Cost of Container Shipping Delays in International Trade: A Quantile Approach

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This study offers new empirical insights into the cost implications of container shipping delays and schedule unreliability on international freight rates, using a quantile regression model to capture market heterogeneity. While literature widely acknowledges the theoretical impact of schedule issues on trade costs, there has been a critical lack of empirical analysis quantifying this relationship under different market conditions. The purpose of this study is to explore the influence of schedule reliability in container transportation on freight rates. By integrating the China Containerized Freight Index (CCFI) with key variables such as average vessel delay, schedule reliability, bunker prices, and the Li Keqiang index as a proxy for demand, this research addresses that gap. Unlike conventional linear models, the use of quantile regression reveals how the effects of delays and reliability differ across various freight rate levels, yielding a U-shaped impact pattern—strongest in the worst and booming market conditions. The findings indicate that even a one-day increase in average delay can raise the CCFI by 100-226 index points, while a one-point decrease in schedule reliability can increase the index by 5-13 points. Therefore, service reliability is important for international trade, and countries, individuals, and ship owners adopt different pricing policies in response to market conditions. This study adds significant value to the field by providing policymakers and logistics stakeholders with actionable metrics on the cost of inefficiencies in global maritime transport, especially in post-pandemic and geopolitically volatile contexts.

KEYWORDS

~ International trade
~ Freight rate
~ Quantile regression
~ Service reliability

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1. INTRODUCTION

Due to features such as the ability of various vehicles (ship, train, truck) to transport containers with different types of cargo, which can then be handled by different types of equipment and facilities (terminal, crane, tugboat, wagon, lifter, warehouse, etc.) throughout the supply chain, from door to door, container transportation is considered one of the most critical steps in the global supply chain (Song, 2021). This mode of transport accounts for more than 50% of the world's maritime trade by value (Lee and Song, 2017). In today's highly competitive environment, the most important factor in determining the costs of container transportation, a key part of the entire supply chain process (Chung and Chiang, 2011), is undoubtedly freight rates (Saeed et al., 2023). Additionally, seaport competition and technical efficiency significantly influence overall supply chain performance and cost structures, especially in container terminals (Kammoun and Abdennadher, 2023a). Studies have shown that the service levels and adequacy of container terminals and their related facilities are correlated with port performance (Kammoun and Abdennadher, 2023a; Yeo, 2010). Due to these factors, container terminal service levels can also be considered one of the important factors affecting shipping line schedule reliability.

Recent studies have increasingly focused on the economic consequences of shipping delays and their broader implications for international trade. Carreras Valle and Ferrari (2025) demonstrated that increasing delivery delays and variability in global sourcing have led to significant output losses and inflationary pressures, highlighting the macroeconomic importance of timing in logistics. Kolacz et al. (2024) provide a detailed assessment of the cost structures associated with container delays, indicating that demurrage and detention fees frequently exceed the opportunity cost of delayed cargo, imposing a substantial financial burden on supply chain stakeholders. Hossen (2023) analyzed shipping behavior at company level in Bangladesh and found that longer delivery times increase costs per shipment and reduce shipment frequency, directly linking time delays to trade friction. Similarly, Verschuur et al. (2020) used vessel-tracking data to estimate the level of the sharp decline in global maritime trade during the early phases of the COVID-19 pandemic, quantifying the economic toll of systemic delays. Complementing these findings, Van Twiller et al. (2025) devised operational strategies for reducing cost inefficiencies under demand uncertainty using machine learning methods, reflecting a growing emphasis on proactive delay mitigation. Together, these studies provide strong empirical and theoretical support for examining in what way service reliability and timing influence freight rates and trade dynamics.

Shipping line schedule reliability affects inland transportation, shippers (Chung and Chiang, 2011), and, most importantly, costs (Notteboom, 2009). Therefore, schedule reliability has a significant impact on operational performance, service quality, and customer satisfaction with container shipping lines (Chung and Chiang, 2011). These effects became even more apparent during the COVID-19 pandemic, when several studies reported notable disruptions in port operations, significantly impacting port activity levels and logistics performance (Kammoun and Abdennadher, 2023b; Kammoun and Abdennadher, 2024).

Cost increase due to delays in container transportation affects not only cargo owners but also increases the final prices of internationally traded goods (Wilmsmeier, 2014:26). As stated in the literature, delivery delays and global supply disruptions cause inflationary pressures (Ferrari, 2025). Shipping delays resulting from supply chain disruptions lead to delays in raw material delivery and rising input costs, affecting the early stages of production and distribution chains and causing product prices to gradually increase from production to the end user (Michail et al., 2022). Asadollah et al. (2024) examined the effects of geopolitical risks and supply chain pressures on global inflation and found that disruptions in global supply chains are the main driver of global inflation. The authors argue that these disruptions are the leading factors behind long-term inflationary pressures and explain most of the volatility in headline, core, and food inflation. Thus, inflationary pressure can be attributed to rising prices, decreased purchasing power, increased demand for foreign currency, higher foreign trade costs, and increased capital costs of goods. Higher foreign trade costs may adversely affect the competitive power of exporters compared to other countries (Guasch, 2022:1). For this reason, service reliability in terms of timing in container transportation is crucial for both countries and individuals. This study aims to reveal the importance of service timing in international trade by empirically analyzing the effect of average delay time and service reliability index on freight rates. Two proxy variables were included in the cost and demand model, which have an indisputable effect on freight rates. Based on the distribution of the freight variable and the generally limited competition in container transportation, we determined that quantile regression analysis was more appropriate for our research. Limited competition may cause the pricing policies of service providers to differ depending on the freight market situation. Quantile approach captures this differentiation by enabling the analysis of the dependent variable (Fitzenberger, 2012:42), such as market conditions, in different distribution regions where freight rates are extremely high, stable, or extremely low. The results show that the effect of delays on freight rates is significant and positive in all quantiles, the effect of reliability on freight rates is significant and negative in most quantiles, the effect of bunker price on freight rates is significant and positive when freight rates are increasing, and the effect of demand on freight rates is significant and positive when freight rates are low. Additionally, the coefficients of these interactions differ by quantile, indicating that ship owners' pricing policies vary depending on market conditions. For our main variables, longer delays increase, while improved reliability decreases freight rates. This finding highlights the importance of timely service for both individuals and countries.

In the literature review section, the formation of freight rates, the main factors affecting freight rates, and the importance of container shipping schedule reliability are discussed in detail. In the data and methodology section, the main variables and control variables used in the analysis are explained: CCFI, container service reliability, average delay time of container ships, bunker price, and the Li-Keqiang index. The results of the study are then presented, followed by conclusions.

2. LITERATURE OVERVIEW

Maritime transportation, which accounts for approximately 90% of international transport activities (OECD, 2023), is the backbone of global trade. Freight rates are among the most crucial elements in determining the cost of these transportation activities (Rodrigue et al., 2006:46). In international maritime transportation, container transportation predominates in the transfer of finished goods (Saeed et al., 2023). As a result, there is a substantial number of studies on the formation and forecasting of freight rates in container cargo transportation. Given the extensiveness of existing studies, a comprehensive overview is beyond the scope of this paper; therefore, only general framework is given.

Stopford (2009) argued that freight rates are formed within the supply-demand relationship and explained the supply and demand variables that determine freight rates in maritime transport by dividing them into five factors. Transportation costs, seaborne commodity trades, random shocks, the world economy, and average haul affect the demand side of maritime transport, while fleet productivity, scrapping and losses, shipbuilding production, world fleet, and freight revenue affect the supply side. According to Efes (2019), freight rates depend on the interaction between these variables, which are at the center of the transportation market and are the most important elements of transportation cost. In addition to these supply and demand factors, the bargaining power of market participants is also crucial in the formation of freight rates. The equilibrium price changes according to market conditions. In a market with low freight rates and relative oversupply, shippers have higher bargaining power, and the agreed price will be slightly below the equilibrium price. Conversely, when supply is limited and demand is high, ship owners have higher bargaining power, and the price will exceed the equilibrium price. Bargaining power may also differ for various cargo owner and ship owner profiles (Karakitsos and Varnavides, 2014:27).

As Stopford (2009) points out, freight rate fluctuations and economic cycles have been part of the shipping industry for hundreds of years. Similar to the global financial crisis in 2009 (Munim and Schramm, 2017), the global pandemic that began in 2019 also affected the maritime industry (UNCTAD, 2022). The pandemic caused demand fluctuations in 2021, severely disrupting global supply chains, increasing port congestion and ship waiting times, and slowing hinterland transport. As a result, container freight rates rose significantly in 2021 (UNCTAD, 2022) and reached record levels, as shown by the China Containerized Freight Index (CCFI) data in Figure 1.

A disruption in one area of the complex global supply chain system in which maritime transport operates can quickly spread to other areas. During the pandemic, labor shortages, container shortages, port closures, congestion, constraints in hinterland transport, and limited storage and warehouse capacity caused delays, increased vessel waiting times and congestion, and reduced effective shipping capacity. For example, in 2020-2021, when the pandemic was at its peak, global container tariff delays approximately doubled. As a result, the inability of container carriers to load and unload efficiently led to decreased reliability of services and schedules (UNCTAD, 2022).

Given that maritime transportation is a vital part of the global supply chain, the reliability of container shipping lines is critical (Chung and Chiang, 2011). Schedule reliability is one of the main factors in liner shipping. Containerization, which emerged in the 1950s to become a breakthrough in maritime transport, facilitated Just-in-Time (JIT) production by improving safety, decreasing transport times, and increasing schedule reliability at lower cost (Notteboom, 2006). Shippers often rely on schedule reliability to make the best choice for their supply chain during the container shipping line selection process. Schedule disruptions reduce the reliability of line services and cause additional inventory or production costs (Notteboom, 2006; Chung and Chiang, 2011; Song, 2021).

While the importance of container shipping schedule reliability is well established in the literature, the Drewry Shipping Consultants group, which monitored the schedule reliability of 5,410 ships on 23 different routes over a six-month period in 2006, reported a notable finding. They concluded that more than 40% of the monitored ships failed to comply with the schedule. Of these tracked vessels, 52% arrived at their estimated time of arrival (ETA), 21% were delayed by one day, 8% by two days, and 14% by three or more days. The remaining 4% arrived earlier than their planned ETA (Vernimmen et al., 2007). In the post-pandemic period, due to the imbalance of supply and demand in container transportation, major problems arose in the timely arrival of ships. In January 2022, record 69.6% of ships failed to arrive on time (Sea-Intelligence, 2023) which increased freight rates by restricting supply.

The main source of schedule unreliability is identified in the literature as port- and terminal-related variables. According to Notteboom (2006), 93% of schedule unreliability issues are caused by port congestion and uncertain handling time variables (Song, 2021). Vernimmen et al. (2007) stated that unfavorable weather conditions at sea, port traffic jams, labor strikes, ship collisions, ship groundings, and container services supply and demand imbalances are among the reasons for unreliable schedule times. Okur and Tuna (2022) analyzed 5,080 shipping line transport records and concluded that season, vessel TEU capacity, type of service, and vessel age are also important factors affecting schedule reliability. Chang et al. (2015) and Chang et al. (2019) treated schedule unreliability as a risk, given that it directly affects supply chain success, causes delays, and damages the reputation of shipping companies. They advised shipping lines to be flexible when designing schedules, noting that adding at least some buffer time to accommodate minor delays would reduce this risk.

In recent years, the growing complexity of global trade networks has drawn greater attention to the role of container shipping reliability and delays in shaping international trade dynamics. Numerous studies have examined the multifaceted impact of delays on cost structures, operational efficiency, and macroeconomic outcomes. These contributions provide a strong empirical and theoretical foundation for analyzing the relationship between freight rates and service reliability in container transportation. Carreras Valle and Ferrari (2025) investigated the broader economic consequences of delivery delays and variability within global supply chains. Using a dynamic general equilibrium model, they found that disruptions between 2018 and 2024 resulted in a 2.6% contraction in global output and contributed to a 0.4% rise in aggregate price levels. Their findings highlight the persistent inflationary effects of logistical disruptions and underscore the need to evaluate time-induced trade costs more precisely. Kolacz et al. (2024) examined the economic and legal ramifications of container shipment delays through an empirical analysis of operational data from key ports and shipping companies in 2020-2023. Their study shows that demurrage and detention charges often exceed the opportunity cost of delayed goods, indicating that delays impose not only logistical but also substantial financial burdens. These findings reinforce the real-world cost implications of service unreliability in container transport. In a company-level study, Hossen (2023) explored the impact of extended delivery times on the behavior of exporters in Bangladesh. The study found that increased shipping delays reduce shipment frequency and increase costs per shipment, with a 10% cost increase resulting in a 3.45% decline in shipment frequency. This microeconomic evidence supports studies that emphasize time as a critical trade cost, directly justifying the use of delay variables in freight rate modeling. Using AIS-based maritime tracking data, Verschuur et al. (2020) quantified the effects of COVID-19-related restrictions on global shipping activity. Their analysis estimated a 7% - 9.6% reduction in global maritime trade in the early pandemic period, resulting in trade value losses approaching $412 billion. The study demonstrates how systemic delays, driven by external shocks, can significantly disrupt international trade flows. Van Twiller et al. (2025) applied deep reinforcement learning techniques to optimize container stowage under uncertain demand conditions. Their model aimed to minimize operational inefficiencies by dynamically adjusting storage decisions in response to real-time changes in cargo flow. While their approach is technological, it offers valuable insights into managing and mitigating the cost impacts of shipping delays. Earlier foundational works continue to inform current research. Notteboom (2006) provided an early conceptual framework for understanding the role of schedule reliability in liner shipping and its impact on shippers' logistics planning. The study argues that time reliability is as important as cost and frequency in determining service value, laying the theoretical groundwork for later empirical studies. Together, these studies show that container shipping delays are not only operational challenges but also macroeconomic stressors with significant implications for international trade, cost structures, and service reliability.

In general, regardless of the source, delays in container transportation services can negatively affect a company's competitive position by reducing service reliability and causing a loss of prestige at the micro level. At the macro level, the effects of cumulative delays and decreased service reliability are even more significant. First, international trade slows as cargo cannot be delivered on time, which in turn slows the rate of increase in societal welfare. Second, this situation increases capital costs for shippers and decreases their sustainable growth rate. Third, delays also increase freight rates by reducing available capacity on the supply side. This is an important issue for the global economy for several reasons: (i) it increases the cost of international trade and reduces trade volume; (ii) it creates inflationary pressure by raising final product prices; (iii) quality of life and welfare decline as societies can purchase less with their budgets; (iv) countries require more foreign currency to conduct international trade. In this context, we analyzed the impact of global delays and changes in service reliability on container freight. Although the increasing effect of delays has been theoretically addressed in the literature, there is little empirical evidence to quantify this effect. Additionally, since container market freight rates are not directly determined by the market, shedding light on this empirical relationship is challenging. With this in mind, we estimated our model using the quantile approach and presented results on the magnitude of the effects of delay and reliability.

3. MATERIALS AND METHODS

The China Containerized Freight Index (CCFI) has been published since January 1998 and has become the most effective and useful freight index in the world after the Baltic Dry Index (BDI). It provides information to shipping companies, commercial enterprises, governments, investors, and regulatory authorities by measuring traffic from China to other countries, based on China's status as the world's largest manufacturing base (SSE, 2023). The CCFI consists of the prices of containers shipped from major ports in China. It is a composite index that combines spot and contract rates (Notteboom, 2022:36). As shown in Figure 1, the decrease in trips due to decreasing demand during the pandemic, reduced ship capacities, the problem of empty containers, booming online shopping, and port congestion after the pandemic caused a record increase in freight rates. This increase in freight rates was also supported by higher oil prices, but rates started to decline as demand decreased. Additionally, a large number of new container ships were ordered in 2021, i.e. approx. 18%

of the existing fleet. In a few years, these new ships will likely increase supply and cause a long-term decrease in freight rates, as macroeconomic measures taken to curb inflation reduce demand.

The delay variable represents the global average delay for late vessel arrivals. The data, collected by Sea Intelligence (2023), measures the average number of days per month that container ships are delayed in arriving to the ports they serve. When examining the historical trend of delays in Figure 1, the average delay time increased significantly, especially after the onset of COVID-19. In January 2022, the average delay time reached the all-time high of 7.9 days. The main reason for this was the supply-demand imbalance and supply chain problems experienced during and after the pandemic, which paralleled the situation in freight rates. Although container transportation is known for not waiting for delayed cargo at the port, port congestion causes ships to unload their cargo late, resulting in delays at the following ports. Toward the end of 2020, port congestion in the Los Angeles/Long Beach area and the blockage of the Suez Canal by a ship in March 2021 increased pressure on the supply chain and caused further delays.

The reliability variable represents global schedule reliability. The data compiled by Sea Intelligence (2023) measures the monthly reliability of container shipping services. The calculation is as follows:

$$\frac{Total\ Sails - Lost\ Sails}{Total\ Sails} \tag{1}$$

Ships arriving only one day after the ETA are considered to have arrived on time. This measures the number of vessels providing container transportation services that reach their destination port on time. The reliability index is related to the average delay variable but measures a different aspect. With the increase in delays, reliability reached historically low levels during the pandemic and immediately thereafter. Recently, it has begun to recover as the supply chain returned to normal and economic activity slowed down due to inflationary concerns.

The Li Keqiang Index is named after its creator, who served as the premier of the People's Republic of China from 2013 to 2023. It is an economic indicator developed as an alternative measure of China's economic situation. The index consists of three components with different weights: electricity consumption (40%), railway freight volume (25%), and bank lending (35%). For a long time, the index has been calculated and published monthly, except for January. This index was developed due to suspicions that China's official GDP figures may be manipulated. For example, in some periods, high GDP growth was reported while electricity consumption and railway freight volumes declined. As a result, the index is more volatile than GDP and better captures economic downturns and upswings (Ebbers, 2019:8). However, despite its popularity, it is considered a better indicator for commodity-intensive sectors owing to its components. Its quality as an indicator for the overall economy remains low, as it does not reflect a significant share of the service sector (Wang, 2023:251). In addition to the Li Keqiang Index, several other macroeconomic and financial indicators have been used in the literature as proxies reflecting the impact of global or regional demand on maritime transportation. For example, composite equity market indices, such as the Wilshire 5000 Index (Michail and Melas, 2023), the Dow Jones Industrial Average (Kawasaki et al., 2022; Acik et al., 2025), and the Shanghai Composite Index (Chen et al., 2021), are frequently used to reflect investor trends, economic expectations, and overall business cycle conditions. These indicators are particularly useful in container shipping analysis, as they capture changes in consumption and industrial activity that drive trade volumes. One of the main reasons for the increasing use of such indices as demand-side proxies is their higher publication frequency compared to traditional macroeconomic variables such as GDP or trade volumes, allowing for a more responsive and timely market dynamics modeling. While the Li Keqiang Index is particularly relevant for commodity-heavy and export-oriented economies like China, including broader financial market indicators in future research could improve our understanding of demand-side dynamics in maritime transport.

In the period shown in Figure 1, economic activity declined significantly due to pandemic-related shutdowns. However, with subsequent normalization, economic intensity peaked as previously unmet demand was met. Recently, the index has remained below average due to global stagnation.

The bunker variable represents the global 20-port average price of VLSFO. The data are published on the Ship & Bunker (2023) website and reflect bunker price per ton. To ensure data consistency, monthly averages of the daily data were used. Bunker prices are strongly correlated with oil prices. A strong positive correlation of 0.89 ($t = 17.54$, $p = 0.00$) was found between our variable and West Texas Intermediate (WTI) oil prices. Bunker prices decreased due to falling oil demand due to declining economic activity during the pandemic. Subsequently, as oil production was cut, increasing demand caused prices to rise again. The invasion of Ukraine by Russia, one of the world’s major oil producers, created supply problems and resulted in very high prices. However, the subsequent economic slowdown and inflationary expectations reduced the demand for oil, causing prices to drop.

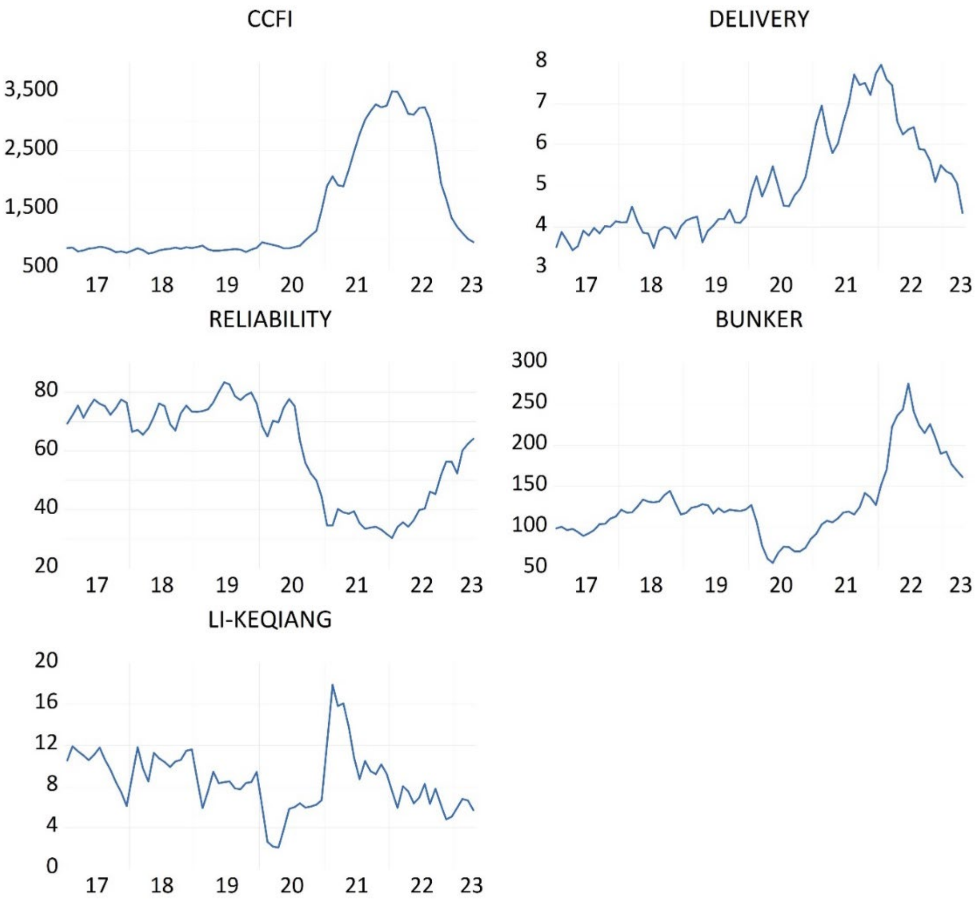

Figure 1. Course of the variables (Source: Sea-Intelligence (2023); Ship & Bunker (2023); SSE (2023)).

Descriptive statistics for the variables are given in Table 1. To examine the proportional and distributional characteristics of the variables, statistics are provided in both raw and log return forms. Since the Li Keqiang index was not published in January, the December and February averages for the relevant period were used to complete the missing observation. When the distribution characteristics of the raw variables are examined, all exhibit abnormal distributions at the 90% confidence level. In the case of return forms, all variables except Delivery have abnormal distributions. The abnormal distribution and autocorrelation of our dependent variable, CCFI, support the rationale for using quantile regression analysis instead of linear regression. Additionally, the fact that all skewness values in the return series are negative indicates that negative news had a greater impact during the period under consideration. Although peaks were observed, the declines from those peaks were more severe than the rises. When the standard deviation to means ratios are examined, variation coefficients are 64% for CCFI, 36% for Bunker, 34% for Li Keqiang, 28% for Reliability, and 25% for Delivery. This further supports the importance of choosing the quantile approach by highlighting the riskiness and volatility of the CCFI, or freight rates.

	CCFI	DEL.	REL.	BUN.	KEQ.	Δ Ln CCFI	Δ Ln DEL	Δ Ln REL	Δ Ln BUN.	Δ Ln KEQ
Mean	1453.3	5.03	60.8	129.8	8.61	0.0015	0.0028	-0.0010	0.0065	-0.0081
Median	871.6	4.51	67.4	120.1	8.44	0.0075	0.0070	-0.0001	0.0128	-0.0243
Maximum	3510.8	7.94	83.4	274.8	17.8	0.2686	0.1315	0.1507	0.2674	0.6168
Minimum	751.5	3.44	30.4	56.9	2.06	-0.2853	-0.1580	-0.2497	-0.3194	-0.8312
Std. Dev.	936.7	1.27	16.9	46.7	2.92	0.0834	0.0684	0.0706	0.0891	0.2221
Skewness	1.14	0.78	-0.53	1.17	0.43	-0.07	-0.28	-0.53	-0.47	-0.02
Kurtosis	2.64	2.39	1.72	3.95	3.92	5.79	2.34	4.34	5.35	5.42
Jarque-Bera	17.04	8.85	8.85	20.37	5.18	24.4	2.34	9.28	20.1	18.3
Probability	0.00	0.01	0.01	0.00	0.07	0.00	0.30	0.00	0.00	0.00
Observations	76	76	76	76	76	75	75	75	75	75

Table 1. Descriptive statistics for the variables (Source:Sea-Intelligence (2023); Ship & Bunker (2023); SSE (2023)).

In this study, quantile regression analysis was used instead of linear regression to model relationships between variables. The main advantage of quantile regression is its ability to provide a more comprehensive understanding of the relationship between variables across the entire distribution of the dependent variable, rather than focusing only on the conditional mean as in traditional linear regression. This is particularly important in maritime and trade-related datasets, where market responses to explanatory variables may vary significantly across different levels of freight rates. Additionally, quantile regression is less sensitive to outliers, making it a robust alternative in the presence of heavy-tailed distributions. These strengths are especially valuable in our study, where the volatility and asymmetric behavior of container freight rates require a methodology capable of capturing these nuances. By modeling multiple points in the conditional distribution, quantile regression helps policymakers and market participants understand not only central tendencies but also tail risks associated with shipping delays and macroeconomic indicators. Quantile regression, developed by Koenker and Bassett (1978), bends many of the stringent assumptions of linear regression. It is robust to outliers because it makes predictions using different quantiles of the dependent variable's distribution and addresses the issue of abnormality in the dependent variable. Since it analyzes the effects of independent variables on different parts of the dependent variable's distribution, it is capable of providing more inclusive results than linear regression analysis. Especially in financial markets, where very high and very low values can occur, its ability to reveal relationships in high and low quantile regions improves our understanding of the market (Uribe and Guillen, 2020:2).

Linear regression analysis examines relationships between variables by analyzing changes in the conditional mean. By contrast, quantile regression analyzes changes in conditional quantiles, dividing the dependent variable into multiple equal quantiles (Fitzenberger, 2012:42). When the distribution of the dependent variable is abnormal and heteroscedastic, the quantile estimator can identify relationships more effectively than the linear estimator (Hao and Naiman, 2007). Although abnormality and heteroscedasticity in the dependent variable justify moving beyond ordinary least squares, other robust regression methods — such as regression with heteroscedasticity-consistent (robust) standard errors — could also be considered. However, these methods still focus on the conditional mean and do not fully capture the asymmetric effects that independent variables may have at different points in the conditional distribution. By contrast, quantile regression allows us to determine whether variables such as bunker prices or reliability have disproportionate effects during periods of extremely high or low freight rates. Therefore, compared to other robust estimators, quantile regression provides a richer analytical framework for detecting heterogeneous effects and distributional shifts, aligning more closely with the objectives and data characteristics of this study.

The quantile regression model estimated in this study is presented in Equation 1. The coefficients denoted by q are specific to each estimated quantile. Since we estimated the model for 10 quantiles, the distribution of the dependent variable is divided into 10 regions, and 9 coefficients are estimated for both the constant and each independent variable, allowing for the behavior of the coefficients across quantiles to be followed and interpreted. EViews econometrics software was used in the analysis.

$$CCFI = \hat{\alpha}_q + \hat{\beta}_{q1} Delivery + \hat{\beta}_{q2} Reliability + \hat{\beta}_{q3} Bunker + \hat{\beta}_{q4} LiKeqiang \tag{2}$$

4. RESULTS

Raw data were used instead of log-transformed values in all analyses conducted in this research. This approach was intended to make the effects of the delay and reliability variables on the dependent variable easier to interpret. Specifically, this study aims to show how a one-day increase in average delay time is reflected in freight rates. While logarithmic transformations are recognized for mitigating the impact of extreme values and facilitating the interpretation of proportional effects, raw data were deliberately used to preserve the direct interpretability of the variables, especially for delay and reliability. In practice, stakeholders in maritime logistics — such as freight forwarders, shippers, and port authorities — are typically more interested in understanding how a one-unit (e.g., one-day) increase in delay affects freight rates in absolute terms rather than in relative percentages. Using raw data allows us to maintain this intuitive and policy-relevant interpretability. Additionally, applying log transformation to variables like reliability, which is usually measured on a bounded percentage scale, could distort meaning and reduce transparency necessary for operational decision-making. Therefore, using raw data supports our goal of providing actionable insights, particularly for time-sensitive metrics that reflect supply chain performance.

Augmented Dickey-Fuller (ADF) (1979) and Phillips-Perron (PP) (1988) unit root tests were applied to the series, as the series should be stationary for both linear and quantile regression analyses. The PP test is derived from the ADF test and was developed to address some of the shortcomings of the ADF test, offering advantages such as robustness to autocorrelation and heteroscedasticity in the series. As shown in Table 1, the distributions of the raw series are inconsistent with normal distribution. Additionally, correlogram analysis reveals dependencies with past values. Therefore, our results were strengthened by applying both tests.

The null hypotheses of these tests indicate that the series are nonstationary. In both the ADF and PP tests, the null hypothesis could not be rejected at the level for the CCFI, delivery, reliability, and bunker variables. This indicates that these four series contain unit roots and become stationary when their first differences are taken. For the Li Keqiang variable, the null hypothesis of a unit root at the level was rejected by both tests. Thus, the Li Keqiang variable is I(0), while all other variables are I(1).

Testing for stationarity is a crucial step in time series analysis, as the presence of a unit root implies that shocks to a variable may have long-lasting effects and that the series does not revert to a mean or trend quickly. In our case, the CCFI, delivery, reliability, and bunker price variables were found to be non-stationary in levels but stationary in first differences, indicating that they follow an I(1) process. This means that changes in these variables are persistent over time, and past shocks can have long-term effects. In economic terms, this highlights the importance of structural shifts or disruptions in global trade and shipping — such as those caused by supply chain congestion or fuel price volatility — which do not dissipate quickly. In contrast, the Li Keqiang Index was found to be stationary (I(0)), suggesting that fluctuations in real economic activity in China, as proxied by this index, tend to revert to a long-term mean. Both ADF and PP tests were used to ensure the robustness of these results, with the PP test providing additional confidence given its ability to handle potential data autocorrelation and heteroscedasticity.

Test	Variable	Level		First Difference		Conclusion
		Intercept	Intercept & trend	Intercept	Intercept & trend	
ADF	CCFI	-1.75	-1.85	-4.13	-4.22	I (1)
	DELIVERY	-1.43	-0.69	-7.08	-7.14	I (1)
	RELIABILITY	-1.42	-1.41	-6.30	-6.30	I (1)
	BUNKER	-1.58	-1.91	-6.14	-6.10	I (1)
	LI-KEQIANG	-3.39**	-3.55**	-6.93***	-6.88***	I (0)
PP	CCFI	-1.30	-0.97	-3.43**	-3.45*	I (1)
	DELIVERY	-1.48	-0.83	-6.95***	-7.00***	I (1)
	RELIABILITY	-1.04	-0.86	-6.21***	-6.19***	I (1)
	BUNKER	-1.49	-1.82	-6.14***	-6.09***	I (1)
	LI-KEQIANG	-2.80*	-2.98	-6.92***	-6.85***	I (0)

Notes: (1) CVs for ADF and PP are -3.52 for ***1%, -2.90 for **5%, -2.58 for *10% at intercept; -4.08 for ***1%, -3.47 for **5%, -3.16 for *10% at trend and intercept. (2) Schwarz Information Criteria were used to select lag length in ADF. (3) Barlett kernel spectral estimation and Newey-West Bandwidth methods were used in PP.

Table 2. Unit root test results

The distributions of the first difference and log return of our dependent variable, CCFI, by quantiles are presented in Figure 2. As shown in the left chart, approximately 40% of the changes are between -23 (0.3) and 25 (0.7). In other words, the index is stable within these ranges. The changes are quite high in the initial 20% and last 20% segments. The maximum negative change was 644, while the maximum positive change was 414. When the quantile graph with percentage values is considered, the maximum negative change was 28.5%, and the maximum positive change was 26.8%. The index in the central 40% is between +3% (0.3) and -3% (0.7). Especially in the first 10% and last 10%, monthly change reached very high values. As a result, the distribution of the variable is not normal and exhibits a pronounced tail effect. There is also a high degree of autocorrelation. For this reason, quantile regression analysis is considered more appropriate than linear regression.

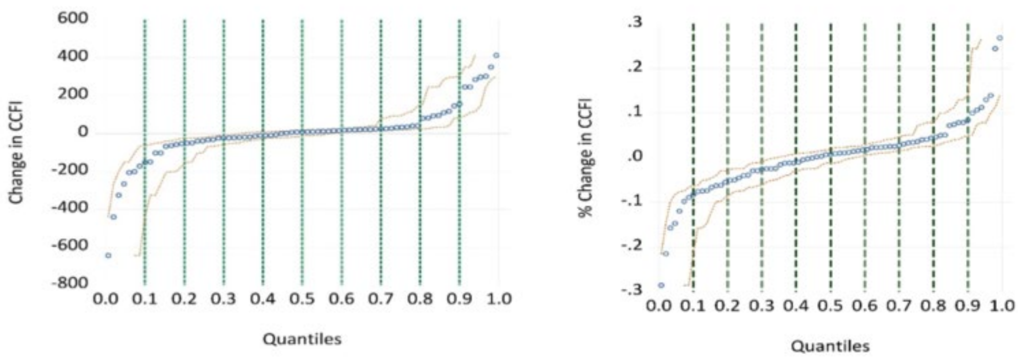

Figure 2. Quantiles of first difference and log return of CCFI

First, linear regression estimation was performed to compare it with quantile regression and determine whether the assumptions regarding residuals were valid. According to the results presented in Table 3, all independent variables except bunker price have a significant effect on freight rates. The coefficients are in the expected direction. An increase in delay increases freight rates, a decrease in the reliability index increases freight rates, an increase in bunker price increases freight rates, and an increase in economic activity in China increases freight rates. As bunker prices are the most influential factor for ship cost per mile, it is unexpected for this variable to be insignificant. This may vary depending on market conditions. Quantile regression analysis can reveal effects that vary depending on freight market situation. However, it is important to note that the residuals of the linear regression model exhibit heteroscedasticity, autocorrelation, and abnormality, which is contrary to classical OLS assumptions. These discrepancies may bias standard errors and affect the reliability of hypothesis tests, including the interpretation of the R^2 value. To address these issues, the model was re-estimated using the HAC (Heteroskedasticity and Autocorrelation Consistent) covariance matrix, which provides more robust standard error estimates under such conditions. Nonetheless, since linear regression only models the conditional mean, it was complemented with quantile regression, which offers deeper insights across freight rate distribution.

Variable	Coefficient	Std. error	t-statistic	Prob.
Δ DELIVERY	169.7867	42.944	3.9536	0.0002
Δ RELIABILITY	-9.2717	4.0973	-2.2628	0.0268
Δ BUNKER	1.6642	1.1926	1.3954	0.1673
LI-KEQIANG	11.9594	5.4390	2.1987	0.0312
C	-105.3151	61.415	-1.714792	0.0908
R-squared	0.3692	Wald F statistic		4.9727
Adjusted R-squared	0.3331	Prob (Wald F stat.)		0.0013

Notes: (1) The ARCH heteroscedasticity test was applied to residuals, and the null hypothesis of homoscedasticity was rejected. (2) The Q-stat autocorrelation test was applied to residuals, and the null hypothesis of no autocorrelation was rejected. (3) The Jarque-Bera normality test was applied to residuals, and the null hypothesis of normality was rejected. (4) The Breusch-Godfrey Serial Correlation LM Test was applied to residuals, and the null hypothesis of no serial correlation was rejected. (5) The model was re-estimated using the HAC covariance method to address autocorrelation and heteroscedasticity.

Table 3. OLS regression estimation results

The regression equation for the 0.5 quantile was estimated first, making it possible to establish how coefficients differ across other quantiles. In our estimation for the 0.5 quantile, the effect of China's economy on freight rates is insignificant. All other variables are significant, and the signs of their coefficients are theoretically reasonable. The changes in coefficients across 10 quantiles were examined next. The coefficients obtained from the 0.5 quantile estimation substantially differ from those estimated by OLS, particularly in magnitude and significance. This notable divergence is empirical evidence that the conditional distribution of the dependent variable is not symmetric or normally distributed, supporting the appropriateness of quantile regression over mean-based methods. Starting with the median quantile thus serves as a robust benchmark and the basis for exploring coefficient variations across the full distribution.

Variable	Coefficient	Std. error	t-statistic	Prob.
Δ DELIVERY	100.7188	44.4036	2.2682	0.0264
Δ RELIABILITY	-5.7657	2.8023	-2.0574	0.0434
Δ BUNKER	3.1294	1.6049	1.9498	0.0552
LI-KEQIANG	3.3129	3.6943	0.8967	0.3729
C	-26.2201	33.1239	-0.7915	0.4313
Pseudo R-squared	0.1477	Quasi-LR statistic		22.3477
Adjusted R-squared	0.0990	Prob (Quasi-LR stat)		0.0001

Notes: (1) Huber Sandwich Method was used for Covariance estimation. (2) Kernel and Hall-Sheater methods were used for Sparsity Estimation. (3) Rankit Quantile Method and Epanechnikov Kernel Method were used. (4) Initial value for the Quantile to Estimate was chosen as 0.5.

Table 4. Quantile regression estimation results

The nine estimated coefficients for each variable across ten quantiles are presented in Table 5. The effect of the delay variable on freight rates is significant for all quantiles when rates are dropping, stable, or increasing rapidly. The coefficients generally decrease from where freight rates show a sharp decline until they reach areas where they are stable. After reaching stability, the coefficients increase as freight rates move into areas of high growth, as shown in Figure 3. The effect of the reliability variable is negative and significant at the 0.2, 0.3, 0.5, and 0.8 quantiles. Its pattern is similar to that of the delay variable, with a U-shaped structure, but negative.

In the linear regression analysis, bunker price, which was found to have a negligible effect on freight rates, is significant at the 0.5, 0.6, 0.7, and 0.8 quantiles. The effect is positive, and generally, the higher the quantile, the weaker the effect. Increases in bunker prices are also reflected in freight rates when freight movements are relatively positive and stable. In market conditions where freight rates strongly increase, bunker price increase is not reflected in freight rates. In addition, increases in bunker prices are not reflected in freight rates when freight rates are decreasing or decreasing rapidly.

The Li Keqiang index has a significant and positive effect on freight rates at the 0.1, 0.2, and 0.7 quantiles. Excluding the 0.7 quantile, this indicates that positive news from the Chinese economy had a positive effect on freight rates in periods of a strong downward trend in freight rates. No significant effect was detected at other quantiles.

	Quantile	Coefficient	Std. error	t-statistic	Prob.
Δ DELIVERY	0.100	135.9109	46.43172	2.927114	0.0046***
	0.200	158.5990	39.83920	3.980978	0.0002***
	0.300	150.5385	48.16007	3.125794	0.0026***
	0.400	127.0557	56.24357	2.259026	0.0270**
	0.500	100.7188	44.40360	2.268256	0.0264**
	0.600	138.1112	51.27929	2.693314	0.0088***
	0.700	127.3787	57.58885	2.211864	0.0302**
	0.800	174.6679	57.51278	3.037028	0.0034***
	0.900	226.5277	65.16911	3.475998	0.0009***
Δ RELIABILITY	0.100	-7.773254	5.241650	-1.482978	0.1426
	0.200	-8.508005	3.142669	-2.707255	0.0085***
	0.300	-5.919782	3.323157	-1.781373	0.0792*
	0.400	-4.532710	2.800534	-1.618516	0.1100
	0.500	-5.765737	2.802392	-2.057434	0.0434**
	0.600	-4.500307	2.901686	-1.550928	0.1254
	0.700	-7.566820	4.952965	-1.527735	0.1311
	0.800	-13.21510	6.915220	-1.911017	0.0601*
	0.900	-10.69612	8.733692	-1.224697	0.2248
Δ BUNKER	0.100	-0.380779	1.083178	-0.351539	0.7262
	0.200	0.078224	1.830603	0.042731	0.9660
	0.300	1.380992	3.191893	0.432656	0.6666
	0.400	2.138349	2.294270	0.932039	0.3545
	0.500	3.129491	1.604992	1.949849	0.0552*
	0.600	3.239791	1.586255	2.042414	0.0449**
	0.700	3.015962	1.498490	2.012667	0.0480**
	0.800	2.141361	1.257057	1.703471	0.0929*
	0.900	2.055440	1.494956	1.374917	0.1735
LI-KEQIANG	0.100	14.11470	6.300450	2.240269	0.0282**
	0.200	8.903339	4.733273	1.881011	0.0641*
	0.300	6.933802	5.567853	1.245328	0.2172
	0.400	6.198566	4.487029	1.381441	0.1715
	0.500	3.312923	3.694300	0.896766	0.3729
	0.600	4.812795	3.710469	1.297085	0.1989
	0.700	8.699204	5.035719	1.727500	0.0885*
	0.800	9.876098	10.16690	0.971397	0.3347
	0.900	1.361635	7.459490	0.182537	0.8557
C	0.100	-233.6594	71.42879	-3.271221	0.0017
	0.200	-133.2588	48.60643	-2.741588	0.0078
	0.300	-89.82064	56.68622	-1.584523	0.1176
	0.400	-68.81122	43.45320	-1.583571	0.1178
	0.500	-26.22015	33.12396	-0.791577	0.4313
	0.600	-26.31046	33.64479	-0.782007	0.4368
	0.700	-34.34286	39.69330	-0.865206	0.3899
	0.800	-1.405634	89.07035	-0.015781	0.9875
	0.900	122.7115	77.79363	1.577398	0.1192

Notes: (1) Null of insignificance rejected at *90%, **95%, ***99%.

Table 5. Quantile regression coefficients for 10 quantiles

The changes in the coefficients of the independent variables according to the quantiles of the dependent variables are presented in Figure 3. Thus, when analyzed together with Figure 2, it becomes possible to interpret the change according to market conditions. Of course, their significance should also be considered. In addition, the Quantile Slope Equality Test was applied to our model. The null of slope equality cannot be rejected when applied for 10 quantiles (X2=36.5, p=0.26), while it is rejected when applied for 8 quantiles (X2=37.2, p=0.04). This shows that the relationship between the dependent variable and the independent variable can change according to quantiles, i.e., market conditions.

The quantile regression results highlight important shifts in the influence of explanatory variables across the freight rate distribution. Delivery delays exhibit a U-shaped pattern: their coefficients are highest at the lower and upper quantiles and lower around the median, indicating that freight markets are especially sensitive to delays during both downturns and periods of extreme congestion, when capacity constraints or service disruptions may amplify cost effects. Reliability shows a significant negative correlation mainly around the middle quantiles, indicating that service consistency plays a more central role in average freight rate periods. Bunker prices become statistically significant from the median quantile upward, supporting the view that the effect of fuel costs is greater when freight rates are high and carriers face increased cost pressures. The Li Keqiang Index is significant only at the lower quantiles, implying that China's economic activity has an effect on pricing primarily in low demand conditions.

Together, these results show that freight rate drivers are not constant across the distribution and prove the value of quantile regression for capturing asymmetric and market-condition-dependent effects.

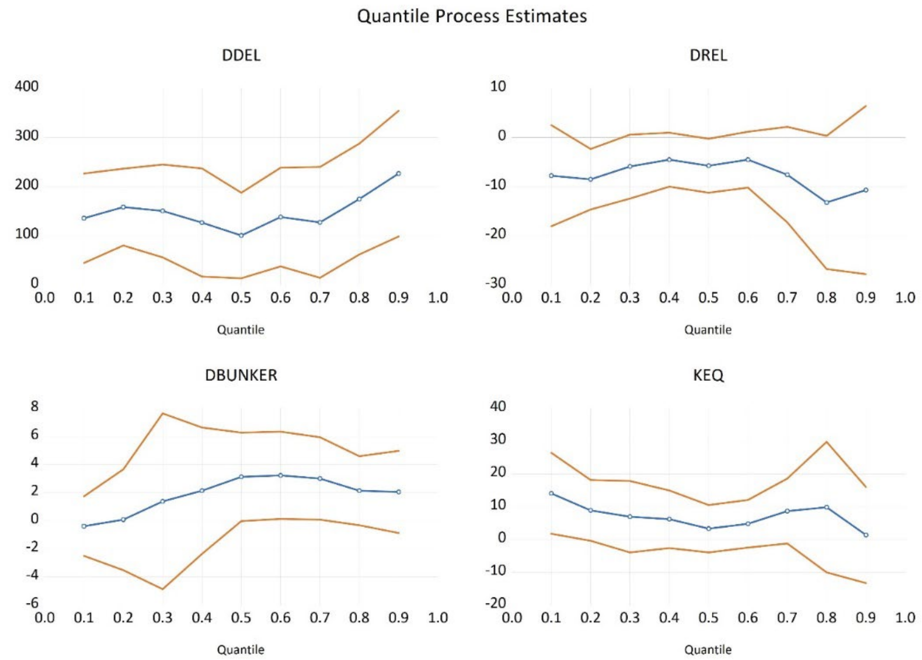

Figure 3. Coefficients in different quantiles

5. DISCUSSION

This research explored the impact of the inability of container shipping companies to deliver their services on time on global freight rates. Any delay is primarily reflected as a cost increase to shippers, which indirectly raises the prices paid by the end consumers. As seen in the post-pandemic period, extreme freight rate increases have generated inflationary pressures at the national level and had a negative impact on welfare. Therefore, determining the factors affecting freight rates is important for developing proactive policies, especially for policymakers. Our model included cost and demand variables, which have an indisputable effect on freight rates. Bunker price averages in 20 global ports were used as a proxy for maritime transportation costs and the Li Keqiang index, one of China's alternative economic indicators, as a proxy for the demand for maritime transportation. The validity of the model without these two important variables would be questionable. Quantile regression was our method of choice, both due to the distribution characteristics of the dependent variable, CCFI, and the assumption that the effects of independent variables may differ depending on freight rate distribution.

The results indicate that an increase in average delay time causes a contraction on the supply side and naturally leads to higher freight rates. Although the effect varies by quantile, a 1-day increase in delay raises freight rates by 100-226 index points on the China Containerized Freight Index (CCFI). The coefficients are significant across all quantiles and display a U-shaped pattern. The effect of delay is greater in areas where freight rates tend to decrease or increase, and lower in areas where freight rates are relatively stable. Although the effect of the reliability index is not significant in all quantiles, it is negative and also follows a U-shaped pattern. In general, both delay and reliability, negative conditions during periods of extreme upward trends in freight rates, have a strong impact on freight rates. For example, in the 0.90 quantile of delay, a 1-day delay increases CCFI by approximately 226.5 points, while a 1 point decrease in the reliability index increases freight rates by 13.2 points in the 0.80 quantile. These coefficients are the highest values across all quantiles of the independent variables. Interpreting the data obtained by average CCFI value (1453), an increase in the average delay time by 1 day raises freight rates by approximately 15%. On the other hand, a 10 point decrease in the reliability index increases freight rates by approximately 9%. Even the effect of increase in demand on freight rates is not as pronounced as the increase in delays and decrease in reliability. These increases are passed directly to cargo owners and then to final consumers. This situation increases the need for foreign exchange, especially for developing countries, and fuels inflationary pressure. In addition, it has a negative effect on country market competitiveness due to increased export costs. As a result, delays and unreliable schedule times, by increasing freight rates, make international trade more expensive. This finding also supports Notteboom (2006), which indicates that delays in liner shipping cause unreliable schedule times and incur additional costs. Therefore, it is important to prevent delays and maintain high service reliability. Chung and Chiang (2011) classified measures to increase schedule reliability into four categories: operating strategy, staff, process management in shipping lines, and port conditions. Their study emphasized the importance of avoiding unsafe ports or planning more efficient terminals, working with more committed personnel, improving personnel performance, and planning berthing windows. They also stated that schedule reliability has a significant impact on freight rate negotiations. The suggestions developed in this study based on our findings support their conclusions.

The variation in coefficient values across quantiles reveals meaningful patterns for understanding market behavior under different freight rate conditions. The U-shaped distribution of the delay variable suggests that shipping lines and cargo owners are more sensitive to delays in bear or bull markets, indicating that operational disruptions have the greatest pricing impact under stress conditions. For schedule reliability, although significance levels vary, the observed U-shape similarly implies that reliability concerns weigh more heavily on freight pricing when markets are far from equilibrium. These findings have practical implications for the shipping and logistics sectors, especially in periods of volatility. In low-rate conditions, even minor service disruptions can further erode margins, while in high-rate conditions, schedule failures can intensify congestion and raise costs exponentially. Freight forwarders, port authorities, and shippers should therefore prioritize service reliability and delay reduction not only as a competitive advantage but also as a tool to stabilize freight rate volatility. The asymmetry of these effects across quantiles confirms the need for dynamic pricing strategies and risk management approaches tailored to different market conditions.

In addition to port-based factors, global factors have also increased delays in container transportation. Due to port congestion in the Los Angeles/Long Beach area, ships could not unload their cargo and waited for days. This delay grew so much that the number of ships waiting for loading and unloading operations reached 106 in early 2022 (Statista, 2023). When the Suez Canal was closed for six days in March 2021, 369 ships had to wait to cross the canal (BBC, 2021). Ships that chose not to wait took the longer South African route, which extended voyage times, caused supply-side interruptions, and increased delays. Additionally, many routes were changed, canceled, or shifted to other regions due to the Russia-Ukraine war, contributing to increased delay times and decreased service reliability. At macro level, alternatives to strategic sea passages located in unique global locations can be developed. Intermodal transportation, which is well-suited for container loads, allows route diversification and minimizes the costs of delays in international trade.

Further studies could model the factors affecting average waiting time on an event basis and analyze their effects on international trade in detail. Various optimization models can also be developed, and the effects of delays on international trade can be examined using scenario-based simulations. By examining routes, transit ports, ship capacities, and geopolitical events, lowest-risk alternatives for international trade can be developed.

CONFLICT OF INTEREST

Authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this paper.

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