Naval Research Logistics (NRL)

WILEY

RESEARCH ARTICLE OPEN ACCESS

Navigating the Waves: The Global Pandemic's Impact on Container Shipping and Freight Rates Across Different Policy Scenarios

Shiyuan Zheng[1] | Changmin Jiang[2]

[1]School of Transportation, Shanghai Maritime University, Shanghai, China | [2]Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University, Hong Kong, China

Correspondence: Changmin Jiang (changmin.jiang@polyu.edu.hk)

Received: 19 March 2024 | **Revised:** 14 January 2025 | **Accepted:** 22 February 2025

Handling Editor: Xin Chen

Keywords: differential game | freight rates | international container shipping | pandemic | susceptible–infected–recovered (SIR) equation

ABSTRACT

The COVID-19 pandemic has reverberated across global industries, including the international container shipping industry, where freight rates have become highly volatile. However, shipping lines appeared to thrive, particularly during the pandemic's initial 2 years. In this paper, we focus on the effects of the pandemic and the governments' related policies on the container shipping industry. The differential game models are developed to analyze the dynamics of the international container shipping market during the global pandemic. By utilizing a modified susceptible–infected–recovered (SIR) equation, we examine the pandemic's impact on shipping activities. Additionally, we compare the effects of two government policy groups in response to global shocks: movement restriction policies and infection-targeted policies. Our findings reveal that the pandemic has varying effects on the container shipping market at different stages. Initially, it disrupts shipping supply, and later, it suppresses shipping demand. This asynchronous impact on demand and supply leads to fluctuating freight rates and profits for shipping lines throughout different phases of the pandemic. Surprisingly, the alliance strategy adopted by shipping lines does not significantly enhance their profits during the pandemic's early stage, thus disassociating it from the surge in freight rates observed during 2020–2021. Our results also indicate that movement restriction policies not only result in increased shipping outputs but also lead to a higher infected population compared to infection-targeted policies. We calibrate our model using real data and further extend it to incorporate various forms of modified SIR equations through numerical experiments. Our analysis reveals that factors such as the pandemic's impact on shipping demand, recovery rate, and the influence of shipping activities on infection growth rate negatively affect freight rates, outputs, and profits of shipping lines, as well as the infected population and societal welfare. Conversely, positive outcomes are associated with the pandemic's effect on shipping supply, infection rate, and the delay of the pandemic's impact on shipping demand. Interestingly, our findings indicate that vaccination rates exhibit a dual effect during the pandemic. Initially, they adversely affect outcomes, but as time progresses, their impact becomes beneficial. Using the pandemic, shipping, policy, and macroeconomic data from January 1, 2020, to December 31, 2022, we empirically verify our main theoretical conclusions.

1 | Introduction

The COVID-19 pandemic has reverberated across global industries, leaving no sector untouched. One area significantly impacted is international container shipping, where freight rates have become highly volatile. As illustrated in Figure 1, the China Container Freight Index (CCFI) experienced remarkable fluctuations: a 50% surge in 2020, followed by an even more impressive 110% increase in 2021. However, during the pandemic's final stage in 2022, it plummeted by over 150%. These seismic shifts introduced substantial uncertainties and risks, affecting the shipping market, global supply chains, and the world economy.

Interestingly, amidst this turbulence, shipping lines (SLs) appeared to thrive, particularly during the pandemic's initial 2 years. Alphaliner reported that the profit margin of the top SLs reached unprecedented levels in 2021 (see Figures 2 and 3). Simultaneously, strategic alliances among the top 14 SLs solidified their dominant position in the international container shipping market (refer to Table 1). This prompts us to question the role of SLs in the soaring freight rates during the pandemic and whether these shipping alliances significantly contributed to the surge.

In the face of the pandemic, nations worldwide implemented a spectrum of strategies to combat the virus, each with distinct repercussions for maritime commerce. Lockdowns, for instance, are stringent regulations designed to halt the flow of individuals and goods into or out of designated zones, aiming to curb viral transmission. Such measures significantly impede not only passenger mobility but also the free movement of freight, disrupting normal logistical operations. Conversely, travel bubbles represent bilateral or multilateral agreements that permit cross-border travel without mandatory quarantine for countries demonstrating effective viral containment. Quarantine protocols, prevalent in many regions, serve as a barrier to limit the pandemic's spread. Additionally, vaccination campaigns are critical governmental initiatives to administer vaccines, safeguarding the populace against infection, severe illness, or mortality due to COVID-19. These inoculation efforts contribute to diminishing the risks associated with viral contagion, community spread, hospital admissions, and fatalities. While these policies predominantly influence human migration, their economic ramifications, particularly on maritime logistics, are profound. It is imperative to analyze the extent to which such public health measures have shaped the operational landscape of shipping firms and the broader maritime market.

Amidst the pandemic, ports—the pivotal nodes of the global shipping network—descended into disarray. The phenomenon of port congestion, characterized by the accumulation of cargo and containers due to sluggish processing, emerged as a significant impediment for the maritime sector. This congestion was attributed to a confluence of pandemic-induced factors: a contraction in container shipping capacity, COVID-19 outbreaks among dockworkers, and disruptions in overland transport and distribution networks. This bottleneck not only strained the shipping industry but also exerted upward pressure on freight rates, further jolting the economy. In response, authorities deployed a suite of strategies to mitigate port congestion. Notably, they initiated round-the-clock operations at key ports, including Los Angeles and Long Beach, which collectively manage 40% of the nation's container imports. The Biden administration played a pivotal role in orchestrating this initiative, even appointing a dedicated port envoy to synchronize efforts across the shipping sector's diverse stakeholders. Further measures encompassed fiscal incentives and infrastructural enhancements aimed at port modernization—expanding docking facilities, upgrading cranes, augmenting yard space, extending gate hours, and integrating advanced digital systems. Additionally, regulatory interventions sought to curtail port dwell times—the duration containers linger on the docks. Some ports levied surcharges for protracted dwell times or unclaimed cargo, while others instituted reservation systems or designated time slots for truckers to streamline container pickups and deliveries at terminals.

To encapsulate, policy measures enacted in response to the pandemic can be broadly categorized into two groups: those aimed at infection control and those imposing movement restrictions. Infection control policies encompass direct interventions such as vaccination programs, quarantine mandates, and the establishment of travel bubbles. While these do not target the shipping industry per se, they exert an indirect influence on maritime operations. On the other hand, movement restriction policies are designed to curtail the pandemic's spread by limiting the transit of individuals and goods. This paper endeavors to dissect the ramifications of these dual policy types on the shipping sector amidst the pandemic. Additionally, it scrutinizes the efficacy of port congestion alleviation efforts and their interplay with these policy measures.

Our research aims to address the following specific questions:

1. What were the underlying factors that led to the surge in freight rates in the container shipping market during 2020–2021? Was this a natural response of the market, or was it influenced by the collusion or alliance strategies of SLs?
2. How do policies targeting infections and restricting movement impact the decisions and profits of SLs, as well as the welfare related to shipping? Is there a policy that holds more sway?
3. What are the effects of government measures, such as vaccination programs and efforts to alleviate shipping supply blockages (e.g., port congestion), on the decisions of SLs and the welfare related to shipping?

Employing differential game models, this study dissects SLs' competitive strategies amid the pandemic, contrasting freight rates and profits across different pandemic phases. It identifies a scarcity in shipping supply, induced by the pandemic, as a key driver of surging freight rates and evaluates the advantages of SLs forming alliances during such tumultuous times. Additionally, it assesses the impact of various pandemic policies and vaccination initiatives enacted by governments.

Our research enriches the existing body of knowledge in several key areas. Firstly, we refine the shipping demand model to account for the ramifications of the pandemic. This enhanced

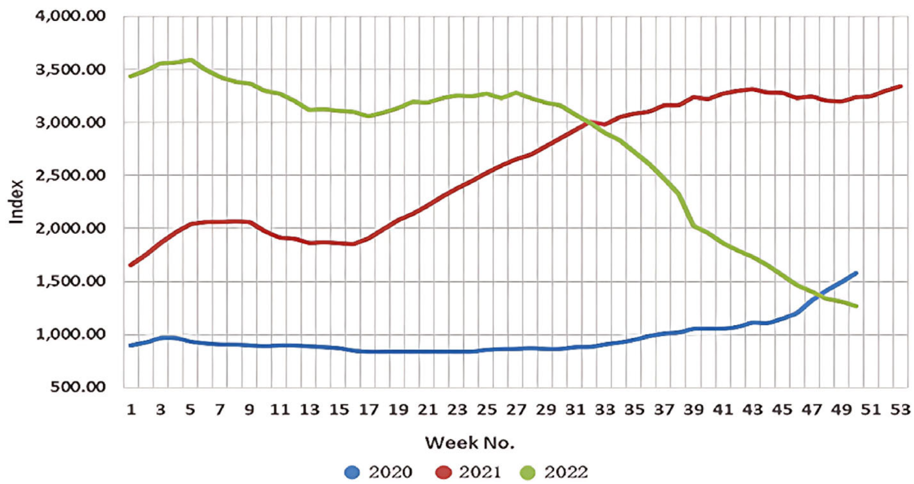

FIGURE 1 | CCFI index in 2020–2022. *Source:* Shanghai Shipping Exchange.

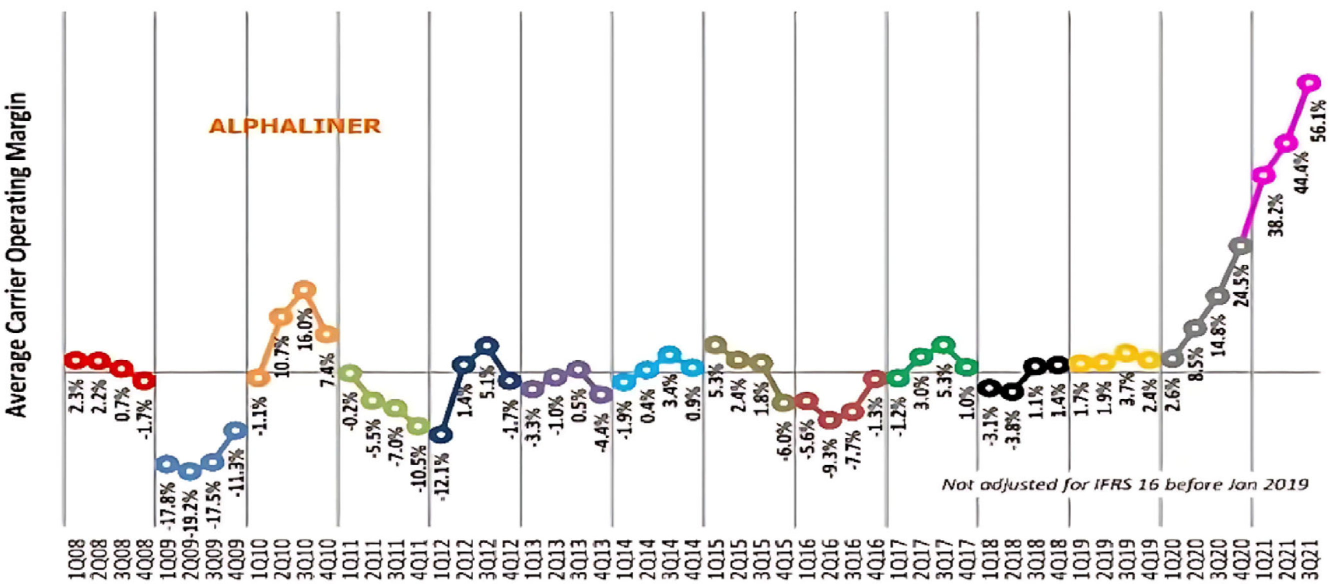

FIGURE 2 | Average container operating margin in 2008–2021. *Source:* Alphaliner.

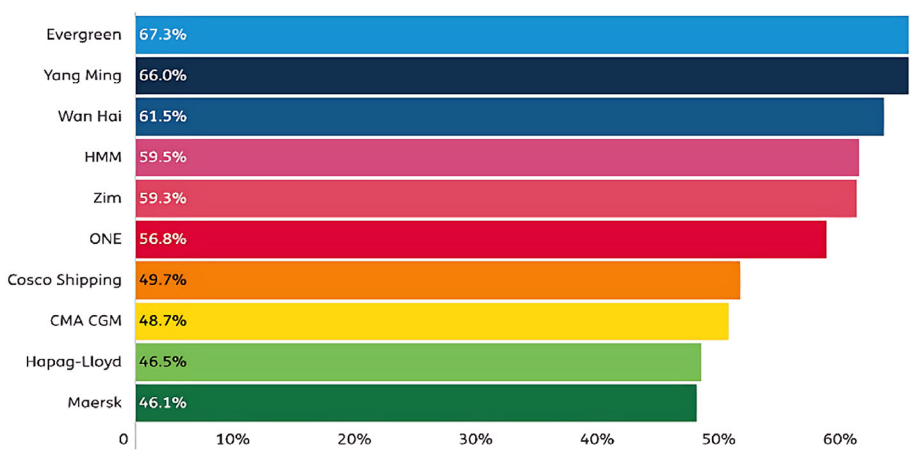

FIGURE 3 | Carriers' operating margins in Q3 of 2021. *Source:* Alphaliner.

TABLE 1 | Evolution of the international container shipping alliances.

Year	Shipping alliance	Members	Market share
2014	2 M	Maersk, MSC	73.7%
	O3	CMA-CGM, CSG, UASC	
	G6	APL, OOCL, MOL, Hyundai, Hapag- Lloyd, NYK	
	CKYHE	COSCO, K-Line, Yangming, Hanjin, Evergreen	
2017	2 M	Maersk, MSC	78.6%
	OCEAN	CMA-CGM (APL), COSCO Shipping, Evergreen, OOCL	
	THE	Yangming, Hapag-Lloyd, MOL, NYK, K-Line	
2020	2 M	Maersk, MSC	82.4%
	OCEAN	CMA-CGM(APL), COSCO Shipping (OOCL), Evergreen	
	THE	Yangming, Hapag-Lloyd, HMM, ONE	

Note: Maersk and MSC decided not to continue their alliance after the agreement expires in 2025.
Source: Alphaliner.

model precisely delineates the pandemic's initial impact on shipping supply and its subsequent influence on demand as the crisis progressed. To explore the strategic responses of SLs amidst the pandemic, we have formulated a differential game model. This approach diverges from the majority of extant studies that concentrate on SLs' static competition strategies—strategies that prove inadequate in the fluid and evolving context of a pandemic, characterized by fluctuating infection rates and market potentials. Through rigorous analytical methods, we have solved the differential game model, extracting the equilibrium strategies for the SLs. Furthermore, our study ventures into uncharted territory by modeling the effects of diverse governmental pandemic responses and vaccination initiatives on the shipping industry—an aspect notably absent from current scholarly discussions.

Secondly, building on the policy implications, our study sheds light on the factors contributing to the dramatic surge in shipping freight rates in 2021. We establish that shipping alliances were not the main drivers of the steep climb in freight rates during the pandemic. Our analysis reveals that policies restricting movement tend to result in increased shipping outputs and a larger infected population when compared to policies directly targeting infections. Intriguingly, efforts to alleviate shipping supply blockages, such as port congestion, yield divergent outcomes depending on the policy in place. Additionally, our research uncovers that the impact of vaccinations on the shipping market and associated social welfare varies across different phases of the pandemic. These insights are particularly valuable, providing a deeper understanding of the challenges and responses of the shipping industry and governmental bodies throughout the pandemic period.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 develops models to examine the SLs' competition strategies and the effects of the governments' policies during the pandemic. Section 4 calibrates our models using real data. Moreover, we extend the models to account for the delayed effects of the pandemic on shipping demand, the various ways in which shipping activities influence the pandemic, and the effects of vaccination. Section 5 makes the empirical studies to test our main theoretical conclusions. Section 6 summarizes the conclusions.

2 | Literature Review

Three distinct streams of literature intersect with our paper: COVID-19-related research within the field of Operations Management (OM) and Supply Chain Management (SCM); analysis of container shipping markets, particularly during the pandemic; and studies on competition and alliances among container shipping companies.

Abundant recent studies in the realm of OM and SCM have delved into the multifaceted impacts of COVID-19. Notably, a special issue of *Production and Operations Management* explores six broad themes: public policies and government interventions, hospital operations and capacity, propagation of pandemics, humanitarian operations, private partnerships, and vaccine production (Anderson et al. 2023). Among this wealth of research, a specific group of studies aligns closely with our investigation. These papers ingeniously integrate epidemiological models into their operational analyses. For instance, the work of Chen and Kong (2023) stands out. They meticulously develop and rigorously test a model that examines the impact of medical resources on reducing cumulative deaths and containing virus spread. Their approach considers a capacity constraint on hospital beds. By extending the classic SEIR model, they delve into the intricate dynamics of individuals' access to limited medical resources. Furthermore, they compare three distinct hospital admission systems adopted by various countries: hierarchical, mixed, and the innovative Fangcang system. Remarkably, the Fangcang system outperforms both alternatives, particularly when medical capacity is constrained. Evgeniou et al. (2023) propose a comprehensive framework for pandemic management, leveraging machine learning predictions to assess individual risk of severe symptoms. Their approach involves a modified SEIR model, which allows them to simulate diverse isolation and exit policies based on risk classifications. By analyzing COVID-19 data from France, they demonstrate that their policies could significantly ease isolation measures for millions of people, all while ensuring that ICU capacity remains manageable. However, they also delve into the practical challenges and implications of implementing such policies. Perakis et al. (2023) delve into pandemic dynamics using a combination of queueing theory and SIR-based models. Their focus centers on critical metrics related to peak load, which directly correlates with the demand for healthcare resources. Applying these metrics to 15 US states, they predict infection waves under varying policy scenarios. Additionally, they provide valuable recommendations for mitigating transmission risk and effectively managing peak load. Shahmanzari et al. (2023) engage in a thought-provoking analysis, balancing the delicate trade-off between economic activity and minimizing loss of life during a pandemic. Employing a stochastic multi-objective dynamic program, they determine the optimal level and timing of government interventions. By comparing static and dynamic containment policies, they identify a Pareto-efficient set—policies that strike a balance, ensuring lives are saved without compromising economic vitality. Moreover, many studies focus on the logistics issues in the pandemic, for example, resource management (Mehrotra et al. 2020; El Hajj et al. 2022; Luo and Mehrotra 2024) and vaccination supply management (Bertsimas et al. 2022; Seranilla and Löhndorf 2024). Besides, a substantial body of literature explores the interactions between the pandemic and various transport modes (e.g., Lu et al. 2021; Sun et al. 2023; Hu et al. 2024; Yimga 2025).

Our study diverges from the existing literature in two fundamental ways. Firstly, our focus is on the pandemic's impact on a specific industry and its responses. In contrast, most studies primarily explore the pandemic's effects on public health and the broader societal economy. While these studies strive to uncover the pandemic's general patterns, they often overlook industry-specific elements. For instance, our research zeroes in on the dynamic competition strategies of SLs during the pandemic and their influence on the evolution of shipping freight rates. We also delve into the role of firm alliances in shaping market prices. Conventional economic theories suggest that firms' alliance strategies are the primary drivers of price increases. However, our findings challenge this notion, particularly in the context of the container shipping market during the pandemic. Furthermore, despite the abundance of research on government policies and vaccination programs during the pandemic, none provide a detailed analysis of their impacts on a specific industry. This might be problematic as different industries may experience varying outcomes due to their unique characteristics. Secondly, from a technical standpoint, most OM/SCM studies during the pandemic employ simulation techniques. In contrast, we develop a differential game model and derive closed-form solutions. These analytical results enable us to gain a deeper understanding of the pandemic's mechanism (specifically within an industry) and yield more policy implications.

Numerous studies have examined the container shipping market from various perspectives, including works by Luo et al. (2009) and Otani and Matsuda (2023). Our focus, however, is on analyzing this market in the context of the pandemic. Complementing this, Jin et al. (2022) utilized automatic identification system (AIS) data to scrutinize the alterations in the international container shipping network during the pandemic. In a similar vein, Dirzka and Acciaro (2022) implemented a three-stage network analysis approach to investigate the dynamics of the global shipping network in the pandemic's initial stage. In addition, Zhao et al. (2022) devised an exponential smoothing model to gauge the shipping market's responses to the pandemic, with a specific focus on the dry bulk and container shipping sectors. They used data from the Baltic Dry Index (BDI), the China Coastal Bulk Freight Index (CCBFI), and container throughputs. Monge (2022) applied time-frequency analysis to examine the evolution of bunker fuel and commodity prices, as well as shipping market indices during the pandemic. Risk mitigation strategies have also been a focal point of research. Bastug et al. (2023) utilized the spherical fuzzy (SF) methodology in the container shipping market to mitigate risks from significant events like the COVID-19 pandemic and related supply chain disruptions. Khan et al. (2023) employed the Generalized Supremum Augmented Dickey–Fuller test to determine the presence of bubbles in the dry bulk shipping freight during the pandemic. The impact of pandemic lockdown policies on global port calls was quantified by Bai et al. (2022), which provided a comprehensive understanding of how lockdown measures have affected port operations worldwide. Bai et al. (2023) presented a data-driven approach to assessing the resilience of the global liner shipping network. The study provided insights into the network's static and dynamic resilience under various disruptive scenarios. Shi et al. (2023) constructed resilience mechanisms in response to container shipping market volatility during the pandemic period, offering a perspective on market supervision and provides strategies for managing market volatility. Lastly, the environmental impacts of the pandemic on the shipping industry were investigated by Xu et al. (2023), who examined the impacts of the COVID-19 epidemic on carbon emissions from international shipping. This study provided an environmental perspective on how the pandemic has affected the shipping industry's carbon footprint.

While many studies have analyzed the container shipping market during the pandemic, the majority are empirical and seldom delve into the effects of dynamic competition strategies employed by SLs, or the impact of government policies and measures, such as vaccination programs and port congestion relief. Our paper seeks to bridge this gap, offering deeper insights into the evolution of the shipping industry amidst the pandemic.

The body of literature on competition and alliances among container shipping companies is vast. Our focus is on studies that apply game models, with the majority of studies in this category employing non-cooperative game models (e.g., Alvarez-SanJaime et al. 2013; Wang et al. 2014; Zheng and Luo 2021; Zhong et al. 2021). A smaller subset of studies utilizes cooperative game models (e.g., Agarwal and Ergun 2010; Zheng et al. 2015, 2017). Despite their use of game theory, these studies predominantly rely on static models. In these models, the competition strategies of SLs remain constant over time. This static approach fails to capture the dynamic adjustments that SLs make in response to changing market conditions during a pandemic. In contrast, our research introduces a differential game model. This model allows for dynamic optimization, where SLs' strategies are governed by dynamic equations and can be adjusted in response to real-time changes in the infected population. Our model provides a valuable addition to the literature on shipping competition, particularly in considering the impacts of a pandemic.

3 | Models

3.1 | Mode Setting

Two SLs (each from a different country) offer differentiated services in the international container shipping market between two countries. Suppose the demand function in the period before the pandemic is

$$P_{it} = 1 - Q_{it} - bQ_{jt} \tag{1}$$

where P_{it} and Q_{it} is SL i's price and outputs at time t, respectively. The market potential is normalized to 1. b is the service substitute degree or the competition degree between the two SLs. Here the SLs' operation costs are normalized to 0. To model the global spread of COVID-19, we use the following susceptible–infected–recovered (SIR) model

$$\frac{dx_t}{dt} = \lambda x_t\left(1 - x_t\right) - \delta x_t \tag{2}$$

where x_t is the infected individuals at period t, λ is the infection rate, and δ is the recovery rate. Equation (2) indicates that the change rate of the infected individuals is determined by two factors: the interactions between the infected individuals and the susceptible individuals (the term $\lambda x_t\left(1 - x_t\right)$) and the recovery of the infected individuals (the term δx_t). Moreover, the shipping activities lead to increase the contact and transmission rates among different regions. We propose the following revised function for COVID spread:

$$\frac{dx_t}{dt} = \lambda x_t\left(1 - x_t\right) - \delta x_t + \epsilon\left(Q_{1t} + Q_{2t}\right) \tag{3}$$

where $\epsilon > 0$ indicates more shipping outputs lead to more infected people. In Equation (3), we add a term "$\epsilon\left(Q_{1t} + Q_{2t}\right)$" in the standard SIR Equation (2) to indicate the impacts of the shipping activities on the change rate of the infected population. For the sake of simplicity, our analysis initially assumes that shipping activities have additive impacts on infections. We will explore other possibilities, such as the multiplicative impacts of shipping activities on infections, in the subsequent section. The pandemic has adversely affected shipping businesses by reducing both the demand and supply sides of the market. However, these impacts are not uniformly distributed across different types of shipping activities.

Reflecting on the history of the Covid-19 pandemic, it becomes evident that the early stage of the pandemic had a more pronounced impact on supply than on demand. At the onset, China, being the world's primary manufacturing hub, swiftly and effectively curtailed the spread of COVID-19. As a result, its manufacturing and export sectors remained largely unscathed by the pandemic. This is evident from the relatively high growth rate of its exports compared to 2019 (National Bureau of Statistics of China), indicating that shipping demand remained robust. However, on the supply side, the pandemic posed significant challenges. The increase in infected seafarers and port workers diminished shipping capacity and efficiency. Ports, particularly those in America and Europe, faced severe congestion, leading to a substantial number of containers being stuck and disrupting the global supply chain (Port Congestion Report 2021). Consequently, the pandemic greatly reduced shipping supply.

The year 2022, widely regarded as the pandemic's final year, saw COVID-19 become less menacing due to the mild symptoms associated with the Omicron variant. Most countries, particularly in America and Europe, progressively relaxed their border restrictions, significantly alleviating port congestion and nearly restoring shipping supply to pre-pandemic levels. However, China faced a severe wave of COVID-19 and enforced stringent lockdowns in numerous major cities throughout the year. For example, Shanghai, China's economic epicenter, experienced a 2-month total lockdown. These lockdowns drastically affected China's manufacturing industry, leading to a significant drop in its exports (Stumpner 2022). Consequently, the shipping demand was heavily impacted in the pandemic's final stage.

The SIR equation, a nonlinear ordinary differential equation (ODE), presents several challenges for our ensuing analysis. We thus aim to simplify it and incorporate the characteristics of how the pandemic influences shipping demand and supply. We partition the entire pandemic into two stages. In the first stage, the infected population increases at an accelerating rate, leading to a surge in the infected population. In contrast, the second stage sees the infected population increase at a decelerating rate, resulting in a gradual stabilization of the infected population. Based on these assumptions, the first term in (3) can be approximated by the following piecewise linear function:

$$\lambda x_t\left(1 - x_t\right) \approx \begin{cases} \frac{1}{2}x_t & \text{if } x_t < \frac{1}{2} \\ -\frac{1}{2}x_t + \frac{1}{2} & \text{if } x_t > \frac{1}{2} \end{cases}$$

Thus, the infection equation in the first period of the pandemic can be expressed as follows:

$$\frac{dx_t}{dt} = \frac{1}{2}\lambda x_t - \delta x_t + \epsilon\left(Q_{1t} + Q_{2t}\right) \tag{4}$$

To guarantee the possible stable conditions on the infections, we assume that $\Phi = \lambda/2 - \delta < 0$.[1] Moreover, it is the shipping supply that is mainly affected in the first period of the pandemic. The demand function is:

$$P_{it} = 1 - \left(Q_{it} - k_S x_t\right) - b\left(Q_{jt} - k_S x_t\right) \tag{5}$$

where $k_S > 0$ is the parameter indicating the impacts of the pandemic to the shipping supply. Equation (5) is a revised inverse demand function of SL i during the first period of the pandemic. In this equation, $Q_{it} - k_S x_t$ and $Q_{jt} - k_S x_t$ denote the on-time delivered cargo volume of SL i and SL j, respectively, after some shipping supply was disrupted by the pandemic. Figures 4 and 5 illustrate the sharp increases in port dwell time and cargo freight time from the beginning of the pandemic to mid-2021. These port blockages and cargo delivery delays severely impacted shipping service quality, resulting in longer waiting times and delayed cargo receipt for consignees. This disruption was the primary factor driving the increase in average shipping prices P_{it} during the early period of the pandemic. Shippers (shipping users) had to bid against each other for scarce on-time delivery slots (Bell et al. 2023), driving up the average shipping freight rates in the market. Specifically, some shippers had to pay higher freight charges to maintain their original schedules, while others had to endure longer delays caused by supply blockages. However, it is important to note that all cargo will eventually be delivered, as the shippers have already paid for the service.

In the second period of the pandemic, the infection equation is

$$\frac{dx_t}{dt} = -\frac{1}{2}\lambda\left(x_t - 1\right) - \delta x_t + \varepsilon\left(Q_{1t} + Q_{2t}\right) \tag{6}$$

And the demand function is

$$P_{it} = 1 - k_D x_t - Q_{it} - bQ_{jt} \tag{7}$$

where $k_D > 0$ is the parameter indicating the impacts of the pandemic to the shipping demand. Equation (7) is a revised inverse demand function of SL i in the second period of the pandemic, where the term $k_D x_t$ indicates the reduction of the shipping demand potential caused by the pandemic.

Several justifications are necessary to support our assumptions and model settings. First, in (3) we assume that the shipping activities contribute to an increase in infections. This is due to the fact that more shipping activities necessitate a larger workforce, including crews and port laborers, leading to increased human contact and, consequently, more infections. While it could be argued that these workers constitute a small fraction of a region or country's total population, and that governments could implement measures to isolate them from the general populace to limit the spread of infection, there are other factors to consider. More shipping activities and cargoes not only require more crews and port laborers but also necessitate inland transportation and urban logistics to deliver the shipping cargoes to end consumers and manufacturers. These inland transports and urban logistics significantly impact human contact, thereby leading to a surge in infections. In Section 5, we use the real data from January 1, 2020 to December 31, 2022 to empirically test this assumption. On another note, (3) highlights the impacts of shipping activities on the rate of increase in infections. Even a minor effect from shipping activities can eventually lead to a significant number of infections. Furthermore, our model stipulates that the impacts of shipping activities on the rate of increase, denoted by the parameter ε, should not be very large. This stipulation, which is detailed further in section 3.2, aligns with our initial assumption.

Secondly, in (5), we posit that the pandemic diminishes the shipping supply. Generally, the pandemic results in a higher number of infected individuals, which in turn affects labor supply. A labor shortage at ports leads to decreased efficiency and severe congestion. Concurrently, infections among crew members result in many vessels being laid up and operations being halted. These factors contribute to blockages and a shortage in shipping supply. The severe port congestion experienced in North America in 2021 serves as a testament to this assertion.

Thirdly, in (7), we hypothesize that the pandemic also curtails shipping demand. The pandemic's impact on shipping demand is twofold. On one hand, lockdowns and isolation measures provide workers with more leisure time, potentially leading to increased consumption of food and related family activities, which could boost shipping demand (Chen et al. 2024; KANTAR 2020). On the other hand, a rise in infections and factory shutdowns result in fewer manufactured products and spare parts, thereby reducing shipping demand. It is widely acknowledged that manufactured goods constitute a larger proportion of shipping cargoes compared to food and family-related products. For instance, in 2021, agricultural products accounted for only 18% of China's imports and exports by value, while manufactured products made up 80% (National Bureau of Statistics of China 2024). Although these figures do not precisely reflect the contrast between the demand for shipping manufactured goods and family-related goods, they

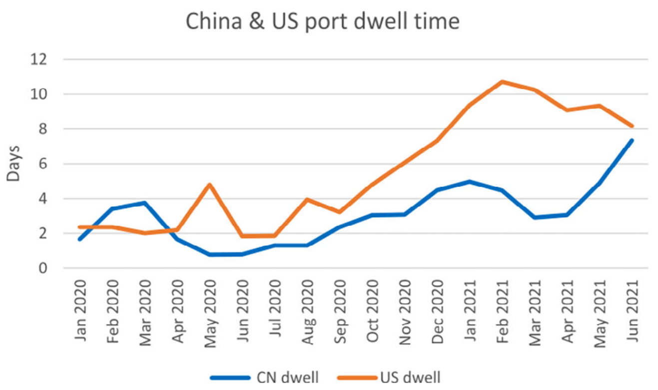

FIGURE 4 | China and US port dwell time. *Source:* cited from Figure 3 in Bell et al. (2023).

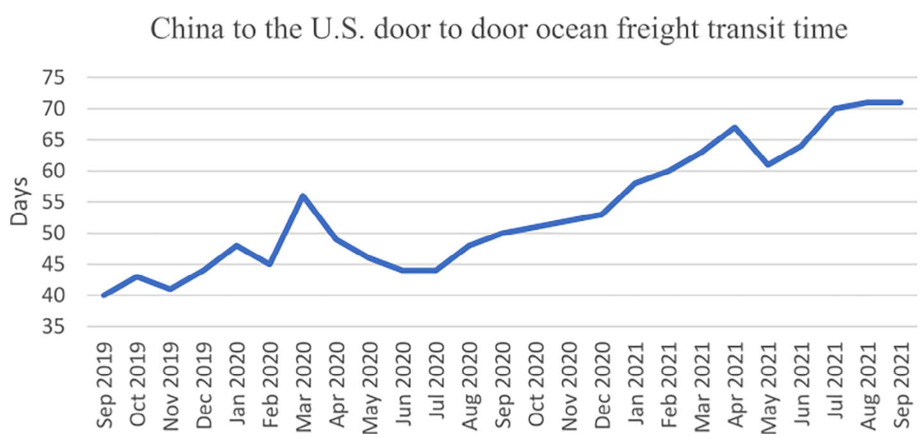

FIGURE 5 | China to the US door-to-door ocean freight transit time. *Source:* cited from Figure 1 in Bell et al. (2023).

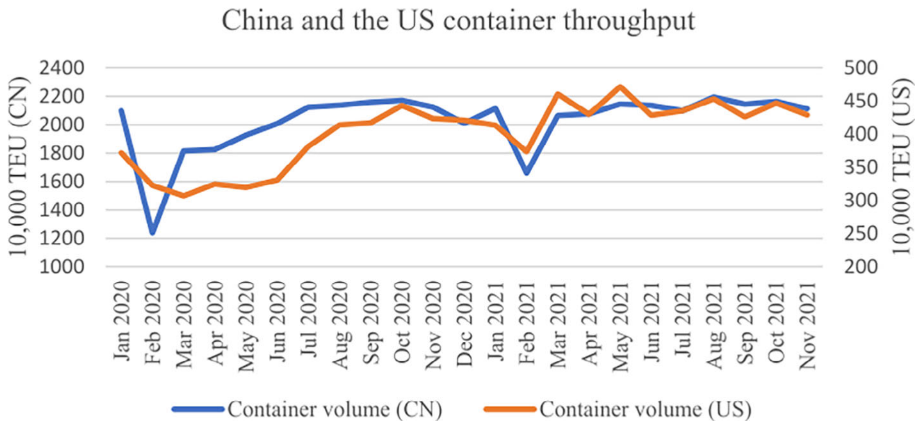

FIGURE 6 | Container throughputs in China and the US. *Source:* cited from Figure 2 in Bell et al. (2023).

do corroborate the assertion that the former significantly outweighs the latter. Ultimately, the pandemic leads to a decrease in shipping demand.

Each SL's total discounted profit in the pandemic is

$$\Pi_i = \int_0^\infty P_{it} Q_{it} dt \tag{8}$$

For each period t, the two SLs engage in a Cournot game and face the following optimal control problem in the first period of the pandemic:

$$\max_{Q_{it}} \Pi_i \tag{9}$$

s.t. (4).

where P_{it} follows (5).

As previously mentioned, the pandemic primarily caused cargo blockages at ports and delivery delays during its early stages. However, it is important to note that the booked shipping volume, or the carriers' shipped cargoes, did not experience a significant reduction. Figure 6 illustrates the container throughputs in China and the US during the first 2 years of the pandemic. It is evident that shipping volumes did not show a sharp decrease in most months. These shipped cargoes are transported by the carriers, and their freight charges are included in the carriers' profits, represented by the term $P * Q$ in Equation (8), where Q is the shipped cargo or the carrier's capacity in equilibrium.

In the second period of the pandemic, each SL faces the following problem:

$$\max_{Q_{it}} \Pi_i \tag{10}$$

s.t. (6).

where P_{it} follows (7).

The linear demand function and Cournot competition are widely used in many maritime studies, such as those by Lam et al. (2007), Fu et al. (2010), and Crotti et al. (2020). Generally, in these studies, the shipping outputs represent the volume of shipped cargoes or the shipping demand in the market equilibrium. In our model, to reflect the severe cargo delivery delays and port blockages in a dynamic setting, which are the main reasons for the increase in shipping freight rates during the early periods of the pandemic, we introduce the "booked shipping cargoes" and "on-time delivered cargoes" in the SLs' profit functions and the inverse demand function, respectively.

3.2 | SLs' Strategies in the Pandemic

We study how the two SLs compete in the first stage of the pandemic, assuming that they are symmetric and offer differentiated services. Solving the two SLs' problem (9) simultaneously (the details and the proofs of all the following lemmas and propositions can be found in Appendix S1), we obtain each SL's optimal operation plan, which can be expressed by an ODE. Lemma 1 summarizes the main results of the differential game between the two SLs. Here, we consider the symmetric equilibrium between the SLs, that is, $Q_{1t} = Q_{2t} = Q_t$. To keep the positive output and infected population, we assume $\epsilon k_S < \frac{-(2+b)\Phi}{3+3b}$.

Lemma 1. *The SL's optimal operation plan in the first period of the pandemic can be described as the following ODE*:

$$\frac{dQ_{it}}{dt} = \frac{2\Phi(1+b)k_S x_t + \left[(1+b)\epsilon k_S - (2+b)\Phi\right]Q_t + \Phi}{2+b} \tag{11}$$

If the two SLs are symmetric, that is, $Q_{1t} = Q_{2t} = Q_t$, the differential game between the SLs in the first period of the pandemic has a Nash equilibrium where the output is $Q_i^I = \frac{\Phi}{(2+b)\Phi+3(1+b)\epsilon k_S}$ and the related infected population is $x_i^I = \frac{-2\epsilon}{(2+b)\Phi+3(1+b)\epsilon k_S}$.

The ODE (11) gives us implications on how the SLs change their outputs in the first period of the pandemic. In Figure 7, the shadow area indicates that the SL needs to increase its output in the next term, thatis, $dQ_{it}/dt > 0$. It shows that the SL should only increase its output when the infected population is small and the current output is high, which is the case at the onset of the pandemic. As the pandemic progresses, the supply chain disruption caused by the rising infected population drives up the freight rates, which discourages the shipping market demand. This leads to the SLs reducing their outputs and further increasing the freight rates. Lemma 1 also reveals that there is a positive

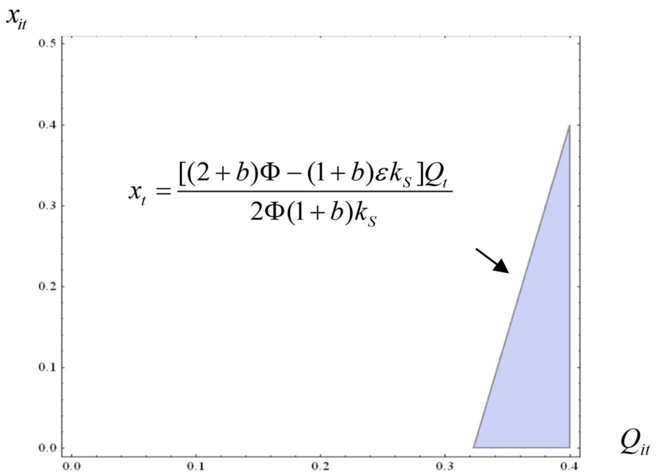

FIGURE 7 | The SL's output plan in the first period of the pandemic. $b = 0.5$, $\lambda = 0.2$, $k_S = 0.2$, $\varepsilon = 0.1$, $\delta = 0.15$.

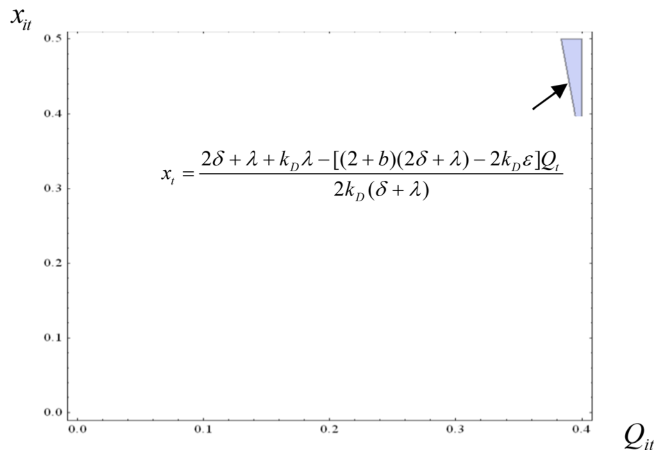

FIGURE 8 | The SL's output plan in the second period of the pandemic. $b = 0.5$, $\lambda = 0.2$, $k_D = 0.2$, $\varepsilon = 0.1$, $\delta = 0.15$.

relationship between the SLs' outputs and the infected population in the early stage of the pandemic. This makes sense because more shipping activities entail more contacts among different regions and result in more infections.

For the equilibrium of the differential game between the SLs, that is, SLs' problem (9), we use the "open loop equilibrium" (Dockner et al. 2000). In the SLs' competition, the open loop equilibrium means that SL i chooses its optimal output plan Q_{it}^* to maximize its total profit, that is, Equation (8), given SL j's optimal output plan Q_{jt}^*. The solutions of the SLs' differential game are described by the ODE system of (4) and (11). The transversality condition could be imposed to limit the solutions which converge to the steady state[2]. In other words, although many solutions can be found to satisfy the ODE system related to the differential game, we care on the stable ones, because they represent a dynamic stable state for the players' optimal strategies, which are consistent with the open loop equilibrium. In the SLs' differential game (9), both the SLs' objective functions and the constraints do not contain the time parameter t explicitly. Such a differential game is called as autonomous and it is reasonable to consider a stationary Markovian Nash equilibrium (SMNE) (Dockner et al. 2000). In the SMNE, both SLs' strategies and their value functions are time independent. Moreover, the SMNE of the SLs' game means that both the SLs' optimal output strategies are based on the stable infected population. To find such SMNE, we impose $dQ_t/dt = 0$ and $dx_t/dt = 0$ to find the SLs' optimal output strategies and the related infected population in the stability. In the proofs of Lemma 1, we show that the dynamic system of $dQ_t/dt = 0$ and $dx_t/dt = 0$ is saddle stable, which means that such a SMNE can be achieved. The SLs' profits and the related social welfare under the SMNE can be used as the approximation to assess the SLs' strategies and the governments' policies. Moreover, in the model calibrations, we use the numerical experiments (based on the real parameters) to fully investigate the SLs' strategies and the governments' policies (not only based on their stability). Most conclusions still hold in the numerical experiments, which means that the SMNE is a good approximation to facilitate our analysis.

Lemma 1 provides us with the following insights. In equilibrium, there is a positive relationship between the SLs' outputs and the infected population in the first stage of the pandemic. This means that increased shipping activities lead to more contacts among different regions, resulting in more infections. This insight is crucial for our understanding of the performance and tradeoffs of the government policies, which will be discussed in the next section. Moreover, the SLs should only increase their output when the infected population is small and the current output is high, which is typical at the onset of the pandemic. As the pandemic progresses, the infected population increases, reducing the "on-time delivery" of cargoes and further driving up shipping freight rates. Such cargo blockages and increasing infections cause the SLs to reduce their outputs in the subsequent period. These insights suggest that the SLs should adopt an inverse "U" shape strategy for their dynamic output plans in the first stage of the pandemic.

Next, we investigate the SLs' competition strategies in the second period of the pandemic. Solving the two SLs' problems (10a) and (10b) simultaneously, we have the following lemma.

Lemma 2. *The SL's optimal operation plan in the second period of the pandemic can be described as the following ODE*:

$$\frac{dQ_t}{dt} = \frac{2k_D(\delta+\lambda)x_t + \left[(2+b)(2\delta+\lambda) - 2k_D\varepsilon\right]Q_t - 2\delta - \lambda - k_D\lambda}{2(2+b)} \tag{12}$$

If the two SLs are symmetric, that is, $Q_{1t} = Q_{2t}$, *the differential game between the SLs in the second period of the pandemic has a Nash equilibrium where the output is* $Q_i^{II} = \frac{2\delta+\lambda-k_D\lambda}{(2+b)(2\delta+\lambda)+6k_D\varepsilon}$ *and the related infected population is* $x_i^{II} = \frac{(2+b)\lambda(2\delta+\lambda)+2\varepsilon(4\delta+2\lambda+k_D\lambda)}{2(2\delta+\lambda)\left[(2+b)(2\delta+\lambda)+6k_D\varepsilon\right]}$.

The ODE (12) gives us implications on how the SLs change their outputs in the second period of the pandemic. In Figure 8, the shadow area indicates that the SL needs to increase its output in the next term, that is, $dQ_{it}/dt > 0$. It reveals that the SL could increase its output only when the infected population is large and the current output is high. When the pandemic develops, the decreasing infected population alleviates its shock on the economy and the shipping demand is gradually recovered. The recovered demand requires the SLs to put more supplies in the market and thereby decreases the freight. Meanwhile, in the equilibrium, the shipping outputs and the infected population are positively related.

Then, we compare the market outcomes, that is, the shipping freight rates and the SLs' profits, in the different periods of the pandemic, which are summarized in the following proposition. Let $\varepsilon_1 = \frac{(2+b)(2\delta-\lambda)}{6k(1+b)}$. Meanwhile, to sharp the conclusion, we assume that $k_D = k_S = k$, that is, the impacts of the pandemic on the shipping demand and supply have the same scalar.

Proposition 1. *Comparing shipping market outcomes in the first and second periods of the pandemic, we obtain the following results*:

1. *The equilibrium shipping freight rate is higher in the first period than in the second period, if the SLs compete intensely with each other*.
2. *The SLs earn higher profits in the first period than in the second period, if the shipping outputs have a low impact on the infected population*, that is, $\varepsilon < \varepsilon_1$.
3. *The gap between the shipping freight rates in the first and second periods widens with the influence of the infection on the shipping market, if the SLs face a high level of competition*, that is, $\partial\left(P^I - P^{II}\right)/\partial k > 0$.

We can draw the following insights from Proposition 3. (1) The pandemic affects the shipping market differently in different stages. In the first stage, the pandemic disrupts the shipping supply, leading to capacity shortage and higher freight rates. In the second stage, the pandemic mainly reduces the market potential (which is delayed from the start of the pandemic) and thereby lowers the freight rates. The mismatch between the pandemic's effects on the shipping demand and supply is the main reason for the fluctuation of the freight rates and the SLs' profits. (2) The difference in freight rates between different stages of the pandemic depends on how much the shipping activities contribute to the infected population, that is, k_D and k_S. We can see that a larger k_D (or k_S, respectively) implies a greater decrease (or increase, respectively) in the freight rates, which we call the demand (or supply, respectively) effect caused by the pandemic. The net change in the freight rates depends on how these two effects compare in magnitude. From the demand function (1), the marginal effect of the pandemic on the demand is k_D, while the marginal effect of the pandemic on the supply is $(1+b)k_S$. When $k_D = k_S = k$, the freight rate difference between the two stages of the pandemic is enlarged by k.

3.3 | Should the Shipping Alliance Be Blamed for the Skyrocketing Freight Rates?

As we mentioned in the introduction section, people may wonder how the shipping alliance affects the high freight rates during the pandemic. In this section, we first examine the SLs' output strategies if they form an alliance. Then, we discuss whether their alliance strategies lead to the high freight rates. Note that the high freight rates seem to occur only in the first stage of the pandemic (recalling Figure 1). Therefore, our analysis in this section focuses on the first stage of the pandemic. When the two SLs form an alliance, they maximize their total profits by deciding their outputs jointly. Because our focus is to discuss whether the shipping alliance is the main force to push up the shipping freight rates in the first period of the pandemic, we mainly analyze its strategies at that time and compare their profit to the case where the SLs operate independently. In the first period of the pandemic, the shipping alliance faces the following problem

$$\max_{Q_{it},Q_{jt}} \Pi_i + \Pi_j \tag{13}$$

s.t. (4).

where P_{it} follows (5).

After comparing the shipping freights and the SLs' profits, we find that although forming an alliance may promote the freight rates, it reduces the SLs' profits, that is, $P^I_N < P^I_A$ and $\pi^I_{i,N} > \pi^I_{i,A}$. Therefore, we have the following proposition.

Proposition 2. *The SLs have no incentive to form an alliance in the first period of the pandemic. Therefore, the high freight rates in the pandemic are not caused by the SLs' collusion.*

Proposition 2 provides a negative answer to one of our main research questions, that is, the shipping alliances are NOT responsible for the surge in freight rates during the pandemic. Proposition 1 shows that the freight rates are mainly driven by the shipping supply disruption caused by the infections. The SLs could increase the freight rates further by forming an alliance, but this would be counterproductive for their profits, as it would excessively reduce the demand.

3.4 | Government's Pandemic Policies

The shipping-related social welfare (social welfare hereinafter) of each country in the pandemic consists of its shippers' utilities, its own SL's profit, and the public health costs. The instantaneous social welfare function[3] is

$$W_i = \int_0^{Q_i} P_i dQ_i - c(x/2)^2 \tag{14}$$

where c is the parameter in the function of social cost caused by the pandemic. In Equation (14), the first term $\int_0^{Q_i} P_i dQ_i$ is the sum of the shipping users' net utilities and the profits of the SLs, and the second term $c(x/2)^2$ is the social cost caused by the pandemic. The social welfare in the pandemic is affected by various factors, such as the economic slowdown, the health and medical costs, the damage to the tourism and transportation sectors, and other social costs (such as domestic violence), as discussed by Nicola et al. (2020). Oum and Wang (2020) use a cubic function to capture the health and medical costs of COVID-19. For simplicity, we use a quadratic function to represent the social costs of the pandemic and examine the social welfare under the equilibrium outcome of the SLs' competition.

The governments may implement the movement restriction policies, which limit and regulate the manufacturing activities. These policies affect the shipping volume by reducing the import and export of goods. Strictly, each government faces a differential game where its objective is (14) and its constraint is (4) or (6). Analytically solving such a differential game is challenging. Given the government's policies are relative stable, here we focus on the government's policy design in the system stability condition, that is, the pandemic (the infected individuals x_{it}) keeps unchanged. Although such system stability is an approximation to the reality, it is enough to assess the performance of the government's policy. In this case, each government faces the following problems:

$$\max_{Q_i} W_i \tag{15}$$

s.t. (4) = 0 or (6) = 0.

where the constraint (15b) indicates that we discuss the government's policy design in the stability of the system. (4) (or (6), respectively) describes the development of the infected population in the first (or second, respectively) period of the pandemic. When it equals to 0, it means that there is no change on the infected population, that is, x_t keeps constant. Thereby the pandemic is in the stability. Both the governments' objective functions (Equation (14)) and the constraints (Equation (4) or (6)) do not contain the time parameter t explicitly. As we mention in Section 3.2, considering the SMNE where both the governments' optimal regulated strategies are based on the stable infected population is reasonable. To find such SMNE, we impose $dQ_{it}/dt = 0$ and $dx_t/dt = 0$ to obtain the governments' optimal regulated output strategies and the related infected population in the stability. We investigate the government's movement restriction policy in the different periods of the pandemic. In the first period the demand function in W_i in (15a) takes the form of (5), and in the second period the demand function in W_i in (15a) takes the form of (7).

In our model, two governments negotiate an acceptable fraction of the infected population x_t if they use the infection-targeted policies. They agree to allow the transportation services between their countries if the fractions of the infected population in both countries are equal to or lower than this threshold. Otherwise, they stop the transportation services, that is, $Q_{it} = 0$. Also we discuss their infection-targeted policies in the system stability. This is equivalent to a Nash bargaining problem that the two governments face:

$$\max_{x_t} W_i W_j \tag{16}$$

s.t. (4) = 0 or (6) = 0.

We continue to analyze the infection-targeted policy when the pandemic is in a stable condition (i.e., the infected population keeps unchanged), and therefore the constraint (16b) has the same meaning as (15b). We solve Problems (15a)–(15b) and (16a)–(16b) to obtain the optimal movement restriction policy and infection-targeted policy of the governments. The results and the derivation processes are presented in Appendix S1. We then compare these two policies in terms of shipping outputs and the infected population. We state the following proposition.

Proposition 3. *The movement restriction policy results in more shipping outputs and higher infected population than the infection-targeted policy*.

At first glance, Proposition 3 might seem counterintuitive, as the movement restriction policy appears to impose more constraints on shipping activities compared to the infection-targeted policy. The rationale behind this lies in the high social costs of the pandemic, which compel governments to prioritize COVID control—a strategy supported by numerous cases and practices during the pandemic. Under the infection-targeted policy, if a government accepts a higher infected population, it must shoulder the increased health costs alone. Simultaneously, it allows the other government to reap the benefits from augmented shipping activities (and the associated international trade, which is positively correlated with infections) due to the relaxed infection population standard. Consequently, neither government is willing to adopt this approach, and both insist on a strict standard, aiming for a lower infected population as their agreed target. However, under the movement restriction policy, the two governments engage in a "Cournot" game, where each country's shipping outputs are substitutable with the other's. One country's increased shipping outputs suppress the other's. Although higher shipping outputs may lead to more infections and escalate the social costs related to COVID, the benefits derived from high shipping outputs can partially offset these social costs. Therefore, the movement restriction policy encourages both the shipping outputs and the infected population.

As we mentioned that the blockage of the shipping supply (e.g., port congestion) is one of the factors that drives up the freight rates in the early stage of the pandemic. A natural question is: how does reducing the blockage, for example, relieving the port congestion, affect the shipping outputs and the infected population under these two policies? The following proposition answers this question.

Proposition 4. *The effects of reducing the shipping supply blockage are opposite under the two policies. It increases both the shipping outputs and the infected population under the movement restriction policy, while it decreases them under the infection-targeted policy*.

Proposition 4 shows us that improving the shipping supply efficiency has different impacts under the two policies. The main reason for this difference is the different focus of the two policies. Under the movement restriction policy, the governments care more about the welfare from the shipping outputs. When the blockage is reduced and more shipping supply is available, the governments can relax the output restriction and enjoy higher welfare from more shipping outputs. On the other hand, under the infection-targeted policy, the governments focus more on the infections and realize that more shipping outputs from the supply blockage reduction will lead to a more infected population. To offset this negative effect on social welfare, they have to use a stricter standard with a lower targeted-infected population. Proposition 4 has useful policy implications to guide the governments to invest in reducing the shipping supply blockage. It illustrates the various outcomes of improving the shipping supply efficiency under different COVID policies.

4 | Model Extensions and Calibrations

In this section, we calibrate our models using real-world data. The purpose of these calibrations is twofold: to validate our theoretical analysis and to glean insights that were elusive in our previous analysis. Concurrently, we refine the models introduced in Section 3 to better reflect reality. In Section 4.1, we sample real data and assign values to the parameters used in our models. Following this, in Section 4.2, we opt for the standard SIR equation over the stepwise approximation used previously. Our initial analysis assumed that shipping activities have additive impacts on infections. However, in Section 4.3, we explore an alternative scenario where shipping activities have multiplicative impacts on infections. Finally, in Section 4.4, we examine the effects of vaccination on the competition strategies of SLs and the shipping market as a whole.

4.1 | Parameter Values

Our models consist of two parts: the stylized competition model and the SIR equation to describe the pandemic evolution. For the competition model, we use the classic Cournot model (which is incorporated into a dynamic problem), with its main parameter, that is, the competition degree b, which varies in $[0, 1]$. Therefore, we focus on the parameters related to the pandemic. There are numerous studies on the pandemic parameters, which depend on the sample time and regions. However, we find that the crucial one is the infection–recovery ratio or R_0, that is, λ/δ. As a highly infectious disease, the infection–recovery ratio of COVID is thought to be greater than 3. However, as we explained in Section 3.1, its value in our model is lower than the standard SIR model. Given the values of λ and δ should be less than 1, we take $\lambda \in [0.2, 1]$ and $\delta \in [0.1, 0.5]$ in our study, with $\lambda > \delta$. These values are consistent with many studies using the empirical data, for example, Li (2023). For the parameter of the pandemic social cost, that is, c, we follow Li (2023) and take $c = 0.001$. Then, we use the following logic to assess the values of k_D and k_S. We know that the world container shipping volume in 2022 reaches 0.2 billion TEU, decreasing 3.1%, compared to 2021[4]. Meanwhile, the infected population in 2022 reaches 0.65 billion worldwide, which occupies 8.13% in the global population (being 8 billion in 2022)[5]. Then, we can estimate that $k_D = 0.031/0.0813 = 0.381$. Considering the possible estimation bias, we take $k_D \in [0.1, 0.8]$ in our numerical studies. On the other side, we use the data in 2021 to estimate k_D, because it is the severest year for the shipping supply blockage. It is known that in 2021 there were 2.37 million TEU capacities in the state of waiting worldwide, occupying 10% in the global container vessels[6]. Meanwhile, the infected population in 2021 reaches 0.28 billion worldwide, which occupies 3.69% in the global population (being 7.58 billion in 2022)[3]. In our model (see (5)), the total shipping supply is $(1+b)Q_t$(if the two SLs are symmetric as we suppose), the total supply loss is $(1+b)k_S x_t$. Therefore, $0.1(1+b)Q_t = (1+b)k_S 0.0369$. In our model, $Q_t \in [0, 0.5]$. Therefore, $k_S \in [0, 1.4]$. To satisfy our discussions in Section 3.1, we take $\epsilon \in [0.01, 0.05]$. Note that we have considered the possible bias from these rough estimations and thereby the vast sensitivity analysis is made to check the robustness of the numerical results.

4.2 | Standard SIR Equation and Integrated Shipping Demand Function

In this section, we use the integrated demand function, rather than the different demand functions in the different periods of the pandemic. Moreover, in order to indicate the delayed impacts of the pandemic on the demand side, we change the demand function as

$$P_{it} = 1 - k_D x_{t-z} - \left(Q_{it} - k_S x_t\right) - b\left(Q_{jt} - k_S x_t\right) \tag{17}$$

where the subscript z indicates the delayed period for the impacts of the pandemic on the shipping demand. Thus, we combine our analysis into one stage, where the impacts of the pandemic on the shipping supply are instantaneous while its impacts on the demand are delayed. We use the standard SIR equation (with the shipping effects), that is, (3), rather than using the linear approximation as in Section 3. The derivation process between the two SLs' competition and the governments' policies can be found in Appendix S1. It is difficult to obtain the closed-form solution when we use the demand function (17) and the standard SIR equation. Therefore, we use the numerical experiments based on the parameter values in Section 4.1 to solve our model. Besides the parameters in Section 4.1, we take $z = \{1, 2, 3\}$, $Q_{1,0} = Q_{2,0} = 1/(2+b)$, $x_0 = 0.01$. From the numerical experiments we find that the main conclusions in Section 3 still hold qualitatively, that is, the SLs' alliance strategy does not necessarily lead to their higher profits and the movement restriction policy leads to higher shipping outputs and the infected population than the infection-targeted policy, when we integrate the pandemic affection into one demand function. Moreover, we make the sensitivity analysis on the following parameters: k_D, k_S, λ, δ, ϵ, and z. We examine their impacts on the freight rates, the SLs' outputs and profits, the infected population and social welfare, which can be found in Figures S1–S6 in Appendix S2. Based on the numerical experiments, we obtain the following observations.

Observation 1. *An increased impact of the pandemic on shipping demand results in a decrease in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

Observation 2. *A greater impact of the pandemic on shipping supply leads to an increase in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

Observation 3. *A higher infection rate results in an increase in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

Observation 4. *An increased recovery rate leads to a decrease in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

Observation 5. *A greater impact of SLs' outputs on the infection growth rate results in a decrease in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

Observation 6. *More delayed impacts of the pandemic on shipping demand lead to an increase in freight rates, SLs' outputs and profits, the infected population, and social welfare.*

These observations yield some intriguing insights. Firstly, the pandemic impacts both shipping demand and supply, leading to diverse outcomes on the shipping market, COVID-19 spread, and social welfare. This is consistent with our analysis in Section 3. Interestingly, we find that the positive effects of the pandemic on shipping supply (and consequently on social welfare) outweigh its negative impacts on shipping demand. This is because, despite the pandemic's disruption of the realized shipping outputs, SLs are incentivized to ramp up production due to higher freight rates. This leads to increased shipping outputs and profits for SLs. Although this may result in a larger infected population, the increased health costs may be offset by the rise in user surplus (from the increased shipping outputs) and profits for SLs. On the other hand, when the pandemic reduces shipping demand, SLs have no alternative but to scale down their production. While this leads to a smaller infected population, the reduction in user surplus (from the decreased shipping outputs) and profits for SLs negatively impacts social welfare. These conclusions hinge on conditions where health costs for infected individuals are not excessively high and "shipping-related" infections are not substantial.

Secondly, during the pandemic, freight rates are influenced not only by shipping outputs but also by the infected population, as per (17). An increase in shipping outputs has a dual effect on freight rates. On one hand, it decreases freight rates, as indicated by the negative relationship in (17). On the other hand, it simultaneously increases the infected population, as per the positive relationship in (3), which subsequently elevates freight rates. The effect of output on decreasing freight rates is linear, while the growth of the infected population is nonlinear and accelerates, especially during the early stages of the pandemic. Ultimately, increased outputs lead to higher freight rates during the pandemic. This positive feedback loop of high output–high freight rate enhances profits for SLs. In scenarios with mild health costs from the pandemic and "shipping-related" infections, increased shipping outputs lead to higher "shipping-related" social welfare. This forms the fundamental positive feedback loop in our shipping–pandemic system.

Thirdly, the delayed repercussions of the pandemic on shipping demand prove to be advantageous for social welfare. As elucidated in Section 3, international trades, which constitute the primary source of shipping demand, are negotiated and established in advance. As a result, the tangible reduction in shipping demand, instigated by the pandemic, manifests itself only after a certain period following the initial outbreak. This delay results in asynchronous impacts of the pandemic on shipping demand and supply. When the effects on shipping demand are more delayed, it is the initial, smaller infected population that triggers an increase in freight rates and increased output, ultimately leading to enhanced social welfare.

4.3 | Multiplicative Impacts of the Shipping Activities on the Infections

Now, we assume that the impacts of the shipping activities on the infections are multiplicative and the infection equation becomes

$$\frac{dx_t}{dt} = \lambda\left(Q_{1t} + Q_{2t}\right)x_t\left(1 - x_t\right) - \delta x_t \tag{18}$$

In this section, we continue to use the distinct demand functions as represented in (5) and (7) during different periods of the pandemic. The derivation process involving the two SLs and the governments' policies can be found in Appendix S1. Using the parameters outlined in Section 4.1, we conduct an extensive numerical experiment employing the multiplicative infection equation. The results align with those in Section 3, indicating that our models are robust regardless of whether the impacts of shipping activities on infections are additive or multiplicative.

4.4 | Considering the Impacts of Vaccination

If we consider the impacts of the vaccine on the infections, the infection equations become

$$\frac{ds_t}{dt} = -\lambda x_t s_t - u s_t \tag{19}$$

$$\frac{dx_t}{dt} = \lambda x_t s_t - \delta x_t + \varepsilon\left(Q_{1t} + Q_{2t}\right) \tag{20}$$

$$\frac{dr_t}{dt} = u s_t + \delta x_t \tag{21}$$

where s_t and r_t are the susceptible and recovered individuals at period t, respectively. u is the proportion of the vaccination. Then, the demand functions in periods 1 and 2 become

$$P_{it} = s_t + x_t + r_t - \left(Q_{it} - k_S x_t\right) - b\left(Q_{jt} - k_S x_t\right) \tag{22}$$

$$P_{it} = s_t + x_t + r_t - k_D x_t - Q_{it} - bQ_{jt} \tag{23}$$

The social welfare function of country i becomes

$$W_i = \int_0^{Q_i} P_i dQ_i - c(x/2)^2 - gus_t/2 \tag{24}$$

where g is the marginal cost of vaccination.

Based on the parameters outlined in Section 4.1, we conduct numerical experiments, particularly focusing on the impacts of vaccination. The results of these experiments can be observed in Figures S7 (which can be found in Appendix S1). We see that most conclusions from Section 3 hold qualitatively. We also find that the effects of vaccination on the shipping market and social welfare vary across different stages of the pandemic, which is summarized in the following observation.

Observation 7. *A higher vaccination rate decreases freight rates, the SLs' outputs and profits, and social welfare in the first stage of the pandemic, while it increases freight rates, SLs' outputs and profits, and social welfare in the second stage of the pandemic.*

Observation 7 highlights the varying effects of vaccination across different stages of the pandemic. We know that vaccination reduces the infected population. In the first stage, the pandemic primarily affects shipping supply and a smaller infected population leads to decreased freight rates. Simultaneously, a smaller infected population alleviates supply blockage, thereby reducing the incentive for SLs to increase production. All these factors (low freight rates and fewer SLs' outputs) result in lower SLs' profits and "shipping-related" social welfare. In the second stage, the pandemic mainly affects shipping demand and a smaller infected population leads to increased freight rates. Simultaneously, a smaller infected population indicates a larger market potential, thereby incentivizing SLs to increase production. All these factors (high freight rates and more SLs' outputs) result in higher SLs' profits and "shipping-related" social welfare. It is worth emphasizing that we are discussing "shipping-related" social welfare, and this does not imply that vaccination negatively impacts general social welfare in the first stage of the pandemic.

5 | Empirical Studies

To evaluate our theoretical predictions, we employ real data from the pandemic, maritime sector, and macroeconomic indicators to conduct empirical analyses.

5.1 | Hypothesis

Our primary objective is to empirically test the following four hypotheses based on our theoretical predictions:

H1. *The implementation of lockdown measures yields greater maritime output compared to the travel bubble approach.*

H2. *Alleviating port congestion enhances maritime output under lockdown conditions but diminishes it when a travel bubble policy is in place.*

H3. *An increased vaccination rate reduces maritime output during the initial phase of the pandemic; however, it boosts output during the latter phase.*

H4. *Maritime operations contribute to an escalation in infection rates.*

Within these hypotheses, H1 corresponds to Proposition 3, H2 to Proposition 4, H3 to Observation 7, and H4 to one of our fundamental (and potentially most contentious) assumptions. Herein, "lockdown policy" denotes measures restricting movement and "travel bubble policy" signifies strategies targeting infections (as delineated in Section 1). Additionally, "port congestion" serves as a proxy for impediments to shipping supply within these empirical studies.

5.2 | Data and Sample

The sample encompasses pandemic, shipping, policy, and macroeconomic data from January 1, 2020 to December 31, 2022. Specifically, the shipping data pertain to 10 container shipping routes between China and the rest of the world, representing the primary indicator of the international container shipping market, namely the China Containerized Freight Index (CCFI). According to Clarksons' data, the traffic volume along these 10 routes accounts for over 80% of China's container shipping market. The countries on each selected container shipping route are listed in Table 2. For each country, we select one or two representative ports and obtain ship movement data among these ports from the AIS database[7]. During the specified period, there are approximately 1.1 million ship calling records. We extract the relevant records that passed through the investigated ports and calculate the corresponding ship movement numbers or shipping frequency among these ports. Shipping frequency here refers to the result obtained by selecting the main ports of the countries through which the CCFI routes pass, counting the total number of ships arriving at China (Shanghai Port) from these ports on a monthly basis, and summing them up by country. This measurement intuitively reflects the intensity of shipping activity. The choice of monthly data is due to the prolonged nature of shipping operations, where shorter time spans (such as daily or weekly data) would not effectively capture vessel movements. However, in the data matching process, we mapped monthly data to each day of the corresponding month to maintain the completeness of the temporal dimension. Although this may reduce data variability, it preserves the maximum amount of usable data. Additionally, we collect pandemic and macroeconomic data for these countries from *Our World in Data*[8], and policy data (lockdown and travel bubble) from government documents, news reports, and websites. The variable definitions are based on annotations from the database[9]. Specifically, we measure the total infection rate using total confirmed COVID-19 cases per 1 000 000 people. The pandemic data is daily national-level data, which serves as the basis for constructing a panel. We match the monthly ship movement data to the corresponding month. The merged dataset is a balanced panel data set containing a total of 81 909 observations.

TABLE 2 | The countries on each selected container shipping route.

Route	Countries
Africa	Djibouti, Mauritius, Togo, Ghana, Cameroon, Benin, Nigeria, Ivory Coast, Kenya, Congo, Angola
Australia/New Zealand	Marshall, Kiribati, Fiji, Tonga, New Caledonia, Vanuat, Solomon, Micronesia, New Zealand, Australia
East Coast of NA and West Cost of NA	Canada, USA, Bahamas, Jamaica, Mexico, Guatemala, Panama
Europe	Germany, Belgium, UK, France, Netherlands, Portugal
Mediterranean	Morocco, Egypt, Turkey, Greece, Italy, Spain, Israel, Slovenia, Croatia, Malta, Lebanon, Libya, Romania, Ukraine
Persian/red sea	Oman, Saudi Arabia, Jordan, Bahrain, Iraq, Qatar, Iran, Poland, Sweden, Denmark, UAE
South Africa	South Africa, Namibia
South America	Colombia, Peru, Brazil, Argentina, Uruguay, Chile
Southeast Asia	Malaysia, Sri Lanka, Singapore, Vietnam, India, Thailand, Pakistan, Bangladesh

5.3 | Empirical Results

5.3.1 | H1

To test H1, which postulates the influence of lockdown and travel bubble policies on maritime shipping output, we establish the

TABLE 3 | Estimate results of the model (25).

Ship volume			
Model	**Lockdown**	**Bubble**	**Lockdown and bubble**
Lockdown	1.745***		2.138***
	(0.4993)		(0.549)
Bubble		2.299***	−0.00452
		(0.5584)	(0.648)
POP	0.344***	−0.0750***	0.187***
	(0.0034)	(0.0039)	(0.00176)
GDP	−0.0180***	0.00280***	−0.0282***
	(0.0002)	(0.0001)	(0.000320)
HDI	2011***	−252.3***	4006***
	(27.0661)	(19.4420)	(50.72)
Observations	8775	9750	7800
R-squared	0.965	0.962	0.965
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

Note: Results in parentheses are robust standard errors. ***$p < 0.01$.

subsequent econometric model:

$$\text{Ship volume}_{ct} = \alpha_1 \text{lockdown}_{ct} + \alpha_2 \text{bubble}_{ct} + \left(\sum_j \alpha_{j,ct} \text{controls}_{j,ct}\right) + \delta_c + \delta_t + \varepsilon_{ct} \tag{25}$$

where c represents the country, and t represents the date. The dependent variable "Ship volume" is used to quantify maritime shipping output. Independent variables comprise two binary variables "lockdown" and "bubble," which are deduced from governmental records, media sources, and online platforms. Control variables encompass population density (POP), GDP per capita (GDP), and the Human Development Index (HDI) of a country to adjust for macroeconomic influences. Yearly, monthly, and country-specific fixed effects are also accounted for in this model. The findings presented in Table 3 suggest that both policy measures exert a substantial and positive effect on maritime shipping outputs as indicated by α_1 and α_2 in Columns 2 and 3 in Table 3. Furthermore, as shown by α_1 and α_2 in Column 4 in Table 3, it is evident that lockdown policies have a more pronounced effect on maritime shipping outputs compared to travel bubble policies. This verifies H1.

5.3.2 | H2

To test H2, which examines the effects of port congestion relief on shipping outputs under the two policies, we develop the following econometric model:

$$\begin{aligned}\text{Ship volume}_{ct} = {} & \gamma_1 \text{lockdown}_{ct} + \gamma_2 \text{bubble}_{ct} + \gamma_3 \text{CI}_{ct} + \gamma_4 \text{CI}_{ct} \\ & \times \text{lockdown}_{ct} + \gamma_5 \text{CI}_{ct} \times \text{bubble}_{ct} \\ & + \left(\sum_j \gamma_{j,ct} \text{controls}_{j,ct}\right) + \delta_c + \delta_t + \varepsilon_{ct}\end{aligned} \tag{26}$$

TABLE 4 | Estimate results of the model (26).

Ship volume			
Model	**Lockdown × congestion**	**Bubble × congestion**	**Both**
Lockdown	15.11***		6.734*
	(3.4601)		(4.0448)
CI × lockdown	−17.10***		−7.726*
	(3.9657)		(4.5665)
Bubble		−9.722***	−17.27***
		(1.9275)	(3.5053)
CI × bubble		13.58***	18.41***
		(2.3424)	(4.0936)
CI	−28.02***	−33.52***	−47.83***
	(1.5388)	(2.3478)	(3.8234)
POP	0.378***	−0.0615***	0.201***
	(0.0038)	(0.0039)	(0.0018)
GDP	−0.0189***	0.00227***	−0.0308***
	(0.0002)	(0.0001)	(0.0003)
HDI	2115***	−173.3***	4417***
	(27.0834)	(19.8612)	(53.1381)
Observations	8775	9750	7800
R-squared	0.967	0.963	0.967
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

Note: Results in parentheses are robust standard errors. ***$p < 0.01$ and *$p < 0.1$.

where CI represents the port congestion index, which is obtained from the Clarkson database. The coefficients γ_4 and γ_5 illustrate how the implementation of lockdown and travel bubble policies influence the effect of changes in port congestion on shipping outputs. Due to the absence of specific disclosures regarding relief policies, pinpointing the exact timing of port congestion relief measures is challenging. Nevertheless, we can examine the combined impact of lockdown and travel bubble policies, along with the port congestion index, on shipping outputs. The results are presented in Table 4. The signs of γ_4 and γ_5 in Column 4 of Table 4 indicate that port relief (a decrease in the port congestion index) has opposite effects on shipping outputs under the two policies, with an increase in shipping outputs under the lockdown policy and a decrease under the travel bubble policy. This verifies H2.

5.3.3 | H3

To test H3, which examines the effects of vaccination on shipping outputs, we develop the following econometric model:

$$\text{Ship volume}_{ct} = \beta_1 \text{vaccination}_{ct} + \left(\sum_j \beta_{j,ct} \text{controls}_{j,ct}\right) + \delta_c + \delta_t + \varepsilon_{ct} \tag{27}$$

where vaccination refers to the number of COVID-19 vaccination doses administered per 100 individuals in the total population.

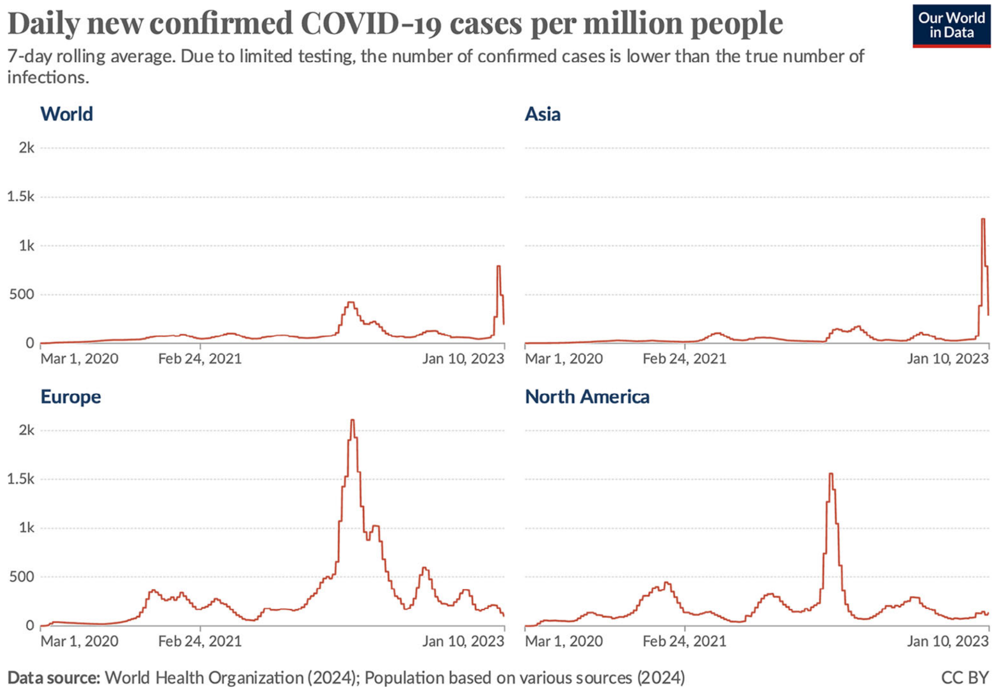

FIGURE 9 | Daily new confirmed cases. *Source:* World Health Organization (2024); Population based on various sources (2024).

TABLE 5 | Estimate results of the model (27).

Period	**After 2021.05**	**After 2021.05**
Ship volume		
Vaccination	−0.0854***	0.121***
	(0.0313)	(0.0139)
POP	−0.0932***	−0.0743***
	(0.0074)	(0.0063)
GDP	0.00252***	0.00269***
	(0.0001)	(0.0001)
HDI	−166.9***	−280.8***
	(37.3541)	(33.5105)
Observations	3844	2469
R-squared	0.985	0.941
Year FE	Yes	Yes
Month FE	Yes	Yes
Country FE	Yes	Yes

Note: Results in parentheses are robust standard errors. ***$p < 0.01$.

To more precisely assess the impact of the COVID-19 pandemic and maintain consistency with Observation 7, we divide the sample into two periods based on the peak of daily new confirmed cases (7-day rolling average) in May 2021, when the Delta variant was designated as a variant of concern (VOC)[10]. These periods are depicted in Figure 9. The results are presented in Table 5. The signs of β_1 in Columns 2 and 3 of Table 5 indicate that vaccination has opposite effects on shipping outputs during different phases of the pandemic, with negative impacts in the first period and positive impacts in the second period. This verifies H3.

5.3.4 | H4

To test H4, which examines the impact of shipping activities on infection rates, we develop the following econometric model:

$$\text{Infection}_{\text{ct}} = \theta_1 \text{ ship volume}_{\text{ct}} + \left(\sum_{\text{j}} \theta_{\text{j,ct}} \text{controls}_{\text{j,ct}} \right) + \delta_i + \delta_t + \varepsilon_{it} \quad (28)$$

where "infection" refers to the total confirmed cases of COVID-19 per 1 000 000 individuals (including probable cases where reported). The results are presented in Column 2 of Table 6. The sign of θ_1 in Column 2 of Table 6 suggests that shipping activities have a positive impact on infection rates. This verifies H4.

Although the positive and significant coefficient of shipping volume indicates that shipping activities positively impact infection rates, thereby partially verifying H4, this estimation may not be sufficient and robust to confirm our crucial assumption. Therefore, we examine the lagged effects on H4 to alleviate potential endogeneity in Equation (28). The results, also presented in Table 6, confirm the robustness of our estimates and further verify that shipping activity contributes to the increase in infection rates. When shipping volume is lagged by one to three periods (daily level) in the model, the coefficients remain significantly positive, indicating that the impact of shipping activity on infection rates is both present and persistent.

It is worth noting that in Equation (4) the rate of change in infection rates, dx/dt, is heavily influenced by infection peaks. Near these peaks, the change in infection rates can exhibit large short-term fluctuations. For example, the rate remains relatively stable ($dx/dt \approx 0$) during the incubation period, becomes significantly positive ($dx/dt \gg 0$) during the onset period, and decreases rapidly ($dx/dt < 0$) during recovery. Such short-term

TABLE 6 | Estimate results of the model to verify H4.

Variables	(1) Infection	(2) Infection	(3) Infection	(4) Infection
Ship volume	226.3***			
	(43.1547)			
L.ship volume		225.3***		
		(43.1538)		
L2.ship volume			224.4***	
			(43.1570)	
L3.ship volume				223.0***
				(43.1645)
POP	110.1***	110.4***	110.7***	111.0***
	(16.9463)	(16.9730)	(16.9996)	(17.0259)
GDP	0.0267	0.0307	0.0348	0.0402
	(0.3648)	(0.3653)	(0.3659)	(0.3664)
HDI	331 758***	331 785***	331 802***	331 698***
	(83 905.9279)	(84 039.8905)	(84 172.3858)	(84 303.8455)
Observations	11 686	11 687	11 688	11 689
R-squared	0.798	0.798	0.798	0.798
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Note: Results in parentheses are robust standard errors. ***$p < 0.01$.

spikes in dx/dt substantially reduce the effectiveness of empirical identification. Additionally, because shipping activities often span several months, our study covers the entire pandemic period and considers shipping activity from a global perspective. It is not feasible to fully isolate and identify all infection peaks within the dataset. As shown in Figure 9, infection peaks vary across regions and may reflect shifting patterns of new infections, which could lead to the insignificant average effect observed in the full sample. Therefore, we have chosen to use the total infection rate as the dependent variable to avoid regional heterogeneity in new infection rates. By controlling for yearly and monthly fixed effects, we capture the average impact of shipping activities over a long-term horizon. Furthermore, examining lagged effects not only confirms the model's robustness but also sheds light on short-term impacts at the daily level. In summary, Equation (28) comprehensively verifies H4.

6 | Conclusions

In this study, we utilize differential game models to scrutinize the competitive strategies of SLs and explore the dynamics of the international container shipping market amidst the pandemic. We employ a modified SIR equation to encapsulate the influence of shipping activities on infection rates. Our findings reveal that the pandemic's impact on the container shipping market varies across different stages, from both supply and demand perspectives. The asynchronous effects on demand and supply lead to elevated (or reduced) freight rates and profits for SLs in the early (or later) stages of the pandemic. Interestingly, the alliance strategies of SLs do not bolster their profits in the pandemic's early stage, debunking the notion that these strategies were responsible for the high freight rates observed in 2020–2021. Furthermore, we compare the effects of government COVID policies, specifically movement restriction and infection-targeted policies, on the shipping market and societal welfare. Our results suggest that the movement restriction policy results in increased shipping outputs and a higher infected population compared to the infection-targeted policy. We also extend our models to accommodate different forms of the modified SIR equations through the model calibrations and numerical experiments. The outcomes affirm the robustness of our models and offer additional policy implications for the international container shipping industry during the pandemic. Finally, using the pandemic, shipping, policy, and macroeconomic data from January 1, 2020 to December 31, 2022, we empirically verify our main theoretical conclusions.

Future research could explore a multitude of potential extensions. Our models could be broadened to encompass other stakeholders in maritime logistics or the entire supply chain, such as port operators, manufacturers, and consignees. The pandemic has had significant impacts on these entities, and their decisions profoundly influence both SLs and the infected population. Modeling the interactions among various parties throughout the supply chain during a pandemic presents an intriguing and important avenue for future research. Furthermore, while our study employs the basic SIR equation to chart the progression of the pandemic, other equations have been developed to capture more nuanced details of a pandemic. These include the susceptible-exposed–infected–recovered (SEIR) model, susceptible–exposed–infected–susceptible (SEIS) model, and epidemic network models. These models address aspects not covered in our study, such as exposed individuals, quarantine measures, and the network effects of COVID-19. Incorporating these elements into future models could yield deeper insights into the interplay between a pandemic and the international container shipping market.

Acknowledgments

Financial supports from the National Science Foundation of China (No. 72371074, 72072113) and the Natural Science Foundation of Beijing Municipality (No. IS23129) are gratefully acknowledged.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] In the standard SIR equation, it is required that $\lambda > \delta$. Many empirical studies find that the COVID has higher $R_0 > 3$, which means that $\lambda > 3\delta$. It is worth emphasizing that in our revised SIR equation, the impacts of the shipping activities are expressed by the term $\varepsilon\left(Q_{1t} + Q_{2t}\right)$. Therefore, λ in our model should be less than in the standard SIR equation.

[2] The details can be found in the proofs of Lemma 1 in the appendix.

[3] Let Q_i^j be the shipping volume from the users in country j who use SL i in each period (where the superscript indicates the country and the subscript indicates the SL). Thus, the social welfare in country 1 should be $W_1 = \int_0^{Q_1^1} P_1 dQ_1^1 + \int_0^{Q_2^1} P_2 dQ_2^1 - P_1 Q_1^1 - P_2 Q_2^1 + P_1\left(Q_1^1 + Q_1^2\right) - c(x/2)^2$, where the term $\int_0^{Q_1^1} P_1 dQ_1^1 + \int_0^{Q_2^1} P_2 dQ_2^1$ is the users' surplus in country 1, and the term $-P_1 Q_1^1 - P_2 Q_2^1$ is their payments to the SLs. Similar expression can be used in W_2. In the symmetry between the two countries and SLs, we have $Q_1^1 = Q_1^2 = Q_1/2$, $Q_2^1 = Q_2^2 = Q_2/2$ and $P_1 = P_2$. Therefore, W_i can be expressed as (14).

[4] http://wap.eworldship.com/index.php/eworldship/news/article?id=189224.

[5] http://www.who.int/.

[6] https://www.163.com/dy/article/GPQ6A3R80530KEJV.html.

[7] Here, "ship movement data" refer to the number of vessels traveling between Port A and Port B within a given month. Ideally, the volume of cargo transported on each route would serve as the most accurate indicator of shipping outputs in our model. However, due to the unavailability of such detailed statistical data, we utilize ship movement data, which can be precisely tracked through the AIS, as a proxy for shipping outputs in our model.

[8] https://ourworldindata.org/covid-cases.

[9] https://github.com/owid/covid-19-data/tree/master/public/data.

[10] https://www.who.int/activities/tracking-SARS-CoV-2-variants.

References

Agarwal, R., and O. Ergun. 2010. "Network Design and Allocation Mechanisms for Carrier Alliances in Liner Shipping." *Operational Research* 58, no. 6: 1726–1742.

Alvarez-SanJaime, O., P. Cantos-Sanchez, R. Moner-Colonques, and J. J. Sempere-Monerris. 2013. "Competition and Horizontal Integration in Maritime Freight Transport." *Transportation Research Part E* 51: 67–81.

Anderson, E., S. Gupta, N. Joglekar, and M. Starr. 2023. "Managing Pandemics: A POM Perspective and Directions for Future Research." *Production and Operations Management* 32, no. 5: 1295–1306.

Bai, X., Z. Ma, and Y. Zhou. 2023. "Data-Driven Static and Dynamic Resilience Assessment of the Global Liner Shipping Network." *Transportation Research Part E* 170: 103016.

Bai, X., M. Xu, T. Han, and D. Yang. 2022. "Quantifying the Impact of Pandemic Lockdown Policies on Global Port Calls." *Transportation Research Part A* 164: 224–241.

Bastug, S., H. Haralambides, E. Akan, and K. Kiraci. 2023. "Risk Mitigation in Service Industries: A Research Agenda on Container Shipping." *Transport Policy* 141: 232–244.

Bell, M. G. H., Z. Wang, K. F. Cheung, and S. Zhu. 2023. "A System Dynamics Analysis of the Trans-Pacific Trade Lane During the Pandemic." *Transportation Research Part A* 176: 103802.

Bertsimas, D., V. Digalakis Jr, A. Jacquillat, M. L. Li, and A. Previero. 2022. "Where to Locate COVID-19 Mass Vaccination Facilities?" *Naval Research Logistics* 69, no. 2: 179–200.

Chen, R., T. Li, and Y. Li. 2024. "Analyzing the Impact of COVID-19 on Consumption Behaviors Through Recession and Recovery Patterns." *Nature Scientific Reports* 14: 1678.

Chen, Z., and G. Kong. 2023. "Hospital Admission, Facility-Based Isolation, and Social Distancing: An SEIR Model With Constrained Medical Resources." *Production and Operations Management* 32, no. 5: 1397–1414.

Crotti, D., C. Ferrari, and A. Tei. 2020. "Merger Waves and Alliance Stability in Container Shipping." *Maritime Economics & Logistics* 22: 446–472.

Dirzka, C., and M. Acciaro. 2022. "Global Shipping Network Dynamics During the COVID-19 Pandemic's Initial Phases." *Transport Policy* 99: 103265.

Dockner, E. J., S. Jorgensen, N. V. Long, and G. Sorger. 2000. *Differential Games in Economics and Management Science*. Cambridge University Press.

El Hajj, H., D. R. Bish, E. K. Bish, and H. Aprahamian. 2022. "Screening Multi-Dimensional Heterogeneous Populations for Infectious Diseases Under Scarce Testing Resources, With Application to COVID-19." *Naval Research Logistics* 69, no. 1: 3–20.

Evgeniou, T., M. Fekom, A. Ovchinnikov, R. Porcher, C. Pouchol, and N. Vayatis. 2023. "Pandemic Lockdown, Isolation, and Exit Policies Based on Machine Learning Predictions." *Production and Operations Management* 32, no. 5: 1307–1322.

Fu, X., A. K. Ng, and Y. Y. Lau. 2010. "The Impacts of Maritime Piracy on Global Economic Development: The Case of Somalia." *Maritime Policy & Management* 37, no. 7: 677–697.

Hu, J., H. Lu, M. Li, Y. Long, Y. Li, and Y. Zeng. 2024. "Impact of Newly Extended Metro Line Opening on Commuting Carbon Emissions: A Comparative Study Before and During the Pandemic." *Transport Economics and Management* 2: 203–213.

Jin, L., J. Chen, Z. Chen, X. Sun, and B. Yu. 2022. "Impact of COVID-19 on China's International Liner Shipping Network Based on AIS Data." *Transport Policy* 121: 90–99.

KANTAR. 2020. "China Consumption Report in 2020, Series 2." https://www.kantar.com/zh-cn/inspiration/consumer/china-fmcg-growth-hits-deflation-for-first-time-in-five-years.

Khan, K., A. Khurshid, and S. D. Köseoglu. 2023. "Are There Bubbles in Shipping Freight During COVID-19?" *Research in Transportation Economics* 100: 101319.

Lam, J. S., W. Y. Yap, and K. Cullinane. 2007. "Structure, Conduct and Performance on the Major Liner Shipping Routes." *Maritime Policy & Management* 34, no. 4: 359–381.

Li, X. 2023. "A Two-Level Policy for Controlling an Epidemic and Its Dynamics." *Omega* 115: 102753.

Lu, J., A. Lin, C. Jiang, A. Zhang, and Z. Yang. 2021. "Influence of Transportation Network on Transmission Heterogeneity of COVID-19 in China." *Transportation Research Part C: Emerging Technologies* 129: 103231.

Luo, F., and S. Mehrotra. 2024. "Service Center Location Problems With Decision Dependent Utilities and a Pandemic Case Study." *Naval Research Logistics* 71, no. 1: 3–26.

Luo, M., L. Fan, and L. Liu. 2009. "An Econometric Analysis for Container Shipping Market." *Maritime Policy & Management* 36, no. 6: 507–523.

Mehrotra, S., H. Rahimian, M. Barah, F. Luo, and K. Schantz. 2020. "A Model of Supply-Chain Decisions for Resource Sharing With an Application to Ventilator Allocation to Combat COVID-19." *Naval Research Logistics* 67, no. 5: 303–320.

Monge, M. 2022. "Bunker Fuel, Commodity Prices and Shipping Market Indices Following the COVID-19 Pandemic: A Time-Frequency Analysis." *International Economics* 172: 29–39.

National Bureau of Statistics of China. 2024. "Statistical Communiqué of the People's Republic of China on the 2024 National Economic and Social Development." https://www.stats.gov.cn.

Nicola, M., Z. Alsaf, C. Sohrabi, et al. 2020. "The Socio-Economic Implications of the Coronavirus Pandemic (COVID-19): A Review." *International Journal of Surgery* 78: 185–193.

Otani, S., and T. Matsuda. 2023. "Unified Container Shipping Industry Data From 1966: Freight Rate, Shipping Quantity, Newbuilding, Secondhand, and Scrap Price." *Transportation Research Part E* 176: 103186.

Oum, T. H., and K. Wang. 2020. "Socially Optimal Lockdown and Travel Restrictions for Fighting Communicable Virus Including COVID-19." *Transport Policy* 96: 94–100.

Perakis, G., D. Singhvi, O. Skali Lami, and L. Thayaparan. 2023. "COVID-19: A Multiwave SIR-Based Model for Learning Waves." *Production and Operations Management* 32, no. 5: 1471–1489.

Port Congestion Report. 2021. "Port Congestion Report 2021." https://www.hellenicshippingnews.com/2021-port-congestion-report/.

Seranilla, B. K., and N. Löhndorf. 2024. "Optimizing Vaccine Distribution in Developing Countries Under Natural Disaster Risk." *Naval Research Logistics* 71, no. 1: 140–157.

Shahmanzari, M., F. Tanrisever, E. Eryarsoy, and A. Sensoy. 2023. "Managing Disease Containment Measures During a Pandemic." *Production and Operations Management* 32, no. 5: 1362–1379.

Shi, J., Y. Jiao, J. Chen, and S. Zhou. 2023. "Construction of Resilience Mechanisms in Response to Container Shipping Market Volatility During the Pandemic Period: From the Perspective of Market Supervision." *Ocean and Coastal Management* 240: 106642.

Stumpner, S. 2022. "How Much Do China's Regional Lockdowns Affect International Trade?" https://www.banque-france.fr/en/publications-and-statistics/publications/how-much-do-chinas-regional-lockdowns-affect-international.

Sun, X., C. Zheng, S. Wandelt, and A. Zhang. 2023. "Air Transportation and COVID-19: A Tale With Three Episodes." *Transport Economics and Management* 1: 13–21.

Wang, H., Q. Meng, and X. Zhang. 2014. "Game-Theoretical Models for Competition Analysis in a New Emerging Liner Container Shipping Market." *Transportation Research Part B* 70: 201–277.

World Health Organization. 2024. https://ourworldindata.org/coronavirus.

Xu, L., Z. Yang, J. Chen, and Z. Zou. 2023. "Impacts of the COVID-19 Epidemic on Carbon Emissions From International Shipping." *Marine Pollution Bulletin* 189: 114730.

Yimga, J. 2025. "Air Travel-Induced COVID-19 Risk and Mortality Across US Counties." *Transport Economics and Management* 3: 9–22.

Zhao, H. M., H. D. He, K. F. Lu, X. L. Han, Y. Ding, and Z. R. Peng. 2022. "Measuring the Impact of an Exogenous Factor: An Exponential Smoothing Model of the Response of Shipping to COVID-19." *Transport Policy* 118: 91–100.

Zheng, J., Z. Gao, D. Yang, and Z. Sun. 2015. "Network Design and Capacity Exchange for Liner Alliances With Fixed and Variable Container Demands." *Transportation Science* 49, no. 4: 886–899.

Zheng, S., and M. Luo. 2021. "Competition or Cooperation? Ports' Strategies and Welfare Analysis Facing Shipping Alliances." *Transportation Research Part E* 153: 102429.

Zheng, S., R. R. Negenborn, and X. Zhu. 2017. "Cost Allocation in a Container Shipping Alliance Considering Economies of Scale: A CKYH Alliance Case Study." *International Journal of Shipping and Transport Logistics* 9, no. 4: 449–474.

Zhong, H., F. Zhang, and Y. Gu. 2021. "A Stackelberg Game Based Two-Stage Framework to Make Decisions of Freight Rate for Container Shipping Lines in the Emerging Blockchain-Based Market." *Transportation Research Part E* 149: 102303.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.