A STUDY ON THREE CONTEMPORARY ISSUES IN THE SHIPPING INDUSTRY: COST, COVID-19, ONLINE PLATFORM

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A Study on Three Contemporary Issues in The Shipping Industry: Cost, COVID-19, Online Platform

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CERTIFICATE OF ORIGINALITY

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_______________________________(Signed)

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ABSTRACT

This dissertation consists of three independent studies associated with maritime transportation changes. It aims to provide policy implications regarding cost studies, impact of COVID-19, and digitization in maritime transportation.

Despite their indispensability to international trade, no comprehensive review of maritime and airline freight cost analysis has ever been conducted. The first study reviews and summarizes cost modelling, studies investigate these two industries and classifies the models into item-based cost formulations and aggregated cost formulations. We further compare the different models in order to identify general cost forms within the two industries. We also analyze how these cost models evolve over time and provide frequently used databases. This study also explains the underlying justifications for model specification, and outlines future research directions in cost modelling of these two industries.

The recent experience of lockdowns during COVID-19 highlights the prolonged impact a pandemic could have on ports and the shipping industry. The second study uses port call data derived from the Automatic Identification System (AIS) reports from the world's 30 largest container ports to quantify both the immediate and long-term impact of national COVID-19 lockdown policies on global shipping flows. The analysis uses the Difference-in-Difference (DID) and combined regression discontinuity design (RDD)-DID models to represent the effects of lockdown policies. The combination of RDD and DID models is particularly effective because it can mitigate time trends in the data, e.g., the Chinese New Year effect on Chinese ports. This study further examines the potential shock propagation effects, namely, how lockdown policy in one country (i.e., China) can affect the number of port calls in other countries. We categorize ports

in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group, using a proposed connectivity index with China derived from individual vessel trajectories obtained from the AIS data. The results provide a clearly measurable picture of the kinds of trade shocks and consequent pattern changes in port calls over time caused by responses to lockdown policies of varying levels of stringency. We further document the existence of significant shock propagation effects. As the risk of pandemics rises in the twenty-first century, these results can be used by policy makers to assess the potential impact of different levels of lockdown policy on the maritime industry and trade flows more broadly.

In the digital era, major shipping lines are developing instant quote and online booking platforms. As one of the first attempts to investigate the post-event effects of this trend, the third study evaluates how a shipping line's online quote platform impacts its shipper portfolio and the ordered container volume. In order to control for unobserved, time-varying effects that could be correlated with the platform's implementation, we apply the regression discontinuity design (RDD) method to the import trade data from 2016 to 2019 of a top shipping line that released its platform in August 2018. We also adopt global polynomial regression and local liner regression so as to control for the effects of different polynomial time trends, and to test different bandwidths of effect time. Our findings suggest that, overall, the container volume assigned to the shipping line declined slightly after the online platform was launched. The container orders of small shippers with monthly container volume of less than 5 TEUs increases by 3.97 TEU on average after online platform adoption. The volume of assigned containers from other shippers, meanwhile, declines.

On the whole, this dissertation provides useful insights for stakeholders in shipping industry. Researchers in maritime transportation can learn from the cost studies in air freight transportation to better understand the main economic characteristics of costs. Understanding the effect of lockdown on container port calls helps maritime players to manage their capacity during lockdowns more effectively and to respond more flexibly to changing demand in seaborne transportation. These findings of online quote platform on container orders hold fruitful implications for shipping lines. A significant increase in the number of small shippers and their container volumes demonstrate administrative cost saving and risk mitigation for a shipping line. However, it also leads to possible loss of large customers.

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LIST OF ABBREVIATIONS

AA	American Airlines
AEA	Association of European Airlines
AI	Airbus Industries
AIS	Automatic Identification System
API	Application Programming Interfaces
ASL	Average Stage Length
ATA	Air Transport Association
ATMF	Available Ton-miles of Freight
ATR	Air Transport Reporting
BCTI	Baltic Clean Tanker Index
BDI	Baltic Dry Index
BDTI	Baltic Dirty Tanker Index
BHP	Brake Horsepower
CE	Cost Efficiency
CNM	Cumulative Navigated Miles
COVID-19	Coronavirus Disease of 2019
CTM	Capacity Ton Miles
DID	Difference-in-Difference
DLH	Deutsche Lufthansa
DOC	Direct Operating Cost
DWT	Dead Weight Tonnes
ECA	Emission Control Area
EDI	Electronic Data Interchange
EMSA	European Maritime Safety Agency
EOD	Economies of Density
EOS	Economies of Scale
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GHG	Greenhouse Gas Emissions
ICAO	International Civil Aviation Organization
ICT	Information and Communication Technology

IMF	International Monetary Fund
IMO	International Maritime Organization
LF	Load Factor
LNG	Liquefied Natural Gas
LPG	Liquefied Petroleum Gas
MQC	Minimum Quantity Commitment
MTOW	Maximum Take-off Weight
NASA	National Aeronautics and Space Act
NPS	Number of Points Served
NTEU	Net Twenty-foot Equivalent Unit
NVOCCs	Non-vessel-operating Common Carriers
QUAL	Quality of Service
RAM	Revenue Aircraft Miles
RDD	Regression Discontinuity Design
RDP	Revenue Departures Performed
RPK	Revenue Passenger Kilometres
RPM	Revenue Passenger Miles
RTK	Revenue Tonne Kilometres
RTM	Revenue Tonne Miles
SFA	Stochastic Frontier Analysis
SFOC	Specific Fuel Oil Consumption
TEU	Twenty-foot Equivalent Unit
TFP	Total Factor Productivity
TOC	Total Operating Cost
TOE	Technology-Organization-Environment
UNCTAD	United Nations Conference on Trade and Development
USDOT	United States Department of Transport
VAR	Vector Autoregressive
WTO	World Trade Organization

Chapter 1 Introduction

1.1 Background

Maritime transportation is regarded as the backbone of global trade and the global economy, often dubbed the "life blood of world trade". The shipping industry is developed along with different changes in its history, and these changes have brought different impacts to the industry. Some of these changes transform shipping industry by providing a free trade environment, reducing greenhouse gas emissions (GHG) and creating laws and regulations. Other changes have devastating impacts on maritime transportation, leading to disruption in port operations, bankruptcy of shipping companies and shrinking trade volumes. It is important for shipping stakeholders including the International Maritime Organization (IMO), governments, shipowners, shipbuilders, port operators, and shippers etc. to cope with these changes by better understanding their impacts. We divide the changes into three categories: policies, external shocks, technological innovations.

Policies have greatly impacted maritime transportation. The international maritime and transport laws, such as The Rotterdam Rules, provide mandatory standards of international conventions in maritime transportation. To fight against climate change and cut GHG emissions from maritime transportation, IMO has adopted a set of international mandatory measures to improve ships' energy efficiency since 2011. The IMO 2020 regulation which limits sulphur in ships' fuel oil to a maximum 0.5% has been in force since 1 January 2020. Ship operators, shipowners and other stakeholder took measures to comply with this rule several years ago (Li, 2019). Maritime transportation has undergone considerable expansion in recent decades, thanks to the different types of trade agreements. The WTO reduces tariff barriers and provides a framework for trade liberalization since China has been a member of WTO on 11 December 2001 (Parameswaran, 2004).

External shocks sometime have damaged maritime transportation hard. Natural disasters (e.g. the Kobe earthquake in 1994), COVID-19 pandemic, financial crisis (e.g. the US financial crisis of the early 1990s, the 2007-2008 financial crisis), oil crisis in 1973, the nationalization and subsequent closure of the Suez Canal in 1956, etc. have great impact on maritime transportation. Political developments may disrupt shipping market to some extent, such as wars (the Korean War started in 1950; the Gulf War in August 1990; the Russia-Ukraine war started in 2022).

Technological innovations have dramatically transformed maritime transportation. To begin with, the steam engines free ships from dependence on the wind and increase sailing speed overwhelmingly (Atkinson et al., 2018). Second, iron hulls replace wooden sailing ships and allowed much larger vessels to be built (Geels, 2002). Third, screw propellers make vessels more seaworthy (Bourne, 1852). Fourth, the deep-sea cable network allows traders and shipowners to communicate across the world (Fornari and WHOI, 2003). Fifth, containerization drastically cut transportation cost by reducing time spent to loading and uploading ships in ports (Guerrero and Rodrigue, 2014). Nowadays, maritime transportation actively embraces digitalization to adapt to this new technology world (Sanchez-Gonzalez et al., 2019).

The study will help to enrich the toolboxes in studying the shipping changes. In particular, it can help the industry stakeholders to have a better understanding of the cost formulation/model in maritime transportation and air freight transportation, the COVID-19 impact on container port calls, as well as the shippers booking behavior changes caused by online quote platform.

1.2 Problem Statement and Objectives

The cost study has always been the focus of transportation economies. Maritime transportation is an ancient industry compared to other modes (air, rail and road), but the cost studies are less than other industries. This is due to limited knowledge of cost. The cost study in maritime transportation begins with the cost allocation derived from management accounting, such as capital cost, crew cost, fuel cost, port cost, cargo handling cost etc. The basic objective of this kind of cost study is to identify major cost items in order to evaluate and estimate a company's or an industry's operating costs at different level of aggregation. With the development of theory of cost function, researchers learn from the cost function adopted from other transportation modes, like log-log cost function, linear cost function, semiology cost function, and translog cost function. Those cost functions establish the relationship between cost and traffic volumes, input prices, operational characteristics, and network size. They are used to evaluate the economic characteristics of costs and identify their key determinants. For example, the existence of economics of scale and economies of density have been studies in maritime transportation.

The cost studies in maritime transportation surges, due to the availability of cost data and development of cost functions. Drewry shipping release shipping operating costs annual review and forecast to facilitate researchers with detailed cost data. Combining the cost data at company level with the output, input prices, operational characteristics allow the establishment of cost function in maritime transportation. Whereas it lacks a comprehensive review of cost studies in maritime transportation. We summarize and compare cost studies in maritime and air freight transportation using air freight as a benchmark. The reason is that both air freight and maritime are long-haul transportation and play an indispensable role in international trade.

The first objective of this thesis is to summarize and compare the differences in the specifications and the characteristics of cost studies in the maritime and air freight transportation and explore the reasons causing the differences.

China is the first country to implement stringent national lockdown in early 2020 (Chinese New Year holiday) to contain a viral breakout. Some factories in China reduced or stopped production, with disruptions in logistics as well as the supply of raw materials and components (Tahir and Masood, 2020). As a result, the demand for maritime transportation has contracted due to low export volumes. Additionally, crew change restrictions and labor shortages at ports have led shipping companies to skip some Chinese ports (Alamoush et al., 2022). China overwhelmingly dominates the global container ports rankings. Of the top 10 container ports, seven are in China: Shanghai, Ningbo-Zhoushan, Shenzhen, Guangzhou-Nansha, Qingdao, Tianjin and Hong Kong (Alphaliner, 2022). How the lockdown in China effect container port calls in China deserves evaluation. Besides, little is known about the propagation effect of Chinese lockdown on container port calls in other countries.

The propagation effect (or the so-called ripple effect) refers to the spread of a disruption throughout multiple echelons, typically occurring in banking study (Giannetti and Saidi, 2019), financial crisis (Brunnermeier and Oehmke, 2013), and supply chain (Hosseini and Ivanov, 2020). The complex and vast voyages routes constitute a huge maritime traffic network, especially in container shipping. Once the port in a country or region is interrupted, it will lead to corresponding delays or suspensions of subsequent ports. In this study, we aim to evaluate how the lockdown policies effect the number of port calls in their own countries and other countries.

Beginning with the first lockdown in China, other countries and cities continued to implement lockdown throughout 2020. We call the large-scale lockdowns outside

China the second lockdown, mainly announced on 18 March 2020 and implemented in Asia, Europe and North America. By then, China has almost ended the lockdown. Production has gradually resumed in China, compared with other countries that have reduced production due to the second lockdown. In order to mitigate these effects going forward, it is crucial to define the exact effects of lockdown measures for policymakers.

To help shipowners, shippers, shipbuilders and policy makers make rational anticipation of the effect of COVID-19 on maritime transport and recover from disruptions, it is crucial to have a good understanding of how the COVID-19 pandemic affect maritime transport. Thus, the second objective of this thesis is to examine the effect of national lockdown policies on maritime transportation by analyzing the port call data of the world's largest 30 container ports. We aim to tackle two specific research questions: 1) What is the impact of national lockdown policies on local port calls, both in the short term (i.e., one or two weeks) and long term (i.e., four to six weeks)? 2) Is there evidence of disruption propagation effects on ports across different regions? (ii) To evaluate how container port calls are affected by COVID-19 and compare the different patterns between Chinese ports, Asia ports and European and US ports; to find the underlying reasons causing the differences among different regions.

As a traditional-driven industry, maritime transportation actively embraces the new technologies, such as EDI, blockchain, IoT, and artificial intelligence. But online quote platform that have been adopted by other industries decades ago has not been embraced by the maritime transportation as quickly as others. The COVID-19 pandemic has disrupted maritime transportation to some extent, but it has also accelerated the digitization progress and innovation of the industry. By 2022, eight of the top 10 container carriers have developed online quote platforms for customers to get quotes online and secure a space for their freight, compared with only two or three in 2018.

Two years after the online quote platform was implemented, about half of Maersk's customers are now booking online, rather than booking via email or telephone (Wackett, 2022).

The third objective of this thesis is to evaluate how a shipping line's online quote platform impacts its shipper portfolio and the ordered container volume. Specifically, this study investigates: (a) whether an online quote platform affects the volume of containers ordered by different shippers, and (b) how shippers react after the release of an online quote platform by a shipping line.

1.3 Dissertation Overview

The remainder of this dissertation is organized as follows. Chapter 2 reviews existing studies relevant to cost studies in air freight transportation and maritime transportation, COVID-19 and maritime transport, DID and RDD application in COVID-19 and transportation studies, and new technology adoption in maritime transportation field.

In Chapter 3 to 5, the three studies corresponding to the three research objectives are analyzed respectively.

Chapter 3 first summarize the cost studies in air freight transportation and maritime transportation, respectively. Then, we compare the cost studies of the two industries and summarize the development of cost studies and the most frequently used databases for cost studies.

Chapter 4 adopts both DID and RDD-DID methods to quantify the immediate and long-term impact of national COVID-19 lockdown policies on global shipping flows. We further examine the potential shock propagation effects, namely, how lockdown policy in one country can affect the number of port calls in other countries.

Chapter 5 evaluates how a shipping line's online quote platform impacts its shipper portfolio and the ordered container volume. Both local linear regression and global polynomial regression of RDD methods are applied to control for the unobserved, time-varying effects that could be correlated with the platform implementation.

Chapter 6 concludes the key findings and proposes recommendations for future research.

Chapter 2 Literature Review

In this chapter, we first present the review research in cost studies in the transportation field. Secondly, we summarize the COVID-19 and maritime transport; and, DID and RDD-DID application in COVID-19 and transportation studies. Lastly, we show the related study in digitization of maritime transportation and RDD application from previous studies.

2.1 Cost Studies in Air Freight Transportation and Maritime Transportation

While we are not aware of any general review of the item-based cost formulation in the transportation industry, several papers review the modelling and estimation approach of the aggregated cost formulation. Jara-Diaz (1982a) review transportation cost functions from a methodological perspective, especially their characterization and treatment of transportation output. Some define transportation production, discuss how to theoretically derive the transportation cost function from a transportation production function, and summarize functional forms of transportation costs (Jara-Diaz, 1982b; Winston, 1985). Others review the application of cost functions in estimating economies of scale (EOS) and economies of density (EOD), assess their efficiency, and their efficiency decomposition (Oum and Waters, 1996; Basso et al., 2011). All of these reviews take a general view and mainly focus on road (truck and bus), rail, and air transportation. In the case of air transportation, the focus of previous literature review has centered on passenger airlines. Notably, no scholars have reviewed the cost studies of maritime and air freight transportation, or compared the cost modelling of these two long-haul freight transportation modes.

2.2 Related Studies in COVID-19 and Maritime Transportation

This section briefly reviews two strands of literature that are related to our study, namely, COVID-19 and maritime transport; and, DID and RDD-DID application in COVID-19 and transportation studies.

2.2.1 COVID-19 and Maritime Transport

COVID-19 has significantly affected global supply chains and maritime transportation in 2020. Researchers have mainly used the comparative analysis method to examine the economic indicators of 2020 against those from the same period in previous years in order to assess the impact of COVID-19 on maritime transport (see, for example, UNCTAD, 2020; Millefiori et al., 2020; EMSA, 2020; Depellegrin et al., 2020; Alamoush et al., 2022). The indicators used mainly include port calls, volume of cargo carried, deployed capacity, cumulative navigated miles, and time in ports.

UNCTAD (2020) use the AIS data from the first 24 weeks of 2020 to estimate how COVID-19 affects port calls and the container liner shipping connectivity index. This study found that during the first half of 2020, global ship calls contracted by 8.7% compared with the number of ship calls in the first half of 2019. In another study, Cumulative Navigated Miles (CNM) and the number of active and idle ships are derived from AIS in order to measure the global maritime mobility change between 2016 and 2020 (Millefiori et al., 2020). The dataset contains more than 50,000 commercial ships across the globe, and the analysis of this data reveals that CNM declines significantly across all categories of commercial shipping from March to June of 2020. These results suggest that the number of idle ships increases significantly across all types of ships globally in the first six months of 2020. EMSA (2020) issues a report evaluating the impact of COVID-19 on shipping traffic using data mainly from the Union Maritime Information and Exchange System. This study finds that the number of vessel calls at EU ports declines by 12.3% in the first 52 weeks of 2020 compared to the same period in the previous year. Depellegrin et al. (2020) estimate the impact of one national lockdown on maritime traffic in the Veneto Region of Italy. The AIS data culled for this study covered fishing vessels, passenger ships, tanker and cargo vessels and compared shipping traffic from March to April in 2017 and 2020. The results showed that vessel activity decreased by 69% during the lockdown. Zhu et al. (2020) use monthly container port calls and berthing time data derived from the AIS from January to April 2020, and select Shanghai, Ningbo-Zhoushan and Tianjin as sample ports. When they compare the data from 2020 with that from the previous year, they find that the number of ships arriving at Chinese ports is not significantly affected; but, the average berthing time of ships at port decreases significantly from January to April 2020. Notteboom et al. (2021) evaluate and compare the disruptions and resilience caused by COVID-19 and financial crisis in 2008.

Using global port call as a proxy of demand, Michail and Melas (2020) estimate how freight rates (dry bulk, clean, and dirty tankers) have been affected by rapid changes in the macro-economic environment. They adopt both GARCH and Vector Autoregression (VAR) specifications for the purposes of their analysis. The independent variables are global calls, China calls, the world total confirmed cases, Shanghai Composite Index, and the S&P 500. Dependent variables are the Baltic Clean Tanker Index (BCTI), Baltic Dry Index (BDI), and Baltic Dirty Tanker Index (BDTI). The daily data covers the period from January 3, 2019 to June 1, 2020. They find that that freight rates are negatively related to the number of coronavirus cases, while global port calls are significantly, positively related with freight rates. In summary, the comparative data analysis method and related econometric methods (GARCH, VAR) have been popularly adopted in evaluating the impact of COVID-19 on maritime transport. Since the initial COVID-19 lockdown coincided with the Chinese New Year, however, comparative analysis and time series analysis (e.g., GARCH, VAR) techniques cannot isolate the impact of COVID-19 lockdown policy on port call changes from those associated with Chinese New Year. Therefore, quasi-experimental research design methods including DID and RDD models may more accurately allow researchers to examine the real impact of COVID-19 lockdown policy on maritime activities.

2.2.2 DID and RDD Application in COVID-19 and Transportation Studies

The DID model is a quasi-experimental research design that researchers frequently use to study causal relationships in transportation. It measures not only the differences of outcome between a treatment group and the control group, but also the differences between the pre-treatment period and the post-treatment period. Fang et al. (2020) apply DID to study the impact of the lockdown on human mobility in Wuhan. They collect city-pair population migration data and the intra-city population movement data from Baidu Migration. The data covers 22 days before and 38 days after the city lockdown on January 23, 2020. In order to eliminate the Spring Festival effect, the data from the same lunar calendar period in 2019 is included in the analysis as the control group. They find that the lockdown reduces inflows to Wuhan by 76.98%, outflows from Wuhan by 56.31%, and movement within Wuhan by 55.91%. DID has also been used to estimate the impact of COVID-19 lockdowns on the decline in motor traffic collision (Vandoros, 2021) and in road traffic-related deaths and injuries (Oguzoglu, 2020).

In the maritime domain, Baldwin and Evenett (2020) use a DID model and AIS data to investigate the impact of the COVID-19 pandemic and the subsequent policy response on shipping activity in Norway. As March 12, 2020 is the day when Norwegian government implemented restrictions on movement and activity, the authors select five weeks prior to and five weeks after March 12th across the years 2020, 2019, 2018 in the

DID model. In general, in 2020 the number of ships drops by 6% compared to the change observed in previous years. The authors' contention is that national restrictions on sea transportation are responsible for the decline in shipping activity during the pandemic. The authors combine information from vessels departing from Norway with cross-country information on crew change restrictions to further assess the hypothesis. They find that voyages to destinations where crew changes are prohibited are down by almost 20% for container ships, as compared to a decline of 6% to destinations which imposed milder restrictions, such as screening rules.

An RDD model is also a quasi-experimental design to study the causal effects of interventions. When an intervention happens, it is regarded as a cutoff, or threshold. RDD estimates the average treatment effect by comparing the observations that lie closely on either side of the threshold. RDD has been adopted to examine the effect of the COVID-19 lockdown and reopening on the daily movement of individuals (Ding et al., 2021). The authors record the number of daily steps of 815 Chinese adults living in Shanghai before, during and after the lockdown as a measure of movement during each of these periods. At the beginning of the lockdown, it is observed that the average daily step count drops sharply by 3,796 steps. Subsequently, the daily step count increases by an average of 34 steps/day until the end of the lockdown. On the other side of the globe, Barnes et al. (2020) use the RDD method to estimate the lockdown's effect on mobility and traffic accidents in the state of Louisiana. They collect data from Google Community Mobility reports and Uniform Traffic Crash Reports from the Louisiana Department of Transportation and Development (LaDOTD). They also adopt the RDD-DID method to control for changes over the same period in 2019. They find that the stay-at-home order causes a significant decrease in mobility, as measured through road traffic.

To summarize, previous studies mainly use the DID or RDD methods to estimate the impact of lockdowns on human mobility, using either step-monitoring or traffic accidents as a proxy for individual movement. The impact of lockdowns on maritime transport, on the other hand, has most often been investigated using the comparative analysis methods described above, and less frequently through more rigorous statistical methods like RDD or DID models that can give a more precise account of this causal relationship.

2.3 Digitization of Maritime Transportation

Our study evaluates the adoption of technological innovation in maritime transportation, and in particular, the effect of the online quote platform. In order to do this, we adopt the post-event, quasi-experimental, pretest-posttest method known as RDD.

Digital technologies are being used to increase competitiveness and enhance operational efficiency in maritime transportation. The new technology trends that will transform maritime transportation include artificial intelligence, sensor technology, robotics and 3D printing, big data and IoT, autonomous control, augmented reality, ship propulsion systems, cloud computing, and advanced materials (Justyna, 2021; Pedro-Luis et al., 2019). Scholars summarize the drivers, success factors, pitfalls, barriers and future research directions to digital transformation in the maritime transportation sector (Tijan et al., 2021; Fruth and Teuteberg, 2017; Tsvetkova et al., 2021; Babica et al., 2019). Digital technology has greatly improved the efficiency of maritime transportation, such as ship design and shipbuilding, vessel navigation, port operation and communication between different stakeholders (World bank, 2020). But online quote platforms are not adopted by maritime transportation as quickly as other industries such as air transportation, and hotel bookings.

The majority of studies evaluating the adoption of new technologies (including of digital products) in maritime transportation mainly focus on the analysis of influencing factors. For example, Mondragon et al. (2017) show that government legislation and dominant organizations have great influence on the adoption of information and communications technology (ICT). Yang (2019) finds that customs clearance and management, the digitalizing and streamlining of paperwork, overall standardisation, and platform development dimensions positively affect the decision to use block chain technology in maritime transport. In collecting data from an online survey of trucking operators, Chen et al. (2020) find that risk tolerance has a positive effect on the adoption of a cargo-truck matching system. Zeng et al. (2020) identify that industry characteristics, the systems' information confidentiality, supply chain trade partners' power, governmental power, and the ownership structure of an organization are critical factors affecting the adoption of open platforms for container booking, and more generally, in adopting the technology-organization-environment (TOE) framework. From the inter- and intra-organizational perspective, the pressure from trade partners and leading organizations, as well as organizational compatibility are the main factors that influence the adoption of an e-booking system in container shipping (Zeng et al., 2021). These studies thus give us detailed insight into the array of factors that incentivize participants at all levels of the supply chain to adopt technological innovations. It deserves notice that, most of these studies identify the factors after the shipping companies adopting the new technology. It belongs to the post-event study of new technology adoption. In summary, previous studies mainly focus on identifying factors that influence the new technology adoption, our study measures how new technology changes customers behaviour. As the adoption of online quote platforms has increased in the shipping industry, it has started to attract the attention of researchers in recent years. Zeng et al., (2020) summarize five channels by which to book cargo space on a ship: (1) Traditional approaches such as email and telephone; (2) Classical inter-organizational information systems such as the Electronic Data Interchange (EDI); (3) Online quote platforms developed by freight forwarders; (4) Online quote platform developed by shipping lines (such as Quick Quotes developed by Hapag-Lloyd); (5) Third-party booking platforms developed by tech start-ups, like ASIASHEX and Freightos. Hu et al. (2019) assess the impact of an online quote platform on a shipping line's revenue. They develop a yield optimisation model based on the expected marginal revenue between long-term contract shippers and scattered consigners who reserve space via an online quote platform. The simulation results suggest that an online quote platform improves the liner's revenue. Sun et al. (2021) construct a two-stage game model that considers an ES channel (a shipping e-commerce platform and spot market) and a CS channel (contract and spot markets) in order to study shippers' ordering decisions and a liner company's pricing strategy. They find that the demand gap between high- and low-demand seasons, the allocated capacity within each channel, and the unit compensation cost all play an important role in determining whether a strategy is win-win or not. In contrast to the literature on the incentives of shipping lines, our current understanding of the behavior and incentive structures of the consigners looking to buy cargo space is far more limited. Our study aims to build on the foundations laid out here and clarify shippers' responses to the adoption of online quote platforms.

The tool we have selected for the purposes of our study, the RDD model, is a quasi-experimental, pretest-posttest method of studying the causal effects of interventions, and can be broadly applied to an analysis of a wide variety of interventions and their consequences. For instance, the RDD method is frequently used to study the effect of policy interventions on air quality, given the effective date of US gasoline content regulations as the threshold (Auffhammer and Kellogg, 2011; Davis, 2008). Burger et al. (2014) adopt RDD in order to evaluate whether bans on hand-held cell phone use reduce accidents. Lang and Siler (2013) measure the effect of energy efficiency projects on energy consumption, using the implementation date of the project as the threshold. Zhang et al. (2020) gauge the effects of emissions control area policy on sulphur dioxide concentrations in Shanghai, and use the establishment date of the Emission Control Area (ECA) as the threshold. In this study, we argue that the launch date of the online platform is an appropriate threshold for us to adopt this method as a means of investigating the effects of an online quote platform on shippers' booking behaviour.

To summarize, previous studies mainly explore the factors influencing the effect of online platforms using the TOE framework. The data used in these studies is collected either from surveys or interviews, which is subjective to some extent (Hoffmann et al., 2021). The impact of an online quote platform on shippers' booking behaviour has not yet been investigated using rigorous statistical methods with post-event data, which can give a more precise account of this causal relationship. To our knowledge, this is the first attempt to evaluate empirically the impact of online quote platforms on changes of consigners' booking behaviour.

2.4 Summary

This chapter provides a comprehensive summary of previous studies regarding cost study in transportation sector, COVID-19 and maritime transportation, digitization of maritime transportation. Besides, the DID and RDD application in COVID-19 and transportation are also introduced. We also clarify the research gap after each subsection. The next three chapters will explain in detail how to fill the research gaps, covering the data and methodologies used, empirical results, and discussions.

Chapter 3 A Comparative Analysis of Cost Studies in Maritime and Air Freight Transportation

3.1 Introduction

Cost study has attracted great attention from researchers and industry personnel alike in both maritime and air freight transportation. One primary objective of cost study is to identify major cost items (or components) in order to evaluate and estimate a company's or an industry's operating costs at different levels of aggregation. While the cost of a voyage or a trip can be determined by summing up all the cost items incurred during a specific expedition, costs at higher levels of aggregation (such as the route level, the regional level, or even the company level) must be determined by adding up both the associated travel costs and the other costs not attributable to a particular voyage or trip. Airlines and shipping companies alike attach great importance to cost estimation because it supports their operational and strategic decisions. For example, route development decisions rely on the knowledge of a vessel's voyage cost or an aircraft's trip cost along the route under consideration. The focus of such analysis is to estimate individual cost items via a pre-defined formula or through rules associated with either a set of given aircraft (or ship) parameters or operational parameters, and these cost items can be added up to obtain the voyage or trip cost, or even the company's total operating cost (TOC). This type of costing exercise is a prerequisite of any advanced analysis that establishes the relationship between a set of costs and their key determinants. In this study, we classify this stream of studies as item-based cost formulation.

Another objective of cost analysis is to better understand the main economic characteristics of costs and identify their key determinants, such as scale, traffic density, vessel size, and trip distance, among others. For example, there has long been interest in the existence of EOS and EOD among both maritime and air freight operators. The existence (or nonexistence) of these features has implications for the unit costs of network expansion and alliance formation, as well as decisions related to vessel or aircraft size and service frequency. The quantification of EOS and EOD can help policymakers to better understand the potential improvements in cost efficiency via forming alliances or mergers between operators, which is one important consideration for approving such business decisions. EOS and EOD are commonly measured by estimating firm-level cost functions with an econometric approach. Those cost functions establish the relationship between cost and traffic volumes (output), input prices, operational characteristics, and network size in log-log or translog forms. We consider the cost analysis undertaken by those studies to be aggregated cost formulation.

The first study summarizes and compares cost studies in maritime and air freight transportation conducted from the 1960s to the 2010s, an analysis made possible due to the similarities between their operation. Both maritime shipping and air freight are long-haul transportation, and both play an indispensable role in international trade. Both shipping companies and airlines are asset-heavy businesses with terminal and line-haul activities, and profitability is largely affected by the utilization of assets (especially vessels and aircraft) and their load factors. In this study, we will review and summarize the common cost items and their formulation methods in item-based cost formulation, as well as the general functional forms of aggregated cost formulation. We believe this can help transport operators and policymakers to determine the most appropriate method of estimating costs. To our knowledge, the focus of research in the maritime industry is somewhat different from that in air freight transportation. This study thus also provides a comparison between these two foci of research and enriches the analytical toolbox of cost studies across the two industries. Moreover, our evolutionary approach sheds light on fruitful future directions for cost study in the maritime and air freight transportation industries.

The rest of the study is organized as follows: in Section 3.2 and Section 3.3, we review and summarize the cost studies of air freight and maritime transportation, respectively. As both passenger aircraft and freighters (all-cargo airplanes) are widely used to carry air freight, in addition to all-cargo airlines (such as Polar Air) and integrators (air express operators), we also include studies on passenger and combination airlines into the review.[1] In Section 3.4, we discuss the similarities and differences between cost studies of air freight and maritime transportation, and examine whether certain general functional forms can be applied to modelling costs in the two industries. Section 3.5 investigates how cost studies evolve over time and summarizes the databases commonly used to study shipping and aviation costs. We draw conclusions and illustrate future research directions in Section 3.6.

3.2 Cost Studies in Air Freight Transportation

3.2.1 Item-based Cost Formulation

Since the 1960s, air transportation organizations, airlines, and large aircraft manufacturing companies have developed methodologies by which to calculate the direct operating cost (DOC) of aircraft. As its name implies, the DOC only includes costs directly linked to the operation of the aircraft or the flight. The Air Transport Association (ATA) proposed the first set of empirical equations with which to estimate DOC in 1967, and these are the foundation of all the other methods, as the cost components included in the ATA method, (depreciation, insurance, flight crew, maintenance, and fuel) are included in almost all later-proposed methods. Later, American Airlines (AA) proposed the AA method in 1980, and Lufthansa proposed the DLH method in 1982. Since then, the AEA method (proposed by the Association of European Airlines in 1985) has been accepted as the basis for European aircraft DOC comparisons. Airbus Industries proposed the AI method in 1989. The most recent method was proposed by

[1] Passenger airlines rely on a passenger aircraft's belly space for cargo business, while combination carriers use both the belly space of passenger aircraft and freighters to ship cargo.

NASA in 1995 (Liebeck et al., 1995). Table 3.1 below summarizes the components of DOC that are included in different methods. Obviously, the estimated DOC is largely affected by the inclusion and exclusion of specific cost items. In their application of the ATA, AEA, and NASA methods to the same Airbus and Boeing aircraft, Ali and Al-Shamma (2014) find that AEA generates the highest DOC value, due to the different definitions of DOC. As a result, the maintenance cost accounts for 20-25% of DOC for ATA, 8% for NASA, and less than 1% for AEA.

Table 3-1 Components of DOC in different methods

Cost component	**ATA (1967)**	**AA (1980)**	**DLH (1982)**	**AEA (1989)**	**AI (1989)**	**NASA (1995)**
Depreciation						
based on aircraft price	√	√	√	√	√	√
based on spare parts	√		√	√	√	√
Insurance	√	√	√	√	√	√
Flight crew	√	√	√	√	√	√
Maintenance	√	√	√	√	√	√
Fuel	√	√	√	√	√	√
Interest			√	√	√	√
Flight attendants		√	√	√	√	√
Landing fee		√	√	√	√	√
Navigation fee		√	√	√	√	√
Ground handling fee		√	√	√		

Although most methods include similar cost components, the functional form of each component can differ across methods. Usually, each cost component is formulated with three types of variables: aircraft variables, operational variables, and price variables. Aircraft variables indicate the characteristics of the aircraft, such as the number of seats, the cost of engines or the airframe, the number of engines, etc. Operational variables are closely related to the usage of the aircraft, and include stage length (flight distance), number of flight crews (pilots), annual block hours (number of hours in use), number of trips per year, block speed (average speed over the distance from the departure gate to the destination parking spot), among others. Price variables mainly refer to the market-based price index, and integrate insurance rates, interest rates and fuel prices. In addition to these variables, cost equations may include certain constant parameters, the values of which are specified by researchers through regression analysis. For example, NASA (1995) sets the landing fee as 2.2 times the maximum landing weight for domestic operations and 6.25 times the maximum take-off gross weight for international operations. AEA (1989) meanwhile uses 7.8 as the multiplier for both domestic and international operations.

Table 3.2 compares the variables used in the ATA and NASA methods. The variables and functional forms are quite similar for most cost items, such as flight crew, and insurance, although the assumed values of the constant parameters can be quite different. The variables and functional forms differ significantly between these two methods for other cost items, such as depreciation and fuel, even though both methods produce similar fuel cost.

Table 3-2 Variables in the formulation of the ATA and NASA methods

Items	**ATA (1967)**	**NASA (1995)**
Depreciation based on aircraft price based on spare parts	Aircraft cost Block speed Block hours Stage length	Aircraft cost Depreciation period Residual value
Insurance	Aircraft cost Insurance rate	Aircraft cost Insurance rate
Flight crew	Maximum take-off weight Block hours	Maximum take-off weight Block hours
Maintenance	Airframe/engine labor cost (number of engines, takeoff thrust of one engine) Airframe/engine material cost (airframe purchase cost, flight time, block time, block speed) Engine maintenance overhead (proportional to airframe/engine labor cost)	Airframe/engine labor cost Airframe/engine material cost Engine maintenance overhead
Fuel	Block fuel (fuel consumption of a trip per engine) Number of engines Unit cost of fuel and oil	Block fuel Fuel price
Interest	N/A	Aircraft cost Interest rate Block hours
Flight attendants	N/A	Number of seats Cost per block hour Block hours
Landing fee	N/A	Maximum landing weight or Maximum take-off weight
Navigation fee	N/A	Maximum take-off weight

When formulating individual cost items, the variables and functional forms are chosen based on the knowledge of aircraft operation, the availability of data, and the patterns observed in historical data; the constant parameters, on the other hand, are usually estimated through statistical analysis. For example, Harries (2005) takes a data-driven approach and uses simple statistical tools in order to facilitate the formulation of cost items. Unlike the studies discussed in Section 3.2.2, which apply generalized econometric models with multiple determinants and sophisticated estimation methods, Harries' approach relies on simple regression analysis in order to discover the relationship between a cost item and a key variable, and to determine the parameter values. For example, by using a 1999 dataset of 46 passenger and 21 cargo airlines in the United States, Harries (2005) found that the flight crew cost per block hour has a positive relationship with the maximum take-off weight (MTOW) of the aircraft, and is also affected by route and airline characteristics. Thus, the flight crew cost is modelled as:

$$Flight\ crew\ cost = \alpha \times \beta \times MTOW^{\gamma} \times Block\ Hour \qquad (3\text{-}1)$$

The first three terms indicate the flight crew cost per block hour, where α is a parameter determined by the region of operation, the airline business model (regional versus major airlines), and crew size. β is an airline-specific parameter, which provides a constant scalar adjustment for all aircraft belonging to the same airline. γ captures the nonlinear relationship between the flight crew cost per block hour and MTOW. All three parameters are obtained via simple regression analysis of the 1999 dataset in order to produce the final formulation of this cost item.

These formulations of individual cost items are particularly essential when evaluating and comparing different aircraft models and designs in terms of DOC (Ali and Al-Shamma, 2014). For example, NASA (1995) allows the comparison of the DOC of a 225-seat, passenger, subsonic aircraft with engines using 1995 technology and the same aircraft with engines using 2005 technology. This kind of comparison is relevant both when making aircraft purchasing and route development decisions. In building upon previous ATA and NASA methods, Chao and Hsu (2014) develop a model that formulates cost items incurred during the cargo transportation process of freighters. These items include the air cargo terminal cost, as well as the costs of aircraft operation, maintenance, crew, and fuel among others. They use this model to explore the optimal payload and flying distance of various aircraft under different fuel prices.

Apart from adding up the cost items in order to obtain the DOC, an alternative method is to estimate the trip cost as a function of several key variables. For instance, Swan and Adler (2006) propose a simple trip cost function (with reference to the DOC formulation) for passenger aircraft, in which they model the trip cost as a function of stage length and seat capacity. The trip cost for certain types of passenger aircraft can also be estimated as a function of MTOW (Ali and Al-Shamma, 2014). We do not, however, find any study that constructs trip cost functions for air cargo.

Theoretically, one can obtain the aggregated (airline-level) costs by adding up the DOC of all the individual flights estimated using the abovementioned methods. In many cases, however, this is either impossible to achieve due to the unavailability of disaggregated data, or unnecessary due to the nature of the research questions. Some accounting approaches have been developed that provide a rough (but reasonably good) estimation of costs at a higher level of aggregation. For example, Bießlich et al. (2018) develop a model of airline-level annual total operating cost (TOC) by adding together eight DOC items and four indirect operating cost (IOC) items at the company level. IOC includes costs that are not directly associated with operating the aircraft, such as the costs of passenger service, aircraft servicing, traffic servicing, reservations and sales, advertising and promotion, and general administration, to name several. Each cost item is calculated by multiplying the company-level quantity of the cost item used per year and the price of the cost item. That is,

$$TOC = \sum_{i=1}^{12} q_i p_i \tag{3-2}$$

where q_i is the quantity of cost item i and p_i is the price of cost item i. For example, the fuel cost is calculated by multiplying the total amount of fuel consumed and the cost per litre of fuel. The maintenance cost is calculated by multiplying the number of annual block hours by the unit maintenance cost per block hour. The model’s accuracy is demonstrated by comparing the financial data of AirAsia X and KLM. The results show that the model is more accurate for

KLM (3% underestimated) than for AirAsia X (19% overestimated). As shown in Section 3.3.1, this accounting approach is widely applied in estimating cost items in maritime shipping, while it seems less popular in air transport.

3.2.2 Aggregated Cost Formulation

In air freight transportation studies, log-log and translog regression are the econometric specifications broadly applied in aggregated cost formulations of the relationship between airline-level costs and various potential influencing factors.

3.2.2.1 Log-log cost function

The log-log cost function considers a linear relationship among log-transformed variables. It can be viewed as the log-transformed Cobb-Douglas function, and is generally written in the following form:

$$lnC = \alpha + \sum_{i=1}^{n} \beta_i lnV_i \tag{3-3}$$

where *C* stands for the airline-level costs (such as TOC and the total aircraft operating cost). V_i $(i = 1, \dots n)$ indicates an independent variable i that may affect the airline's total cost, and may include factors such as output (transported freight), the input prices (labour, fuel, capital, material), the load factor (LF), the average stage length (ASL), and the network size (usually measured by the number of points served (NPS)), among others.

Table 3.3 summarizes the studies that apply a log-log cost function in order to examine influential factors in airline-level costs. The findings of these studies tend to show that LF and aircraft utilisation are negatively related to airlines' operating costs (Mayer and Scholz, 2012; Zuidberg, 2014). Fuel price, ASL, depreciation cost per unit of traffic, labour price, and the landing fee are positively related to airline operating cost (Mayer and Scholz, 2012).

Table 3-3 Summary of studies using a log-log cost function

		Kiesling and Hansen (1993)	Lakew (2014)	Mayer and Scholz (2012)	Zuidberg (2014)
Airline type		Integrator (FedEx)	Integrator (FedEx and UPS)	All-cargo and combination airlines	Passenger and combination airlines
Research question		Study the cost structure	Study the cost structure	Identify influential factors in airline expenses	Identify determinants of airline expenses
Dependent variable		Total cost	Total cost	Total aircraft operating cost	Average operating cost per aircraft movement
Independent variables	**Output**	RTM	RTM	---	---
	Input prices	Fuel price Labour price	Fuel price Labour price Materials price	Fuel price Labour cost Depreciation Average landing fee	Fuel price Labour price
	Operation characteristics	ASL LF NPS	ASL LF NPS	ASL LF	ASL LF NPS
	Fleet variables	---	---	---	Aircraft size, aircraft age, aircraft utilization, fleet commonality
	Other variables	Time trend	---	---	Time trend
Main findings		EOD:2.36~4.07, EOS:0.54~0.62	EOD: FedEx: 1.75~3.15 UPS: 2.06~3.07, EOS: FedEx: 1.45~2.72 UPS: 2.04~3.46	Fuel price, labour price, depreciation cost per unit of traffic, and ASL are positively related to aircraft operating cost; LF and aircraft utilisation are negatively related.	LF and aircraft utilization are negatively related to the operating cost of each movement. Aircraft size has no statistically significant relationship to operating cost per movement.

Notes: RTM = Revenue ton-miles

3.2.2.2 Translog cost function

The translog cost function is the most popular cost function in the transportation industry (Oum and Waters, 1996). The widespread application of the translog cost function is due to its flexible functional form, which provides the second-order approximation to any general cost function (Caves et al., 1984). The translog cost function with one output (Q), the prices of n inputs (P_i), the network size (N), operation characteristics (Z), and time trend (t), is generally written in the following way:

$$
\begin{aligned}
lnC = {} & \alpha_0 + \beta_Q ln\, Q + \sum_{i=1}^{n} \beta_i\, ln\, P_i + \beta_Z ln\, Z + \beta_N ln\, N + \beta_t t \\
& + \tfrac{1}{2}\gamma_Q (ln\, Q)^2 + \tfrac{1}{2}\textstyle\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}\, ln\, P_i\, ln\, P_j + \tfrac{1}{2}\gamma_Z (ln\, Z)^2 + \tfrac{1}{2}\gamma_N (ln\, N)^2 + \tfrac{1}{2}\gamma_t t^2 \\
& + \textstyle\sum_{i=1}^{n} \gamma_{Qi}\, ln\, Q\, ln\, P_i + \gamma_{QZ}\, ln\, Q\, ln\, Z + \gamma_{QN}\, ln\, Q\, ln\, N + \gamma_{Qt} t\, ln\, Q \\
& + \textstyle\sum_{i=1}^{n} \gamma_{Zi}\, ln\, Z\, ln\, P_i + \sum_{i=1}^{n} \gamma_{Ni}\, ln\, N\, ln\, P_i + \sum_{i=1}^{n} \gamma_{ti} t\, ln\, P_i \\
& + \gamma_{ZN}\, ln\, Z\, ln\, N + \gamma_{Zt} t\, ln\, Z + \gamma_{Nt} t\, ln\, N
\end{aligned}
\qquad (3\text{-}4)
$$

where $\gamma_{ij} = \gamma_{ji}$, $\sum_{i=1}^{n} \beta_i = 1$ and $\sum_{i=1}^{n} \gamma_{ij} = \sum_{i=1}^{n} \gamma_{Qi} = \sum_{i=1}^{n} \gamma_{Zi} = \sum_{i=1}^{n} \gamma_{Ni} = \sum_{i=1}^{n} \gamma_{ti} = 0$.

Table 3-4 summarizes the studies that use firm-level translog cost functions. In general, similar independent variables are used in translog and log-log cost functions. Classical economic theory assumes a single output for the cost function, but multiple outputs are common in the transportation industry. This is less an issue for all-cargo airlines and integrators, as RTM or revenue tonne-kilometre (RTK) is the single output. Cargo and passenger transportation, however, occur simultaneously for passenger airlines and combination carriers. Oum and Yu (1998) identify five types of outputs for combination airlines, which are scheduled passenger service (measured in revenue passenger-kilometres, RPK), scheduled freight service (measured in RTK), mail service (measured in RTK), non-scheduled services (measured in RTK), and incidental service (non-airline business).[2] The lion's share of the total operating costs cannot be accurately attributed to an individual output, such as passenger or cargo. As a result, it is more reasonable to model the total cost with multiple outputs instead of developing a separate cost model for cargo alone when studying passenger and combination carriers. The multi-output nature of the transportation industry thus makes the specification of the cost function different from the classical cost function (Oum and Waters, 1996). Oum and Waters (1996) describe two approaches to dealing with multiple outputs. The first is to increase the number of outputs to be evaluated on the right-hand side of the translog cost function. For example, Oum and Zhang (1991) and Keeler and Formby (1994) consider the five outputs of passenger airlines in the translog cost function. The other approach is to develop an aggregate measure of outputs, such as an output index by combining several different categories of outputs into one output (Baltagi et al., 1995; Oum and Yu, 1998).

[2] Incidental services refer to a carrier's non-airline business, including catering services, ground handling, aircraft maintenance, reservation services for other airlines, technology sails, consulting services, hotel business, etc.

Table 3-4 Summary of studies using the translog cost function

		Caves et al. (1984)	Bauer (1990)	Gillen et al. (1990)	Kumbhakar (1991)	Oum and Zhang (1991)	Atkinson and Cornwell (1994)
Airline type		US passenger airlines	US passenger airlines	Canadian passenger airlines	US passenger airlines	Canadian passenger airlines	US passenger airlines
Research question		Distinguish EOS and EOD and explain why small, local airlines can compete with large, trunk airlines	Decompose TFP growth of airlines	Compare the cost structure of Canadian airlines	Apply a cost function to evaluate technical and allocative inefficiencies	Study the cost function of Canadian passenger airlines	Estimate technical efficiency of airlines
Dependent variable		Total cost, variable cost	Total cost	Total cost	Total cost	Total cost	Total cost
Independent variables	**Output**	Aggregated output	RTM, RPM	Scheduled RPK, RTK	Aggregated output	Passenger, Freight, Charter	Capacity ton miles (CTM)
	Input price	Labour price Fuel price Capital-materials[a]	Labour price Fuel price Capital price Material price	Labour price Fuel price Capital price Material price	Labour price Fuel price Capital price	Labour price Fuel price Material price	Labour price Fuel price Capital price Material price
	Operation characteristics	ASL NPS LF	ASL LF	ASL NPS	ASL NPS LF	ASL NPS	ASL QUAL
	Technical change	Time trend, firm dummy	Time trend	Time trend	Time trend	Time trend	Time trend
	Other variables	Capacity[b]	---	---	---	Capital[c]	---
Main findings	**EOD**	Total cost: 1.243 Variable cost: 1.179	---	1.21	---	1.301	---
	EOS	Total cost: 1.068 Variable cost: 0.988	1	0.97	1	1	1.35

Notes: [a]Capital-materials is a multilateral index that aggregate capital and materials. [b]Capacity is measured as the sum of the annual flows (in dollars) spent on flight equipment, ground property, and equipment. It is a measure of the capacity to produce output in any given year. [c]Capital here refers to capital services. This variable is similar to the operation characteristics (NPS and ASL). It is a quasi-fixed factor and consists of two parts: rental price, and the depreciation cost.

		Keeler and Formby (1994)	Baltagi et al. (1995)	Oum and Yu (1998)	Onghena et al. (2014)	Roberts (2014)	Balliauw et al. (2018)
Airline type		US passenger airlines	US passenger airlines	Worldwide passenger airlines and combination airlines	US integrators (UPS and FedEx)	US integrators (UPS and FedEx) and passenger airlines	US integrators (FedEx and UPS) and all-cargo airlines (Polar Air Cargo, etc.)
Research question		Compare the cost structure of airlines before and after deregulation	Analyse the cost change for US airlines before and after deregulation	Compare the cost competitiveness of major airlines	Analyse the cost change for US airlines before and after deregulation	Compare the cost competitiveness of major airlines	Compare the cost structure and cost efficiency of US all-cargo carriers
Dependent variable		Total cost	Variable cost	Variable cost	Total cost	Total cost	Total cost
Independent variables	**Output**	ASM ATMF	RPM RTM	Aggregated output	RTK	RTK	RTM
	Input price	Labour price Fuel price Capital price Other inputs	Labour price Fuel price Material price	Labour price Fuel price Capital price	Labour price Fuel price Capital price Material price	Labour price Fuel price Capital price Material price	Labour price Fuel price Capital price Material price
	Operation characteristics	ASL	ASL NPS LF	ASL NPS	ASL NPS	ASL NPS LF	ASL NPS LF
	Technical change	---	Time trend	Time trend	Time trend	Time trend	Time trend
	Other variables	Traffic density	Capital	---	---	---	---
Main findings	**EOD**	Greater than 1	1.04	---	4.525	FedEx: 1.60 UPS: 3.02	Integrator: 1.66 Non-integrator: 1.34 Pooled: 1.29
	EOS	1.03	0.93	---	3.077	FedEx: 0.87 UPS: 0.81	Integrator: 1.63 Non-integrator: 1.21 Pooled: 1.22

Notes: RPM = Revenue passenger-miles; RPK = Revenue passenger-kilometres; RTK = Revenue tonne-kilometres; ASM = Available seat-miles; ATMF = Available ton-miles of freight

Both the log-log and translog functional forms are widely applied in order to measure and distinguish EOS and EOD. Airlines provide services over a network of geographically distributed points (Caves et al., 1984), and as a result an airline's size has two dimensions, namely, output (the amount of cargo and passengers carried over the distance flown) and network size. EOS is defined as the reduction in unit cost due to the proportional increase in output and network size, keeping traffic density constant. EOD is defined as a reduction in unit cost caused by an increase in output over a fixed network size (Caves et al., 1984). Based on these definitions, including both network size (*N*) and output (*Q*) in the cost function can help to distinguish between EOS and EOD, after controlling for other factors. EOS is calculated as the inverse of the sum of the elasticities of total cost with respect to output and network size. EOD is equivalent to the inverse of the elasticity of total cost with respect to output. That is,

$$EOS = \frac{1}{\varepsilon_Q + \varepsilon_N} \qquad EOD = \frac{1}{\varepsilon_Q} \tag{3-5}$$

where ε_Q is the elasticity of total cost with respect to output, and ε_N is the elasticity of total cost with respect to network size. An above (or below) unity EOS implies economies (or diseconomies) of scale, because the total cost increases slower (or faster) than the proportional increase in output and network size, leading to a decline in unit cost. Similarly, when EOD is above (or below) one, we say that there exist economies (or diseconomies) of density. According to Tables 3-3 and 3-4, a strong EOD has been found in passenger airlines and all-cargo airlines (and integrators) (Keeler and Formby, 1994; Baltagi et al., 1995; Onghena et al., 2014; Roberts, 2014; Balliauw et al., 2018). In contrast, EOS has a wide range, from 0.54 to 3.46 for all-cargo carriers (Kiesling and Hansen, 1993; Lakew, 2014; Onghena et al., 2014). For combination airlines, EOS fluctuates around 1, from 0.93 (Baltagi et al., 1995) to 1.35 (Atkinson and Cornwell, 1994). Balliauw et al. (2018) ascertain that the EOS and EOD of integrators are greater than for non-integrators.

In addition to measuring EOS and EOD, log-log and translog cost functions are used to estimate cost efficiency and decompose it into technical efficiency and allocative efficiency. A cost function is theoretically a frontier that represents the minimum expense necessary to produce a given level of output with given input prices and existing production technology (Mundlak and Volcani, 1973). Traditional econometric methods for estimating cost functions also assume that all firms are successful in reaching this efficient frontier. In fact, however, not all firms are equally efficient. Therefore, the average relationship estimated by the log-log and the translog cost functions does not reflect the efficient cost frontier. Cost efficiency is defined as the ratio of the minimum feasible cost to the observed expenditure.

Stochastic frontier analysis (SFA) has also been frequently utilized to measure the cost efficiency of firms or industries (Schmidt and Lovell, 1979). We denote the cost efficiency of a typical airline as CE. Suppose the efficient cost, given (Q,P,N,Z), is $C^* = C(Q,P,N,Z)$. According to Farrell (1957), the input-based measure of cost efficiency is defined as

$$CE = \frac{C^*}{C}, \text{ where } 0 < CE \leq 1 \tag{3-6}$$

where $C^* = C(Q,P,N,Z) \cdot \exp\{v_j\}$ is the stochastic cost frontier. $C(Q,P,N,Z)$ is deterministic and is common to all carriers, and $\exp\{v_j\}$ is a carrier-specific random part which captures the effects of random shocks on carrier j. Thus, the cost efficiency of carrier j becomes

$$CE = \frac{C(Q,P,N,Z) \cdot \exp\{v_j\}}{C} \tag{3-7}$$

If we consider a single-output cost frontier with the log-log functional form, then the stochastic cost frontier of carrier j can be written as

$$lnC = \beta_0 + \beta_Q lnQ + \sum_{i=1}^{n} \beta_i lnP_i + \beta_Z lnZ + \beta_N lnN + v_j + u_j \tag{3-8}$$

where v_j is random noise, and u_j is the cost inefficiency component.

Equation (6) can then be written as

$$\ln C = C(Q, P, N, Z) + v_j + u_j \tag{3-9}$$

Using Equations (5) and (7), the cost efficiency can be derived as

$$CE = \exp\{-u_j\} \tag{3-10}$$

Any departure from cost efficiency has two potential sources: technical inefficiency and allocative inefficiency (Farrell, 1957). Technical inefficiency results from a failure to produce the maximum possible output with the given set of inputs. Allocative inefficiency arises from the choice of sub-optimal input proportions, given input prices and marginal productivities (Kumbhakar, 1991). Both technical inefficiency and allocative inefficiency can be derived from the cost function (Kopp and Diewert, 1982). Balliauw et al. (2018) find that integrators like FedEx and UPS have lower technical efficiency compared with non-integrated, all-cargo carriers. UPS performs better than FedEx in terms of technical efficiency, with a score close to 100% versus 88% (Roberts, 2014).

Another application is to calculate and decompose the total factor productivity (TFP) growth of airlines. Total factor productivity growth can be decomposed into several items, as shown below:

$$T\dot{F}P = \left(1 - \varepsilon_Q\right)\dot{Q} + \dot{T} + \dot{A} - \varepsilon_Z \dot{Z} - \varepsilon_N \dot{N} + \sum_{i=1}^{n} \left(\frac{p_i x_i}{C} - \varepsilon_i\right)\dot{P_i} \tag{3-11}$$

where ε_Z and ε_N are the elasticities of total cost with respect to operational characteristics and network size, respectively. Equation (3-11) shows that TFP growth can be decomposed into terms related to ε_Q, changes in technical and allocative efficiencies ($\dot{T}$ and $\dot{A}$), changes in operational characteristics and network size, and a residual price effect term (Bauer, 1990).

3.3 Cost Studies in Maritime Transportation

3.3.1 Item-based Cost Formulation

Unlike air freight transportation, the field of maritime shipping has not reached a high level of consensus on cost classification. Consequently, researchers classify costs in their own way when evaluating the costs of a voyage. One common approach is to divide costs into voyage fixed costs and freight variable costs (Chow and Chang, 2011; Ting and Tzeng, 2013). The freight variable cost changes along with freight volume, while the voyage fixed cost is independent of freight volume. Table 3-5 shows a variety of cost classifications applied in the studies reviewed here. Shintani et al. (2007) divide the voyage cost into ship related costs and port related costs. Cullinane (1999) divide the cost of liner shipping into daily operating costs, daily fuel costs, and daily capital costs.

Table 3-5 Methods of classifying voyage cost

Cost components	Detailed cost items	References
Daily operating cost	Insurance, administration cost, crew cost, repair and maintenance cost	Cullinane (1999)
Daily capital cost		
Daily fuel cost		
Ship related costs	Ship depreciation cost, insurance cost, crew cost, interest, repair and maintenance cost, fuel cost	Shintani et al. (2007)
Port related costs	Port entry cost, cargo handling cost	
Operating cost	Crew cost, insurance, administration cost	Stopford (2009)
Cargo handling costs	Cargo handling costs, cargo loading charges, cargo discharge costs, cargo claims cost	
Voyage costs	Fuel cost, port charges, canal dues, tugs and pilotage	
Maintenance cost		
Capital costs		

Voyage fixed costs Freight variable costs	Port charges, bunker costs, container ship costs, administration fees Handling costs, container costs, transshipment costs, shipping agency commission charges, other costs	Chow and Chang (2011) Ting and Tzeng (2013)
Operating cost Capital cost Fuel cost Canal tolls Icebreaker fees	Repair and maintenance cost, insurance, administration cost, crew cost	Xu et al. (2018)

Despite the lack of broader agreement, three approaches are widely used in combination to model individual cost items in maritime transportation (Table 3-6). First, regression analysis is adopted in order to formulate the relationship between certain cost items and key cost determinants. For example, the capital cost has been estimated as a function of ship size (DWT, surface area, volume) (Thorburn, 1960; Jansson and Shneerson, 1987), but the fitness of the linear regression model has been shown to be low (with R^2 being 0.34). Cullinane and Khanna (1999) improved the fitness of the regression model by regressing the logged ship contract price on the logged ship capacity in nominal TEU (NTEU), and obtained a higher R^2 (0.93) in their analysis of a dataset of 153 vessels. The daily operating cost is generally calculated as a function of ship size (Janssona and Shneerson, 1987; Heaver, 1968; Goss and Mann, 1974). While fuel cost is a multiplication of the fuel price by the fuel consumption rate, the latter is usually considered as a function of sailing speed in various non-linear forms. The parameters of these fuel consumption functions are derived from regression analysis (Wang and Meng, 2012; Ronen, 1982; Gorbett et al., 2009; Fagerholt et al., 2010; Yin et al., 2014). Cullinane and Khanna (1999) assume the daily fuel oil consumption is determined by the installed brake horsepower (bhp), and bhp is a function of NTEU that is estimated through regression analysis. A ship's other daily costs are represented by a linear function of TEU capacity through regression analysis, using data from the Drewry Market Report (Shintani et al., 2007).

In the second approach, some cost items are collectively approximated as a proportion of another cost item. Repair and maintenance fees, insurance fees, administrative costs, and crew costs are collectively categorized as operating costs. The operating cost is estimated as a proportion of the capital cost, and the assumed proportion varies significantly. Tran and Haasis (2015) assume 16% for an 11000 TEU container ship, and 52% for a 1200 TEU ship; Zhao et al. (2016) suppose approximately 80% for a 4,800 TEU ship; Zhang et al. (2016) post 56% for a 13,892 TEU ship, while Xu et al. (2018) assume 50% for all ship sizes. An alternative method is to divide the operating cost into crew costs and other costs. These other costs are assumed to collectively approximate 3-5% of the capital cost (Cullinane and Khanna, 1999; Gilman, 1983; Pearson, 1988; Ryder and Chappell, 1979).

Third and finally, some cost items are calculated via an accounting approach by multiplying the quantity of the cost item by the price of the cost item. For instance, the crew cost is obtained by multiplying the number of crews and the salary per crew, and the number of crew numbers is assumed based on the ship size. The port cost is determined by number of port calls and port entry cost per call.

Table 3-6 The modelling of maritime cost items in the literature

Cost items	Model	Methods	Authors
Capital cost	$\ln(ship\ price) = 4.8097 + 0.759\ln\ (NTEU)$	Regression	Cullinane and Khanna (1999)
	Annual capital cost = new building price/depreciation period	Accounting	Xu et al. (2018)
Operating cost (crew cost + other cost)	Crew cost = crew numbers $*$ salary per crew	Accounting	Cullinane and Khanna (1999)
	$Daily\ operating\ cost = f(ship\ size)$	Regression	Jansson and Shneerson (1987), Heaver (1968) Goss and Mann (1974)
	$Other\ cost = 0.035 * capital\ cost$	Approximation	Cullinane and Khanna (1999)
	$Operating\ cost = 0.5 * capital\ cost$	Approximation	Xu et al. (2018)
Fuel cost = Daily fuel consumption * fuel price, or Fuel cost = $f(v)$ * fuel price	$f(v)$ is daily fuel consumption at speed v		
	$f(v) = a * v^3$ a is estimated with cubic regression	Regression	Ronen (1982), Gorbett et al. (2009), Fagerholt et al. (2010), Yin et al. (2014)
	$f(v) = a * v^b$ a and b are estimated for each vessel with fractional rational regression	Regression	Wang and Meng (2012), Du et al. (2011)
	$f(v) = a * e^{(b \cdot v)}$ a and b are estimated for each vessel with exponential regression	Regression	Westarp (2020)
	Daily fuel consumption = installed bhp * SFOC * utilization * 24/1000000, where $ln(bhp) = a + b\ ln(NTEU)$, and a and b are estimated with regression	Regression	Cullinane and Khanna (1999)
Other daily ship costs	$C = 6.54 * TEU + 1422.52$	Regression	Shintani et al. (2007)
Port cost	Port cost = port entry cost per call * number of port calls	Accounting	Shintani et al. (2007)
Handling cost of laden containers	Handling cost = Handling cost per laden container * number of containers	Accounting	Shintani et al. (2007)
Handling cost of empty containers	Handling cost per empty container $*$ number of empty containers	Accounting	Brouer et al. (2011), Wang (2013), Huang et al. (2015)
Canal cost	Canal tolls	Accounting	Xu et al. (2018)

Notes: SFOC = Specific fuel oil consumption; C means a ship's other daily costs.

Once the cost models are established and the individual cost components are evaluated, the voyage cost can be obtained by adding the cost components together, according to the classifications provided in Table 3-5 in order to address various research questions. For example, the voyage cost can be converted to the cost per unit of cargo (per ton or per TEU), and this unit cost can be compared with ship size in order to assess the economies of ship size (Cullinane, 1999; Stopford, 2009). Taking container ships as an example, certain costs (such as capital costs, operating expenses, and fuel costs) do not increase proportionally with an increase in container ship capacity. As a result, larger container ships enjoy the economies of ship size. As the size of the ship increases beyond a certain level, however, the economy of ship size diminishes (Stopford, 2009). By comparing the voyage costs, one can also assess the economic feasibility of a certain route, such as the Northern Sea Route (Xu et al., 2018).

In certain optimization problems, the objective is to minimize the voyage cost. As a result, instead of evaluating the voyage cost numerically, the voyage cost is modelled as a function of a few decision variables, such as sailing speed, the number of ships, and the number of empty containers (Wang and Meng, 2017). Some optimization problems may even require the evaluation of additional cost items that are traditionally excluded from the voyage cost classifications provided in Table 3-5. For example, because of trade imbalances, empty containers accumulate in import-oriented ports and need to be repositioned to export-oriented ports. The costs associated with these empty containers, including loading, unloading, repositioning and storing, are then included in the voyage cost (Francesco et al., 2009; Huang et al., 2015). Some studies take the ship repositioning cost into account if a ship reposition happens during the voyage (Wang, 2013). Containers' transshipment costs and penalty costs for a delay are also considered in container transhipment problems (Reinhardt and Pisinger, 2012; Bell et al., 2013).

3.3.2 Aggregated Cost Formulation

The number of studies that use sophisticated econometric models is much smaller in maritime shipping than in air transportation. Unlike air transportation research, in which aggregated cost formulations are mainly applied to firm-level analysis, the maritime field has applied aggregated cost formulation to different levels of aggregation, including at the voyage level, the vessel level and the firm level. There are four widely used functional forms, namely, the linear cost function, the semilog cost function, the log-log cost function, and the translog cost function.

3.3.2.1 Voyage-level linear and semilog cost functions

At the voyage level, the focus is on estimating the cost of a voyage. Pirrong (1992) is the only voyage-level study that we are aware of. He adopts the linear and semilog cost functions in order to investigate the cost structure of container ships, and he finds that competition between liner shipping companies is inefficient. The linear and semilog cost functions can be written in a general format as follows:

$$C = \alpha + \sum_{i=1}^{n} \alpha_i V_i + \varepsilon \tag{3-12}$$

$$ln(C) = \alpha + \sum_{i=1}^{n} \alpha_i V_i + \varepsilon \tag{3-13}$$

where C is the cost of a voyage, and V_i $(i = 1, .., n)$ refers to n variables listed in Table 3-7 which may affect the voyage cost.

3.3.2.2 Vessel-level translog cost function

As shown in Table 3-7, vessel-level cost modelling is used to study the cost structure of tankers (Talley et al., 1986) and bulkers (Tolofari et al., 1987). In the studies that we reviewed, the translog cost function with one output (Q) and n input-related variables (P_i) is specified as:

$$lnC = \alpha_0 + \beta_Q ln\, Q + \sum_{i=1}^{n} \beta_i\, ln\, P_i + \frac{1}{2}\gamma_Q (ln\, Q)^2 + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}\, ln\, P_i\, ln\, P_j + \sum_{i=1}^{n} \gamma_i\, ln\, Q\, ln\, P_i \tag{3-14}$$

where $\gamma_{ij} = \gamma_{ji}$, $\sum_{i=1}^{n} \beta_i = 1$, and $\sum_{i=1}^{n} \gamma_{ij} = \sum_{i=1}^{n} \gamma_i = 0$.

Outputs are either measured by tanker capacity (in dead weight tonnage, or DWT) or ton-miles of bulkers. The input-related variables include the prices of inputs (e.g., labor, maintenance, lubricating oil) and the number of inputs used (e.g., barrels of fuel consumed). As the cost function is estimated at the vessel-level, we can obtain ship-size elasticity from the estimated model. Similar to the estimation of economies of scale or density, one can estimate economies of ship size by taking the inverse of the ship-size elasticity. In fact, Talley et al. (1986) find that economies of ship size diminish as ships become larger.

Table 3-7 Summary of studies of vessel-level and voyage-level cost functions

	Talley et al. (1986)	Tolofari et al. (1987)	Pirrong (1992)
Research question	How ship size of a given type affects a tanker ship's operating cost	Study the translog cost function of bulkers and tankers	Study the cost structure of container ships to evaluate the market structure of liner shipping industry through core theory
Cost function	Vessel-level translog	Vessel-level translog	Voyage-level linear and semilog
Dependent variable	Daily operating cost of a tanker ship	Total cost of a vessel	Voyage cost
Independent variables	Output (DWT) Average daily wage and subsistence per crew member Average other, daily, labor-related costs (except wage and subsistence) per crew member Average barrels of fuel consumed per day	Output (Ton-miles) Labour price Maintenance price Lubricating oil price Capital cost	Amount of cargo carried eastbound Amount of cargo carried westbound Number of empty containers Ship-type dummy variables
Main findings	Ship-size elasticities vary with ship size; ship size economies for large ships may disappear	Discusses elasticities with respect to factor prices and factor substitutability	Because of the existence of avoidable cost, competition between liner shipping companies is inefficient

3.3.2.3 Firm-level log-log and translog cost functions

At the firm level, all studies are based on container liners (Table 3-8) and are similar to the case of air transportation cost analysis, in that they apply both log-log (Tran and Haasis, 2015) and translog (Wu, 2009, 2012; Wu and Lin, 2015) cost functions. The log-log cost function is generally written in the following form:

$$lnC = \alpha + \sum_{i=1}^{n} \beta_i lnV_i \tag{3-15}$$

where C is the growth rate of a shipping line's total cost, and V_i $(i = 1, \dots n)$ are the growth rates of n cost determinants, such as ship size, fleet capacity, slot utilization and oil prices (Tran and Haasis, 2015).

The translog cost function with one output (Q), prices of n inputs (P_i), operational characteristics (Z) and time trend (t), is generally written in the following way:

$$\begin{aligned} lnC = {} & \alpha_0 + \beta_Q ln\,Q + \sum_{i=1}^{n} \beta_i\, ln\,P_i + \beta_Z ln\,Z + \beta_t t \\ & + \tfrac{1}{2}\gamma_Q (ln\,Q)^2 + \tfrac{1}{2}\textstyle\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}\, ln\,P_i\, ln\,P_j + \tfrac{1}{2}\gamma_Z (ln\,Z)^2 + \tfrac{1}{2}\gamma_t t^2 \\ & + \textstyle\sum_{i=1}^{n} \gamma_{Qi}\, ln\,Q\, ln\,P_i + \gamma_{QZ}\, ln\,Q\, ln\,Z + \gamma_{Qt} t\, ln\,Q \\ & + \textstyle\sum_{i=1}^{n} \gamma_{Zi}\, ln\,Z\, ln\,P_i + \sum_{i=1}^{n} \gamma_{ti} t\, ln\,P_i + \gamma_{Zt} t\, ln\,Z \end{aligned} \tag{3-16}$$

where $\gamma_{ij} = \gamma_{ji}$, $\sum_{i=1}^{n} \beta_i = 1$, and $\sum_{i=1}^{n} \gamma_{ij} = \sum_{i=1}^{n} \gamma_{Qi} = \sum_{i=1}^{n} \gamma_{Zi} = \sum_{i=1}^{n} \gamma_{ti} = 0$.

Table 3-8 Summary of firm-level cost functions for container shipping

		Tran and Haasis (2015)	Wu (2009)	Wu (2012)	Wu and Lin (2015)
Research question		Find the most influential factors on container shipping liners' expenses	Determine optimal slot capacity so as to minimize costs	Measure the capacity utilization ratio for a shipping line	Measure the TFP growth of a shipping line
Cost function		Log-log	Translog	Translog	Translog
Dependent variable		Growth rate of total cost	Variable cost	Total cost	Total cost
Independent variables	**Output**	---	Total TEUs	TEU-mile	TEU-mile
	Input price	Growth rate of oil price	Labour price Fuel price Material price	Labour price Fuel price Capital price Material price	Labour price Fuel price Capital price Material price
	Operational characteristics	Growth rate of fleet capacity Growth rate of average ship size Growth rate of slot utilization Growth rate of oil price Growth rate of freight rate	TEU-miles Total slot capacity	Slot capacity per ship Total slot capacity	Slot capacity per ship
	Technical change	---	Technology index	Technology index	Time trend
Main findings		Slot utilization, fleet capacity, freight rate, and oil price are positively related to the growth rate of total cost	Container shipping lines with deep-sea service routes are likely to deliberately hold excess capacity	Fleet capacities as a whole are underutilized	Scale economies and ship size economies play the dominant roles in improving TFP growth

3.4 Comparison of Cost Studies in Maritime and Air Freight Transportation

After reviewing the above cost studies in air freight and maritime transportation, we find that they not only share similar cost items, but also adopt similar methods (e.g., regression analysis and accounting approaches) in order to model the designated cost items. Simultaneously, we can also identify specific differences in the approaches to estimating cost between the two transportation modes. For example, the log-log cost function and translog cost function are applied at the voyage and ship levels in maritime transportation, but are only used at company level for air freight. Figure 3-1 summarizes and compares the cost models of the two industries.

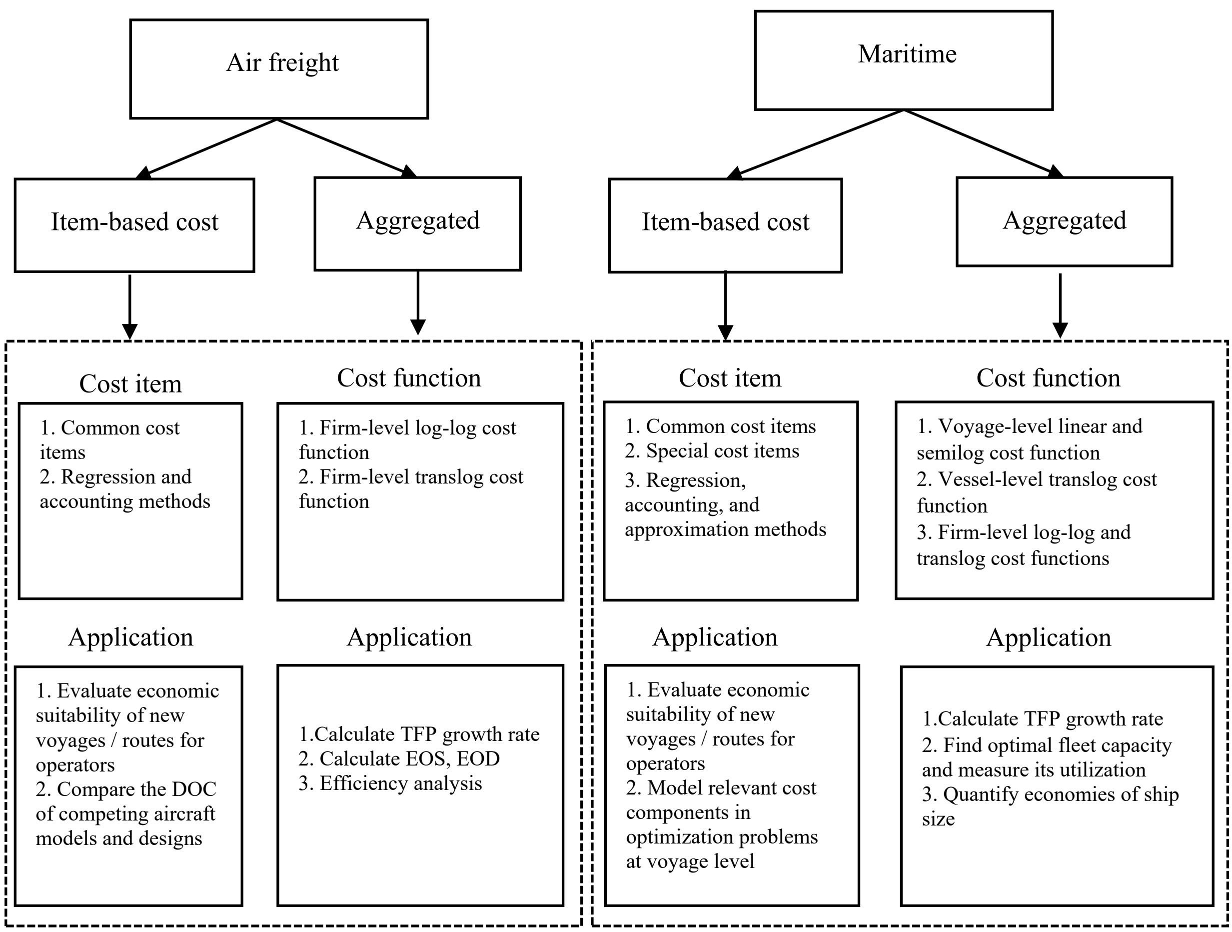


Figure 3-1 Comparison of cost models in air freight and maritime transportation

Table 3-9 maps and compares the major cost items found in airlines' DOC analysis with the major cost items found in studies of shipping companies' voyage costs. It can be observed that many cost items are common to these two transportation modes, including capital costs, carrier and cargo insurance, carrier crew costs, fuel costs, maintenance costs, and station costs. The same cost item may incorporate different elements, however, or have a different nature, depending on the industry. For example, a shipping company's station cost mainly takes the form of payments to seaports, and includes port charges for the usage of seaport facilities (including docking and wharfage charges, pilotage, towage, etc.), and cargo handling fees collected by the seaport. In contrast, airlines' station costs include not only payments to airports for various services and facilities, but also costs associated with the ground staff employed by the airlines. The cost of cargo-related services provided by the airport (such as storage, handling, and special service fees) are also commonly included in the station cost.

In addition to the common cost items listed in Table 3-9, a number of specialized cost items are identified in the form of mode-specific costs and other costs. For example, ships will incur canal fees and congestion costs when passing through the Suez or the Panama Canals. The expenses of breaking ice when sailing across the Arctic Ocean, as well as the cost of safety equipment and guards when transiting through zones with a high risk of piracy are all specific to ships and irrelevant to air transportation. Traditionally, the administration cost is included in the voyage cost in maritime transportation, while it is excluded from DOC in air freight transportation.

Although maritime shipping and air freight transportation have almost identical cost items, they differ somewhat in their modelling approaches. Cost items in air freight transportation are more sophisticated and elaborately modelled than in shipping. Each DOC item in air freight transportation is generally a function of aircraft variables (e.g., cost of airframe, number of engines), operational variables (e.g., stage length, block speed), price variables, and constant parameters (derived from regression analysis). While the simpler accounting approach is also used in air transportation studies, regression analysis is dominant. On the other hand, the approximation and accounting methods are heavily utilized in maritime transportation cost analysis. Regression analysis is mainly used to model fuel and capital costs with much simpler functional forms than air transportation.

Table 3-9 Cost items in maritime and air freight transportation

Cost items	Sea	Air
Capital	Depreciation	Depreciation
Carrier[a] and cargo insurance	Hull and machinery insurance; third party insurance; other voluntary insurance	Flight equipment insurance; cargo insurance
Carrier crew	Salaries and wages, pensions, insurance, victuals, and repatriation expenses	Pay and allowances, pensions, insurance, travelling
Fuel	Bunker and marine diesel oil cost	Fuel cost
Maintenance	Inspections, repairs, extraordinary dry-dockings, and classification survey costs	Direct maintenance labour, maintenance material, and overhead for both the airframe and engines
Station cost	Seaport fee: cargo handling fee (loading, discharging costs and cargo claims); docking and wharfage charges; pilotage; towage, etc.	Airline station staff cost[b]: pay, allowances and expenses. Airport fee: landing charges; cargo fees[c]; security, parking and hangar charges, etc.
Mode-specific cost	Canal dues, ice-breaking cost	---
Other cost	Administration cost[d]	Navigation cost

Notes: [a] Carrier refers to ship and aircraft operators.

[b] Paid to station staff for handling cargo, packing and materials, station accommodation costs, storekeepers' pay, etc.[c] Levied by an airport for cargo related service, and includes storage, handling, and special service fees, among others. [d]Administration cost: Overhead cost for the voyage management.

Sources: Stopford (2009); Morrell and Klein (2011).

One common application of modelling and estimating cost items is to obtain the cost of a voyage (or trip) and the cost of a route. Such knowledge helps shipping companies, aircraft manufacturers, and airlines to evaluate the economic suitability of new services, routes, or aircraft (Xu et al., 2018; Liebeck et al., 1995), and to choose the optimal ship or aircraft size to invest in and operate (Chao and Hsu, 2014; Stopford, 2009). Aircraft manufacturers and airlines use DOC, not only for comparisons of cost for different types of aircraft, but also to make predictions about the actual operating cost of an aircraft in service with a specific airline. As for maritime scholars and shipping operators, adding up cost items is popularly used to obtain voyage cost as an objective function in order to minimize voyage costs.

In studies that develop aggregated cost formulations, log-log cost and translog cost functions are the two general forms applied in order to model total costs in both industries. In air freight transportation, total cost tends to be analysed at the airline level, while in maritime transportation, aggregated cost formulations are also modelled at the voyage and vessel levels. The dependent and independent variables included in the econometric specifications are similar in studies across both industries, but differences still exist. For example, network size is usually included in cost functions for air freight transportation, but not in the cost functions of maritime shipping. Moreover, container liners in general only have one single output (TEU-miles), while multiple outputs are a common issue when modelling costs for combination airlines and passenger airlines, as passenger, freight, and mail services are jointly offered by these airlines and their costs cannot be easily separated. Finally, both industries use the translog cost model to calculate TFP growth rate. Studies in air freight transportation, however, focus more on the existence of EOS, EOD, and cost efficiency, while studies in maritime transportation are more interested in finding optimal fleet capacity and measuring that capacity utilization. As network size is not included in the cost functions for maritime shipping, little has been done to quantify EOS and EOD. Instead, economies of ship size have been studied widely with vessel-level cost functions, while we only find one paper in airfreight transportation (i.e., Zuidberg, 2014) that explicitly estimates the economies of aircraft size. This study finds that large aircraft size is not associated with low unit cost.

3.5 Evolution of Cost Studies and Data Availability

With the development of econometric techniques (e.g., the use of translog functions since the 1970s), the broad application of optimization methods since 1997, and the increase in general data availability, cost studies in the maritime and aviation industries have evolved over time. In this section, we summarize the development of cost studies and the most frequently used databases for cost studies.

3.5.1 Evolution of Cost Studies

We use Figure 3-2 to display the development of cost studies in air freight and maritime transportation since the 1960s. For item-based cost formulations in the field of air freight transportation, the DOC items were formulated as early as 1967 by the ATA, and then followed by a series of refinements. There was no major methodological development until Harries (2005), who proposed a data-driven method. Then, Bießlich et al. (2018) used accounting methods to calculate cost items at the airline level. By contrast, the item-based cost formulation method has not changed dramatically in the field of maritime transportation research since 1960. Although the item-based cost formulation appeared in air freight transportation earlier than in maritime transportation, the total number of studies in maritime transportation is significantly larger than that in air freight transportation. In terms of application, item-based cost formulation was adopted in air freight transportation in order to compare two aircraft prior to 2000, and this approach was also applied to the evaluation of airline-level cost items. In maritime transportation research conducted before 2000, the item-based cost formulation was broadly used to calculate cost per TEU or cost per DWT in order to demonstrate the economies of ship size. After 2000, the stylized modelling of individual cost items has been broadly developed to formulate an objective function that can be used in optimization problems to minimize voyage costs. Since then, the number of studies has begun to increase dramatically.

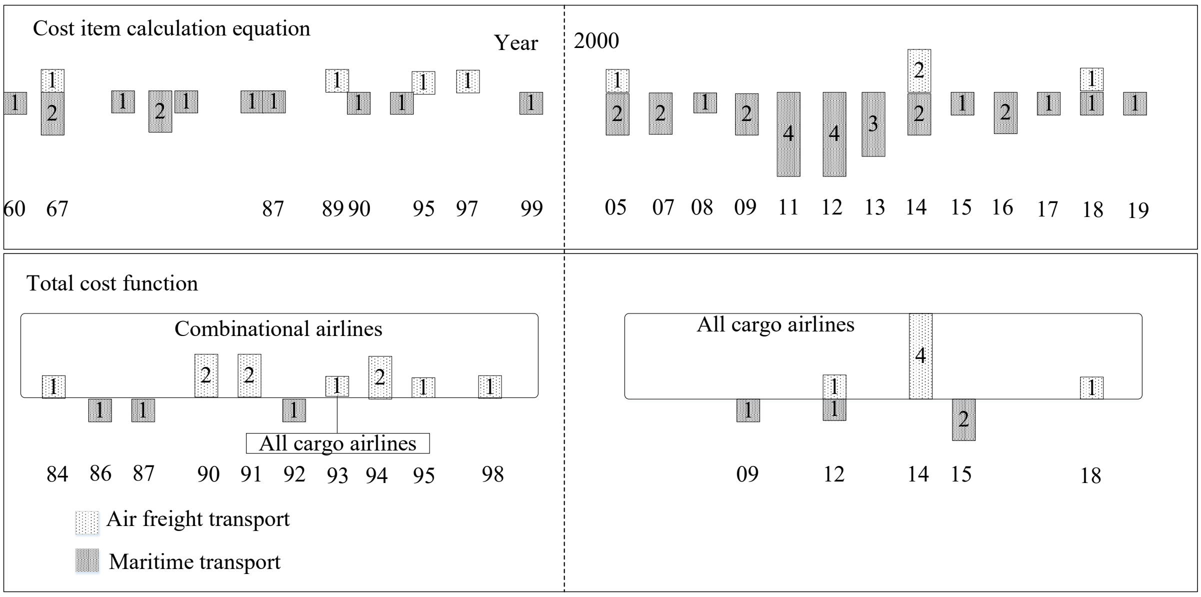


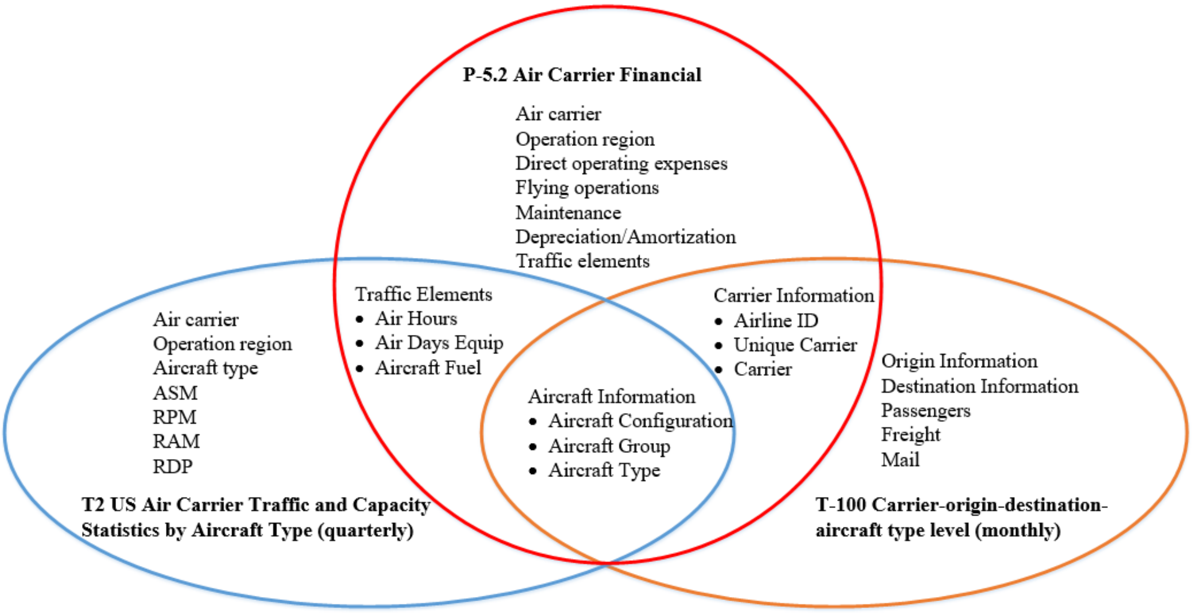
Figure 3-2 Evolution of cost studies

The expansion of aggregated cost formulation research was triggered by the appearance of flexible forms of economic cost functions (e.g., translog cost function) in the early 1980s. Due to the availability of airline annual cost data from the Civil Aeronautics Board (Caves et al., 1984), firm-level cost functions have been widely developed and applied in order to study the EOS and EOD of passenger and combination carriers since 1984. The US federal law requires most American airlines (whether publicly listed or privately owned) to report their financial and operating information to the United States Department of Transport (USDOT) on a monthly, quarterly, and annual basis. As a result, USDOT Form 41 became a source of comprehensive cost data in 1990. In 1993, Kiesling and Hansen (1993) adopted the log-log cost function in order to calculate the EOS and EOD of UPS. Since 2012, studies on the firm-level cost functions of cargo airlines have increased, and the research focus in cost functions has gradually shifted from passenger and combination airlines to all-cargo airlines and integrators. By contrast, shipowners are reluctant to release their cost details at company level (Tolofari et al., 1987). As a result, maritime researchers rely on voyage-level and vessel-level cost data collected from surveys and synthesised from regression analysis conducted before 1993. The first firm-based translog cost function appeared in 2009, and the data was collected from the annual financial statements of three container shipping lines. The research focus related to these cost functions has shifted from quantifying economies of ship size towards finding the optimal fleet capacity and measuring its utilization.

3.5.2 Data and Data Quality

Data plays a crucial role in cost studies: As Oum and Waters (1996) have noted, cost models are useless if the data are of poor quality. Table 3-10 lists frequently used databases in studying air freight transportation costs, and Table 3-11 summarizes the databases for maritime shipping research.

The USDOT provides a comprehensive database of airlines' financial and traffic data. Form 41 Financial Data covers Schedule P-5.2 (a quarterly DOC itemization for US airlines) and Schedule P-7 (the total operating expenses, comprising DOC and IOC items). Schedule P-5.2 provides detailed information on DOC at the aircraft level, such as total air hours, air days assigned, air fuel issued, depreciation, and flying operations, to name a few items. Form 41 Traffic T-100 contains monthly airline traffic information. It includes origin airports, destination airports, aircraft type, aircraft hours, and LF, among other details. The US Air Carrier Traffic and Capacity Statistics by Aircraft Type T-2 provides ASL, LF, NPS, and either RTK or RTM. Researchers usually combine the Schedule P-5.2 financial data with the T-2 traffic data in order to estimate cost functions, because they each include several traffic elements. In addition, Schedule P-5.2 can also be merged with the T-100 and T-2 forms in order to obtain airline-aircraft level data. Figure 3-3 shows the relationship between Schedule P-5.2, T-2 and T-100.



Notes: ASM = Available Seat Miles; RPM = Revenue Passenger Miles; RAM = Revenue Aircraft Miles; RDP = Revenue Departures Performed

Figure 3-3 Airline traffic and financial data (T2, P-5.2, T-100), with key attributes

Apart from the DOT Form 41, the International Civil Aviation Organization (ICAO) also provides monthly, quarterly, and annual series of traffic, fleet, personnel, and financial data from airlines (Table 3-10). The Air Transport Reporting (ATR) Forms from ICAO cover information about flight origin and destination, traffic information divided by flight stage, fleet and personnel information, airline financial data, airport traffic data, airport financial data, air navigation services financial data, en-route service traffic statistics, and fuel consumption. The ICAO data is thus very similar to that collected by DOT Form 41. Airlines' financial reports also include cost data useful to researchers. Still, in many cases these official databases need to be supplemented with other data sources in order to empirically estimate an aggregated cost formulation. One of these frequently used supplemental data sources is the average annual oil price, collected from the Europe Brent Spot price FOB and published by US Energy Information Administration (Zuidberg, 2014; Chao and Hsu, 2014).

Table 3-10 Databases used frequently in air freight transportation cost analysis

US DOT Form 41	ICAO statistics program (ATR Forms)	Cost items reported in airlines' financial reports
Aircraft operating expenses: DOC: — Flight crew — Fuel — Maintenance — Depreciation — Aircraft rental — Other flight costs IOC: — Passenger services — Aircraft servicing — Traffic services — Reservations and sales — Advertising and publicity — Transport-related expenses **Traffic data:** Carrier Aircraft type Available capacity Aircraft hours Revenue ton miles (RTMs) Available ton miles (ATMs)	**Aircraft operating costs:** Flight crew Fuel Insurance Rental cost Other expenses Depreciation Landing and associated airport charges Air navigation charges Station expenses Passenger services General and administrative Ticketing, sales, and promotion Other operating expenses **Traffic data:** Origin Destination Fleet information Airport traffic data	Salaries and employee benefits Rentals and landing fees Depreciation and amortization Fuel Maintenance and repairs

Table 3-11 summarizes the databases used in maritime cost studies. Among all of those listed, the Clarkson's Shipping Intelligence Network is one of the most widely used databases. It includes a wide range of data, covering information from fleets, shipowners, and builders to orderbooks, sales, and freight rates. Lloyd's List Intelligence provides detailed information on vessels, shipping companies, and ports. The Shipping Operating Costs Annual Review and Forecast provided by Drewry Shipping provides a complete annual assessment of ship operating costs. The report covers major ship types and their different sizes, including container, dry bulk, oil, chemical, LNG, LPG, general cargo, reefer, ro-ro, and car carrier categories. It also includes the assessment of ship operating costs by main cost heading (e.g., insurance) and sub-cost component (e.g., hull and machinery insurance) in terms of vessel age (newbuild, 5, 10, 15, and 20 years) at the date of the report's publication. Also available in the report are historical trends, annual ship operating costs, and annual projections of total ship operating costs. With the increasing quality of Automatic Identification System (AIS) data, which provides real-time ship position information and individual ship data (Yang, et al., 2019), ship voyage costs can be estimated based on the operational characteristics derived from AIS, such as voyage distance and speed (Andersson and Ivehammar, 2017). In addition to the databases mentioned above, researchers also collect cost data from surveys and from annual financial statements of listed shipping companies.

Table 3-11 Databases used frequently in maritime transportation cost analysis

Clarkson's Shipping Intelligence Network	Drewry Shipping: Shipping Operating Costs Annual Review and Forecast	Annual financial statements of listed shipping companies
Newbuild price Second-hand ship price Freight rate **Other data:** Shipowner Fleet Builders Orderbook Capital markets Sales	Manning Insurance Stores and spares Lubricants Repairs, maintenance, and dry docking Management and administration	Vessel operating expenses Voyage expenses General and administrative expenses Depreciation and amortization

3.6 Remarks

Cost modelling is an essential tool in both maritime and air freight transportation research that is used for strategic decision making. Chapter 3 is one of earliest attempts to review and summarise the cost models most frequently applied in existing literature in both of these fields. We classify the cost studies into two categories: item-based cost formulation and aggregated cost formulation.

In item-based cost formulation, air freight and maritime shipping research shares many common items, such as capital costs, carrier crew costs, fuel costs, and maintenance costs, among others. Regression analysis and accounting approaches are both commonly used in formulating the cost items for both industries; however, maritime transportation cost analysis also adopts the approximation method. We find that the application of item-based cost formulation also differs between the two industries. For maritime transportation, the item-based cost formulation is commonly used to assess economies of ship size, to evaluate the economic feasibility of a new route, or to formulate an objective function for a cost optimization problem. As for air freight transportation, the item-based cost formulation is widely employed in order to obtain the DOC that can then be used for the comparative analysis of several aircraft, explore the optimal payload for various aircraft types, and the appropriate flying distances in the face of fuel price fluctuations.

In regard to aggregated cost formulation, we identify two general function forms, the log-log cost and translog cost functions. These forms are applied solely at the company level for air transportation cost analysis. In the field of maritime transportation research, it is also used at the vessel and voyage levels. In aviation, the scholars adopt these functions primarily to calculate EOS and EOD, estimate cost efficiency, decompose the TFP growth rate, and demonstrate the factors that affect airlines' total cost. In maritime transportation, the primary application of these functions is to find the optimal fleet capacity, measure fleet utilization, and quantify economies of ship size.

With the development of econometric techniques and the improvement in data availability, the study of cost in the air freight and maritime industries has evolved over time. Several aviation associations proposed formulas with which to calculate cost elements of DOC as early as 1967. Today, the USDOT publishes airline level cost data, making the econometric modelling of aggregated costs of airlines, and the subsequent cost efficiency analysis feasible. On the other hand, the lack of a standard cost database hinders the similar development of maritime transportation cost research.

Chapter 4 Quantifying the Impact of Pandemic Lockdown Policies on Global Port Calls

4.1 Introduction

The spread of the COVID-19 virus has brought severe effects on global society and the world economy due to the policy responses of national leaders. Governments have implemented unprecedented national lockdown policies (dubbed the Great Lockdown by the IMF) to contain the spread of the virus since early 2020. While effective in slowing down the spread of the virus, these containment measures have negatively affected economies around the world and, particularly, the global supply chain which relies on freight transportation. Disruptions caused by the pandemic on supply chains are often characterized by the existence of disruption with unpredictable scaling effects and few warning signs; the existence of the ripple effect (i.e., disruption propagations) accompanying the spread of the virus; wide geographical coverage; and, disruptions in demand, supply and logistics infrastructures simultaneously (Ivanov, 2020; Notteboom et al., 2021). Needless to say, ensuring the functioning of supply chain and transportation networks is critical for economic development, as much of it is enabled and powered by freight transportation (Loske, 2020). Among all the categories of freight transport, maritime freight alone moves over 80% of the volume of world trade (UNCTAD, 2019), which further underscores the importance of maritime transport in trade and development.

The impact of the COVID-19 outbreaks and associated national lockdown policies on the maritime transport industry is seen as unprecedented in that lockdowns deal multiple blows to the industry on two fronts simultaneously (Heiland and Ulltveit-Moe, 2020). On the one hand, the industry faces a contraction in demand for seaborne transportation due to the Great Lockdown. A massive number of production facilities have been shut down across countries and sectors, leading to collapsing demand for transport services and subsequently cancelled voyages. On the other hand, shipping companies also face novel regulations as countries have implemented direct restrictions on port access and sea transport. For instance, some countries have banned marine vessels from sailing into certain ports, which has forced such vessels to change their original destinations. Sometimes, the entry of vessels has been prohibited because their last ports of call happened to be located in a country with a high risk of epidemic spread. Countries have also implemented rules concerning crew changes and seafarers' mobility on incoming ships. It should further be noted that these restrictions affect not only the imposing countries and shipping companies, but also all of their trading partners (Heiland and Ulltveit-Moe, 2020).

In order to mitigate these effects going forward, it is crucial to define the exact effects of lockdown measures for policymakers. The objective of this research is thus to examine the effect of national lockdown policies on maritime transportation by analyzing the port call data of the world's largest 30 container ports. After the initial spread of COVID-19, there have been two waves of large-scale national lockdowns around the world in the first half of 2020. The first lockdown was announced in China on 23 January 2020 (i.e., Week 4 in 2020), and the second one was announced on 18 March 2020 (i.e., Week 12 in 2020), mainly in Asia, Europe, and North America. With this in mind, we aim to tackle two specific research questions: 1) What is the impact of national lockdown policies on local port calls, both in the short term (i.e., one or two weeks) and long term (i.e., four to six weeks)? 2) Is there evidence of disruption propagation effects on ports across different regions? Heiland and Ulltveit-Moe (2020) have pointed out that the propagation effect of local disruptions through the liner shipping network can be detrimental and long-lasting. Little is known, however, about how the shock propagates, and to what extent. In order to address these questions, a Difference-in-Difference (DID) model is proposed to measure the impact of national lockdowns on the number of port calls in the medium to long term. The DID model is widely used for analyzing average medium to long term effects of social policies, making it a well-adapted tool for our analysis. For the first question, we quantify the immediate effect of national lockdowns on port calls through a combined regression discontinuity design (RDD)-DID model of the data collected from a few weeks pre- and post- lockdown. The combination of RDD and DID models can thus mitigate the time trend in the data, especially as it relates to the effect of the Chinese New Year on ports. In order to answer the second question, specifically how lockdown policy in China might affect port calls in other countries, we first categorize ports in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group; we do this by using a proposed connectivity index. Then, we separately examine the impact of Chinese lockdown on each of the different port groups.

Recent studies have evaluated the impact of COVID-19 on transportation by comparing indicators of 2020 with those of the same period in previous years with (quasi-) experimental research methods, such as DID and RDD (Vandoros, 2021; Barnes et al., 2020). We aim to extend the analysis to ports and address the potential problems when applying the (quasi-) experimental method to our research objective, e.g., separating the effect of Chinese New Year from that of COVID-19 on ports. Concretely, our contribution is three-fold: First, by applying the quasi-experimental research methods, e.g., DID and RDD models, we provide a method to isolate the impact of COVID-19 lockdown policy on port call changes clearly from those associated with the Chinese New Year. The method can exclude the noise and give more reliable results compared to comparative analysis or time series analysis that have been commonly used in existing literature. Second, we propose a new port connectivity measurement method based on dynamic ship data extracted from the Automatic Identification System (AIS) data. The data is particularly useful, as it can provide near real-time information on maritime transport and trade. Third, by taking port connectivity into consideration, we also identify the propagation effects of one country's lockdown policy on the shipping activities of other countries, which has not been addressed before. Our results provide significant guidance for policy makers when drafting national lockdown policies, and help diverse groups of stakeholders to understand and estimate the impact of lockdown policies, both at local and global levels.

The remainder of the study is structured as follows: Section 4.2 introduces data and methodology. Section 4.3 reports the direct lockdown effects on ports in certain countries, while Section 4.4 takes shock propagation into consideration and examines the indirect lockdown effects. Section 4.5 provides policy suggestions based on these empirical results, and Section 4.6 concludes the study.

4.2 Data and Methodology

This section first presents the analytical framework, our construction of weekly port call data drawn from the AIS. Then the DID and RDD-DID models are introduced.

The analytical framework is provided in Figure 4.1. To begin with, we gauge the direct effect of the first lockdown on Chinese top seven container ports and the direct effect of the second lockdown on the top ten ports in other countries. Next, we separately examine the indirect effects of Chinese lockdown on high-connectivity Asian ports, high-connectivity European ports, and low-connectivity ports.

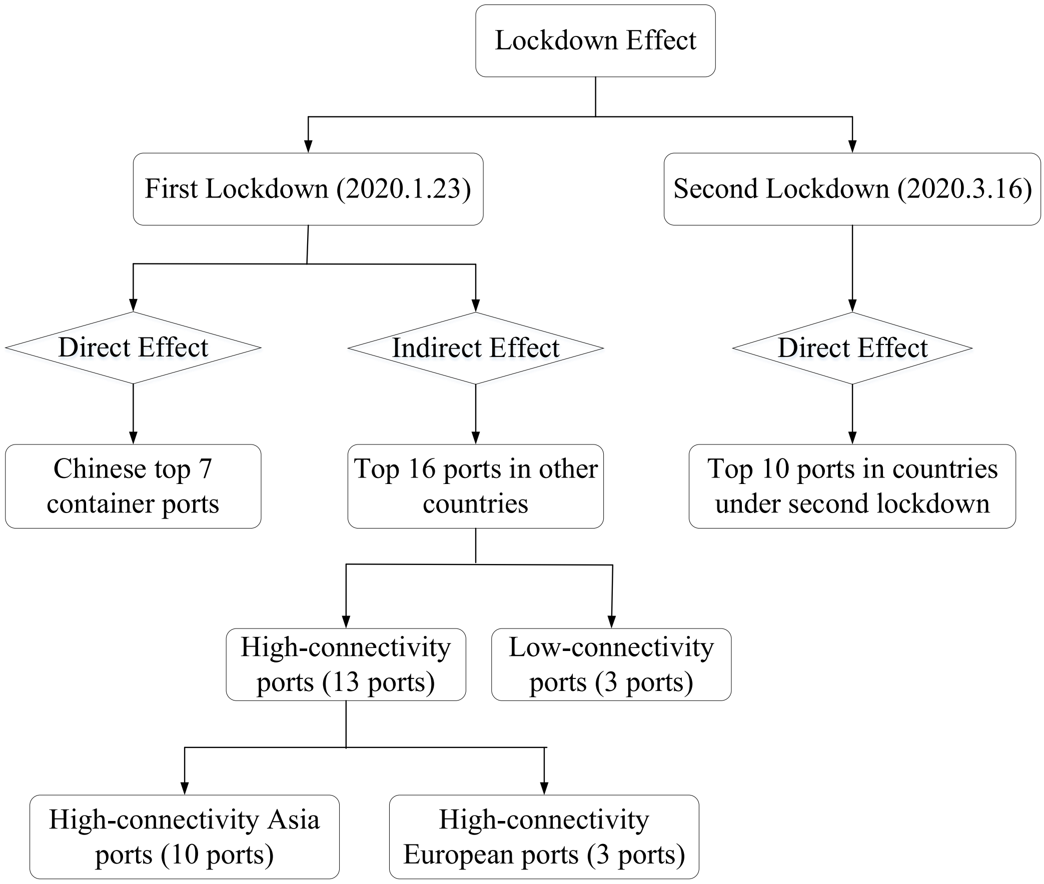


Figure 4-1 Analytical framework

4.2.1 Data

We selected for analysis the world's 30 largest container ports (measured in terms of throughput) located in countries that implemented lockdown policies during the period from January 2020 to March 2020. Among them, as shown in Table 4.1, seven Chinese ports were affected by the lockdown policy implemented in China in January 2020, including Shanghai, Shenzhen, Ningbo-Zhoushan, Guangzhou, Qingdao, Tianjin, and Xiamen. Ten other ports worldwide were affected by lockdown policies in their respective countries in March 2020, including Rotterdam, Port Klang, Antwerp, Los Angeles, Tanjung Pelepas, Hamburg, New York, Colombo, Bremerhaven, and

Piraeus.[3] We use port call as the indicator, because it is broadly treated as demand and port traffic proxy of port in previous studies (UNCTAD, 2020; Michail and Melas, 2020; Baldwin and Evenett, 2020). The necessary time windows from before and after the lockdown announcements were selected based on trends in the number of port calls and the results of a parallel trend test, which will be discussed in subsequent sections.

Table 4-1 Ports affected by two waves of lockdown policy

	Time	Scope	Ports affected
First wave of lockdown	January 2020	China	Shanghai, Shenzhen, Ningbo-Zhoushan, Guangzhou, Qingdao, Tianjin, Xiamen
Second wave of lockdown	March 2020	Europe, Asia, and America	Rotterdam, Port Klang, Antwerp, Los Angeles, Tanjung Pelepas, Hamburg, New York, Colombo, Bremerhaven, Piraeus

The AIS data can track individual ship movements and provide specific information, including a ship's identity, location, speed, and draft, among other details. (Yang et al., 2019). Combined with vessel information from Lloyd's List Intelligence, including IMO number and vessel type, we can derive dynamic movement records for any given container ship.

The following criteria are, moreover, used to identify port calls: every time a ship stays within 30 km of any port for more than 1 hour with speed less than 1 knot will be considered as one port call for that port. If the ship is mooring at the overlapping region of several ports, then the nearest port will be chosen.

[3] World Shipping Council: https://www.worldshipping.org/about-the-industry/global-trade/top-50-world-container-ports

Notably, the first wave of lockdowns in China was implemented on January 23, 2020, just before the Chinese New Year, which is often characterized by a reduced numbers of port calls at Chinese ports during this time period. Due to the coincidence of the lockdown policy and the Chinese New Year holiday, we need to first identify the reason for the decrease in port calls. Figure 4.2 plots the weekly port calls in the selected seven Chinese ports during the 2019 and 2020 Chinese New Year periods, respectively. It can be observed that port calls went down significantly during the Chinese New Year period in both years. In order to remove the Chinese New Year effect on port calls data and to obtain the pure lockdown effect, we selected the same period of port calls data for both 2019 and 2020 (i.e., six weeks before and after the Chinese New Year) for the DID model.

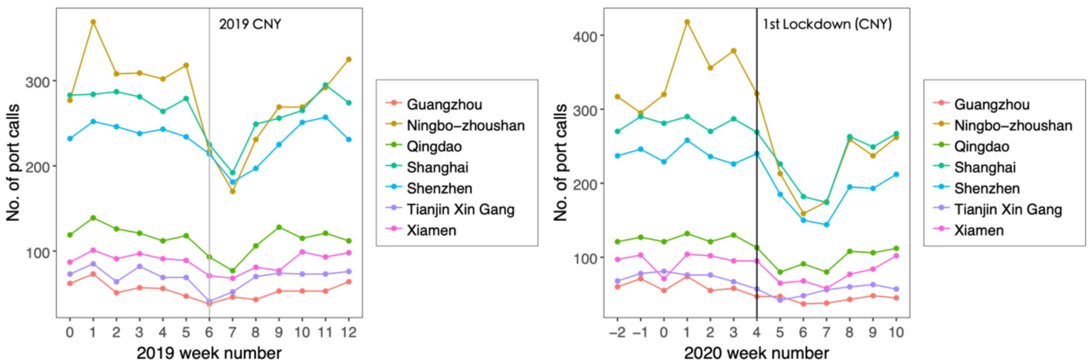


Figure 4-2 Port calls data of seven Chinese ports during 2019 and 2020 Chinese New Year Period

Notes: The 2019 week number represents the actual week number in 2019; Week 0 (starting 24 December 2018) represents Week 52 of 2018, that is, the last week in 2018. In 2019, the Chinese New Year began in Week 6 (starting 04 February 2019). For 2020, the week number represents the actual week number in 2020, and Week 0 (starting 23 December 2019), Week -1 (starting 16 December 2019), Week -2 (starting 09 December 2019) represent Week 52, Week 51 and Week 50 in 2019, respectively; that is, the last three weeks in 2019. In 2020, the Chinese New Year celebration took place in Week 4 (starting 20 January 2020).

We propose a connectivity index between each port in other countries and Chinese ports in order to measure their connectivity. Specifically, for every ship, we obtain the time series of sequential port calls through AIS data based on the method described before.

Then, for each port under investigation, we use the following equation to calculate a port c's connectivity index with Chinese ports.

$$Connectivity_c = \sum_{i=1}^{n} Y_i \cdot \left(\sum\nolimits_{j=1}^{m} C_j\right) \tag{4-1}$$

where n is the total number of global ships' port call time series in 2019. Y_i equals 1 if this time series of port calls contains port c and 0 otherwise. In this equation, m is the number of port calls in one ship's time series, and C_j is a dummy variable which takes a value of 1 if the port call is a Chinese port and takes a value of 0 otherwise.

4.2.2 Difference-in-Difference Model

The DID model has been broadly applied to quantify the effect of an experimental treatment by comparing the average change in the outcome variable over time in control and treatment groups, respectively, thus eliminating the effects of extraneous factors and selection bias (Meng et al., 2018; Alemi et al., 2018). In our study, the ports in the control group and treatment group are the same. We distinguish the treatment and control group in terms of the occurrence time (year of 2019 and 2020). The port call in 2019 is used as control group and the port call in 2020 is selected as the treatment group. The following DID model is constructed:

$$W_{i,c} = \beta_0 + \beta_1 Year_i + \beta_2 T_i + \beta_3 T_i \cdot Year_i + \mu_i + \rho_c + \epsilon_{i,c} \tag{4-2}$$

$\boldsymbol{T_i}$ is a dummy variable that takes the value of 1 after the intervention (lockdown) date and 0 before the intervention. For Chinese ports, it is 1 after the 4th week and 0 before the 4th week of 2020; it is 1 after the 6th week and 0 before the 6th week of 2019. For ports in other countries, the dummy variable takes the value of 1 after the 12th week of the years of 2019 and 2020, and 0 before the 12th week. Table 4-2 shows the value of $\boldsymbol{T_i}$ on different dates. $\boldsymbol{Year_i}$ is a dummy variable that takes the value of 1 in 2020, and

0 in 2019. The model includes port fixed effect $\boldsymbol{\rho_c}$ as well as week fixed effect $\boldsymbol{\mu_i}$ to control the port and time variance. $\boldsymbol{\beta_0}$ reflects the baseline average. $\boldsymbol{\beta_1}$ reflects the difference of port calls between the years of 2019 and 2020 before the lockdown implementation (it is the week 4 for 2020 and the week 6 for 2019). $\boldsymbol{\beta_2}$ represents the time trend in control group (port calls of 2019). $\boldsymbol{\beta_3}$ indicates the average effect of lockdown on affected ports.

Table 4-2 Value of $\boldsymbol{T_i}$ on different dates

T_i	2019		2020	
Chinese ports	Pre-week 6 0	Post-week 6 1	Pre-week 4 0	Post-week 4 1
Other ports	Pre-week 12 0	Post-week 12 1	Pre-week 12 0	Post-week 12 1

For the DID model, our key assumption is that without the lockdown policy, the port calls data would have changed in the same way as the previous year, i.e., a parallel trend assumption. In order to ensure the validity of this assumption, we also perform a parallel trend test through an event study model, which is detailed in Section 4.2.4.

4.2.3 Regression-Discontinuity-Design (RDD)-DID Model

In order to further quantify the immediate effect caused by lockdown policies, we propose an RDD-DID model. The proposed model builds on the RDD model, which can estimate potential breaks in a relatively short time period around the policy intervention date (Brodeur et al., 2020). We assume the lockdown announcement date as the cutoff, then week *i* can be considered in the treatment group if week *i* is after the date; otherwise, week *i* is in the control group. The equation is given by:

$$W_{i,c} = \beta_0 + \beta_1 T_i + \mu_i + \rho_c \tag{4-3}$$

where $W_{i,c}$ is the number of port calls in affected port c in week i. We define $T_i = 1$ if week i is after the lockdown announcement, 0 otherwise; and the week fixed effect is represented by μ_i. β_1 is the immediate change measurement that we are interested in.

Applying nonparametric estimation on Eq. (4-3), a running variable D is defined as the absolute distance in weeks from the lockdown policy implementation date; the value is negative for the weeks before and positive for the weeks after the lockdown, while the week of the lockdown implementation is set at 0. The lockdown implementation dummy T_i is defined in a similar way as in the DID model. The RDD regression equation is written as:

$$W_{i,c} = \beta_0 + \beta_1 T_i + \beta_2 f(D_i) + \beta_3 T_i \cdot f(D_i) + \beta_4 W_{i-1,c} + \mu_i + \rho_c \qquad (4\text{-}4)$$

where $f(D_i)$ is a polynomial function of D_i, which interacts with T_i, and can be used to allow for different effects on either side of the cutoff date, and $f(0) = 0$. $W_{i-1,c}$ is the port calls data the week before, which eliminates any self-regression effects. Our regression model uses polynomials of order one. As for the other independent variables, we include the same controls as in the DID model. β_1 indicates the immediate effect of the lockdown announcement on port calls data in the lockdown announcement week aside from self-regression.

In order to eliminate the time trend in the data from Chinese ports for each of the two years selected, we propose the RDD-DID model. This allows us to remove the effects of Chinese New Year and accurately estimate the true effects of the lockdown on maritime freight. In the RDD-DID model, we first calculate data breaks in 2019 and 2020, respectively; the port call break in 2019 can be related to the Chinese New Year.

We then take the difference between the 2020 break and the 2019 break to obtain the port calls break caused purely by COVID-19 lockdown policy.

The RDD-DID model can be written as follows:

$$W_{i,c} = \beta_0 + \beta_1 T_i \cdot Year_i + \beta_2 f(D_i) \cdot T_i \cdot Year_i + \beta_4 f(D_i) \cdot T_i + \beta_5 T_i + \beta_6 W_{i-1,c} + \mu_i + \rho_c + \epsilon_{i,c} \tag{4-5}$$

where we include the same control variables as in the RDD model. β_5 indicates the immediate break of port calls data in 2019, and $(\beta_1 + \beta_5)$ indicates the break in 2020. The immediate effect of the lockdown policy on port calls is measured by β_1.

4.2.4 Event Study and Parallel Trend Tests

To choose appropriate analysis time window and verify the validation of DID models, we perform an event study to test the parallel trends in the data used in the DID models and RDD-DID models; we also test for adaptation effects to the lockdown, namely, how trends in port calls changed after the lockdown announcement. The event study model can be written as follows:

$$W_{i,c} = \sum_k \alpha_k E_{k,c} \cdot Year_i + \sum_k \beta_k E_{k,c} + \mu_i + \rho_c + \epsilon_{i,c} \tag{4-6}$$

where $E_{k,c}$ are a group of k dummy variables that represent weeks in the DID and RDD-DID models, which take a value of 1 for week k and 0 for the other weeks. The week before the lockdown announcement (treatment) is the reference period. The estimated coefficients of the $E_{k,c}$ dummies (α_k) should therefore be interpreted as being in week k, the effect difference between two years.

For an ideal dataset used in both the DID and RDD-DID models, the effect difference of the weeks before the lockdown treatment should not be significant, which would indicate that the port calls trend in 2019 and 2020 would have stayed the same without the lockdown announcement.

4.3 Empirical Results of Direct Lockdown Effects

4.3.1 Descriptive Analysis

We begin our analysis by examining port call data within the six week period before and after the beginning of lockdowns in 2020 in seven critical Chinese ports (the lockdown policy was announced in the Chinese New Year week, that is, Week 4). At first glance, port calls at these harbors experienced a relatively sharp decrease after the lockdown date, and kept decreasing for about three weeks before beginning to recover.

Figure 4-3 plots the trends around the Chinese New Year date for both 2019 and 2020. In both years, there were a sharp decrease in port call data around the Chinese New Year, but in 2020, the declining trend lasted for a longer time, which may have been caused by the lockdown policy.

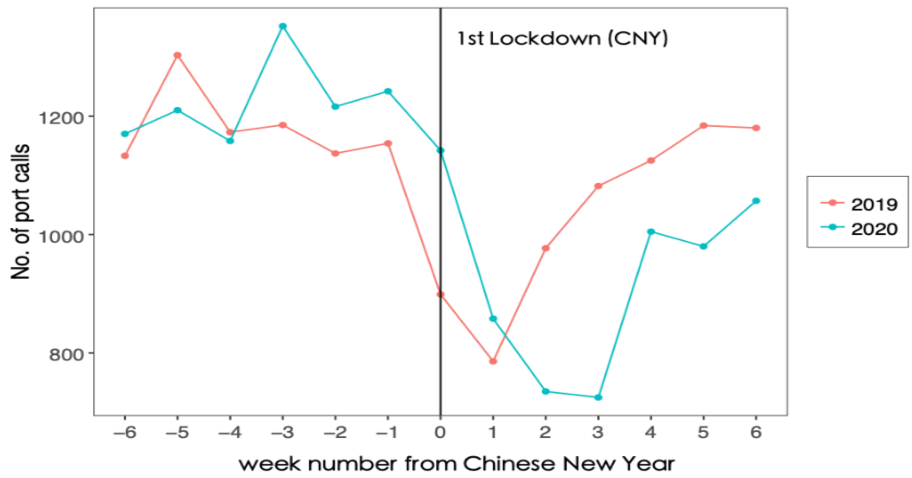


Figure 4-3 Total port calls at seven Chinese ports around the 2019 and 2020 Chinese New Year

Notes: The week number in the figure above shows the relative weeks between the actual week and the Chinese New Year week. Week 0 represents the Chinese New Year week, that is actual

Week 6 in 2019 (starting February 4, 2019) and actual Week 4 in 2020 (starting January 20, 2020).

As for the top container ports in other countries that announced a lockdown policy in Week 12 of 2020 (refer to Table 4-1 for affected ports and lockdown policy), Figure 4-4 shows the port call changes in these ports from Week 7 to Week 16 in 2019 and 2020. The decrease in port calls around the lockdown announcement in 2020 can thus be observed against the trends of the prior year.

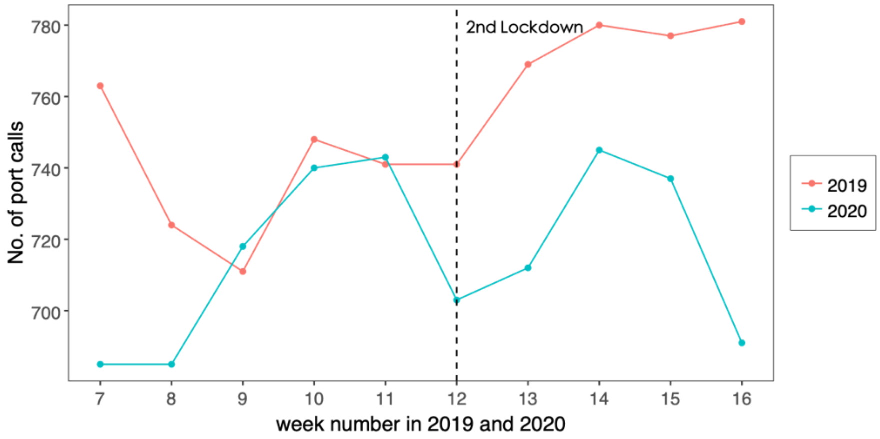


Figure 4-4 Total port calls at other countries' ports during the sampling period (Week 7-Week 16 in 2019 and 2020)

Notes: The week number here represents the actual week number in 2019 and 2020. For these countries, the lockdown policy was implemented in Week 12 in 2020 (starting 16 March 2020).

4.3.2 Results of Direct Lockdown Effects on Chinese Ports

The direct lockdown effects on Chinese ports calculated using the DID model and RDD-DID models are presented in Table 4-3. To gauge the average effect of lockdown on Chinese ports, we apply the DID estimator. We select data from four weeks before and after the Chinese New Year in 2019 and 2020 as our estimation time window, based on the parallel trend tests outlined in Section 4.4. The DID estimator is significantly negative at the 10% significance level, indicating that the lockdown policy in China had a significant impact on port calls at Chinese ports. The results show that the number of port calls in the top seven Chinese ports decreased by 21.5 per week, or 13.0% on average (in 2019, the average number of weekly port calls at these Chinese ports is 165). On the other hand, using the same study period, the RDD-DID estimator is not significant, indicating that after taking Chinese New Year effect into account, Chinese lockdown policy did not cause an immediate port call break near the lockdown date; this suggests rather, that the effect of lockdowns was gradual in magnitude.

Table 4-3 The direct effects of lockdown on Chinese ports

	DID model	RDD-DID model
Time period	week -4 – week 3	week -4 – week 3
$T_i \cdot Year_i$	-21.536*	16.437
	(10.90)	(9.77)
Port FE	Yes	Yes
Year and week FE	Yes	Yes
Autoregressive Effect	No	Yes
N	112	112
adj. R^2	0.959	0.977

Notes: The results in the above table are estimated based on Eqs. (4-2) and (4-5) for the DID model and RDD-DID model, respectively. Coefficient estimates for $T_i \cdot Year_i$ are presented. Standard errors are reported in parenthesis. The symbols *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The treatment group for the DID model and RDD-DID model is four weeks before and after 2020 Chinese New Year, while the control group is four weeks before and after 2019 Chinese New Year, respectively.

4.3.3 Results of Direct Lockdown Effects on Other Ports

In order to test the direct lockdown effect on ports in other countries during the second wave of national lockdowns, we apply the same DID and RDD-DID models. We select the time span from four weeks before the lockdown announcement to four weeks after that date. As verified in the parallel trend tests in Section 4.3.4, during this time period port call data at these ports in 2020 was not affected by the mid-January Chinese lockdown, illustrating the same trend as 2019 before lockdown. Estimators of the DID and RDD-DID models indicate that there was an immediate and significant decrease in port call data at these ports at the start of lockdowns, although the magnitude of the effect was moderate at best, as presented in Table 4-4. Within four weeks of the announcement of lockdown policies, the average port call levels of these harbors decreased by 3.3 per week (or 4.5%) compared to before (in 2019, the average weekly port calls at these ports is 73.75).

Table 4-4 The direct effects of lockdown on other ports

	DID model	RDD-DID model
Time period	week -4 – week 3	week -4 – week 3
$T_i \cdot Year_i$	-3.300**	-4.225**
	(1.59)	(1.83)
Port FE	Yes	Yes
Year and week FE	Yes	Yes
Autoregressive Effect	No	Yes
N	160	160
adj. R^2	0.979	0.980

Notes: The results in the above table are estimated based on Eqs. (4-2) and (4-5) for the DID model and RDD-DID model, respectively. Coefficient estimates for $T_i \cdot Year_i$ are presented. Standard errors are reported in parenthesis. The symbols *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The treatment group for the DID model and RDD-DID model is four weeks before and after 2020 Chinese New Year, while the control group is four weeks before and after 2019 Chinese New Year, respectively.

4.3.4 Event Study and Parallel Trend Tests for Direct Lockdown Effects

In order to confirm the validity our DID and RDD-DID models presented above, we perform an event study based on Eq. (4-6). The purpose of this is to test the common trend assumption, namely, that the same port call trends existed in 2020 before the announcement of lockdowns as in 2019.

Specifically, for Chinese ports, we perform an event study on port calls in 2019 and 2020 from five weeks before and after the Chinese New Year. The corresponding results are shown in Figure 4-5. As modelled below, the 95% confidence intervals for coefficients before the Chinese New Year all include zero, indicating that the trends in 2019 and 2020 from before the Chinese New Year can be considered identical.

The results of the event study model for ports affected by the second lockdown wave in March 2021 are shown in Figure 4-6. The time range is from five weeks before the lockdown date to five weeks after the date. As can be seen in the graph, in Week 7 (the fifth week before the lockdown date), there is a significant difference in port call data between 2019 and 2020, which violates the common trend assumption between the treatment and control group before the policy intervention. Thus, we only use a four-week time span for our direct effect DID and RDD-DID models across all ports examined in order to retain consistency. As depicted in Figures 4-5 and 4-6, the four-week time span satisfies the common trend assumption and confirms the validity of the DID and RDD-DID models.

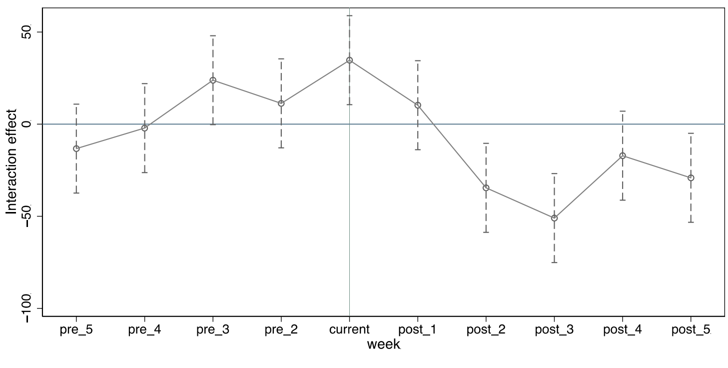


Figure 4-5 Coefficient plots for DID and RDD-DID models analyzing the direct lockdown effects on Chinese ports during the first wave of lockdown

Notes: Based on Eq. (4-6). Current week refers to the cutoff week (lockdown announcement week). The last week before the treatment (pre_1) is the reference week.

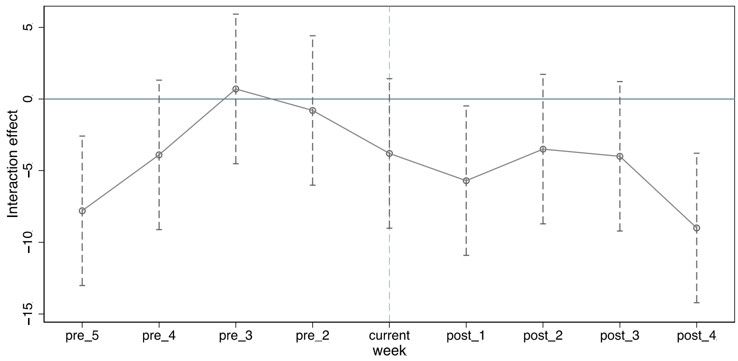


Figure 4-6 Coefficient plots for DID and RDD-DID models analyzing the direct lockdown effects on international ports affected by the second wave of lockdowns

Notes: Based on Eq. (4-6). Current week refers to the cutoff week (lockdown announcement week). The last week before the treatment (pre_1) is the reference week.

4.4 Empirical Results of Indirect Lockdown Effects

In order to further examine port call changes in the ports affected by the second wave of lockdowns, Figure 4-7 plots port calls for these ports from Week 1 to Week 16 of 2020. As seen, there seems to be an unexpected break in most of these port calls around Week 7 in 2020 (i.e., about three weeks after the start of the Chinese lockdown policy). Considering that it takes about two to three weeks for international container ships to travel across continents, the Chinese lockdown policy may also have affected these ports indirectly through the container shipping network.

Next, we examine this potential indirect lockdown effect, namely, how lockdown policy in one country can affect port calls in other countries through the container shipping network. In order to formally examine this shock propagation effect, we first classify ports based on their connectivity to Chinese ports. Then, we run the DID and RDD-DID models separately on high-connectivity and low-connectivity groups, using the date when the effects of the Chinese lockdown propagated to each group as the policy intervention date.

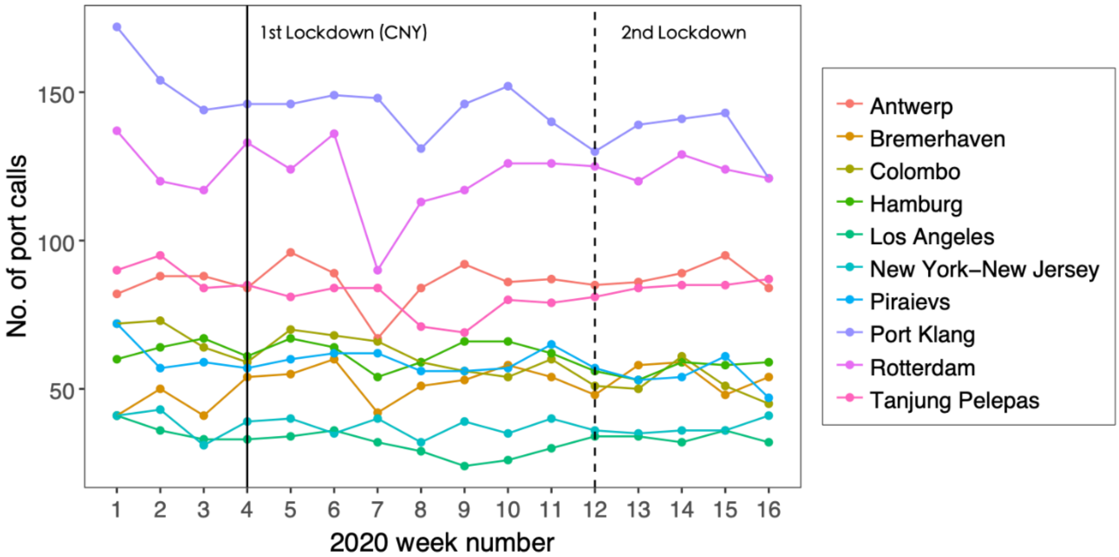


Figure 4-7 Port calls at ports affected by the second wave of lockdown from Week 1 to Week 16 of 2020

Notes: The week number represents the actual week number in 2020. For these countries, the lockdown policy was implemented in Week 12 (starting from March 16, 2020).

4.4.1 Connectivity with China

Based on the trends in port calls shown in Figure 4-7, we hypothesize that the impact of lockdown policy in China on port calls in other countries varied across ports due to different connectivity levels with Chinese ports. To verify this point, we categorize ports in other countries into a high-connectivity (with Chinese ports) group and a low-connectivity group by using a proposed connectivity index introduced in Section 4.2. Based on each port's connectivity index and the port location, we grouped these ports into three categories for further analysis, as shown in Table 4-5. The standard for being a high connectivity port is that the number of ship visits between this port and Chinese ports in 2019 is more than 2,000.

Table 4-5 Classification of ports in other countries with connectivity index and location

High-Connectivity Ports		Low-Connectivity Ports
Asian Ports	European Ports	
Pusan (16138), Hong Kong (14313), Singapore (13952), Port Klang (7852), Tanjung Pelepas (5605), Ho Chi Minh (4916), Manila (4156), Colombo (3835), Mina Jabal Ali (3459), Jakarta (2688)	Rotterdam (3275), Hamburg (2166), Antwerp (2161),	New York (1602), Bremerhaven (1095), Piraeus (1798),

Notes: Connectivity is in parentheses.

4.4.2 Empirical Analysis of High Connectivity Ports

Figure 4-8 plots the total port calls in high-connectivity ports in 2019 and 2020 around the Chinese New Year week, respectively. Two weeks after the Chinese New Year, the trends in port calls in 2019 and 2020 varied significantly: while the number of port calls in 2019 recovered quickly to the same level as before the Chinese New Year, port calls in 2020 remained at a low level for about three more weeks before showing signs of recovery. This indicates that the effect of Chinese lockdown policy almost certainly propagated to other ports with high connectivity to Chinese ports. Considering the different propagation times along the global shipping network (i.e., the amount of time necessary for propagation would be longer for cross-regional routes and shorter for intra-regional routes), we separately investigate the propagation effects on high-connectivity ports in Asia and Europe.

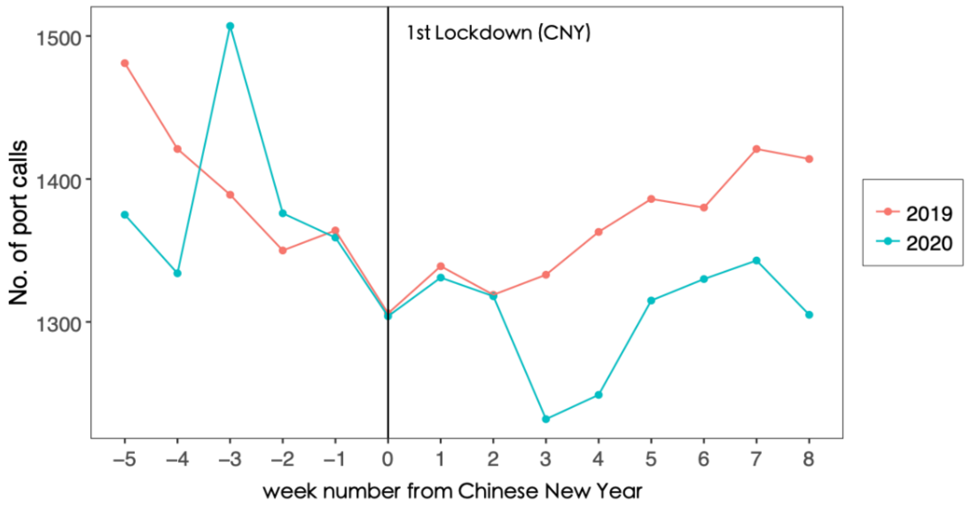


Figure 4-8 Total port calls in high-connectivity ports in 2019 and 2020 around Chinese New Year

Notes: The week number in this figure represents the relative weeks between the actual week and the Chinese New Year week. Week 0 represents the week of Chinese New Year, that is Week 6 in 2019 (starting February 4, 2019) and Week 4 in 2020 (starting January 20, 2020).

4.4.2.1 Empirical Analysis of High-connectivity Asian Ports

The total number of port calls at Asian high-connectivity ports in 2019 and 2020 are plotted in Figure 4-9. As seen from the chart, there exists a significant difference between 2019 and 2020 port calls. In 2019, from two weeks after the Chinese New Year, the port calls gradually increased to the same level as before the New Year. Alternatively, in 2020, the number of port calls at these Asian ports continued to decline, due to the propagation effects of China's lockdown. Therefore, it is reasonable to use two weeks as the shock propagation time from China to other high-connectivity ports in Asia after the lockdown announcement in China. In the subsequent model set up for Asian ports, we use two weeks after the Chinese implementation of lockdown as the cutoff point.

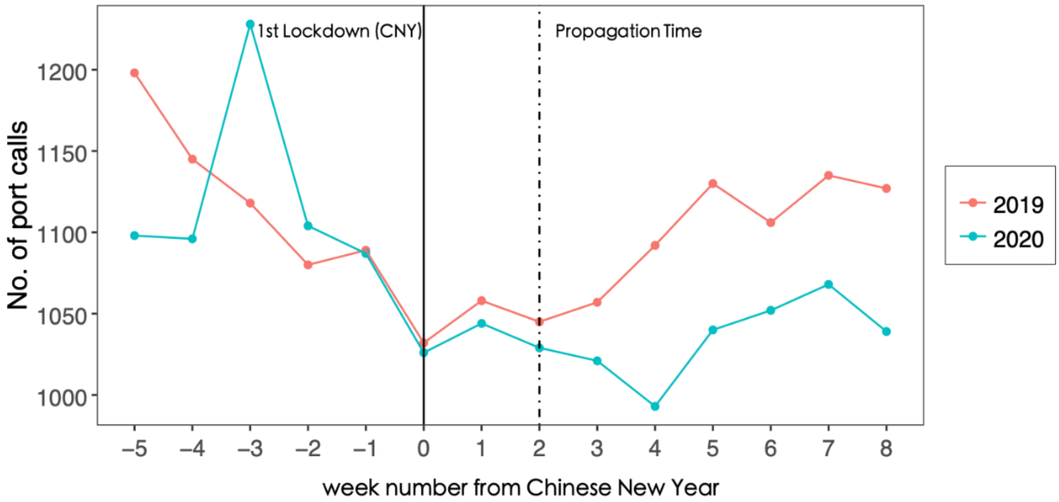


Figure 4-9 Total port calls in high-connectivity ports in Asia in 2019 and 2020 around Chinese New Year

Notes: Refer to the notes for Figure 4-8. The black line in week 2 indicates that Chinese lockdown effects propagated to high-connectivity ports in Asia two weeks after the policy's announcement.

Table 4-6 shows the DID and RDD-DID model estimation results for Asian high-connectivity ports. Different time spans are considered. Specifically, we consider port calls that are four, three, and two weeks before and after the cutoff point so as to examine the impact duration of the shock propagation effect. In the DID models, the coefficient of the models with a four-week span is significant at the 1% level, indicating that the propagation effect of Chinese lockdown policy led to a relatively prolonged decrease in port calls at high-connectivity Asian ports. Using the four-week span, the average number of port calls in high-connectivity Asian ports decreased by 8.23. The coefficients of all RDD-DID models examined and DID models with a shorter span are not significant, suggesting that this effect is neither short-term nor immediate.

Table 4-6 DID and RDD-DID estimation results for high-connectivity Asian ports

	DID model			RDD-DID model		
Time period	week 0 – week 3	week -1 – week 4	week -2 – week 5	week 0 – week 3	week -1 – week 4	week -2 – week 5
$T_i \cdot Year_i$	-3.900	-6.200	-8.225***	5.935	7.673	3.017
	(27.54)	(3.49)	(2.89)	(15.31)	(9.19)	(6.50)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive Effect	No	No	No	Yes	Yes	Yes
N	80	120	160	80	120	160
adj. R^2	0.371	0.985	0.987	0.985	0.986	0.988

Notes: Results are estimated based on Eqs. (4-2) and (4-5) for the DID model and RDD-DID model respectively. The symbols *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The week number in the table represents the relative weeks between the actual week and the week of Chinese New Year. Week 0 represents the Chinese New Year week, that is Week 6 in 2019 and Week 4 in 2020. The policy intervention (cutoff) time is Week 2 (two weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention in 2020; the control group is the same period in 2019.

4.4.2.2 Empirical Analysis of High-connectivity European Ports

We further examine the propagation effects of Chinese lockdown policy on European ports. Figure 4-10 shows the port call data in these ports around the Chinese New Year in both 2019 and 2020. As seen below, these ports experienced a sharp decline in port calls three weeks following the Chinese lockdown, but recovered quickly. At first glance, the impact seems to be rather severe and short-lived. Based on the graph below, as well as the voyage durations between China and Europe, we identify Week 3 after China's implementation of lockdowns as the cutoff point for the subsequent statistical analysis using DID and RDD-DID models.

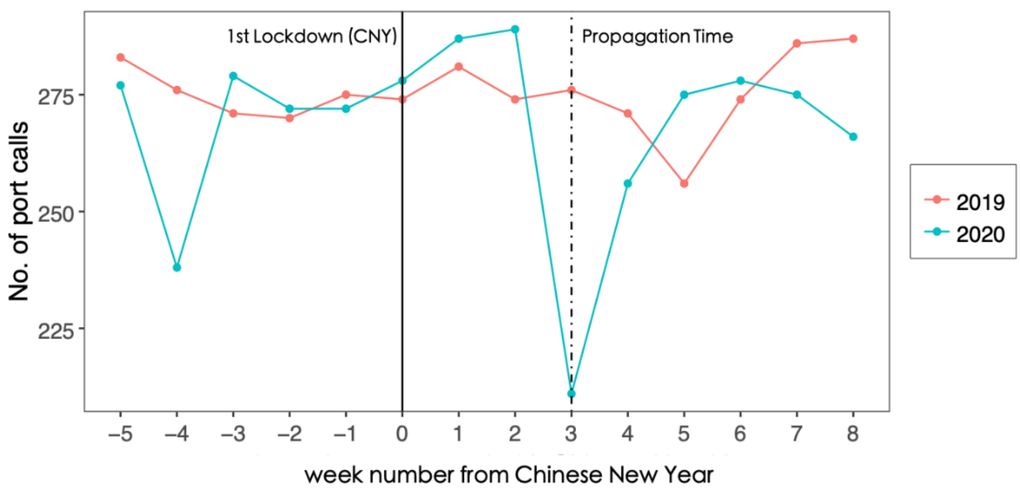


Figure 4-10 Total port calls in high-connectivity ports in Europe in 2019 and 2020 around Chinese New Year

Notes: Refer to the notes in Figure 4-8. The line in Week 3 indicates that the effects of the Chinese lockdown propagated to high-connectivity ports in Europe three weeks later.

The DID and RDD-DID estimation results for high-connectivity European ports (with a cutoff week of three weeks after the announcement of lockdowns in China) are presented in Table 4-7. Models with different time spans are also examined. The coefficients of the RDD-DID models under different bandwidths and DID models with shorter bandwidth are all significant, indicating that at three weeks after the Chinese lockdown, port calls in high-connectivity European ports experienced a sharp and immediate drop. As for the DID model, however, when using a four-week and a three-week span, the coefficient is not significant, suggesting that the drop in port calls recovered quickly and that the propagation effect only lasted for two to three weeks in high-connectivity European ports. The coefficient of the two-week span DID model indicates that the Chinese lockdown policy led to the reduction of port calls by 16.83 on average in high-connectivity European ports.

Table 4-7 DID and RDD-DID estimation results for high-connectivity European ports

	DID model			RDD-DID model		
Time period	week 1 – week 4	week 0 – week 5	week -1 – week 6	week 1 – week 4	week 0 – week 5	week -1 – week 6
$T_i \cdot Year_i$	-16.833***	-9.556*	-6.583	-57.222	-61.383***	-43.497***
	(5.75)	(5.03)	(3.93)	(33.46)	(14.38)	(9.82)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive	No	No	No	Yes	Yes	Yes
N	24	36	48	24	36	48
adj. R^2	0.926	0.916	0.928	0.940	0.946	0.949

Notes: Refer to the notes for Table 4-5. The symbols *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The policy intervention (cutoff) time is Week 3 (three weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention date in 2020; the control group is the same period in 2019.

4.4.3 Empirical Analysis of Low-connectivity Ports

As for low-connectivity ports, after the implementation of lockdowns in China, port calls at these ports did not exhibit any obvious decreasing trend, as evidenced by Figure 4-11.

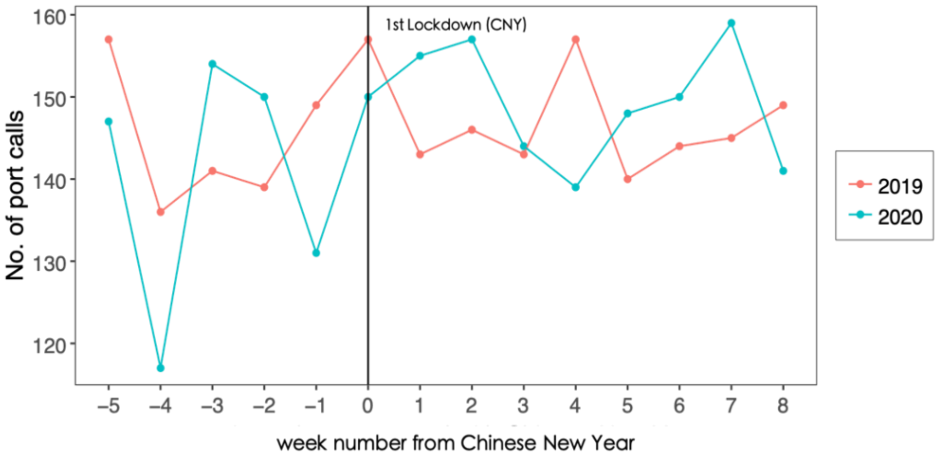


Figure 4-11 Total port calls in low-connectivity ports in 2019 and 2020 around Chinese New Year

Notes: The week number in this figure represents the relative weeks between the actual week and the week of Chinese New Year week. Week 0 represents the Chinese New Year week, that is Week 6 in 2019 and Week 4 in 2020.

In order to empirically test the effect of China's lockdowns on these ports, we run the DID and RDD-DID models on port calls in low-connectivity ports using two weeks after the implementation of Chinese lockdown policy as the cutoff, considering the average voyage duration of container ships. The results are presented in Table 4-8. As seen below, none of the coefficients in the DID and RDD-DID models are significant at the 10% level. Therefore, we conclude that there exists no significant propagation impact on these low-connectivity ports.

As a short summary, we find the coefficient of DID model is significant with four-week span for high-connectivity Asian ports and the results of the three RDD-DID models are not significant for these ports. It means that the Chinese lockdown policy leads to a relatively prolonged reduction in port calls in high-connectivity Asian ports.

Meanwhile, the coefficients of DID models with two-week span and three-week span and RDD-DID models with three-week span and four-week span are all significant for high-connectivity European port. It indicates that port calls in high-connectivity European ports experienced a sharp and relatively prolonged drop. We find that the coefficients of all DID models are not significant for the low-connectivity ports. It means that there exists no significant propagation effect on these low-connectivity ports.

Table 4-8 DID and RDD-DID estimation results for low-connectivity ports

	DID model			RDD-DID model		
Time period	week 0 – week 3	week -1 – week 4	week -2 – week 5	week 0 – week 3	week -1 – week 4	week -2 – week 5
$T_i \cdot Year_i$	1.167	0.778	0.333	11.290	15.016	4.196
	(3.57)	(3.03)	(2.56)	(12.95)	(7.90)	(6.25)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Autoregressive Effect	No	No	No	Yes	Yes	Yes
N	24	36	48	24	36	48
adj. R^2	0.802	0.805	0.799	0.801	0.824	0.796

Notes: Refer to the notes for Table 4-5. The symbols *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. The policy intervention (cutoff) time is Week 2 (two weeks after the Chinese New Year considering the propagation time) in 2019 and 2020. The treatment group for the DID model and RDD-DID model is four, three, and two weeks before and after the policy intervention date in 2020; the control group is the same period in 2019.

4.4.4 Event Study and Parallel Trend Tests for Indirect Lockdown Effects

Similar to Section 4.3.4, we perform a further event study based on Eq. (4-6) on port calls for all three groups of ports to confirm the validity of the proposed models. The corresponding coefficient plots are presented in Figures 4-12, 4-13, 4-14. As shown in the graphs, from four weeks before each model's cutoff point to the cutoff point, the 95% confidence intervals for coefficients all include 0, thus indicating that there is no significant difference between the control group (2019 data) and the treatment group (2020 data) before the indirect effect of Chinese lockdown policy kicks in. Therefore, the application for DID and RDD-DID models using a four-week span can be justified.

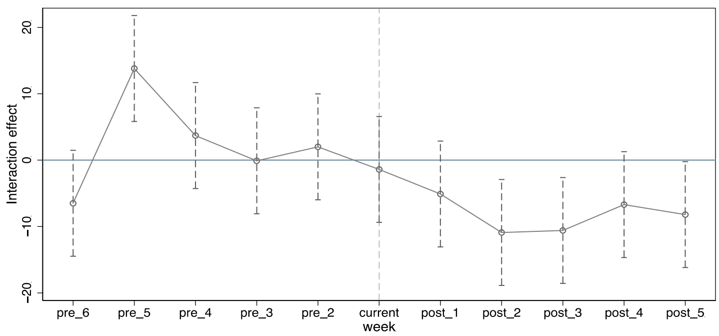


Figure 4-12 Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effect in high-connectivity Asian ports

Notes: Based on Eq. (4-6). Current week refers to the cutoff week, i.e., two weeks after the Chinese lockdown. The last week before the current week (pre_1) is the reference week.

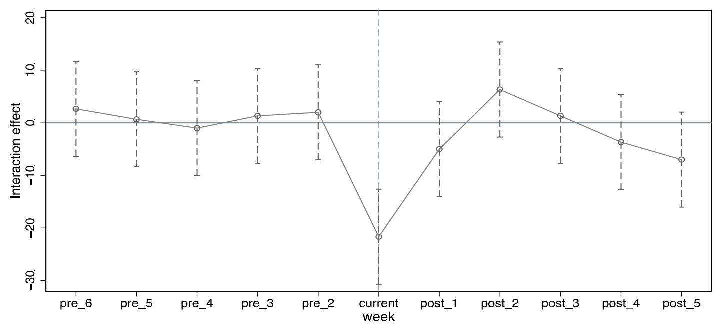


Figure 4-13 Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effect in high-connectivity European ports

Notes: Based on Eq. (4-6). Current week refers to the cutoff week, i.e., three weeks after the Chinese lockdown. The last week before the current week (pre_1) is the reference week.

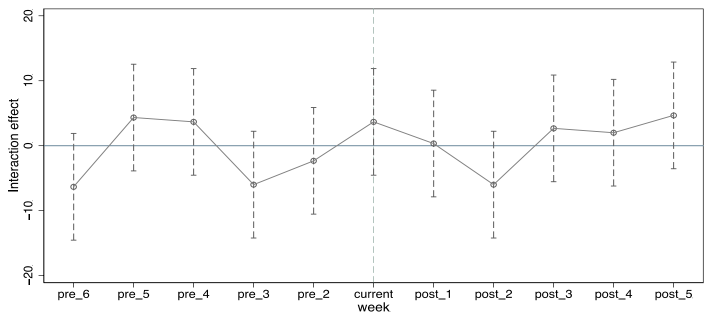


Figure 4-14 Coefficient plots for DID and RDD-DID models analyzing the indirect lockdown effects in low-connectivity ports

Notes: Refer to the notes for Figure 4-12.

We acknowledge the estimation bias may exist without controlling some external effects, such as the international trade. However, we believe the effect is minor as the results of event study demonstrate that the port calls in 2019 and 2020 have the same trends without the lockdown announcement.

4.5 Implications

The results above clearly show that the direct impact of national COVID-19 lockdowns on local port calls varied across regions. The impact on Chinese ports tended, on average, to be strong with no immediate break; the effects on the other ports under investigation were less severe in magnitude, with an immediate break after the lockdown announcement. The reason for the non-existence of an immediate break in the data for Chinese ports is that, after the sudden outbreak of COVID-19 in China in January 2021, it took time for container lines to realize the severity of the COVID-19 pandemic and adjust their capacity accordingly. On the other hand, container lines appear to have been more responsive during the second wave of national lockdowns, given the experience of the first lockdown wave.

The difference in impact magnitude is mainly because the level of stringency of the lockdown policies varied between China and the rest of the world, and, consequently, the nature of disruptions brought about by those policies is different. As Notteboom et al. (2021) pointed out, the response to COVID-19 has been characterized by several sequential phases from a supply chain perspective. The first phase started from mid-January 2020, with hard lockdown measures announced in China (mandatory stay-at-home orders with few exceptions), causing a major supply shock. Most of the workforce and major industrial production facilities were suddenly affected, resulting in a sharp drop in Chinese port throughput due to the combined effects of reduced export volume and limited workforce in ports.

The second phase started in mid-March 2020 as different lockdown policies were implemented globally, leading to dampened global demand for transoceanic shipping due to lower industrial and consumer confidence. Thus, the disruption in the second phase for the countries investigated in this study was mainly considered as the result of a demand shock. On the one hand, the lockdown policies implemented in the Asian and European countries under investigation were often more moderate, compared to those in China. Thus, production of those regions was not as heavily influenced. On the other hand, demand for most consumer products witnessed a drastic decline except for certain essential goods (e.g., food and medicines). Compared to a supply shock, a demand shock generally happens gradually, as it takes time for individual consumer behaviours to become observable in the aggregate. Considering the differences between lockdown policies and the nature of the shock, container lines adopted slightly different capacity adjustment strategies, which was then reflected in changes in the number of port calls. In response to the first wave of lockdowns in China characterized by hard lockdown measures and an induced production shock, container lines reacted (after a slight delay) by significantly reducing the number of vessels calling at Chinese ports. On the other hand, during the second wave of lockdowns characterized by moderate lockdown measures and an induced demand shock, container lines took more prompt yet moderate port call reduction measures due to the reduction in demand. Therefore, we observe a significant drop in port calls with no immediate break at Chinese ports during the first wave of lockdowns in

China, while the decrease in port calls at ports affected by the second wave of lockdown is less severe in magnitude, with an immediate break after the lockdown announcement.

The second major implication is that through the interconnected global shipping network, a local shock in one country can propagate to other regions and becomes a global shock. The results presented here show that, in February 2020, port calls at those ports with high levels of connectivity to Chinese ports were significantly affected by Chinese lockdown policies, with a time lag of two to three weeks, depending on the voyage duration of a container ship. The indirect shock of China's lockdown on close neighbours varied slightly from that on highly connected ports in distant regions. There was no significant immediate break in the number of port calls to Asian countries with high connectivity to Chinese ports, while a significant break did exist in European ports with high connectivity to Chinese ports, as evidenced by the RDD-DID model results.

These effects can largely be attributed to the capacity adjustment strategies implemented by container lines, which led to shock propagations throughout the global network. Container lines nowadays are better at capacity management, compared to decades past. In order to cope with declining demand for seaborne transportation amid the COVID-19 outbreak, container lines implemented blank sailings, a term used to describe the situation in which a vessel skips a port call along its route or an entire journey is cancelled. By doing so, container lines could reduce the fleet supply available in the market, thus maintaining a reasonable level of freight rate and vessel utilization. After the lockdown announcement in China at the end of January 2020, container lines reacted by implementing the first wave of blank sailings in February 2020. Specifically, around 36% of Asia-to-Europe and 28% of transpacific shipping capacity was withdrawn during that period. Considering the sailing time between China and Europe, these effects were only realized in European ports by the end of February 2020. From April to May 2020, around 11% of the world's container fleets were idle (Notteboom et al., 2021). The impact of blank sailing was more visible in ports located in the major long-haul trading routes (e.g., from Asia to Europe). The empirical results also confirm that blank sailings due to Chinese lockdown policies had a significant and immediate effect on European ports at the end of February 2020. The immediate impact of blank sailings on Asian ports, however, were not significant due to the substitution phenomenon between Chinese ports and adjacent Asian ports. When port operations were significantly disrupted due to a limited workforce, certain container volumes originally destinated for China were diverted to adjacent ports like Pusan Port which, in a way, compensated for the port call losses due to blank sailings at these adjacent ports. Nonetheless, on average, port calls declined in Asian ports with high connectivity to Chinese ports in February 2020.

The results carry significant implications for policy makers, port operators, and container lines. During a pandemic outbreak, any sudden changes in demand and supply can be quickly reflected in shipping and port activities. Thus, weekly port call statistics can serve as a timely and high-frequency economic indicator that reflects a country's trade flow changes in real time. The impact of various lockdown measures demonstrated here on changes in both local and global port call numbers can provide an additional source of information for policy makers when crafting lockdown policies. Policy makers can make more informed decisions, weighing the different levels of supply and demand shocks brought by lockdown policies with different levels of stringency and their associated immediate and longer-term impacts on trade volume changes. For port operators, understanding the potential impact of local lockdowns on local port call changes help them adjust port operations in a more timely manner. In addition, the lockdown policies in other regions may also affect the port calls of local ports due to the propagation effect, thus port operators need to prepare in advance for the possible port call changes, such as increasing connectivity to regions without shock. From the perspective of container lines, the results presented here can help them understand the effects of blank sailing on the broader global liner network. Furthermore, the findings on the impact of national lockdown policies on local port call numbers provide decision support for container lines to better manage their capacity and adjust their network service arrangement, by considering various lockdown policies in different ports across the globe. To better manage capacity, container lines can adopt parallel service to maintain connectivity through the alliance network and allocate idle vessels to longer routes to maintain higher ship utilization rates.

4.6 Remarks

The recent COVID-19 pandemic response highlights the prolonged impact that a similar pandemic outbreak could have on ports and shipping. This study quantifies both the immediate and longer-term impact of COVID-19 national lockdown policies on port calls in major international container ports using DID and RDD-DID models. The results show that lockdown policies with different levels of stringency can lead to different types of trade shocks and, consequently, different patterns in changes in the numbers of port calls. We further document the existence of significant shock propagation effects. Specifically, we find that the initial lockdown in China induced container lines to take up capacity adjustment strategies so as to cope with a decline in seaborne transport demand. This response in turn created propagation effects from Chinese ports through the global container shipping network to harbors in the rest of the world with a high degree of connectivity to Chinese ports.

The existing studies compare port call data for the same period in 2019 and 2020 to quantify overall changes in port calls caused by COVID-19. Alternatively, we account for the impact from Chinese New Year in our model, so our results eliminate the seasonal changes in port calls around Chinese New Year and can capture the pure changes in port calls in short term due to pandemic lockdowns. Unlike the existing studies that gauge the impact of COVID-19 on certain regions, we also measure the propagation effect of container shipping from China to

Europe and the United States referring to their connectivity to Chinese ports.

This research contributes to the literature on the impact of pandemic outbreaks on the transportation sector. First, an analytical framework is proposed to evaluate the impact of national lockdown policies on both local port calls and global port calls through propagation effects. The framework is based on DID and RDD-DID models that can evaluate both the immediate break and the longer-term impact of a policy. Results can be used by policy makers to assess the potential impact of different levels of lockdown policies during pandemic outbreaks on the maritime industry and trade flows in the longer term and on a broader scale. Maritime players can also use the findings to better manage their capacity and cope with changing demand for seaborne transportation. Second, our study also constructs weekly, high-frequency port call data for global ports, which provides a timely picture of changes in shipping activity, as well as trade flow changes. The exact shock propagation mechanism can be further investigated in future research.

Chapter 5 Effect of Online Quote Platform on Container Orders

5.1 Introduction

Online quote platforms, which have become prevalent in many industries, including aviation, the hotel industry, and perhaps most notably, in car insurance, have also gained traction in the container shipping industry. Unlike other cargo transportation modes such as air and rail, which have a relatively small transport capacity, container shipping lines generally require both a higher cargo volume and a greater level of ship utilization (due to the ultra-large size of container ships), so as to achieve the breakeven point. Traditionally, in order to ensure the high utilisation of each ship, the majority of slots are allocated to larger shippers with an existing service contract, or Minimum Quantity Commitment (MQC), which is a minimum space protection commitment between the shipper and the shipping line. Shipping lines also rely on freight forwarders and non-vessel-operating common carriers (NVOCCs), which book space on ships in large quantities at low rates and subsequently sell space to shippers in smaller amounts, to consolidate cargoes from individual, local shippers. Only a minority of slots are put on the open market for scattered shippers, and the sale of this remainder is known as a spot market.

For smaller companies seeking to book one of these spaces on the spot market, the traditional booking process is labour-intensive and inefficient. Shippers usually have to request space via email or telephone, and multiple conversations are often necessary in order to confirm space and negotiate the freight rate and other charges. The managing director of the digital channel for Hapag-Lloyd (one of the top five shipping lines), said that salespeople send 300 quotes per day to small shippers for every five bookings received (Johnson, 2018). This results in high administrative costs for relatively low returns. Small and medium-sized shippers frequently join shipper associations or gravitate toward ordering space from freight forwarders or NVOCCs because they have less bargaining power in the market and are unable to secure space directly from the shipping lines. Freight forwarders who have MQCs with a shipping line act as an intermediary in order to provide various logistics services to these small and diffuse shippers.

Online quote platforms offer the potential for changing this state of affairs, as these mediums offer a range of new and complimentary services, including faster ocean transits, booking guarantees, space protection, fixed prices, and the further integration of land-side logistics into the supply chain. These platforms appear to particularly benefit those small and medium-sized consigners that do not have a close relationship with a shipping line, and whose cargo priority always comes last. Quicargo (2021) conducted a survey in 2020 and found that compared with the traditional quotation process, the real-time pricing provided by the online quote platform led to a cost-saving of up to 31% for small shippers on European routes. At the same time, although shipping lines may wish to digitise their businesses so as to differentiate their services and reshape the boundaries of the industry, most hesitate to abandon existing commercial practices and adopt online quote platforms. Among the shipping lines, only the top ones, such as Maersk, MSC, CMA CGM, Hapag-Lloyd, Zim, Evergreen, COSCO, OOCL, ONE etc, have adopted online quote platforms, others remain on the fence. On the one hand, shipping companies are reluctant to expose their freight rates to the public for fear of their business being commoditised. By developing a proprietary online quote platform, one firm’s transparency in setting freight rates could pose a threat to liner companies seeking to protect their rate’s opacity and their bargaining position. In the same vein, the offline booking process also protects demand secrets from leaking to competitors. Shipping companies also do not want to jeopardize their relationships with big volume shippers by having to commoditize their prices.

Despite the resistance of some of the major shipping companies, however, online quote platforms are merely an extension of a process already underway. As digitally savvy freight forwarders have entered the market, shipping lines can no longer protect freight rate information. As freight forwarders have become adept at leveraging application programming interfaces (API) to aggregate and publish freight rates online already, the customary opacity surrounding rates cannot be preserved much longer in the market. Established freight forwarders, such as Kuehne + Nagel, have already launched their own instant quote and booking platforms to support their NVOCC subsidiaries. Some third-party start-ups have also developed electronic booking platforms for shippers to find and compare freight rates by aggregating quotes from major shipping lines and other NVOCCs, such as ASIASHEX. In response, shipping lines are being more or less compelled to adopt online quote platforms in order to avoid being outflanked in the digital realm. Hapag-Lloyd was one of the first shipping lines to offer shippers an instant quote service in August 2018, followed by COSCO, CMA CGM, and Maersk. As other shipping lines have also released online quote platforms in the past three years, it is worth exploring the impact of this development and how consigners' purchasing behaviour has changed in response.

Many studies have been conducted to explore the means and the factors that affect the adoption of digital products and technologies in maritime transportation. Few, however, investigate the post-event effects, that is, how online quote platforms have changed shippers' booking behaviour. Fewer still have done so on the basis of new methods such as regression discontinuity design (RDD) and industrial dataset (instead of surveys or interviews). In order to fill this research gap, we will empirically evaluate the impact of online quote platforms on consigners' booking behaviour, with the latest released data from shipping lines. Specifically, this research investigates: (a) whether an online quote platform affects the volume of containers ordered by different shippers, and (b) how shippers react after the release of an online quote platform by a shipping line. We adopt a quasi-experimental method by using monthly ordering data from a top shipping line that was collected between 2016 and 2019. The implementation of the online booking platform by this shipping line is treated as the intervention.

The structure of this study is presented as follows: the specifications of the RDD are introduced in Section 5.2. The data and their properties are given in Section 5.3. Section 5.4 discusses the findings and implications. Finally, Section 5.5 concludes this study.

5.2 Methodology

A growing number of studies have adopted RDD as a means to evaluate the causal effects of policy interventions (Lee, 2008). RDD distinguishes between the impact of the implemented policy and other continuous influencing factors, both those observed and unobserved (Zhang et al., 2020). Lee and Lemieux (2010) summarize two reasons for its popularity: (1) The assumptions required for RDD are relatively milder when compared to other non-experimental approaches; (2) The causal inferences from RDD are potentially more reliable than other methods. RDD, with time as the running variable, can reduce bias through incorporating control variables, assuming that the unobserved time-varying factors correlated with the running variable (time) may have a great impact on the regression results. There are two types of strategies for controlling the unobserved time-varying factors, namely, global polynomial regression and local linear regression (Burger et al., 2014; Hausman and Rapson, 2018).

Global polynomial regression uses all of the observations in the dataset. The regression includes different functional forms of the running variable (time), such as linear, quadratic, and cubic, so as to minimize bias. Local linear regression, meanwhile, approaches the estimation of the treatment effect as a local randomization, and restricts the analysis to observations located near the cut-point. The functional form of the running variable (time) is linear, according to this method. Global polynomial regression and local linear regression thus differ in both their datasets and regression models. Specifically, the purpose of global polynomial regression is to find the optimal function to fit the full set of data, while local linear regression tries to find the optimal dataset that will fit a linear regression (Jacob et al., 2012). Since the global polynomial regression utilises all the data points within a given set, it generally has greater precision than local linear regression.

As for our problem, it is difficult to distinguish whether the observed change in the assigned container volume is due to the implementation of the online quota platform or to change over time, considering the broad timespan of data. Thus, adopting global polynomial regression may actually lead to a larger bias. On the other hand, although local linear regression may have a smaller bias through a progressive narrowing of the data to a relatively small bandwidth (Imbens and Lemieux, 2008), the estimation accuracy may be affected due to the inclusion of far fewer observations. Therefore, we apply both strategies for more reliable results. In this study, we first adopt panel data regression as a benchmark model. Then, we conduct global polynomial and local linear regressions of RDD in order to investigate the long-term and short-term effects of the online quote platform's launch within the selected window.

We follow the most adopted form of the classic RDD (e.g., Shin, 2021; Merkel and Lindgren, 2022) and incorporate specific variables within the shipping context when formulate the basic panel data specification of RDD. It is presented as follows:

$$TEU_{it} = \alpha + \beta \times Online_t + \gamma_1 TEU_{i(t-1)} + \gamma_2 OCarrier_{it} + \gamma_3 Carrier_t + S_i + Y_t + M_t + \epsilon_{it} \qquad (5\text{-}1)$$

where TEU_{it} …… $TEU_{i(t-1)}$ is the one-order lag of TEU_{it}. $OCarrier_{it}$ is the quantity of container volume that shipper i booked from other shipping lines in the period t. This variable is used to control for shipper i's demand on other carriers in period t, thus helps eliminate the effect from different demand changes across shippers. $Carrier_t$ is the assigned container volume of all shippers on the shipping line in time t. This variable controls for all shippers' demand on the carrier we studied in time t, to remove the effect from market demand change on the carrier. The shipper fixed effects (S_i), the year fixed effects (Y_t), and the month fixed effects (M_t) are also included, while ϵ_{it} is an error term.

Global polynomial regression discontinuity design uses all the observations in our sample to estimate the change in container volume. A flexible, global, n^{th} order polynomial time trend $f(t)$ is added to Eq (5-1), as shown below:

$$TEU_{it} = \alpha + \beta \times Online_t + f(t) + \delta X_t + \epsilon_{it} \tag{5-2}$$

where the additional control variables in Eq (5-1) are collapsed into X_t. The function $f(t)$ controls the unobserved factors that evolve with time (that is, are time-varying) and are uncorrelated to the online platform's implementation. As long as $f(t)$ is continuous at the release month, β measures the magnitude of the discontinuity in container volume at the release date. Different functional forms of the time trend (e.g., linear, quadratic, cubic, quartic, and quintic) are used to minimise any bias in the regression model.

Local linear regression of the RDD method estimates the treatment effect as a local randomization, and limits the analysis to observations near the cut-point. We thus narrow the observed time period pre- and post-launch date of the online platform so as to disentangle the effect of the online quote platform from the effect of other, unobserved time-varying factors that influence shippers' container volumes. The local, linear RDD model is presented as follows:

$$TEU_{it} = \alpha + \beta \times Online_t + f(t) + \delta X_t + \epsilon_{it} \tag{5-3}$$

A linear time trend $f(t)$ is here added to Eq (5-1). We vary the bandwidth between 15 months (68% of our data), 12 months (56% of our data), 9 months (42% of our data), and 6 months (29% of our data), with separate linear trends $f(t)$ on either side of the implementation month.

In this study, we first estimate the overall impact of the online quote platform on all shippers, and then we use global polynomial RDD and local linear RDD models to evaluate the impact on various shippers according to their size. We check the robustness of our results in the following two ways: First, we use the linear, quadratic, cubic, quartic, and quintic time trends in the global polynomial regression; second, we apply local linear RDD with 15-month, 12-month, 9-month, and 6-month bandwidths.

5.3 Data

We obtain the container order data of US import trade from a shipping company, which provides each bill of lading (B/L) from 2016 to 2019, including carrier name, carrier code, port of departure, port of arrival, shipper, consignee, container size, type of cargo, TEUs, etc., except for the rate-related information. Corresponding vessel details are also included in the database, including vessel number, and vessel name.

In international container shipping, the top 10 shipping line groups accounted for 84.7% of the world's capacity in 2020 (Alphaliner, 2021). These major shipping lines may be generally more willing to develop online quote platforms, considering that the amount saved from manual booking covers the costs of the online booking platform's development and cyber security. An overview of the U.S. import shipment data is provided in Table 5-1. Hapag-Lloyd, which we use for this study, ranked fifth among all shipping lines, with a total TEU of approximately 12 million.

Table 5-1 U.S. import data of shipping lines from 2016 to 2019

	Carrier	Carrier Code	Total TEU	Number of B/L
1	MSC	MSCU	20,285,952	6,690,632
2	ONE	ONEY	19,912,706	8,494,418
3	Maersk	MAEU	14,783,558	5,389,428
4	Ever Green	EGLV	13,415,909	5,438,550
5	Hapag-Lloyd	HLCU	12,385,154	5,563,816
6	CMA CMG	CMDU	12,122,895	4,525,406
7	COSCO	COSU	12,067,226	3,697,658
8	APL	APLU	8,807,350	3,623,232
9	OOCL	OOLU	8,701,926	2,976,170
10	Yang Ming	YMLU	6,740,738	2,539,492
11	Others	Others	28,272,426	10,882,212

A couple of shipping lines have released proprietary online quote platforms since 2018. Among them, Hapag-Lloyd was the first to release Quick Quotes in August 2018. We selected Hapag-Lloyd for this study because, among all shipping lines, only it provides sufficient observations for analysis. The online quote platform Quick Quotes achieved great success after its launch. Figure 5-1 shows that, after the release of Quick Quotes, the proportion of shippers booked with Hapag-Lloyd to the total number of shippers in the market increased from 9.58% to 11.42%. The proportion of container volume booked from Hapag-Lloyd to the total number of containers on the market also increased from 8.16% to 9.14%. Hapag-Lloyd's annual report from 2020 indicates that, when Quick Quotes was released in 2018, the TEU booked through Quick Quotes accounted for 5.2% of the company's total assigned containers. This proportion further increased to 7.9% in 2019, and 11.1% in 2020, accounting for 1.3 million of TEUs (Hapag Lloyd, 2020).

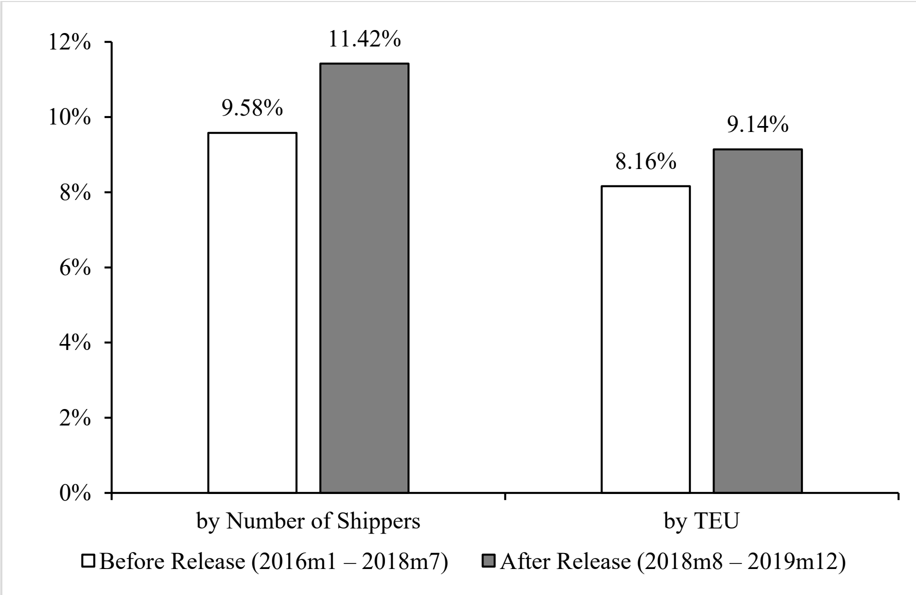


Figure 5-1 Market share of Hapag-Lloyd before and after online quote platform release

In order to conduct empirical analysis, we clean the raw data on shipments via the following process: First, we delete the shipper's names and codes displayed as "N/A" and "1," as the shippers do not wish their data to be released. Next, we only use the observations of containerised dry shipment, excluding the data on reefer, tank, and hazardous materials shipments. These awkward cargoes require more document processing, and online quote platforms generally do not provide services to these special containers as of yet. Last, we aggregate the monthly data by shippers. In total, 276,618 observations remain after this cleaning of the database. The total number of shippers is 57,755. Figure 5-2 shows the schematic illustration of data cleaning.

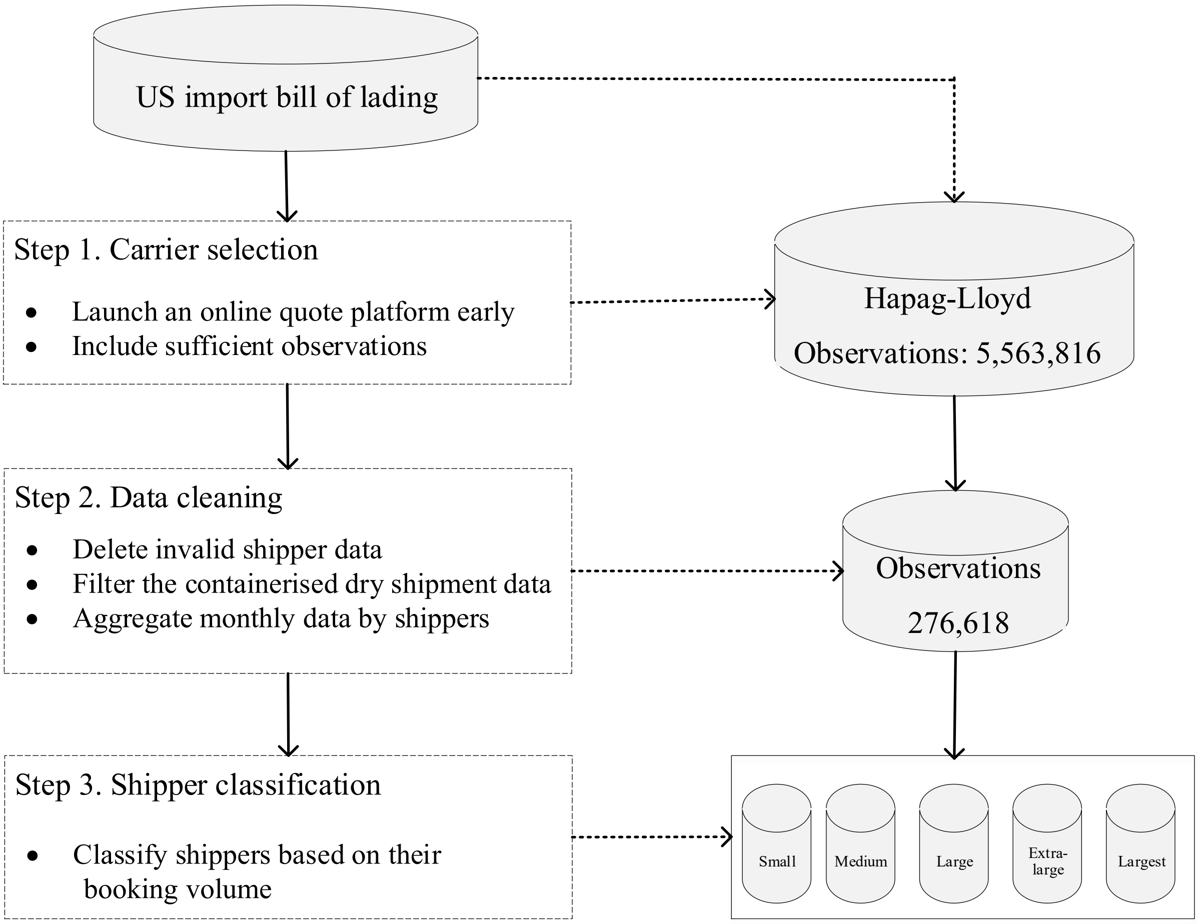


Figure 5-2 Schematic illustration of data cleaning

The shippers of Hapag-Lloyd are both numerous and scattered. Table 5-2 shows the distribution of Hapag-Lloyd consigner in terms of assignment size from January 2016 to December 2019, after cleaning the dataset. Frequency in Table 5-2 refers to the number of times shippers ordered containers from Hapag-Lloyd. If the frequency is equal to 1, it means the shipper has booked only once within the studied period; thus, out of 57,755 shippers, approximately 52.3% (30,192) booked only once within 48 months. In contrast, only 281 shippers ordered 48 times, meaning that they assigned a container to Hapag-Lloyd every month. Notably, 96% of the shippers included in our dataset booked less than 24 times.

Table 5-2 Hapag-Lloyd's shipper distribution

Frequency	Observations	Unique shippers	Frequency	Observations	Unique shippers
1	30,192	30,192	25	3,800	152
2	14,046	7,023	26	4,186	161
3	11,349	3,783	27	3,591	133
4	10,544	2,636	28	3,724	133
5	9,330	1,866	29	3,741	129
6	9,222	1,537	30	3,660	122
7	8,512	1,216	31	3,627	117
8	7,808	976	32	2,816	88
9	7,083	787	33	3,729	113
10	6,640	664	34	2,720	80
11	6,699	609	35	3,640	104
12	6,300	525	36	2,628	73
13	5,694	438	37	2,923	79
14	5,418	387	38	2,280	60
15	5,730	382	39	2,886	74
16	5,648	353	40	3,160	79
17	5,117	301	41	2,583	63
18	5,112	284	42	2,562	61
19	5,282	278	43	3,182	74
20	5,080	254	44	2,684	61
21	4,389	209	45	3,465	77
22	4,818	219	46	2,944	64
23	4,600	200	47	3,666	78
24	4,320	180	48	13,488	281
			Total	276,618	57,755

Furthermore, we note that Hapag-Lloyd shippers are generally small in scale. Table 5-2 illustrates the Hapag-Lloyd's monthly TEU composition of assignment sizes from January 2016 to December 2019. Among the 276,618 observations, approximately 45% of bookings are for less than 5 TEUs, while 17% are bookings of 5-10 TEUs, about 30% are bookings of 10 to 100 TEUs, 5% are bookings of 100 to 1000 TEUs, and less than 1% are bookings of more than 1,000 TEUs. Table 5-3 gives the descriptive statistics of the variables.

Table 5-3 Descriptive statistics of the variables

Variable	Observations	Mean	Std. Dev.	Min	Max
TEU_{it}	276,618	30.16	97.11	1	3,920
$Online_t$	276,618	0.389	0.488	0	1
$TEU_{i(t-1)}$	276,618	47.43	124.7	1	3,844
$Carrier_t$	276,618	261,590	38,469	191,841	321,955
$OCarrier_{it}$	276,618	171.7	918.6	1	48,035

By interviewing Hapag-Lloyd senior managers, we divided the 57,755 shippers into five groups based on their average monthly booking size, that is, small shippers, medium shippers, large shippers, extra-large shippers, and largest shippers. Table 5-4 shows the five shipper groups and their corresponding average monthly booking volume range. It is noted that Hapag-Lloyd shippers are generally small in scale. Approximately 65% of shippers have an average monthly booking volume of less than 5 TEUs, i.e. small shippers, while 17% are from medium shippers (5-10 TEUs).

Table 5-4 Shipper size distribution

Shipper group	Average monthly booking volume (TEU)	Number of shippers (Proportion)	Number of observations
Small shippers	(0,5]	37,647 (65.18%)	85,264
Medium shippers	(5-10]	9,846 (17.05%)	61,425
Large shippers	(10-20]	5,483 (9.49%)	50,499
Extra-large shippers	(20-50]	3,240 (5.61%)	45,420
Largest shippers	50+	1,539 (2.66%)	34,010

5.4 Result Analysis and Discussion

In this section, we first conduct a basic panel data regression and global polynomial regression of RDD in order to gauge the effect of the online quote platform on monthly container volume allocated by different shippers. Next, we adopt the global polynomial regression model to estimate the effect of the online quote platform on different shipper groups. Finally, we apply local linear regression, which can reduce bias by narrowing the bandwidth from 15 months to 6 months for each of the five shipper groups.

5.4.1 Result Analysis

Figure 5-3 plots the monthly number of assigned containers for all shippers from January 2016 to December 2019, including the date of the online quote platform's implementation. The dots in Figure 5-3 represent the total number of assigned containers per month, and the lines show the polynomial fit of order 2. The vertical lines in the figure indicate the launch of the online quote platform. Notably, there is a sharp decrease in volume that can be observed around the initial month of the online quote platform's release.

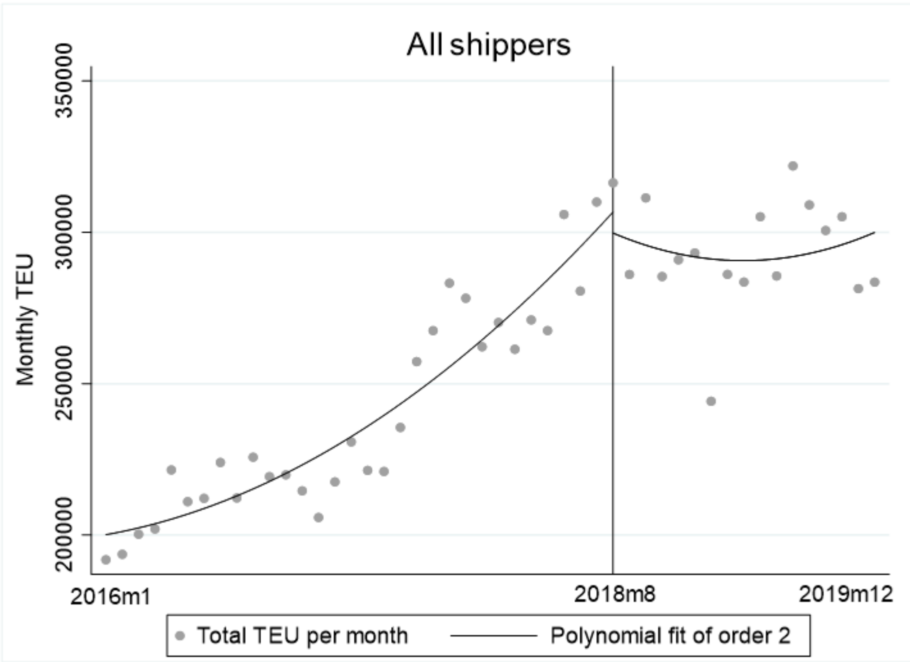


Figure 5-3 Quadratic time trend of container volume before and after the online quote platform's implementation

Table 5-5 presents the results of the basic panel data (monthly) regression with the different polynomial time trends. Shipper fixed effect, year fixed effect, and month fixed effect are controlled in these regressions and hereafter. On average, we find that a shipper reduces its order of containers by about 2.86 TEUs with a linear time trend, and by about 2.99 TEUs with a quadratic time trend (both are significant at the 1% significance level), after the online platform is put into use. The coefficients of time trends larger than the cubic are not significant.

Next, we investigate the effect of the online quote platform on the different groups of consigners.

Table 5-5 Estimates of the online quote platform effect on the monthly volume of containers ordered

Time trend	None	Linear	Quadratic	Cubic	Quartic	Quintic
Online	-2.855***	-2.855***	-2.985***	-2.088*	-0.208	0.363
	(0.83)	(0.83)	(0.84)	(1.14)	(1.44)	(1.47)
OCarrier	0.040***	0.040***	0.040***	0.040***	0.040***	0.040***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TEU(t-1)	0.547***	0.547***	0.547***	0.547***	0.547***	0.547***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Carrier	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-58.540	-63.273	-66.008	-70.307	-69.933	-70.415
	(51.35)	(51.44)	(51.49)	(51.62)	(51.62)	(51.62)
Observations	116,694	116,694	116,694	116,694	116,694	116,694
R^2	0.537	0.537	0.537	0.537	0.537	0.537

Note: Standard errors are in parentheses. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 5-6 displays the regression results for different shipper groups (on their monthly container volume). For a large consigner, at the 10% significance level, we find only a tiny increase of 0.61 TEUs in their assigned container volume. The assigned container volume of the largest shippers decreases by 7.39 TEUs, significant at the 1% significance level. In summary, the overall decrease in container volume shown in Table 5-5 mainly results from a drop in orders from the largest shippers.

Table 5-6 The effect of the online quote platform on different shipper groups: global linear regression

	Small	Medium	Large	Extra-large	Largest
Online	0.133	0.030	0.610*	-0.580	-7.394***
	(0.09)	(0.16)	(0.32)	(0.67)	(2.86)
OCarrier	0.019***	0.014***	0.024***	0.040***	0.040***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TEU(t-1)	0.013	0.113***	0.224***	0.375***	0.651***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Carrier	0.000***	0.000	0.000**	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.803**	-0.642	-4.879	-24.131	-268.663
	(0.80)	(3.70)	(10.22)	(16.88)	(282.13)
N	19,801	32,755	34,685	36,173	30,627
R^2	0.177	0.265	0.331	0.388	0.444

Note: Standard errors are in parentheses. The symbols *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 5-7 presents the RDD estimates from the global polynomial regression for different shipper groups. After controlling for the fixed effects of the shipper, the year, and the month, the results indicate that a medium shipper also shows a slight reduction of 0.46 TEUs in container volume assigned to Hapag-Lloyd with a cubic time trend, at the 10% significance level. For an extra-large shipper, the monthly average number of containers assigned declines significantly, by approximately 1.34 TEUs at the 5% significance level with a linear time trend, and by about 1.61 TEUs at the 10% significance level with a quadratic time trend. A consigner from the largest shipper group has an average decrease of 8.58 TEUs and 8.84 TEUs with linear and quadratic time trends, respectively, at the 1% significance level. For the small and large groups, we find no significant change in their monthly assigned container volume with different polynomial time trends. In short, the global polynomial regression models indicate that the medium, extra-large, and largest shippers decrease their number of containers allocated to Hapag-Lloyd after the introduction of an online booking platform.

Table 5-7 Estimates of the effect of HLCU online platform on the monthly volume of containers ordered by shippers

Shippers	Variable	Time Trend				
		Linear	Quadratic	Cubic	Quartic	Quintic
Small	online	-0.009	-0.057	-0.160	-0.072	-0.094
		(0.14)	(0.14)	(0.19)	(0.23)	(0.23)
	N	9,273	9,273	9,273	9,273	9,273
	R^2	0.025	0.026	0.026	0.027	0.027
Medium	online	-0.116	-0.229	-0.463*	0.059	-0.099
		(0.20)	(0.20)	(0.27)	(0.33)	(0.34)
	N	21,427	21,427	21,427	21,427	21,427
	R^2	0.038	0.038	0.038	0.039	0.039
Large	online	0.579	0.467	0.199	0.532	0.358
		(0.36)	(0.37)	(0.49)	(0.62)	(0.63)
	N	26,840	26,840	26,840	26,840	26,840
	R^2	0.081	0.082	0.082	0.082	0.082
Extra-large	online	-1.341*	-1.605**	-1.209	0.259	0.685
		(0.72)	(0.72)	(0.98)	(1.25)	(1.28)
	N	30,841	30,841	30,841	30,841	30,841
	R^2	0.226	0.227	0.227	0.227	0.227
Largest	online	-8.578***	-8.835***	-5.326	-0.771	1.012
		(2.97)	(2.99)	(4.13)	(5.32)	(5.43)
	N	28,313	28,313	28,313	28,313	28,313
	R^2	0.556	0.556	0.556	0.556	0.556

Note: Standard errors are in parentheses. The symbols *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Finally, Table 5-8 shows the estimates with bandwidths of 15 months, 12 months, 9 months, and 6 months, respectively, with a linear time trend. The assignment of a small shipper increases by 3.97 TEUs within a 9-month bandwidth at the 10% significance level. A medium shipper decreases its volume of containers booked from Hapag-Lloyd by 8.05 TEUs within a 6-month bandwidth at the 10% significance level. An extra-large shipper witnesses a sharp drop of about 28.66 TEUs within a 9-month bandwidth at the 5% significance level. Both the extra-large and the largest shippers allocate less container volume to Hapag-Lloyd within a 15-month bandwidth, but reduce their orders by different amounts. Specifically, an extra-large shipper reduces its volume of containers by about 1.84 TEUs, while the largest shipper reduces its order by 7.63 TEUs, both at the 5% significance level. In summary, small shippers see an increase in their assignments to Hapag-Lloyd within the 9-month interval. Medium shippers reduce the volume of containers assigned to Hapag-Lloyd in the short-term. The extra-large and largest shippers, however, decrease the volume of containers purchased from Hapag-Lloyd over a relatively long period.

Table 5-8 Estimates of the effect of the HLCU online platform on the monthly volume of containers ordered by shippers: local linear regression

Shippers		6 months	9 months	12 months	15 months
Small	online	1.688	3.973*	-0.219	-0.186
		(2.92)	(2.10)	(0.26)	(0.17)
	N	2,716	3,987	5,336	6,609
	R^2	0.186	0.057	0.040	0.026
Medium	online	-8.048*	-1.410	-0.070	-0.264
		(4.38)	(3.15)	(0.38)	(0.23)
	N	6,555	9,459	12,282	15,032
	R^2	0.183	0.066	0.056	0.049
Large	online	-10.468	-5.776	1.208*	0.673
		(7.75)	(5.78)	(0.69)	(0.41)
	N	8,104	11,798	15,364	18,876
	R^2	0.048	0.050	0.066	0.050
Extra-large	online	-22.690	-28.661**	-1.427	-1.835**
		(15.38)	(11.55)	(1.35)	(0.81)
	N	9,126	13,452	17,632	21,715
	R^2	0.118	0.154	0.170	0.179
Largest	online	-106.778	-72.339	8.281	-7.683**
		(68.82)	(50.28)	(5.82)	(3.42)
	N	8,676	12,643	16,480	20,175
	R^2	0.188	0.279	0.346	0.405

Note: Standard errors are in parentheses. The symbols *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Overall, this empirical study finds an increase in container volume booked by small shippers as a result of the release of the online quote platform in the short term. The medium, extra-large, and largest shippers, however, decrease container volume that they order from Hapag-Lloyd for a relatively longer period.

5.4.2 Discussion

Perhaps the most interesting discovery from our regressions is that the overall container volume assigned to the shipping line decreases after the online quote platform is launched. This decline in container volume ordered by the largest consigners cannot be offset by the increasing container volume ordered by the small shippers, either. Notably, however, the decrease in assignments does not indicate a corresponding reduction in revenue, as the large shipper always enjoy discounted prices due to their greater bargaining leverage vis-à-vis the shipping line.

For small shippers, the increase in booking volume can be attributed to the fact that they are more flexible and thus more prepared to switch to online quote platforms already provided by freight forwarders. In addition, the special services provided by online quote platforms, such as real-time pricing and space protection, are more attractive to small shippers that have less bargaining power relative to larger shippers like freight forwarders and NVOCCs. Large shippers including freight forwarders and NVOCCs book space directly from shipping lines via bulk discounts, and then provide services to small shippers at a mark-up in order to earn a profit. Regardless of whether the platform is provided by an intermediary (such as a freight forwarder) or directly through the shipping line, online booking provides small consigners with more options, and is thus an attractive alternative to the current methods of booking space.

For larger shippers, the decision of some small shippers to split from them and buy space independently may lead to the decline of the larger shipper's assignment. In addition, the no-show penalties charged through an online quote platform can also cause decreases in their assignments. Indeed, larger shippers often face supply chain delays due to manufacturing, trucking, and equipment issues. In peak season, as a strategy to secure shipment for their cargo, larger shippers deliberately reserve space from multiple shipping lines, which eventually leads to a large number of cancellations. Due to their greater bargaining power, shipping lines will generally not charge them for a no-show. The larger shippers prevail at this game and impose the costs and risks of cancellation on the shipping lines. In response to the likelihood of cancellation, shipping lines also overbook, sometimes causing larger shippers' cargo to be left behind. In the traditional business model, it has become a standard practice for shipping lines not to penalise larger shippers for failure to adhere to their contract. This vicious circle makes accurate demand forecasting difficult, and contributes to the inefficient operation of shipping lines. Online booking platforms, by forcing larger shippers to compete more directly with smaller consigners and to bear some of the costs of inaccurate demand forecasting through penalties, may thus discourage shippers from overpurchasing cargo space.

These empirical results thus carry significant implication for shipping lines. Online quote platform provides access to some undiscovered segments, such as small and medium-sized shippers. A significant increase in the number of containers and volume from small shippers demonstrates significant savings in administrative costs for shipping lines. This is likely because the online quote platform reduces the number of salespeople required to provide service and improves the general efficiency of the quote compilation process. The increase in the number of small shippers via the online quote platform also increases the diversity of shipping line customers, thereby reducing a line's financial risk. In day-to-day operations, many shipping lines prefer greater diversity in shippers, and may assign quotas so as to limit the order volumes of individual larger shippers and thus prevent any sudden shortfall from one shipper. Furthermore, freight forwarders currently provide end-to-end services to these small and disparate shippers. In order to persuade small and diffuse shippers to book directly with the shipping lines and maintain their loyalty, major shipping companies have strategically leveraged the logistics services of their subsidiary logistics companies in order to provide competing end-to-end services (Maersk, 2021). Finally, online quote platforms can also increase the revenue of shipping lines, because they attract more small shippers into booking directly with the line, and the freight rates quoted are higher than those offered to larger shippers, who usually receive bulk discounts.

5.5 Remarks

In this study, we investigate the effects of online quote platform on shippers' booking behaviour. We treat the implementation of the online quote platform as a quasi-experiment, applying RDD with panel data. In order to control for the unobserved time-varying effects that could also be correlated with the changes in container volume, we adopt two regression discontinuity models: a highly flexible, global polynomial model, and a local linear regression design. The U.S. import trade data of a top shipping line, gathered over the period from January 2016 to December 2019, is used for the empirical test. Our study finds that, during the time period and across all shippers, on average, the online quote platform causes a reduction in container volume ordered. This reduction mainly results from the decline in volume reserved by large shippers, while the online quote platform attracts more small and scattered shippers, with an average contracted volume of less than 5 TEUs per month. This result is believable, given the fact that the booking platform entices smaller shippers to split from freight forwarders and book cargo space from the shipping line directly. The medium and extra-large shippers reduce container booking volume over a relatively longer period. These findings hold fruitful implications for shipping lines and shippers alike as they seek to develop appropriate marketing strategies. Shipping lines may find it advantageous to develop proprietary quote platforms in order to better control their own risk and increase their revenue. Small shippers can leverage their bargaining power when choosing whether to use an online platform provided by a shipping line or by a freight forwarding company. For larger shippers, the no-show penalties discourage them from over-purchasing cargo space.

Chapter 6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this thesis, we conduct three studies to evaluate shipping industry changes. We briefly summarize the main findings of the three studies as follows.

In the first study, we review and summarize the cost models most frequently applied in maritime transportation and air freight transportation. We first classify the cost studies into two categories: item-based cost formulation and aggregated cost formulation. We find that the two industries share many common items and adopt both regression analysis and accounting approaches to formulate the cost items. But the application of item-based cost formulation differs between the two industries. In regard to aggregate cost formulation, log-log cost function and translog cost function are two general functional forms applied in the two industries, but at different levels. For air freight transportation, they are adopted at the company level, while for maritime transportation, they are also used at the vessel and voyage level. The primary application of these functions is to calculate EOS and EOD, estimate cost efficiency, decompose the TFP growth in air freight transportation. In maritime transportation, they are used to find the optimal fleet capacity, measure fleet utilization, and quantify economies of ship size.

In the second study, we take the Chinese New Year into account and use the DID and RDD-DID methods to quantify the impact of pandemic lockdown policy on global port calls. Using the port call data of both Chinese ports and foreign ports in 2019 and 2020, we gauge both the immediate and longer-term impact. For direct lockdown effect, we find that the Chinese lockdown policy did not cause an immediate port call near the lockdown date of Chinese ports, thus the effect of lockdowns is gradual in magnitude, but cause an immediate and significant decrease in port call data of other ports. For indirect lockdown effects, we classify the ports in other counties into a high-connectivity (with Chinese ports) group and a low-connectivity group based on their connectivity index and location. We find the Chinese lockdown policy leads to a relatively prolonged reduction in port calls in high-connectivity Asian ports and results in a sharp and relatively prolonged drop of port calls in high-connectivity European ports. There exists no significant propagation effect on the low-connectivity ports.

In the third study, we investigate the effects of online quote platform on shippers' booking behaviour. We treat the implementation of the online quote platform as a quasi-experiment, applying RDD with panel data. The U.S. import trade data of a top shipping line, gathered over the period from January 2016 to December 2019, is used for the empirical test. Our study finds that, during the time period and across all shippers, on average, the online quote platform causes a reduction in container volume ordered. This reduction mainly results from the decline in volume reserved by large shippers, while the online quote platform attracts more small and scattered shippers, with an average contracted volume of less than 5 TEUs per month. This result is believable, given the fact that the booking platform entices smaller shippers to split from freight forwarders and book cargo space from the shipping line directly. These findings hold fruitful implications for shipping lines and shippers alike as they seek to develop appropriate marketing strategies. Shipping lines may find it advantageous to develop proprietary quote platforms in order to better control their own risk, while shippers can leverage their relative bargaining power when choosing whether to use an online platform provided by a line or by a freight forwarding company.

6.2 Future Work

For the first study, we propose several potential directions for future research. For air freight transportation, the item-based cost formulations developed in previous literature mainly focus on passenger aircraft, while analysis of cargo aircrafts lags behind. As these two types of aircraft can have very different cost items and even different functional forms for the same item, it is inappropriate and inaccurate to simply apply the item-based cost formulation of passenger aircraft to cargo aircraft. With the swift development in air freight transportation due to the booming of e-commerce, it is worthwhile to develop dedicated cost formulas for cargo aircraft that can assist aircraft manufacturers, airlines and policymakers to make decisions. In addition, as the proportion of belly cargo in passenger aircraft continues to increase, the allocation of trip-level costs and company-level costs between passengers and cargo is also an urgent question for passenger airlines and worth further study. Airlines currently use a fleet assignment model for assigning aircraft types to flights and for scheduling flight departures so as to minimize operating costs in passenger air transportation (Rexing et al., 2000). It will be interesting to adopt similar methods so as to minimize the aircraft-specific operating cost of cargo aircrafts.

As data availability and data quality in the maritime industry continues to improve significantly, future research may enrich current cost studies with more detailed cost data. For example, maritime researchers may be able to estimate cost items at the voyage level more precisely with the detailed information harvested by AIS. Previous studies have also adopted the translog cost function in order to study the cost structures of independent shipping lines. As shipping alliances become increasingly dominant in the market, it will become necessary to investigate how shipping alliances affect firm-level cost functions. Moreover, the economies of network size have rarely been explored in the field of maritime transportation from the perspective of aggregated cost formulation, an area of research well established in the study of airline freight transportation. In terms of economies of density, by referring to the field of air freight transportation research, the maritime scholar can take network size into consideration by including the number of seaports served in the aggregated cost formulation. Future researchers in both fields should also continue to look to the contrasts in focus and emphasis between their disciplines in order to find new approaches to cost formulation as databases and mathematical methods evolve.

The second study can be further improved with more available company (shipping line) level data. For example, the shipping cancellation data combined with the change of port call can help to reveal more details of strategies adopted by the shipping line during the lockdown, such as, the preference of shipping lines to ports, the network effect and etc., which have important implications on managing shipping capacity. Integrating our findings from this study with port performance data such as congestion, berthing time, and etc., researchers can also investigate port's resilience ability during shock with appropriate methods, such as dynamical system model and network theory.

While our results provide a great deal of insight, we also acknowledge the limitations of the third study. First, we are unable to identify which transactions were booked through the online quote platform and which via traditional channels. Further extensions of the data collection may require capturing the difference in booking channels. With this information, we would be able to analyse more granular changes in shippers' booking behaviour as they switch from email and phone conversations to online quote platforms. Second, this study does not take shipper characteristics into account. It would be both interesting and useful to find out, for example, how freight forwarders, NVOCCS, and cargo shippers react differently to an online quote platform. Third, we notice the difference in carriers' operational and marketing strategies. It will be interesting to compare the influence of online quote platform on container orders across different carriers. These are questions that require further exploration, and we believe that our study opens the path to other, fruitful lines of inquiry.

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