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# Do Shipping Alliances Affect Freight Rates? Evidence from Global Satellite Ship Data

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**Abstract:** Shipping alliances (SAs) can facilitate their members' coordination on price and capacity decisions. Although this helps reduce the oversupply of capacity and cutthroat competition during market downturns, the possible freight rate increase due to potential collusion among member shipping lines is another concern. This study aims to empirically investigate the impacts of SAs on container freight rates on nine major shipping corridors for the period from 2015 to 2020. To measure market concentration, data from a satellite-based Automatic Information System (AIS) is used to identify liner shipping companies' services in each market. We propose to use the alliance-level Herfindahl-Hirschman Index (HHI) and Concentration Ratio Index (CR) to measure market concentration. Then we used the simulated market concentration measures as the instrumental variable to address the endogeneity issue between freight rates and alliances' market share. The main finding is that both alliance-level HHI and CR are negatively associated with freight rates, implying that SAs may help reduce prices. This finding provides new insights for antitrust authorities when investigating alliance applications in the liner shipping sector.

***Keywords:*** Shipping alliance; Liner shipping; Freight rates; Market concentration; AIS

## 1. Introduction

Strategic alliances have become particularly prevalent in network-oriented industries such as the airline, international shipping, and logistics industries. A strategic alliance refers to the partnership between separate organizations to share resources collaboratively in pursuit of mutually beneficial goals (Tjemkes, Vos, and Burgers 2017). The benefits of strategic alliances for alliance members include extended access to resources, technologies, customers, and efficiency gains in the form of variable and fixed cost reductions (Gayle & Xie, 2019). Concerns about strategic alliances rest primarily on the reduction of market competition and the increase of market power (Bilotkach, 2005). The formation of a strategic alliance may eliminate direct competitors in a market, leading to a further decrease in output and an increase in price for customers (Bilotkach & Huschelrath, 2013; Hüschelrath & Müller, 2015).

The competition effects of strategic alliances have been investigated both theoretically and empirically, primarily in the airline industry, but no consensus has yet been reached. Most scholars hold the view that airline alliances tend to increase fares on overlapping routes (also called substitute, parallel, inter-hub, or gate-to-gate routes), where alliance members offer substitute flights before allying, due to the loss of effective competitors and increased market power (Borenstein, 1990; Fageda & Perdiguero, 2014; Jain, 2015; Kim & Singal, 1993; Kwoka & Shumilkina, 2010; Luo, 2014; Veldhuis, 2005; Werden et al., 1991). However, empirically, it is also common to find mixed or no evidence of price effects on overlapping routes (Dobson & Piga, 2013; Jiménez & Perdiguero, 2018; Park & Zhang, 2000; Wan et al., 2009; Zhang & Round, 2009). On interline routes (also known as complementary, non-overlap routes), theoretical predictions and empirical findings tend to be more consistent. That is, an airline alliance might bring down prices where two carriers link up with each other to provide connecting services for an origin-destination city pair due to the elimination of double marginalization (Bilotkach, 2007; Brueckner & Singer, 2019; Brueckner & Whalen, 2000; Carlton et al., 2019; Das, 2019; Oum et al., 1996; Park et al., 2001; Park & Zhang, 1998).

Although the formation of shipping alliances (SAs) can be traced back to as early as 1994, research on SAs is much scarcer than that on airline alliances (Ghorbani et al., 2022). SA members mainly cooperatively decide capacity over specific routes, including ship type and size, sailing schedules, and itineraries, share terminal facilities, and coordinate the global circulation of empty containers (Panayides & Wiedmer, 2011). Through the utilization of economies of scale, shipping alliances enable carriers to improve their efficiency. This can be achieved by deploying larger vessels or replacing two partially loaded vessels with a single vessel of comparable capacity, thereby boosting the load factor. The use of larger vessels reduces the costs of one unit of available capacity, whereas the consolidation of cargo onto a single vessel reduces capacity wastage and unnecessary expenditures, thereby increasing space occupancy efficiency (Chen et al., 2022; Ghorbani et al., 2022). However, efficiency gains are insufficient to relieve the antitrust authorities' concern about consumer surplus. It is essential to empirically investigate the effects of SA on prices (in this case, the freight rate).

The technical challenge of investigating the impacts of SAs on freight rates is twofold: data inaccessibility and endogeneity. First, there is no publicly available database for the historical data of carrier-route-level freight rates and market share of individual shipping carriers in long-term series. Second, the market share of SAs could be endogenous to the freight rate due to unobserved demand or supply shocks that could affect both SAs competition and the freight rate.

To address the above technical issues, we first propose a novel method for calculating the carrier-route-level market share of shipping carriers and alliances. The global satellite ship data allows us to estimate the deployed capacity of different liner companies on different routes. In this study, we use a 72-month sample of panel data from 2015 to 2020 to examine the relationship between container freight rate and alliance-level market concentration, measured by the HHI. Then, we use an instrumental variable strategy to account for the potential correlation between unobserved shocks to market concentration and freight rates. The main finding is that alliance-level market concentration is significantly and negatively associated with container freight rates, implying that the dominant position of SAs might induce freight rate reduction.

The rest of the paper is structured as follows. Section 2 outlines the development of SAs. Section 3 reviews prior research on the price effect of alliances. Section 4 describes the data and the process of calculating market shares using global satellite ship data. Section 5 specifies the regression models. Section 6 presents the results of our regression analysis. The final two sections discuss and conclude the findings.

## 2. Development of shipping alliances

The SA is a form of horizontal operational cooperation where carriers are authorized to exchange information regarding operational data on vessels and terminals, schedule performance, productivity reports, and standard port charges (Ghorbani et al., 2022). To secure competition and comply with antitrust laws, SA members are not allowed to exchange information on prices, freight rates, customer lists, marketing plans, or their bids on shippers' container transportation auctions (Panayides and Wiedmer 2011). Besides information sharing, other types of collaborative agreements between SA members include vessel sharing agreements (VSAs) and slot charter agreements (SCAs) (Panayides & Wiedmer, 2011). VSA and SCA require designated vessels or a fixed percentage of vessel capacity to be exchanged between the carriers during a specific time.

The structure and composition of SAs have undergone great changes since SA's first appearance in 1994 (Chen et al., 2022). The most recent wave of changes, as shown in Table 1, started with Hanjin Shipping's bankruptcy in 2016. Since then, the global shipping market has been restructured from four major alliances, namely, the 2M Alliance, Ocean Three or Ocean Alliance (O3), Grand Alliance (G6), and CKYHE Alliance, into three giants after April of 2017: the 2M Alliance, Ocean Alliance, and THE Alliance. In 2023, the top nine container lines will account for 82.3% of global container shipping capacity and will all be operating within one of the three SAs (Alphaliner, 2023).

Concerns have grown significantly about the impact of SAs' market power on price manipulation. Governments of major economies have attached stricter requirements and scrutiny to the formation of SAs and the cooperation between SA members. In June 2013, the world's top three liner shipping companies—Maersk Line, Mediterranean Shipping Company (MSC), and CMA CGM—announced the formation of a long-term vessel-sharing agreement called the P3 Alliance (Yap, 2014). The alliance aims to reduce costs on three routes—Eurasian, Trans-Pacific, and Trans-Atlantic—by consolidating 255 vessels and sharing 2.6 million containers of cargo capacity (Maersk, 2013). Although the proposed alliance has been approved in Europe and the US, China issued a ban on the P3 alliance in June 2014 because the alliance would control 47% of the container freight volume on the Asia-Europe route, significantly increasing market concentration (Bloomberg, 2014). In February 2022, the Government of the United States released the Fact Sheet on "*Lowering Prices and Leveling the Playing Field in Ocean Shipping"* to make sure that three global SAs cannot raise prices for American businesses and consumers.[1] However, there lacks empirical evidence to support whether government policy should encourage or restrict international carriers from forming alliances, while taking account of any potential anticompetitive effects. Therefore, the price effects of the alliance have warranted stringent academic interest.

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[1] https://www.whitehouse.gov/briefing-room/statements-releases/2022/02/28/fact-sheet-lowering-prices-and-leveling-the-playing-field-in-ocean-shipping/

Table 1 Members of SAs from 2015 to 2020

| **Q2 2015** | | **Q4 2016** | | **Q2 2017** | | **Q2 2020** | |
|---|---|---|---|---|---|---|---|
| **Alliance** | **Members** | **Alliance** | **Members** | **Alliance** | **Members** | **Alliance** | **Members** |
| 2M | Maersk Line | 2M | Maersk Line | 2M | Maersk Line (Hamburg-Sud) | 2M | Maersk Line |
| | MSC | | MSC | | MSC | | MSC |
| | | | | | | | ZIM* |
| Ocean 3 | CMA-CGM | Ocean 3 | CMA-CGM (APL/NOL) | Ocean | CMA-CGM | Ocean | CMA-CGM |
| | CSCL | | China COSCO Shipping (COSCO/CSCL) | | China COSCO Shipping | | China COSCO Shipping (OOCL) |
| | UASC | | UASC | | OOCL | | Evergreen |
| | | | | | Evergreen | | |
| G6 | MOL | G6 | MOL | THE | MOL | THE | ONE (MOL/NYK/K Line) |
| | NYK | | NYK Line | | NYK | | Hapag-Lloyd |
| | APL/NOL | | Hapag-Lloyd | | Hapag-Lloyd (UASC) | | Yang Ming |
| | Hapag-Lloyd | | OOCL | | HMM | | HMM |
| | OOCL | | HMM | | K Line | | |
| | HMM | | | | Yang Ming | | |
| CKYHE | COSCO | CKYHE | Hanjin | | | | |
| | Hanjin | | K Line | | | | |
| | K Line | | Yang Ming | | | | |
| | Yang Ming | | Evergreen | | | | |
| | Evergreen | | | | | | |

Notes:

a. *ZIM does not belong to any alliance, but it has shared vessels with 2M on China-North America east coast routes since September 2018 and on China-Mediterranean and China-North America west coast routes since March 2020.

b. Liner companies that were acquired or merged by others are shown in brackets.

## 3. Literature Review

This section reviews the price effects of horizontal mergers and alliances of airlines and shipping lines discovered in the literature. Methodologies for analyzing the price effects of alliances include descriptive analysis, theoretical modeling, and econometric modeling. Descriptive analysis generally works by directly comparing price changes before and after the merger or formation of an alliance (Borenstein, 1990). Theoretical models are mainly based on the application of game theories to explain the mechanism behind price impacts by deriving and comparing equilibrium prices with and without the formation of alliances. The model settings can vary in market structures, forms of cooperation, and types of games. Following the spirit of the game theoretical models, merger simulation models have been developed to conduct an ex-ante prediction of the price impacts of mergers with real-life data. However, as these simulation models rely on strong assumptions about the post-merger behavior of demand, costs, and conduct, the predicted post-merger prices were found to substantially deviate from observed post-merger prices (Peters, 2006). Econometric models are mainly used for the ex-post quantification of the impacts by establishing the relationship between price and alliance-related variables. Because descriptive analysis usually does not control for various confounding factors, the section reviews findings based on theoretical and econometric models and discusses the differences between airline and shipping practices before selecting the proper model setting for analysis.

The theoretical literature mainly focuses on the airline industry. In theoretical models, alliances are usually modeled as a merger-like joint venture where alliance members maximize joint profit on routes covered in the partnership agreement. The general finding is that an alliance between two airlines offering complementary flights on interline routes is likely to reduce fares due to the removal of double marginalization and the increase in traffic density. On the other hand, an alliance between airlines offering competing flights on overlapping routes tends to raise fares due to the reduction in the number of competitors (Brueckner, 2001; Park et al., 2001). However, the price of overlapping routes might drop post-alliance due to efficiency gains. If the marginal costs of the merging firms are reduced by a ‘sufficient amount’, the merged entity has an incentive to increase output, leading to lower prices. The amount of cost reduction necessary to prevent a price increase depends on the merging firms’ market shares and market demand elasticity (Werden & Froeb, 1998).

Empirically, the above theoretical predictions have been found to largely hold true in the airline industry, but this stream of studies mainly relied on data from the US market. In *interline markets*, the evidence is clearly in favor of the hypothesis that incremental levels of cooperation between airlines offering complementary flights lead to fare reduction (Bilotkach, 2007; Brueckner, 2001; Brueckner & Singer, 2019; Calzaretta et al., 2017).

In *overlapping markets*, consistent with the theoretical prediction that market power and efficiency gain jointly determine the price effect, the empirical findings are mixed. Price increases were mainly found in the context of airline *mergers* before 2000. Kim and Singal (1993) examined price changes associated with airline mergers during 1985-1988 and found efficiency gains were more than offset by the exercise of increased market power, leading to a net increase in post-merger airfare. Evans et al. (1993) found a positive correlation between route-level market concentration and price. Kwoka and Shumilkina (2010) examined the impacts of a merger between an incumbent and a potential entrant, using data collected for the 1987 merger of US Air and Piedmont Airlines. They found that prices rose after eliminating the potential entrant via the merger. However, studies on mergers after 2000 in general found a much milder or even negative price effect. For example, in the US domestic market, after the 2009 merger of Delta and Northwest, the real price on overlapping routes was found to increase by 11% in the short term but only by 3% in the long term due to the competition from post-merger entries (Hüschelrath and Müller, 2015). The 2013 merger of American Airlines and US Airways was found to reduce prices in large markets but increase prices in small markets (Das, 2019). Carlton et al. (2019) found these two mergers reduced nominal fares by 4.4% and 12.3%, respectively, but the merger of United Airlines and Continental Airlines in 2010 had no statistically significant impacts on airfare. Luo (2014) investigated the merger of Delta Airlines and Northwest Airlines between 2008 and 2010 and discovered no significant change in airfare on routes where one of the merging airlines left service after the merger. Fan (2020) examined the price effects of merging firms, legacy rivals, and low-cost carriers in response to the Continental and United Airlines merger on different overlapping routes. On routes where at least one endpoint airport is a hub for merging firms, merging firms and legacy carriers were found to significantly raise fares, whereas low-cost carriers (LCCs) reduced fares after the merger. On leisure routes where endpoint cities rely heavily on accommodation earnings, the merging firms reduced prices. On routes connecting two major metropolitan areas, the merging firms increase fares for business travelers but not for leisure passengers. In Europe, Dobson and Piga (2013) studied Ryanair’s takeover of Buzz and EasyJet’s acquisition of Go Fly in early 2000. The acquiring firms had generally kept most fares below the pre-takeover period by substantially reducing the early booking fares while increasing the late booking fares.

In the case of airline *alliances* on *overlapping* routes, a general price increase has not been observed in the empirical literature. Brueckner and Whalen (2000) found no statistically significant effect of alliances between US airlines and non-US airlines in overlapping international markets. In the transatlantic air travel markets, Star Alliance and SkyTeam Alliance had no statistically significant price impact, while the Oneworld Alliance was found to significantly lower business class airfares (Wan et al., 2009). The anticompetitive effects of alliances are either negligible or counterbalanced by efficiency gains. The alliance of Delta, Sabena, and Swissair was found to even reduce the fare by 19% because the decrease in alliance partners' combined costs on the overlapping routes outweighed the increase in markup ratio (Park & Zhang, 2000). Between 1998 and 2015, Calzaretta et al. (2017) found no significant fare increase associated with antitrust-immunized airline alliances or joint venture partnerships on international routes departing from the U.S. Brueckner & Singer (2019) extended the work of Calzaretta et al. (2017) by dividing the samples into prior-2010 and post-2010 groups and found insignificant anticompetitive effects prior to 2010, but statistically significant anticompetitive effects of antitrust-immunized airline alliances and joint ventures after 2010 using confidential fare data reported by the foreign alliance partners of the US carriers.

Despite abundant literature in the airline industry, we only find three related studies in shipping. Quartieri (2017) theoretically modelled the impacts of vessel sharing agreements among SAs and found a decrease in the equilibrium freight rate and each alliance partner's marginal cost. Using data from six east-west container liner shipping routes, Hirata (2017) found non-positive and statistically insignificant correlations between freight rate and market concentration, implying that the liner shipping market is contestable and, as a result, dominant shipping lines will find it difficult to exercise market power and raise prices. Barkley and McLeod (2022) found weak evidence that prices declined following the merger of barge companies. None of these three studies provided a direct investigation into the impacts of shipping alliances. Note that the price effects of airline alliances and ocean transport alliances are only comparable on overlapping routes. While interlining is not uncommon in container shipping, to our knowledge, container transshipment mainly occurs between feeder carriers and ocean carriers. However, shipping alliances are primarily formed among ocean carriers, and we are not aware of any feeder carrier member in all the shipping alliances that our data covers.

Many factors might contribute to the mixed empirical findings. First, as discussed in various theoretical studies mentioned above, the market power and the efficiency gains brought by the increased scale and market share can impose opposite impacts on post-alliance prices. Second, the alliances' ability to exercise market power and raise prices would be affected by market entry barriers and the enforcement of antitrust laws. In industries with high entry barriers, alliances may have a greater ability to manipulate fares due to reduced competition and market asymmetry (Snider & Williams, 2015; Werden et al., 1991). When there are no entry barriers, the merger decision must be made due to the expectation of efficiency gain, as entry makes the merger unprofitable (Werden & Froeb, 1998), and hence a post-merger price reduction would be expected. On the other hand, antitrust laws could limit anti-competitive behavior, such as joint pricing or capacity coordination, to prevent alliance members from performing like a merged firm (Bilotkach & Huschelrath, 2013; Gayle & Xie, 2019). Finally, the pricing strategy in the container shipping sector may also play a role. The container shipping industry applies two kinds of prices: long-term contract rates and short-term spot rates. The long-term contract price tends to be lower than short-term spot rates (Meng et al., 2019; Wang et al., 2022). SAs, through their ability to provide broader route coverage and more frequent services, have the capacity to attract customers to sign more long-term contracts due to enhanced service reliability and flexibility. SAs may influence customers' preferences for these two types of rates, thereby ultimately influencing the average market price. In sum, the effects on post-alliance prices may vary substantially across industries, necessitating a dedicated study on container shipping.

## 4. Data

### 4.1 Sample and dataset

The study covers a sample of ten international shipping routes, with monthly observations from January 2015 to December 2020. Each route corresponds to a distinct market and is defined by an ordered sequence of ports. Due to the availability of data, all routes in this study start in China and are thus named after their destinations. The departure ports in China include Dalian, Tianjin, Qingdao, Shanghai, Nanjing, Ningbo, Xiamen, Fuzhou, Shenzhen, and Guangzhou. Table 2 shows the route names, destination ports, and host countries of the destination ports.

Table 2 Shipping routes included in the study

| No. | Route name | Destination ports | Host country |
|---|---|---|---|
| 1 | West coast of America | Los Angeles, Long Beach, Oakland | U.S. |
| 2 | East coast of America | New York, Savannah, Norfolk, Charleston | U.S. |
| 3 | Europe | Hamburg, Rotterdam, Antwerp, Felixstowe, Le Havre | Germany, Netherlands, Belgium, UK, France |
| 4 | Mediterranean | Barcelona, Valencia, Genoa, Naples | Spain, Italy |
| 5 | Persian Gulf/red sea | Dubai | United Arab Emirates |
| 6 | Australia/New Zealand | Melbourne | Australia |
| 7 | Southeast Asia | Singapore | Singapore |
| 8 | West east Africa | Apapa-lagos | Nigeria |
| 9 | South Africa | Durban | South Africa |
| 10 | South America | Santos | Brazil |

The key information needed is the freight rate and service capacity of individual shipping lines. The freight rate is the dependent variable in the regression analysis. The freight rates of individual liner companies are not publicly available. Academic researchers often use secondary data, such as freight rate indices published by research institutions and consulting firms (see two review articles on shipping freight rates, Jeon et al., 2021; Ke et al., 2022). We use the monthly average China Export Container Freight Rate Index (CCFI), which is a conventional index of the freight rates of the shipping market (Zhao et al., 2020). Shanghai Shipping Exchange uses the weighted freight rate to construct the CCFI for each of the 12 international shipping routes from China to other countries. In this study, we exclude the China-Japan and China-South Korea routes for their short lengths.

The service capacity of individual shipping lines is essential to constructing the variable of interest, i.e., alliance-level market concentration. As this information is not publicly available, we estimate market shares of individual shipping alliance and liner firms based on global ship position data from the AIS and shipping company information from the Lloyd's List Shipping Intelligence Database. The idea is to combine the information from these two sources to identify container vessels that operated on each route in each month as well as the operating shipping lines of these vessels. Section 4.2 provides a detailed explanation of the data processing algorithm. The output of this data processing algorithm is a vessel-level database, which contains information about the service capacity of each ship, its operating route in each month, its operating company, and the alliance membership of the operating company. This database is used to construct market shares and market concentration variables.

## 4.2 Construction of vessel-level database

We propose a five-step algorithm to identify the container ships, their sequence of port calls, the service route, the months of operation, the operator company, and the alliance. Fig. 1 shows the data sources, input data framework, filter criteria, and output data for each step.

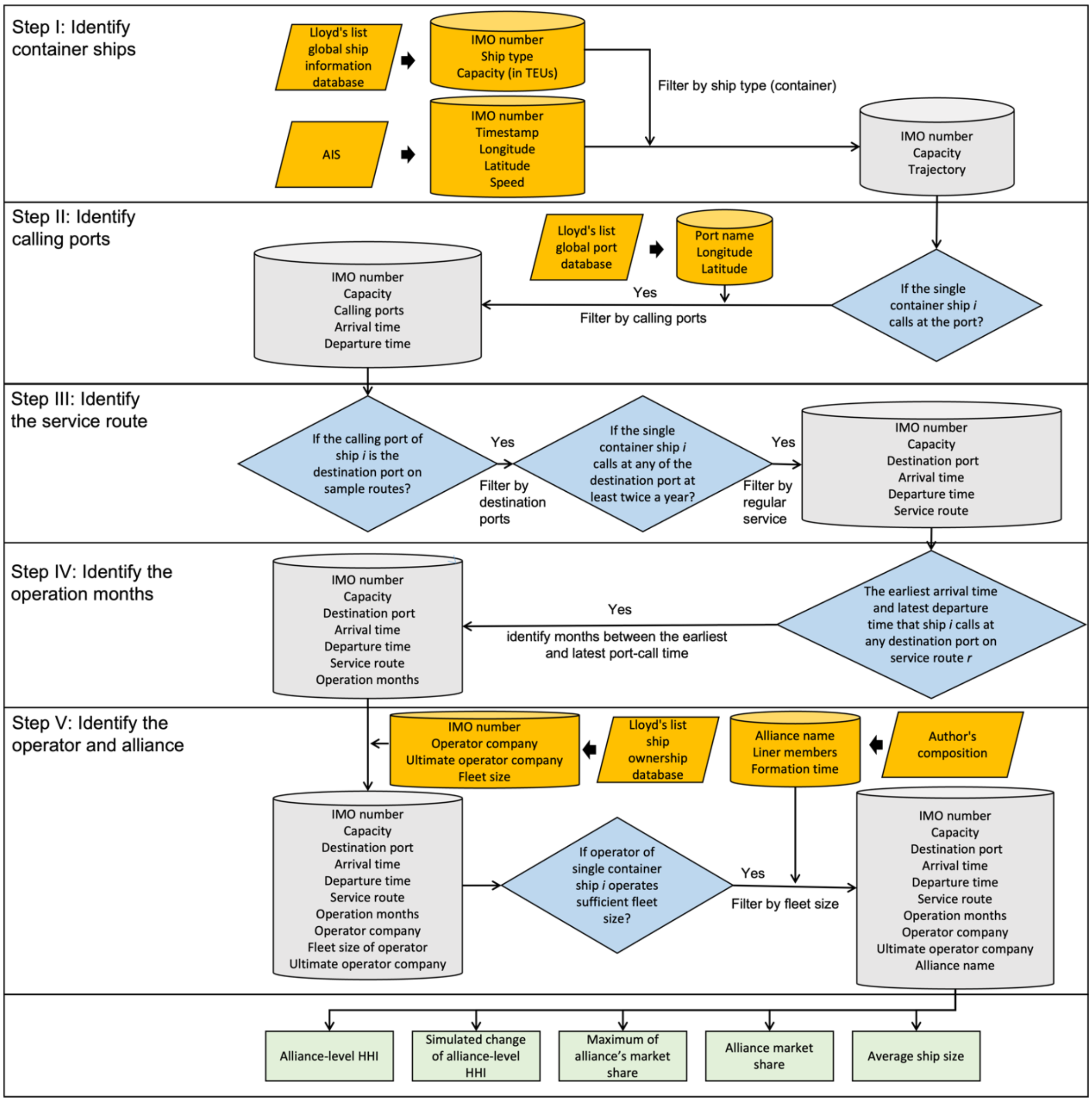

Fig. 1. Algorithm for market shares construction

*Step I: identify container ships*

We first extract the dynamic trajectory records of all types of ships globally from the Automatic Information System (AIS). AIS is a self-reporting surveillance system installed on board to record and transmit the ship's activity information (Yang et al., 2019), including timestamps, ship identification (a unique IMO number), ship position (latitudes and longitudes), speed, voyage destination, estimated time of arrival (ETA), etc. The term "timestamp" refers to a time slot indicating the UTC second when the report was generated by the electronic position system. In recent years, AIS has gained popularity for acquiring real-time information on all ocean-going vessels' past routes and expected future ports of call (Li et al., 2023; Yang et al., 2021; Yin et al., 2022).

Lloyd's List Shipping Intelligence Database includes the IMO number, ship type (e.g., container, bulk, tanker), capacity (in TEUs), and historical operator companies for a particular vessel from its berth to death. The database also offers shipping company information, including its fleet size and ultimate (parent) company in 2022. In Step I, we use IMO number, ship type, and ship capacity data from the Lloyd's List database and match them with ship trajectory data based on unique IMO numbers. As liner firms typically operate container ships, we filter by ship type; thus, the outputs from step I are the capacity and trajectory for individual container ships. The trajectory is a sequence of longitudes, latitudes, and speed data ordered by the timestamp.

### *Step II: identify the calling ports*

Ships generally keep stationary when calling at ports. Lloyd's List database also holds the latitude and longitude of all global ports. Therefore, we believe the ship calls at the specific port whenever it is moored (speed less than 1 knot) within 30 kilometers of any port in the Lloyd's List port database for more than one hour (Bai et al., 2022). The first time the ship's trajectory falls into the port range is the arrival time, and the last time it overlaps is the departure time. Note that when the ship is within an overlapping region of two ports, the nearest port is chosen. Due to congestion at ports, in certain cases, ships will moor for hours at the anchorage, then travel a short distance through the navigation channel, and then moor again for hours at the berth, which can result in duplicate visits at the same port. When such duplication is identified in a ship's route sequence, then the duplicate visits are removed. Step II adds the series of calling ports, the arrival time, and the departure time of each port call to the outputs from the previous step.

*Step III: identify the service route*

In the previous step, we identified the sequence of port calls for each ship during the research period. If one ship visits any of the destination ports of a route specified in Table 2, we classify it as serving the focal route. Liner services are characterized by ships following a fixed itinerary of ports, adhering to a repetitive cycle or loop. Therefore, we kept liner ships by considering ships that make at least two annual calls at any of the designated destination ports.

Ships that exclusively call at ports in Western Europe can be accurately identified as serving the Western European route. However, some ships originating from China and bound for Western European destinations may drop by ports in the Mediterranean Sea. As a result, these vessels would be counted twice and erroneously identified as simultaneously serving the European route and the Mediterranean route. To avoid double-counting of these kinds of ships, we classify ships that only call at ports in the Mediterranean, Persian Gulf, and Southeast Asia as serving those routes, respectively. Our route classification records are more accurate than AIS ship destination records, which are often incomplete or contain errors because of manual recoding (Yang et al., 2021). In Step III, we extract the service route, arrival time, and departure time when ships call the destination ports on the sample route and dismiss all calling port records for excessive size and uselessness.

*Step IV: identify the operation month*

Step IV figures out how long each ship will be in service by route from 2015 to 2020. For each route, we consider the earliest arrival time that a ship calls at any of the destination ports as the commencement of liner service and the latest departure time at any destination port as the termination of service. Then, the time in between indicates the operational period for the particular ship on the service route. Step IV outputs all months in the operational period to the data.

*Step V: identify the operator and alliance*

Using the unique IMO number, we can match the operator company information from Lloyd's List with the outputs from Step IV. Some of the operator companies do not own any fleets. We filter by fleet size greater than zero to ensure they are valid liner firms. Besides, the operator company may be a branch of a business group. We follow Das (2019) and aggregate all operator companies into their ultimate (parent) business groups.

The information about alliance memberships was collected from public websites, literature, and the most recent news about liner companies. We then match the ultimate operator company name with alliance member names to see which alliance the ship serves. In the "alliance name" attribute, alliance ships are labeled with the alliance name, while non-alliance ships are labeled with the ultimate operator company name. Though ZIM is not an alliance member, it shares vessels with alliance members on several routes. We will also consider them as alliance members. Step V outputs a dataset of vessels that includes the IMO number, ship capacity, destination port, arrival time, departure time, service route, service months, operator company, ultimate operator company, and alliance name.

Following a five-step data cleaning process, we have constructed a comprehensive database comprising 116,606 ship-route-month-level observations covering 10 international routes from January 2015 to December 2020. Each observation in the dataset describes one specific ship's capacity, serving routes, alliance affiliation on a certain route and a certain month. The database captures 2,839 unique active ships. Their unique operator company sums up to 621, while their unique ultimate company totals 441. As a very small number of vessels were identified on the China-Persian Gulf/Red Sea route, all observations on the China-Persian Gulf/Red Sea were removed from the sample, leaving nine routes to prepare the variables for regression.

## 5. Econometric models

### 5.1 Model specification and variables

Empirical studies on the price impacts of alliances tend to identify the impacts by using a dummy variable that indicates the formation or existence of alliances in a certain market. Unfortunately, this strategy cannot be applied in our context because the changes in alliances in our study period were mainly triggered by shipping lines' membership switching from one alliance to the other. Depending on the member shipping lines' presence in individual markets, the membership changes in one single alliance may affect each market in different ways. Some markets may see an increased influence of the alliance, while others may see a reduced influence. This is further complicated by the fact that multiple alliances experienced membership changes at the same time. Thus, unlike the clearcut cases of forming new alliances or adding new members to an alliance, our context does not allow for using a 0-1 binary variable to capture the structural changes of alliances. As a result, we have to use alliance-related market concentration to capture the influence of alliances.

We first use the Herfindahl-Hirschman Index (HHI) to measure the alliance-related market concentration at the route level, as it is well established in the literature, both theoretically and empirically, that liners (or even airlines) compete in capacity (Calzada et al., 2022). We calculate the alliance-level HHI using Eq. (1)

$$HHI_{alliance_{rt}} = \sum_{j=1}^{J}\left(\sum_{i \epsilon N_{jt}} S_{irt}\right)^2 + \sum_{i \epsilon M_t} S_{irt}{}^2 \tag{1}$$

where $i$ denotes the individual liner firm and $r$ means route, $t$ denotes the year-month time. Thus, $S_{irt}$ represents the market share of liner firm $i$ on route $r$ at time $t$. $N_{jt}$ indicates the set of liner firms belonging to alliance $j$ ($j = 1,2, \dots, J$) at time $t$ and $M_t$ is the set of liner firms not belonging to any alliance at time $t$. The market share of alliance $j$ on route $r$ at time $t$ equals the sum of all members' market share $\sum_{i \epsilon N_{jt}} S_{irt}$. Then the first term on the right-hand side of Eq. (1) denotes the sum of squared alliance market shares. Similarly, the second term on the right-hand side of Eq. (1) computes the sum of squared market shares of all non-alliance firms. This means that we treat non-alliance firms as single-member alliances when constructing $HHI\_alliance_{rt}$ and this variable ranges from 0 to 1.

Then we constructed three concentration ratios (CR) as alternative measures of market concentration. CR is another widely used proxy for market concentration by scholars in shipping (Ha & Seo, 2013; Merk & Teodoro, 2022; Sys, 2009). CR reflects the aggregated market shares of the top players in the market. As we are interested in the changes of memberships among the four shipping alliances, and each alliance has a larger market share than a non-alliance firm, naturally the top players in our case are alliances. Thus, we construct CR1, CR2, and CR3 to capture the market shares of the top one, top two, and top three alliance(s). The formal definition is provided by Eq. (2) where $S_{jrt}$ represents the market share of alliance $j$ on route $r$ at time $t$ and $k$ is the number of top alliances whose market shares are aggregated. $CR1_{rt}$ represents the market share of the largest alliance on route $r$ at time $t$.

$CR2_{rt}$ is the sum of the market shares of the top two alliances on route $r$ at time $t$. $CR3_{rt}$ computes the sum of the market shares of the top three alliances.

$$CRk_{rt} = \sum_{j=1}^{k} S_{jrt} \tag{2}$$

The main specification of the regression model is presented in Eq. (3):

$$\ln(CCFI_{rt}) = \alpha + \beta_1 \ln(HHI\_alliance_{rt}) + \beta_2\, ln(GDP\_P_{rt}) + \beta_3\, ln(Export_{rt}) + \omega_r + \gamma_t + \varepsilon \tag{3}$$

The dependent variable $CCFI_{rt}$ is the monthly average CCFI index on route $r$ at time $t$. The variable of interest is the $HHI\_alliance_{rt}$. The variation in shipping demand is captured by the averages of the host countries' GDP per capita, $GDP\_P_{rt}$, as well as the values of export goods from China to foreign host countries, $Export_{rt}$. The route fixed effect $\omega_r$ captures time-invariant characteristics of each route (e.g., the route distance). The time fixed effect $\gamma_t$ captures time-varying impacts on all routes, such as world-wide economic and political shocks at specific years, business cycles, the development of global container fleets, and fuel prices. We take natural logs for all continuous variables to reduce the difference between variables and allow for the interpretation of the coefficients of alliance variables as elasticities (Calzada et al., 2022). Fig. 2 shows the value of alliance-level HHI and CR by routes.

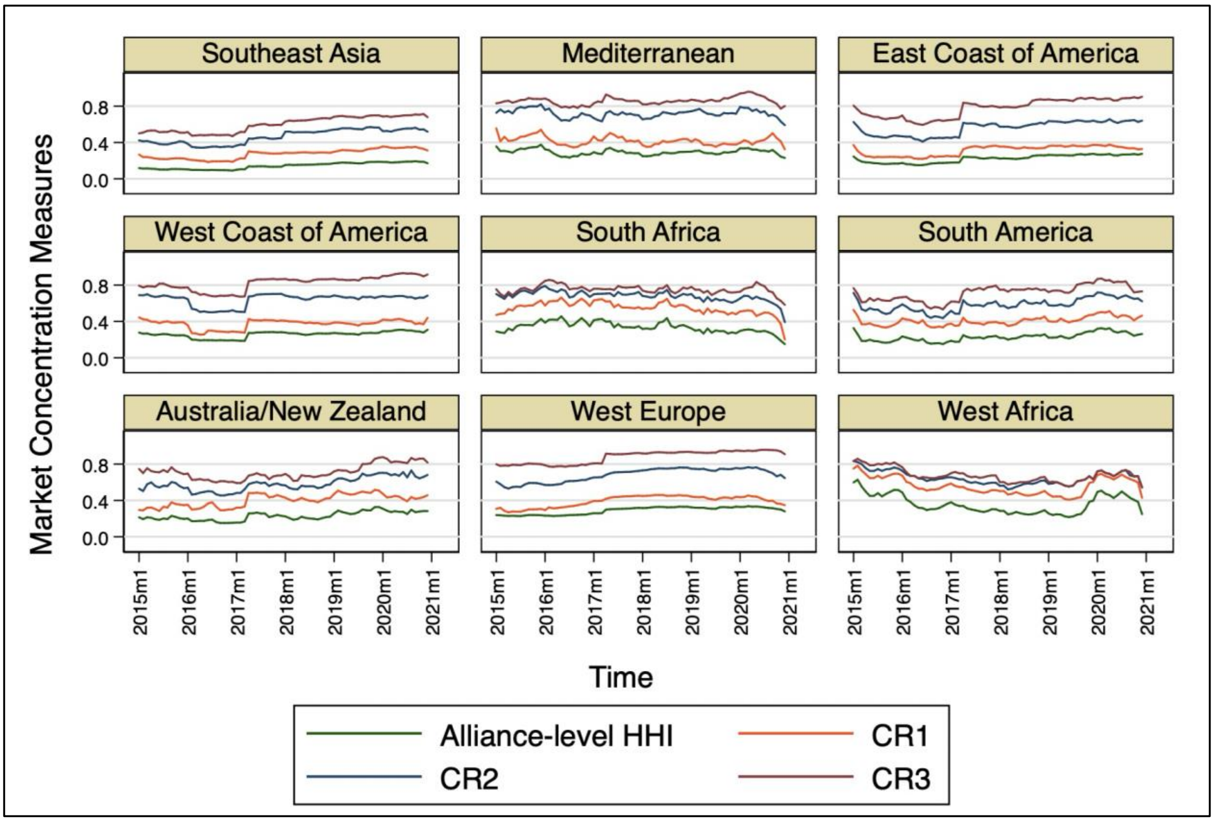

Fig. 2. Market concentration measures by routes

## 5.2 Instruments

We assume the changes in alliance memberships are exogenous while acknowledging that changes in the market shares of alliance members and other companies are endogenous (Song & Panayides, 2002). In our context, 0-1 dummy variables cannot effectively capture the structural changes of each alliance because, during the study period, membership changes occurred in multiple alliances at the same time, and each alliance membership change affected all routes but in different ways. Thus, to identify the impacts of alliance structure changes, it is essential to capture the changes in market concentrations of these alliances. However, this introduces an endogeneity problem as the market price and firms' and alliances' market shares may be co-determined. Fluctuations in market prices can further influence the behavior of shipping lines. By rapidly increasing vessel speed, shipping firms can increase their capacity and generate greater revenue as market prices rise. Members of shipping alliances are major players that operate more and larger ships. Shipping alliances are better positioned than non-aligned companies to rapidly increase capacity via speed upgrades, resulting in greater market shares for alliances. This indicates that a price increase might increase market concentration at the alliance level. Thus, the coefficients of alliance-level HHI and CR are expected to be adjusted downward after accounting for the above endogeneity problem using instrumental variables.

To address the endogeneity issue, we used a Bartik-style instrument for the HHI and CR (Bartik, 1991). We use shipping lines' market shares on each route in the year prior to the alliance membership changes to calculate the simulated market shares of each alliance per route. Then we use these predicted market shares of the alliance to compute the simulated HHI and CR. We further calculate the difference between the predicted alliance-level HHI (or CR) for the period after the membership changes and the actual alliance-level HHI (or CR) before membership changes (Ashenfelter et al., 2015; Barkley & Mcleod, 2022; Forbes & Kosová, 2023; Greenfield, 2014). The instrument satisfies the exclusion restriction, as market prices after the changes in alliance memberships cannot affect the market shares of shipping firms before these changes. The variation in HHI (or CR) is solely driven by the changes in alliance memberships but not influenced by unobserved factors related to freight rates or the freight rates themselves. Our instruments are built on the market shares of shipping firms before alliance changes and are thus independent of the price effects on shipping firms' speeding-up strategies. Therefore, the impacts of price on alliance-level HHI (or CR) are isolated.

All alliance membership adjustments happened after 2015 in this study. Thus, we treat all time periods in 2015 as the base periods. Given that the dataset contains monthly data, and we have 12 months of base periods, this leaves us with two ways to calculate the base-period market shares of individual firms. These base-period market shares of individual firms are in turn used to calculate alliance shares in the base periods and to predict alliance shares in the rest of the years when membership adjustments occurred.

The first approach is to use firm $i$'s *annual* market share in 2015 as its base-period market share. That is, the same market share of firm $i$ is used for all the months throughout the study periods. For example, firm $i$'s annual market share in 2015 is used to simulate its share in all the time periods (i.e., every month of 2015, 2016, etc). Thus, the monthly variation in market shares is removed.

The second approach uses firm $i$'s *monthly* market shares in 2015 as its base-period market shares. Thus, each month has its own base-period market share. For example, firm $i$'s market share in January 2015 is used to simulate its market share in every January of each study year (i.e., 2015, 2016, etc.). To simplify the description, we use the same notation of base-period market share for both approaches. That is, we use $S_{ir0}$ to indicate firm $i$'s base-period market share on route $r$ in which the last subscript zero stands for base period.

Then, we use base-period firm-level market shares to calculate alliance shares for all the study periods according to the changing alliance memberships in various periods. This forms the so-called simulated (or predicted) alliance shares. These simulated alliance shares and base-period non-alliance firms' market shares are used to compose the simulated alliance-level HHI ($simHHI$). The detailed formula is shown in Eq. (4) for every time period $t$. Note that Eq. (4) differs from Eq. (1) in the sense that when calculating $simHHI$, the base-period market shares are used in all time periods (base and non-base periods) while the alliance membership (captured by set $N_{jt}$ and $M_t$) varies in time. That is, $simHHI$ reflects base-period firm-level market shares and actual alliance membership, and hence is the predicted alliance-level HHI. In Eq. (1), however, both firm-level market shares and alliance memberships vary in time periods and hence Eq. (1) produces actual alliance-level HHI. As the same market shares are used in Eq. (1) and Eq. (4) when calculating actual alliance-level HHI and simulated alliance-level HHI in the base periods ($t = 0$), simulated alliance-level HHI and actual alliance-level HHI are equivalent in the base period, i.e. $simHHI_{r0} = HHI\_alliance_{r0}$ would hold.

$$simHHI_{rt} = \sum_{j=1}^{J}\left(\sum_{i\in N_{jt}} S_{ir0}\right)^2 + \sum_{i\in M_t} S_{ir0}{}^2 \tag{4}$$

As shown in Eq. (5), the simulated change in alliance-level HHI on route $r$ at time $t$ is the difference between the simulated alliance-level HHI at time $t$ and the simulated alliance-level HHI at the base period.

$$sim\Delta HHI_{rt} = simHHI_{rt} - simHHI_{r0} \tag{5}$$

Similarly, we use base-period firm-level market shares to calculate the simulated market shares of each alliance $j$ at each time period $t$ on route $r$, i.e., $\sum_{i\in N_{jt}} S_{ir0}$, considering the shifting alliance memberships over time. Then we use the simulated market shares of the largest $k$ individual alliances to calculate simulated CR of the top $k$ alliances on route $r$ at time $t$ as shown in Eq. (6). Then the simulated changes in CR on route $r$ at time $t$ is the difference between simulated CR at time $t$ and the simulated CR at the base period, as shown in Eq. (7)

$$simCRk_{rt} = \sum_{j=1}^{k} \sum_{i \in N_{jt}} S_{ir0} \tag{6}$$

$$sim\Delta CRk_{rt} = simCRk_{rt} - simCRk_{r0} \tag{7}$$

Figs. 3a through 3d show the values of variables of interest and corresponding instruments. As expected from the definition, simulated changes in market concentration measures are zero throughout the base periods in 2015. No seasonal patterns are present in simulated changes in market concentration measures when the 2015 annual market shares are used as base-period market shares. However, when the monthly market shares in 2015 are used as base-period market shares, the seasonal changes in certain firms' market shares may lead to seasonal patterns in simulated changes in market concentration measures.

Fig. 3a shows that the simulated change in alliance-level HHI can be either positive or negative. When a liner firm quits a larger alliance and joins a smaller one, the market shares of individual alliances become more evenly distributed, resulting in a decrease in market concentration and a negative change in simulated HHI. If a member of a larger alliance acquires a firm from a smaller alliance or a non-alliance company, the larger alliance will gain an even greater market share, increasing market concentration and causing a positive simulated change in HHI.

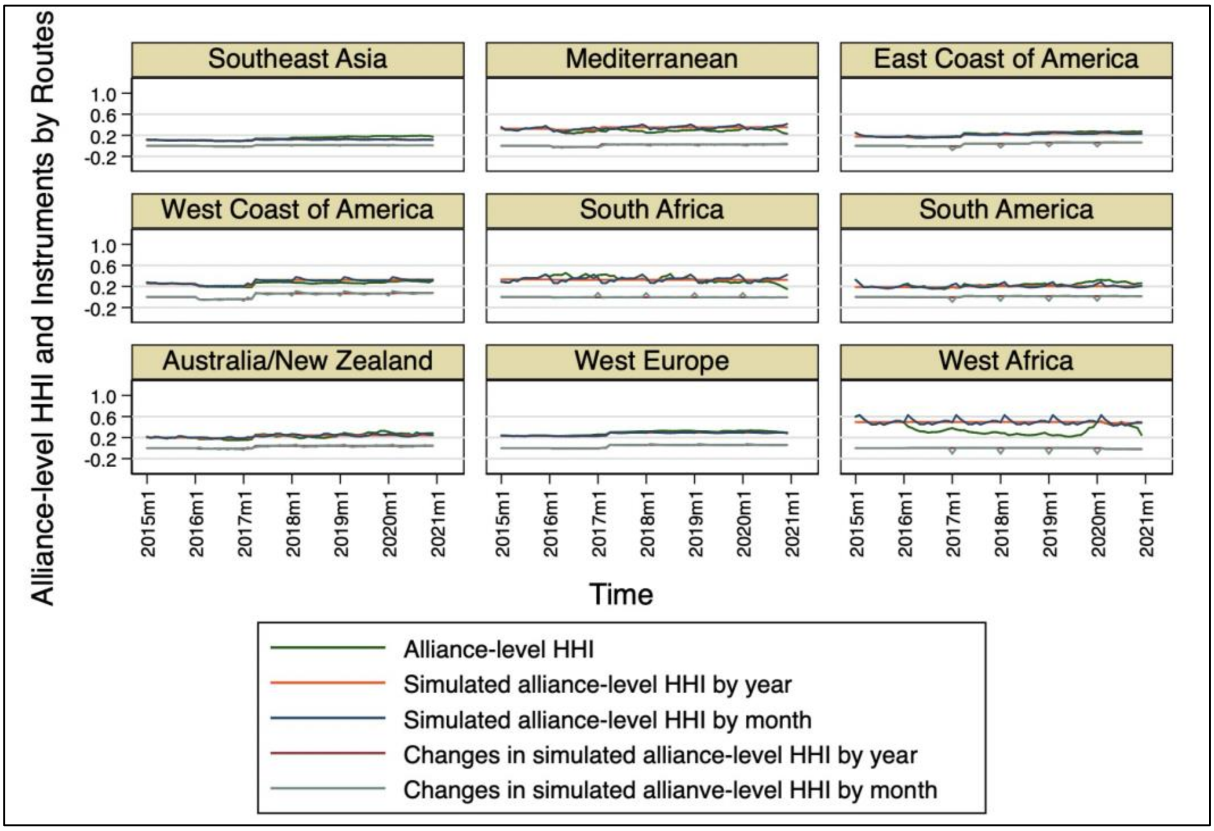

Fig. 3a. The Alliance-level HHI and Instruments

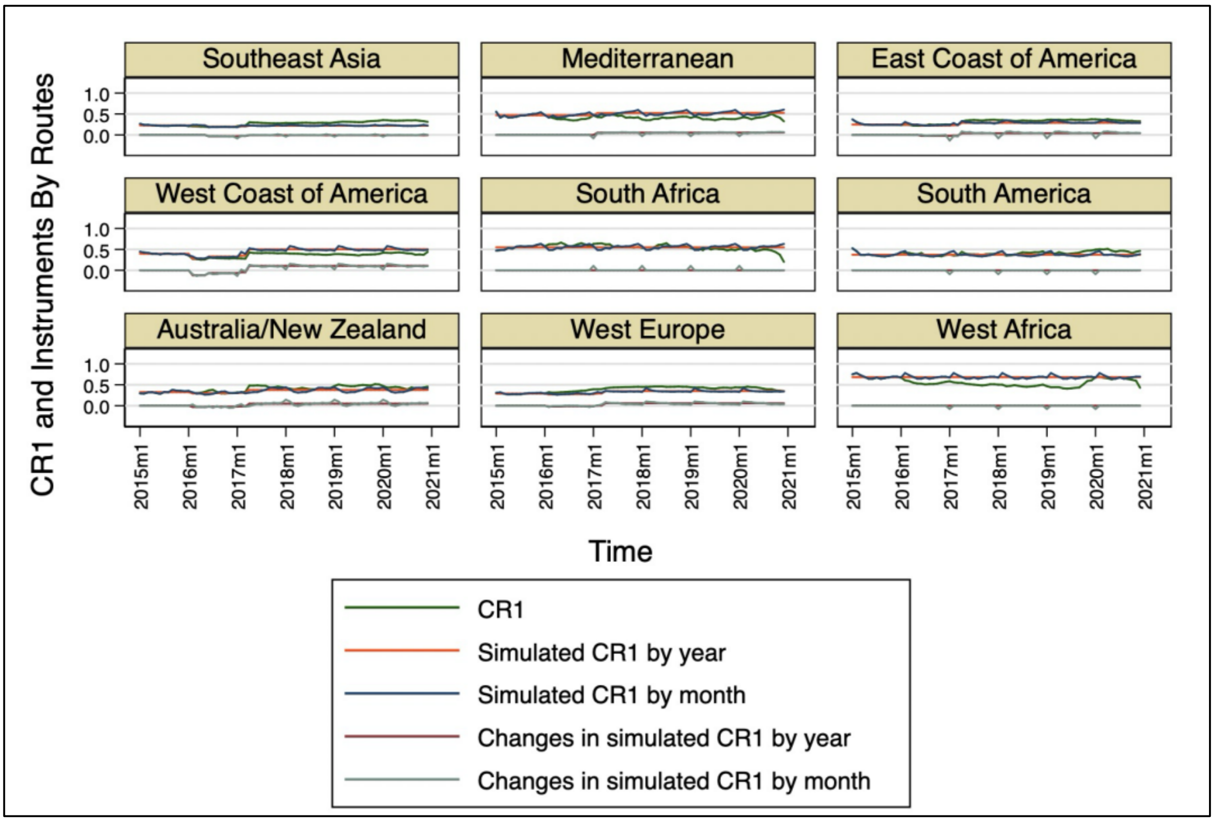

Fig. 3b. CR1 and Instruments

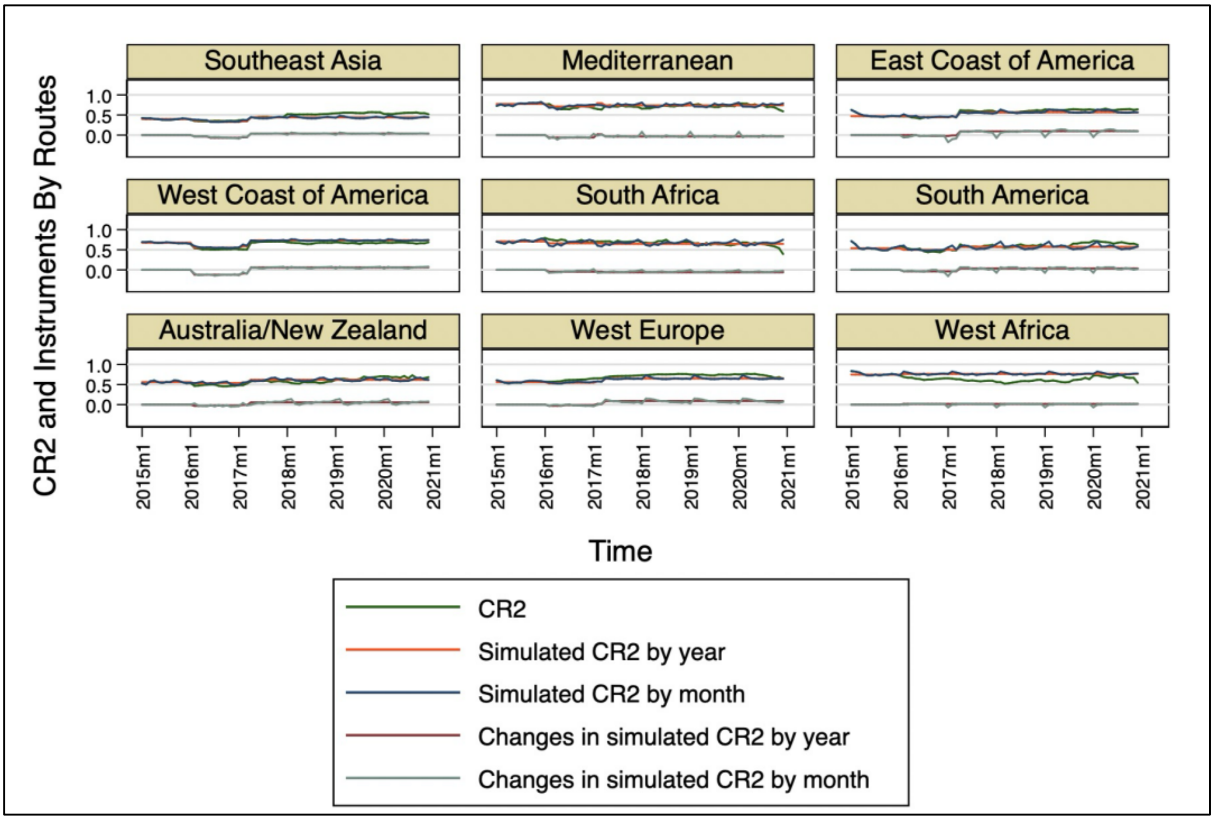

Fig. 3c. CR2 and Instruments

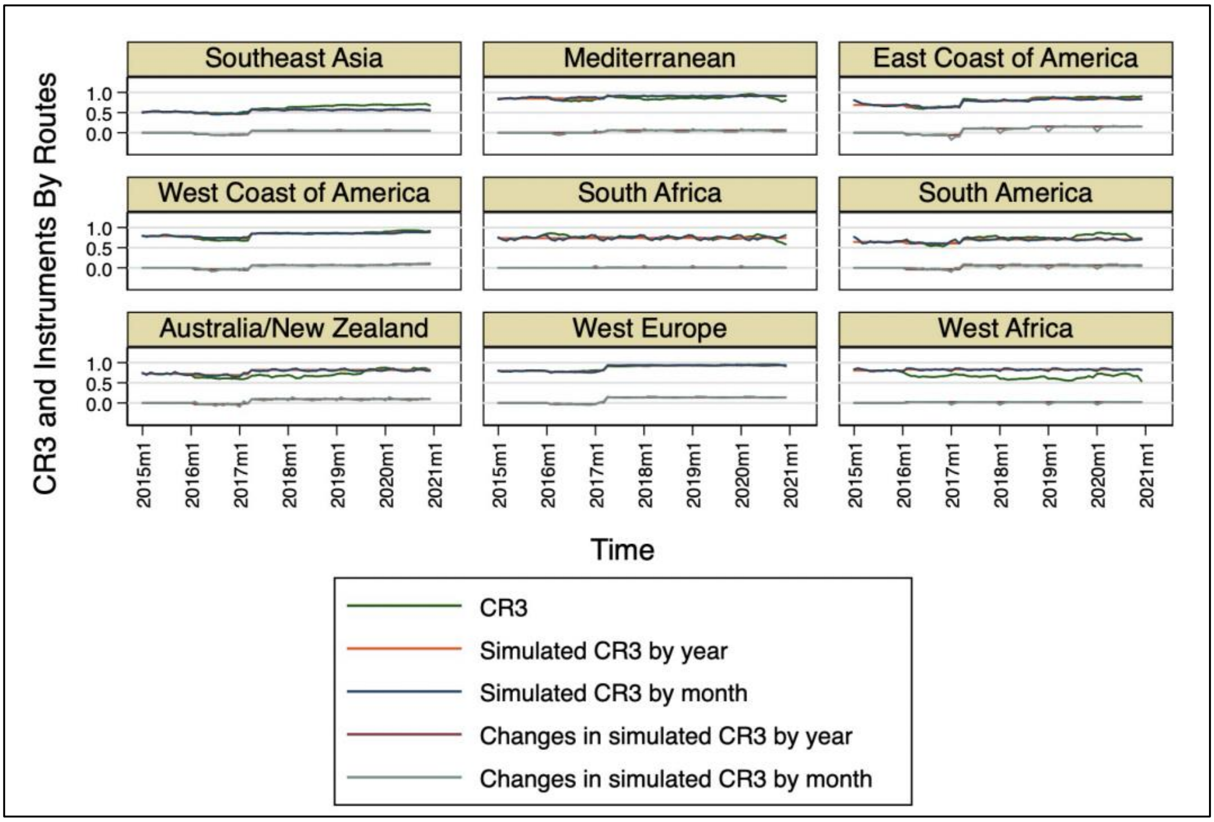

Fig. 3d. CR3 and Instruments

Combining data from the AIS and other sources, we constructed an unbalanced monthly panel of nine international maritime routes from 2015 to 2020, covering 648 observations in total. Table 3 presents the definition and data sources of all variables. Table 4 shows the statistical summary of all variables.

Table 3 Description of variables

| **Types** | **Variable** | **Description** | **Reference** |
|---|---|---|---|
| Dependent variable | *CCFI* | Monthly average all-in weighted freight rate of 10 trade lanes starting from 10 China hub ports, including freight and seaborne surcharges. | Merk and Teodoro (2022) |
| Variable of interest | *HHI_alliance* | Sum of squaring the market share of each ultimate company or alliance competing in a route, ranging from 0 to 1. | Calzada et al. (2022), Kwoka and Shumilkina (2010) |
| | *CR* | The sum of market shares of a number of top alliances. | Ha and Seo. (2013), Sys (2009), |
| Control variables | *GDP_P* | Annual GDP per capita of all destination ports' host countries on a route in US dollars. | Calzada et al. (2022) |
| | *Export* | Annual export value of goods from China to destination port's host countries on a route, in billion US dollars. | Jiang et al. (2018) |
| Instruments | $simHHI$ | Simulated alliance-level HHI based on alliance shares calculated by base-period firm-level market shares. | |
| | $sim\Delta HHI$ | Simulated change in alliance-level HHI compared to base-period alliance-level HHI. | Ashenfelter et al. (2015), Barkley and McLeod. (2022), Greenfield (2014) |
| | $simCR$ | Simulated concentration ratio based on alliance shares calculated by base-period firm-level market shares. | |
| | $sim\Delta$CR | Simulated change in concentration ratio compared to base-period concentration ratio. | Ashenfelter et al. (2015), Barkley and McLeod. (2022), Greenfield (2014) |

Note: Information about the oil price is available from Clarkson Shipping Intelligence Database. Annual GDP per capita is collected from Worldbank. Annual export value of goods from China is obtained from National Bureau of Statistics of China.

Table 4 Descriptive statistics of variables

| Variable Name | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| CCFI | 648 | 795.10 | 228.48 | 311.21 | 2213.09 |
| HHI_alliance | 648 | 0.26 | 0.08 | 0.09 | 0.63 |
| simHHI_year | 648 | 0.27 | 0.11 | 0.09 | 0.50 |
| simHHI_month | 648 | 0.28 | 0.11 | 0.09 | 0.63 |
| simΔHHI_year | 648 | 0.02 | 0.03 | -0.05 | 0.08 |

| | | | | | |
|---|---|---|---|---|---|
| simΔHHI_month | 648 | 0.02 | 0.03 | -0.11 | 0.11 |
| CR1 | 648 | 0.41 | 0.11 | 0.18 | 0.78 |
| simCR1_year | 648 | 0.41 | 0.14 | 0.19 | 0.68 |
| simCR1_month | 648 | 0.42 | 0.15 | 0.18 | 0.78 |
| simΔCR1_year | 648 | 0.02 | 0.04 | -0.12 | 0.11 |
| simΔCR1_month | 648 | 0.02 | 0.04 | -0.14 | 0.15 |
| CR2 | 648 | 0.62 | 0.10 | 0.34 | 0.83 |
| simCR2_year | 648 | 0.62 | 0.11 | 0.33 | 0.79 |
| simCR2_month | 648 | 0.62 | 0.12 | 0.32 | 0.83 |
| simΔCR2_year | 648 | 0.01 | 0.05 | -0.12 | 0.10 |
| simΔCR2_month | 648 | 0.01 | 0.05 | -0.18 | 0.15 |
| CR3 | 648 | 0.76 | 0.11 | 0.47 | 0.96 |
| simCR3_year | 648 | 0.77 | 0.11 | 0.46 | 0.93 |
| simCR3_month | 648 | 0.77 | 0.11 | 0.45 | 0.94 |
| simΔCR3_year | 648 | 0.04 | 0.06 | -0.06 | 0.15 |
| simΔCR3_month | 648 | 0.04 | 0.06 | -0.18 | 0.17 |
| GDP_P | 648 | 5.47E+04 | 5.02E+04 | 1.97E+03 | 1.90E+05 |
| Export | 648 | 1.40E+07 | 1.63E+07 | 9.70E+05 | 4.80E+07 |

## 6. Empirical results

Table 5 shows the regression results of price on alliance-level HHI. The first column shows the result of a two-way fixed effect OLS model, while columns 2 through 9 show, accordingly, the first and second-stage regression results of using four kinds of instruments. In the OLS model, the coefficients of alliance-level HHI are negative and statistically significant. As shown in column 1, a 1% increase in the $HHI\_alliance$ associates with a 0.226% decrease in the freight rate. The magnitude of alliance-level HHI's coefficient increases when instruments are used. That is, the 2SLS estimations are more negative than the OLS estimation, which is consistent with our expectation mentioned in Section 5.2. Using either $sim\Delta HHI\_year$ or $simHHI\_year$ as the instrument yields the same results. A 1% increase in $HHI\_alliance$ is associated with a freight rate drop of 0.456% when using either of them as the instrument. Because $sim\Delta HHI\_year$ equals $simHHI\_year$ minus a fixed value of simulated HHI at the base period, the volatility characteristics of these two instruments are identical[2]. Using $simHHI\_month$ as the instrument, a 1% increase in $HHI\_alliance$ results in a 0.348% decrease in freight rates. A

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[2] This logic also applies to simulated CR and simulated changes in CR when using annual firm-level market share of 2015 to estimate the alliance-level market shares in following years.

1% increase in $HHI\_alliance$ corresponds to a 0.406% decrease in freight rate when $sim\Delta HHI\_year$ is the instrument. The reported CD Wald F-statistics for all instruments are well above the threshold (e.g., 10) typically used to identify "weak" instruments (Stock & Yogo, 2005), indicating that all selected instruments are not weak. The GDP per capita and the value of export goods from China to the host countries reflect the economic condition and market demand of each shipping route. Their positive correlations identified in Table 5 with freight rates are intuitive.

Table 5 OLS and 2SLS regression results of alliance-level HHI

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
|  | OLS | 2SLS |  | 2SLS |  | 2SLS |  | 2SLS |  |
|  |  | IV = simHHI_year |  | IV = simHHI_month |  | IV = simΔHHI_year |  | IV = simΔHHI_month |  |
|  |  | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(HHI_alliance) | -0.226*** |  | -0.456*** |  | -0.348*** |  | -0.456*** |  | -0.406*** |
|  | [0.04] |  | [0.07] |  | [0.11] |  | [0.07] |  | [0.09] |
| ln(simHHI_year) |  | 1.349*** |  |  |  |  |  |  |  |
|  |  | [0.10] |  |  |  |  |  |  |  |
| ln(simHHI_month) |  |  |  | 0.532*** |  |  |  |  |  |
|  |  |  |  | [0.07] |  |  |  |  |  |
| ln(simΔHHI_year) |  |  |  |  |  | 1.349*** |  |  |  |
|  |  |  |  |  |  | [0.10] |  |  |  |
| ln(simΔHHI_month) |  |  |  |  |  |  |  | 0.829*** |  |
|  |  |  |  |  |  |  |  | [0.10] |  |
| ln(GDP_P) | 0.351*** | 0.533*** | 0.559*** | 0.754*** | 0.461*** | 0.533*** | 0.559*** | 0.659*** | 0.514*** |
|  | [0.11] | [0.13] | [0.12] | [0.14] | [0.14] | [0.13] | [0.12] | [0.13] | [0.12] |
| ln(Export) | 0.351*** | 0.492*** | 0.377*** | 0.272** | 0.365*** | 0.492*** | 0.377*** | 0.369*** | 0.371*** |
|  | [0.10] | [0.12] | [0.09] | [0.12] | [0.09] | [0.12] | [0.09] | [0.12] | [0.09] |
| Constant | -2.909 | -12.292*** | -6.043*** | -13.261*** | -4.570** | -15.308*** | -6.043*** | -14.814*** | -5.362*** |
|  | [1.78] | [2.18] | [1.92] | [2.47] | [2.10] | [2.20] | [1.92] | [2.41] | [2.03] |
| Route FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 |
| CD Wald F |  | 182.153 |  | 67.905 |  | 182.153 |  | 95.846 |  |
| Adj. R2 | 0.75 | 0.806 | 0.736 | 0.771 | 0.75 | 0.806 | 0.736 | 0.781 | 0.743 |

Dependent variable is ln(CCFI).
Standard errors in parentheses * $p<0.1$, ** $p<0.05$, *** $p<0.01$

The OLS and 2SLS regression results of price on CR1 are shown in Table 6. In the OLS estimation, the correlation between CR1 and price is significantly negative (column 1). A 1% increase in CR1 is correlated with a 0.246% pricing decrease. Columns 2 through 9 display consistent negative correlations between CR1 and price, and the coefficient of CR1 increases in magnitude when four distinct instruments are employed. Using either $simCR1\_year$ and $sim\Delta CR1\_year$ as the instrument, a 1% increase in CR1 will result in a 0.593% price decrease. When $simCR1\_month$ and $sim\Delta CR1\_month$ are used as instruments, the price may decrease by 0.384% or 0.446% if CR1 rises by 1%. As the CD Wald F-statistics are larger than 10, all instrumental variables passed the weak instrument test. Consistent with Table 5's findings, the correlation between two control variables remains strongly positive.

Table 6 OLS and 2SLS regression results of CR1

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS IV = simCR1_year | | 2SLS IV = simCR1_month | | 2SLS IV = simΔCR1_year | | 2SLS IV = simΔCR1_month | |
| | | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(CR1) | -0.246*** | | -0.593*** | | -0.384*** | | -0.593*** | | -0.446*** |
| | [0.04] | | [0.11] | | [0.13] | | [0.11] | | [0.13] |
| ln(simCR1)_year | | 0.749*** | | | | | | | |
| | | [0.08] | | | | | | | |
| ln(simCR1)_month | | | | 0.457*** | | | | | |
| | | | | [0.06] | | | | | |
| ln(simΔCR1_year) | | | | | | 0.749*** | | | |
| | | | | | | [0.08] | | | |
| ln(simΔCR1_month) | | | | | | | | 0.450*** | |
| | | | | | | | | [0.06] | |
| ln(GDP_P) | 0.282*** | 0.394*** | 0.473*** | 0.453*** | 0.358*** | 0.394*** | 0.473*** | 0.450*** | 0.392*** |
| | [0.10] | [0.10] | [0.11] | [0.11] | [0.11] | [0.10] | [0.11] | [0.11] | [0.11] |
| ln(Export) | 0.316*** | 0.114 | 0.304*** | 0.07 | 0.311*** | 0.114 | 0.304*** | 0.063 | 0.309*** |
| | [0.10] | [0.10] | [0.09] | [0.09] | [0.09] | [0.10] | [0.09] | [0.10] | [0.09] |
| Constant | -1.499 | -6.181*** | -3.845** | -6.657*** | -2.428 | -7.290*** | -3.845** | -7.147*** | -2.847 |
| | [1.77] | [1.98] | [1.90] | [2.05] | [1.83] | [2.01] | [1.90] | [2.07] | [1.94] |
| Route FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 |
| CD Wald F | | 76.158 | | 60.48 | | 76.158 | | 46.531 | |
| Adj. R2 | 0.75 | 0.761 | 0.722 | 0.755 | 0.748 | 0.761 | 0.722 | 0.749 | 0.742 |

Dependent variable is ln(CCFI).
Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

Table 7 contains the regression results for CR2. Using the OLS model, we found a significant negative correlation between CR2 and price, as shown in the first column. The 2SLS regression results from column 2 to column 9 indicate that a 1% increase in CR2 will result in a 0.488% to 0.646% decrease in price. The decrease was enhanced by the usage of instruments. In addition, as evidenced by the results of the first-stage regression, all instrumental variables exhibit a strong correlation with the endogenous variable and are not weak instruments. The results of control variables remain consistent and intuitive.

Table 7 OLS and 2SLS regression results of CR2

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
|  | OLS | 2SLS |  | 2SLS |  | 2SLS |  | 2SLS |  |
|  |  | IV = simCR2_year |  | IV = simCR2_month |  | IV = simΔCR2_year |  | IV = simΔCR2_month |  |
|  |  | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(CR2) | -0.361*** |  | -0.646*** |  | -0.496*** |  | -0.646*** |  | -0.488*** |
|  | [0.07] |  | [0.08] |  | [0.11] |  | [0.08] |  | [0.10] |
| ln(simCR2)_year |  | 1.305*** |  |  |  |  |  |  |  |
|  |  | [0.06] |  |  |  |  |  |  |  |
| ln(simCR2)_month |  |  |  | 0.753*** |  |  |  |  |  |
|  |  |  |  | [0.05] |  |  |  |  |  |
| ln(simΔCR2_year) |  |  |  |  |  | 1.305*** |  |  |  |
|  |  |  |  |  |  | [0.06] |  |  |  |
| ln(simΔCR2_month) |  |  |  |  |  |  |  | 0.756*** |  |
|  |  |  |  |  |  |  |  | [0.06] |  |
| ln(GDP_P) | 0.304*** | 0.314*** | 0.428*** | 0.357*** | 0.363*** | 0.314*** | 0.428*** | 0.351*** | 0.359*** |
|  | [0.11] | [0.06] | [0.10] | [0.07] | [0.11] | [0.06] | [0.10] | [0.07] | [0.10] |
| ln(Export) | 0.334*** | 0.180*** | 0.342*** | 0.141** | 0.338*** | 0.180*** | 0.342*** | 0.146** | 0.338*** |
|  | [0.10] | [0.05] | [0.09] | [0.06] | [0.09] | [0.05] | [0.09] | [0.06] | [0.09] |
| Constant | -1.973 | -5.764*** | -3.661** | -6.183*** | -2.772* | -6.966*** | -3.661** | -6.846*** | -2.725 |
|  | [1.77] | [1.08] | [1.68] | [1.26] | [1.66] | [1.09] | [1.68] | [1.24] | [1.70] |
| Route FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 |
| CD Wald F |  | 454.254 |  | 195.698 |  | 454.254 |  | 174.804 |  |
| Adj. R2 | 0.75 | 0.828 | 0.743 | 0.77 | 0.751 | 0.828 | 0.743 | 0.764 | 0.751 |

Dependent variable is ln(CCFI).
Standard errors in parentheses * $p<0.1$, ** $p<0.05$, *** $p<0.01$

In Table 8, we present OLS and 2SLS regression results for CR3. The coefficients of CR3 are significantly negative in all the models, indicating that an increase in CR3 correlates with a decrease in price. Specifically, a 1% increase in CR3 will result in a 0.531% decrease in price in the OLS regression. When we use instrumental variables to address the endogeneity problem, the magnitude of the price decline increases. The first-stage regression of endogenous variables on instruments is substantially positive, and the CD Wald F-statistics are greater than 10.

In sum, the findings using HHI, CR1, CR2 and CR3 are consistent. A strong negative relationship between alliance-level concentration and freight rate is observed. After addressing the potential endogeneity issue, this negative relationship becomes even stronger. Roughly, a 1% increase in alliance-related market concentration is expected to reduce freight rates by more than 0.4% in most cases and sometimes even over 0.7% when CR3 is in concern.

Table 8 OLS and 2SLS regression results of CR3

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS<br>IV = simCR2_year | | 2SLS<br>IV = simCR2_month | | 2SLS<br>IV = simΔCR2_year | | 2SLS<br>IV = simΔCR2_month | |
| | | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage | 1st stage | 2nd stage |
| ln(CR3) | -0.531*** | | -0.721*** | | -0.604*** | | -0.721*** | | -0.651*** |
| | [0.08] | | [0.11] | | [0.13] | | [0.11] | | [0.12] |
| ln(simCR3)_year | | 1.301*** | | | | | | | |
| | | [0.07] | | | | | | | |
| ln(simCR3)_month | | | | 0.828*** | | | | | |
| | | | | [0.06] | | | | | |
| ln(simΔCR3_year) | | | | | | 1.301*** | | | |
| | | | | | | [0.07] | | | |
| ln(simΔCR3_month) | | | | | | | | 0.898*** | |
| | | | | | | | | [0.07] | |
| ln(GDP_P) | 0.385*** | 0.292*** | 0.470*** | 0.331*** | 0.418*** | 0.292*** | 0.470*** | 0.317*** | 0.439*** |
| | [0.11] | [0.06] | [0.11] | [0.06] | [0.11] | [0.06] | [0.11] | [0.06] | [0.11] |
| ln(Export) | 0.292*** | 0.061 | 0.280*** | 0.03 | 0.287*** | 0.061 | 0.280*** | 0.046 | 0.285*** |
| | [0.10] | [0.05] | [0.09] | [0.05] | [0.09] | [0.05] | [0.09] | [0.05] | [0.09] |
| Constant | -2.221 | -3.801*** | -3.079* | -4.088*** | -2.55 | -4.655*** | -3.079* | -4.694*** | -2.761* |
| | [1.70] | [0.97] | [1.65] | [1.09] | [1.66] | [0.97] | [1.65] | [1.07] | [1.68] |
| Route FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 |
| CD Wald F | | 326.547 | | 173.054 | | 326.547 | | 182.769 | |
| Adj. R2 | 0.76 | 0.839 | 0.756 | 0.806 | 0.759 | 0.839 | 0.756 | 0.808 | 0.758 |

Dependent variable is ln(CCFI).
Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

## 7. Discussions

The empirical results indicate that the formation of large and dominant shipping alliances results in lower ocean freight rates. We found that several characteristics of the international shipping market might support our findings.

First, alliances allow shipping lines to build large networks, thereby making long-term contracts more attractive to customers (Mitsuhashi & Greve, 2009). CCFI includes both long-term contract rates and spot rates. The freight rate of a long-term contract is generally lower than the spot market price because a long-term contract can provide a more stable shipping demand for liner shipping companies, giving them incentives to charge less (Wang et al., 2022). Large freight forwarders and international trading companies prefer to have long-term (usually one year or more) contracts with shipping lines that operate highly interconnected route networks. The authors have interviewed two representatives of liner companies, and they suggested that SAs will motivate freight forwarders to establish more long-term contracts than spot market agreements, which could possibly reduce the average market price.

Second, the actual direction of price changes in the post-alliance period depends on the dominate effects of efficiency gains and market power (Prager & Hannan, 1998). The empirical results indicate that capacity sharing among alliance members may provide efficiency gains for shipping lines. Alliances allow members to cooperate on capacity on different routes, reducing costs, reallocating excess space resources, and more importantly, improving load factors.[3] It is anticipated that by swapping vessels or positions with alliance members, individual liner companies will have more capacity available for drop-shipment and the opportunity to promise more positions to shippers. Overbookings can be absorbed by other alliance members, resulting in an overall increase in the loading factor within the alliance (Song & Wang, 2022). Improving load factor is particularly crucial under poorer market conditions, such as the 2015–2020 period of this study, when capacity far exceeds demand and liner companies can share the risk with alliance members.

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[3] Dobson & Piga, (2013) found the acquiring airlines' load factor increased after Ryanair's takeover of Buzz and EasyJet's acquisition of Go Fly.

Our results seem different from the findings in the airline industry, where airline alliances were found to have an insignificant impact on prices on overlapping international routes in most cases. Three possible reasons might explain why.

The benefits of efficiency gains from alliances, though relevant to airlines as well, can be much stronger for shipping lines because shipping lines have a lower level of service information transparency. In shipping, e-booking is underdeveloped, and there is a lack of an integrated and transparent container booking platform (Zeng et al., 2021). Though some pioneers, such as Maersk, Onetouch of Alibaba Group, Flexport, and Freight Hub, have offered e-booking services, the majority have failed or are struggling (Zeng et al., 2021). Most small shippers only have access to the price and slot information of a limited number of liner companies, making it highly common that some liner companies run out of slots while others hold lots of unsold slots. Air passengers enjoy a higher level of information transparency when searching for deals than maritime shippers. Air passengers have access to real-time information on fares and the availability of seats and flights for almost all airlines operating in the market via consistent and well-integrated platforms, such as the global distribution systems. Multiple sales channels, such as online travel agents, airlines' own websites, and offline travel agents, can all provide transparent information and reduce passengers' searching costs. As a result, passengers and empty seats tend to be well matched for airlines. The consequence is that shipping lines are more challenged to maintain a high average load factor. In such cases, alliances offer a channel for shipping lines to overcome the information sharing barrier and lift service efficiency by coordinating capacity with alliance members.

Besides, even if market concentration is relatively high, incumbents may be unable to exercise market power if potential entrants can start producing substitutes easily and rapidly (Hüschelrath & Müller, 2015). Airlines face more entry barriers, especially for passenger services, than shipping lines, primarily due to the traffic rights restrictions governed by the air service agreements. These barriers help airline alliances exercise market power without being undercut by new entrants. In most cases, only airlines registered in the states who are the signing parties of the air service agreements have the chance to be designated to operate on related international routes. That is, the nationality of the airline and the traffic rights granted in the air service agreements jointly determine whether a certain airline can enter a specific international route or not. These barriers can effectively prevent competitors, regardless of size, from entering the affected international routes. However, shipping lines face no such restrictions on their entry to international routes compared with the airline. Therefore, post-alliance entry in the liner shipping industry is more likely to mitigate the market power of alliances.

Finally, maritime alliances face more restrictions than airline alliances in price cooperation and are hence more likely to lower prices in the presence of rivals and efficiency gains. Antitrust immunities have been granted to airline alliance members, allowing for joint pricing and scheduling decisions and even revenue sharing (Bilotkach, 2005; Bilotkach & Hüschelrath, 2019). While both theoretical and empirical evidence has shown that airline alliances operating with antitrust immunity tend to lower fares on interline routes (Brueckner, 2001, 2003; Brueckner et al., 2011; Whalen, 2007), studies of antitrust immunity on overlapping air routes are more relevant to our context. Theoretical predictions by Brueckner (2001) and Bilotkach (2005) indicate that air alliances that are immune to antitrust regulations would increase fares on overlapping air routes. However, using transatlantic flight ticket data in the third quarter of 1999, Bilotkach (2007) failed to observe a robust positive price effect for non-stop travel between hubs of alliance partners with antitrust immunity. Brueckner & Singer (2019) empirically quantified the fare impacts of antitrust immunity granted to US air carriers and their foreign partners on overlapping gateway-to-gateway air routes. Their research suggests that granting antitrust immunity to two previously unaligned carriers is equivalent to eliminating a competitor from the route, leading to increased ticket prices.

In contrast, antitrust immunities are rarely granted to shipping lines on major routes in nowadays' alliances. Shipping lines used to be granted the privileges of price-fixing and capacity coordination in the form of liner conferences in the 20th century (Notteboom et al., 2022), but the European Union repealed the antitrust immunity in 2008, effectively ending the era of liner conferences in Europe. These conferences have been replaced by alliance agreements, which are regulated against anti-competitive behaviors such as price fixing. In the United States, the Federal Maritime Commission (FMC) exercises regulatory authority to review and approve agreements such as consortiums or alliances, scrutinizing them for compliance with antitrust laws. Additionally, China's *Anti-Monopoly Law* and the *Regulations of the People's Republic of China on International Shipping* also restrict the monopolistic behavior of alliances. Therefore, the prohibition on price cooperation in ocean transport would lessen the anticompetitive effects of SAs.

## 8. Conclusions

The shipping industry has recently undergone a substantial reorganization of alliances, prompting the question of the price effects of these alliances. To the authors' best knowledge, this is the first attempt to empirically evaluate the actual effects of shipping alliances on prices. To address the problem of unavailability of data, this paper utilizes the global satellite data of ship position from the AIS database during 2015-2020 to estimate the market share of different alliances and derive the concentration of alliances. Another challenge is the endogeneity of the alliance's concentration and price. We employed simulated change in market concentration as instrumental variables to control the endogeneity. Using panel data for nine international shipping routes, we find that the increase in alliance-level HHI led to a price drop, holding other factors constant. Similar results are obtained when using the CR indices to measure market concentration. From a practical perspective, the findings reassure policymakers that competition in the global shipping industry is sufficiently strong to mitigate the market power effects of large consolidations.

Empirical studies on the price effect of alliances in shipping are much fewer than those on airlines. Our study is a novel attempt to extend the focus to the shipping field. Although our result differs from airline alliance studies, which found no significant price effect of alliances on overlapping routes, three different characteristics of the airline and shipping line industries may explain why. First, shipping alliances may increase the demand for long-term freight contracts with reduced prices, thereby lowering the average market price. Second, shipping lines may experience greater efficiency gains than airlines as a result of low information transparency. Finally, shipping lines face fewer entry barriers than airlines in the international route markets, leading to a stronger threat of potential entrants and hence downward pressure on price.

Future research may extend in several directions if quality data becomes available. Due to data limitations, the study assumes alliance members share all their vessels among each other. If detailed alliance agreement information is available, it will be interesting to examine the heterogeneous impacts due to different levels of cooperation by considering the actual proportions of vessels being shared among members. As our sample routes all pass through China and are therefore subject to Chinese antitrust law, we only consider the cooperation of alliance members in terms of capacity and not cooperative price in this paper. Chinese law prohibits horizontal price coordination among shipping companies. Few countries permit the inter-alliance price cooperation of airlines, and the rationality of price cooperation is being investigated by an increasing number of researchers. Cooperative pricing in the shipping industry (e.g., liner conference) still exists on few shipping routes. Future research might as well consider the distinctions and applicability of inter-alliance price cooperation mechanisms in aviation and shipping.

In this study, the alliance-level HHI is utilized as a quantitative metric to assess the impact of alliances. However, it is essential to recognize the inherent limitations of this measure. The HHI assumes a simplistic linear relationship between market share and market competition, positing that a larger market share corresponds to reduced levels of competition. However, in practical settings, market competition is influenced by a multitude of intricate factors, including barriers to entry, product differentiation, and supply chain efficiency, which the HHI fails to fully capture. Moreover, market definition plays a pivotal role in determining HHI values, and in this study, the market is defined at the shipping route level, disregarding capacity exchanges between routes. Future research endeavors should aim to refine the HHI measure by incorporating granular company-level capacity data, thereby enhancing its robustness and accuracy in assessing market competition.

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