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Slow-Steaming Climate Strategies For Abatement Efforts In Maritime Shipping

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Abstract

Maritime shipping is a major contributor to climate change – accounting for 2.89% of Global CO_2 emissions in 2018. Given the "light hand" of regulatory institutions governing commercial activities on the high seas, attempts to reduce the emissions of ocean-going ships have not been successful.

In this thesis, the impacts of emission policies and incentives for cooperation in the international maritime shipping industry are examined. The International Maritime Organization (IMO) – the regulator – GHG Strategy puts forth both "speed optimisation" and "speed reduction" as candidate measures for short-term emission abatement. These terms are poorly defined, however, leading to different interpretations.

Slow steaming, or deliberately reducing ships' speed, allows firms to decrease fuel consumption and therefore, emissions. Grounded in this rationale, a flexible numerical simulation model is developed for a market comprised of heterogeneous shipping companies to investigate maritime shipping abatement dynamics under various slow steaming policies. First, we project firms' business-as-usual (BAU) operations and then analyse both policies: Speed reduction – relative to BAU levels and Speed optimisation – as firms' climate strategy response to meet various emission caps.

The simulation results suggest that firms already slow-steam when economically optimal (i.e. by evaluating the trade-off between fuel savings and time-dependent operating costs). Even more so, they show that speed optimization -as an abatement strategy- provides firms with the flexibility to derive their optimal Slow-Steaming rates to sustain a regulator's environmental policy. In contrast, we find that Slow-Steaming - as a command and control policy- shifts regulatory focus and is difficult to enforce in international waters.

The simulation model was also used to analyze a two-stage, cooperative game of coalition formation with heterogeneous firms and individual abatement strategies. In the first stage, firms decide whether to join a coalition or not (membership decision). Coalition signatories adopt the operational slow-steaming climate strategy over the planning horizon and choose the abatement levels that maximise the sum of their payoffs under a joint emission budget constraint. On the other hand, non-signatories to the coalition (singletons) optimise their own abatement level by maximising individual payoffs, subject to their own individual caps.

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Our results indicate that cooperation allows firms with heterogeneous abatement cost curves to pool resources and properly allocate speed reduction endeavours to sustain an emission target. Thus, industry-level climate strategies withhold the potential to improve environmental sustainability through cooperation for ocean shipping.

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Introduction

1.1 Background

During the past few decades, growing concerns over the dire consequences of climate change have rendered environmental policies increasingly critical to government agendas. Severe repercussions could range from extreme weather shocks to frequent natural disasters, and nations worldwide have and will endure substantial economic and social losses due to changing climate. However, the potential increases in the frequency and strength of these events could be mitigated through cooperative endeavours. To this end, much of the environmental literature depicts global warming as one of the greatest market failures and one of the the world's most challenging public goods problem (Sinn, 2008).

Some level of cooperation on Greenhouse Gas (GHG) abatement is therefore essential to climate policies. Since emissions are global, cooperation between countries for mitigation typically manifests through international environmental agreements (IEAs) (Wagner, 2001). The academic literature has investigated those conditions associated with the stability and efficiency of IEAs since the early 1990s. However, pollution externalities extend beyond national borders and give rise to free-riding incentives that can make international cooperation difficult to achieve (Barrett, 1994, 1997, 2002; Barrett & Stavins, 2003; Carraro & Siniscalco, 1993; d'Aspremont, Jacquemin, Gabszewicz, & Weymark, 1983; Eyckmans & Finus, 2006; Hoel, 1992; Hoel & Schneider, 1997; Rubio & Casino, 2005; Rubio & Ulph, 2003)

Ocean shipping occurs in international waters, which makes the appropriation of its emissions to individual nations challenging. Furthermore, the current set of international environmental agreements governing country-level emissions only accounts for domestic land-based pollution, thereby severely restricting nations' remaining budgets to monitor the maritime industry (IPCC, 1998). Thus, the primary impediment to maritime shipping abatement governance is the inherent international scope of the industry, leading to inconsistent or ambiguous regulatory oversight when compared to industries or firms that operate within state-level jurisdiction. So while the maritime industry is currently a prime target of environmental policy discussions because of its non-trivial contribution to global emissions, it has always escaped environmental scrutiny and remained absent from IEAs (Gilbert & Bows, 2012;

Raza, 2020). Several affiliated nations were advised to collaborate with the International Maritime Organization (IMO) to curb their emissions (Protocol, 1997). However, in the span of about a quarter century since being asked to mitigate maritime shipping emissions, the IMO's progress has remained painfully slow (Wang, Zhen, Psaraftis, & Yan, 2021). Consequently, while there has been substantial research on industry-level cooperation for environmental initiatives in other sectors, little research if any, investigated cooperative abatement endeavours in maritime shipping. Thus, this thesis aims to bridge this gap and investigate maritime shipping abatement dynamics within the framework of an industry-level climate coalition.

In this thesis, we examine industry-level climate strategies in the context of ocean shipping, an important source of emissions in need of better environmental governance. Ocean shipping emitted $1,076$ million tonnes of CO_2 in 2018, accounting for 2.89% of the total global CO_2 emissions for that year. However, with its rapidly growing fleet size and the tripping of world trade from 2020 to 2050, emissions are projected to reach 90-130% of 2008 emissions by 2050 for a range of plausible long-term economic and energy scenarios (S. Faber et al., 2020). While the projected growth isn't significant, decarbonising the industry will require substantial planned mitigation efforts. To increase the industry's abatement endeavours, the International Maritime Organisation (IMO) introduced an initial GHG Strategy in 2018 and pledged to halve the industry's emissions by mid-century relative to its 2008 level. Furthermore, the governing body is mandating a cut of 40 % by 2030 and 70% by 2050 in carbon emissions per transport work (compared with 2008) (IMO, 2018). To reach their objective, the industry is currently relying on trust and voluntary participation to commit to these policies (S. Faber et al., 2020; IMO, 2018; Psaraftis, 2019a; Wang, Psaraftis, & Qi, 2021).

Maritime shipping firms are currently taking the initiative to combat climate change through global international environmental organisations, despite currently being exempt from IEAs and other national regulations. Considering the significant technical and economic consequences of climate change faced by the industry, one particular organization of interest is The Clean Shipping Coalition (CSC) initiative, which is currently advocating for a cleaner energy market and a greener sector. This group encompasses more than 90% of the global shipping fleet and is calling for market-based mechanisms (MBMs) to establish a $5-billion US fund for implementing a zero-carbon-emission ship (Sean, 2019). Participants emphasized the need for a 'global solution' and acknowledge the lack of firms' incentive to curb their emissions in the absence of regulation (Linder, 2018). However, owing to a dearth of international law or institutions able to bind the agreements, environmental governance in ocean shipping hinges on self-enforcement in the form of voluntary participation and restricting individual manipulation of strategic incentives. The prevailing consensus remains that while cooperation on emissions abatement is necessary, individual firms lack the incentive to mitigate transboundary pollution since abatement benefits are non-excludable and non-rival. Thus, within such a complex industrial and regulatory framework, decarbonizing the industry will likely be only achieved through industry-level coalition formation.

There are several mitigation measures for maritime shipping including slow steaming (speed reduction), fuel switching, alternative fuel consumption and the use of exhaust gas cleaning systems (scrubbers). However, the only one relevant to this analysis is the use of speed regulations as an abatement strategy. In today's IMO proceedings, regulating vessel speed remains at the heart of policy controversies. The Clean Shipping Coalition, a prominent nonprofit organization in the industry, has been lobbying for speed limit policies and managed to convince the IMO to incorporate it as a short-term abatement candidate in its initial GHG strategy. CSC is emphasizing the policy's potential to immediately curb the industry's emission growth, further branding it as a bridge measure until more permanent procedures are put forth (Psaraftis & Zis, 2021). All the while, Chile and Peru are opposing these regulations and raising concerns about the underlying repercussions for their agricultural exports. Relevant negotiations should be finalized and agreed upon between 2018 and 2023 (Psaraftis, 2019b).

This research investigates speed-related mitigating strategies, examining the trade-off between global benefits and costs arising from optimal abatement. However, we also acknowledge the need for investigating adaptive measures as they are essential in driving free-riding incentives and cooperation within a coalition. Burned gas throughout the engine combustion process comprises the foremost source of GHG emissions from ships. Speed reduction as an abatement strategy results in lower fuel consumption, costs, and emissions, while it also leads to longer transit times and fewer transits per unit time. Under a slow steaming policy, additional ships need to be deployed to sustain cargo throughput, which in turn increases other costs such as non-fuel ship operating costs. Therefore, owing to the non-linear (at least cubic) relationship between fuel consumption and vessel speed, relevant climate impact assessment studies represent a multidimensional problem, whereby profit margins hinge on the chosen operational speed, fleet size and the amounts of CO_2 emitted from fuel consumption and combustion (Corbett, Wang, & Winebrake, 2009; J. Faber et al., 2009; Lindstad, Asbjørnslett, & Strømman, 2011; Lindstad & Mørkve, 2009; Psaraftis & Kontovas, 2010).

This thesis contributes to the maritime speed-limiting debate by introducing a numerical simulation framework aimed at exploring the formation of Industry Level Climate Coalitions (ILCC), using slow steaming as the abatement policy of interest. The (ILCC) framework assumes a standard maritime freight service model in which shipping firms transport goods using a fleet of container ships from origin/supply port A to destination/demand port B, using a fixed shipping route and schedule. This specification is designed to reflect the characteristics of many industrial shipping services, (Fagerholt, Laporte, & Norstad, 2010; Psaraftis & Kontovas, 2010), which in turn, provides detailed information on different vessels' fuel consumption and emissions data.

The computational simulation endogenizes the industry's projected GDP growth, fuel consumption, speed levels and container ships emissions for different economies of scale investments and environmental policies while maintaining firms' annual throughput. It generates an inter-temporal mixed-integer non-linear profit maximization model, drawing on the trade-off between optimal vessel speeds and fleet size. Thus, owing to the difficulty of solving for stable Nash equilibria in this multi-dimensional game situation, the framework leverages an evolutionary genetic algorithm procedure to solve for optimal levels of slow steaming while considering current and past abatement over the planning horizon. The simulation output enables us to better understand firm-level incentives for chosen speed levels in the container ship industry and allows us to investigate to what extent these decisions are influenced by bunker fuel prices. ILCC models environmental policy regulations and endeavours to derive credible abatement cost curves for different economies of scale investments and emission caps.

1.2 Research Objectives

In light of the ongoing speed debate, distinguishing between mandatory speed reduction policies -slow steaming as a command-and-control policy- and speed optimisation as a climate strategy to sustain a regulator's emission cap becomes not only essential but timely. This thesis investigates how to leverage the relationship between vessels' speed and fuel consumption to decrease maritime shipping GHG.

The overarching objectives of this thesis are threefold. First, to project firms' business-as-usual (BAU) operations in the absence of environmental policy. Second, to model heterogeneous firms' behaviour under various mandatory speed reduction policies – relative to BAU levels and Third, to analyse speed optimisation – as firms' climate strategy abatement response to meet various emission caps in an All-Singleton and A Grand Coalition market structures. Here, carbon budget constraints are derived from firms' projected (BAU) emission paths.

Grounded in the industry's oligopoly structure, the research also seeks to better understand how shipping companies might either individually (All Singleton market structure) or collectively (within a Grand Coalition market structure) react to emission cap regulations within a dynamic game of abatement. The allocation of a joint carbon budget constraint to the coalition is feasible within the industry since environmental regulation would approve carbon trading schemes among the industry's already established alliances (Benjaafar, Li, & Daskin, 2012). Furthermore, ILCC investigates how the design of lenient to more stringent emission caps would affect firms' incentives to join a slow-steaming climate coalition and the industry's potential for environmental sustainability through cooperation and coalition formation.

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1.3 Organization Of The Study

This thesis is organized as follows: Chapter 2 reviews the relevant strands of the literature, and motivates the study's theoretical framework, providing an overview of the simulation and its game-theoretic structure. Chapter three outlines the Industry Level Climate Coalition model development while chapter four summarizes our input data, and also describes the evolutionary algorithmic procedure leveraged in solving for optimal abatement policies. Findings generated using the baseline simulation as well as model extensions are analyzed and discussed in Chapter five. Finally, policy implications, along with the research's limitations, and possible future research avenues are described in Chapter six.

2

Literature Review And Theoretical Framework

2.1 Introduction

In this section, we consolidate two diverse strands of the literature on sustainable green shipping and environmental policy governance in international environmental agreements. We provide an overview of relevant seminal research work in maritime shipping, in particular, pertaining to slow steaming as well as the shipping industry's market structure. We then leverage the theoretical framework behind the STACO (Stability of Coalitions) national-level pollution abatement model in order to help us bridge the gap concerning research into cooperative abatement for an important but smaller economic sector, the container ship industry. Finally, we lay our theoretical framework and introduce our two-stage pollution game and the concept of coalition stability.

2.2 Slow Steaming As A Climate Policy

International maritime shipping remains at the heart of environmental scrutiny from many policymakers, accounting for 2.89% of 2018 's global emissions with an estimated growth between 90% and 130% by 2050 (S. Faber et al., 2020). As a partial response to this reality, in 2018, the International Maritime Organization (IMO) introduced an initial GHG strategy for achieving more sustainable and greener shipping. As written, the plan endeavours to curb the industry's future emissions growth by 50% for 2050 and decrease its carbon intensity per transport work by at least 40% by 2030, and 70% by 2050 - all assessed relative to 2008 levels (MEPC, 2018) .

Amongst the governing agent's short-term candidate strategies for meeting emissions targets, this research stresses the following: *"Consider and analyze the use of speed optimization* *and speed reduction as a measure, taking into account safety issues, distance travelled, distortion of the market or trade and that such measure does not impact on shipping's capability to serve remote geographic areas"* (Psaraftis, 2019b).

The IMO document's *"Speed Reduction and Speed Optimisation"* depicts two promising and slightly nuanced mitigation strategies. In theory, the rationale for buttressing these particular abatement strategies is driven by the historic cubic relationship governing vessel speed and fuel consumption, and thus emissions (Brahimi, Cheaitou, Cariou, & Feillet, 2021; Corbett et al., 2009; Fagerholt*, 2004; Ronen, 2011; Wang & Meng, 2012). However, the actual policy design is not yet clear on how the sector should best leverage this non-linear relationship to limit emissions. As per the overall ambiguity of how these goals will be achieved, notice the use of both "speed reduction" and "speed optimisation" in their proposal.

Psaraftis (2019b) notes that certain South American nations (mostly Chile and Peru) opposed the use of "speed reduction" as a short-term measure since it could threaten their perishable agricultural commodity exports towards Asia. Rather, they proposed to leverage the concept of speed optimisation. Eventually, the compromise led to including both terms in the decision document. Nevertheless, whether it's speed reduction or speed optimisation, the IMO seeks to regulate, Psaraftis (2019b) notes that neither term is well defined. The policy wording remains vague and subject to a wide range of interpretations.

Consequently, Psaraftis (2019b) highlights the lack of consensus over the definition of speed reduction in relevant research, including IMO drafts and stakeholders' proposals. He notes that some consider the measure in its basic meaning, ie, slow steaming, portraying the regulation as a voluntary endeavour of lowering ship speed regardless of the method leveraged to reach the % reductions. Alternatively, other research interprets the policy as a mandatory speed limit regulation. Moreover, slow steaming could also be a carrier's choice, lowering fleet speed levels during a depressed market or with soaring bunker fuel prices, or their best response when subjected to market-based environmental policies. Consequently, a better definition of the design of the policy, whether it falls under command-and-control regulation or a more flexible market-based policy, could help policymakers better assess the feasibility and the potential outcomes of such policies and also moves towards better governance.

Cost optimisation provides ocean carriers with a comparative advantage in today's connected global transportation market. Thus, to remain profitable, maintaining cost reductions become essential in strategic business operations. Accounting for at least 30 to 60% of maritime shipping firms' operational costs, bunker fuel consumption and by extension firm profitability hinges on optimizing chosen speed levels (Lashgari, Akbari, & Nasersarraf, 2021).

The economics of slow-steaming research was pioneered by Ronen (1982). Their cost minimisation model illustrated the slow steaming trade-off between fuel consumption and a loss of revenue from longer transits due to reduced voyage speed. Ever since, a growing literature has leveraged this inter-dependency to investigate various research questions, most being geared toward curbing industry emissions, while highlighting the effectiveness of slow steaming in reaching such an endeavour. Throughout this line of research, vessel speed has been investigated in conjunction with other choice variables to examine fleet deployment, fleet size, schedule design, shippers' revenue management, disruption recovery, sulfur emissions control areas (SECAs) and many more. For a comprehensive review, the reader may wish to consult (Psaraftis & Kontovas, 2013) and (Psaraftis, 2019b). Albeit to the best of our knowledge, no research has yet been conducted to investigate the nature of industry-level cooperation amongst ship companies on speed reduction in order to reach an industry abatement target.

2.3 Container-ship Market Structure

The containership industry's substantial fuel consumption and leading contributions to ocean shipping's GHG emissions ignite all sorts of pollution policy discussions to curb the sector's future emissions. The latter have not only been characterized by the fastest growth rate in the shipping industry (UNCTAD (2011)) but also were responsible for 20% of ocean shipping's pollution (Figure 2.1), despite only accounting for 4% of world feet in 2007 (Psaraftis & Kontovas, 2009).

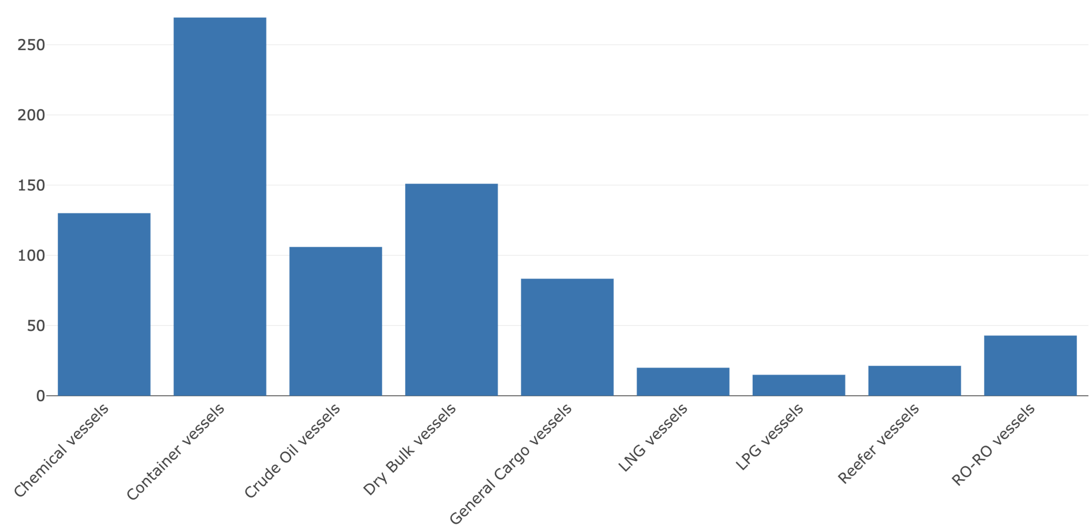

Figure 2.1: CO_2 emissions per vessel category (million tonnes), world fleet, 2007, *Adapted from (Psaraftis & Kontovas, 2009)*

Much of the international container ship market has long been governed by small numbers of firms or oligopolies. In earlier years, the industry's collusive agreements were consolidated within conferences to later transition toward alliances. To this end, T. Notteboom (2021) demonstrates the high level of market concentration in the container shipping industry and reports that 89.7% of 2019's market capacity is held by its top 20 carriers. A capital stock that has evolved from 83% in 2009, 56% in 1990 and merely 26% in 1980, such that, 79% of the depicted 89.7% is managed by the industry's top 4 firms. This figure also grew from 60% in 2015 and 42% in 1995. Besides the concentration trend in market capacity, the current market landscape is governed by 3 strategic operational coalitions that were formed in 2017 known as '2M', 'Ocean Alliance' and 'The Alliance'. Table 2.1 reports their market shares and their operating fleet capacities (in TEU) along with notable signatories.

Table 2.1: The Container-ship Market Shipping Alliances

Coalition	Signatories	Market share	Slot capacities (in TEU)
2M	(MSC , Maersk Line ,Hamburg Sud)	29%	44, 501, 890
Ocean Alliance	(CMA CGM Group, COSCO group , Evergreen)	29%	6, 732, 725
The Alliance	(ONE, Yang Ming, Hapag-Lloyd , HMM)	17%	4, 364, 658

Adapted from (T. Notteboom, 2021) and (Placek, 2021)

Notwithstanding their different signatories, the coalitions operate equivalently. They establish joint operational centres throughout the world to ensure efficient coordination and operational productivity. However, their cooperation extends beyond consolidating slot capacities, such as signatories jointly collaborating on problem-solving, vessel and resource allocation, scheduling, capacity and stowage planning. Note that together, these partnerships dominate the global container market through a 75% joint market share. In most cases, an alliance provides its members with increased market shares and profit margins, cost savings, more control over freight rates, diversified trade lanes, and an overall enhanced global service coverage through the exploitation of economies of scale and scope. The inherent high fixed costs of maritime shipping buttress the formation of these alliances, as they allow signatories to scale up production, explore new markets, and mitigate the risk of investing in giant container ships. A weekly service is contracted to satisfy demand and would sail regardless of their utilisation rate (Florian, 2021). In today's market, 1 in every 3 vessels is being (back)hauled empty (Transmetrics, 2019). Accordingly, Boston Consulting Group (BCG) estimates a $20 billion yearly industry cost, induced by a total of 60 million empty containers being shipped around annually, thereby reinforcing the need for more efficient fleet allocations and vessel sharing agreements (VSA) among the signatories to increase utilisation rates and pool the risk of hauling semi-empty vessels. The VSA depicted that within the firms' mergers and acquisition activities are agreements reached within the coalition to jointly operate specific trade lanes. For example, the 2014 partnership between Maersk and MSC included a 10-year vessel sharing agreement (VSA), incorporating 185 vessels with an overall shared capacity of $2.1 MTEU$. The more pooled vessels and trade lanes a signatory contribute to the coalition, the higher their returns. When ratifying the 2M partnership, Maersk supplied 59% of total capacity and in turn, estimated that they obtained about $\$350 million$ in cost savings from the alliance (Florian, 2021) .

These maritime business partnerships also publicly negotiate fuel type regulations and environmental factors. However, little action to date has been set in place to address environmental pressures from the downstream supply chain, unlike the coalition of giant retailers, including Amazon, Ikea, Unilever, Michelin and Patagonia that are pledging to only use zero-emission shipping by 2040. Different stakeholder forces are actively engaged in the regulatory landscape of the market . On one hand, we have the maritime industry's downstream signatories encouraging governments to implement regulations and market-based instruments to decarbonize the industry (Shaban, 2021) , and on the other hand, we have the Marshall and the Solomon Island governments; two islands that retain some of the world's largest shipping fleets, proposing a $100 per ton carbon tax (Press, 2021). Other forces calling for market-based mechanisms to establish a $5-billion US fund towards implementing a zero-carbon-emission ship include the Clean Shipping Coalition (CSC) initiative is a non-profit non-governmental organisation that represents more than 90% of the global shipping fleet (Sean, 2019) .

Consequently, owing to the current lobbying for different proposals and the ongoing debates over environmental regulations from policymakers, NGOs, and retailers, we argue that it's in the 2M, Ocean Alliance and The Alliance's best interests to find a way to self-regulate, potentially by incorporating emission targets into their operational planning. Greener more sustainable alliances could potentially gain a competitive advantage and increase their market share when considering the downstream supply chain pressure. Thus, environmentally-based coalitions should extend beyond cost-cutting and start taking responsibility for their carbon emissions. Signatories could collaborate on abatement endeavours and incorporate a holistic approach to tackle climate change. Given how such norms have evolved to date, most individual businesses tend to ignore the environmental damage caused by their production. So as a market-level externality issue, ocean carriers necessarily supply less than the socially optimum level of pollution abatement level in the absence of environmental regulation. Subsequently, welfare analysis of any green shipping coalition hinges on internalising the environmental costs of their collective pollution.

Corbett et al. (2009) notes that "in a realistic market setting, authorities may mandate speed reduction ", but firms and industry would respond differently to speed limits or carbon quotas. Consequently, an imposed unilateral policy on speed limits won't be as sustainable as a similar policy driven by the coalition itself to account for the heterogeneity of its signatories, their shipping routes and fuel prices. Recognizing this, a self-serving rationale for a slow-steaming industry-level climate coalition should gain momentum, grounded in having market participants coordinate their abatement efforts to identify heterogeneous firm-dependent speed permits as per the coalitions' marginal abatement cost.

The extent of cooperation within the computational game constructed here primarily seeks the sharing of emission budgets to cost-effectively sustain the industry's carbon budget. Firms joining the coalition to leverage an efficient abatement climate strategy per a joint carbon threshold will converge upon a single market price for emissions, such that the coalition's abatement cost is distributed equitably among its signatories because the mechanism allows them to leverage abatement endeavours in ascending order of their marginal costs.

2.4 STAbility Of Climate COalitions Framework (STACO)

This analysis leverages the seminal work of the Environmental Economics, Natural Resources and Operations Research Groups of Wageningen University in The Netherlands. Their research project, referred to as STAbility of CLimate COalitions (STACO), depicts a hybrid integrated assessment model that links climate change to economic growth through a game-theoretic testbed. They relate emission paths to GHG concentrations and atmospheric temperature changes to distinguish business-as-usual emission paths, abatement costs and benefits for twelve heterogeneous (and large) world regions. Aiming to identify efficient climate policies at the regional level, STACO investigates which potential coalitions are stable and which enforcement mechanisms foster abatement incentives. (Bosetti et al., 2009; R. Dellink, 2011; Nagashima, Dellink, Van Ierland, & Weikard, 2009). Over a discrete planning horizon, the model simulates all possible coalition structures and evaluates each nation's net present value based on the trade-off between avoided damages (i.e. abatement benefits) and individual abatement costs. It assesses the internal and external stability of the coalition and then derives a country's incentive to change membership in the coalition. (Babiker et al., 2001; Lessmann et al., 2015; Nagashima, Weikard, de Bruin, & Dellink, 2011). Through time, various researchers have advanced the STACO project to account for more efficient emission reduction pathways as they incorporated more 'sophisticated' modelling issues than those presented in our study. Overall, STACO has been used to investigate membership rules (Finus, Altamirano-Cabrera, & Van Ierland, 2005), multiple coalition formation (Sáiz, Hendrix, & Olieman, 2006), transfer schemes (Altamirano-Cabrera & Finus, 2006; Weikard, Finus, & Altamirano-Cabrera, 2006), and stability likelihood under uncertainty (R. Dellink, Finus, & Olieman, 2008).

In its second version, the static model was re-worked as a Ramsey type growth model by R. B. Dellink et al. (2009) and incorporated specific adaptations to account for this framework (R. Dellink, 2011; R. Dellink, Dekker, & Ketterer, 2013; R. Dellink & Finus, 2012; Nagashima & Dellink, 2008; Weikard & Dellink, 2014; Weikard, Dellink, & Van Ierland, 2010). The 3^{rd} version revised the initial marginal abatement costs calibration and updated population paths, GDP and emissions. The most recent version was later modified by R. Dellink et al. (2015) to cover a more flexible number of regions and planning horizons. As can be inferred, the STACO framework was developed within the landscape of a larger and long-term project. Given the limited scope of this industrial research, we leveraged a simple version of STACO to focus on firm incentives to participate in an industry-level climate coalition.

2.5 Industry Level Climate COalition (ILCC)'s Theoretical Model

Moving ahead, we adapt some elements of the STACO framework to the international container ship market through a different design scheme, building upon the green maritime literature in terms of pollution and abatement strategies. The cooperative game we design and simulate assumes that maritime shipping firms gather to sign an international agreement to cut their carbon emissions per a defined threshold. In the game-theoretic literature, games of coalition formation are modelled as two-stage game membership situations. In our first stage, firms decide on their membership strategy and in our second stage, they choose their optimal abatement strategies. Grounded in cartel and oligopoly theory, smooth function optimization means that only one optimal coalition (agreement) can be formed in this manner. Note that this is not a repeated game among members, but rather a simplified one-shot membership decision based on discounted payoffs, meaning that firms can't continuously revise their strategy. As we shall see, despite these limiting assumptions, the simulation generates very interesting and robust results. In what follows, we present the two stages of our designed pollution game.

2.5.1 Stage 1 Of The Coalition Formation Game: Membership Decision And Announcement

The first stage of the coalition formation game depicts an announcement and participation game. Firms decide on their membership strategy and whether or not to ratify the agreement. Firm i 's membership strategy set is given by $\Sigma_i = \{0, 1\}$, whereas its particular membership decision vector is denoted by σ_i . The announcement is characterised by a binary membership vector C, where the player set $N^{firms} = \{1, ..., n\}$ denotes the number of firms involved in the game.

$$C = [\sigma_1, .., \sigma_n] \tag{2.1}$$

$$\text{Where} \begin{cases} \sigma_i = 1 & \text{if the } i^{th} \text{ firm joins coalition and ratifies agreement} \\ \sigma_i = 0 & \text{if the } i^{th} \text{ firm doesn't join coalition and refuses to sign agreement} \end{cases}$$

Non-signatory firms choose not to ratify the agreement and remain singleton players, whereas, firms announcing that they will join the coalition become signatories and form a unique coalition. Consequently, agents with membership decisions $\sigma_i = 0$ produce the singleton coalition $C^{\{i\}}$, whereas signatories form a non-trivial coalition. Note that a non-trivial coalition includes at least two members since one firm is not a coalition in our sense. Subsequently, coalitions C depicts the non-empty sets contained within the grand coalition $C^{\{N^{firms}\}}$, such that, $C \subseteq C^{\{N^{firms}\}}$. In total, we can investigate $(2^{|N^{firms}|} - |N^{firms}| - 1)$ different coalition structures and we distinguish among them by the following:

- *A Grand Coalition Structure* ($C^{\{N^{firms}\}}$): a coalition of all firms, denoted by $[\sigma_i] = 1 \;\forall i \in N^{firms}$

- *An All-Singletons Coalition Structure* ($C^{\{i\}}$): a coalition where none or just one of the firms signs the agreement, denoted by $[\sigma_i] = 0 \;\forall i \in N^{firms}$

- *Specific Characteristics Coalition Structure* (C): an industrial coalition such that membership decisions vary, denoted by $[\sigma_1, ..., \sigma_n] = [[\sigma_{n'}], [\sigma_{n''}]]$

$$\text{Where} \begin{cases} n' + n'' = n \\ [\sigma_{n'}] = 1 & \forall n' \text{ firms joining the coalition} \\ [\sigma_{n''}] = 0 & \forall n'' \text{ firms not joining the coalition} \end{cases} \tag{2.2}$$

2.5.2 Stage 2 Of The Coalition Formation Game: Abatement Strategy And Emission Caps

The second stage of this simulation framework aims at developing a proof of concept in support of cooperative environmental efforts within the container-shipping market landscape. To do so, we investigate a cooperative game of abatement, such that firms engage in a pollution game with slow steaming as the policy of choice. The chosen economic strategies directly determine carbon emissions and abatement paths throughout the planning horizon.

Throughout this research, t indexes the years in the planning period for which an environmental agreement among the signatories holds. Notwithstanding the uncertainty of future abatement technologies and the speculative nature of market growth projections, this analysis warrants a sufficiently long time horizon to model the accumulation of GHG emissions and climate change damage occurring in the longer run. Consequently, the simulation adopts a discrete planning horizon spanning over 25 years. Coalition members are assumed to ratify their emissions agreement in 2018, which in turn sets their abatement paths until 2042, following future benefits and costs.

Note that even though other abatement strategies exist for vessel owners in order to comply with IMO emission targets, this analysis investigates slow steaming (speed change) as the primary policy to reduce emissions. What this thesis address is the issue of potential abatement associated with smaller industry-level coalitions using a specific abatement strategy. Constant mergers and acquisitions amongst this industry's leading market participants coupled with successful horizontal integration throughout the years ought to promote the creation and sustainability of environmental coalitions.

As our policy of choice, slow steaming allows the coalition to curb its emissions under a market-wide carbon budget. Derived from the industry's business-as-usual projected emission growth, our simulated targets allow the computation of several hypothetical use cases, spanning from lenient to stringent regulatory frameworks. In other words, the second stage of the environmental game solves every firm's climate strategy under a carbon budget assuming a 1% emission reduction (concerning BAU levels) to the maximum possible abatement levels through slow steaming Q^{max}.

To date, environmental policymakers have often preferred emission schemes over carbon taxes. Hence, our modeling rationale for considering a unilateral industry emission cap. After all, the overarching objective of environmental policies is to halt climate change, and not to generate revenue or incite consumer pass-through. Subsequently, a carbon budget is the most direct instrument for achieving emission reductions. It offers more certainty against attaining the targeted levels, over the indirect effect of imposing a tax, since a simple levy will potentially leave emissions coming up short of set goals (Gerlagh, Heijmans, & Rosendahl, 2021).

Deriving the optimal abatement strategy vector from a partnership standpoint enables us to distinguish between the winners and losers for particular abatement schemes. The solution will also allow us to distribute abatement responsibilities among heterogeneous firms to achieve emissions targets at the least cost (Bloch, 1997; Chander & Tulkens, 2006). Consequently, a simulated cooperative game theory framework becomes appropriate given our assumptions to analyse coalitional abatement endeavours.

2.5.3 Environmental Governance And The Stability Of Industry-Level Climate Coalitions

This research investigates the potential for the success of self-enforcing environmental coalitions applied to the container shipping industry. We assume that coalition membership decisions are taken within the first stage of the game, followed by the players' optimal abatement strategies. However, the equilibrium concept extends beyond simply deriving vessel speeds and optimal fleet size for all possible coalition structures. We also leverage d'Aspremont et al. (1983)'s concept of cartel stability under open membership to investigate the number and size of stable coalitions that might emerge under the conditions of the maritime (container) shipping industry.

As a game construct, coalition formation is often distinguished by the characteristics of its members. Restricted access (i.e. exclusive) games require consent from the coalition prior to changing membership decisions, whereas open access games allow membership decisions to freely change without any restriction from the existing coalition's members. Our specific membership model assumes that abatement strategies and membership decisions are adopted simultaneously and that only a single member deviation from the coalition is investigated. So in the simulations, when a shipping firm flips its strategy and leaves the coalition to become a singleton, a smaller coalition survives among the remaining signatories. Considering that the latter is done for tractability, our scope mainly investigates coalition stability under free access agreement strategies (Finus & Rundshagen, 2009).

Subsequently, following cartel formations that can occur in a static oligopolistic, Cournot-Nash framework, a coalition structure C is only considered stable if it's both internally and externally stable. Formally, internal stability implies that no signatories $i \in C$ have an incentive to leave the coalition. External stability assumes that non-coalition members $j \notin C$, receive lower payoffs by switching their membership, and therefore, lack an incentive to join the extant coalition.

$$\begin{cases} \text{Internal Stability: } \Pi_i(C_{-i}) \leq \Pi_i(C) \;\; \forall i \in C \\ \text{External Stability: } \Pi_j(C_{+i}) \leq \Pi_j(C) \;\; \forall j \notin C \end{cases} \tag{2.3}$$

Furthermore, we leverage the standard individual rationality assumption, computing each member's incentive to change coalition membership (*ITCM*). *ITCM* is affected by the payoff function. It quantifies gains, and therefore the incentives for switching membership, holding all else constant. When leaving the coalition, signatories with positive values receive higher payoffs and coalition members with a negative *ITCM* would be giving up their gains. Similarly, singletons with positive *ITCM* would benefit from joining the coalition (d'Aspremont et al., 1983; Finus et al., 2005; Lessmann et al., 2015).

$$ITCM_i(C) = \Pi_i\Big(C_{-i} \vee C_{+i}\Big) - \Pi_i\Big(C\Big) \tag{2.4}$$

3

Industry Level Climate Coalition's Model Development

3.1 Introduction

The purpose of the following chapter is to detail the Industry Level Climate Coalitions simulation model. We specify the governing functions, assumptions as well as parameters needed to investigate joint slow-steaming abatement efforts under a uniform carbon quota regulation. Our research primarily targets container ships because of their substantial fuel consumption and leading contributions to emissions. The latter type of ship has not only been characterized by the fastest growth rate in the shipping industry (UNCTAD, 2011) but also was responsible for 20% of ocean shipping pollution despite only accounting for 4% of world fleet in 2007 (Psaraftis & Kontovas, 2009).

To project business-as-usual emission growth in the simulation, we first scale market demand for the chosen planning horizon. Then, we set up the market structure and derive firm-level demand. We address the slow-steaming trade-off and introduce firm-level supply (cost) functions and discounted net profits under BAU profit-seeking behaviour in the absence of regulation. Ultimately, we compute the emission paths, which in turn, allows us to delineate a Grand Coalition as well as An All Singleton model under uniform emission caps regulations. Average abatement cost curves and the cost of slow steaming are also represented in order to explore the potential of speed regulation as a joint abatement policy.

3.2 Industry Level Climate Coalition's Business As usual Projections & Governing Assumptions

Our cooperative game of environmental governance assumes a marketplace of N^{firms} heterogeneous firms, each with their own (parametrized) benefit and cost structure on slow steaming as an abatement strategy. We follow the industrial shipping framework of Fagerholt et al. (2010) and Psaraftis and Kontovas (2010) and develop a basic speed optimisation and fleet decomposition model for a typical shipping market that captures the primary characteristics of the container-ship sector.

Our base model assumes that firms transport containers over the ocean between a supply node A to a demand node B, based on fixed schedules and shipping routes. Liner service means that shipping companies operate according to a fixed port rotation, with calls and schedules. Due to this, maritime shipping firms can leverage contract commitments with their shippers to optimally plan their fleet structure. These agreements can cover up to 1 year of shipments and usually stipulate cargo volumes over the specified period so that shippers can leverage deterministic freight rates. Indeed, these types of long-term contracts operate on 98% of the major US and EU shipping trade routes (Marlow & Nair, 2008). Thus, assuming we focus on a fixed route, every shipping company offers annual freight transportation services based on its market share.

The optimization model generates a non-linear mixed-integer objective function that captures the trade-off between vessel speed and fleet size. Considering that firms' optimal fleet structure per period is a discrete and discontinuous function of their sailing speed (V_i), our objective function is not a continuous function of V_i so that traditional tools like convex optimization cannot be used to solve the ocean shippers' environmental optimisation problem, rather we resort to a meta heuristic search methodology to solve our shippers' problem. Carbon and sulfur emissions are estimated through fuel consumption. This means when a ship reduces its operating speed, fuel consumption/cost decreases dramatically along with emissions. However, this "slow steaming" strategy prolongs total voyage times per round trip and therefore is associated with two significant side effects: (i) longer transit times, which implies fewer goods transported per unit time, additionally requiring additional vessels to maintain contracted annual throughput or service frequency; and (ii) an increase in non-fuel vessel operating costs such as crew, insurance, repair and maintenance, stores and lubrication (Brahimi et al., 2021). BAU emissions for the system are endogenously determined for each period by maximising the net present value of the annual payoff stream. Further, we assume that each shipping company has perfect foresight, and consequently optimises its BAU operational speed V^{BAU} and fleet size N^{BAU} in each period.

Consistent with the literature on slow steaming (Doudnikoff & Lacoste, 2014; Psaraftis & Kontovas, 2010; Ronen, 2011), we also incorporate the following assumptions, governing our carriers' optimisation problem:

A1: Fleet structure :

The simulation model assumes an identical fleet of container ships per firm. However, firm-level structure and vessel characteristics may differ from one shipping company to another. But for our purposes, A1 seems to be a sensible industry assumption for analysing inter-continental shipping markets (Doudnikoff & Lacoste, 2014; Psaraftis & Kontovas, 2010; Ronen, 2011). We assume all shipload cargo is transported using twenty-foot-equivalent (TEU) containers, without a constraint over the number of vessels per firm deployed in the service.

We find ourselves with an un-capacitated optimisation problem, under the assumption that all firms fulfil their annual freight demand. In other words, we assume that there will always be available additional vessels to serve the route when needed. As to the realism of this assumption, recently, container shipping has been characterized by overcapacity, especially after the 2008 economic-financial crisis (Giovannini & Psaraftis, 2019). Nevertheless, while we don't constrain the number of vessels per firm, each ship is subject to a maximum carrying capacity of k_i. Furthermore, all vessels in service have similar characteristics, and their chosen sailing speed is assumed constant during the whole trip cycle.

A2: Logistic Context

Our simulation framework assumes a fixed routing of liner service. The sequence of port calls is determined in advance. Each shipload is carried from port A to Port B and back with constant service periods (frequency).

A3: Port Time

Besides sailing time, a vessel's journeys may include loading and unloading procedures during port berthing. To this end, we assume that port operators allocate more cranes and infrastructure for larger ships, which renders the time spent by each vessel at a port constant and independent of its size.

A4: Exogenous Deterministic Market Demand

Following related literature, we leverage the causal relationship between ocean shipping and global economic growth (GDP) in order to forecast market demand (Ø. Buhaug et al., 2009; Corbett et al., 2010; Eyring, Köhler, Van Aardenne, & Lauer, 2005; IMO, 2015; D. S. Lee & CE, 2019; UNCTAD, 2015; Valentine, Benamara, & Hoffmann, 2013). Thus in the simulations, we assume annual deterministic demand for freight shipments that are independent of the number of vessels deployed within the market, the service period or the frequency.

A5: Exogenous Freight Rates

Average freight rates on the shipping route track global supply and demand and are excluded from the carrier's decision set. Moreover, the model stipulates that shipping rates are known for the round-trip and should remain generally constant over the planning horizon (Corbett et al., 2009).

A6: Operational Capacity

Following Ø. Buhaug et al. (2009), we assume every vessel is limited by its operational capacity. Typically, ocean engineering literature assumes that a fleet sails 24 hours a day, but can only spend 270 days at sea per year. Consequently, Equation 3.1 depicts the ship's annual working time.

$$\tau = 270 * 24 = 6480 \ \textit{hours per year}. \tag{3.1}$$

A8: Fuel Consumption Function and Emission Inventory

Following the literature on maritime shipping emissions, we employ a bottom-up approach through the simulation using the vessel and fleet activity. This activity-based approach assumes a cubic function to compute a ship's fuel consumption, and consequently, its total amount of emissions (Psaraftis, 2019a; Psaraftis & Kontovas, 2013)

This mixed-integer nonlinear profit maximization problem, specific to container ships, will help determine the optimal sailing speed as well as the optimal number of deployed vessels by the liner service considering its overall fleet characteristics. In this section, we provide a detailed motivation for the specification of firms' operational equations used in the computational analysis to derive business-as-usual projected emissions paths.

The slow steaming decision is constrained by an upper and a lower threshold on the ship's power plant. The upper threshold is the vessel's maximum speed V_i^{max}, as measured by the main engine's Maximum Continuous Rating (MCR) (MAN Diesel & Turbo, 2009), whereas the lower threshold V_i^{min} ensures safe steering and prevents stalling. Thus, the feasible search space region is defined by Equation 3.2.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{3.2}$$

Fuel consumption is a crucial cost component for ships, and vessel speed reduction leads to energy-saving potential (Corbett et al., 2009). Thus, energy use, vessel speed and freight revenues are coupled within our shipping fleet objective function to evaluate the trade-off of firm cargo revenues $R_{i,t}$, fleet variable main and auxiliary bunker fuel consumption costs $\left(CB_{i,t}^{main}, CB_{i,t}^{aux}\right)$ as well as fixed costs $\left(FC_i \times N_{i,t}\right)$. The shipping companies are assumed to maximize their discounted future stream of revenues π_i, where r is the chosen discount rate and FC_i is the annual non-fuel fixed operating cost per vessel (Equation 3.3).

$$\max_{N_{i,t},V_i} \pi_i = \sum_{t=1}^{T} (1+r)^{-t} \left[R_{i,t} - CB_{i,t}^{main} - CB_{i,t}^{aux} - \left(FC_i \times N_{i,t} \right) \right] \forall i = 1,..,N^{firms} \tag{3.3}$$

To better understand how we developed the BAU objective function, the following details the firm's revenue and cost structure. In particular, we outline the firm level demand, fleet supply, bunker fuel consumption and operating costs .

3.2.1 Shipping Market Transportation Demand

Our research departs from most of the common liner shipping optimization literature because we incorporate a flexible framework for profit maximisation, rather than a cost minimization model. While market demand will remain exogenous across the use case investigated in this thesis, the rationale for profit maximisation rather than cost minimisation is twofold. First, to illustrate a more flexible framework that aligns with the STACO international environmental agreement theory. Likewise, considering that higher output growth induces higher baseline emissions, regardless of the chosen abatement measure, estimating the industry's projected emission path per GDP projections provides the researcher with the flexibility of investigating firms' responses to a shock in market demand (Doukas, Spiliotis, Jafari, Giarola, & Nikas, 2021). Furthermore, such a shock could even be endogenous by modelling damages to GDP from the industry's emissions contribution. Second, modelling the demand side withholds the opportunity to analyse the industry's ability for potential tax pass-through and consumers' substituting away from container ships.

Today, container ships transport goods in standardized shipping containers or total equivalent units (the 20-foot container) or TEUs. These ships are typically faster than bulk carriers and tankers, and their capacities are often quoted in TEUs. While the industry serves many trade routes, major shipping firms like Maersk and MSC typically provide scheduled freight services to transport freight from port to port at a specific rate per delivered TEU within a scheduled time frame (Giovannini, 2017).

This type of scheduled and containerized ocean shipping market has been a powerful driver of modern globalization as it encourages increasingly rapid intercontinental shipments at stable or falling rates. The latter explains the widely-based presumption of a strong historic causal relationship between freight demand and global economic growth (GDP) (Ben-Hakoun, Shechter, & Hayuth, 2016; Ø. Buhaug et al., 2009; Corbett, Firestone, & Wang, 2007; Corbett et al., 2010; Corbett, Winebrake, et al., 2007; Eyring, Corbett, Lee, & Winebrake, 2007; Eyring et al., 2005; IMO, 2015; D. S. Lee & CE, 2019; UNCTAD, 2015; Valentine et al., 2013). Using well-established GDP projection paths over the model's planning horizon, we are able to provide a reasonable estimate of market demand in this industry.

This data linkage has been pursued by other researchers in the field, allowing us to leverage the work proposed by Parry, Heine, Kizzier, and Smith (2018), whereby the latter forecast containership transport using GDP and income elasticity, reflecting a 0.8 per cent rise in market demand per one per cent increase in GDP. They also incorporate a constant -0.7 own price elasticity to account for consumers substituting away from container shipped goods for (non-shipped) commodities. Finally, they hypothesize that future container ship demand will vary positively with GDP (through income elasticity) but negatively with land-based freight rates.

Following the Parry et al. methodology and IMF projections, ocean freight market demand is forecast as follows:

$$\frac{Y_t^{AB}}{Y_0^{AB}} = (\frac{GDP_t}{GDP_0})^v \times (\frac{\rho_t}{\rho_0})^\eta \tag{3.4}$$

$$\Rightarrow Y_t^{AB} = (\frac{GDP_t}{GDP_0})^v \times (\frac{\rho_t}{\rho_0})^\eta \times Y_0^{AB} \tag{3.5}$$

$$\Rightarrow Y_t^{AB} = (\frac{GDP_1}{GDP_0} \times \frac{GDP_2}{GDP_1} \times \ldots \times \frac{GDP_{t-1}}{GDP_{t-2}} \times \frac{GDP_t}{GDP_{t-1}})^v \times (\frac{\rho_t}{\rho_0})^\eta \times Y_0^{AB} \tag{3.6}$$

$$\Rightarrow \begin{cases} Y_t^{AB} = (\prod_{k=1}^{t} \left(1 + g_k\right))^{v} \times (\frac{\rho_t}{\rho_0})^{\eta} \times Y_0^{AB} \\ \frac{GDP_k}{GDP_{k-1}} = 1 + g_k \end{cases} \tag{3.7}$$

such that :

- Y_t^{AB} : The simulation framework's market demand at time t in *TEU* to be transported from port A to port B
- GDP_t: Real global gross domestic product at period t
- g_k : Real GDP growth in period k
- $v = 0.8\%$: Income elasticity for container products, showing the percentage increase in container shipping demand following a 1% rise in GDP. The simulation's market demand increases with GDP according to v. This parameter is assumed to remain constant over the planning horizon.
- $\eta = -0.7\%$: Own-price elasticity of demand delineates the per cent change in market demand per 1% increase in freight rate at time t. Again, this parameter is assumed constant over the planning horizon.
- ρ_0,ρ_t: Average freight rate at base year (2018) and period t (respectively) to transport one *TEU* from port A to port B, expressed in [US$/TEU].

3.2.2 Market Structure And Firm Level Demand

Our simulation is populated with N^{firms} heterogeneous firms, while each firm's level of transportation service $X_{i,t}^{A,B}$ between port A and port B depends on their extant market share s_i and the industry's demand at period t $Y_t^{A,B}$. Market share is assumed to be an exogenous parameter and ought to reflect the size of the firm in the simulation framework. Consequently,

$$X_{i,t}^{A,B} = s_i Y_t^{A,B} \tag{3.8}$$

3.2.3 Firm Level Supply

A firm's supply is subject to operational assumptions and constraints. As previously depicted by the operational capacity A6, we assume each vessel can only be deployed for

$$\tau = 270 \times 24 = 6480 \ \textit{hours per year} \tag{3.9}$$

Moreover, the average total sailing time in hours for a ship is computed as follows:

$$t_{sea_{i,t}} = \frac{d}{V_{i,t}} \tag{3.10}$$

where $V_{i,t}$ is the ship's operational sailing speed in nautical miles *nm* per hour and d, is the distance of the voyage in nautical miles. Assuming t_{port} is the average port time during the trip, a ship will spend in total $time_{i,t}$ hours on a round-trip during its allocated cycle time.

$$time_{i,t} = t_{sea_{i,t}} + t_{port} \tag{3.11}$$

Subsequently, the number of trips that **can** be performed by one vessel in a year is given by :

$$n_{i,t}^{trip} = \frac{\tau}{time_{i,t}} = \frac{270 \times 24}{time_{i,t}} \tag{3.12}$$

Given that all carriers are contracted to satisfy annual demand $X^{AB}_{i,t}$, the total number of **required** trips per carrier $N^{trip}_{i,t}$ becomes:

$$N^{trip}_{i,t} = \lfloor \frac{X^{AB}_{i,t}}{k_i} \rfloor \tag{3.13}$$

such that k_i is the firm's fleet vessel's capacity. The minimum number of vessels to be deployed by the firm in period t is is therefore the following:

$$N^{vessel}_{min_{i,t}} = \lceil \frac{N^{trip}_{i,t}}{n^{trip}_{i,t}} \rceil \tag{3.14}$$

The number of vessels deployed in period t must be a positive integer and be at least equal to the minimally required fleet size $N^{vessel}_{min_{i,t}}$. This supply constraint is given by:

$$\begin{cases} N_{i,t} \in Z^{+} \\ N_{i,t} \geq N^{vessel}_{min_{i,t}} \end{cases} \tag{3.15}$$

3.2.4 Firm Cost Structure

Considering a fleet's main engines $CB^{main}_{i,t}$, auxiliary engines $CB^{aux}_{i,t}$ and non-fuel operating costs $FC_i \times N_{i,t}$, the firm's total incurred cost $CT_{i,t}$ is the sum of their fuel and non-fuel costs:

$$CT_{i,t} = CB^{main}_{i,t} + CB^{aux}_{i,t} + FC_i \times N_{i,t} \tag{3.16}$$

The extant literature discusses two main approaches for evaluating fuel operating costs, either through acquiring vessel consumption data (top-down) or through ship sailing activity (bottom-up) (Nunes, Alvim-Ferraz, Martins, & Sousa, 2017). Our research follows the latter and considers the sailing time along with the engine's energy efficiency as well as load factors. We estimate operating costs per number of trips carried throughout the year, such that the per-trip consumption, shared among the main and auxiliary engines is evaluated using vessel specifications and the combustion temperature of the chosen bunker fuel. The following details the firms main engine and auxiliary engines' bunker fuel consumption, as well as the fleet's operating costs structures.

Main Engine Fuel Consumption Operating Costs $\left(CB_{i,t}^{main}\right)$

In the maritime sector, there exists a non-linear relationship between a vessel's speed and fuel consumption. Often, the hourly-at-sea per-trip consumption for the main engine follows a cubic law of design to set operational speed. The third-power relationship depicting the vessel's daily fuel consumption elasticity to speed is a good approximation for mean speed values ranging from $10kt$ to $25kt$. According to Ronen (1982), lowering a vessel's speed by 20% would reduce its daily fuel consumption by 50% (Brahimi et al., 2021; Corbett et al., 2009; Fagerholt*, 2004; Ronen, 2011; Wang & Meng, 2012).

Fuel operating costs are driven by the vessel's power, load factors EL, the period during which the engine is running and the engine's brake Specific Fuel Consumption rates $SFOC$ (g/kwh). Lower values of $SFOC$ are preferred since they show the engine's internal combustion fuel efficiency. This metric delineates the fuel consumption ratio in $gram/seconds$, combined with its braking power kW (Tadros, Ventura, & Guedes Soares, 2020). Thus, leveraging various engineering technical formulas and parameters as presented by Corbett et al. (2009) and Doudnikoff and Lacoste (2014), we derive the following equations for main engine hourly fuel consumption:

$$F_M(t/hour) = SFOC_0^M(g/kWh) \times EL^M(\%) \times PS^M(KW) \times 10^{-6} \tag{3.17}$$

such that

- $SFOC^M$: main engine specific fuel oil consumption [g/kWh]
- EL^M : engine load during sailing [%]
- PS^M main engine power output [kW]

Mindful of the cubic law of design and operational speed, hourly-at-sea main engine per-trip fuel consumption can be derived as follows:

$$F = F_M \times (\frac{1}{V_i^s})^3 \times V_i^3 = \varphi_i \times V_i^3 \tag{3.18}$$

Using the vessel's specifications and the design speed V_i^s, we define the ship's energy efficiency φ_i as follows:

$$\varphi_i = F_M \times (\frac{1}{V_i^s})^3 \tag{3.19}$$

Subsequently, the total one trip fuel consumption for the main engine ,when incorporating the ship's energy efficiency φ_i corresponds to the per-trip, per-hour fuel consumption (F) multiplied by the trip's sailing time in hours at-sea :

$$F_{i,t}^{main,trip} = F \times t_{sea_{i,t}} = \varphi_i \times (V_i)^3 \times t_{sea_{i,t}} \tag{3.20}$$

We translate per trip fuel consumption into annual consumption ($F_{i,t}^{main}$) by multiplying the engine's per trip consumption with the firms' number of required trips to meet its scheduled demand $N_{i,t}^{trip}$ in year t.

$$F_{i,t}^{main} = N_{i,t}^{trip} \times F_{i,t}^{main,trip} \tag{3.21}$$

Finally, The fleet's main engine bunker fuel consumption costs CB^{main} depends the firm's choice of fuel and corresponding bunker price (η_t^{fuel})

$$CB_{i,t}^{main} = F_{i,t}^{main} \times \eta_t^{fuel} \tag{3.22}$$

Auxiliary Engine Fuel Consumption Operating Costs $CB_{i,t}^{aux}$

Auxiliary ship engines burn marine gas oil (MGO) to supply the vessel with onboard electricity. Unlike the main engine, the auxiliary engine doesn't follow the cubic law of design and operational speed. Instead, its bunker fuel consumption mainly depends on the engine's specification and time spent at sea. Subsequently, the hourly auxiliary engine fuel consumption for the cycle is only composed of a fixed component equal to (Cariou & Cheaitou, 2012)

$$F_A(ton/hour) = SFOC^A \times EL^A \times PS^A \times 10^{-6}$$

such that:

- $SFOC^A$: auxiliary engine specific fuel oil consumption g/kWh
- EL^A: the engine load of the auxiliary engine (%)
- PS^A: the power output of the auxiliary engine (kW).

The per-trip fuel consumption for the auxiliary engine corresponds to its hourly auxiliary engine fuel consumption multiplied by the trip's sailing time in hours at-sea $(t_{sea_{i,t}})$:

$$F_{i,t}^{Aux,trip} = F_A \times t_{sea_{i,t}} \tag{3.23}$$

To translate the per-trip fuel consumption into annual consumption, once again we multiply the per trip fuel consumption for the auxiliary engine by the number of required trips to meet the scheduled demand $N_{i,t}^{trip}$, Therefore, annual bunker consumption $F_{i,t}^{aux}$ and fuel operating costs $CB_{i,t}^{aux}$ for the auxiliary engine are:

$$F_{i,t}^{aux} = N_{i,t}^{trip} \times F_{i,t}^{Aux,trip} \tag{3.24}$$

$$\Rightarrow CB_{i,t}^{aux} = \eta_t^{MGO} \times F_{i,t}^{aux} \tag{3.25}$$

Vessel fixed operating costs

Non-fuel operating costs are computed per the number of vessels used in service to satisfy annual freight demand. FC_i are the fixed costs associated with operating a vessel, including maintenance and repair, crew, insurance, management, and (possibly) capital expenses (Ronen, 2011).

$$FC_i \times N_{i,t} \tag{3.26}$$

3.3 Industry Level Climate Coalition's Emission Path Projections

Having presented our ocean shipping carriers' profit maximisation problem, we move on to computing firms' projected BAU emissions growth. Using an emission factor, we assume estimates for carbon and sulfur emissions are proportional to fuel consumption. As previously mentioned, there are two approaches to evaluating fuel consumption and as such there are two methodologies for quantifying greenhouse gas emissions.

On one hand, a data-driven top-down approach can be used, leveraging fuel sales data and an emission multiplier to derive emissions per quantity of fuel sold. However, since the main and auxiliary ship engines consume different types of fuel, the data collection process is very tricky and may lead to reliability issues in the simulation. Likewise, such derived estimates often differ from the bottom-up approach that is usually associated with simulation analysis (Psaraftis, Kontovas, & Kakalis, 2009).

Thus, our research uses bottom-up methodology and leverages fleet activity in terms of voyage time, engine specifications, vessel speed, ship capacity and energy efficiency. To generate emission estimates, we need to multiply our activity data by a factor dictated by the type of consumed fuel, along with the relevant pollutant (H. Buhaug, 2010; Kontovas, 2014; Psaraftis & Kontovas, 2009).

Consequently, our framework estimates greenhouse gas inventories through projections of firm-level fleet activity within the ocean carrier's transportation routing based on market shares and projected economic growth throughout the planning horizon. Since the CO_2 and SO_x emitted by the main and the auxiliary engine are obtained by multiplying average fuel expenditure with the fuels' carbon and sulfur ratios, the latter emission factors are regularly adopted in maritime research H. Buhaug (2010); Kontovas (2014); Psaraftis and Kontovas (2009).

Exploring sulfur emissions alongside carbon within the simulation framework allows us to investigate the impact of market-wide carbon quotas on firms' sulfur abatement from slow steaming. To this end, relevant research estimates that 97.753% of the sulphur present in bunker fuel gets converted to sulfur oxide, whereas the remaining 2.247% sulphate aerosol becomes particulate matter. Moreover, some studies report that 98% of SO_x 's emission inventory stems from sulfur dioxide SO_2. Thus, owing to its 0.02 molecular weight in sulphur oxide and the sulfur content S present in bunker fuel, we use the following equation to derive the sulfur dioxide fuel-based emission factor, (Kontovas, 2014) :

$$\varepsilon^{SO_x} = 0.02 \times 0.97753 \times S \tag{3.27}$$

In short, Table 3.1 summarises each critical pollutant's emission factor per available bunker fuel choices. The current and common fuel alternatives on the market range from heavy fuel oil (HFO) with a 3.5 % sulfur content, ULSFO (Ultra Low Sulfur Fuel Oil) with a 0.5 % sulfur content or Marine Gas Oil (MGO) with a sulfur content of 0.1 %.

Table 3.1: Emission Factors For Different Bunker Fuels

	Emission Factors	
Fuel Type	CO_2	SO_x
HFO (3.5%)	3.1144 (tonnes/tonnes of Fuel)	0.07 (tonnes/tonnes of Fuel)
ULSFO (0.5%)	3.206 (tonnes/tonnes of Fuel)	0.01 (tonnes/tonnes of Fuel)
MGO (0.1%)	3.206 (tonnes/tonnes of Fuel)	0.002 (tonnes/tonnes of Fuel)

Adapted from: (Kontovas, 2014) and (IMO, 2015)

Consequently, our projected Business As Usual (BAU) emission paths $\overline{e_{i,t}^{GHG}}$ in tonnes of each pollutant CO_2 and SOx are given by multiplying firms' main and auxiliary bunker fuel consumption with the corresponding fuel's emission factor. Recall that the auxiliary engine only burns marine gas oil, while the main engine might choose any of the other alternative presented in Table 3.1 .

$$\begin{aligned}&\forall\, \text{GHG} \in \{CO_2, SO_x\}:\\&\overline{e_{i,t}^{GHG}}[tonnes_{(GHG)}] = \varepsilon_{fuel}^{GHG} \times F_{i,t}^{main} + \varepsilon_{MGO}^{GHG} \times F_{i,t}^{aux}\end{aligned} \tag{3.28}$$

where ε_{fuel}^{GHG} and ε_{MGO}^{GHG} depict the corresponding GHG emission factor estimate for the carriers choice of fuel for the main and auxiliary engines respectively.

3.4 Industry Level Climate Coalition's Climate Strategies & Emission Caps

Under the laissez-faire business-as-usual scenario and in the absence of any emission regulation, shipping firms ignore emission damages induced by their economic activity. Regarding internalizing the environmental costs of pollution, Benchekroun and Chaudhuri (2011) notes that businesses' projected carbon emission paths $\overline{e_{i,t}^{CO_2}}$ accumulate throughout a planning horizon to form their firm-level pollution stock $\overline{S_{i,t}^{CO_2}}$ following a stock and flow system given by:

$$\begin{cases}\overline{S_{i,t=1}^{CO_2,2018}} = 0 \;\; \forall i\\ \overline{S_{i,t+1}^{CO_2}} = \overline{e_{i,t}^{CO_2}} + (1-\delta) \times \overline{S_{i,t}^{CO_2}} \;\; \forall i\end{cases} \tag{3.29}$$

where firms' BAU initial stock of pollution $\overline{S_{i,t=1}^{CO_2,2018}}$ at the base year 2018 is assumed 0. The stock's natural rate of decay, δ is also set to 0 in our simulation for ease of exposition. Consequently, BAU firm-level accumulated pollution stock by the end of simulation period $\overline{S_{i,26}^{CO_2,2043}}$ would correspond to the sum of their baseline carbon emissions $\sum_{t=1}^{T=25} \overline{e_{i,t}^{CO_2}}$

To curb the industry's emission inventory growth, this ILCC (Industry Level Climate

Coalitions) simulation model requires a market-wide carbon budget constraint or quota. Derived from the projected market's BAU pollution stock in 2043, $\overline{S_{i,26}^{CO_2,2043}}$, we establish simulated targets depicting several hypothetical use cases spanning from lenient to more stringent uniform regulatory polices. In other words, the second stage of the environmental game solves every market participant's climate strategy under a carbon budget varying from a $Q = 1\%$ emission reduction (relative to BAU levels) to the maximum possible abatement levels Q^{max}, accomplished through slow steaming.

3.4.1 All-Singletons $C^{\{i\}}$ Market Structure

Regarding the coalition structure C, each firm outside of the partnership $i \notin C$ is assumed to individually plan its own climate strategy q_i, in effect, optimising its own average speed level V_i^* and fleet size $N_{i,t}^*$ under its own inventory budget constraint, by the end of the planning horizon $\beta_{i,Q}^{2043}$.

$$\beta_{i,Q}^{2043} = (1 - \frac{Q}{100}) \times \overline{S_{i,2043}^{CO_2}} \;\forall\, Q = 1\%, 2\%, 3\%, .., Q^{max} \;\forall i \tag{3.30}$$

This simulation design allows us to investigate the inter-temporal optimization problem of internalising environmental damages in conjunction with the ocean shipper's profit maximization problem. In doing so, we leverage the BAU results and solve for each firm's climate strategy following their singleton membership decision $C^{\{i\}}$.

The simulation framework for the singletons market can be summarised by the following set of equations.

$\forall$ abatement strategy $Q = 1\%, 2\%, 3\%, .., Q^{max}$, we solve for each singleton $j' \notin C$ s climate strategy per the following;

$$\begin{aligned}\max_{N_{j',t},V_{j'}} \pi^{j'} = \sum_{t=1}^{T=25} (1+r)^{-t} \Bigg[& \rho_t \ X^{AB}_{j',t} \\ & - \left(\eta_t^{fuel} \ \lceil \frac{X^{AB}_{j',t}}{k_{j'}} \rceil \ d \ \varphi_{j'} \ (V_{j'})^2 \right) \\ & - \left(\eta_t^{MGO} \ \lceil \frac{X^{AB}_{j',t}}{k_{j'}} \rceil \ d \ F_A \ \frac{1}{V_{j'}} \right) \\ & - \left(FC_{j'} \ N_{j',t} \right) \Bigg] \end{aligned} \tag{3.31}$$

such that:

Firm Level Demand :

$$X^{A,B}_{j',t} = s_{j'} Y^{A,B}_t = s_{j'} \times (\frac{GDP_t}{GDP_0})^{v} \times (\frac{\rho_t}{\rho_0})^{\eta} \times Y^{AB}_0 \tag{3.32}$$

Firm Level Supply and Operational Constraint :

$$\begin{cases} V_j'^{min} \leq V_{j'} \leq V_j'^{max} \\ N_{j',t} \in Z^{+} \\ N_{j',t} \geq N^{vessel}_{min_{j',t}} = \frac{X^{AB}_{j',t} \times \left(\frac{d}{V_{j'}} + t_{port} \right)}{k'_j \times \tau} \end{cases} \tag{3.33}$$

Firm level, emissions, pollution stock and carbon budget constraint

$$\begin{cases} e_{j',t}^{CO_2} = \frac{X_{j',t}^{AB}}{K_{j'}} \times d\left(\varepsilon_{fuel}^{CO_2} \times \varphi_{j'} \times (V_{j',t})^2 + \varepsilon_{MGO}^{CO_2} \times \frac{F_A}{V_{j',t}}\right) \\ S_{j',26}^{CO_2,2043} = \sum_{t=1}^{T=25} e_{j',t}^{CO_2} \\ S_{j',26}^{CO_2,2043} < \beta_{j',Q}^{2043} \end{cases} \tag{3.34}$$

Firm level Abatement

$$q_{j'} = \overline{S_{j',26}^{CO_2,2043}} - S_{j',26}^{CO_2,2043} \tag{3.35}$$

3.4.2 Coalitions (C) Market Structure

Firms that form a slow-steaming coalition abate cooperatively under a shared allocated carbon quota β_Q^{2043} supporting the simulation framework chosen decarbonisation plan Q, such that β_Q^{2043} is the sum of the signatories j firm-level emission inventory budget;

$$\beta_{C,Q}^{2043} = \sum_{j \in C} \beta_{j,Q}^{2043} \, \forall j \in C \tag{3.36}$$

Thus, signatories j choose the speed and abatement levels that maximize their aggregate net present value subject to the emission constraint. In doing so, coalition members aim to reach a joint carbon budget/quota by reducing their business-as-usual emissions in the following manner;

$\forall$ abatement strategy $Q = 1\%, 2\%, 3\%, .., Q^{max}$, we solve for the signatories $j = \{1, .., n'\} \in$

C's climate strategy:

$$\max_{N_{j,t},V_j} \Pi^C = \sum_{t=1}^{T} \sum_{j=1}^{n'} (1+r)^{-t} \Bigg[\rho_t \; X_{j,t}^{AB} \\ - \left(\eta_t^{fuel} \; \lceil \frac{X_{j,t}^{AB}}{k_j} \rceil \; d \; \varphi_j \; (V_j)^2 \right) \\ - \left(\eta_t^{MGO} \; \lceil \frac{X_{j,t}^{AB}}{k_j} \rceil \; d \; F_A \; \frac{1}{V_j} \right) \\ - \left(FC_j \; N_{j,t} \right) \Bigg] \tag{3.37}$$

such that :

Coalition Demand:

$$X_{C,t}^{A,B} = \sum_{j=1}^{n'} X_{j,t}^{A,B} = \sum_{j=1}^{n'} s_j Y_t^{A,B} = \sum_{j=1}^{n'} s_j \times (\frac{GDP_t}{GDP_0})^v \times (\frac{\rho_t}{\rho_0})^\eta \times Y_0^{AB} \;\; \forall j \in C \tag{3.38}$$

Coalition Supply Operational Constraint :

$$\begin{cases} V_j^{min} \leq V_j \leq V_j^{max} \\ N_{j,t} \in Z^+ \\ N_{j,t} \geq N_{min_{j,t}}^{vessel} = \frac{X_{j,t}^{AB} \times \left(\frac{d}{V_j} + t_{port} \right)}{k_j \times \tau} \end{cases} \tag{3.39}$$

Coalition emissions, pollution stock and carbon quota/budget constraint

$$\begin{cases} E_t^{CO_2,C} = \sum_{j=1}^{n'} e_{j,t}^{CO_2} = \sum_{j=1}^{n'} \frac{X_{j',t}^{AB}}{K_j} \times d\left(\varepsilon_{fuel}^{CO_2} \times \varphi_j \times (V_{j,t})^2 + \varepsilon_{MGO}^{CO_2} \times \frac{F_A}{V_{j,t}}\right) \\ S_{C,26}^{CO_2,2043} = \sum_{t=1}^{T=25} E_t^{CO_2,C} \\ S_{C,26}^{CO_2,2043} < \beta_{C,Q}^{2043} \end{cases} \tag{3.40}$$

Coalition joint abatement level

$$q_C = \sum_{j=1}^{n'} \overline{S_{j,26}^{CO_2,2043}} - S_{C,26}^{CO_2,2043} \tag{3.41}$$

Future related research could also incorporate vessel-sharing agreements, resource allocation and/or logistics pooling to enable the coalition to reach its carbon quota, assessing the potential of joint slow-steaming abatement actions.

3.5 Average Abatement Cost Curves

Average abatement cost depicts the net costs associated with each unit (tonne) of carbon reduction. For maritime shipping, it also reflects slow steaming's maximum abatement potential as a policy within climate coalitions. Given the complexity of this game theoretic problem, we limit the analysis to the evaluation of market outcomes for the all-singleton and the grand coalition structures, out of the $(2^{|N^{firms}|} - |N^{firms}| - 1)$ possible coalition structures. We offer that these cases are more than sufficient in illustrating the benefits of cooperative abatement and a unified industry-level climate strategy. In doing this, we simulate the outcomes for both markets and derive Average Abatement Cost Curves ($AACC$) in $\$/ton\ \ CO_2$ following individual firm membership decisions as well as Corbett et al. (2009)'s methodology:

$$\begin{cases} AAC^{CO_2}_{i \in Grand\ Coalition\ market} = \frac{\Pi^*_{i,BAU} - \Pi^*_{i \in Coalition}}{\overline{S^{*,CO_2,2043}_{i,26}} - S^{*,CO_2,2043}_{i \in\ Coalition,26}} \\ AAC^{CO_2}_{i \in All\ Singelton\ market} = \frac{\Pi^*_{i,BAU} - \Pi^*_{i,Singelton}}{\overline{S^{*,CO_2,2043}_{i,26}} - S^{*,CO_2,2043}_{i,Singelton,26}} \end{cases} \tag{3.42}$$

3.6 The Opportunity Cost Of Slow Steaming

We also formalise each market participant's incentive to cheat on the emissions policy, regardless of their membership decisions, through the opportunity cost of slow steaming under a carbon constraint;

$$\begin{cases} ITC_i(i \in C) = \Pi_i^{BAU} - \Pi_i(i \in C) \\ ITC_i(i \notin C) = \Pi_i^{BAU} - \Pi_i(i \notin C) \end{cases} \tag{3.43}$$

4

Industry Level Climate Coalition's Simulation Methodology

4.1 Introduction

This chapter provides an extension of the environmental governance game by scaling the market-level simulation. First, we motivate the evolutionary algorithmic procedure leveraged in deriving optimal firm-level abatement paths in both theory and application. Then, we depict ILCC's input data derived from a meta-analysis of relevant seminal work in the literature.

4.2 Industry Level Climate Coalition's Simulation Methodology

A mixed-integer profit maximization model was developed to determine optimal average speed levels and annual fleet size. The number of vessels in each period is a discrete variable and as such is a discontinuous function of the sailing speed V_i. Consequently, the objective function is not a continuous function of V_i so traditional tools like convex optimization cannot be used to solve the ocean shippers' environmental optimisation problem. Following the literature (Doudnikoff & Lacoste, 2014; T. E. Notteboom & Vernimmen, 2009; Ronen, 2011), we resort to a heuristic search methodology due to the non-smoothness of the objective functions. For this research, we leverage an evolutionary genetic algorithm approach.

The simplicity of genetic algorithms, combined with their robustness and flexibility in dealing with non-continuous objective functions render them an appealing search heuristic candidate for complicated optimization problems as compared to traditional approaches. Their population-based design drives the robustness of the algorithm as it allows escape from local optima owing to the exploration and exploitation trade-off. Overall, GAs represent an efficient and widely successful algorithmic way to solve both constrained and unconstrained problems (Michalewicz, Dasgupta, Le Riche, & Schoenauer, 1996). Appendix(A) provides more details on the evolutionary genetic algorithm's implementation.

The modelled simulation is a multi-stage process. To derive feasible firm-level carbon budget constraints, we first have to solve for each market participant's BAU speed and fleet size and determine their projected emission paths. Then, we leverage the BAU-derived simulation data to simulate the feasible budget constraints for the grand coalition and all singleton specifications. We note that each market structure requires its own version of the developed evolutionary algorithm, both at the firm and by abatement level. In summary, the simulation was implemented in python on a MacBook Air (M1, 2020) with a 16 GB of memory. Various runs of the designed algorithms were conducted to ensure consistency and robustness.

We note that the derived results share the evolutionary process. However, the simulated fitness design functions for our grand coalition differs from the all-singleton as well as the BAU market structure, since the grand coalition solves for an evolutionary cooperative game and the BAU does not endogenize pollution externalities. Moreover, the models' constraints would have to be incorporated into evaluating the fitness function and generated populations, such that for each algorithm all choice variables have to satisfy each firm's carbon inventory constraint. A use-case-specific subroutine was derived for each model to ensure that the fitness function, i.e., the market participant's objective function evaluated at the chosen choice variables, reverts to 0 if violating any constraint.

4.3 Industry Level Climate Coalition's Input Data

Properly estimating our simulation model turned out to be a challenging endeavour. Unfortunately, firm-level service, trade and fleet characteristics data for the container shipping sector isn't publicly available. To this end, we assume a marketplace governed by 5 heterogeneous firms operating the North Europe - Asia liner service. The modeled corridor conveys more than 22% of the world container traffic (by TEU) and is considered one of the world's critical trade passages (Brahimi et al., 2021). As parameters, Doudnikoff and Lacoste (2014) report a 23, 000 *nm* cycle distance and a 10 *day* average port time.

Real growth rate data was derived from IMF (2021), while base line containerized trade flows were adapted from UNCTAD (2021) per Table 4.1.

Table 4.1: Containerized Trade Market Demand for Europe–Far East service

	2018	2019	2020	2021
Containerized Trade on EuropeFar East service	7 (*Million TEU*)	7.2 (*Million TEU*)	7.2 (*Million TEU*)	7.8 (*Million TEU*)

Adapted from : (UNCTAD, 2021)

Maritime research is still limited by restrictive data reporting (B. K. Lee, Lee, & Chew, 2018; Pesch & Kuzmicz, 2020; Song, Zhang, Liu, & Chu, 2019; Wang & Meng, 2017). Knowing this, the choice of the number of marketplace participants in our simulation is primarily driven by the scarcity of public data and should not be seen as a limitation of the model. Our research design can easily be scaled up to account for any number of firms or market share.

Table 4.2 illustrates the ocean shipping firm-level characteristics used in our simulation[1]. In a capital-intensive market with low product differentiation, market entry into the liner-shipping industry warrants substantial capital investments (Agarwal & Ergun, 2010). These hypothetical firms span the sector's economies of scale with different vessel capacity, costs and

[1]Fixed Operating Costs were estimated by multiplying vessels' daily cost with the annual number of days.

fuel efficiency parameters[2].

Table 4.2: Firm Level Characteristics

Parameters	Notation	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
Vessel capacity (TEU)	k_i	14,000	12,000	10,000	8,000	6,000
Main engine power (kW)	PS_i^M	89,700	82,100	74,000	68,500	57,100
Auxiliary engine power (kW)	PS_i^A	14,000	14,000	12,000	12,000	12,900
Specific fuel oil consumption (main engine) (g/kWh)	$SFOC_{0,i}^M$	175	133	159	143	114
Specific fuel oil consumption (auxiliary engine)(g/kWh)	$SFOC_{0,i}^A$	32	28	24	24	26
Fixed Operating Cost ($million\ USD/year$)	FC_i	18.25	16.74	15.24	13.73	12.22
Average Engine load factor (main engine) (%)	EL^M	0.8	0.8	0.8	0.8	0.8
Average Engine load factor (auxiliary engine) (%)	EL^A	0.5	0.5	0.5	0.5	0.5
Maximum Vessel speed ($knots$)	V_i^{max}	28.0	28.0	28.0	28.0	28.0
Minimum Vessel speed ($knots$)	V_i^{min}	12.0	12.0	12.0	12.0	12.0
Design speed ($knots$)	V_i^s	25.0	25.0	25.0	25.0	25.0

Adapted from : (Brahimi et al., 2021)

In combining numerical simulation and optimization to explore self-governance in the absence of regulation, we hold freight rates constant throughout the simulation at $822\$/TEU$ (UNCTAD, 2020). Associated issues such as pass-through and market demand response to rate changes are beyond the scope of this initial research. Fuel prices along with their emission parameter are summarised in Table 4.3.

Finally, the discount rate reflects individual willingness to wait on consumption and captures subjective valuation of time preferences. The net present value of the profits declines faster at a higher discount rate. Within the scope of this research, we start with a low positive discount rate $r = 0.02$ among the participants to better account for future environmental damages than current ones (Wangler, Altamirano-Cabrera, & Weikard, 2013; Yu, van Ier-

[2] Regarding the chosen vessels for our hypothetical firms, Drewrys Shipping Insight breaks down the 2021 global container fleet structure distribution per the following : Small Feeder: 100-2,000 (TEU) (42.5%), Small neo-Panamax: 5,300-10,000 (TEU) (16.4%), Classic Panamax & wide-beam: 3,000-5,300 (TEU) (16.1%), Large Feeder: 2,000-3,000 (TEU) (13.4%), VLCV - Maxi neo-Panamax: 12,500-14,500 (TEU) (4.24%), Large neo-Panamax: 10,000-12,500 (TEU) (3.13%), ULCV: 18,000+ (TEU) (2.61%), VLCV - Neo post-Panamax: 13,000-18,000 (TEU) (1.52%) (Tyler Data & Insights, 2021).

Table 4.3: Fuel Price and Emission Estimates

	HFO (3.5%)	ULSFO (0.5%)	MGO (0.1%)
Global 20 Ports Average fuel Prices	422.5 $\$/tonne$	525.5 $\$/tonne$	597 $\$/tonne$
Carbon Emission Factor	3.114	3.206	3.206
Sulfur Emission Factor	0.07	0.01	0.002

Adapted from: (IMO, 2015; Kontovas, 2014; Ship & Bunker, 2021)

land, Weikard, & Zhu, 2017).

4.4 Industry Level Climate Coalition's Policy Applications

In this model, a significant increase in global demand for transporting containerized goods warrants an increase in transportation throughput, thereby inducing higher fuel consumption and higher emissions because of the relationship governing emissions and fuel consumption. Thus, independent of the industry's chosen abatement policy - whether we're investigating greener fuel, slow steaming or exhaust scrubbers - projecting industry demand from 2022 to 2042 is necessary to estimate this market simulation and to assess the feasibility and operational benefits of any joint abatement endeavours (Doukas et al., 2021).

Based on IMF forecasts, our discrete time-period simulation goes out to 2042 and begins with an average of 7.3 $MTEU$ container-ships doing the shipping for Europe–Far East service between $2018 - 2021$ (UNCTAD, 2021). This capacity is projected to grow , based on a 0.8 constant income demand elasticity as well as a 3.96% average real GDP growth between $2022 - 2024$ and a steady 4.9% thereafter (IMF, 2021).Figure 4.1 delineates the simulated maritime market transport demand.

As of this writing, the ongoing market landscape and various supply chain distortions are

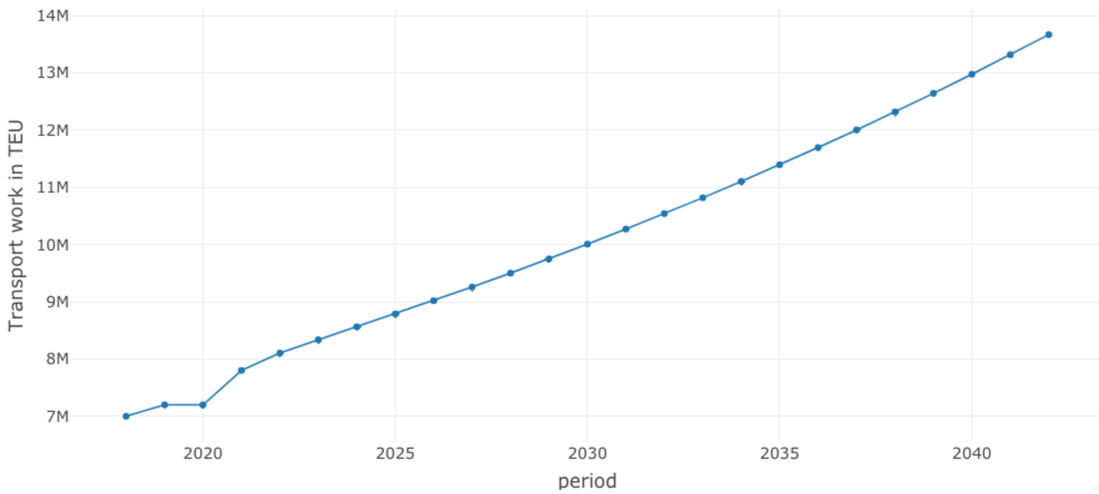

Figure 4.1: Simulated Market Transport Demand. *Source: Author's compilation*

leading to the highest maritime emission rates since 2008. Economic disruptions coupled with a worldwide post-pandemic surge in demand for containerized cargo are set to undo decades of industry abatement efforts (Bethany, 2021). Currently, transporting goods via container is at a record high with global container freight index rates exceeding 10,000 (as of the end of 2021) (*FBX: Freightos Baltic index: World freight container index*, 2021). Competition in this market is fierce and carriers are effectively ignoring their environmental responsibilities to compete . Vessels on the Asian-US east cost routes are recording at least a 22% increase in cruising speed in good weather, notwithstanding their fuel consumption costs (Almendral, 2022). Conversely, crossing the Pacific Ocean would take at least six weeks or more post-financial crisis of 2007–2008. it was reported that shippers were receiving very slim margins and container vessels were sailing at $12 - 14$ knots instead of the $24 - 26$ range. However, as a consequence, industry emissions dropped significantly at that time (Almendral, 2022).

Thus, there needs to be an incentive for maritime shipping firms to deploy slow steaming beyond firm-level bunker fuel cost minimisation seen during economic crises. Even more so, firms need to commit to sustainably decarbonise the industry through speed regulation policies that prevent ships from sailing too fast. Subsequently, our research output stresses the need for additional policy measures to ensure slow steaming practices are sustainable in the longer run. As we saw, the"***cubic law of speed design***" governing the efficiency of slow steaming as an abatement policy is really a double-edged sword, with vessels sailing twice as fast estimated to consequently release several times as much emissions. Without the introduction of large technological changes (like nuclear or electric ships) or cost effective synthetic fuel , some form of mandatory slow steaming seems essential. It has even been promoted by French President Emmanuel Macron as "one of the most effective ways to reduce greenhouse gas emissions globally" (*Macron Takes an Unsteady Grip on Shipping's Environmental Path*, n.d.).

The applied ILCC simulation model begins by projecting the business-as-usual emission growth. It considers a marketplace composed of five heterogeneous firms $\{1, 2, 3, 4, 5\}$, with 20% equal market shares from 2018 to 2042. The choice of equal market shares allows us to control for firm-level demand and enables us to create a model within which we can evaluate the strategic behaviour of heterogeneous players with different abatement structures under various climate policies. Over the planning horizon, the model simulates a level of $50.65\ MTEU$ per firm output.To this end, the first use case of the model endeavours to explain the economics of the slow-steaming trade-off and explores firm-level incentives for the observed chosen sailing speed on the European–Far East service, considering different economies of scale investments.

The second application of the model benchmarks the cost-effectiveness of the proposed IMO's "speed reduction" regulations to "speed optimization". Considering that persistent lobbying has been successful in introducing (mandatory) speed reduction/limit regulations into the IMO's initial strategy for short-term abatement candidate policies, Psaraftis (2019b) discusses the current market "speed Limiters' pitch" and illustrates the limitation of CE Delft's recent research that has been leveraged by many ocean and shipping NGOs to lobby for speed limits/regulation via the IMO (J. Faber, Huigen, & Nelissen, 2017). In a command and control market, a governing agent (IMO) enforces environmental regulatory measures to control factors responsible for the industry's emissions. For instance, a heavy-handed regulator could introduce a benchmark for vessel design and energy efficiency, limit fuel consumption or regulate ships' speed, in a manner similar to current proposals. To this end, we interpret regulating vessels' speed in the open sea with the ongoing "speed Limiters' debate" as a slow-steaming command-and-control policy.

Likewise, the applied ILCC simulation model explores the economic and environmental implications of "speed optimization" as a short-term abatement strategy to curb the industry's emission growth. In doing so, it assumes an ALL-Singleton market structure and simulates the IMO's candidate policy as firms engage in optimal slow-steaming and maximise their own profits under heterogeneous carbon budget constraints. Derived assuming a uniform % emission reduction relative to firms' projected BAU emissions, the ILCC's speed optimization analysis begins by assuming a lenient 1% reduction, and then gradually increases the stringency of the policy by 1% until it reaches a tighter budget constraint under a 40% abatement regulation.

Finally, ILCC simulation output extends the market structure to investigate a Grand Coalition market and explores joint and optimal slow-steaming abatement endeavours under a market-wide budget constraint. This extension leverages the industry's alliance structure and allows us to explore the potential environmental and economic outcomes of cooperative slow-steaming endeavours.

5

Results and Discussion

5.1 Introduction

This chapter presents the results obtained from the maritime shipping simulation model (ILCC). It begins with a depiction of the slow-steaming trade-offs while considering different economies of scale investments to motivate the simulated market participants' incentives for their chosen profit-maximising BAU operations. The second section reports on optimal sailing speed, fleet size and the industry's projected profits and emissions over the planning horizon, while the subsequent section explores the use of vessel speed limits as a unilateral command-and-control policy and outline the benefits of optimal slow steaming abatement under a market-wide carbon quota or constraint. Finally, we use our findings to discuss the industry's potential for environmental sustainability through cooperation and coalition formation.

5.2 Slow Steaming Cost Trade-off & TEU Investments

Figure 5.1 illustrates the impact of ships' speed on firms' discounted fuel consumption ($DFCC$) and operating costs ($DFOC$) in $\$/TEU$ and captures the slow steaming trade-off. To better understand the underlying dynamics governing optimal firm strategic behaviour, we first investigate the costs trade-off between increasing ships' speed and fleet size by simulating firms' economic operations within their feasible operational range (from 12 to 28 knots).

The upper panel of Figure 5.1 shows that shippers incur different operating costs that are held constant within four derived speed level intervals. The threshold points for the depicted intervals are 16.6 *knots*, 21.8 *knots* and 27.4 *knots*, respectively. In this analysis, firms convey the same intervals because the simulation assumes identical economic parameters across its

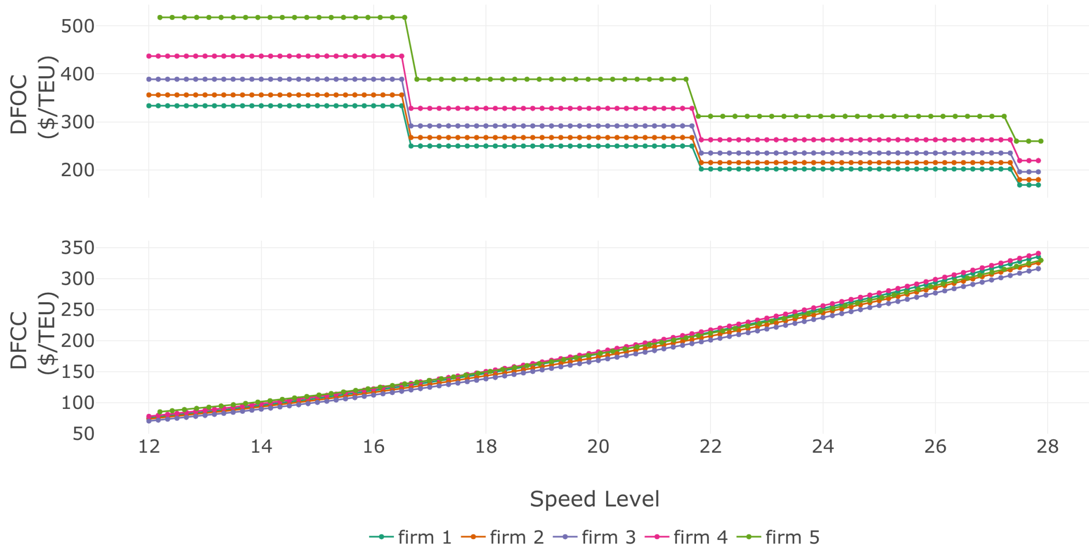

Figure 5.1: The Slow Steaming Trade-Off For Various Simulated Speed Levels. *Source: Author's compilation*

market participants. Recall that, in this application of the ILCC model, the simulated industry is contracted to fulfil the same demand and honour the same service level agreement under the same freight rate and bunker prices. Each speed interval depicts a certain fleet structure that allows each firm to sustain transportation throughput without necessitating additional ships to meet demand per its capacity. However, when the simulation moves towards higher speed intervals, operating costs decrease because of the smaller number of faster ships that can withstand the same demand. Conversely, lower speed levels offer fuel savings but affect firms' profit margins by generating higher operating costs to maintain the same throughput.

The lower panel of Figure 5.1 shows that firms 1 to 4 's fuel consumption costs evolve with a parallel trend. As speed increases, firm 4 has the highest bunker cost per TEU starting at $78\$/TEU$ and reaching $341\$/TEU$, followed by firm 1 ($75 - 335\$/TEU$), firm 2 ($73 - 325\$/TEU$) and then firm 3 ($70 - 316\$/TEU$). In comparison, firm 5's bunker costs fluctuate throughout the simulation, indicative of the highest consumption rate, for speed levels below 17.5 *knots*, starting at 85$/*TEU* and 2[nd] highest behind firm 4 for levels below 20.3 *knots*. Afterwards, with its bunker costs reaching 330$/*TEU*, firm 5 generates the 3[rd] most expensive rates after firm 4 (341$/*TEU*) and 1 (335$/*TEU*).

Figure 5.2 presents the broad evolution of our ocean shipping simulated cost curve. Since freight rates are assumed exogenous, our profit maximization problem can be rendered into a cost minimisation problem. The piece-wise function reveals that firms' total expenditure rises with higher operational speed levels in each of the four distinct intervals. Consequently, carriers' best strategy is to sail at the lowest speed possible to save on fuel within each interval, since a vessel sailing twice as fast, would burn roughly eight times as much fuel.

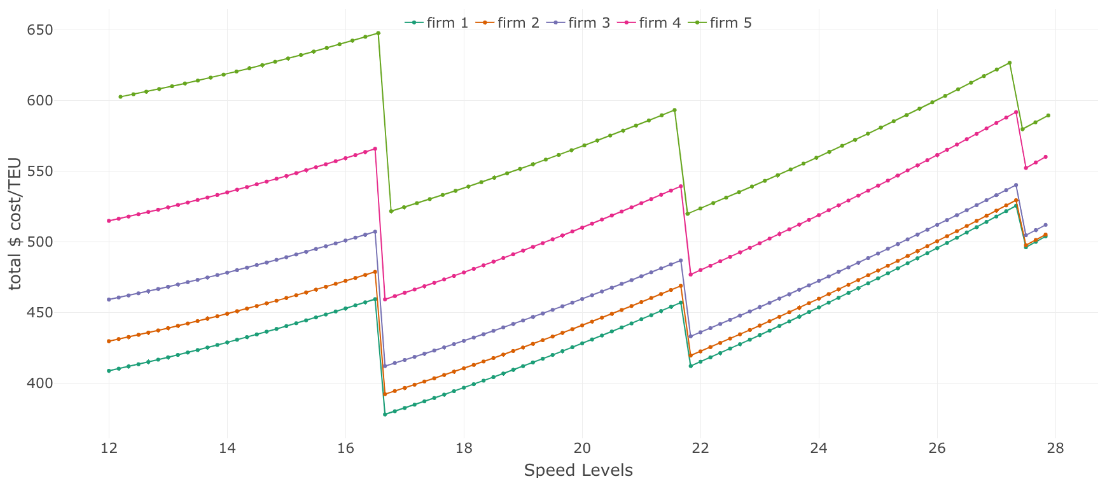

Figure 5.2: Firms' Total Discounted Costs Per TEU For Various Simulated Speed Level. *Source: Author's compilation*

Considering vessel size and firms' return on capacity investments, Firm 5 with its lowest 6000 TEU capacity incurs the highest TEU cost, followed by firms 4, 3, 2 and 1. In this simulation, firm i invests in an additional 2000 *TEU* capacity , when compared to firm $i+1$ tn this simulation. The smaller-vessel-sized fleets enjoy more savings when speed intervals jump from one level to another. Here, firm 5 saves 129$/*TEU* (from 16.5 to 16.6), 77$/*TEU* (from 21.6 to 21.8) and 52$/*TEU* (from 27.3 to 27.4), whereas firm 1 savings include 84$/*TEU* (from 16.5 to 16.6), 48$/*TEU* (from 21.6 to 21.8) and 33$/*TEU* (from 27.3 to 27.4). Furthermore, while the economies of scale investments are held constant from the former to the latter, the differences in their incurred costs vary from one to another. In particular, when averaging across the various speed levels, we find that firm 5's transports one *TEU* at a 58$ higher cost than firm 4. All the while the estimated cost gap between (4 *to* 3) , (3 *to* 2) and (2 *to* 1) , is evaluated at 34 , 21 and 18 in $/*TEU*respectively. The cost gaps amongst the firms decrease with increasing speed levels and are higher between firm 5 and firm 4 such that 5 's costs are (81$/*TEU* , 61$/*TEU* , 49$/*TEU* , 40$/*TEU*) higher than firm 4 , as opposed to the (27$/*TEU* ,23$/*TEU* , 13$/*TEU* , 11$/*TEU*) increase between firm 2 and firm 1.

5.3 BAU Projections

The evolutionary algorithm discussed in the previous chapter was implemented to solve the maritime shipper's optimal discrete fleet size and vessel speed without internalising pollution externalities. Table 5.1 reports on the simulated framework's BAU operations findings and outlines firms' Net present values (*NPV*), discounted fleet operating (*DFOC*) , discounted fuel consumption costs (*DFCC*), and emission inventory per TEU for sulfur and carbon[3]. Having assumed rational agents in this simulation, our shippers' main objective is to maximise profits and solve for the stow steaming trade-off between their fuel savings and operating costs.

[3]To buttress the robustness of our evolutionary heuristic procedure, we also ran a one-year simulation analysis on an excel spreadsheet using Microsoft's built-in evolutionary solver. The findings for each firm aligned with our python implementation.

Table 5.1: BAU Framework Simulation Result. *Source: Author's compilation*

Firm	Optimal Speed (knots)	Vessel Capacity (TEU)	Main Energy Consumption	Aux Energy Consumption
Firm 1	16.66697	14,000	0.8	224
Firm 2	16.66671	12,000	0.56	196
Firm 3	16.66683	10,000	0.6	144
Firm 4	16.6667	8,000	0.5	144
Firm 5	21.78	6,000	0.3	168

(a) The fuel parameters for the main and auxiliary engines are in $(ton/hour) \times knot^{-3} \times 10^{-6}$ and $10^{-6} \times ton/hour$.

Firm	Net Present Value ($/TEUs)	Discounted fleet Operating Costs ($/TEUs)	Discounted Fuel Consumption Costs ($/TEUs)
Firm 1	246	250	128
Firm 2	232	268	125
Firm 3	212	292	120
Firm 4	165	328	131
Firm 5	104	312	208

Firm	Carbon Emissions (tonnes/TEUs)	Sulfur Emissions (tonnes/TEUs)
Firm 1	1.22	0.0258
Firm 2	1.18	0.0250
Firm 3	1.14	0.0243
Firm 4	1.24	0.0262
Firm 5	1.98	0.0425

Table 5.1 shows that the additional investment in $8k$, $6k$, $4k$ and $2k$ *TEUs* per vessel for firms 1 to 4 over firm 5's $6k$ *TEU* vessel provides a saving of 142$/*TEU*, 128$/*TEU*, 108$/*TEU* and 61$/*TEU*. That is a 136%, 122%, 103% and 58% cost advantage per unit transported, respectively. Consequently, our simulation results indicate that larger container ships provide firms with a competitive advantage and higher profit margins. Following market data on vessel characteristics, these findings are consistent with the incontrovertible basic theory of economies of scale (Lim, 1998).

Vessel capacity and engine efficiency in combination with fuel prices and operational costs promote our equilibrium speed levels and thus firms' fleet structure. A vessel's main engine energy efficiency decreases with capacity. However, this assumption does not extend to the auxiliary engine, such that firms 3 and 4 exploit the most efficient auxiliary engines instead of firm 5, followed by 2 and 1. Based on this simulation's economics and trade route estimates, we identify an optimal speed of 16.67 knots (rounded to the second decimal place) for all but firm 5. The latter settled for a higher 21.78 knots operational speed for equilibrium between fuel consumption and fleet size per capacity. However, when considering speed levels at a 5 digit precision, we found that firm 4 would be the slowest, followed by firms 2, 3,1 and 5 (slowest to fastest). Overall, our simulated solution aligns quite well with the 16.4 knots average reported service speed on the European–Far East shipping market (as of 2019) (Cheaitou & Cariou, 2019).

Figure 5.3 illustrates the required round trips to satisfy each firm's demand and the evolution of their fleet along the planning horizon. We find that firm 5 requires - on average - nearly double that of the other firms' required round trips $N_{i,t}^{trip}$ to satisfy the same contracted demand because of its capacity constraint. Although, by tradeoff design, the firm's main engine is very efficient at burning fuel, meaning that it would only consume 0.3 $(ton/hour) \times knot^{-3} \times 10^{-6}$compared to the average of 0.6 for the other hypothetical firms. Consequently, it shouldn't be a surprise that this firm solves for the greatest fleet velocity.

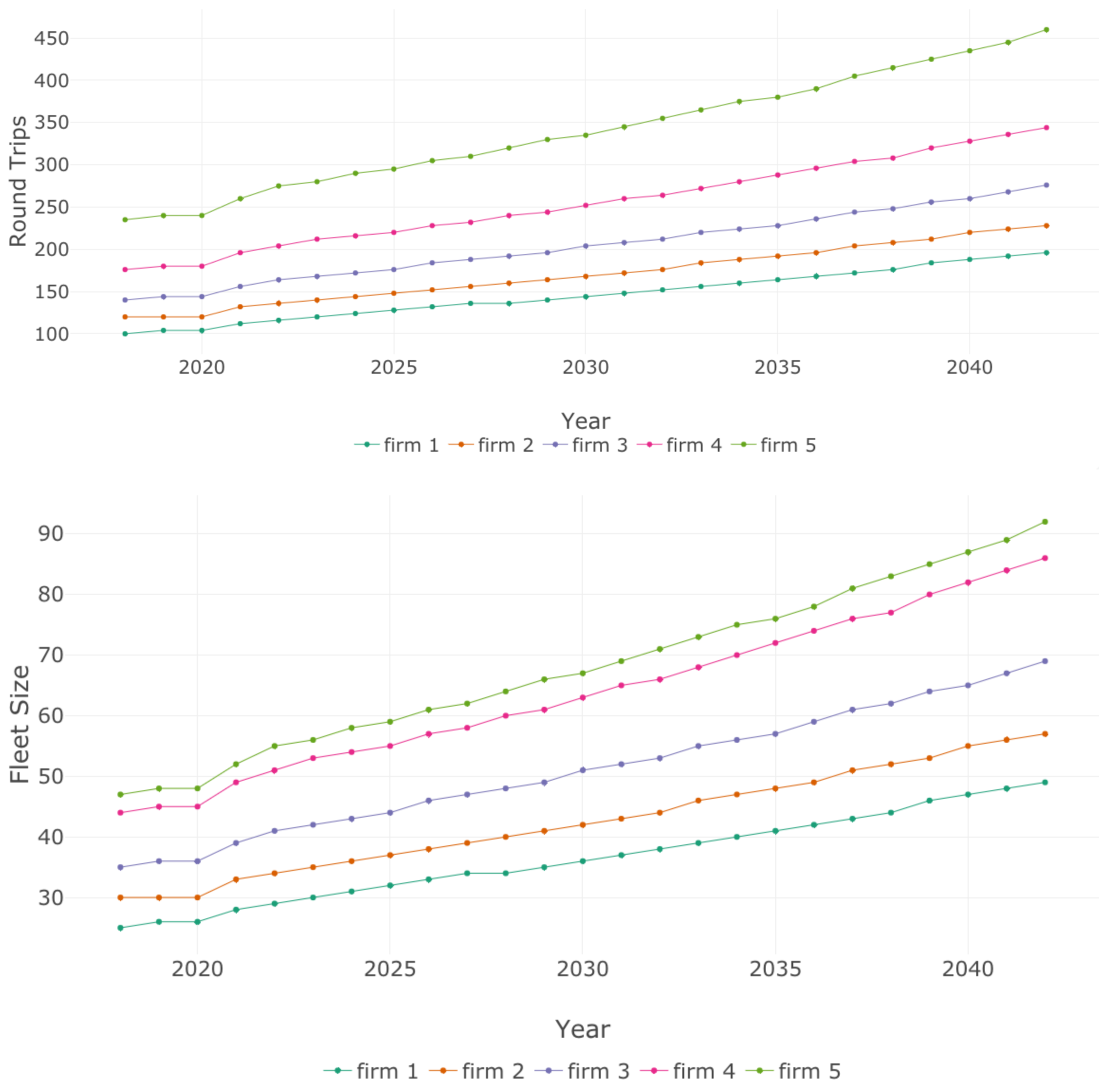

Figure 5.3: Required Round Trips To Satisfy Demand & Evolution Of Fleet Size. *Source: Author's compilation*

Notwithstanding its more efficient engines (Φ_4, F_{A_4}), we find that firm 4 consumed more fuel, yet was marginally slower than 2, 3, and 1, if we were to consider the simulation's output at a 5 digit precision. This firm also had the highest operating costs overall in this simulation. Given its capacity, this firm was only contracted to run a quarter of firm 5's round trips. In fact its fleet - again, on average - is only 5 vessels short of the latter (one can observe this in Figure 5.3). So, essentially firm 4 didn't run as many voyages as firm 5, but relied on a bigger fleet than firms 3,2,and 1. This led the former to be the slowest fleet in order to save as much fuel as possible.

In this simulation, emissions are driven by fuel consumption. Firm 5 depicts the dirtiest market participant, followed by firms 4, 1,2 and 3 (in order). Owing to the cubic law governing fuel consumption and speed, 5's discounted bunker costs and emissions are dramatically higher than the other shipping firms.

5.4 Mandatory Speed Reductions Policies

Figure 5.4 simulates the economic and environmental outcomes of mandatory speed reductions percentages relative to the firms' BAU operations. The response functions describe the relationship between speed reduction (%), emission (%) and forgone profits (%) for firms with heterogeneous fleet characteristics relative to their baseline operations. Numerically, we find that a 29%Speed reduction from BAU induces a 43% and 48% decrease in carbon and sulfur emissions, respectively, at a 30% loss in industry profits over the planning horizon due to the additional capacity investments to sustain firms' throughput at lower speed levels, assuming firms adhere to the speed reduction percentage. In other words, our simulated containership markets' opportunity cost to cut 147Mt CO_2 and 3.5Mt SO_x relative to its BAU level is estimated to be USD 4.6B. In comparison, we note that the IMO's 40% emission reduction target by 2030 relative to 2008 figures is about 320 million tonnes (Goicoechea & Abadie, 2021). We, therefore, conclude that given our data and simulations, decreasing firms' average speed is effective in targeting both carbon and sulfur emissions.

While this market simulation is very stylized in nature and our analysis is limited by data availability on precise firm-level characteristics, our findings about slow steaming effectiveness in dramatically decreasing industry emissions align well with prior research (Corbett et al., 2009) and are further buttressed by the ongoing debate (as of this writing) over using slow steaming as an enforced operational measure through the IMO. Additionally, our simulation seems to show that the execution of this type of policy should be left to ship owners to plan out, given a clear and well-rationalized emission target as well as knowledge of their own fleet's strengths and weaknesses.

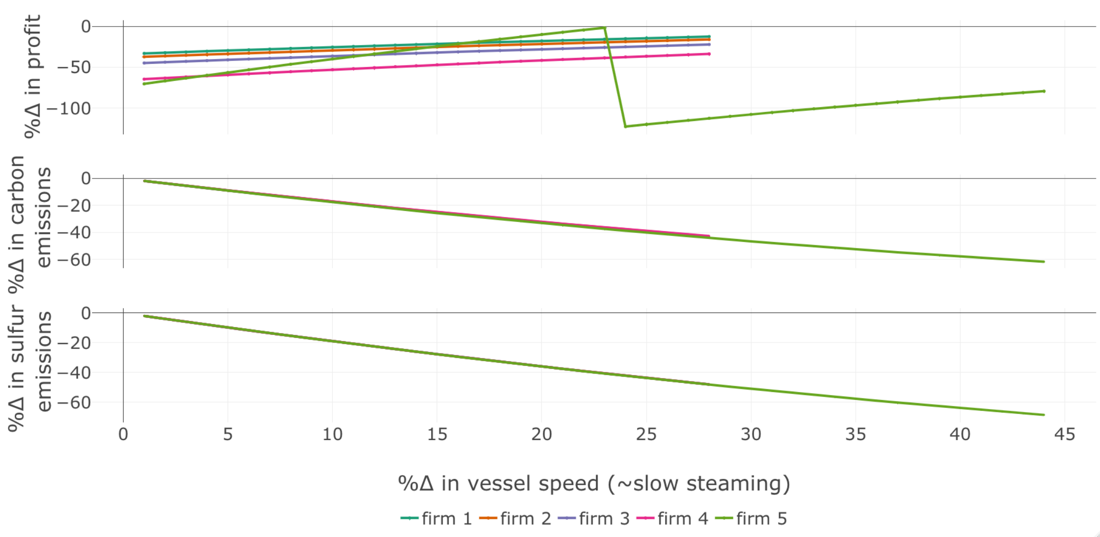

Figure 5.4: Mandatory Speed Reductions Policies. *Source: Author's compilation*

The divergence in the incurred costs across the shipping firms indicates that a uniform speed regulation affects firms' bottom line and emissions differently since vessels' operational speed levels are a key factor in firm profit margins. Recall that the cost of slow steaming lies with forgone profits, with a compliant fleet operating at non-profit maximizing speed levels supported by additional ships. Consequently, speed reduction policies remain a sensitive regulatory outcome that cannot be deployed ad-hoc, meaning that policy design should factor in the heterogeneity of firms, vessels and shipping routes.

Speed should be optimised at the discretion of ocean carriers, conditioned on their internal parameters in order to achieve an allocated carbon reduction quota. We offer that the focus of the IMO should be geared towards governing firm-level emission rates rather than regulating market sailing speeds. To this end, we need to differentiate between leveraging slow steaming as an abatement policy for carriers to optimise towards reaching an emission target against imposing speed regulation limits across markets. In effect, sailing speed reductions should be sought out as a choice that carriers opt for amongst a set of abatement measures in order to reach an emission target. In summary, the shortcomings of imposed speed reduction/speed limit regulations as an instrument to control GHG emissions within a command and control policy are threefold. The policy design is challenged by the difficulty of identifying firms' baseline speed levels and appropriate benchmarks, its enforcement & governance requirements as well as its impact on innovation and fair competition.

1. **Identification of baseline speed levels & appropriate benchmarks**

During depressed market conditions, speed limit regulations are useless and redundant, since the existing fleet would already be leveraging slow steaming to reduce fuel consumption. Given this dichotomy, there will be an inefficient use of resources allocated to monitor and enforce such a regulation, notwithstanding distorting the market by imposing the same speed limits in both boom and depressed markets (Psaraftis, 2019b).

The identification of vessels' speed benchmarks to lower emissions is a challenging endeavour since it requires specific knowledge of vessel design and carriers' operational procedures. So how should the IMO allocate speed permits? Evidently, imposing a uniform $\bar{V}$ policy is unreasonable. Again, the threshold would either be superfluous for some vessels or restrictive for others, conditional on market and weather conditions, bunker fuel prices, and many other parameters that are most likely beyond the IMO's control (Psaraftis, 2019b). To illustrate the potential consequences of such a policy, Figure 5.5 shows the relationship between fuel prices and firm optimal sailing speeds. Slow steaming is highly correlated with fuel prices, and assuming otherwise by imposing market-wide speed regulation could induce all sorts of market distortions in the industry (Psaraftis, 2019b).

Consider a uniform speed limit regulation (cap) of $\bar{V} = 17$ knots, and further assume that shipping companies are rational and profit maximizers. For our simulated market, imposing this policy entails that firm 5 would have to optimize its operations accordingly and adjust its sailing speed from 21 knots to 16.67 knots. But what about other market participants in our simulations? To this end, the imposed policy would only be targeting vessels that are efficient at burning fuel, which could hinder research development and innovation in the ship-building field, or even reward free-riding. Regarding the latter, ocean carriers could try to use only those vessels that are able to sail at the chosen "speed level" with no regard for emissions. The goal of a speed control policy is to try to decarbonize the sector and not target a certain group of ships.

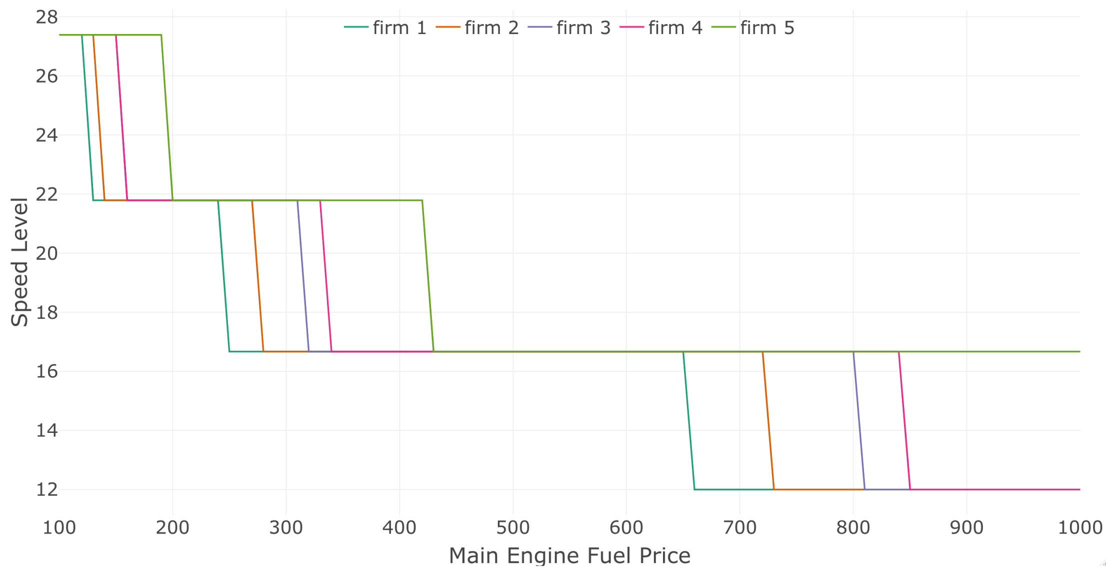

Figure 5.5: Optimal Speed Under Fuel Price Simulation. *Source: Author's compilation*

Conversely, one could argue for a heterogeneous treatment. Under such a design, how should we segment the market to assign group-specific baseline speed levels? Should the regulator allocate these permits based on vessel sizes and/or type, market routes and/or weather and market conditions or other parameters? To this end, the Clean Shipping Coalition proposed a specific vessel type and size-specific speed limit, whereas Psaraftis (2019b) highlights the industry's speed directional imbalances. The latter notes that average speed might be slower on one route and not another. For instance, vessels often sail faster from the Far East to Europe than from Europe to the Far East. So, again this type of policy might be redundant in one way and hindering in the other.

Identifying baseline speed levels for heterogeneous vessel types operating across different markets isn't a straightforward endeavour. In our BAU simulation, we controlled for all economic variables across the different ships/firms and varied vessel characteristics to the best of our ability following data availability and yet, there is no rule of thumb for exogenously assigning speed permits. Given the chosen economic parameters and route characteristics from the simulation, we identified, notwithstanding varying their vessel sizes, almost the same operational speed for firms 1-4 and a significantly higher velocity for the remaining market participant. Thus, the IMO can't make a decision rule for assigning baseline speed unless it identifies every use case possible, which might not be realistic in an international, evolving and dynamic market like ocean shipping.

Moreover, assume that a governing regulator identifies a baseline sailing speed level, what percentage reduction is most suitable to meet the industry's emission target? In the simulation, considering firms' baseline speed levels and the minimally tolerated vessel design speed, in fact, there lies a heterogeneous threshold among the firms as to the maximum and feasible operational speed reduction/limit. Again, a small reduction might be redundant for some or actually binding for others, and further reductions might not be feasible in the real world if the fleet is already operating under slow steaming.

2. **Enforcement & Governance in a heterogeneous international market**

As an administrative endeavour, collecting market data to identify heterogeneous baseline sailing speed levels would be challenging. Psaraftis (2019b) calls into question the practicality and complexity of enforcing such regulation. Besides, enforcement and monitoring of these regulations to prevent free-riding could warrant substantial resources in a vast international market like maritime shipping (Lagouvardou, Psaraftis, & Zis, 2020).

Alternatively, Figure 5.6 provides the rationale for advocating a fuel-driven emissions policy rather than by regulating velocity to curb industry-projected CO_2 growth. Here we see that emissions decrease across the board as speed levels adjust to higher bunker fuel prices. Besides, collecting bunker fuel consumption data holds the potential for proxying ship-level emissions, whereby monitoring fuel consumption across international markets should be a relatively simpler endeavour for a regulatory body.

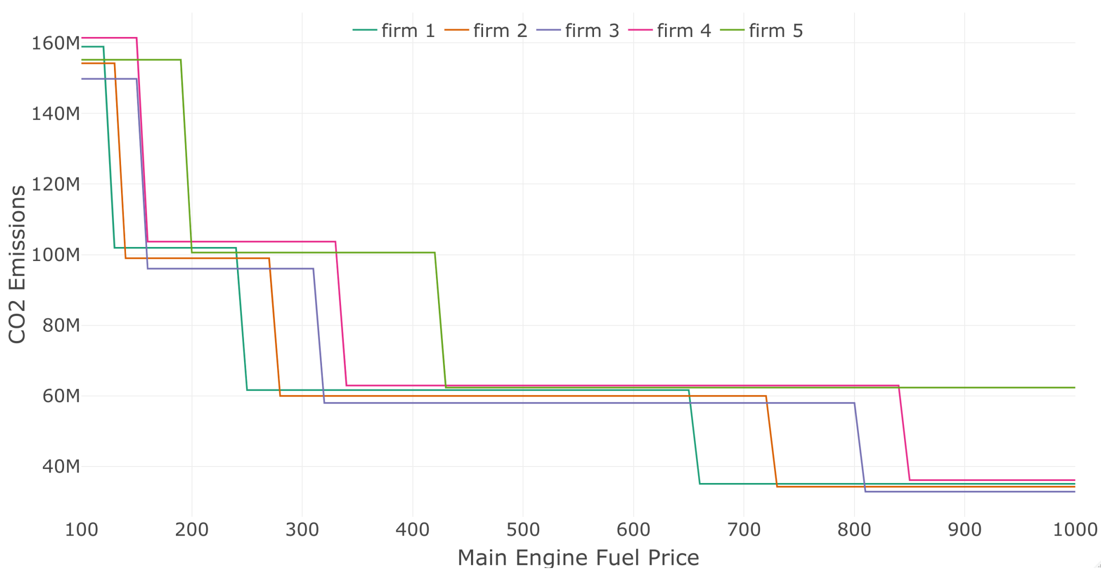

Figure 5.6: Emissions Under Fuel Price Simulation. *Source: Author's compilation*

3. Hindering innovation & distorting competition

Command and control sailing speed regulations will surely not encourage green innovation and investments, relative to market-based instruments. Such a policy is not likely to motivate firms to efficiently plan their operations by improving their fleets' energy consumption to reach higher sailing speeds with lower fuel consumption rates. Consequently, under such a policy, it seems that hardly any advancement or research will be made toward reaching more energy-efficient infrastructure solutions (Lagouvardou et al., 2020).

By design, this policy might end up hindering those greener firms, considering as designed it doesn't take into account the type of bunker fuel burned by the ships. Available even today, cleaner fuels are still more expensive. Consequently, why would a firm invest in greener fuel-powered ships if it already complies with an abatement policy that targets sailing speeds? To save on those fuel consumption costs, market participants will opt for the least cost option and in the long run, the expectation is that low carbon fuel prices will remain relatively higher. Forcing ships to sail at the same speed levels, regardless of firm and market conditions, favours the least energy-efficient fleets and provides them with an unfair market advantage over the others, while the policy effectively ignores any green investments made in energy-efficient propulsion technology (Lagouvardou et al., 2020). Furthermore, the design of such a policy doesn't necessarily ensure emission reduction. One can envision a scenario where firms require more vessels to sustain throughput and build more ships to bypass the "speed limit/-time constraint" and this outcome might induce even more emissions than the status quo (Psaraftis, 2019b)

In summary, simulating the various potential speed reductions allowed us to identify feasible carbon regulation. In what follows, we simulate firm-level participation in two extreme policy situations, but under uniform carbon regulation. These are 1) an all-singleton market structure, where firms plan their operations; and 2) a grand coalition market structure where firms share a joint emissions budget, and sailing speed reduction is a decision tool for reaching these goals. Over 250 simulations were run to ensure consistency among the presented findings for both grand coalition and all-singletons optimisation problems.

5.5 ILCC s Climate Strategies & Emission Caps

This simulation embodies a uniform regulatory framework, whereby a firm's best response is to either decrease output or otherwise increase abatement endeavours. In this set of simulations, we hold shippers' output constant and investigate optimal abatement behaviour. This policy framework entails that a governance agent distributes carbon quotas relative to the firms' current as well as projected emission rates, in order to reach an industry-level target by 2043.

In the absence of an alternate regulatory enforcement mechanism, targeted carbon abatement percentages for the firms and the industry were derived following our simulation framework speed reduction analysis. Feasible carbon quotas over the planning horizon could range from a lenient Q =1% to a more stringent Q = 40% reduction, relative to firms' BAU operations. In fact, stricter budgets are more likely to be enforced, given the industry's current rate of emissions and the ongoing pressure from supply chain participants as well as policymakers to decarbonize the industry within the near future. Here, when subjected to these emission caps, firms will re-optimise their slow-steaming efforts to reach their individual carbon quota.

Figure 5.7 illustrates firm-level emission target per transport output by the end of our planning horizon at 2043. The carrier operating the fleet with the smallest capacity (6,000 TEUs) , firm 5, was allocated a very generous carbon constraint. More precisely, 5's allocations span from 1.97 tonnes/TEU to 1.19 tonnes/TEU, whereas the remaining firms (3,2,1 and 4), these thresholds varied from 1.13, 1.17, 1.2 and 1,23 tonnes/TEU to 0.69, 0.71, 0.73 and 0.75 respectively. Furthermore, Table 5.2 benchmarks the quota allocations with regards to firm 5.

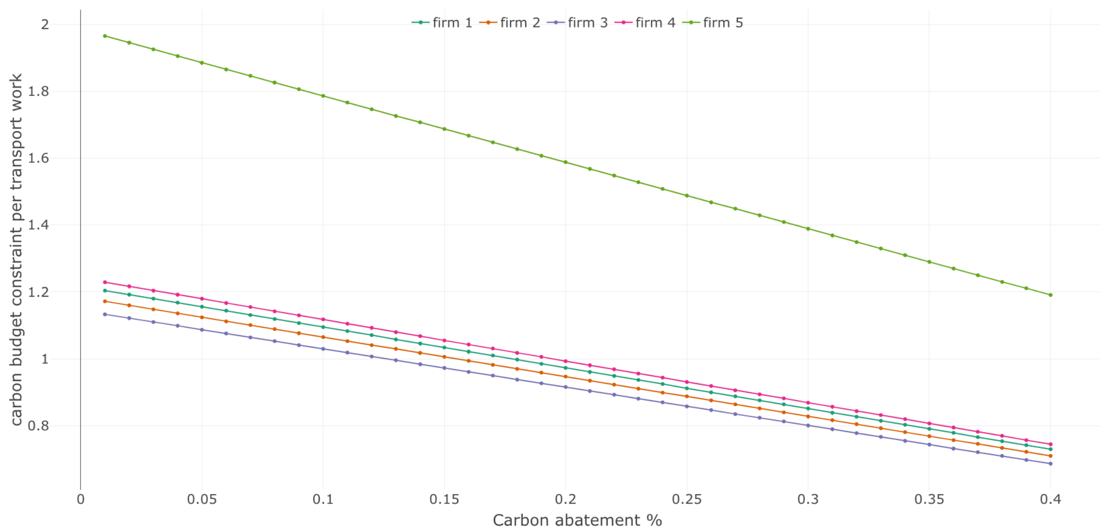

Figure 5.7: Firm Level Carbon Budget Per TEU. *Source: Author's compilation*

So, is it "fair" to assign the firm with the smallest capacity such a higher budget constraint/quota in comparison? In the simulation, we impose uniform regulations. By design, carbon caps were proportional to the firms' BAU levels. Consequently, with 5's baseline emissions being 60% higher than the rest, a relative assignment policy will not subject the firms to the same constraint and therefore, they may not be equitable across the market. Such a design might provide an additional incentive for heavy emitters to partake in an environmental policy. To this end, we observe free carbon allowances in industries like aviation to buttress their transition toward a greener economy, and 2021 draft legislation for a phase-in period incorporating maritime shipping into the EU emissions trading system with allowances relative to baseline emissions. The EU's proposal aims to fade emissions through time permits of 20%, 45% , 70% , and 100% relative to firm-level verified emissions in 2024, 2025, 2026 and each year thereafter (*EU Emissions Trading System (ETS) – latest developments*, 2022). Besides, imposing the same carbon budget across the firms in $tonCO_2/TEU$, without considering baseline operations, might yield an infeasible benchmark, owing to the heterogeneity of the firms and their minimally operational emission levels per output. In our simulation environment, the maximum absolute and feasible emission cap target in tonnes/TEU were the following : 0.75 (firm 5), 0.71(firm 4) ,0.69(firm 1), 0.68 (firm 2), 0.65(firm 3).In practice, the governing agent could proxy firms' emissions with their fuel consumption data and fleet characteristics to derive heterogeneous emission caps to reach its GHG strategy.

Table 5.2: Firm Level Carbon Budgets Relative To Firm 5. *Source: Author's compilation*

	firm 1	firm 2	firm 3	firm 4	firm 5
Budget	61%	60%	58%	63%	100 %

5.5.1 ILCC's Climate Strategies for an All-Singletons Market structure

Table 5.3 summarizes firm-level incentives in the singleton shipping market under different uniform regulations. We see that each firms' optimal abatement exceeds their targets because the optimisation model leads the singletons to re-optimise their operations for the lowest speed levels when economically feasible. Figure 5.2 already illustrated that for ocean shippers 1 to 4, their second-best strategy was to sail at 12 knots once forced to operate beyond profit maximisation. Averaged optimal abatement across these firms reached 43% for all simulated (1 to 40%) emission thresholds. On the other hand, the firm with the smallest fleet, firm 5, opted to re-optimise for a second and a third climate strategy per their emission targets. The decrease in their sailing speeds dropped from 21.78 to 16.67, and later on towards 12 knots. In doing so, they achieved 38% and 62% abatement levels. Consequently, for every simulated abatement target, the all-singleton market exceeded their 1% to 40% abatement objectives by reaching an optimal abatement level of 41% for targets below 38% and 49% under tighter regulations.

Table 5.3: All Singleton Market - Singletons. *Source: Author's compilation*

Abatement Target %	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	
	1-40	1-40	1-40	1-40	1-37.99	38-40
Optimal Abatement (tonnes/TEUs)	0.52	0.51	0.50	0.53	0.8	1.2
Optimal Abatement (%)	43%	43 %	43 %	43%	38 %	62%
Optimal Speed Levels	12	12	12	12	16.67	12
Speed Reduction (%)	28	28	28	28	23	44
Carbon Emissions (tonnes/TEUs)	0.69	0.68	0.65	0.71	1.23	0.75
ITC ($/TEU)	31	38	47	56	0.6	81
ITC (%)	(13 %)	(16%)	(22%)	(34%)	(0.6%)	(78%)
AAC ($/ton CO2)	59	74	95	105	0.8	66
Optimal Sulfur Abatement (%)	48 %	48 %	48 %	48%	41%	69%

Firm-level output = 50.65$MTEU$

Considering abatement in absolute terms, optimal emission reductions averaged around 0.5 *tonne/TEU* for firms 1 to 4. Notwithstanding being subjected to a more lenient carbon budget constraint, firm 5 achieved the highest abatement levels in absolute terms regardless of the imposed cap. With the smallest fleet, this firm achieved an emission reduction of 0.8 *tonne/TEU* (abatement target < 38% relative to BAU emissions) and 1.2 *tonne/TEU* (abatement target > 38% relative to BAU emissions) under 23% and 44% slow steaming. Recall that throughout the simulation, *TEU* output was held constant across the carriers at 50.65 MTEU

Comparing firms 1 to 4 average abatement cost with slow steaming as the chosen climate strategy, the 4^{th} firm incurred the highest cost ($105\$/tonneCO2$), followed by 3 ($95\$/tonneCO2$), 2 ($74\$/tonneCO2$) and then 1 ($59\$/tonneCO2$) under a 28% speed reduction. In the BAU simulation, these carriers operated at similar speed levels and consequently possessed similar emission rates. This raises the following question - ***How do economies of scale affect firm-level average abatement costs, and will firms investing in larger vessels obtain a lower AAC under a slow steaming abatement policy?***. In theory, the cost of speed reduction in our analysis is driven by the additional ships needed to maintain the same service level. Figure 5.2 depicts total carriers' cost decreasing with vessel capacity, holding speed constant. Driven by the sector's economies of scale, total carriers' cost decreases with vessel capacity, ceteris paribus. Consequently, for firms with the same baseline speed levels (16 knots), the bigger the ship size for a given firm, the lower their AAC and in turn the smaller the incentive for policy infringement. In comparison, firm 5 operated at the simulated market's smallest scale and needed a higher baseline speed. Consequently, it generated the highest emission rates and otherwise had different optimal abatement and speed reduction levels. As a result, firm 5 incurred a relatively small cost of 0.8$/tonne CO_2 reduced for a 23% speed reduction under 1-38% emission reduction targets and a 66$/tonne CO_2 for more stringent policies (38% -40% reduction).

Consistent with the seminal work of Corbett et al. (2009) , our market's AAC for slow steaming falls within the range of $35–$200/tonne CO_2 for speed reductions greater than 20%. Leveraging the opportunity cost of forgone profits when accounting for extra ships to maintain service throughput allows us to better estimate the AAC of speed reduction when compared to fuel cost savings approaches. Otherwise, Corbett et al. (2009) offers that the marginal cost of slow steaming could be underestimated and below carbon market exchange prices. The average 2021 carbon price was estimated to be $53,55 Euro/tonne\ of\ CO_2$ (de Negociación de CO2, 2021). Assuming a 1.183 *US$*/ rate of conversion from the European Central Bank's (ECB) (council of the european union, 2022), the EU cap and trade market's carbon price is therefore estimated at $63.34 USD/tonneCO2$. Thus, inaugurating the sector into the European cap and trade market through the European Green Deal will render some carriers net buyers and others net sellers of carbon permits, depending on their fleet structure and optimal speed reductions %. Indeed, the updated 2021 EU plan "Fit for 55" for a green transition seeks to extend the ETS to the maritime sector with a minimum 40% target emission reduction by 2030 (council of the european union, 2022).

Overall, our all-singletons market simulation results are consistent with the industry's second type of slow steaming. The five maritime shipping firms in the simulation eventually slowed towards the lower operational limit of 12 knots, as it was more economically feasible to operate at those levels (Lotte, 2019). However, this behaviour is not sustainable and is typically only observed during global economic recessions, mainly driven by high bunker fuel prices (Figure 5.5).

Considering simulated firms' forgone profits relative to their BAU operations as their incentive for policy infringement under a 38-40% regulatory framework, the all-singleton market presents some likelihood of defecting that increases as firms' capacity decreases. Consequently, while slow steaming can be an effective policy for emission reduction because of the economics of ocean vessel fuel consumption, the likelihood of policy infringement during favourable market conditions and supply chain chaos remains imminent.

5.5.2 ILCC's Climate Strategies for a Grand Coalition Market : Cooperative Abatement Under Emission Caps

This research attempts to highlight the benefits of joint operational planning in the container shipping industry. In doing so, we investigate whether speed permit allocation within the coalition (market shipping alliance) helps its signatories sustain their emission budgets more cost-effectively than otherwise. Ultimately, we leverage a joint venture among the representative shippers in our simulation to investigate the potential of slow steaming within a coalitional setting under uniform carbon regulation.

Table 5.4 shows the simulation outcomes for the grand coalition, whereas Table 5.5 benchmarks the incentives for both market structures. In the grand coalition, representative carriers undertake slow steaming as a joint venture. In the face of uniform abatement regulation, they cooperate to sustain a joint carbon budget and maximise profits. This is perhaps not surprising because of the successful horizontal integration throughout the years within the industry. The already established market alliances call for more research on future joint emissions abatement efforts within the sector. But we note that given the nature of such externalities, the success of environmental policies will always hinge on firm-level strategic behaviour and decision-making.

Cooperation on speed reduction to sustain a uniform regulation allows firms with different baseline speed levels to pool resources and efficiently allocate speed reduction per vessel type to sustain a cost-effective slow-steaming policy. Under more lenient policies (emission reduction below 11%), the coalition leverages the heaviest emitter with the least cost of slow steaming, (here, firm 5) to meet its collective carbon budget, while the remaining signatories operate at their BAU levels with no cost of abatement. The coalition assigns heterogeneous

Table 5.4: Grand Coalition Market - Signatories. *Source: Author's compilation*

Abatement Target %	Firm 1		Firm 2		Firm 3		Firm 4		Firm 5
	{1-11}	{12-40}	{1-18}	{19-40}	{1-26 ; 34}	{27-33 ; 35-40}	{1-33}	{34-40}	{1-40}
Optimal Abatement (tonnes/TEUs)	0	0.52	0	0.51	0	0.50	0	0.53	0.8
Optimal Abatement (%)	0	43%	0	43%	0	43%	0	43%	38%
Optimal Speed Levels	16.67	12	16.67	12	16.67	12	16.67	12	16.67
Speed Reduction (%)	0	28	0	28	0	28	0	28	23
Carbon Emissions (tonnes/TEUs)	1.22	0.69	1.18	0.68	1.14	0.65	1.24	0.71	1.23
ITC $/TEU	0	31	0	38	0	47	0	56	0.6
ITC (%)	0	(13%)	0	(16%)	0	(22%)	0	(34%)	(0.6%)
AAC ($/ton CO2)	–	59	–	74	–	95	–	105	0.8
Optimal Sulfur Abatement (%)	0	48%	0	48%	0	48%	0	48%	41%

Firm-level output $= 50.65 MTEU$

Table 5.5: Simulation Markets Summary. *Source: Author's compilation*

Abatement Target %	All-Singleton Market		Grand Coalition Market					
	1-37.99	38-40	{1-11}	{12-18}	{19-26}	{27-33}	{34}	{35-40}
Optimal Abatement (%)	41 %	49%	11.1%	18.9%	26.4%	33.7%	34.2%	41.5%
Carbon Emissions (tonnes/TEUs)	0.792	0.695	1.204	1.099	0.997	0.898	0.892	0.792
ITC ($/TEU)	34	50	0.16	6	14	23	25	34
ITC (%)	(18%)	(26%)	(0 .08%)	(3%)	(7%)	(12%)	(13%)	(18%)
AAC ($/ton CO2)	61	77	0.8	25	39	51	54	61
Optimal Sulfur Abatement (%)	46	54	12	21	29	37	38	46

Market level output $= 253.27 MTEU$

speed per individual signatory characteristics, following the joint carbon quota. In doing so, the alliance distributes abatement costs among the signatories and allocates optimal abatement in the ascending order of the firms' AAC to equate these marginal benefits to marginal cost, optimizing the sum of its members' net present values (Table 5.4).

For all the simulated emission targets, the industry's cost of abatement remained smaller under a grand coalition than with an all-singleton market. Furthermore, the likelihood of policy adherence increases with the signatories coordinating their speed reduction. Thus, the coalition formulation allows society to sustain the goals of uniform regulation more cost-effectively and in the absence of an enforcement policy. . Ultimately, cooperation on abatement could allow society to reach industry goals at a lower cost, which in turn renders the policy more sustainable (Table 5.5).

In examining the potential success of self-enforcing environmental alliances, Figure 5.8 investigates firms' incentives to leave the grand coalition, illustrating d'Aspremont et al. (1983)'s *ITCM* equilibrium concepts introduced in Equation 2.4. Recall that ILCC's stability hinges on whether the alliance is both internally and externally stable. For the grand coalition, stability entails that no signatories have the incentive to leave the coalition, as they would receive a lower payoff by switching their membership decision. Regarding firms with the same baseline speed levels and similar emission rates, our findings indicate that signatories with smaller capacity fleets have an incentive to join a coalition under lenient policies. In essence, they get to free-ride on the bigger-sized-vessel firms' optimal abatement behaviour as well as speed reductions to reach the joint budget. However, as policies become more stringent, all firms would have to sustain a tighter carbon budget, converging towards their autarkic style of operations, where each firm leverages its own slow steaming to meet the joint target. We find that the tighter the emissions budget, the less room for free-riding behaviour through a joint speed reduction policy, and the stricter the emissions budget, the higher the likelihood of policy infringement. For stricter policies, firm 5 possesses the highest incentive to remain in the coalition, perhaps not surprising considering that this firms autarkic profit reduction was estimated at 81$/TEU when the abatement target exceeded 38% compared to a 0.6$/TEU as a signatory. Thus, our findings indicate that certain types of firms benefit from joint abatement efforts.

It's noteworthy to report that setting up a uniform carbon regulation for the shipping market induces a higher relative abatement in sulfur.

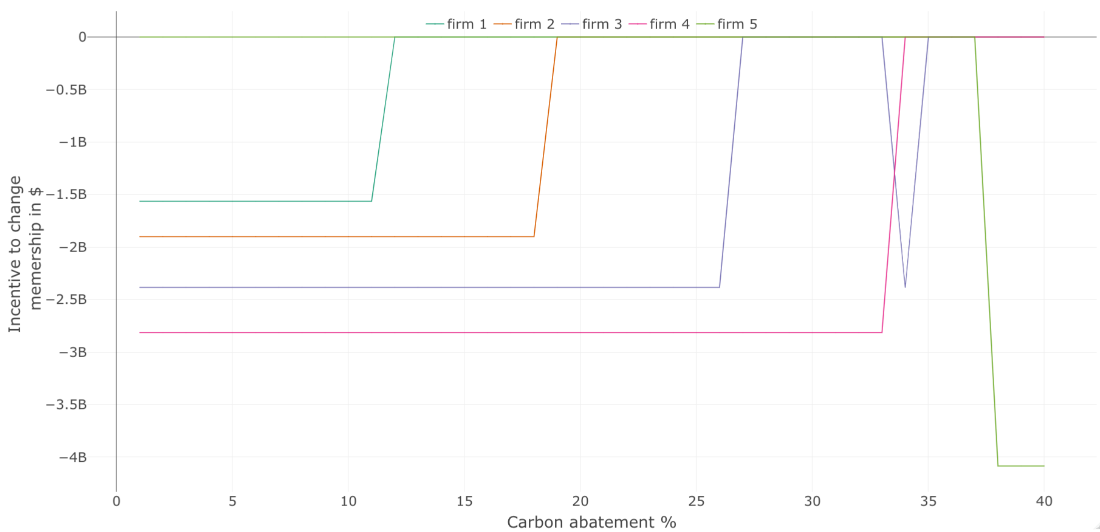

Figure 5.8: Incentive To Change Membership And Exit The Coalition. *Source: Author's compilation*

6

Summary And Implications

6.1 Introduction

This research introduced the structure and functional specification of a novel and flexible numerical simulation for the stability of industry-level climate strategies in maritime shipping. With the ongoing debate over the effectiveness of speed reduction as an abatement policy for container ships, the computational framework explored the relationship governing projected GDP growth, fuel consumption, speed levels and container ships emissions for different economies of scale while maintaining firms' annual throughput.

In short, we used the modelling framework to inform three research objectives; first, to understand firm-level incentives and climate strategies for the observed chosen sailing speed on the European–Far East service while considering different economies of scale investments; second, to examine the distinctions between slow steaming in a command and control regulation and speed optimisation as an abatement policy under emission caps; and finally, to explore whether these emission caps affect sustainability and firms' incentive to form a joint abatement coalition using sailing speed optimisation as the short term climate strategy to meet a joint carbon constraint.

We find that speed optimization not only conveys an effective climate strategy that withholds the potential to significantly curb the industry's emissions but, also provides firms with the flexibility to derive their optimal slow-steaming rates following their carbon budget constraint. On the other hand, speed reduction policies shift regulatory focus and are difficult to regulate when accounting for firms' and vessels' heterogeneity, market conditions and shipping routes. Finally, we show that industry-level climate strategies withhold the potential to improve environmental sustainability through cooperative abatement planning for ocean shipping.

6.2 Policy Implications

Considering the short-run simulations, speed optimisation provides an efficient climate strategy that holds the potential to significantly curb industry emissions. Firms convey incentives to slow down when economically feasible by evaluating the trade-off between their fuel savings and operating costs. In our simulation, we find that optimal speed levels vary with vessels' capacities and market conditions. Likewise, the impact of bunker freight rate fluctuations on the chosen speed and firms' bottom lines depend on their economies of scale investments. Considering the fundamental economies of scale theory, incurred costs diverged across the firms as we incremented firms' vessel capacities from 6k TEU to 14k TEU by 2k. The cost of slow steaming is induced by the forgone profits when ships operate at non-profit maximizing levels due to the acquisition of additional ships. Thus, ceteris paribus, firms with larger container ships are more likely to enjoy a competitive advantage and higher profit margins considering the speed limiter regulation debate. Undoubtedly, a uniform speed regulation impacts firms' profit margins and emissions differently because of the sensitivity of speed as a decision variable in carriers' operation management. Thus, firms would react to mandatory speed reduction policies with a range of optimal speeds and thus emission reduction estimates across the sector's diverse routes and container ships.

From a policy design standpoint, the stakeholders advocating for mandatory speed limits succeeded in convincing the IMO to incorporate both speed optimization and speed reduction as short-term prospect abatement measures in their initial strategy for curbing its industry's emissions, since it's an easy option to implement right away. Likewise, speed reduction policies are buttressed throughout the literature with scholars calling for mandatory speed limits. Apropos, Psaraftis (2019b) emphasises the widespread confusion within the slow-steaming publications and IMO submissions, where speed reduction is often examined as either "speed regulation", "mandatory speed limits" or the voluntary operation of slow steaming. Furthermore, the author alludes to the slow-steaming simulation literature often lacking context and baseline projections in the absence of slow steaming, with scholars assessing the effectiveness of the policy regardless of how % reductions are achieved. Consequently, how the IMO should leverage slow-steaming efforts to curb emissions still remains vague.

We, unlike most research efforts, distinguish between slow steaming as a regulation in itself and optimal slow steaming abatement to adhere to a uniform carbon budget constraint. We show that slow steaming embodied as a command and control policy, where the IMO enforces mandatory speed limits or speed reduction % relative to baseline operations, holds numerous shortcomings. Of these, we stress the difficulty associated with the identification of baseline speed levels and appropriate market benchmarks, the difficulty of enforcement and governance in a very heterogeneous international market and the policy's underlying repercussions of hindering innovation and distorting fair competition.

Speed reduction policies are sensitive regulations that should not be deployed ad-hoc and should factor in the heterogeneity of firms, vessels and shipping routes. We find that optimal slow steaming abatement under a market-wide uniform regulation situation provides firms with the flexibility to derive their optimal slow steaming rates in order to stay within the allocated carbon constraints. Under such a design, we consistently find that optimal abatement exceeds targeted abatement % because firms re-optimise their operations to sail at the lowest speed levels to burn the least amount of fuel when it's economically feasible to hold their fleet structure constant. Speed optimisation provides firms with the opportunity to trade carbon depending on the forgone profits of sustaining throughput with bigger fleets. Whether or not firms in the maritime industry would be net buyers or net sellers would depend on their speed reduction %, market conditions and the firms' investment in their fleets' economies of scale.

Considering stringent emissions caps, firms in the simulation converged towards the minimally feasible operational speed level, thereby mimicking the industry's second method of slow steaming, something mainly observed during economic recessions. Historic firm-level behaviour indicates that the likelihood of policy infringement during favourable market conditions and supply chain chaos would be imminent under such regulations. To mitigate, we draw from the international environmental agreement and green shipping literature in an attempt to promote joint abatement within and potentially among the industry's alliances. The main outcomes of this research are novel discussions of joint abatement in the maritime industry. Research on ocean alliances mainly investigated operational planning and hardly considered industry-level cooperation for environmental initiatives, when compared to other industries. Consequently, we note that the successful horizontal integration throughout the years within the industry call for more research on joint abatement endeavours.

In theory, the extant joint operational centres among the maritime shipping alliances should readily allow representative carriers to undertake slow steaming as a joint venture. Thus, in the face of a uniform abatement regulation, firms should cooperate to sustain a joint carbon budget constraint. In this simulation, we confirm that the cost of abatement decreases for signatories when joining the coalition, and the overall likelihood of policy adherence increases when signatories coordinate their speed reduction. Cooperation on speed optimisation to sustain a uniform regulation allows the firms with different baseline speed levels to pool resources and properly allocate speed reduction per vessel type to sustain a cost-effective slow steaming policy. Thus, industry-level climate strategies withhold the potential to improve environmental sustainability through cooperation for ocean shipping.

6.3 Research Limitations

To date, most maritime research remains governed by restrictive assumptions and simplifications. Likewise, the design of the Industry Level Climate Coalitions (ILCC) simulation framework has been limited by scope and market data availability. Hence, consistent with all numerical simulation analyses, the overall generalizability of these findings ought to be examined with some degree of caution because of the important limitations of this research.

First, the simulation environment assumes exogenous freight rates and therefore ignores the repercussions of slow steaming on trade. Likewise, longer transit times could potentially induce all sorts of market and just-in-time supply chain distortions. For example, short-run implications might include higher freight rate prices and consumer passe through with the decrease in the aggregate supply.

Second, slow steaming is only effective in curbing the industry's projected emission growth, if they are carried out during supply chain chaos and a booming economy. Albeit, historic patterns indicate that shippers would slow steam anyway during economic recessions and high fuel prices.

Other simplifications include underestimating the cost of slow steaming. Sailing at a reduced speed, in the long run, could potentially damage the ship and impact its life expectancy and increase its depreciation rate (Lotte, 2019). Moreover, the cost of slow steaming is contingent on inventory costs and time windows. For example, perishable goods might not withstand longer transit time, while high-valued commodities might warrant higher operational speed. Such constraints might lead firms to rearrange supply chain networks and potentially shift transport modal towards faster more polluting modes.

6.4 Future Research

There are several areas for future research. We could investigate the limitations of the simulation framework or leverage it for multiple simulations with different parameters. Advancements to the empirical estimates of the climate game include developing a route-specific container ship forecasting model linking GDP growth, slow steaming and market distortions induced by longer transit time. The rationale used here for developing a profit maximisation model , rather than a cost minimisation, provides flexibility and motivation for future research, namely for analysing the relationship between abatement and potential tax or rate pass-through under an emission cap. Likewise, a focus on profits allows the researcher to explore any ongoing substitution away from maritime shipping along with the potential impact of slow steaming on international trade.

Furthermore, considering the limited data availability for firm-level service, trade and fleet characteristics for the container shipping sector, other endeavours could acquire more data to model firms with heterogeneous fleets, market shares and vessels' capacity. Such avenues would convey a more accurate depiction of the current state of the market and alliances. One could also extend the design of the coalition to allow for vessel pooling and sharing within a coalition under an emission cap.

Another area of research is to build on the simulation and investigate optimal design mechanisms for carbon quota allocation amongst heterogeneous firms and/or even extend the framework to model slow steaming under an emission trading scheme. Likewise, they could also integrate regulatory oversight in the form of a dynamic taxation policy scheme. Such avenues would render the cooperative game into a non-cooperative game of dynamic pollution, whereby numerically solving firms' climate strategy would provide a novel contribution to the literature. The dynamic design would stem from regulators adjusting their rate per changes in the industry's fuel consumption, thereby, internalising the feedback loop that arises from firms' strategic behaviour, with the aim of inducing a more stable coalition. After all, the success of environmental policies will forever hinge on firm-level strategic behaviour.

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A

Evolutionary Genetic Algorithm and implementation

[4] The modern theory of evolutionary computing is grounded in Darwin's (1859)'s principle of natural selection and Mendel (1865)'s research on genetics. The algorithm structure lever-

[4]For a thorough depiction of the ILCC simulation algorithms, the reader may wish to visit https://github.com/feryellassoued/UOS_MSC_project/tree/master/Average_Speed

ages the genetic evolution of well-adapted "species" from one generation to another (Mendel, 1865), that are more likely to survive and reproduce in a given environment when compared to less adapted individuals (Darwin's, 1859). The implementation of such algorithms changes from one problem to another, given that the GA's design is driven by the set and choice of parameters. In any case, Kelly Jr and Davis (1991) states that all implementation of GA's must convey a selection, crossover, mutation and a fitness evaluation procedure to find robust and consistent results. In implementing this in the context of the current research, our evolutionary process can be summarised via the following:

1. **Chromosome Encoding & Initial Population** : The researcher begins by identifying and encoding genetic information governing decision variables. This genetic information simulates human chromosomes, the foundation of the algorithm. The GA encodes various chromosomes or types, which are often represented as binary variables. However, other data structures can also be appropriate according to the scope of the problem. Chromosomes are encoded within simulated individual units, which in turn are bred together to eventually yield a solution to the problem. The set of offspring per generation would then form a population over which to evaluate fitness, and so on for each generation (Johansson & Evertsson, 2003).

   To spawn the initial population of $\psi = 1000$ individuals, we first identify appropriate speed levels and vessel sizes as our model's baseline "chromosomes". In doing so, we randomly generate ψ speed levels for individuals $CV^r_{i,k}$ $\forall k \in 1, .., \psi$, indexed by k within the current population and bounded by firm i's minimum and maximum speed levels, through a random draw from a uniform distribution, and upon which, we encode for each market participant i 's fleet size chromosome CN^r_i from CV^r_i per our derived structural equation. Note that all derived chromosomes must adhere to the model's constraint.

```
def generate_chromo(firm: Firm) :
    chromo = np.random.uniform(firm.min_speed, firm.max_speed)
    return chromo
def generate_population(firm:Firm, size: int ):
    return np.array([generate_chromo(firm) for _ in range(size)])
```

2. **Elitism & initial population fitness evaluation**

   We evaluate the first-generation fitness following our shippers' optimisation problem/objective function and implement the notion of ”elitism” by preserving the current population's top 2 fittest (highest objective value) chromosomes. The chosen speed levels and fleet sizes are then transitioned over to the next generation, without any genetic alteration.

3. **Evolution Procedure & Termination Criteria**

   We initiate our evolutionary process and spawn the next generation until we reach our generation limit (calibrated for 2000) or until we meet our convergence criteria (code xx).

```
    def fitness_similarity_chech(max_fitness, number_of_similarity):
    result = 0
    similarity = 0
    for n in range(len(max_fitness)-1):
        if np.round(max_fitness[n], 3 ) == np.round(max_fitness[n+1],3):
```

```
            similarity += 1
        else:
            similarity = 0
    if similarity == number_of_similarity-1:
        result = 1
    return result
```

As the population evolves from one generation into another, the evolutionary procedure follows these steps:

(a) **Selection Subroutine**

This stage of the evolutionary process encompasses nature's survival of the fittest ideology. It assists the GA in navigating the search space towards a more favourable region. Chromosomes with high fitness valuation from the current population are identified for breeding and flagged to generate a mating pool for the next generation (iteration). Relevant research identifies numerous selection models and various derivatives. The most notable procedures are known as Boltzmann selection, ranking selection, roulette-wheel selection, tournament selection and elitist selection (Applegate, Bixby, Chvátal, & Cook, 2003).

In this study, however, we leverage roulette-wheel selection, also known as the fitness proportionate selection procedure - a very frequently used specification in the GA literature. This model warrants non-negative objective valuation in order to scale the function and is driven by the chromosome fitness level. In doing so, it imposes a normalisation procedure that divides individual fitness levels by the population's sum of fitness levels and is then implemented as a probabilistic draw, through a relative fitness assignment of $P(CV^r_{i,k}) = \frac{f(CV^r_{i,k})}{\sum_{i=1}^{n} f(CV^r_i)}, \forall\ CV^r_{i,k}$, where f denotes the fitness function evaluated for each chromosome in the generation (Back, Hammel, & Schwefel, 1997). Consequently, $P(CV^r_i)$ represents the selection probability of each individual $CV^r_{i,k}$, ensuring that better-fitted chromosomes convey a higher survival rate and mating probability as the population evolves from one generation into another. Finally, we also randomly sample the 2 parent chromosomes $\{CV^p_1, CV^p_2\}$ from the distribution without replacement.

```
def selection_pair (population: Population, fitness_func: FitnessFunc,
    weights: list):
   weights = np.asarray(weights).astype('float64')
   weights = weights / np.sum(weights)
   return np.random.choice(np.hstack( population), size = 2,
       replace=False, p= weights)
```

(b) **Mutation & Crossover Subroutine**

The evolutionary process of a genetic algorithm maps a population that must evolve and become better and better with each generation. However, the most efficient mechanism to develop superior populations is through finding the right balance between exploitation and exploration of the search space. This process is carried out through so-called mutation and crossover procedures. On one extreme, a design scheme that only considers crossover operations will not properly explore the genetic material space and the algorithm might end up getting stuck in local optima. On the other hand, evolving through mutation alone will destroy useful information from the superior individuals and will, in theory, be more of a random search heuristic than an evolutionary algorithm (Spears, 1993). Hence, the need for both operators.

Eshelman and Schaffer (1993)'s blend crossover ($BLX - \alpha$) procedure coveys excellent search capacity in real-coded genetic algorithm designs (Takahashi & Kita, 2001). Crossover mainly aims at merging the chosen 2 fit individuals from the previous step (i.e., the parents $\{CV_1^p, CV_2^p\}$), which produce new genetic material contained within the two offspring $\{CV_1^{of}, CV_2^{of}\}$

$BLX - \alpha$ generates the offspring through a random draw from an interval that not only contains the parents but also extends the real number line beyond these thresholds, following a researcher-specified parameter α. (Eshelman & Schaffer, 1993). In this design, we follow the work of Eshelman and Schaffer (1993) and leverage a $BLX - 0.5$ ($\alpha = 0.5$) to construct the interval and randomly draw out the 2 offspring from $\{CV_1^{of}, CV_2^{of}\}$. Analytically, the derivation of the upper and lower bound of the mating pool is defined by :

$$\begin{cases} CV_1^{of} = \min\{CV_1^p, CV_2^p\} - \alpha \times d_i \\ CV_2^{of} = \max\{CV_1^p, CV_2^p\} + \alpha \times d_i \\ d_i = |CV_1^p - CV_2^p| \end{cases} \tag{A.1}$$

```
def BLX_alpha_crossover (a: Chromo, b: Chromo, firm, sim_game) :
   lower = (min(a,b)) - ( (0.5) * (max(a,b) - min (a,b)))
   upper= (max(a,b)) + ( (0.5) * (max(a,b) - min (a,b)))
```

```python
    lower= firm.min_speed if (lower < firm.min_speed) else lower
    upper= firm.max_speed if (upper > firm.max_speed) else upper
    child = np.random.uniform (lower, upper, 2)
    return child
```

Once offspring have been identified, we proceed with a Gaussian mutation, which has been shown to be a promising mutation procedure for real coded GA (Fogel & Atmar, 1990). With a chosen probability, say a mutation rate of 0.05, we distort the genetic information of the offspring to prevent the population from stagnating at a local optimum and further update the fitness values of the two offspring following our shippers' optimization problem and fitness evaluation coding.

```python
def mutation(chromo: Chromo, firm: Firm, sim_game, variance: float,
     probability: float = 0.1 ) :
    mutated_chromo = np.random.normal(chromo, variance, 1) if
        random.random() > probability else chromo
    mutated_chromo = firm.min_speed if mutated_chromo < firm.min_speed
        else mutated_chromo
    mutated_chromo = firm.max_speed if mutated_chromo > firm.max_speed
        else mutated_chromo
    return mutated_chromo
```