Maritime Container Shipping:

Does Coopetition Improve Cost and Environmental Efficiencies?

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Abstract: Global retail supply chains are heavily reliant on efficient container shipping. This study focuses on how a shipping intermediary such as a fourth-party logistics (4PL) provider can enable efficiency gains in retail container distribution. We consider the assignment of cargo to containers and vessels to accommodate downstream retailer demand, aiming to minimize both environmental and economic costs. We develop an integer optimization model that represents the key decisions of which journeys to select to ship various types, and quantities, of products onto containers of various sizes. We generate problem instances using international supply chain data inspired by two large United Kingdom (UK) retailers. Our model is useful for evaluating the feasibility of *coopetition* in container shipping, which we define as a contractual agreement with a 4PL, of which consolidation is one operational dimension. We conduct a variety of sensitivity analyses around the cost of fuel, cost of carbon emissions, and under coopetition or competition, to better understand their effects on model outcomes. Although some studies have mentioned that coopetition can prove economically beneficial, our study has shown that for the data and model we consider, the advantages of coopetition are quite limited. Our findings suggest there are limited economic or environmental benefits associated with the competition or coopetition scenarios when only fuel costs increase. The greatest benefits from an environmental perspective occur when joint increases of fuel and CO_2 costs occur, which result in greater environmental co-benefits in the coopetition case. Alternatively, CO_2 cost increases show that competition contexts had greater environmental benefit.

Keywords: OR in Environment and Climate Change; Maritime Transportation; Coopetition; Container Shipping; Optimization

1. Introduction

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Ocean liner shipping is, on a per unit basis, one of the most economically and environmentally efficient transportation modes (Hoene et al., 2014). Maritime shipping has gained in importance and prevalence since the introduction of shipping containers made this transportation mode cost-effective and efficient (Gonzalez-Torre, 2013). According to the International Chamber of Shipping, a full 90% of world trade is carried by the international maritime shipping industry (http://www.ics-shipping.org/shipping-facts/shipping-and-world-trade). The increasing globalization of supply chains has only added to the importance of this transportation mode.

Retail organizations are heavily reliant on maritime shipping for transportation over long distances. Frequently, retail organizations rely on third-party logistics (3PL) providers to help them manage their transportation logistics (Ballot and Fontane, 2010). From a trucking or shipping perspective, these 3PLs can be managed directly by the retailers. In maritime shipping, however, intermediary shipping agents can be used as brokers amongst various shipping logistics providers and the shipping carriers (the 3PLs). Fourth-party logistics (4PL) providers are one such intermediary (Evangelista, 2005).

Given the economic and environmental pressures from competitors, customers, and regulators, intermediaries like 4PLs can aid retailers in managing their global shipping operations. They add value not only in working with multiple 3PLs (shipping companies). Zacharia et al. (2011) found that 3PLs evolved from providing logistics capabilities to becoming orchestrators of supply chains that create and sustain a competitive advantage. However, 4PLs have the flexibility to work with multiple, competing retailers, ports, and other maritime transportation providers. This situation contrasts with separate 3PLs that might have specific contracts with different retailers. Without the presence of a 4PL, certain efficiency gain opportunities for logistics customers – such as a retailer – can be missed.

This study introduces the notion of coopetition in the context of retail container shipping. As per Zacharia et al. (2019), coopetition is an inter-firm strategy that can be adopted among competitors to add value to their operations. Organizations can collaborate vertically with their suppliers and-or horizontally with their competitors in supply chain collaborative relationships. Horizontal collaboration occurs among independent entities or direct competitors that are positioned at the same level (Simatupang and Sridharan, 2002; Sanchez Rodrigues et al., 2015). For this study we assume collaboration occurs between two retailers and is executed through a neutral intermediary—a fourth-party logistics (4PL) provider. The use of the term coopetition is adopted in this paper, as the retailers focus the collaboration solely on their international shipping operation and compete in all other activities carried out in the market country, the UK. They will agree on this cooperation through a contractual agreement with a 4PL.

While this perspective is applied in the retail industry, we focus on the role of an intermediary, such as a 4PL, for the co-consolidation of containers at the port of origin, where it is difficult for retailers to collaborate directly. It is even possible for competitors to work together through these agents in a mode of coopetition, when competitors partner to collaborate on an activity that is not a core competence of either. Competitors, although competing in a market, may collaborate in activities such as international distribution in pursuit of a common goal. For example, competitors can appoint a fourth-party logistics provider to centralize the planning of their container allocation to ships and subsequent movements for efficiency gains. Such an initiative can result in cost and emissions savings for collaborating competitors. The use of 4PL as a collaborative consortium of retailers is highlighted by Hingley et al. (2011). This coopetition scenario is used by retailers to avoid issues related to fair competition regulations, and to make sure their interests are represented by a neutral party/trustee.

This 4PL coopetition model has been utilized by manufacturers such as Proctor & Gamble and retailers such as Tesco. They found that a global 4PL provider can represent their interests and select the most efficient 3PLs to move their cargo. The greening of supply chains is critical for the long-term competitiveness of organizations and the balance of environmental and economic concerns (Kirchoff, et al., 2016), and retailer shipping decisions play an important role in this landscape (Ghosh and Shah, 2015; Ramanathan et al., 2014). Having 4PLs helping to manage these requirements with a decision planning tool could be beneficial for competitive and social purposes.

Maritime shipping planning occurs at the strategic, tactical and operational levels. An important tactical decision is determining, from the perspective of a 4PL intermediary, the schedule of journeys that satisfies demand while best addressing economic and environmental concerns. Limited research exists on this topic when considering port-to-port shipping decisions in maritime shipping planning, and even less when incorporating environmental dimensions alongside traditional economic factors. Given the volume of maritime shipments, this investigation provides a promising opportunity for understanding associated economic and environmental tradeoffs.

Given the complexities and uncertainties of these interactions – such as environmental and economic tradeoffs, variations in costs, and the many journeys to select from – analytical approaches that can evaluate myriad options and provide recommendations are desirable for supporting tactical and operational decision planning. To address this decision environment, we use an integer optimization model that deals with journey selection and cargo routing decisions. A joint coopetition planning model between multiple retailers is developed and applied by using practical shipping data from major multinational retailers to help in a simulation. For the purpose of this paper, it is assumed that the notion of equilibrium – where each retailer is naturally self-interested and seeks to achieve the optimization of their own container movement planning – will only cooperate with others if further efficiency gains can be found by their common 4PL provider. The study also includes two retailers of similar size and network complexity. UK retailers tend to view that having a similar volume and degree of network complexity as a synergistic factor (Sanchez Rodrigues et al., 2015). The two retailers that informed this study a significant number of common suppliers and sourcing areas—an important synergy that retailers consider prior to building a coopetitive partnership.

We make the following contributions. 1) We develop an integer optimization model to solve the port-to-port journey selection and cargo routing problem from the perspective of an intermediary such as a 4PL acting as the middle logistics broker. 2) Our optimization model specifically incorporates both *economic and environmental* maritime shipping factors, providing a more holistic managerial planning perspective. 3) We consider coopetition in maritime shipping, an important aspect that has received minimal investigation, and particularly so when environmental factors are jointly considered. 4) Using test instances simulated from real maritime supply chain data, we present a robust set of computational experiments that study the journey selection and cargo routing sensitivity under changes to fuel costs and carbon costs, both separately and jointly – as well the effect of coopetition. Based on these results, we provide exploratory research observations for further study.

The remainder of the paper continues with some foundational practical background on maritime shipping and planning. We then introduce the mathematical model, followed by our computational experiments, which detail optimal model recommendations to a variety of potential scenarios induced by varying key parameters. Our experimental analysis is discussed in detail and is followed by a concluding section that summarizes our findings, identifies study limitations, and directions for future research. Appendices contain additional material related to assumptions made to cost and emissions calculations.

2. Background and Literature Review

We now provide some relevant background pertaining to coopetition in supply chain management, and a review of analytical approaches to investigate associated decision problems.

2.1. Coopetition in Supply Chain Management and Logistics

Competition and cooperation are traditionally placed on opposite ends of the business relationship management strategy spectrum (M'Chirgui, 2005). If individual organizations focus solely on traditional economic objectives, they compete with other players in a market where zero-sum games are the norm (Padula and Dagnino 2007). Alternatively, organizations may pursue a cooperative strategy when synergistic interests exist (Padula and Dagnino 2007).

Organizations pursue cooperation to achieve a mutually beneficial goal. Organizational cooperation research includes studies on strategic alliances, networks, supply chains, and other partnership types. Each partnership type has objectives for improving the performance of partners by sharing resources, capabilities and risks (Gnyawali and Park 2011; Bouncken et al., 2015a).

Global supply chain management and logistics may offer situations that are not black (competition) or white (cooperation). Synergistic situations where "grey" exists relate to strategy and designing general networks, common suppliers and supply countries (Lambert and Enz, 2017), similar third-party logistics and shipping providers who share relational resources (e.g. Shao et al., 2017), and sharing similar source and destination ports. Hence, the literature reports on a more dynamic and flexible type of business relation, namely coopetition, defined as when competitors partner, to be a natural conflict that exists in supply chains (Wilhelm, 2011). The global supply chain, with varying regional and global markets, makes the potential for coopetition even more attractive (Naylor et al. 1999). Research on investigating organizational coopetition within a global logistics and supply chain setting, especially within the maritime shipping and shipping liner industry is largely unstudied.

In the retail industry, it can be argued that the further suppliers are located from retail markets and operations, such as secondary distribution centers, the more generic the distribution of cargo is. That is, coopetition arrangements among retailers are more likely when primary distribution flows are located further away from the market country (Fernie et al., 2010). The decoupling point in many retail distribution networks and channels is located at the point of consolidation in secondary distribution centers (Chang, 2008). When the cargo is for direct retail competitors such as large retailers, consolidation of cargo may be viewed as a coopetition activity. When consider alone, however, consolidation need not be coopetition, as it may occur amongst non-competing entities.

Beyond any competitive business reasons for improving supply chain efficiencies, the environmental sustainability of the supply chain may also be positively influenced (Hafezalkotob, 2017). Competitors may have comparable products and materials that are shipped in a similar fashion. This situation may facilitate simpler consolidation on shipping containers, and fourth-party logistics providers may find additional opportunities for consolidation. For example, flexibility in container sizes allows for efficient use of space and capacity, providing greater flexibility in planning, and reducing energy needs and lowering polluting emissions. Coopetition is a potential strategy to improve the environmental performance of maritime-based supply chains.

Hence, one of the main contributions of this paper is the use of an analytical formal modeling approach to investigate coopetition and non-coopetition scenarios in a global shipping setting. Our investigation provides theoretical and practical insights into coopetition strategies in the context of global shipping and sustainability of international logistics operations. Recent research undertaken on horizontal logistics collaboration has mainly focused on the cooperation, rather than a coopetition, approach (Lehoux et al., 2009; IGD, 2012; ECR France, 2012; Verstrepen, 2013; Sanchez Rodrigues at al., 2015).

Supply chain players that can gain from coopetition need "coopetition capabilities" for their supply chains to avoid negative tension dynamics among competitors and provide cost improvement opportunities to suppliers for the sake of joint value creation (Wilhelm and Sydow, 2018). These goals are achieved if there is a neutral intermediary that coordinates core competitor activities. The long-term nature of strategic coopetition partnerships requires managing multiple components of supply chains including fluctuating demand, inventory management, ever-increasing customer requirements and objective alignment (Gibson et al. 2002, Hingley et al. 2011). Effective joint planning to optimize coopetition networks is necessary (Rabinovich et al. 1999, Sanchez Rodrigues et al. 2015). There is a need for synchronized decision-making in strategy planning, order delivery and placement, quality control, stock replenishment, scheduling procurement and demand management among multiple coopetition partners.

We assess the role coopetition can play in driving economic and environmental sustainability gains by cargo owners (e.g. retailers), fourth-party logistics providers, and shippers who participate in coopetition-based global logistics partnerships (Langley, 2005). Our study also assesses the feasibility of coopetition among retailers by considering time, cost, and energy and carbon efficiency as the main output metrics.

In this paper, we focus on modeling several coopetition and competition scenarios in the context of international distribution of retailers managed by a logistics intermediary, such as a 4PL provider. It is within this context that our study introduces an analytical decision-making framework based on integer optimization. We aim to identify various coopetition and competition cases that can enhance tactical and operational planning decisions to determine whether it is beneficial to consolidate cargo owned by two competitors. The decision environment goes beyond simple consolidation, to encompass coopetition in two primary aspects: 1) cargo consolidation is based on a mutually beneficial set of metrics from the perspective of the participating cargo owners who may be direct competitors; and 2) the allocation of cargo to vessels and containers occurs based on contracted decisions made by a logistics intermediary, rather than an arbitrary decision by a third-party logistics provider that may or may not be beneficial for the cargo owner.

2.2. Maritime International Distribution: Optimization, Sustainability, and Coopetition

Studies that investigate problems related to the optimization of maritime cargo routing deal with three principal aspects: strategic, tactical, and operational level decisions. The strategic level for liner shipping involves long-term decisions associated with resource acquisition and determining the fleet size and composition (Agarwal and Ergun, 2008). The tactical level involves medium-term decisions and concern issues such as design of the service network including route frequency, port selection and assignment of ships to routes. The operational level involves short-term planning decisions concerning which cargo to accept/reject for routing and the shipping routes (Agarwal and Ergun, 2008). This section focuses on studies that address problems related to the tactical and operational levels, primarily vessel scheduling and cargo routing in both competition and coopetition settings, as well as environmental considerations. We highlight several representative papers related to our study. For further reading related to optimization models in maritime shipping, we refer the interested reader to surveys by Christiansen et al. (2004), Meng et al. (2013), and Brouer et al. (2017).

Agarwal and Ergun (2008) propose a mixed-integer linear programming model to solve a simultaneous ship-scheduling and cargo-routing problem. Their model considers economic costs and incorporates weekly frequencies as well as transshipment nodes, and they solve the resulting formulation via column generation and Benders Decomposition. Álvarez (2009) tackles the problem of tactical fleet sizing and routing to maximize revenues less a variety of economic costs. They formulate the problem as a mixed integer program; and, propose a solution technique that combines exact mathematical programming together with meta-heuristic guidance. Norstad et al. (2011) present the tramp ship routing and scheduling problem with speed optimization. They consider decisions of which cargo to carry, what ships to carry the cargo, what routes and what legs to schedule, and involve the speed of the tramp ship as a decision. They present two algorithms for the speed optimization problem along a single shipping route.

Bell et al. (2013) consider container assignment in liner shipping via linear programming, and assume that routes, service frequencies, and ship sizes are known in advance. They seek to minimize the cumulative economic costs of container handling, en-route inventory, and the leasing of containers. Wang et al. (2015) extend Bell et al. (2013) by presenting a container assignment problem where the freight rate is influenced by the container shipment demand. Using historical data to estimate demand, they develop a nonlinear optimization model to determine the number of containers to be transported, the optimal freight rates, and how to transport containers to maximize the total revenues less (economic) costs. Zhen et al. (2019) study how to deploy liner fleets to meet demand by varying the number of ships, their speed, and the timing of visits. While they develop a mixed-integer nonlinear program, subsequently linearized, to find high-quality solutions for real-world data, they are only able to solve smaller instances to optimality.

International shipping accounts for at least 2.7% of the CO_2 emitted worldwide; this number is estimated to double or even triple by 2050 if emissions continue unabated (Buhaug et al., 2009). The International Maritime Organizations has agreed, in 2018, to decreasing CO2 emissions – greenhouse gas emissions – by at least 50% by 2050 compared to 2008 (Cariou et al., 2019). In a comprehensive review of CO_2 emissions reduction measures in shipping, it was suggested that technology, together with policies and regulations, can lead to a 75% shipping-based emissions reduction by 2050 (Bouman et al., 2017). With these efforts there is a possibility of a four- to six-fold emissions reduction per freight unit transported. Hull design, power and propulsion, alternative fuels, alternative energy sources, and operations are all examples of activities that can reduce emissions.

In the operations category, potential CO_2 reduction ranges for speed optimization are between 1-60%, voyage optimization can be between 0.1-48%, and capacity utilization between 5-50%. Several studies have investigated maritime cargo routing with respect to carbon emissions. Psaraftis and Kontovas (2013) present a taxonomy of the literature concerning the modeling and optimization of vessel speed, as it is a key factor in CO_2 emissions. With this as a backdrop, the authors present several ways to move forward. Kontovas (2014) considers possibilities for incorporating environmental factors such as emissions into maritime logistics problems and demonstrates how these factors could be included in existing speed optimization and routing models. In response to recent environmental regulations over concerns such as sulphur emissions, Fagerholt et al. (2015) develop a maritime shipping optimization model to determine optimal sailing paths and speeds to minimize overall operating costs over multiple ports. They include a computational study that highlights how regulations affect both shipping routes and society. For further discussions of operations research studies in the context of green freight transportation (including maritime), see the recent review by Bektaş et al. (2019). In particular, Table 1 of Bektaş et al. (2019) highlights maritime transportation studies that consider environmental factors.

The academic literature related to coopetition in maritime freight transportation is somewhat limited (Lin et al., 2017). Analytical maritime studies involving coopetition rarely incorporate environmental objectives or analysis of the international flows as part of the optimization. Heaver et al. (2000) examine the range and form of cooperative business models in the maritime and port industries, noting that some port authorities create dedicated terminals for their main customers. There are also different forms of coopetition in the international shipping industry. Song (2003) presents a conceptual discussion related to port coopetition, presenting a case study of Hong Kong and South China. The author emphasizes the importance of sustaining the right balance between competition and cooperation, where various port or firm specific factors may influence the balance. In Lee and Song (2017), port coopetition is again suggested as a setting where further work is needed. Asadabadi and Miller-Hooks (2018) do just that, considering the dual cooperative and competitive nature of port operations with a game-theoretic approach. Agarwal and Ergun (2010) combine mathematical programming and game theory to design a strategy to guide carriers in a collaborative partnership to engage in a collaborative strategy where all members are motivated to operate in the best interest of the partnership. Lin et al. (2017) formulate a nonlinear mixed-integer problem in liner shipping to determine the optimal levels of coopetition for a single company where the resulting problem is integrated into a general game theoretic framework.

Viewed collectively, we are unaware of another maritime shipping study that simultaneously addresses the following aspects that we address in this study. We 1) consider the perspective of a shipping intermediary in choosing from a palette of existing journeys with associated attributes (such as source and destination ports, timing, speed, capacity) on which to load multi-commodity cargo into containers with limited bay availability, so as to satisfy demand across multiple periods; 2) allow for both coopetition and competition; and 3) develop an objective function that integrates environmental costs along with traditional economic costs. Our mixed-integer programming model allows shipping intermediaries to balance the need for selecting journeys that will ensure multi-commodity demand is met in a timely manner, while weighing environmental considerations, thereby finding solutions that favor the most cost-conservative journeys by which shipments will arrive on time.

Our study aims to inform the literature on how efficient container consolidation can reduce CO2 emissions. It also investigates the importance of fuel and carbon taxes for the reduction of CO2 emissions in competition and coopetition scenarios – scenarios that can be adopted in retail container shipping contexts. The model we next introduce has clear practical relevance to shipping intermediaries such as 4PLs, that are interested in balancing the need for meeting multi-commodity demand on-time while minimizing both economic and environmental costs, in either competition or coopetition modes.

3. Mathematical Modeling

We consider a maritime challenge faced by a shipping intermediary, such as a 4PL: selecting port-to-port journeys to route multi-commodity general merchandise cargo from source port supply locations to destination port demand locations. A retailer places an order of known quantity, volume and delivery time with a shipping intermediary, who arranges the shipment of goods via a *journey*: by which we specify a fixed vessel, source and time of embarkation, and destination and time of disembarkation. Our model is general and handles multiple journeys, retailers, products, and container types. We use a carton (box) as a product unit. The model adopted in this study differs from what is currently being practiced by the two retailers who informed our study. Their consolidation is not currently centralized by a 4PL. While some degree of consolidation actually occurs in the current container shipping operations run by the freight forwarder for each of these retailers, rather than on a planned basis, it is informal and ad hoc in nature.

3.1. Assumptions

We make a number of realistic assumptions to obtain a tractable model. All costs are in British Pound Sterling (notated with £). We assume a port-centric logistics setting; that is, distribution centers are co-located at each destination port. Hence, we do not consider post-arrival distribution costs in our study. We assume that the shipment of general merchandise products are substitutable and have low storage cost. Moreover, because we study retailers with similar scale and size, we consider identical unit costs for retailers. To establish a consistent basis for evaluation, we convert all environmental costs to economic costs. We take 15 knots to be the baseline speed by which excess carbon emissions are calculated, so that speeds beyond 15 knots are subject to inefficiencies of scale in terms of carbon emissions (further discussed in Appendix A).

Concerning time, we consider a weekly delivery schedule, so that journeys arrive on a weekly basis. Moreover, we consider the time needed to fill, load, and unload containers, as compared to the length of the journey, to be negligible. Concerning containers, we assume volume and weight capacities, M_k and

G_k, which are roughly 75% of the actual container capacities, which allows for some settling and manipulation. Moreover, a (liberal) upper bound B_k^j exists on the number of containers of size k an intermediary can place on any journey j. Concerning stock, we assume that demand profiles exist for every retailer $r \in \mathcal{R}$ and product $p \in \mathcal{P}_r$ at each destination port $u \in \mathcal{U}$ for each time period $t \in \mathcal{T}$. Moreover, as the study is not overly concerned with the supply side, we make the simplifying assumption that each source port has sufficient supply of the general merchandise to be shipped. Additionally, where necessary or judicious, our model allows for inventory from earlier periods to meet subsequent demand.

Concerning journeys, we assume traffic schedules exist for every journey $j \in \mathcal{J}$. Thus, we know in advance when each vessel v will embark from source port s at time period t with known average speed σ^v and total twenty-foot equivalent unit (TEU) capacity, to which final destination port u. Moreover, we let data element $z^{j,vsut}$ indicate these known traffic patterns, so that $z^{j,vsut}$ is equal to 1 if journey j is vessel v leaving source port s at time t to (final) destination u, and 0 otherwise. Finally, because every $j \in \mathcal{J}$ represents a unique vessel v leaving source s at time t to destination u, we simplify $z^{j,vsut}$ to z^j.

3.2. Mathematical Programming

We next detail the components of our mathematical programming formulation, starting with set and parameter definitions, continuing to variable definitions, and followed by the complete formulation.

3.2.1. Set and Parameter Definitions

We define the sets used in our mathematical modeling and optimization in Table 1. We consider that each journey j represents a unique vessel $v \in \mathcal{V}$ embarking from source port $s \in \mathcal{S}$ at time period $t \in \mathcal{T}$, traveling at a distinct, known average speed, and disembarking at destination port $u \in \mathcal{U}$. We then use these sets to define the parameters used in our mathematical modeling and optimization In Table 2.

Table 1. Definition of sets used in mathematical modeling.

Set	Definition
$\mathcal{R}$	Set of retailers, or customers (e.g., Retailer 1, Retailer 2), indexed by r
$\mathcal{P}_r$	Set of products for each retailer r, indexed by p
$\mathcal{V}$	Set of vessels (across all carriers), indexed by v
$\mathcal{S}$	Set of source ports, indexed by s
$\mathcal{U}$	Set of destination ports, indexed by u
$\mathcal{T}$	Set of time periods, indexed by t
$\mathcal{K}$	Set of container sizes, indexed by k

Table 2. Definition of parameters used in mathematical modeling.

Scope	Parameter	Definition
Stock	d_{rp}^{ut}	Demand for cases of product p by retailer r at destination port u in period t
Stock	i_{rp}^{u0}	Amount of initial ($t = 0$) cases of inventory of product p for retailer r at destination u
Container	M_k	Container volume capacity (cubic meters) for container size k
Container	G_k	Container weight capacity (kg) for container size k
Journey	B_k^j	Upper bound on number of containers of size k that can be placed on journey j
Journey	δ^j	Travel distance (km) from source port s to destination port u, for journey j
Journey	τ^j	Transit time (days) from source port s to destination port u, for journey j
Journey	α^j	Average speed, in knots, on journey j
Journey	ρ^j	Capacity of the vessel in TEUs (twenty-foot equivalent units) on journey j
Product	w_{rp}	Unit weight (tonne) of case of product p for retailer r
Product	q_{rp}	Unit volume (cubic meters) of case of product p for retailer r
Product	u_{rp}	Unit cost (£) of case of product p for retailer r
Cost	f_{rk}^j	Fixed cost (£) to load/unload a container (handling costs) of size k for retailer r on journey j (£ per container)
Cost	m_{rk}^j	Other costs (management fee, customs, security and port management, documents) for a container of size k for retailer r on journey j (£ per container)
Cost	ϕ_k	Operating cost (£) to transport one container of size k one tonne-km (£ per tonne-km). For 20ft container (one TEU)
Cost	dp_{rpk}^j	Distance-related unit capital and operating cost (£) of transporting one case of product p (£ per unit) for retailer r in container of size k on journey j
Cost	dc_{rpk}^j	Distance-related unit fuel cost (£) of transporting one case of product p (£ per unit) for retailer r in container of size k on journey j; $dc_{rpk}^j = (\delta^j * w_{rp}) * \phi_k$
Cost	h_{rp}^u	Holding cost (£) per unit of product p of retailer r in warehouse at destination port u (£ per case)
CO_2	e_{rk}^j	CO_2 emissions (kg) to load/unload a container of size k for retailer r on journey j
CO_2	φ_k	CO_2 emissions to transport one container of size k one tonne-km (kg per tonne-km). For 20ft container (one TEU), see Appendix A. The 40ft, 40ft HC and 45ft sizes are taken to be at 80%, 76%, and 69.6%
CO_2	$d\varepsilon_{rpk}^j$	Distance-related unit CO_2 emissions (kg per case) for transporting one case of product p for retailer r on journey j; $d\varepsilon_{rpk}^j = (\delta^j * w_{rp}) * \varphi_k$
CO_2	ε_{rp}^u	Unit CO_2 emissions (kg) for holding product p for retailer r in warehouse at destination port u
CO_2	ν	Cost of one kg of CO_2 in £. The estimate we use is £6.08 per tonne = £0.00558 per kg, which was calculated from averaging the daily price of one tonne of CO_2 from recent data obtained from the UK Stock Exchange (July 2014 – May 2016)

3.2.2. Integer Optimization Model

Formulation (1)–(9) uses sets and parameters from Tables 1 and 2 to identify an optimal shipping plan. Binary variables x_{rkb}^{j} indicate whether an intermediary, on behalf of retailer r, loads a b^{th} container of size k on journey j. Nonnegative integer variables y_{rpkb}^{j} represent the number of cases shipped by retailer r of product p in container b of size k for journey j, while i_{rp}^{ut} represent the amount of inventory of product p (unit cases) for retailer r at destination u at time period $t = 1,2,3, \ldots, |\mathcal{T}|$.

$$\begin{aligned} Minimize \quad & \sum_{r\in\mathcal{R}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{b=1}^{B_k^j}\left(f_{rk}^{j} + m_{rk}^{j} + v\, e_{rk}^{j}\right)x_{rkb}^{j} \\ & + \sum_{r\in\mathcal{R}}\sum_{p\in\mathcal{P}_r}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{b=1}^{B_k^j}\left(dc_{rpk}^{j} + dp_{rpk}^{j} + v\, d\varepsilon_{rpk}^{j}\right)y_{rpkb}^{j} \\ & + \sum_{u\in\mathcal{U}}\sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}}\sum_{p\in\mathcal{P}_r}\left(h_{rp}^{u} + v\,\varepsilon_{rp}^{u}\right)i_{rp}^{ut} \end{aligned} \tag{1}$$

$$subject\ to \quad x_{rkb}^{j} \le z^{j} \ \forall\, j \in \mathcal{J}, r \in \mathcal{R}, k \in \mathcal{K}, and \ \ b = 1, \ldots, B_k^j, \tag{2}$$

$$\sum_{p\in\mathcal{P}_r} q_{rp}y_{rpkb}^{j} \le M_k x_{rkb}^{j} \ \ \forall\ j \in \mathcal{J}, \forall\ r \in \mathcal{R}, k \in \mathcal{K}, and \ \ b = 1, \ldots, B_k^j, \tag{3}$$

$$\sum_{p\in\mathcal{P}_r} w_{rp}y_{rpkb}^{j} \le G_k x_{rkb}^{j} \ \ \forall\ j \in \mathcal{J}, \forall\ r \in \mathcal{R}, k \in \mathcal{K}, and \ \ b = 1, \ldots, B_k^j, \tag{4}$$

$$x_{rkb}^{j} \ge x_{rk(b+1)}^{j} \ \ \forall\ j \in \mathcal{J}, r \in \mathcal{R}, k \in \mathcal{K}, and \ \ b = 1, \ldots, B_k^j - 1, \tag{5}$$

$$i_{rp}^{u(t-1)} + \sum_{j\in\mathcal{J}:z^{j,vsut}=1}\ \sum_{k\in\mathcal{K}}\sum_{b=1}^{B_k^j} y_{rpkb}^{j} - i_{rp}^{ut} = d_{rp}^{ut} \ \ \forall\, u \in \mathcal{U}, t \in \mathcal{T}, r \in \mathcal{R}, p \in \mathcal{P}_r, \tag{6}$$

$$x_{rkb}^{j} \in \{0,1\} \ \ \forall\ \ j \in \mathcal{J}, r \in \mathcal{R}, k \in \mathcal{K}, b = 1, \ldots, B_k^j, \tag{7}$$

$$y_{rpkb}^{j} \ge 0 \ and \ integer, \qquad \forall\ \ j \in \mathcal{J}, r \in \mathcal{R}, p \in \mathcal{P}_r, k \in \mathcal{K}, b = 1, \ldots, B_k^j, \tag{8}$$

$$i_{rp}^{ut} \ge 0 \ and \ integer, \qquad \forall\ \ u \in \mathcal{U}, t \in \mathcal{T}, r \in \mathcal{R}, p \in \mathcal{P}_r. \tag{9}$$

The objective function (1) is comprised of three cost components related to whether containers are loaded onto journeys, the quantity of cases of each commodity shipped on loaded containers, and inventory using variables x, y, and i, respectively. We seek to minimize total costs by selecting maritime journeys to route cargo via containers to satisfy demand at destinations. Constraint set (2) ensures containers are only loaded on existing journeys, while constraint sets (3) and (4) ensure that container-level volume and weight capacities are each respected. Constraint set (5) breaks arbitrary symmetry by ensuring that, for identical sized-containers, smaller indexed slots are filled before larger indexed slots. Finally, constraint set (6) maintains flow-balance for all warehouse inventories at destination ports; note that nonnegative initial inventories $i_{rp}^{u(0)}$ are assumed. Variable domains are presented in (7)–(9).

Objective function (1) includes costs in both the traditional economic sense, as well as environmental, in the form of carbon costs. We consider three cost types: fixed (loading and unloading of containers, as well as management fees), variable (transportation of goods), and holding costs (related to inventory held in earlier time periods, to be used for subsequent demand). Collectively, the constraints ensure that demand at destination ports can be met by placing containers in slots on valid journeys, filling them only to their weight and volume capacities, and that any excess inventory is held, if not used in a demand period. We further note that our model is sufficiently general to accommodate either competitive or coopetitive scenarios, such as through demand aggregation.

4. Computational Studies

To evaluate the performance of integer optimization model (1)–(9) and explore the related outcomes of coopetition and environmental impacts, we now discuss the design of our computational studies.

4.1. Data Instance Generation

We have generated our own test instances for two retailers, calibrated using real maritime supply chain data based on actual empirical shipments from the retail sector, that is, from actual origin-to-destination data. Specific attributes include port locations in China and the United Kingdom (UK); journeys and vessels; warehouse, port and transportation cost structures; as well as demand. Recall that each journey j represents a unique vessel $v \in \mathcal{V}$ embarking from source port $s \in \mathcal{S}$ at time period $t \in \mathcal{T}$, traveling at a distinct, known average speed, and disembarking at destination port $u \in \mathcal{U}$. Small random variations were added to the generated values. Having insight into actual international flows provides an important contribution in relation to creating data instances. Secondary data sources also were used to corroborate vessel capacity, speed and emissions, and those values were based on the vessel name, e.g. COSCO

England with some assumptions (AP Moller-Maersk Group 2007, Notteboom and Vernimmen 2009, ECTA 2011, Merk et al. 2015). The distance between origin and destination ports was calculated using the Ports.com website (Sea Routes and Distances, 2018).

Ten random instances were generated, ranging in number of ports in China and UK, retailers, product types, and time periods. The names of the instances reflect those values and are detailed in Table 3. Specific examples of parameters are provided in Tables 4 through 6. For example, data instance *i_d2_s3_r2_p2_t2a* features two UK ports (Southampton and Teesport); three Chinese ports (Fuzhou, Nanjing and Shekou); two product types (with known weight and volume); and two time periods. Data instance *i_d2_s3_ r2_p2_t2b* features different port locations (Hong Kong, Nanjing, and Tianjin in China, and Felixstowe and Southampton in the UK), with different values for other attributes. Each data instance contains values for the following parameters: 'Journey', 'Supply', 'Demand', 'Inventory', 'Fixed Costs', 'Other Management Costs', Unit Holding Cost', 'Product Attributes', 'Container Attributes', 'CO_2 fixed emissions, 'CO_2 Holding emission'.

For coopetition, we considered the setting where the two retailers had their weekly demand per product type aggregated. Accordingly, the same test instances were used for our competition and coopetition experiments, where for the latter, the weekly demands per product type are combined between the two retailers.

Table 3. Details of ten test instances designed for computational experiments.

Instance	Instance Name	Number of Journeys	Destination Ports (UK)	Source Ports (China)	Retailers	Products	Time Periods
1	i_d2_s3_ r2_p2_t2a	18	2	3	2	2	2
2	i_d2_s3_ r2_p2_t2b	21	2	3	2	2	2
3	i_d2_s5_ r2_p3_t3a	34	2	5	2	3	3
4	i_d2_s3_ r2_p3_t5a	68	2	3	2	3	5
5	i_d2_s5_ r2_p2_t2a	18	2	5	2	2	2
6	i_d2_s3_ r2_p3_t5b	84	2	3	2	3	5
7	i_d2_s5_ r2_p5_t5a	139	2	5	2	5	5
8	i_d2_s10_ r2_p3_t5a	151	2	10	2	3	5
9	i_d2_s10_ r2_p5_t10a	210	2	10	2	5	10
10	i_d3_s10_r2_p5_t10a	273	3	10	2	5	10

Table 4. Exemplary fixed and other management cost data (£).

Port	Fixed Costs for Container Size				Other Management Costs
	20'	40'	40'HC	45'	
Southampton	110	110	110	147	36
Teesport	130	130	130	174	24
Shekou	106	203	203	257	15
Fuzhou	87	131	131	171	14
Nanjing	89	133	133	172	16

Table 5. Container-level data; CO_2 emissions estimates from Geerlings and van Duin (2011).

Container Size	CBM	Max payload (kg)	CO_2 Emissions (g) for Loading / Unloading
20'	33	21,710	29,800
40'	68	26,710	53,640
40'HC	76	26,490	53,640
45'	86	25,600	59,600

Table 6. Exemplary CO_2 emissions for holding inventory in warehouses at destination ports.

Product	Destination Port	CO_2 g/per case
1	Southampton	0.001365
2	Southampton	0.002505
1	Teesport	0.000182
2	Teesport	0.000334

4.2. Computational Environment

All computational experiments were conducted on a machine with 64GB of RAM, an Intel(R) Core(TM) i7-6700HQ CPU @ 2.60GHz processor, and running Windows 10 Enterprise. Python was used for the development of the integer optimization model, as well as all corresponding analyses. Gurobi 7.5 was used to conduct the optimization for the associated integer optimization problems (Gurobi 2019). The MIPFocus parameter was set to *prove optimality*, and a time limit was set as appropriate.

4.3. Information Available after a Single Optimization Run

We use the data detailed in Section 4.1 to generate specific test instances of optimization model (1)-(9). Upon solving, a rich array of output is available to inform managerial decision-making. In particular, the output of the model provides an optimal shipping plan of how to place products and quantities into various container sizes on particular journeys to satisfy demand at destination ports. Available cost figures include economic and carbon port handling costs from loading and unloading containers at source and destination ports; distribution costs from fuel, capital, operating, and carbon; and holding costs (both economic and carbon) for destination port warehousing.

We use fuel cost multipliers in the range of {1/9, 1/3, 1, 3, 9}. We use $30 per barrel as a baseline fuel cost, with which we associate a multiplier of 1. In 1999, global fuel costs reached a minimum of $7 per barrel, which is 0.23 of the baseline value of $30, and so encompassed by 1/9. On the other end, the multiplier of 9 is sufficient to cover maximum prices per barrel in recent history. Our fuel cost assumptions follow data from the Energy Intelligence Group (2011). Our carbon cost multipliers are also in the range of {1/9, 1/3, 1, 3, 9}, and use as a baseline recent average carbon market rates of approximately £6.08 per tonne. We note that these are conservative estimates. The overall social costs have been estimated to be at least $36 (£27) per tonne using an average discounted impact (EPA 2013). Other studies assess the true social cost of carbon emissions to be $220 (£167) per tonne (Moore and Diaz, 2015); some high-end estimates place this social cost into the thousands of U.S. Dollars for carbon tax values (Tol, 2018). Again, the range and baseline we consider, while conservative, encompass the current cost of carbon at nearly £27 per tonne, as well as higher costs, to allow for potential future climate change crisis. Hence, we incorporate a multiplier on the cost of fuel and carbon emissions that cover current and possible future scenarios.

4.4. Description of Computational Experiments

We carry out computational experiments on the test instances detailed in Section 4.1. The following four sets of experiments were conducted for both the competition and coopetition scenarios:

1) Computational performance on all ten instances;
2) Vary CO_2 cost multiplier while holding all other parameters fixed;
3) Vary fuel cost multiplier while holding all other parameters fixed;
4) Vary both CO_2 cost and fuel cost multipliers, while holding all other parameters fixed.

Computational experiments 2), 3), and 4) were carried out on the largest test instance detailed in Table 3: i_d3_s10_r2_p5_t10a. We adopted this to be as realistic as possible, and, correspondingly, to provide greater insights.

5. Results and Analysis of Computational Experiments

The results of the computational experiments discussed in Section 4.4 are further detailed in this Section.

5.1. Results of Computational Performance on All Ten Instances

The first set of tests involved baseline fuel costs and carbon costs; and used a four-hour (14,400 seconds) time limit for each optimization solve. Table 7 details the computational results for both the competition scenario (columns 3 through 5), and the coopetition scenario (columns 6 through 8).

As can be seen in Table 7, the first six instances solve within the time limit of four hours (indeed, in under one minute) for both the competition and coopetition scenarios. Moreover, instance 8 in the coopetition scenario solved in approximately one minute. This is perhaps due to the smaller number of product types (< 5), as products are allocated at the container level. Instance 10 in the coopetition scenario also solves under the time limit. For all other instances and scenarios, the time limit of four hours is reached prior to proving optimality. Even so, the optimality gap demonstrates that all solutions and scenarios are within 1% of optimality, with the exception of instance 7 for the coopetition scenario, for which the gap is just over 1%. While computational performance is not the main focus of our study, we believe that formulation (1)–(9), at least for some larger instances and scenarios shown in Table 7, is a challenging optimization problem to solve to optimality.

Table 7. Computational results on all ten instances, under both competition and coopetition.

		Competition Scenario			Coopetition Scenario		
Instance	**Instance Name**	**Time (s)**	**Opt Gap**	**Total Cost**	**Time (s)**	**Opt Gap**	**Total Cost**
1	i_d2_s3_ r2_p2_t2a	< 5	0%	£1,569	< 5	0%	£1,540
2	i_d2_s3_ r2_p2_t2b	< 5	0%	£1,463	< 5	0%	£1,461
3	i_d2_s5_ r2_p3_t3a	17	0%	£3,278	< 5	0%	£2,748
4	i_d2_s3_ r2_p3_t5a	38	0%	£5,071	52	0%	£5,038
5	i_d2_s5_ r2_p2_t2a	36	0%	£2,382	16	0%	£2,057
6	i_d2_s3_ r2_p3_t5b	41	0%	£3,211	27	0%	£2,979
7	i_d2_s5_ r2_p5_t5a	14,407	0.4%	£6,980	14,410	1.1%	£6,779
8	i_d2_s10_ r2_p3_t5a	14,433	0.8%	£5,951	61	0%	£5,666
9	i_d2_s10_ r2_p5_t10a	14,455	0.7%	£16,749	14,412	0.3%	£16,568
10	i_d3_s10_r2_p5_t10a	14,437	0.4%	£24,387	10,491	0%	£24,062

Of note, is that the total cost for coopetition is less than the total cost of competition for every instance in Table 7. In every instance, coopetition does provide some measure of financial benefit, albeit the percent savings range from as little as 0.1%, to up to 16.2%. These results suggest that careful examination of the coopetition context is necessary.

5.2. Preliminary Analysis and Results

We consider how the solution to instance 10 (i_d3_s10_r2_p5_t10a), which is the largest test instance, responds to changes in the CO_2 cost multipliers and fuel cost multipliers – both separately, and jointly. We used five levels of cost multipliers, namely those in the set {1/9, 1/3, 1, 3, 9}, leading to 25 combinations of fuel and CO_2 cost multipliers. Each of these 25 combinations represented a unique test instance for optimization model (1)-(9), as was solved as described in Section 4.2, with a time limit of 3 hours. We evaluated the results under both the completion and coopetition scenarios. Moreover, because our mathematical models estimate fuel costs indirectly via a regression model based on vessel speed and TEU capacity (detailed in Appendix B), there are total fuel costs available, but no direct units of fuel consumption. Hence, as a proxy for consumption, for each of the 25 instances we use the *normalized* fuel cost proxy by dividing the total fuel cost for any particular instance by the associated fuel cost multiplier. So, for example, for a specific run with a fuel cost multiplier of three, dividing the total fuel costs for that instance by 3 gives the normalized fuel cost value.

The overall results show that the coopetition scenario is less sensitive to changes in fuel and CO2 cost multipliers than the competition scenario. The reason for this counterintuitive finding may be that the competition scenario is already highly efficient, mainly due to the separate high container volume the two retailers handled. More detail on this and other findings derived the application of the model are present in the following sections.

5.2.1. Varying CO_2 Cost Multipliers

The values of the CO_2 multiplier were varied in the range {1/9, 1/3, 1, 3, 9} and the results analyzed. As Figures 1 and 2 show, only marginal differences exist between the competition and coopetition scenarios when the CO_2 cost multiplier varies. The total CO_2 emissions under competition are slightly higher than the total CO_2 emissions under coopetition, whereas the values of total cost under coopetition are slightly lower than the values of total cost under competition. Coopetition scenarios appear to be slightly better in terms of cost and slightly worse concerning carbon efficiency when compared to the competition scenarios.

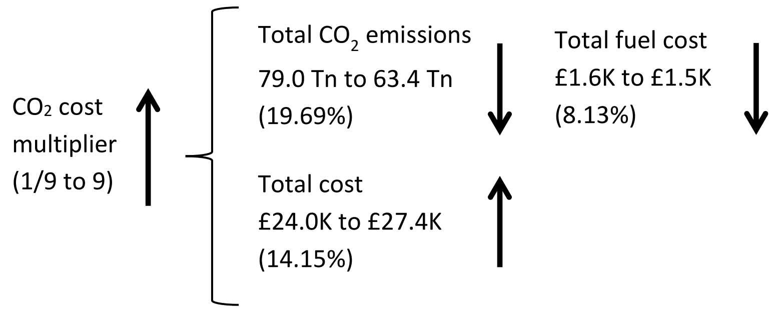


Figure 1. Competition scenarios when varying CO_2 cost multipliers

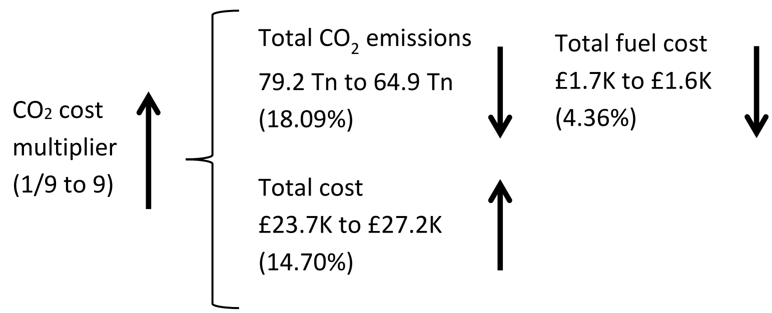


Figure 2. Coopetition scenarios when varying CO_2 cost multipliers

Observation 1: While there are some modest economic benefits under coopetition for shipping container management, the resulting tradeoff is slightly poorer environmental performance.

Figures 1 and 2 also show that when the CO_2 cost multiplier increases from 1/9 to 9, the rise in the total cost is just above 14%, and at the same time, for the same values of CO_2 cost there are decreases in CO_2 emissions between 18 and 20%. This holds true under both competition and coopetition. Furthermore, the same rise in the CO_2 cost multiplier produces less sharp decreases in total fuel cost (between 4.36% and 8.13%). This may be due to the model compensating for the rise in the cost of CO_2 by assigning containers to more efficient journeys, as well as better allocation of products to containers and containers to vessels.

Observation 2: Under increasing CO_2 costs, the coopetition scenario is slightly less sensitive in CO_2 emissions reductions.

Observation 3: Under increasing CO_2 costs, the competition scenario is more sensitive to environmental factors, while the coopetition scenario is more sensitive to economic factors (costs).

Observation 4: Under increasing CO_2 costs, environmental co-benefits of fewer emissions and less fuel usage occur for both the competition and coopetition scenarios.

5.2.2. Varying Fuel Cost Multipliers

The values of the fuel multiplier were varied in the range {1/9, 1/3, 1, 3, 9} and the results analyzed. Figures 3 and 4 present the resulting total costs, total CO_2 emissions and total fuel costs. Similar to the results obtained when varying the CO_2 cost multiplier, there are very small differences between competition and coopetition scenarios. The total CO_2 emissions are nearly the same for coopetition and competition, whereas the values of total cost under coopetition are slightly lower than the values of total cost under competition. For example, for a fuel cost multiplier of 9, the total cost of the competition scenario is £35.9K, which is very close to the total cost of the equivalent coopetition scenario (£35.7K). Coopetition scenarios are just slightly better in terms of cost and just slightly less carbon efficient than competition scenarios. These results further underscore Observation 1.

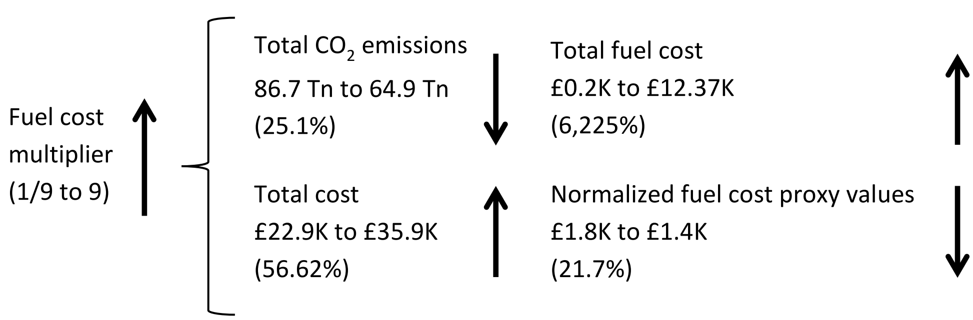


Figure 3. Competition scenarios when varying fuel cost multipliers

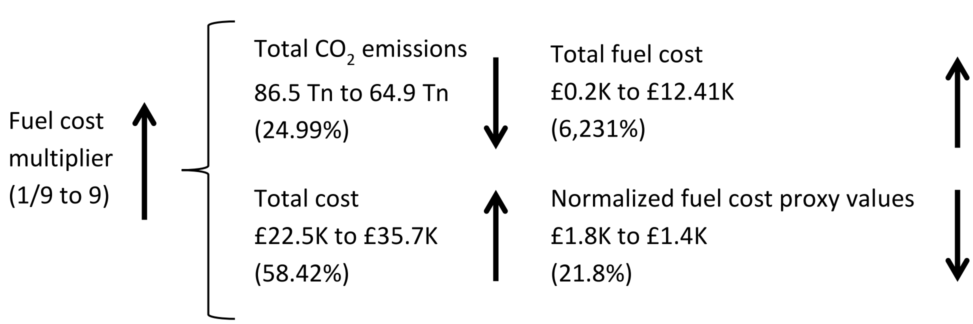


Figure 4. Coopetition scenarios when varying fuel cost multipliers

When the fuel cost multiplier rises from 1/9 to 9, Figures 3 and 4 also show that the rise in the total cost is just above 56%, and the decreases in CO_2 emissions is about 25%. Moreover, the increase in total fuel cost generated is sharp, just above 6,220%. For the same rise in the CO_2 cost multiplier (see Figures 1 and 2), the decrease in total fuel cost is much less sharp. Given that the fuel cost multiplier rises from 1/9 to 9 (8,100%), the fuel cost increase actually rises at a less steep margin, demonstrating that more efficient routing is being chosen. This situation is captured in the normalized fuel cost values, which actually decrease by almost 22% in each scenario.

Observation 5: Under increasing fuel costs, environmental co-benefits exist through reductions in carbon emissions and less fuel usage.

Figures 3 and 4 also show that there are nearly no differences in the values of normalized fuel costs generated by competition and coopetition scenarios.

Observation 6: Under increasing fuel costs, there are no significant cost (economic) or environmental advantages associated between the competition or coopetition scenarios.

When comparing Figures 1 and 2 with Figures 3 and 4, one of the key findings is that carbon emissions in the model are more sensitive to increases in the value of fuel cost multipliers than rises in the values of the CO_2 cost multiplier. This fact may be due to some lower constraint limit on how much fuel can be saved due to shipping requirements. We still make a general observation requiring more investigation.

Observation 7: As a percentage, carbon emissions changes are more sensitive to fuel cost changes than to carbon emissions cost changes.

5.2.3. Varying CO_2 *and* Fuel Cost Multipliers Simultaneously

As Figures 5 and 6 show, comparing like-with-like competition and coopetition instances indicates that the values of total CO_2 emissions, total cost and total fuel costs are very similar. However, at the lower range of values of CO_2 cost and fuel cost multipliers (1/9), the competition scenario has a slightly lower value of CO_2 emissions (89.4 tonnes) than the coopetition scenario (91.5 tonnes). Even so, the values of total costs under the competition and coopetition scenarios are very similar, and in some cases very slightly higher under competition. For example, for the instance with CO_2 cost and fuel cost multipliers both equal to 9, the total cost under competition is £38.7K, whereas under coopetition it is £38.5K.

Figures 5 and 6 also show that the combined effect of increases of CO_2 cost and fuel cost multipliers from 1/9 to 9 generate very sharp rises in total fuel cost of at least 6,770%. Furthermore, this combined effect also produces an increase in total cost of about 62% across competition scenarios, and of almost 64% across coopetition scenarios. Furthermore, the total CO_2 emissions decrease between 43% and 46% with this combined effect at the extreme cost ranges. The combination of increases in fuel and CO_2 cost multipliers also generate increases in total fuel cost of 6,884% in the case of competition scenarios and 6,776% in the case of coopetition scenarios, which when compared with the rise in multiplier levels (8,100%) again demonstrates more efficient routing strategies under higher CO_2 and fuel costs.

In addition, Figures 5 and 6 show that the values of normalized fuel cost values are very similar under the competition and coopetition scenarios. This indicates that both competition and coopetition are able to identify more fuel-efficient strategies.

Additional observations can be made when comparing the single cost alterations that appeared in Figures 1-4 to overall carbon emissions and fuel savings when there are joint alterations in costs as shown in Figures 5 and 6. Two of these observations relate to the relative marginal sensitivities for carbon and fuel emissions. Overall, we see that marginal changes in fuel usage due to joint costs changes are greater than marginal changes in carbon emissions.

Observation 8: When there is a joint increase in fuel costs and carbon emissions costs, the proxy fuel cost (consumption) reduction shows a relatively insignificant improvement over when only one cost (fuel or carbon emissions costs) is increased.

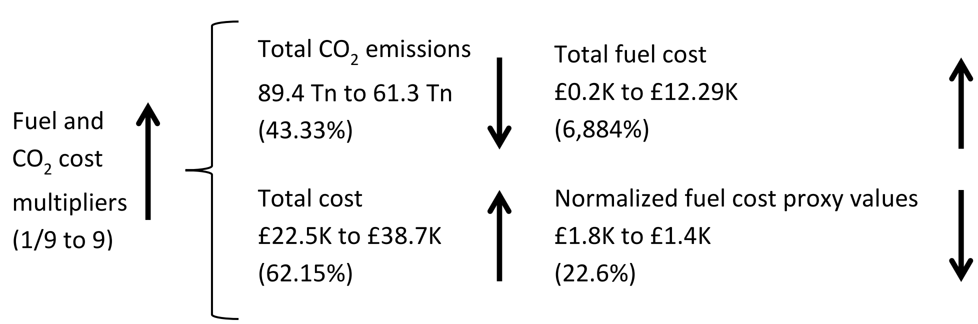


Figure 5. Competition scenarios when varying both CO_2 and fuel cost multipliers

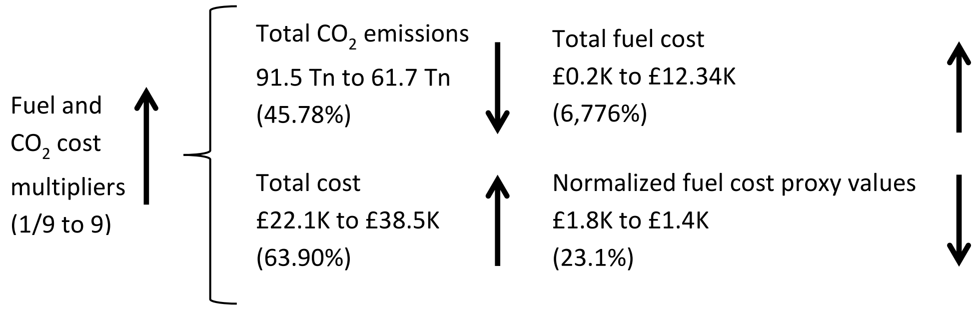


Figure 6. Coopetition scenarios when varying both CO_2 and fuel cost multipliers

A final observation we make with the joint changes in carbon emissions and fuel costs focuses on the competitive environments. Whereas in previous single cost changes to either fuel or carbon emissions, a coopetition context was less sensitive on environmental dimensions than the competitive context. But, in the joint situation we see that coopetition has greater sensitivity than competition environments with joint cost increases. That is, over the joint increase cost ranges in the coopetition case there are 45.78% and 23.1% decreases in carbon emissions and proxy fuel costs (consumption), versus 43.33% and 22.6% decreases in each for the competition case.

5.3. Secondary Analysis and Results

Tables 8 and 9 synthesize various results depicted in Figures 5 and 6. Tables 8 and 9, for competition and coopetition scenarios respectively, include the results of parametric ranges for fuel cost and CO_2 costs, represented in the rows. The columns include, in order: total solution cost, total CO_2 emissions, total fuel cost, and normalized fuel cost values. Table entries provide an overview of the observations. Each entry identifies the direction of the correlation, as well as the effect of cross-factor relationships. For example, the first entry of Table 8 details how the total cost (GBP) is affected by fuel multipliers ranging from factors of 1/9 to 9 of the baseline value of 1. For two values of the CO_2 cost multiplier (1/9 and 9), positive correlations in total cost exist with respect to increasing fuel costs, and these trends in total cost are similar whether the CO_2 multiplier is low (1/9) or high (9). This result is not the same for other dimensions, as can be seen in other entries.

Of those varied, the fuel cost multiplier appears to be the most dominant factor. This is primarily due to fuel cost representing a substantial fraction of the overall shipping cost. When the fuel cost multiplier increases from 1/9 to 9, the total fuel cost under coopetition and competition rises very sharply; though at a lower rate than the multiplier value. Similarly, sharp increases in total fuel cost caused from fuel cost multiplier increases occur across different CO_2 cost multiplier ranges; the CO_2 cost multiplier does not seem to mitigate sharp fuel cost increases from increased fuel cost multipliers. This latter observation sets the foundation for the normalized fuel cost value. If the total fuel cost is the same factor of increase as the multiplier, then one would expect there to be only negligible influence on fuel consumption as the fuel cost increases. However, as the fuel cost multiplier increases, we actually see that the normalized fuel cost value *decreases*. Hence, large rises in the fuel cost multiplier reveal efficiencies in fuel cost when normalized to the baseline, in the range of 22% to 23%.

Table 8. Overview of the results derived from competition scenarios

Multiplier	**Total cost (GBP)**	**Total CO_2 emissions (tonnes)**	**Total fuel cost (GBP)**	**Normalized fuel cost proxy values**
Fuel cost: 1/9 to 9	Positive correlations, steady increases in total cost for increasing values of CO_2 cost multiplier, similar trends for different values of fuel cost multiplier. ***CO_2 cost multiplier = 1/9*** 22.5K (1/9) → 24K (1) → 35K (9) ***CO_2 cost multiplier = 9*** 26K (1/9) → 27.4K (1) → 38.7K (9)	Negative correlations, sharper decreases in tonnes of CO_2 generated for lower values of CO_2 cost multiplier. ***CO_2 cost multiplier = 1/9*** 89.4K (1/9) → 79K (1) → 65K (9) ***CO_2 cost multiplier = 9*** 65K (1/9) → 63.4K (1) → 61.2K (9)	Positive correlations, extremely sharp rises in total fuel cost when the fuel cost multiplier increases, regardless of values of CO_2 cost multiplier. ***CO_2 cost multiplier = 1/9*** 0.196K (1/9) → 1.65K (1) → 12.37K (9) ***CO_2 cost multiplier = 9*** 0.17K (1/9) → 1.5K (1) → 12.29K (9)	Negative correlations, steady decreases in normalized fuel cost proxy values when the fuel cost multiplier rises. The decreases are greater when the CO_2 cost multiplier is lower. ***CO_2 cost multiplier = 1/9*** 1.8K (1/9) → 1.6K (1) → 1.4K (9) ***CO_2 cost multiplier = 9*** 1.6K (1/9) → 1.5K (1) → 1.4K (9)
CO_2 cost: 1/9 to 9	Positive correlations, slight rises in total cost for different values of CO_2 cost multiplier, similar trends for different values of fuel cost multiplier. ***Fuel cost multiplier = 1/9*** 22.5K (1/9) → 22.9K (1) → 26.1K (9) ***Fuel cost multiplier = 9*** 35.5K (1/9) → 35.9K (1) → 38.7K (9)	Negative correlations, sharper reductions in tonnes of CO_2 generated for lower values of fuel cost multiplier. ***Fuel cost multiplier = 1/9*** 89K (1/9) → 86K (1) → 65K (9) **Fuel cost *multiplier* = 9** 65K (1/9) → 64.9K (1) → 61K (9)	Negative correlations, slight reductions in total fuel cost when the CO_2 cost multiplier increases, similar trends for different values of fuel cost multiplier. ***Fuel cost multiplier = 1/9*** 0.198K (1/9) → 0.195K (1) → 0.176K (9) ***Fuel cost multiplier = 9*** 12.37K (1/9) → 12.37K (1) → 12.29K (9)	Negative correlations, slight decreases in normalized fuel cost proxy values when the CO_2 cost multiplier increases. ***Fuel cost multiplier = 1/9*** 1.8K (1/9) → 1.8K (1) → 1.6K (9) ***Fuel cost multiplier = 9*** 1.4K (1/9) → 1.4K (1) → 1.4K (9)

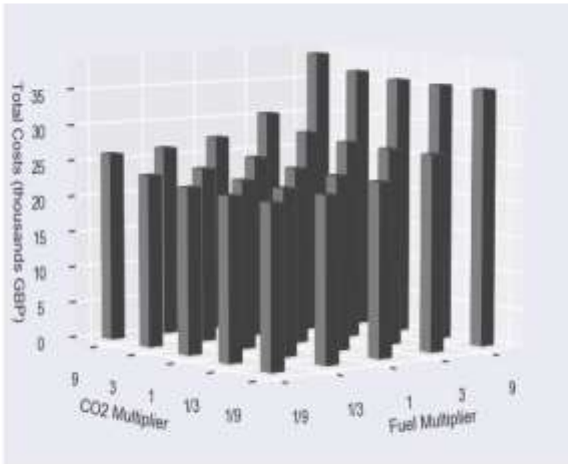
As Tables 8 and 9 demonstrate, the fuel cost multiplier has positive correlations with the total cost; higher multipliers have higher total costs. This trend is similar for different values of CO_2 cost multipliers, which also shows that the CO_2 cost multiplier does not greatly impact the trend between fuel cost multiplier and total cost. The results also show that as the CO_2 cost multiplier increases, the normalized fuel cost values decrease. This demonstrates a modest effect of fuel efficiencies under rising CO_2 costs.

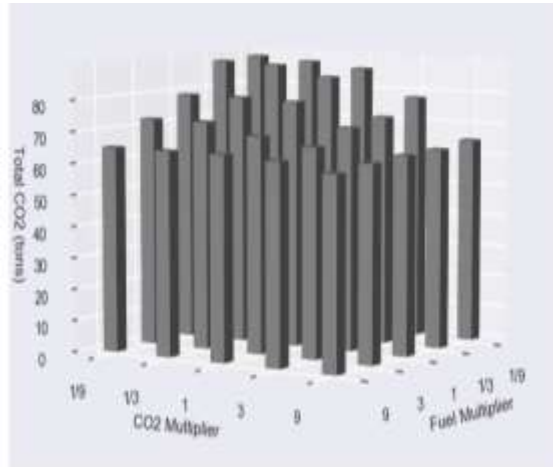
Table 9. Overview of the results derived from coopetition scenarios

Multiplier	Total cost (GBP)	Total CO_2 emissions (Tonnes)	Total fuel cost (GBP)	Normalized fuel cost proxy values
Fuel cost: 1/9 to 9	Positive correlations, steady rises in total cost for different values of CO_2 cost multiplier, similar trends for different values of fuel cost multiplier. ***CO_2 cost multiplier = 1/9*** 22K (1/9) → 23.7K (1) → 35.3K (9) ***CO_2 cost multiplier = 9*** 25.7K (1/9) → 27K (1) → 38.5K (9)	Negative correlations, sharper reductions in tonnes of CO_2 generated for lower values of CO_2 cost multiplier. ***CO_2 cost multiplier = 1/9*** 91.4K (1/9) → 79.2K (1) → 65.4K (9) ***CO_2 cost multiplier = 9*** 65K (1/9) → 64.9K (1) → 61.7K (9)	Positive correlations, drastic rises in total fuel cost when the fuel cost multiplier increases, regardless of values of CO_2 cost multiplier. ***CO_2 cost multiplier = 1/9*** 0.198K (1/9) → 1.7K (1) → 12.34K (9) ***CO_2 cost multiplier = 9*** 0.179K (1/9) → 1.6K (1) → 12.34K (9)	Negative correlations, steady decreases in normalized fuel cost proxy values when the fuel cost multiplier rises. The decreases are greater when the CO_2 cost multiplier is lower. ***CO_2 cost multiplier = 1/9*** 1.8K (1/9) → 1.7K (1) → 1.4K (9) ***CO_2 cost multiplier = 9*** 1.6K (1/9) → 1.6K (1) → 1.4K (9)
$C0_2$ cost: 1/9 to 9	Positive correlation, slight rises in total cost for different values of CO_2 cost multiplier, similar trends for different values of fuel cost multiplier. ***Fuel cost multiplier = 1/9*** 22.1K (1/9) → 22.5K (1) → 25.7K (9) ***Fuel cost multiplier = 9*** 35.4K (1/9) → 35.7K (1) → 38.5K (9)	Negative correlations, sharper reductions in tonnes of CO_2 generated for lower values of fuel cost multiplier. ***Fuel cost multiplier = 1/9*** 91.5K (1/9) → 86.5K (1) → 65K (9) ***Fuel cost multiplier = 9*** 65.4K (1/9) → 64.9K (1) → 61K (9)	Negative correlations, very small reductions in total fuel cost when the CO_2 cost multiplier increases, similar trends for different values of fuel cost multipliers. ***Fuel cost multiplier = 1/9*** 0.198K (1/9) → 0.195K (1) → 0.176K (9) ***Fuel cost multiplier = 9*** 12.37K (1/9) → 12.37K (1) → 12.29K (9)	Negative correlations, slight decreases in normalized fuel cost proxy values when the CO_2 cost multiplier increases. ***Fuel cost multiplier = 1/9*** 1.8K (1/9) → 1.8K (1) → 1.6K (9) ***Fuel cost multiplier = 9*** 1.4K (1/9) → 1.4K (1) → 1.4K (9)

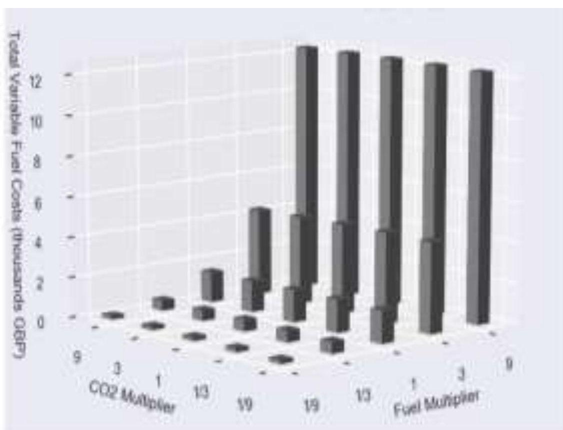
The fuel cost multiplier appears to have a negative correlation with the total tonnes of CO_2 emissions across CO_2 cost multiplier values, as well as with the normalized fuel cost values. There are sharper decreases in total CO_2 emissions for lower values of CO_2 cost multipliers, which again shows that the dominant factor is the fuel cost multiplier rather than the CO_2 cost multiplier. For lower levels of fuel cost multipliers, the normalized fuel cost values are somewhat sensitive to CO_2 cost multiplier increases, but this effect disappears for larger fuel cost multipliers.

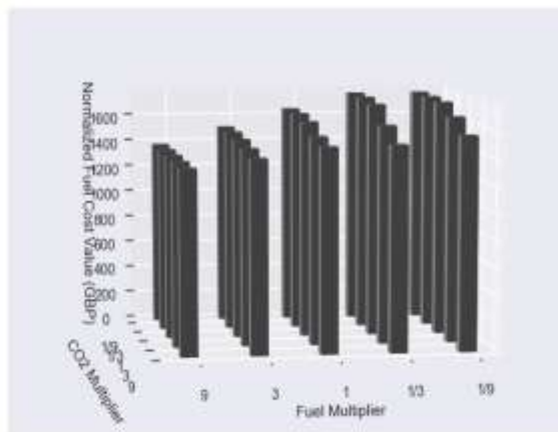
Tables 8 and 9 also demonstrate that increases in the CO_2 cost multiplier generate slight rises in total cost. There are similar trends between the CO_2 cost multiplier and total cost for different values of the fuel cost multiplier. There is a negative correlation between the CO_2 cost multiplier and total CO_2 emissions. Rises in the CO_2 cost multiplier causes reductions in total CO_2, and these reductions are sharper for lower values of the fuel cost multiplier. When fuel cost multipliers are low, the effect of CO_2 cost multipliers on CO_2 emissions becomes apparent, as they represent a larger percentage of costs. At the same time, increases in CO_2 cost multiplier generate very small reductions in the total fuel cost.





(a) Total cost **(b)** Total CO_2 emissions



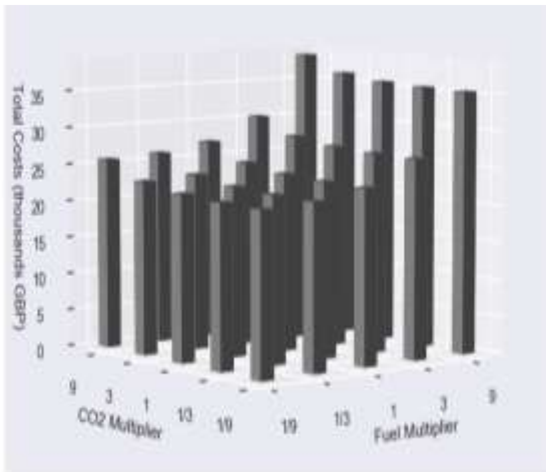


(c) Total fuel cost **(d)** Normalized fuel cost values

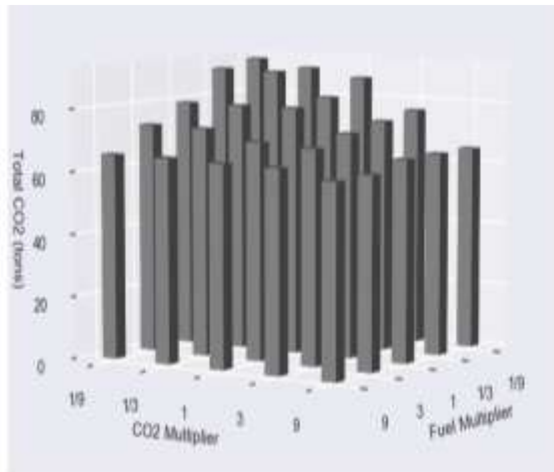
Figure 7. Visualizing competition scenarios when varying both CO_2 and fuel cost multipliers on the largest test instance (i_d3_s10_r2_p5_t10a)

Figures 7 and 8 show, in general, that coopetition scenarios have very marginally lower total cost than competition scenarios; however, coopetition scenarios have very slightly higher fuel costs and total CO_2 emissions than competition scenarios.

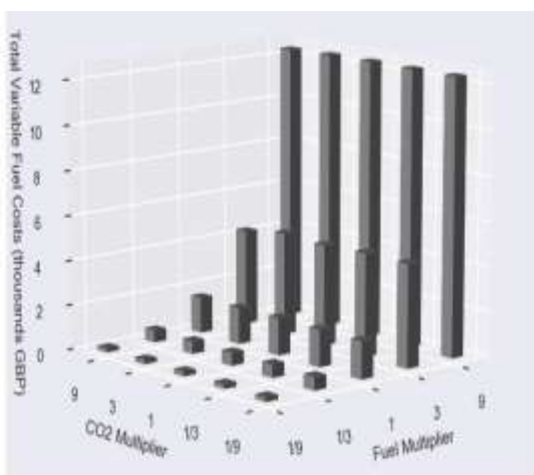
When compared with competition across all ten test instances in Table 3, coopetition appears to have slightly lower fixed costs, as even though they have a few more containers, the smaller containers cost less to load. Coopetition appears to have slightly higher variable costs, while the strategy allows for more full packing of containers, the strategy results in shipping a few more, yet smaller in size, containers. This leads to slightly higher CO_2 emissions and fuel costs. Moreover, coopetition appears to have lower inventory costs at destination port warehouses, as products can be packed into attractive journeys to arrive when needed. There are also efficiencies that appear to arise from loading products into containers; when there are more product types, there are more ways to fully utilize containers. These efficiencies are further emphasized under coopetition.



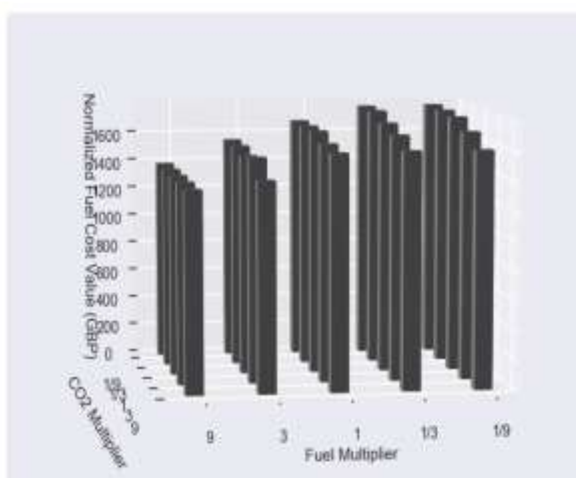
(a) Total cost



(b) Total CO_2 emissions



(c) Total fuel cost



(d) Normalized fuel cost values

Figure 8. Visualizing coopetition scenarios when varying both CO_2 and fuel cost multipliers on the largest test instance (i_d3_s10_r2_p5_t10a)

6. Discussion and Conclusions

Global retail supply chains are heavily reliant on efficient container shipping. This study focuses on how shipping intermediaries such as 4PLs can enable efficiency gains in the distribution of retail freight containers. We develop an integer optimization model that integrates both economic and environmental maritime shipping factors into the objective function to solve the port-to-port journey selection and cargo routing problem.

We study two scenarios, namely competition and coopetition, to evaluate the viability of coopetition as a strategy for container shipping distribution operations. We generate a variety of test instances that are calibrated with real maritime supply chain data from two large UK retailers. Using these instances, we present a robust set of computational experiments that focuses on journey selection and cargo routing sensitivity under changes to fuel and carbon costs, respectively. We also contribute to the literature by estimating the economic and environmental impacts of coopetition in maritime shipping, a topic that has received little attention in the literature. A number of observations for future research are also identified.

The results of our computational experiments may indicate that—while there are some economic benefits from a coopetition context for shipping container management—the resulting tradeoff is poorer environmental performance. The coopetition scenario is also slightly less sensitive to CO_2 emissions reductions when there are increases in carbon costs. Moreover, the competition scenario is more sensitive to environmental factors when carbon costs increase, while the coopetition scenario is more sensitive to economic factors (costs) when carbon costs increase. In each scenario, environmental co-benefits of fewer emissions and lessened fuel usage do not occur when carbon costs increase. Even so, environmental co-benefits exist through reductions in carbon emissions and less fuel usage when fuel costs increase. There are no (economic) cost or environmental benefit advantages associated with the competition or coopetition scenarios when fuel costs increase. This result shows that the competition scenario is already highly efficient, mainly due to the fact that the two retailers contribute with high volumes to their own container allocation operations. Any savings occur when containers cannot be filled with products from one retailer, so the 4PL fills some containers with cargo from both retailers. Also, there could be the presence of indirect container consolidation that is not visible by either of the retailers who participated in this study; therefore, this might indicate an important policy opportunity. The greatest benefits from an environmental perspective occur when joint environmental cost increases occur. Moreover, joint increases in environmental costs result in greater environmental co-benefits in the coopetition case; unlike the situation for single environmental cost improvements, which showed that competition contexts had greater environmental benefit.

Our optimization model is useful for evaluating the feasibility of coopetition in container shipping. Moreover, it may also be useful in freight distribution contexts that are similar to container shipping, such as inland distribution of containers that use different types of origin and destinations, vehicles, routes and transport modes. The benefits of our integer optimization framework would likely be amplified by embedding it into a decision support system. Such a system could allow decision-makers to interact with the model – adjusting various parameters (e.g. fuel and CO_2 costs) or fine-tuning container-to-vessel assignments to vessels, and observing model outcomes. While outside of the scope of the current paper, it is a possibility for follow-up studies. Finally, although economic benefits occurred from coopetition efforts, we do offer a managerial caveat that environmental performance may be influenced negatively.

Our study suggests some policy implications. If there is a goal by governance agencies to attract environmental co-benefits from policy setting, it may be more effective for taxing fuel rather than increasing carbon taxes. Although, there is a question of political feasibility, these initial results point to this practical outcome. For example, in observation 7, we found that carbon emission reductions are more sensitive to increases in fuel costs than in response to carbon emission costs. In this situation, to see better performance in carbon emissions reductions, policy makers should probably favor fuel taxes rather than carbon taxes. From observations 8 and 9, which also utilize earlier observations, a joint policy of carbon and fuel taxes may improve carbon emissions more effectively. Using this joint policy to reduce fuel usage will obtain fewer significant improvements than using fuel taxes alone. Policy makers can also consider coopetition and competition scenarios to help identify opportunities; if cases of coopetition are prevalent and policy makers seek substantial environmental dimension improvements, they should favor joint improvements in carbon emissions and fuel taxes. In competition cases, especially for fuel usage reductions, a single policy can be relatively effective.

Although some studies have mentioned that coopetition can prove economically beneficial, our study has shown that for the data and model we provide, the advantages of coopetition are quite limited. In fact, from an environmental perspective, there might even be a situation where coopetition situations are counterproductive. Clearly, more investigation on this counterintuitive finding is needed – for example, whether the current competition-based efficiency is so high that it leaves little room for gains from coopetition in terms of both economic and environmental efficiency. If the result holds that the economic benefits are relatively minimal, then coopetition may not be a viable alternative, as the additional required activities such as consolidation and deconsolidation of cargo in container shipping can generate the need of greater economic investments. The reasons why coopetition is better in joint cost increases should also be investigated. Each of the ten observations presented were based on initial results obtained from our simulations. Each observation can be investigated using case study, empirical data, and long-term broader policy-based experiments. There are substantial opportunities in both competitive and environmental (fuel and carbon emissions) cost-based studies.

Our study offers the retail and container shipping industries a number of managerial implications. First, it demonstrates the role of a 4PL for consolidation of containers at points of origin, and second, the value of such consolidation. While the value may be limited in some cases, merit is apparent in others, and gains would certainly increase when considering greater scaling of journeys, ports, retailers, products, and time periods. Third, the study shows that in a coopetition scenario, the retailers can have an intermediary acting on their behalf. Fourth, this paper highlights a number of policy implications that are likely to affect the container shipping industry in the next decade, in particular, in terms of fuel and carbon tax increases.

Our study has some limitations. Our study used practical and feasible data from actual shipping lines and organizations. The derived results arise under some assumptions that include a) all demand must be met; b) substitutable, general merchandise is being shipped, which typically has a low storage cost, and thus can be ordered in earlier periods to ensure sufficient inventory to meet demand; and c) secondary markets exist to sell off any unsold materials. Moreover, having a decision support system that updates parameter information would be fitting given the complexity of the model and data requirements. The counterintuitive findings may be due to idiosyncratic data and further investigations are required. The model only focuses on a limited portion of the maritime supply chain. Broadening the focus to multi-modal deliveries to and from ports, expanding the supply chain may provide differing results.

There are several extensions for this work. While our study considered retailers of similar size and complexity, thereby assuming the same cost structures, an avenue of future research is to consider dissimilar retailers with diverse ranges of unit costs, and the effect that economies of scale may have on the model outcomes. Hence, it would be beneficial to test the model with data from a wider range of retail cargo owners. Such testing may further reveal the effect of factors such as unit cost, volume scale and complexity on the model output and performance of competition and coopetition scenarios.

It would also be interesting to study the effect of varying fuel taxation levels, to optimize environmental co-benefits. Such fuel taxes already exist in the North Atlantic, where in the Emissions Control Area (ECA), fuel needs to be clean fuel. Another scenario would be exploring a form of coopetition where retailers are permitted access to previously dedicated shipping lines. The model can also be adapted to a global supply chain context with multiple suppliers and markets located in multiple countries (beyond China and the UK); care would need to be taken to ensure the computational tractability of the model. The model can be applied to different logistics environments, such as inland primary and last-mile distribution, to assess the feasibility of coopetition scenarios against competition scenarios. Another fruitful avenue may be applying the model to a regional multimodal network that includes road and rail transport modes, as well as multiple suppliers, distribution facilities and routes.

Appendix A. Computing φ_k

In this section we discuss how we compute the *unit time-related CO_2 emissions* factor φ_k, which is the CO_2 emissions to transport one container (TEU) of size k one tonne-km. We estimate φ_k using both 1) a TEU component γ_k, and b) a speed component β_k that serves as a multiplicative factor.

The greater the TEUs, the less the per unit contribution of CO_2, because of economies of scale. The greater the speed, the greater the unit contribution of CO_2, due to engine inefficiencies.

For γ_k we use a piecewise linear function with brackets for TEU sizes, where data points for certain TEU values are estimated from midpoints of the ranges sourced from Buhaug et al. (2009), page 131, Table 9.1. We assume that these CO_2 emission values are incurred from an average speed of 15 knots.

Table A1. CO_2 / tonne-km emissions estimates based on TEUs, from Buhaug et al. (2009)

TEUs	kg CO_2 / tonne-km
500	0.0363
1,500	0.0321
2,500	0.02
5,500	0.0166
8,000	0.0125
11,000	0.0072
18,000	0.003
500	0.0363

We form TEU brackets from Table A1 and create the piecewise linear (decreasing) function for γ_k, fitted to the CO_2 / tonne-km emissions estimates. So, for a 13,000 TEU vessel, we obtain $\gamma_k = 0.0072 - ((0.0072 - 0.003) * ((13{,}000 - 11{,}000)/(18{,}000 - 11{,}000))) = 0.006$.

Table A2. Extrapolated data from Maersk infographic (Maersk, 2018).

Knots	% of max (100% speed)	CO_2 Emissions Rate
25	100%	100%
22.5	90%	70%
20	80%	48%
17.5	70%	32%

For β_k, we extrapolate data from a Maersk inforgraphic (Maersk 2018). Using the data from Table A2, we fit an exponential function $y = 0.0227e^{0.1518x}$, where x is the % of max speed, and y is the corresponding CO_2 emissions rate. Working with a *baseline* speed of 15 knots (60%), we obtain a corresponding CO_2 emissions rate of 22.17%. From this 15 knot baseline speed, we create a new exponential function that expresses the increased emission factor β_k based on increase in knots. This gives $\beta_k = 0.1026e^{0.1518\alpha}$, where α is the vessel speed, in knots, for a particular journey. Hence, this exponential function demonstrates an increasing amount of emissions beyond a baseline speed of 15 knots.

Finally, we obtain a vessel's overall CO_2 emissions related to transporting one container (TEU) one tonne-km via the product $\varphi_k = \beta_k * \gamma_k$.

Appendix B. Estimating Fuel Costs

In this section we discuss the estimation of unit bunker fuel costs. There appears to be evidence (Psaraftis and Kontovas, 2013) that fuel cost varies (at least) cubically with respect to vessel speed, and perhaps linearly with respect to total TEU. Hence, we attempt to fit a polynomial model of order 3 to predict the fuel cost using total TEU and speed (knots) as regressors. We used recent data (Notteboom and Vernimmen, 2009; see Table 3) to conduct the regression. We conducted a multiple linear regression model in MATLAB R2016A using the stepwiselm procedure (MathWorks 2019), which returns a linear model for all possible variables up to cubic interaction terms; it uses both forward and backward stepwise regression to add or remove regressors, and returns the best predictive model. It does so by estimating best-fitting beta coefficients for the speed and total TEU regressors, including all terms and their interactions up through order 3. We obtain the following linear regression model:

Estimated bunker fuel costs (in 2009 USD per day) $\approx$ -127,500 + 23,328*speed - 1417.2*speed^2 + 0.0062727*totalTEU*speed^2 + 30.787*speed^3.

Finally, we conducted unit conversions to ensure that associated costs are in 2017 GBP per case of product. We use this model to predict the unit transport cost for the simulated journey data that includes speed and total TEU. This is a reasonable estimate as, while global bunker fuel prices have varied somewhat since 2006, they are at approximately the same level in 2017 as 2006.

Appendix C. Estimating Capital and Operating Costs

Here we discuss the estimation of unit capital and operating costs. We use data from a recent study (Merk et al., 2015) to estimate the per case capital and operating variable costs as speed and total TEU vary. The cost relationship appears strongly linear in speed and total TEU. Thus, we develop a multiple linear regression model to predict cost from total TEU and speed.

Estimated capital and operating variable costs (in 2015 USD per TEU) $\approx$ 256.91 − 0.0035846*totalTEU − 4.2333*speed

We conducted unit conversions to ensure that the variable capital and operating costs are in 2017 GBP per case of product.

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