Co-opetition On The Seven Seas

Global Strategic Alliance In The Container Shipping Industry

Anhua Chen

anhua_chen@g.harvard.edu

March 5, 2025

Abstract

Global strategic alliances have become a defining feature of the container shipping industry, allowing firms to pool resources and coordinate operations to achieve efficiency gains. However, these alliances also raise concerns about their potential to limit competition and enhance market power. This paper examines the formation and dissolution of global strategic alliances in the container shipping industry, with a particular focus on the 2M Alliance between Maersk and MSC. Using empirical data and a multi-market Cournot oligopoly model with capacity constraints, we analyze the incentives behind alliance formation, the efficiency gains from vessel reallocation, and the impact on market competition and consumer welfare. The findings reveal that vessel reallocation plays a crucial role in enhancing supply-side efficiency, but the extent of these gains depends on the comparative advantage of alliance members and aggregate market conditions. Counterfactual simulations demonstrate that alliances can increase efficiency and consumer welfare when members have distinct fleet compositions, but they may also enhance market power under certain conditions. The study concludes with policy implications regarding the regulation and long-term viability of global strategic alliances in the shipping industry.

Keywords: Oligopoly, Innovation, Market Power, Transportation, International Trade

JEL Codes: L13, O31, L13, R40, F13

1 Introduction

Global strategic alliances have become a defining feature of many industries, including airlines, automotive manufacturing, and container shipping. These alliances typically involve some form of supply-side coordination, such as code-sharing in airlines, joint production ventures in the auto industry, and vessel-sharing agreements in container shipping. By pooling resources and coordinating operations, firms seek to achieve efficiency gains that would be difficult to realize independently. However, these alliances have also drawn increasing scrutiny from antitrust regulators due to their potential to limit competition. For instance, the Northeast Alliance between American Airlines and JetBlue was recently blocked by the U.S. Department of Justice on antitrust grounds, while the expiration of the Consortia Block Exemption Regulation (CBER) in the European Union has raised concerns over the future regulatory landscape of container shipping alliances. As these alliances reshape global markets, understanding their incentives, market power effects, and welfare implications becomes increasingly critical.

This paper examines the incentives behind the formation and dissolution of global strategic alliances in the container shipping industry and evaluates their welfare implications. Specifically, it seeks to disentangle the market power and efficiency effects of strategic alliances, and to evaluate their economic impact. The study investigates the primary sources of efficiency gains, such as vessel reallocation, which enhances supply-side efficiency by deploying different vessel classes to markets where they operate most effectively. It also examines how market power and efficiency considerations influence the stability of alliances, exploring whether firms primarily seek these partnerships to increase their cost competitiveness or to gain strategic advantages. Additionally, external factors such as demand fluctuations and the comparative advantage of alliance members are analyzed to understand their role in alliance stability. Finally, the study contrasts the welfare implications of alliances with those of horizontal mergers, highlighting their different impacts on market competition and consumer surplus.

To address these questions, this paper first presents stylized facts about vessel size distribution across different markets, illustrating the existence of varying economies and diseconomies of scale. The analysis documents how the 2M Alliance, formed between Maersk and MSC, led to a reallocation of vessel sizes across trade routes. By strategically deploying different vessels to routes where they are most cost-effective, alliance members can improve efficiency and capacity utilization.

The paper then develops a multi-market Cournot oligopoly model that incorporates capacity constraints across different vessel classes, providing a structural framework to analyze alliance formation. The equilibrium concept is discussed, and a toy example is introduced to illustrate how vessel reallocation enhances efficiency. The model is estimated using a rich dataset on container trade volumes, freight rates, and vessel deployments. The estimation strategy, detailed in the paper, estimates demand and supply-side parameters, ensuring the model accurately reflects observed market behaviors and capacity allocation decisions of carriers. Finally, counterfactual analyses simulate alternative alliance configurations to quantify the effects of alliance formation and dissolution, providing insights into the trade-offs between efficiency and market power.

The findings reveal significant heterogeneity in economies of scale across markets. In long-haul routes, such as those between Asia and Northern Europe, larger vessels achieve substantial cost savings due to economies of scale. Conversely, in shorter routes like trans-Atlantic trade, the benefits of larger vessels diminish, as port congestion and infrastructure limitations erode potential cost advantages. The counterfactual analysis demonstrates that the 2M Alliance led to substantial efficiency gains through vessel reallocation, lowering operational costs and increasing consumer surplus. However, it also enhanced market power, reducing competition in certain markets. Notably, the study finds that the dissolution of the 2M Alliance in 2023 was driven by growing asymmetry between Maersk and MSC. As MSC expanded its fleet and surpassed Maersk in capacity, the alliance became less mutually beneficial, prompting its termination.

The paper also explores how changes in comparative advantage influence alliance stability. When alliance members have distinct fleet compositions, the efficiency benefits of cooperation are more pronounced, increasing the likelihood of alliance formation. However, as fleet compositions converge, the efficiency rationale for maintaining an alliance weakens, making dissolution more probable. Additionally, the analysis shows that aggregate demand conditions play a critical role in alliance incentives. In periods of low demand, alliances are more likely to form as firms seek to consolidate market power to sustain profitability. In contrast, when demand is high, the efficiency gains from vessel reallocation become the dominant driver of alliance formation.

These findings have important policy implications. While alliances can generate substantial efficiency benefits, their potential to enhance market power warrants close regulatory scrutiny. Unlike mergers, alliances are inherently less stable and may dissolve as market conditions change. This natural instability can mitigate some anti-competitive concerns but also raises challenges in assessing their long-term impact on welfare. Policymakers should carefully evaluate the degree of comparative advantage among alliance members when assessing their potential benefits. If alliance members have similar fleet compositions and market positions, the argument for efficiency gains becomes weaker, suggesting that regulatory intervention may be necessary to prevent anti-competitive outcomes.

Related Literature This paper contributes to the vast maritime economics literature on the incentive and impact of global strategic alliances. Ghorbani et al. (2022) provides a systematic review over the literature, and pointed out that economies of scale in vessel size, economies of scope in geographic coverage, and increasing capacity utilization are among the main incentives for carriers to form strategic alliances (See Song and Panayides (2002), Panayides and Wiedmer (2011), Caschili et al. (2014), Cruijssen et al. (2007)). Our paper quantitatively estimates the extent of (dis-)economies of scale of vessel sizes across major trade lanes, and show that reallocation of vessel of different sizes across market improves alliance members' supply side efficiency. The literature (Das (2011), Agarwal and Ergun

(2010), Prashant and Harbir (2009) and Mitsuhashi and Greve (2009)) shows that market complementarity, mainly depending on ship specifications, is a major factor in carriers' alliance partner selection. We show that carriers with larger difference in their comparative advantage in terms of vessel size distribution have larger incentive to form alliance and alliance is more stable.

Given the similarity of strategic alliance and horizontal mergers, this paper also contributes to the literature examining the reallocation of assets and capacities resulting from mergers.[1] Andrade and Stafford (2004) analyze how mergers serve as mechanisms for reallocating existing assets within industries. They find that mergers can either facilitate industry expansion by increasing firms' size and scale or lead to a reduction in the industry's asset base by eliminating duplicate functions and rationalizing operations. Jovanovic and Rousseau (2008) model mergers as reallocation waves, suggesting that mergers spread new technology similarly to the entry and exit of firms. They argue that mergers play a crucial role in reallocating capital, especially during periods of significant technological advancements. Demirer and Karaduman (2024) study the effects of mergers and acquisitions on efficiency within the U.S. power generation industry. They find that acquisitions lead to an efficiency increase in acquired plants, primarily through operational improvements rather than high-cost capital investments. This suggests that mergers can reallocate assets to more productive uses, enhancing overall efficiency. Our paper contributes to this strand of literature by showing a clear case of global asset reallocation in the container shipping industry where comparative advantage of different assets differ across markets.

[1] We explained in detail later in the model section on the difference between horizontal merger and strategic alliances.

2 Data, Institution and Stylized Facts

2.1 Strategic Alliance and Container Shipping Industry

The container shipping industry has undergone a significant transformation from the traditional conference system to the current alliance framework.[2] Historically, shipping conferences—formal agreements among shipping companies—regulated freight rates and coordinated schedules to stabilize the market. However, concerns over anti-competitive practices led to regulatory changes, notably the U.S. Ocean Shipping Reform Act of 1998 and the European Union's repeal of conference exemptions in 2008, which diminished the influence of these conferences. In response, shipping companies began forming strategic alliances in the mid-1990s, allowing them to share vessels and optimize operations without engaging in price-fixing. These alliances enable carriers to offer extensive service networks and achieve economies of scale by pooling resources. Strategic alliances are particularly crucial in the container shipping industry due to high operational costs and the need for global service coverage. By collaborating, carriers can reduce expenses, enhance service frequency, and improve capacity utilization.

The evolution of global alliances in the container shipping industry can be categorized into four distinct generations (See Figure 1 for a visual summary from updated graph of Talley (2011))[3]:

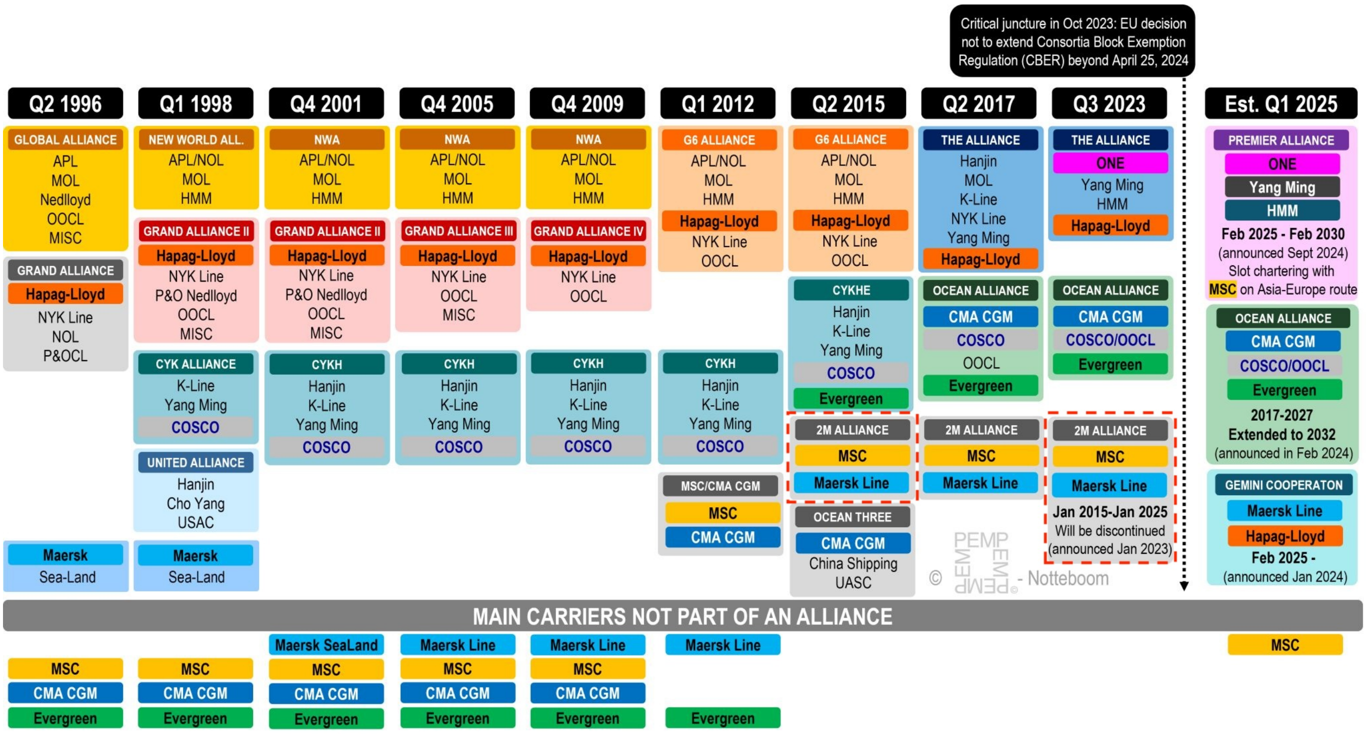
- **First Generation (1996–1998)**: This period saw the emergence of ambitious alliances such as the Global Alliance, Grand Alliance, and the partnership between Maersk and SeaLand. Despite their expansive goals, these alliances were often unstable and short-lived.

- **Second Generation (1998–2012)**: Alliances like the New World Alliance, Grand Alliance, and CKHY characterized this era. These partnerships provided stability

[2] For relevant work, please see Merk (2018), Lim (2020) and Wang (2015). For a review paper, please see Ghorbani et al. (2022).

[3] This categorization of four generations of alliance is from Merk (2018).

Figure 1: Timeline of Global Strategic Alliance



Source: Updated from Notteboom, T. (2012), Chapter 12: Container shipping, in: Talley, W. (ed.), The Blackwell Companion to Maritime Economics, Wiley-Blackwell Publishing, ISBN: 978-1-4443-3024-3, pp. 230-262.

and were predominantly utilized by mid-sized and smaller carriers, allowing them to enhance service offerings and operational efficiencies.

- **Third Generation (2012–2017)**: During this phase, major carriers began participating in alliances, leading to formations such as G6, CKHYE, 2M, and O3. This transition period experienced fluctuating alliance structures, reflecting the industry's efforts to adapt to changing market dynamics.

- **Fourth Generation (2017–Present)**: The current landscape features three primary alliances: 2M, Ocean Alliance, and THE Alliance. Notably, no single carrier dominates these alliances, and they collectively encompass the eight largest global carriers, representing a significant consolidation in the industry

Our data sample mainly covers the third and fourth generation of the strategic alliances in the container shipping industry, where carriers formed alliances in pursuit of economies of scale in vessel size, and economies of scope in coverage, and to improve their capacity utilization, especially with the arrival of ultra large or mega vessels.

2.2 Data

Our empirical analysis is based on two primary datasets. Our first key data source is the weekly capacity and vessel deployment dataset from Sea Intelligence.[4] This dataset provides information on the vessel size of the fleets operated by different firms and alliances, as well as the ownership data of vessels. It provides us with measure of vessel size distribution for both capacity and quantities supplied across markets for each carriers and alliances and also market share information. Second, we use monthly container trade flow volume and price index data from CTS to estimate the demand for container shipping services. This dataset covers 22 origin-destination subregional trade flows, aggregated from more granular monthly port-to-port shipping manifest information. Additionally, we obtained origin-destination container price indices at the subregional level. A key advantage of this price index is that it reflects the *actual* freight rates paid by shippers to carriers, incorporating both spot freight rates and contractual rates.[5]

2.3 Stylized Facts

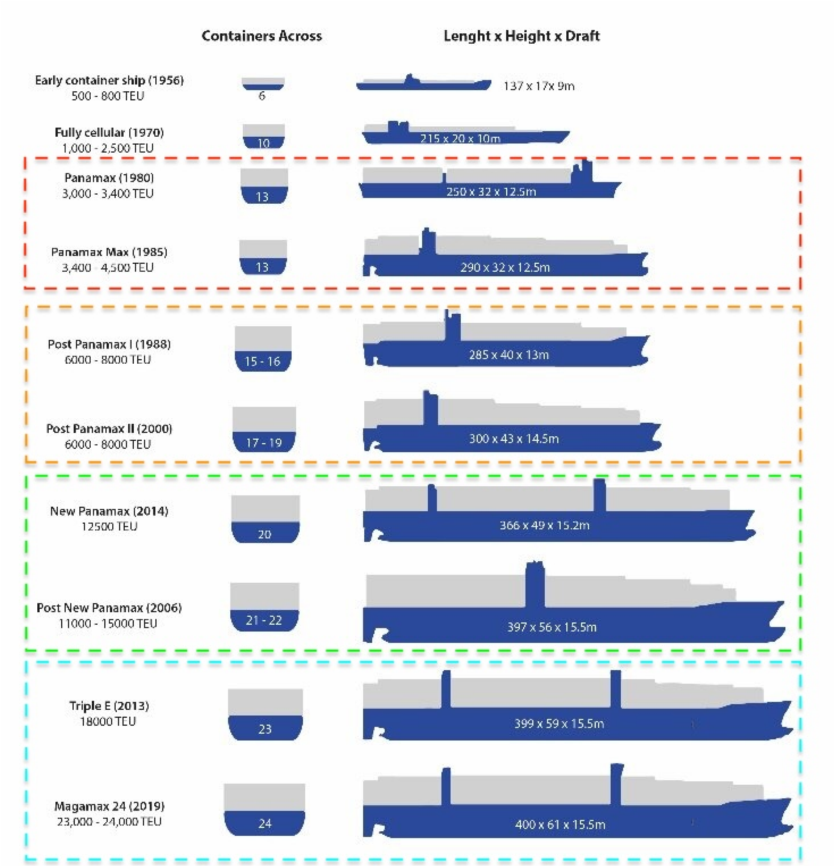
Vessel Size Distribution Across Markets Container ship sizes have grown significantly since the introduction of containerized shipping in the 1960s. As shown in Figure 2, container vessels can be broadly categorized into four size classes:

[4] Sea Intelligence uses this dataset in its flagship TCO reports.

[5] In the container shipping industry, spot freight rates are commonly referred to as "Freight of All Kinds" (FAK), while contractual rates are referred to as "Named Account" (NAC). Because the price index is derived from the *universe* of shipping manifests, it provides a comprehensive and realistic representation of transportation costs by combining spot and contractual rates.Due to legal and regulatory concerns, container shipping freight rate data is rare and difficult to obtain. Excessive disclosure of freight rate information could facilitate tacit collusion or coordinated pricing among carriers. As a result, we rely on an aggregated measure of freight rates, as carrier-specific prices are strictly prohibited from being disclosed by CTS. Wong (2022) also highlights the significant challenges in accessing detailed container shipping freight rate data. However, further insights into carriers' pricing behavior using more detailed proprietary data are provided in the author's other work with logistics technology firms.

1. Panamax (2,000 - 5,000 TEU)
2. Post-Panamax (5,000 - 10,000 TEU)
3. Neo-Panamax (10,000 - 14,500 TEU)
4. Ultra-Large Container Ships (14,500 - 24,000 TEU)

Figure 2: Container Vessel Size Comparison



We define a market broadly as a trade route between an origin region and a destination region. Based on this classification, the global container shipping market consists of the following key trade routes:

- Far-East-West-Bound (FEWB): Asia to Mediterranean, Asia to Northern Europe
- Trans-Pacific-East-Bound (TPEB): Asia to North America West Coast, Asia to North America East Coast

Figure 3: Vessel Size Distribution Across Markets

- Trans-Atlantic: Northern Europe to North America East Coast

Figure 3 presents the distribution of vessel size classes across markets over time. By the mid-2010s, the Asia to Northern Europe market was dominated by ultra-large vessels, while the Asia to Mediterranean market was primarily composed of Neo-Panamax vessels. On trans-Pacific routes, Post-Panamax vessels became the predominant class, whereas smaller vessels were mostly used in trans-Atlantic trade.

One key factor driving these differences in vessel size distribution is the economies and diseconomies of scale associated with vessel size. Larger vessels benefit from economies of scale at sea, as crew and fuel costs do not increase proportionally with vessel size. However, port infrastructure constraints can increase operational costs for larger vessels due to longer berthing, loading, and unloading times. As shown in Table 1, sea distances are significantly longer on FEWB trade routes and shortest on trans-Atlantic routes. This pattern is consistent with the observation that larger vessels are primarily deployed on long-haul routes where economies of scale are most advantageous.

Table 1: Approximate Sea Distances and Transit Times by Trade Route

Trade Route	Distance (nautical miles)	Main Route	Transit Time (days)
Asia to Northern Europe	10,500 – 12,000	Suez Canal	30 – 40
Asia to Mediterranean (West)	8,500 – 10,500	Suez Canal	25 – 35
Asia to Mediterranean (East)	7,500 – 9,000	Suez Canal	25 – 35
Asia to North America (West Coast)	5,500 – 7,000	Trans-Pacific	14 – 18
Asia to North America (East Coast) (via Panama)	10,500 – 12,000	Panama Canal	25 – 35
Asia to North America (East Coast) (via Suez)	12,000 – 13,000	Suez Canal	25 – 35
Trans-Atlantic (North America to Europe)	3,000 – 4,500	Direct Atlantic	8 – 12

The Case of 2M Alliance To analyze how the formation of a global strategic alliance affects the operations of its members, we use the 2M Alliance as a case study. Established in 2015, the 2M Alliance was a long-term vessel-sharing agreement between Maersk Line and MSC (Mediterranean Shipping Company), the two largest container shipping carriers at the time. The alliance was formed in response to industry overcapacity, declining freight rates, and the need for cost efficiencies following the global financial crisis and slowing global trade growth. By pooling their fleets, Maersk and MSC aimed to optimize network efficiency, reduce operational costs, and enhance service reliability on key East-West trade routes, particularly between Asia, Europe, and North America.

At the time of the alliance's formation, Maersk and MSC had distinct fleet compositions. As shown in Figure 4, MSC operated a higher proportion of mid-to-large-sized vessels, while Maersk had a comparative advantage in smaller vessels. To assess how the vessel size distribution changed after the alliance, we compare the fleet compositions of Maersk and MSC in 2014 (pre-2M formation) and 2016 (post-2M formation) in Figure 5.

Prior to the 2M Alliance, Maersk allocated a significant share of its smaller vessels to the Asia-Northern Europe (Asia-NEUR) market, where demand was high, despite larger vessels being more cost-efficient due to economies of scale. After the alliance was established, Maersk's smaller vessels were reallocated to the Asia-North America East Coast (Asia-NAEC), Asia-North America West Coast (Asia-NAWC), and Northern Europe-North America East Coast (NEUR-NAEC) markets, where they could operate more efficiently. Meanwhile, the alliance restricted deployments in the Asia-NEUR market to vessels larger than 12,000 TEU. This case illustrates how forming a global strategic alliance enables carri-

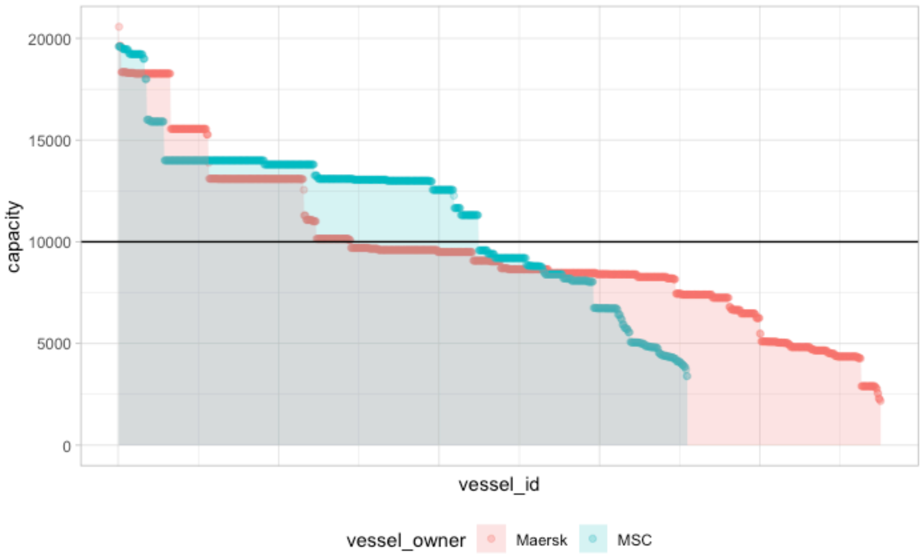


Figure 4: Maersk vs MSC Fleet in 2015

ers to optimize fleet deployment by reallocating vessels to markets where they operate most efficiently.[6]

The shift in vessel size distribution is also reflected in the number of services operated by Maersk and MSC. As shown in Figure 6, the number of services in the Asia-NEUR and Asia-Mediterranean (Asia-MED) markets decreased as larger vessels were deployed in these regions, while the number of services increased in other markets where smaller vessels were more suitable after the formation of the 2M Alliance.

3 Model

3.1 Demand

We assume a log-log demand for each market m at time t:

$$Q_{mt} = A_{mt} P_{mt}^{-\sigma} \tag{1}$$

[6] The reallocation of vessel size is further reflected in the shift in the market share contributions of Maersk and MSC across different regions, as shown in Figure 15 in Appendix A.

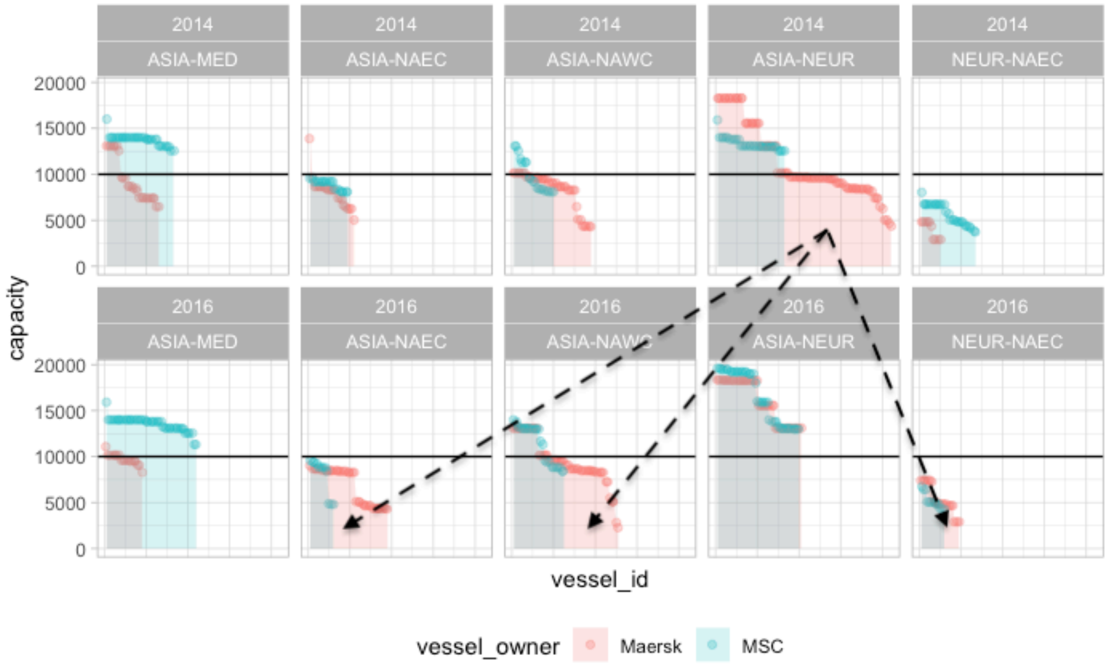
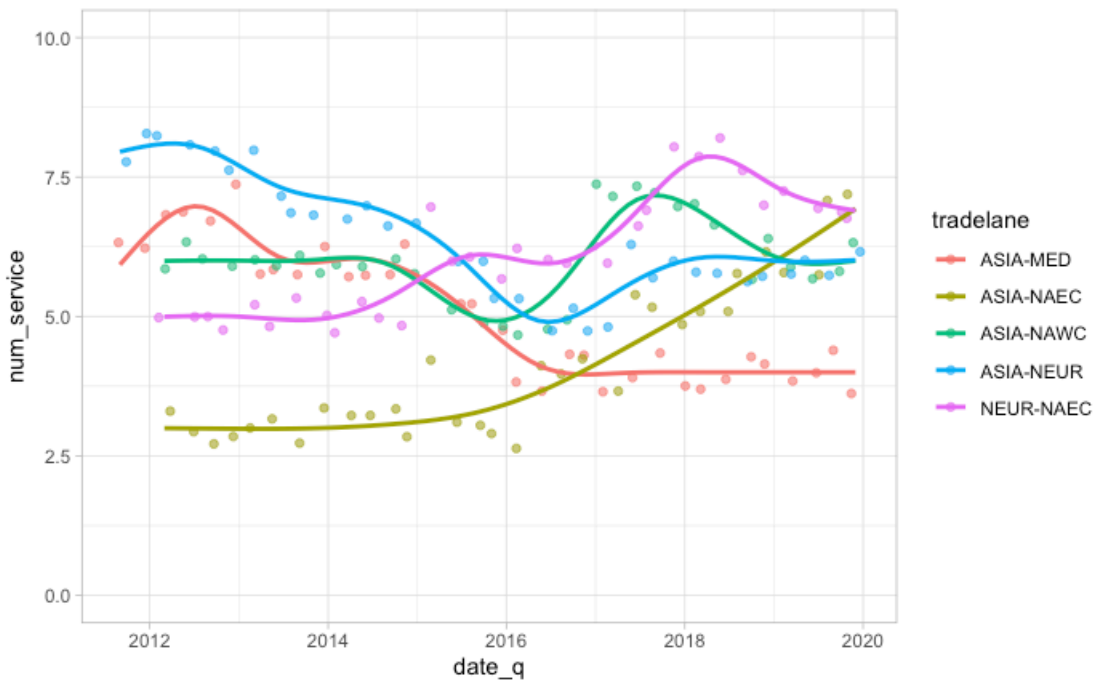


Figure 5: Maersk vs MSC Fleet: 2014 vs. 2016

Figure 6: Number of Services Over Time: 2M Alliance



where A_{mt} is the market-month specific demand shifter. P_{mt}, Q_{mt} are the price and quantity in market m at time t respectively and σ is the constant price elasticity of demand across markets and time.

3.2 Supply

Fleet Capacity Allocation We assume carriers engage in a multi-market quantity-setting game. Carrier$i$ needs to allocate their fleet capacity across different vessel size and across different trade lanes. We summarize their quantity allocation in the following matrix $\boldsymbol{Q}$

$$\underset{|\Phi^i|\times|\mathcal{M}^i|}{\boldsymbol{Q}^i} = \begin{bmatrix} q^i_{m_1}(\phi_1) & \dots & q^i_{m_{|\mathcal{M}|}}(\phi_1) \\ \vdots & \ddots & \vdots \\ q^i_{m_1}(\phi_{|\Phi|}) & \dots & q^i_{m_{|\mathcal{M}|}}(\phi_{|\Phi|}) \end{bmatrix} \tag{2}$$

Each row of $\boldsymbol{Q}$ represents each vessel-size-bin (e.g., Panamax-class, Neo-Panamax-class, ultra-large-class), and each column represents each market carrier i operates in. Carrier i has a capacity constraint for each type of vessel

$$\boldsymbol{Q}^i\mathbf{1} \leq \boldsymbol{\kappa}^i(\Phi^i) \tag{3}$$

where $\mathbf{1}$ is a vector of 1, and $\boldsymbol{\kappa}^i$ is a $|\Phi^i| \times 1$ vector representing carrier i's capacity constraint across different types of vessels. Φ^i represents the range of vessel size in carrier i's fleet. Purchasing larger ships will result in higher Φ^i.

Variable Costs We assume the variable cost of carrier i's fleet is a function of its quantity allocation $\boldsymbol{Q}^i$ and a cost matrix depending on the vessel size and specific market $\boldsymbol{C}$:

$$\underset{|\Phi|\times|\mathcal{M}|}{\boldsymbol{C}} = \begin{bmatrix} c_{m_1}(\phi_1) & \dots & c_{m_{|\mathcal{M}|}}(\phi_1) \\ \vdots & \ddots & \vdots \\ c_{m_1}(\phi_{|\Phi|}) & \dots & c_{m_{|\mathcal{M}|}}(\phi_{|\Phi|}) \end{bmatrix} \tag{4}$$

Each row of $\boldsymbol{C}$ represents vessel-size bin, and each column represents a market. We assume each variable cost can be decomposed into a market-time specific component and a vessel size component capturing the (dis)economies of scale.

$$\log(c_{mt}(\phi)) = \underbrace{\gamma_{mt}}_{\text{market-time specific component}} + \underbrace{h(\phi, m)}_{\text{vessel-size component}} \tag{5}$$

where γ_{mt} is a market-time specific fixed effect, which captures the market-specific supply factors beyond vessel size that could change the variable cost of the shipping. For example, any disruption like the Suez canal being blocked by Evergiven or Houthi's attack will show up in γ_{mt}. This effect will impact all carriers. $h(m, \phi)$ captures the impact of vessel size on the marginal cost conditional on the market m. As we showed in the stylized facts before, the economies of scale of vessel really depends on the sea distance of each market and the state of maritime infrastructure (e.g., port's ability to handle large ships). We will parametrize the function $h(\cdot)$ in our estimation.

Then the total variable cost is the sum of dot product of the cost matrix and quantity matrix:

$$TVC^i = \mathbf{1}^T(\boldsymbol{C} \cdot \boldsymbol{Q}^i)\mathbf{1} \tag{6}$$

Profit Function Then the profit function faced by carrier i is

$$\begin{aligned} &\max_{\boldsymbol{Q}^i} \left(\sum_{m \in \mathcal{M}} P_m(Q_m^i, Q_m^{-i}) Q_m^i \right) - TVC^i \\ &\text{s.t. } \boldsymbol{Q}^i \mathbf{1} \leq \boldsymbol{\kappa}^i(\Phi^i) \end{aligned} \tag{7}$$

where Q_m^i is the column sum of quantity matrix $\boldsymbol{Q}^i$, representing the total quantity carrier i supplied in market m. The optimization problem faced by carrier i is to allocate its total capacity across vessel size class Φ^i across each market to maximize its total profit. One thing to note is that even though only the total quantity in each market Q_m^i will determine the revenue in market m, the composition of vessel of different size class will change the total variable cost, therefore the profit of each carrier.

3.3 Equilibrium

The equilibrium of this capacity constrained multi-market quantity setting game is characterized as that $\forall i \in \mathcal{I}_t$, the following condition holds:

$$\begin{aligned} \boldsymbol{Q}^{i*} = &\arg\max_{\boldsymbol{Q}^i} \left(\sum_{m \in \mathcal{M}} P_m(Q^i_m, Q^{-i*}_m) Q^i_m \right) - TVC^i \\ &\text{s.t. } \boldsymbol{Q}^{i*}\mathbf{1} \le \boldsymbol{\kappa}^i(\Phi^i) \end{aligned}$$

Namely $\boldsymbol{Q}^{i*}$ is a best response to other carriers' strategy $\boldsymbol{Q}^{-i*}$. We currently cannot prove the uniqueness of the equilibrium. And to ensure the solvability of the equilibrium under a fixed-point algorithm, we currently assumed a sequential move equilibrium solution concept. We assume that, with any environment change (e.g., demand change or arrival of new ships), the carrier with the highest capacity $\boldsymbol{\kappa}^i(\Phi^i)$ sets their quantity first. We include the details of the algorithm solving the equilibrium and robustness check in the Appendix B.

To understand the role of capacity constraint plays in the equilibrium, we can examine the first order condition for carriers. In equilibrium, each carrier needs to satisfy the following:

$$MR^i_m(Q^i_m, Q^{-i*}_m) - mc^i_m(\boldsymbol{Q}^i_m) = \begin{cases} 0, & \forall m \in \mathcal{M}^i, i \in \mathcal{I} \text{ if } \boldsymbol{Q}^{i*}\mathbf{1} < \boldsymbol{\kappa}^i(\Phi^i) \\ \iota^i, & \forall m \in \mathcal{M}^i, i \in \mathcal{I} \text{ if } \boldsymbol{Q}^{i*}\mathbf{1} = \boldsymbol{\kappa}^i(\Phi^i) \end{cases}$$

This condition indicates that when the capacity of carrier i is not binding, then the marginal revenue should equals to marginal cost for *all* markets for *all* carriers. If, however, that the capacity constraint is binding, then the difference between marginal revenue and marginal cost (ι^i) should be the same across *all* markets for each carrier. This ensures that there is no incentive for carriers to reallocate quantities across each market. Note that the marginal revenue only depends on the *total* quantity carrier i supplied in market m but the marginal cost depends on the *composition* of different vessel size class carrier deployed in each market given the existence of economies of scale with respect to ship size.

3.4 Alliance Formation

Through the case study on 2M alliance, we noticed a reshuffling of different vessel size classes across various markets. To translate that into the language of our model, the formation of alliance between carrier i and j is similar to a reallocation of their aggregate capacity. Formally the new capacity of carrier i after it forms alliance with carrier j is determined as:

$$\hat{\boldsymbol{\kappa}}^i = \frac{\mathbf{1}^T \boldsymbol{\kappa}^i}{\mathbf{1}^T \boldsymbol{\kappa}^i + \mathbf{1}^T \boldsymbol{\kappa}^j} (\boldsymbol{\kappa}^i + \boldsymbol{\kappa}^j) \tag{8}$$

after carrier i and j formed a strategic alliance, they will firstly pool their total global capacity together $((\boldsymbol{\kappa}^i + \boldsymbol{\kappa}^j))$and then divide it based on the fraction of capacity they contributed $(\frac{\mathbf{1}^T \boldsymbol{\kappa}^i}{\mathbf{1}^T \boldsymbol{\kappa}^i + \mathbf{1}^T \boldsymbol{\kappa}^j})$. An embedded assumption is that carrier i and j will not engage in tacit collusion with each other and the cooperation is strictly on the supply side. This assumption could regarded as too strong by some as the concern of collusive behavior is very prevalent in this industry. Our focus in this paper is on the supply-side efficiency gain from forming strategic alliance. Therefore, we will shut down the market conduct channel by assuming alliance member will still maintain independence in their demand side marketing and pricing activity by competing with each other in a quantity setting game. However, if alliance formation is the same as a merger, then carrier i and j will choose to first maximize their joint profit, and then divide the profit according to the capacity they contributed.

3.5 A Toy Example to Illustrate Efficiency Gain

To illustrate the mechanism of efficiency gain of strategic alliance formation, we devise a toy example of two market, two player, and two type of ships. We assume the following cost matrix (Table 2) where vessel type 1 has a lower variable cost in market 2 while vessel type 2 has a cost advantage in market 1. We assume the two markets are symmetric with a demand shifter of 12, and the original capacity across two carriers are represented in the upper panel of Table 3. After carrier 1 and 2 formed alliance, their capacity changed to the lower panel of Table 3 according to Equation 8.

Table 2: Toy example: cost matrix

	Market 1	Market 2
vessel type 1	1	0.8
vessel type 2	0.8	1

Table 3: Toy example: carrier capacity

Before Alliance		
	carrier 1	carrier 2
vessel type 1	0	8
vessel type 2	8	0

After Alliance		
	carrier 1	carrier 2
vessel type 1	4	4
vessel type 2	4	4

As we can see from Table 4, after carrier 1 and 2 formed alliance, the price in both market decreased and the profit for both carrier increased. The change is from the reallocation of vessel to the market where it's most productive. As we can see from Table 5, before the strategic alliance, both carrier are not utilizing their full capacity because of the inefficient high cost of vessel type 1 in market 1 and vessel type 2 in market 2. After the alliance, however, both carriers would be able to utilize all of their capacity, which increase the total quantity supplied to each market, bringing down price while increasing their profit. This simple toy example uncovered that the efficiency gain of strategic alliance mostly come from the reallocation of productive asset to the right market, which will increase the capacity utilization rate and bring down the price. This efficiency gain will be more nuanced if carriers are closer to their capacity constraint.

Table 4: Toy example: price and profit

Price		
	market 1	market 2
before alliance	1.543	1.543
after alliance	1.402	1.402

Profit		
	carrier 1	carrier 2
before alliance	4.696	4.696
after alliance	4.816	4.816

Table 5: Toy example: change in quantity

carrier 1		
	market 1	market 2
vessel type 1	0	0
vessel type 2	4.121 $\rightarrow$ 4	3.011$\rightarrow$ 4

carrier 2		
	market 1	market 2
vessel type 1	3.011$\rightarrow$ 4	4.121$\rightarrow$ 4
vessel type 2	0	0

4 Estimation and Calibration

4.1 Demand estimation

Given our log-linear demand system, the specification we use is the following:

$$\ln Q_{odt} = -\sigma \ln P_{odt} + \gamma_{ot} + \gamma_{dt} + \gamma_{od} + \varepsilon_{odt} \tag{9}$$

where o, d, t represent origin, destination, and month, respectively. Q_{odt} denotes the TEU volume on tradelane od at time t, and P_{odt} represents the per-TEU container freight price. We include fixed effects for origin-time (γ_{ot}), destination-time (γ_{dt}), and origin-destination pairs (γ_{od}). However, there exists an issue of price endogeneity, as certain origin-destination-time-specific factors in ε_{odt} may simultaneously influence both freight price P_{odt} and container volume Q_{odt}. To address this, we employ an instrumental variable framework.

In late December 2023, the Houthi group began attacking ships passing through the Suez Canal, prompting carriers to gradually divert their vessels to the Cape of Good Hope (see Figure 7). This diversion significantly increased shipping prices on origin-destination routes previously reliant on the Suez Canal (see Figure 8 for a comparison of price dynamics between routes affected and unaffected by the attack). Leveraging proprietary monthly data on container trade volumes and prices across 22 origin-destination pairs from CTS, we observe substantial increases in freight prices on the affected routes. To address the price endogeneity issue, we use the recent Red Sea Crisis as a supply-side instrument for price:

$$\ln P_{odt} = \mathbb{1}\left[\text{o-d route is affected at t}\right] + \gamma_{ot} + \gamma_{dt} + \gamma_{od} + \epsilon_{odt} \tag{10}$$

The identification of our demand estimation relies on the time-series and cross-sectional variations across the 22 main trading routes in our data, under the assumption of constant price elasticity of demand.

We present our demand estimation results in Table **??**. Our analysis estimates the price elasticity of container shipping demand to be -1.22, meaning a 10% increase in freight prices would result in a 12.2% decline in total volume, on average.[7] This elasticity is relatively low compared to estimates in the existing literature. For instance, Kalouptsidi (2014) used ship size and age as instruments for price and estimated the demand elasticity for bulk shipping at -6.17. Similarly, Jeon (2022) applied a comparable strategy and estimated container shipping demand elasticity at -3.89. Wong (2022) employed the round-trip effect as an instrument and found an elasticity of -3. Asturias (2020) used population as an instrument, estimating an elasticity of -5. More recently, Otani (2024) employed a similar approach to Jeon (2022) and estimated an elasticity of -0.89 for the 1966–1990 period, attributing this low value to the limited availability of alternative transportation methods during that era.

Our elasticity estimate is also on the lower end compared to these studies. One pos-

[7]For comparison, we also show the results of a hedonic price regression in column (3) in Table **??**. As we can see from the results, the price-elasticity will not be significantly from 0 if we do not employ our instrumental variable technics.

Figure 7: Red Sea Crisis

sible explanation is that our estimate reflects short-run demand elasticity, where the lack of alternative transportation modes constrains substitution. When combined with additive shipping costs, our results align with a trade elasticity in the range of 7–8. With estimted demand elasticity σ, we can then estimate the demand shifter D_{odt}.

4.2 Cost estimation

To estimate the cost function, we rely on firms' best response functions in their profit optimization problems. Ideally, a full-solution approach would allow us to solve for the equilibrium given an initial guess of the cost function parameters. However, due to the presence of multiple equilibria in our model, developing a robust and stable estimation strategy is

Figure 8: Shipping price for routes affected and not affected by the Houthi's attack

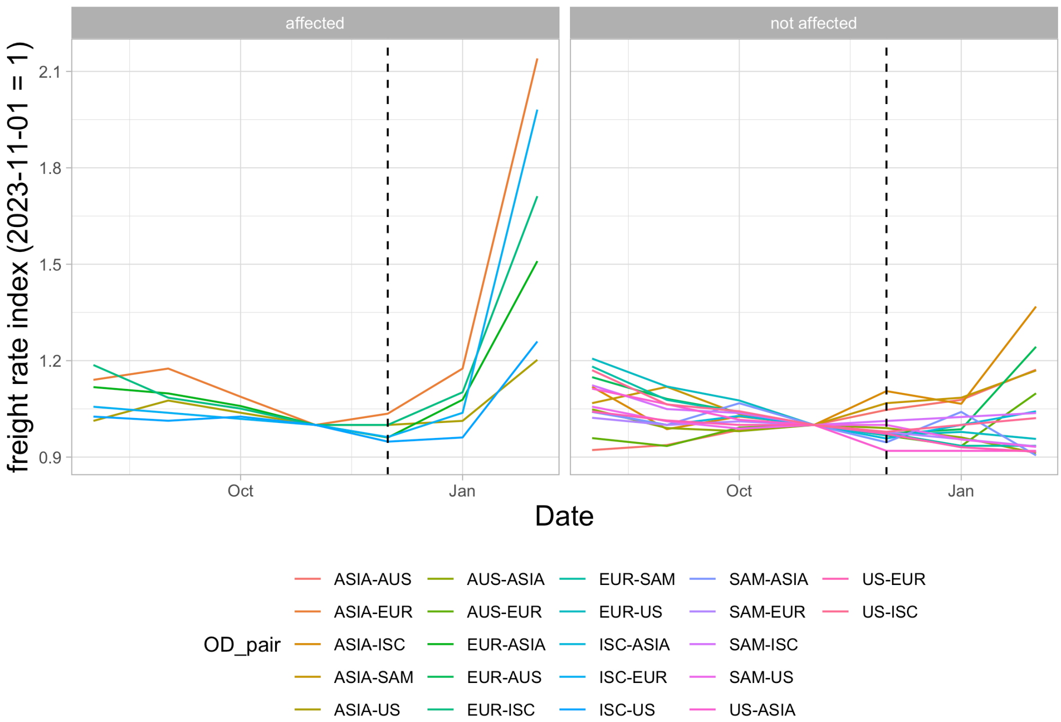


Table 6: Demand Estimation

	IV	IV	OLS
	Stage 1	Stage 2	
	$\ln P_{odt}$	$\ln Q_{odt}$	$\ln Q_{odt}$
disruption dummy	0.120*		
	(0.059)		
P_{odt}		−1.183**	−0.140
		(0.558)	(0.128)
Obs	88	88	88
origin × month	X	X	X
origin × destination	X	X	X
destination × month	X	X	X
Adjusted R^2	0.849	0.998	0.996
F-stat	8.74	-	-

Note: *p<0.1; **p<0.05; ***p<0.01

challenging.

Instead, we estimate the cost function by solving a single firm's optimization problem while keeping its competitors' strategies fixed at their observed values in the data. Specifically, we hold other carriers' supplied quantities at their observed levels and solve the optimization problem in Equation 7, given an initial guess for the marginal cost parameters.

The variable cost of operating a vessel of size ϕ by carrier i in market m at time t is specified as:

$$\log(c^i_{mt}(\phi)) = \gamma^i + \gamma_{mt} + c_m(\phi) \tag{11}$$

where:

- γ^i is a time-invariant carrier fixed effect.
- γ_{mt} is a market-month fixed effect capturing time-specific supply-side factors.
- $c_m(\phi)$ represents the market- and ship-size-specific component of cost, capturing the economies or diseconomies of scale of vessel size across markets.

This cost component is summarized in the following matrix:

$$\underset{|\Phi|\times|\mathcal{M}|}{\boldsymbol{C}} = \begin{bmatrix} c_{m_1}(\phi_1) & \dots & c_{m_{|\mathcal{M}|}}(\phi_1) \\ \vdots & \ddots & \vdots \\ c_{m_1}(\phi_{|\Phi|}) & \dots & c_{m_{|\mathcal{M}|}}(\phi_{|\Phi|}) \end{bmatrix} \tag{12}$$

For each guess of the cost matrix $\boldsymbol{C}$, we solve the following optimization problem for carrier i:

$$\hat{\boldsymbol{Q}}^{i*}(\boldsymbol{C}) = \arg\max_{\boldsymbol{Q}^i} \left(\sum_{m\in\mathcal{M}} P_m(Q^i_m, Q^{-i,data}_m) Q^i_m \right) - TVC^i(\boldsymbol{C}) \tag{13}$$

$$\text{s.t. } \boldsymbol{Q}^i\mathbf{1} \leq \boldsymbol{\kappa}^i(\Phi^i)$$

where $Q_m^{-i,data}$ are the observed quantities of other carriers in the data, and $\hat{\boldsymbol{Q}}^{i*}(\boldsymbol{C})$ represents the optimized quantities for carrier i given an initial guess of the cost parameters $\boldsymbol{C}$.

The estimated cost matrix $\hat{\boldsymbol{C}}$ is then obtained by minimizing the sum of squared deviations between the observed and predicted quantities:

$$\hat{\boldsymbol{C}} = \arg\min_{\boldsymbol{C}} \sum_{i \in \mathcal{I}} (\hat{\boldsymbol{Q}}^{i*}(\boldsymbol{C}) - \boldsymbol{Q}^{i,data})^2 \tag{14}$$

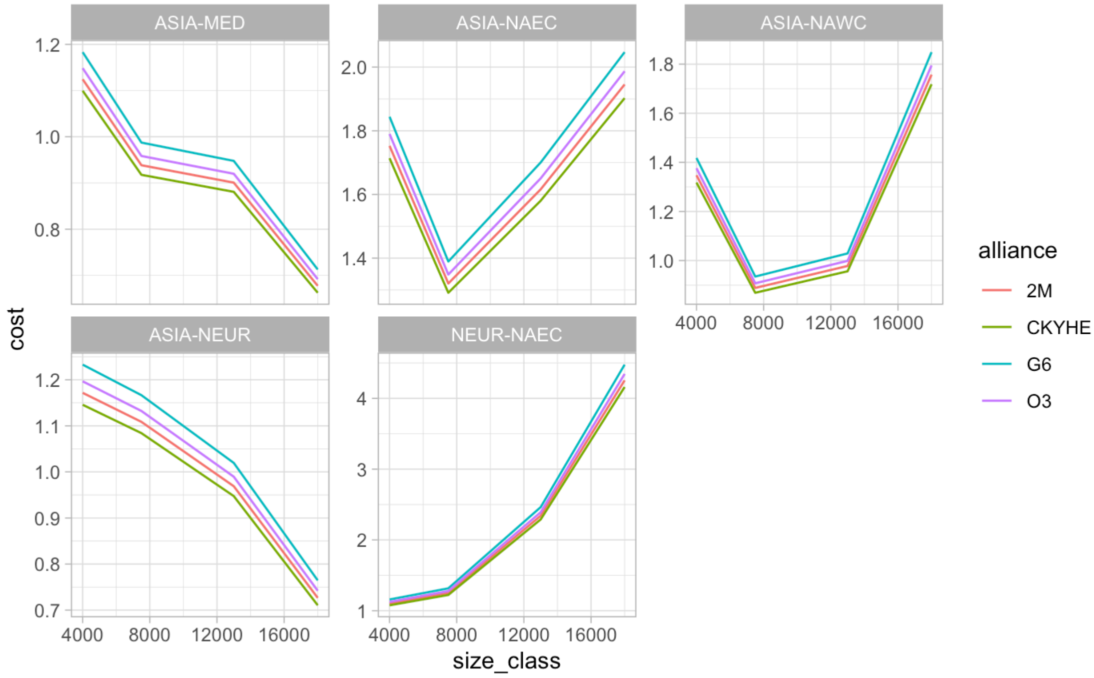
Given the high dimensionality of the cost parameter space, we use a reduced-form regression to obtain initial parameter estimates, improving the efficiency of our estimation. Further details are provided in Appendix C.2.

Figure 9 presents the estimated variable costs by vessel size across markets. In the Far-East-West-Bound markets (ASIA-MED, NEUR), the economies of scale for vessel size are pronounced. In contrast, the estimated variable cost follows a U-shaped pattern in trans-Pacific markets, where vessel size initially reduces costs but reaches an optimal threshold beyond which costs increase. Only smaller vessels operate efficiently in trans-Atlantic routes. This estimated cost structure is consistent with the observed vessel size distribution across markets in the data.

4.3 Model Fit

To assess how well our model fits the data, we solve for the equilibrium using the estimated demand and cost parameters. Figure 10 compares the model-generated quantities of each vessel size supplied to each market by each carrier against the observed quantities in the data. Overall, the model's predictions align well with the data, but it performs less accurately when predicting smaller quantities. This discrepancy is primarily due to the relatively coarse vessel size grid (four categories) used in the estimation. Future work will refine the grid size to improve model accuracy.

Figure 9: Estimated normalized cost over vessel size

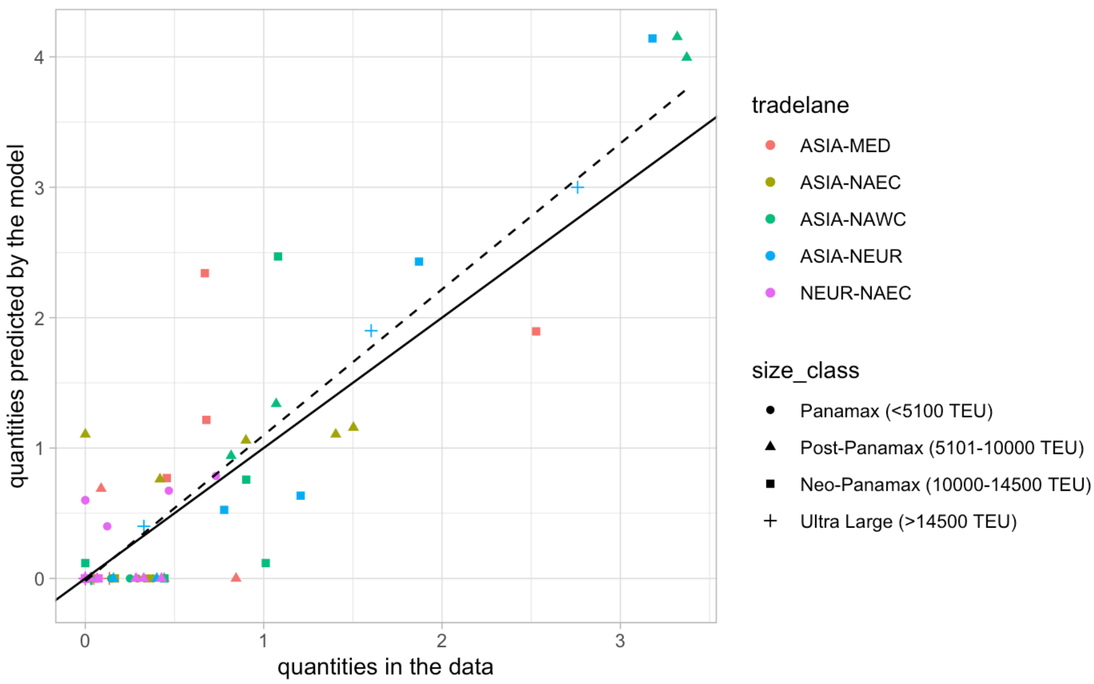


5 Simulation and Counterfactual Studies

In this counterfactual analysis, we investigate the incentives behind the formation and dissolution of global strategic alliances and their welfare implications. Specifically, we analyze the creation of the 2M Alliance in the second half of 2015 and its announced breakup in 2023. Using our estimated model, we simulate alternative market equilibria, examining how the shipping industry would have evolved if the alliance had never formed or if its dissolution had not occurred. This allows us to quantify the motivations of Maersk and MSC for entering and exiting the alliance and assess the resulting impact on freight prices and consumer welfare.

To better understand these effects, we decompose the incentives and welfare impacts into two key components: supply-side efficiency gains from vessel reallocation and demand-side market power effects. We further explore how shifts in comparative advantages among alliance members and changes in aggregate demand influenced both the formation and breakup of the 2M Alliance.

Figure 10: Estimated normalized cost over vessel size



Finally, we summarize the key insights from our counterfactual analysis and discuss their policy implications, offering guidance on the stability and regulatory considerations of global strategic alliances.

5.1 The Formation of the 2M Alliance

As shown in the stylized facts section, Maersk and MSC reallocated their vessels across different markets after forming the 2M Alliance in February 2015. To assess the impact of this alliance, we simulate the 2016 market equilibrium assuming the 2M Alliance was never formed and compare it to the observed equilibrium.

Profit Impact: Efficiency vs. Consolidation Effects Table 7 presents the change in profits due to the alliance. We find that Maersk and MSC's joint variable profit increases by 0.8 billion USD in 2016 when the 2M Alliance is in place, highlighting their incentive to cooperate. To isolate the sources of profit gain, we conduct a counterfactual scenario where Maersk and MSC pool their vessels but continue competing on the demand side. The lower

Table 7: Change in Carrier Profits (Billion USD) in 2016 without the 2M Alliance

With 2M Alliance				
Maersk+MSC		CKYHE	G6	O3
0.80		1.38	1.51	0.82
2M Alliance (Supply Coordination Only)				
Maersk	MSC	CKYHE	G6	O3
0.25	0.03	-0.20	-0.25	-0.11

Note: This table presents the change in profits compared to a baseline scenario where the 2M Alliance was never formed. The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel treats the alliance as equivalent to a merger.

panel of Table 7 shows that Maersk's profit increases by 0.25 Billion USD, while MSC's profit rises by 0.03 billion USD under supply coordination. This implies that the increase in market power contributes to 0.52 Billion USD increase in Maersk's and MSC's joint profit, more than those of efficiency gain.

The profit change of competing alliances differ under different assumption of the market conduct of Maersk and MSC. Under the assumption that Maersk and MSC are competing with each other with only supply side coordination, the formation of the alliance leads to significant profit reductions for competing alliances, including CKYHE, G6, and O3. This is because the 2M Alliance reallocate vessels owned by Maersk and MSC in a more efficient way, leading to the increase in supplied quantities by the 2 carriers which steals business from other alliances/carriers. However, under the assumption that the 2M alliance is equivalent to a full merger, the profit of competing alliance will increase as the 2M will reduce their quantities supplied across the market. This implies the importance to gauge the market conduct between

The fact that these figures closely match the full-merger scenario suggests that almost all profit gains arise from efficiency improvements, with minimal consolidation effects. To further investigate the efficiency gains, Table 8 presents changes in vessel allocations after the alliance's formation.

The results indicate that Neo-Panamax vessels were relocated from Asia-NAWC to Asia-

Table 8: Change in Quantities for 2M (10^6 TEUs)

Consolidation + Supply coordination effect					
Vessel Size	Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC
Panamax (<5100 TEU)	0.00	0.00	0.00	-0.31	-0.41
Post-Panamax (5101-10000 TEU)	0.00	0.46	-0.46	0.00	0.00
Neo-Panamax (10000-14500 TEU)	-0.22	0.00	0.41	-0.19	0.00
Ultra Large (>14500 TEU)	0.00	0.00	0.00	0.00	0.00
Supply coordination effect					
Vessel Size	Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC
Panamax (<5100 TEU)	0.00	0.00	0.00	0.01	-0.01
Post-Panamax (5101-10000 TEU)	0.00	0.13	-0.13	0.00	0.00
Neo-Panamax (10000-14500 TEU)	-0.05	0.00	0.15	-0.08	0.00
Ultra Large (>14500 TEU)	0.00	0.00	0.00	0.00	0.00

Note: This table presents the change in vessel allocation across trade routes after the 2M Alliance was formed.

NAEC and Asia-MED, leading to a reallocation of Panamax vessels to the Asia-NAEC and NEUR-NAEC markets. These findings align with our vessel allocation observations in Figure on 2M vessel allocation.

5.1.1 Consumer Welfare Gains from the 2M Alliance

We also calculate changes in consumer surplus, summarized in Table 9. The total consumer surplus increases by 20.63 billion USD due to the alliance, primarily driven by improved vessel reallocation in Asia-NAEC, Asia-NAWC, and NEUR-NAEC. The formation of the 2M Alliance not only increased Maersk and MSC's profits through vessel reallocation, but also significantly improved consumer welfare, particularly in markets where vessel sizes were previously allocated inefficiently.

5.2 The Breakup of the 2M Alliance

In January 2023, Maersk and MSC announced that the 2M Alliance would be dissolved by January 2025. According to industry reports,[8] the decision reflects a strategic shift, allowing both companies to pursue their individual business models. Maersk has been expanding its integrated logistics services, transitioning into an end-to-end supply chain provider, while

[8] See this link.

Table 9: 2M Alliance: Change in Consumer Surplus (Billion USD) in 2016

With 2M Alliance					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-0.69	1.98	-1.28	-2.99	-3.06	**-6.03**
2M Alliance (Supply Coordination Only)					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-0.32	0.82	0.37	-0.52	-0.06	**0.30**

Note: The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel assumes full cooperation as a merger.

MSC has focused on growing its shipping fleet, becoming the world's largest container carrier by capacity.

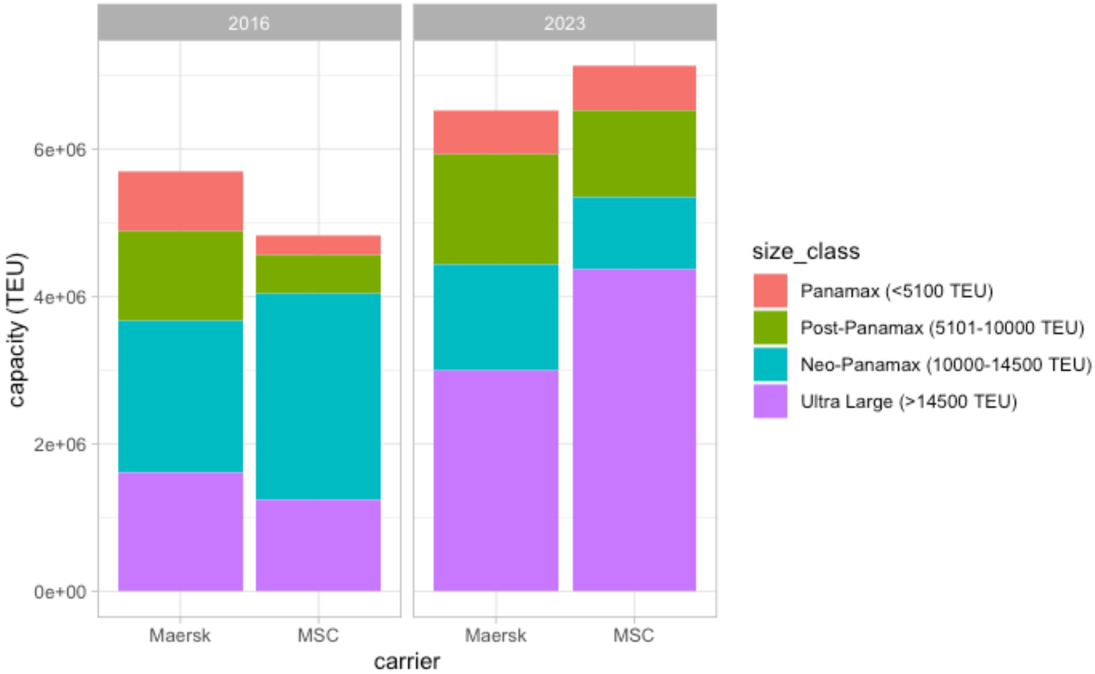
5.2.1 The Role of Capacity Asymmetry

As shown in Figure 11, MSC's capacity has grown significantly faster than Maersk's. Since the formation of the 2M Alliance, MSC's contributed capacity share within the alliance has increased from 46 percent to 52 percent. This growing asymmetry could destabilize the alliance over time, making cooperation less sustainable.

To evaluate the profitability of maintaining the alliance, we compare the 2023 equilibrium outcomes under two scenarios: (1) the 2M Alliance remains intact, and (2) Maersk and MSC operate independently. The upper panel of Table 10 shows that if Maersk and MSC dissolve the alliance, their joint profit increases by 1.82 billion USD in 2023. This suggests that, even with potential direct transfer, the alliance is no longer sustainable.

The lower panel of Table 10 further breaks down the profit redistribution, showing that MSC gains the most from the breakup (1.74 billion USD). Additionally, the dissolution negatively impacts the profits of other alliances and carriers, as MSC's increased market supply intensifies competition.

Figure 11: Capacity comparison between Maersk and MSC. (2016 vs 2023)



5.2.2 Consumer Surplus Effects of the Breakup

Table 11 presents the consumer surplus impact of the 2M Alliance breakup in 2023. We find that the Asia-NAEC market benefits the most, with a 6.44 billion USD increase in consumer surplus. The Asia-NAWC market also sees a 0.8 billion USD increase in consumer surplus.

However, this consumer surplus gain arises solely from increased market competition, rather than from improved supply-side efficiency. This follows from our assumption that the 2M Alliance functioned similarly to a temporary merger.

As shown in Table **??** in Appendix D, if we assume that the 2M Alliance cooperated only on vessel deployment and not on pricing, consumer surplus would remain unchanged. This suggests that the increase in consumer welfare is driven purely by competition rather than by efficiency gains from fleet reallocation.

Table 10: 2M Alliance: Change in Carrier Profits (Billion USD) in 2023 Breakup

2M Alliance Breakup			
Maersk + MSC		Ocean Alliance	THE Alliance
0.57		-2.24	-1.27
2M Alliance Breakup (supply coordination)			
Maersk	MSC	Ocean Alliance	THE Alliance
-1.07	1.07	-0.03	-0.02

Note: This table presents the change in profits for carriers/alliance if 2M is broken up in 2023. The top panel is the change in profit. The bottom panel compares the profits of Maersk and MSC before and after the breakup in 2023. We assume the profits are split according to the capacity Maersk and MSC contributed to the 2M Alliance.

Table 11: 2M Alliance: Change in Consumer Surplus (Billion USD) in 2023 Breakup

2M Breakup					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-0.29	5.28	-0.70	0.30	0.11	**4.70**
2M Breakup (supply coordination only)					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
0.00	0.31	-0.23	0.00	0.00	**0.08**

Note: This table presents the changes in consumer surplus if they formed one global alliance by sharing their vessels together. We are assuming they divide the total capacity based on the capacity they are contributing to this global alliance.

5.2.3 Comparing the Welfare Impact of Formation and Breakup

The effects of the formation (2015) and dissolution (2023) of the 2M Alliance on consumer welfare follow distinct mechanisms. When Maersk and MSC formed the 2M Alliance in 2015, the efficiency gains from vessel reallocation outweighed potential anti-competitive effects, leading to higher consumer welfare. In contrast, the dissolution of the alliance in 2023 improves consumer welfare purely through heightened competition, with minimal efficiency effects.

These findings underscore the dual role of strategic alliances in shaping market outcomes—balancing efficiency improvements against competitive distortions. Our results provide a quantitative framework to assess the long-term viability and regulatory implications of such alliances in concentrated markets.

5.3 Impact of Comparative Advantage on Alliance Incentives and Welfare

In this section, we examine how differences in comparative advantage between carriers influence the incentive to form an alliance and their potential welfare impact. As shown in Figure 11, the fleet compositions of Maersk and MSC became more similar over time, coinciding with the announcement of the 2M Alliance breakup in 2023.

To facilitate an apples-to-apples comparison, we construct a hypothetical fleet for Maersk and MSC in 2016. In this scenario, we preserve their total fleet capacity as observed in the data but adjust the distribution: Maersk's fleet composition is skewed towards smaller Panamax and Post-Panamax vessels, while MSC's fleet has a higher proportion of vessels larger than 10,000 TEU. A summary of this fleet adjustment is presented in Figure 12.

Figure 12: Capacity comparison between observed and hypothetical fleet composition

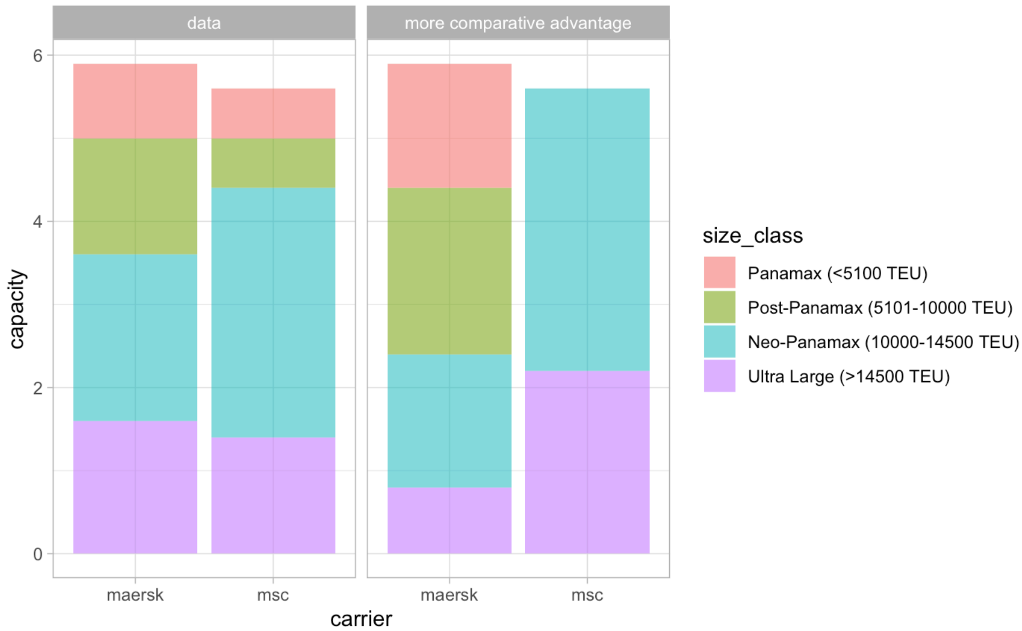
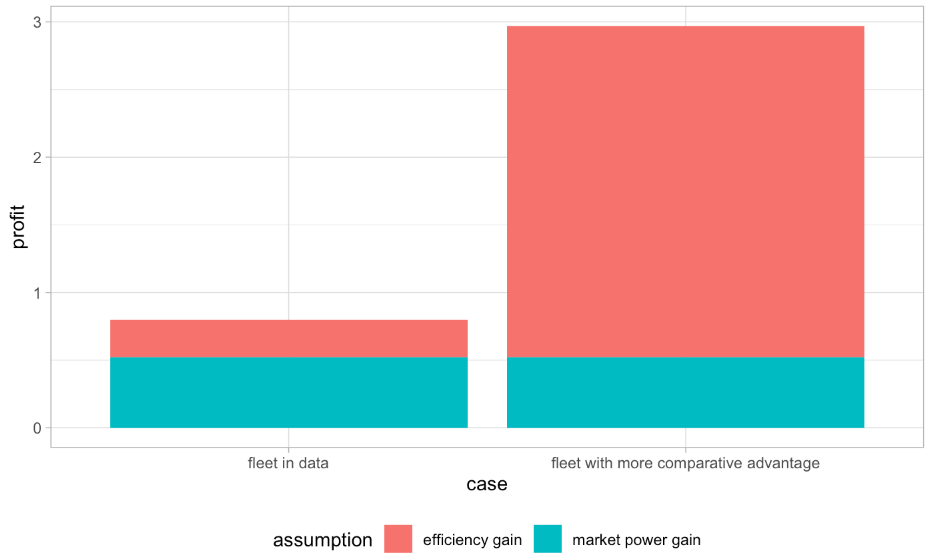


Figure 13 illustrates the change in joint profit (in billion USD, 2016) for Maersk and MSC under two different fleet compositions: i) The observed fleet in the data, ii) The hypothetical fleet with greater differences in vessel composition.

Compared to the observed fleet, a more divergent fleet composition (representing greater comparative advantage across markets) results in a larger share of joint profit gains coming from supply-side efficiency, while the gains from market power remain relatively unchanged.

Figure 13: Change in joint profit of the 2M Alliance under different fleet compositions



The impact on consumer surplus, however, is less straightforward. As shown in the lower panel of Table 13, consumer surplus declines when Maersk and MSC exhibit greater comparative advantage. This suggests that the strategic responses of other carriers and alliances may offset the expected positive impact on consumer welfare. The redistribution of consumer surplus across markets is also more pronounced in this case compared to the observed fleet composition. This finding underscores the complexity of evaluating the welfare effects of strategic alliances.

5.4 Aggregate Demand Change

The container shipping industry experiences highly volatile aggregate demand, making it important to examine how the stability of strategic alliances evolves over the boom-bust cycle. Using 2016 data, we compute the equilibrium under a scenario where aggregate demand is reduced by 20 percent.

As shown in Figure 14, the efficiency gains from the 2M Alliance disappear when aggre-

Table 12: Change in Carrier Profits (Billion USD) in 2016 with a More Different Fleet

With 2M Alliance				
Maersk+MSC		CKYHE	G6	O3
2.97		1.82	1.08	0.84
2M Alliance (Supply Coordination Only)				
Maersk	MSC	CKYHE	G6	O3
2.64	-0.19	0.24	-0.67	-0.09

Note: This table presents the change in profits compared to a baseline scenario where the 2M Alliance was never formed. The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel treats the alliance as equivalent to a merger.

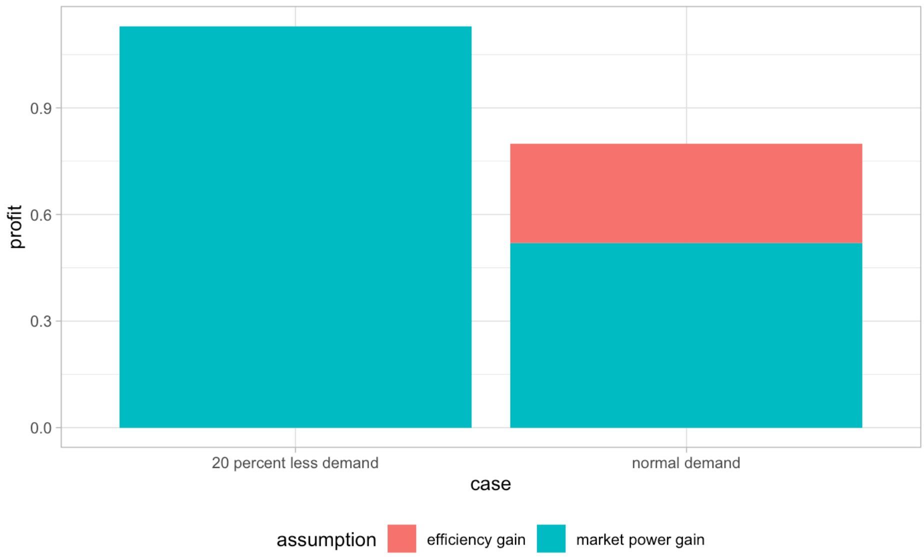
Table 13: 2M Alliance: Change in Consumer Surplus (Billion USD) in 2016 with Different Fleets

With 2M Alliance					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-1.54	3.19	-3.22	-5.74	0.17	**-7.14**
2M Alliance (Supply Coordination Only)					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-1.17	2.03	-1.57	-3.27	3.17	**-0.81**

Note: The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel assumes full cooperation as a merger.

gate demand declines by 20 percent, while the profit gain from increased market power more than double in the low-demand scenario. This result aligns with findings in the literature on tacit collusion and suggests that alliance formation proposals between similar carriers during periods of low demand should be subject to heightened scrutiny.[9]

Figure 14: Change in joint profit of the 2M Alliance under different aggregate demand



5.5 Counterfactual Summary and Policy Implications

This section summarizes key policy insights from our counterfactual analysis.

Comparative Advantage Comparative advantage across carriers plays a crucial role in determining both the formation and dissolution of global strategic alliances. Larger differences in market presence and fleet composition create stronger incentives for alliance formation.

For example, comparing Maersk's and MSC's fleet compositions in 2015 and 2023, we observe that they had more distinct vessel size distributions when forming the alliance in 2015. In our counterfactual experiment, where we further polarized fleet compositions, the supply-side efficiency gains increased even more.

[9]For detailed results on the carrier profit, please refer to Table 15. And for detailed results on the consumer surplus impact, please refer to Table 16.

The extent of comparative advantage also influences the nature of alliance incentives—as differences grow, the gains from supply-side efficiency become more dominant. For policymakers, this underscores the importance of evaluating the degree of comparative advantage when assessing alliance formation proposals. If alliance members have similar vessel size distributions, the argument that alliances enhance supply-side efficiency weakens.

Market Conduct Understanding market conduct within alliances is crucial for evaluating their overall welfare impact. If alliance members coordinate as a single entity on the demand side, our counterfactual analysis consistently shows that market power effects dominate any efficiency gains.

This suggests that policymakers should closely monitor alliance members' competitive behavior, as market power changes can have significant welfare implications. Meanwhile, the welfare effects of supply-side efficiency gains are more nuanced. Other market participants may strategically adjust their supply in response to a new alliance, dampening the expected consumer welfare gains. For instance, the formation of the 2M Alliance may have increased supply in previously underrepresented markets, but other carriers might reduce their output in response, mitigating the positive welfare impact.

Mergers vs. Alliances Unlike horizontal mergers, strategic alliances have a greater tendency to dissolve, which can be beneficial for consumer welfare. Our counterfactual analysis of the 2M Alliance breakup illustrates this point: As MSC's fleet surpassed Maersk's and their vessel compositions became more similar, the incentive to remain in an alliance declined. This breakup ultimately benefited consumer surplus, as increased competition offset any efficiency losses.

This highlights a key distinction between alliances and mergers—alliances are inherently less stable and may naturally break apart under changing market conditions. Policymakers should continuously monitor alliance stability to fully understand its long-term welfare effects.

Aggregate Demand The formation incentives and welfare effects of strategic alliances also depend heavily on aggregate demand conditions. Consistent with the literature, we find that alliances are more stable when demand is low. However, the underlying mechanisms differ. When demand is low, alliance formation is mainly driven by market power considerations. When demand is high, supply-side efficiency gains become more significant.

This reveals an important distinction: aggregate demand has opposite effects on market power incentives and efficiency gains in strategic alliances. Understanding this relationship is essential for designing effective regulatory policies.

6 Conclusion

This study provides an in-depth analysis of the economic incentives, efficiency gains, and competitive effects of global strategic alliances in the container shipping industry. By focusing on the 2M Alliance, we demonstrate that vessel reallocation across trade routes serves as a key driver of efficiency gains, leading to lower operational costs and enhanced capacity utilization. However, these benefits are counterbalanced by concerns over market power, as alliances may reduce competition and increase prices in certain markets.

Our counterfactual analysis highlights that alliances are more likely to form when members possess distinct fleet compositions, allowing them to leverage comparative advantages. Conversely, as fleet compositions converge, the rationale for maintaining an alliance weakens, leading to potential dissolution. The breakup of the 2M Alliance in 2023 serves as a case study in this dynamic, where MSC's rapid fleet expansion and shifting strategic priorities reduced the mutual benefits of continued cooperation. The findings also underscore the importance of aggregate demand conditions in shaping alliance stability. When demand is low, alliances are more likely to form as firms seek to consolidate market power. In contrast, during periods of high demand, efficiency considerations dominate alliance incentives. These insights provide valuable guidance for policymakers, who must weigh the trade-offs between efficiency gains and anti-competitive risks when evaluating alliance agreements.

Finally, this study contributes to the broader literature on horizontal mergers and reallocation by illustrating how strategic alliances differ from full-scale mergers. Unlike mergers, alliances are inherently more flexible and subject to dissolution, which may mitigate long-term antitrust concerns. Nevertheless, regulators must remain vigilant in monitoring alliance behavior, particularly in concentrated industries like container shipping, where even temporary supply-side coordination can have significant market implications.

Future research could explore the role of technological advancements and digitalization in shaping alliance incentives and efficiency gains. Additionally, incorporating firm-level data on pricing strategies and contract structures could provide deeper insights into the competitive dynamics of global shipping alliances. As the industry continues to evolve, understanding the interplay between cooperation and competition will remain critical for both industry participants and policymakers alike.

References

Agarwal, R. and Ö. Ergun (2010). Network design and allocation mechanisms for carrier alliances in liner shipping. *Operations research 58*(6), 1726–1742.

Andrade, G. and E. Stafford (2004). Investigating the economic role of mergers. *Journal of corporate finance 10*(1), 1–36.

Asturias, J. (2020). Endogenous transportation costs. *European economic review 123*, 103366.

Caschili, S., F. Medda, F. Parola, and C. Ferrari (2014). An analysis of shipping agreements: the cooperative container network. *Networks and spatial Economics 14*, 357–377.

Cruijssen, F., W. Dullaert, and H. Fleuren (2007). Horizontal cooperation in transport and logistics: a literature review. *Transportation journal 46*(3), 22–39.

Das, S. S. (2011). To partner or to acquire? a longitudinal study of alliances in the shipping industry. *Maritime Policy & Management 38*(2), 111–128.

Demirer, M. and Ö. Karaduman (2024). Do mergers and acquisitions improve efficiency? evidence from power plants. Technical report, National Bureau of Economic Research.

Ghorbani, M., M. Acciaro, S. Transchel, and P. Cariou (2022). Strategic alliances in container shipping: A review of the literature and future research agenda. *Maritime economics & logistics 24*(2), 439–465.

Jeon, J. (2022). Learning and investment under demand uncertainty in container shipping. *The RAND Journal of Economics 53*(1), 226–259.

Jovanovic, B. and P. L. Rousseau (2008). Mergers as reallocation. *The Review of Economics and Statistics 90*(4), 765–776.

Kalouptsidi, M. (2014). Time to build and fluctuations in bulk shipping. *American Economic Review 104*(2), 564–608.

Lim, J. (2020). From conference to alliance: multiple perspectives.

Merk, O. (2018). Container ship size and port relocation.

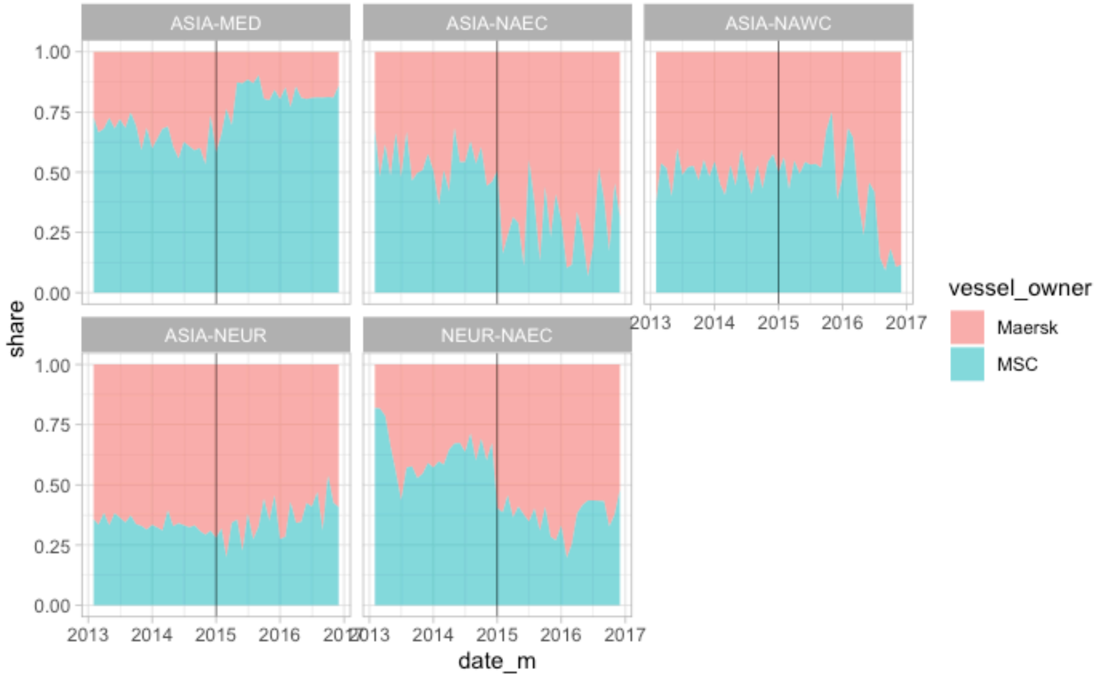
Mitsuhashi, H. and H. R. Greve (2009). A matching theory of alliance formation and organizational success: Complementarity and compatibility. *Academy of management journal 52*(5), 975–995.

Otani, S. (2024). Industry dynamics with cartels: The case of the container shipping industry. *arXiv preprint arXiv:2407.15147*.

Panayides, P. M. and R. Wiedmer (2011). Strategic alliances in container liner shipping. *Research in transportation Economics 32*(1), 25–38.

Prashant, K. and S. Harbir (2009). Managing strategic alliances: what do we know now, and where do we go from here? *Academy of management perspectives 23*(3), 45–62.

Figure 15: 2M capacity supply share (within alliance)



Song, D.-W. and P. M. Panayides (2002). A conceptual application of cooperative game theory to liner shipping strategic alliances. *Maritime Policy & Management 29*(3), 285–301.

Talley, W. K. (2011). *The Blackwell companion to maritime economics.* John Wiley & Sons.

Wang, M. (2015). The formation of shipping conference and rise of shipping alliance. *International Journal of Business Administration 6*(5), 22–36.

Wong, W. F. (2022). The round trip effect: Endogenous transport costs and international trade. *American Economic Journal: Applied Economics 14*(4), 127–166.

A More Details on Stylized Facts

A.1 Micro-foundation of (dis-)economies of scale at vessel level

According to the literature in the maritime economics and maritime engineering, the total variable cost of container shipping could be divided into two components: i) cost at port and ii) cost at sea. Daily operating cost is the main component of the cost at port, and the total cost at port depends on the time spent at port. Given the container processing rate r at port, the time at port could approximately be modeled as

$$T_{port} = \frac{2\phi}{r} \tag{15}$$

where ϕ is the vessel size, the multiplier 2 captures the time of unloading and loading the containers.[10] However, the interpretation of the container handling rate r could also be the processing rate of ships at certain infrastructure chokehold. For example, the handling speed of larger vessel will be longer than those of smaller vessels at canals.

If we further assuming the daily operating cost of ship size ϕ is:

$$C_{op} = c_1 \phi^{\beta_1} \tag{16}$$

where c_1 and β_1 are the parameters governing the level and economies of scale for the operating cost of container ships. The cost at port would be

$$C_{port} = T_{port} C_{op} = \frac{2c_1}{r} \phi^{1+\beta_1} \tag{17}$$

The cost at sea has two components: daily operating cost and daily bunker cost. If we

[10] To be more specific, ϕ should be call size, rather than vessel size, but an empirical work by McKinsey&Co shows a strong positive correlation between call size and vessel size.

assume the bunker cost of the ship is

$$C_{fuel} = c_2 f \phi^{\beta_2} \tag{18}$$

where c_2 governs the efficiency of propulsion, f is the bunker price and β_2 governs the economies of scale in propulsion efficiency. Then the cost at sea is

$$C_{sea} = \frac{d}{s}(C_{fuel} + C_{op}) = \frac{d}{s}(fc_2\phi^{\beta_2} + c_1\phi^{\beta_1}) \tag{19}$$

where d is the distance of a specific route and s is the sailing speed. So the per-TEU[11] marginal cost of operating a ship with size ϕ is

$$c(\phi) = \frac{C_{port} + C_{sea}}{\phi} = \underbrace{\frac{2c_1}{r}\phi^{\beta_1}}_{\text{Diseconomies of scale}} + \underbrace{\frac{d}{s}(fc_2\phi^{\beta_2-1} + c_1\phi^{\beta_1-1})}_{\text{Economies of scale}} \tag{20}$$

The marginal cost of ship with size ϕ has two components: i) diseconomies of scale due to longer handling time at port and other maritime infrastructure and ii) economies of scale due to saving on operating and bunker cost at sea.

A.1.1 Parametrization of vessel-level (dis-)economies of scale

To simplify our setup and make it easier to bring the model to the data, we formulate our marginal cost function as

$$\log(c_m(\phi)) = \delta_m + h(\phi; \gamma_1, \gamma_2, \bar{\phi}_m) \cdot (\log(\phi) - \log(\bar{\phi}_m)) \tag{21}$$

[11]TEU is equivalent to a 20-feet container, which is used as an standardized unit in container shipping.

where γ_m is the market/trade lane level fixed effect of marginal cost[12]. $h(\cdot)$ is a sigmoid-type of function:

$$h(\phi; \gamma_1, \gamma_2, \bar{\phi}_m) = -\gamma_1 + \frac{\gamma_1 + \gamma_2}{1 + \exp(-(\phi - \bar{\phi}_m))} \tag{22}$$

where $\bar{\phi}_m$ is the optimal vessel size in market m. When $\phi < \bar{\phi}_m$, $h(\phi) \approx -\gamma_1$, and when $\phi > \bar{\phi}_m$, $h(\phi) \approx \gamma_2$. Therefore, γ_1 governs the extent of economies of scale due to ship size while γ_2 governs the diseconomies of scale. The optimal vessel size $\bar{\phi}_m$ represents the handling ability of maritime infrastructure. As Figure **??** shows, the marginal cost exhibits economies of scale for vessel size before turning into the region of diseconomies of scale at the optimal vessel size in market 1 (8000 TEU) and market 2 (16000 TEU) respectively. This corresponds to what we observe in our empirical section, where the marginal cost index exhibits a u-shape for Asia-NAWC lanes but exhibits mostly economies of scale for Asia-NEUR and Asia-Med lanes as the ports in the latter lanes are more productive in handling larger vessels.

B More Details On Model

B.1 Solving Equilibrium

We use the Algorithm 1 to solve the equilibrium.

C More Details On Estimation

C.1 CES Demand + Cournot Oligopoly

For simplicity, we start with the calibration of CES Demand and Cournot oligopoly setup. Because we already use the Flexport data to estimate the trade elasticity with regard to freight cost of rought -3, so we could directly use the system of non-linear equations in **?** to directly calibrate the marginal cost.

[12]We will make this market-time specific fixed effect when bringing the model to the data.

Algorithm 1 Fixed Point Algorithm for Solving Equilibrium

Input: Initial guess of quantities $\mathbf{Q}^{(0)}$, tolerance ϵ, maximum iterations N
Output: Equilibrium quantities $\mathbf{Q}^*$
Initialize iteration counter $k \leftarrow 0$
Initialize $\mathbf{Q}^{(0)}$ arbitrarily
repeat
    for each firm $i \in \mathcal{I}$ **do**
        Compute best response $\mathbf{Q}_i^{(k+1)}$ given competitors' strategies $\mathbf{Q}_{-i}^{(k)}$
    end for
    Compute distance $d \leftarrow \|\mathbf{Q}^{(k+1)} - \mathbf{Q}^{(k)}\|$
    Update iteration counter: $k \leftarrow k+1$
until $d < \epsilon$ **or** $k \geq N$
Return equilibrium quantities $\mathbf{Q}^* = \mathbf{Q}^{(k)}$

Assume a representative agent in market m at time t has a CES utility function

$$Q_{mt} = [\sum_{k \in \mathcal{K}_{mt}} q_{mt}(k)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$

where $q_{mt}(k)$ is carrier k's quantity, and $\mathcal{K}_{mt}$ is the set of carriers in market m at time t. Assume carriers engage in Cournot oligopoly competition, their profit function is

$$\pi_{mt}(k) = [p_{mt}(k) - c_{mt}(k)]q_{mt}(k) - F_{mt}(k)$$

The FOC is a system of non-linear equations

$$\frac{\sigma-1}{\sigma} \frac{I_{mt} \cdot q_{mt}(k)^{-\frac{1}{\sigma}}}{(\sum_{l \in \mathcal{K}_{mt}} q_{mt}(l)^{\frac{\sigma-1}{\sigma}})^2} [\sum_{l \in \mathcal{K}_{mt}, l \neq k} q_{mt}(l)^{\frac{\sigma-1}{\sigma}}] = c_{mt}(k) \tag{23}$$

We could solve for the quantity vector $\{q_{mt}(k)\}_{k \in \mathcal{K}_{mt}}$.

Since we also observe aggregate price data. The price (determined in equilibrium) is

$$p_{mt}(k) = \frac{\varepsilon_{mt}(k)}{\varepsilon_{mt}(k) - 1} c_{mt}(k)$$

where the price elasticity is a function of k's market share $s_{mt}(k)$:

$$\varepsilon_{mt}(k) = [\frac{1}{\sigma}(1 - s_{mt}(k)) + s_{mt}(k)]^{-1}$$

To recover price from quantity

$$p_{mt}(k) = I_{mt} \cdot \frac{q_{mt}(k)^{-\frac{1}{\sigma}}}{\sum_{l \in \mathcal{K}_{mt}} q_{mt}(l)^{\frac{\sigma-1}{\sigma}}}$$

and price index is

$$P_{mt} = [\sum_{k \in \mathcal{K}_{mt}} p_{mt}(k)^{1-\sigma}]^{\frac{1}{1-\sigma}} = I_{mt}[\sum_{k \in \mathcal{K}_{mt}} \frac{q_{mt}(k)^{\frac{\sigma-1}{\sigma}}}{(\sum_{l \in \mathcal{K}_{mt}} q_{mt}(l)^{\frac{\sigma-1}{\sigma}})^{1-\sigma}}]^{\frac{1}{1-\sigma}} \tag{24}$$

We will use Equation 24 to recover the market specific demand I_{mt}. Then we plug demand shifters into Equation 23 to recover the marginal cost.

For the benchmark estimation, we assume the carriers in one alliance is similar to a merger, and we treat the non-allianced carriers as a single oligopoly carrier. We will try to ease this assumptions later on in our sensitivity analysis.

C.2 Determining the initial parameters value in cost estimation

To speed up the cost estimation algorithm, we use a reduced form regression of implied cost on average vessel size to set the initial starting point for our cost parameter estimation. A simpler and more tractable way of estimating the variable cost would be to assume each carrier has a *representative* vessel size in each market for each month, which is the capacity-weighted average vessel size:

$$\phi_m^i = \frac{\sum_{\phi \in \Phi_m^i} \phi \kappa_m^i(\phi)}{\sum_{\phi \in \Phi_m^i} \kappa_m^i(\phi)} \tag{25}$$

This indicates that the FOC for each carrier in each market is satisfying the following condition: Then the F.O.C. of the alliance i is

$$P_{mt}(Q_{mt}) + P'_{mt}(Q_{mt})q^i_{mt} = (1 - \frac{s^i_{mt}}{\sigma})A_{mt}(Q_{mt})^{-\sigma} = (1 - \frac{s^i_{mt}}{\sigma})P_{mt} = \hat{c}^i_{mt} \tag{26}$$

where $\tilde{c}^i_{mt}$ is the *effective* marginal cost of alliance i in market m at time t. And $s^i_{mt} = \frac{q^i_{mt}}{Q_{mt}}$ is the market share of carrier i in market m at time t. And σ is the price elasticity of shipping demand. This gives us an expression to back out *effective* marginal cost as a function of market price and each alliance's market share and the price elasticity of demand.

We further parametrize the implied marginal cost into the two components:

$$\log(\hat{c}^i_{mt}) = \gamma_{mt} + \log(\tilde{c}^i_{mt}) \equiv \gamma_{mt} + h(m, \phi^i_m) + \varepsilon^i_{mt} \tag{27}$$

where we regress the implied variable cost on a market-time fixed effect to extract $\log(\tilde{c}^i_{mt}) \equiv h(m, \phi^i_m) + \varepsilon^i_{mt}$. Then we try to estimate the function $h(\cdot)$ using both a non-parametric and a hyperbolic function approach to uncover the extent of (dis)economies of scale of vessel size in my different markets. As we can see from Figure 16, the estimated cost is following a U-shape over vessel size implying a transition from economies of scale to diseconomies of scale also predicted in our Appendix B discussing the source of (dis)economies of scale.

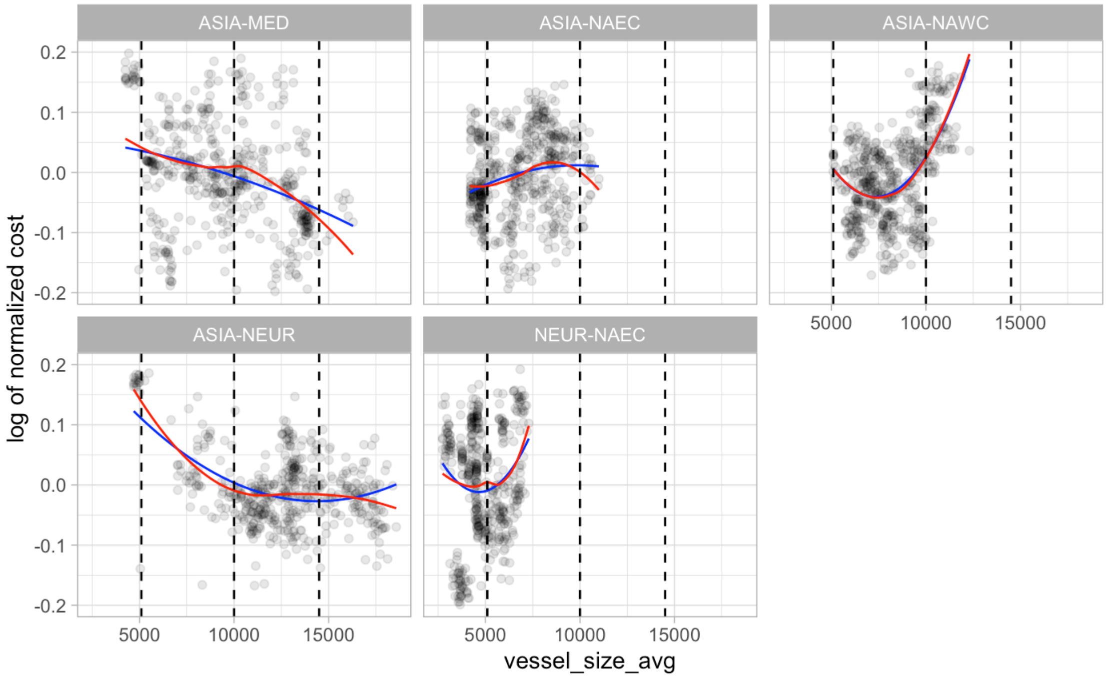
To quantify the extent of economies of scale, we run the following parametric regression of the calibrated cost ($\hat{c}^i_{mt}$) on the carrier-market specific weighted average vessel size (ϕ^i_m)

$$\log(\hat{c}^i_{mt}) = \gamma_{mt} + \beta_m \log(\phi^i_{mt}) + \varepsilon^i_{mt} \tag{28}$$

The regression result is summarized in Table 14 in Appendix C.[13] fr a 10% increase in the average vessel size, the cost of transporting a container on Asia-Europe routes will decrease by 25% on average, and the reduction in cost will be 20% for Asia-Mediterranean routes. The economies of scale in Asia-North America west coast and east coast is not significantly

[13] For a comparison of our estimated economies of scale with those estimated in the literature, please refer to Appendix C.

Figure 16: Effective marginal cost versus average vessel size



from zero. However, this estimates mask the strong non-linearity (U-shape) especially for Asia-North America west coast routes we saw in Figure 16 .

The case of Panama Canal expansion

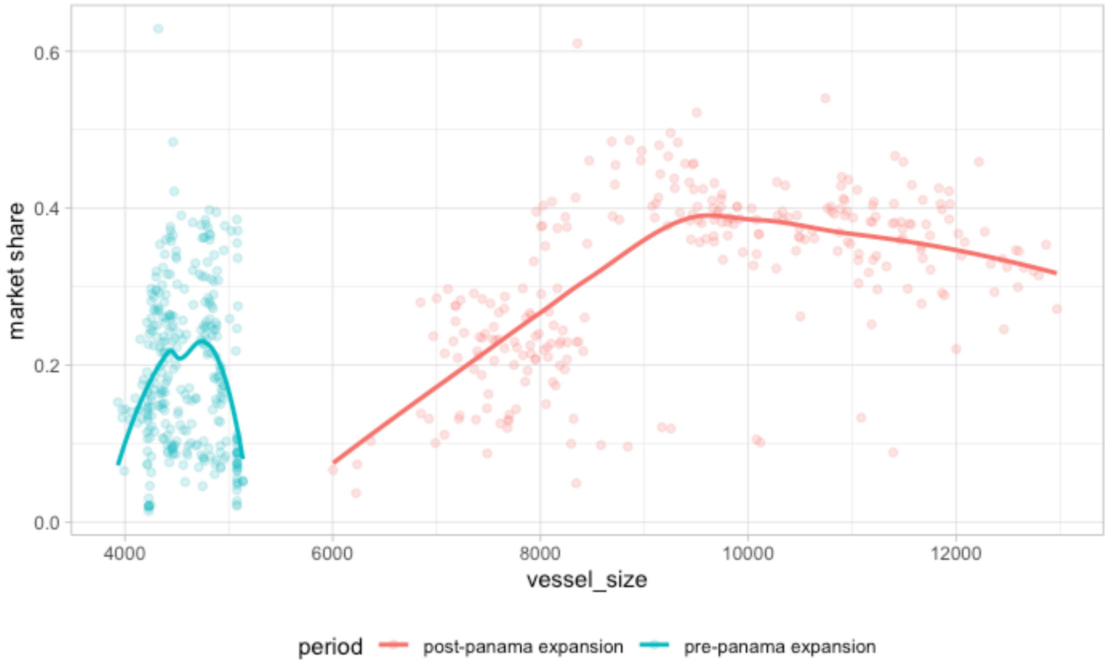
The Panama Canal expansion project significantly enhanced the canal's capacity by allowing larger vessels to transit. Prior to the expansion, the canal accommodated only Panamax ships with a maximum capacity of approximately 5,000 TEUs. The project, completed in mid-2016, added a third set of locks, widened and deepened navigation channels, and upgraded infrastructure, enabling the passage of New Panamax (Neo-Panamax) ships with capacities of up to 14,000 TEUs. This more than doubled the canal's cargo capacity, facilitating the use of larger and more efficient vessels on this critical maritime route.

We separate the time periods to be pre-enlargement and post-enlargement, and we plot the estimated cost over vessel size for these two periods in Figure 17. Before the enlargement, we saw the marginal cost follows a U-shape, and as the vessels approaches the capacity upper limit of 5100 TEU, the implied marginal cost actually increases. However, after the

Table 14: Cost Function Estimation Results

	Dependent variable:		
	log(c)		
	(1)	(2)	(3)
ϕ: ASIA-MED	4.123***	5.161***	−2.177
	(0.677)	(1.544)	(2.177)
ϕ: ASIA-NAEC	−1.475	3.988	−2.408
	(1.089)	(2.444)	(2.948)
ϕ: ASIA-NAWC	−12.513***	−8.874**	−1.204
	(1.446)	(3.756)	(5.304)
ϕ: ASIA-NEUR	1.378**	4.299***	3.847**
	(0.674)	(1.177)	(1.618)
ϕ: NEUR-NAEC	−6.414***	−15.181***	−20.080***
	(1.053)	(2.493)	(3.793)
ϕ^2: ASIA-MED	−0.237***	−0.298***	0.113
	(0.037)	(0.085)	(0.121)
ϕ^2: ASIA-NAEC	0.082	−0.232*	0.133
	(0.062)	(0.139)	(0.168)
ϕ^2: ASIA-NAWC	0.701***	0.496**	0.062
	(0.081)	(0.209)	(0.299)
ϕ^2: ASIA-NEUR	−0.085**	−0.249***	−0.222**
	(0.037)	(0.064)	(0.090)
ϕ^2: NEUR-NAEC	0.382***	0.907***	1.184***
	(0.062)	(0.148)	(0.228)
Observations	2,693	2,693	2,693
R^2	0.975	0.790	0.826
Adjusted R^2	0.969	0.780	0.814
Residual Std. Error	0.072 (df = 2190)	0.192 (df = 2570)	0.176 (df = 2520)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 17: Change in Implied Marginal Cost Pre-/Post-Panama Expansion



expansion, the cost implies a significant economies of scale with respect to vessel size. This change in the economies of scale due to maritime infrastructure improvements also caused carriers to reallocate larger vessels to the Asia-North America East coast

D More Details on Counterfactual Exercise

Table 15: Change in Carrier Profits (Billion USD) in 2016 with 20% Lower Demand

With 2M Alliance				
Maersk+MSC		CKYHE	G6	O3
1.13		2.69	0.96	0.70
2M Alliance (Supply Coordination Only)				
Maersk	MSC	CKYHE	G6	O3
0.06	-0.06	0.00	0.00	0.00

Note: This table presents the change in profits compared to a baseline scenario where the 2M Alliance was never formed. The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel treats the alliance as equivalent to a merger.

Table 16: 2M Alliance: Change in Consumer Surplus (Billion USD) in 2016with 20% Lower Demand

With 2M Alliance					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
-2.43	5.55	-2.88	-5.12	-2.17	**-7.05**
2M Alliance (Supply Coordination Only)					
Asia-Med	Asia-NAEC	Asia-NAWC	Asia-NEUR	NEUR-NAEC	**Total**
0	0	0	0	0	**0**

Note: The top panel assumes Maersk and MSC coordinate only on capacity, while the bottom panel assumes full cooperation as a merger.