: 15/15

Screen copy of a player's decision: the departure ports are in column, the arrival ports are in rows and the cells contain the number of deployed ships under the specific demand conditions. The cumulated number of ships used is displayed below the Table in green once all the ships have been deployed.

A3. Evolution of the individual average fleet and profit by voyage in the 4 treatments (C1, C2, P4, P5)