



Research paper

China-Europe freight transportation under the first wave of COVID-19 pandemic and government restriction measures

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ABSTRACT

International freight transportation experienced significant disruptions during the COVID-19 pandemic. The impact of the pandemic and related government restriction measures on international freight transportation is worth analysing for the development of transportation policies and practices in the post-pandemic period, but has received limited attention. To fill the gap, this study applies structural equation models to analyze the impact of the COVID-19 pandemic on the international transportation market and the relationships among the pandemic, government restriction measures, and international transportation market. The impact is also differentiated for different modes of transportation. Results confirm that both demand and supply of international transportation services have been negatively affected by the first wave of the pandemic, with sea transportation being more affected by the reduction of demand and air transportation more by the supply volatility. The government restriction measures are found to play a mediation role, in the way that the impact of the pandemic on the supply of transportation service is suppressed through the government restriction measures. Our findings provide important guidance for transportation industry players and governments in their decision-making process facing with global market shocks such as a pandemic.

1. Introduction

The outbreak of the COVID-19 pandemic developed in 2020, and government restriction measures to contain the pandemic have led to an inevitably huge blow to the world economy and widespread challenges (Fang & Guo, 2022; Guan et al., 2020; Rodrigues et al., 2021; Xu, Shi, et al., 2021). Studies have suggested that the pandemic led to a cliff-like decrease in international trade in 2020, and the transportation sector, as the main undertaker of international trade, bore the brunt of the decline (Dube et al., 2021; Guan et al., 2020; Verschuur et al., 2021; Xu, Yang, et al., 2021). Although a relative rebound was observed in the second half of 2020, it remained negative on the year-over-year basis (UNCTAD, 2021).

The pandemic not only has an impact on the demand for transportation services which stems from international trade, but also on the supply of transportation. The maritime shipping sector, for example, experienced surges in the number of blank or skipped sailings and idle containership capacity in the first half of 2020 (Xu, Shi, et al., 2021). Effective capacity management by liner shipping companies helped to prevent the initial collapse of freight rates (UNCTAD, 2020). However,

in the second half of 2020, there has been a spike in freight rates hitting record levels, as a combining result of capacity management, burgeoning transportation demands and shortages of containers (Cullinane & Haralambides, 2021). Air transportation is also one of the sectors which were hit hard by the pandemic (Ariane et al., 2022).

Airports shutting down, border closures, and travel restrictions have drastically affected both air transport's capacity and prices: after the first-half year with low performance in terms of both capacity and prices, a significant recovery in capacity was observed in the last two quarters of 2020 (Dube et al., 2021). Meanwhile, in contrast to air and maritime shipping, rail transportation was nearly uninterrupted. (Ariane et al., 2022).

Given the severe impact of the COVID-19 pandemic on the transportation and logistics sector, scholars have widely investigated the topic for a range of modes (e.g., air (Li, 2020; Suau-Sanchez et al., 2020), sea (Notteboom & Haralambides, 2020; UNCTAD, 2020), rail (Tardivo et al., 2020), and highway (Fang & Guo, 2022)). However, most relevant research studies focused on domestic markets, with few studies analyzing the international market.

Furthermore, as many studies have shown, government restriction

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measures to contain the pandemic could trigger a highly unexplored ripple effect (Guan et al., 2020; Ivanov, 2020). The freight transportation sectors provide services to support international trade flows, while governments have adopted various levels of restriction measures to fight against the pandemic spread but also have caused more uncertainties and disturbances in the transportation markets. Xu, Shi, et al. (2021) argued that the strictness of government restriction measures is positively correlated with import trade but negatively correlated with export trade. However, the role that government intervention in overall international transportation and different transportation modes is not fully understood.

Therefore, this study's first aim is to understand the early impact of the pandemic and especially, government restriction measures, on the supply and demand of international transportation through an analysis of EU imports from China during the first wave of the COVID-19 pandemic. As China was the largest exporter for EU (the world's second largest importer) and it is also the third largest importer in 2020 (Eurostat, 2021), the container exports from China to EU are highly representative of the international trade situation.

Furthermore, it is observed that the international trade and transportation market performed differently in different waves of the pandemic. Thus, the second motivation of this study is to analyze the different performances of the three main modes of international transportation, that is, sea, rail, and air under the impact of the COVID-19 pandemic and government measures.

To achieve our research goals, eight hypotheses are brought forward and tested using Structural Equation Model (SEM), a multivariate analysis technique. With respect to the unevenly distributed transportation supply and demand in modes during the pandemic, a disaggregate analysis on the three main international transportation modes is then conducted from a more microscopic perspective, using the mode-based shipping volumes of EU imports from China.

To the best of our knowledge, this study is the first study that simultaneously investigates the severity of the pandemic, the strictness of government restriction measures, and transportation infrastructure to evaluate the impact of the COVID-19 pandemic on international freight transport. Particularly, the mediation effect of the government containment measures on the freight transportation market and the heterogeneous pandemic impacts on the three types of transportation modes for international trade flows are for the first time analyzed in the literature. This analysis strives to offer insights into the different market mechanisms governing the international transportation modes, and therefore, could help policymakers and private companies better understand different performance outlooks of the different modes under a global market shock like the pandemic, and offer guidance for the development and resilience of international transportation sector in the post-pandemic period.

The rest of this study is structured as follows. In Section 2, a review of the existing literature relevant to COVID-19 and the logistics and transportation system is conducted, followed by the research hypotheses development for this study. Next in Section 3, the methodology and data are presented. Section 4 presents the results of the empirical analysis. Section 5 highlights discussions and implications of the study. Conclusion with contributions and limitations for future research is lastly presented in Section 6.

2. Literature review and research hypothesis development

2.1. COVID-19 and the logistics and transportation systems

The COVID-19 crisis has caused heavy disruptions in the transportation sector. An increasing number of studies have analyzed this phenomenon, but are mainly associated with passenger transportation, such as travel behaviours, disease spread, and the reciprocal relations of the two. A limited amount of research has been undertaken to analyze the impact on freight transportation. Cui et al. (2021) examined the

impacts of the COVID-19 pandemic on the performance of transportation sectors in China through a general equilibrium model. Rodrigues et al. (2021) provided a general picture of the impacts of COVID-19 on EU transportation sector and Ariane et al. (2022) analyzed the influences of the pandemic on EU freight transportation and global trade and provided policy recommendations to overcome the negative impacts.

Additionally, several researchers have looked separately at how the pandemic has affected transportation modes. With regard to the impacts on maritime shipping, Notteboom et al. (2021) investigated the supply and demand shocks of COVID-19 on the container shipping industry. The strategic behaviour of the liner shipping operators, terminal operators, and the ports are analyzed on how they fit within complex supply chains to cope with external shocks. Koyuncu et al. (2021) established a Seasonal Auto Regressive Integrated Moving Average model to study how COVID-19 has impacted the container throughput index for the maritime trade in the short term. Menhat et al. (2021) conducted an overview of the pandemic impact on the maritime sector in Malaysia. Xu, Yang, et al. (2021) focused on the impact of the COVID-19 pandemic on the operation of 14 Chinese ports and found a significant negative effect of the pandemic on import and export throughput of ports, while Chinese government restriction measures have a certain degree of positive effect on exports and no impact on import throughput. Gavalas et al. (2022) used a market-model event study approach to investigate how the COVID-19 outbreak impinges on the maritime shipping markets.

Concerning the impact on the air transportation market, Dube et al. (2021) confirmed that the pandemic had severe negative impacts on global aviation and examined potential recovery pathways. Li (2020) conducted a SWOT analysis on China's air cargo. Kim et al. (2020) analyzed the air cargo market before and after COVID-19 for Korean export. Gudmundsson et al. (2021) estimated the recovery time for both air passenger and freight transportation and found recovery times varied across regions given the different pre-pandemic levels and the various governments' restrictive measures adopted.

Most prior studies mainly focused on the national market or one transportation sector, and cannot be applied to the international transportation market, as the two are very different in terms of both shipping requirements and transportation competition situation. It is also worth noting that the existing studies mainly focus on a single transportation mode. In addition, few of them considered the impact of government restriction measures.

Therefore, this study fills the gaps in the existing literature and helps to understand the early impacts of the pandemic and government restriction measures on international freight transportation and guide the development and resilience of the transportation sector in the post-pandemic period.

2.2. Research hypothesis development

Based on the existing literature and expert consulting, eight hypothesized relationships among the five factors are proposed to analyze the COVID-19 impacts on the transportation services for EU's imports from China: the severity of COVID-19 pandemic (COVID), the government restriction measures (GovMeasure), the international trade volume (TradeQ), the market performance of international freight transportation (TrasnpMkt), and the transportation infrastructure connectivity level (TIC). The interactions are hypothesized as below.

2.2.1. Impact of COVID on TradeQ

Literature has demonstrated that the swift and massive shock of the pandemic has plunged the global economy into a severe contraction, which directly led to a cliff-like decrease in the international trade (Hayakawa & Mukunoki, 2021; World Bank, 2020; Xu, Shi, et al., 2021). This direct effect comes from massive shutdowns of production across industry sectors and countries worldwide, substantial job losses and

uncertainties, and consumption demand declines (Cui et al., 2021; European Commission, 2020; McKibbin & Fernando, 2020). This leads to the first hypothesis:

Hypothesis 1. (H1): COVID negatively influences TradeQ, which represents the demand for international freight transportation services.

Based on the literature and reports, we used four measures as observation variables for COVID: (i) the monthly-reported new COVID-19 related cases, (ii) the monthly-reported new COVID-19 related deaths, (iii) average monthly 14-day notification rate of new COVID-19 cases per 100 000 population and (iv) average monthly 14-day notification rate of new COVID-19 deaths per 100 000 population.

2.2.2. *Impacts of COVID and CovMeasure on Trasnpmkt*

Government restriction measures are activated to contain and deal with the pandemic’s fallout (ECDC, 2020; Hale et al., 2021). Governments typically implement stricter government restriction measures to control the pandemic when daily confirmed cases substantially grow (Chung et al., 2021). The stringency index defined by the Oxford COVID-19 Government Response Tracker (OxCGRT) is adopted in this study to measure the strictness of government restriction measures. This index is composed based on nine response indicators including stay at home requirement, workplace closure, and international travel control, rescaled to a value from 0 to 100 (100 = strictest) (Hale et al., 2021). It tracks how many of the relevant indicators a government has acted upon, and to what degree (Chung et al., 2021).

The COVID-19 data of daily confirmed cases and deaths can be obtained from the European Centre for Disease Prevention and Control (ECDC) website (ECDC, 2020). As shown in Fig. 1, as a preliminary observation, the rapid disease spread in European Union led to more stringent measures in 2020, which indicates a significant and positive relationship between the two. Therefore, we hypothesize the following:

Hypothesis 2. (H2): COVID positively influences CovMeasure.

Although government restriction measures help constrain the COVID spread and will alleviate the pandemic situation, they also directly lead to a high level of uncertainties and inefficiency in the transportation service market. Restrictions such as additional screening and mandatory quarantines lead to immediate market responses such as service cancellation and terminal closures, which resulted in shrinking transportation capacity and rising freight rates (Heiland & Ulltveit-Moe, 2020).

For maritime shipping, liner shipping had quickly adjusted their supply to the weak transportation demand caused by the sudden outbreak of the pandemic, by cancelling some routes, taking blank sailing, applying slower speed or taking longer rotation, such as via the

Cape of Good Hope instead of the Suez Canal (Cullinane & Haralambides, 2021; Xu, Shi, et al., 2021).

As for air shipping, it was severely affected at the beginning of the pandemic (Lau et al., 2020) due to the widely cancelled passenger flights (60% reduction in 2020 (ICAO, 2021)) which normally provides 70% of the capacity for air cargo. As reported by IATA (2020a), the available airline cargo capacity in tonne-kilometres fell by 23.3% in 2020 overall. Along with the dramatic capacity drop, a 4-time surge in air freight rate has been observed for the Shanghai-Europe route, and a 2-time surge for Shanghai-North America route from March to May in 2020 (Knowler, 2020).

In other words, the reduction in transportation capacity, quarantine rules, and personnel shortage caused by the implementation of government restriction measures to fight the COVID-19 pandemic has thrown the transportation market in turmoil (Xu, Shi, et al., 2021). This can be considered as the indirect effect of COVID through government response (CovMeasure) on the transportation service market (Trasnpmkt), which is a mediating effect. The relationships between the three factors: COVID, CovMeasure, and Trasnpmkt are described as Hypotheses 3, 4, and 5 below:

Hypothesis 3. (H3): COVID has a direct negative effect on Trasnpmkt, that is, causing shrinking transportation capacities and rising freight rates.

Hypothesis 4. (H4): CovMeasure has a direct negative effect on Trasnpmkt.

Hypothesis 5. (H5): CovMeasure has a mediating effect on the impact between COVID and Trasnpmkt.

2.2.3. *Impact of TradeQ on Trasnpmkt*

The impact of transportation demand on supply is also included as the basic economics assumption. It is normally expected that an increase in demand for transportation services will push up freight rates, which in turn motivates transportation capacity (e.g., more ships) to cover the increasing transportation demand (Bai & Lam, 2019; Bensassi et al., 2014; Korinek & Sourdin, 2009, p. 7; WTO, 2020). This leads to the sixth hypothesis:

Hypothesis 6. (H6): TradeQ positively influences Trasnpmkt.

2.2.4. *Impact of TIC on COVID and TradeQ*

Finally, two more hypotheses are added regarding the role of a country’s transportation infrastructure prior to COVID-19 in terms of the impact on COVID and TradeQ.

International trade is not only influenced by the pandemic, but also

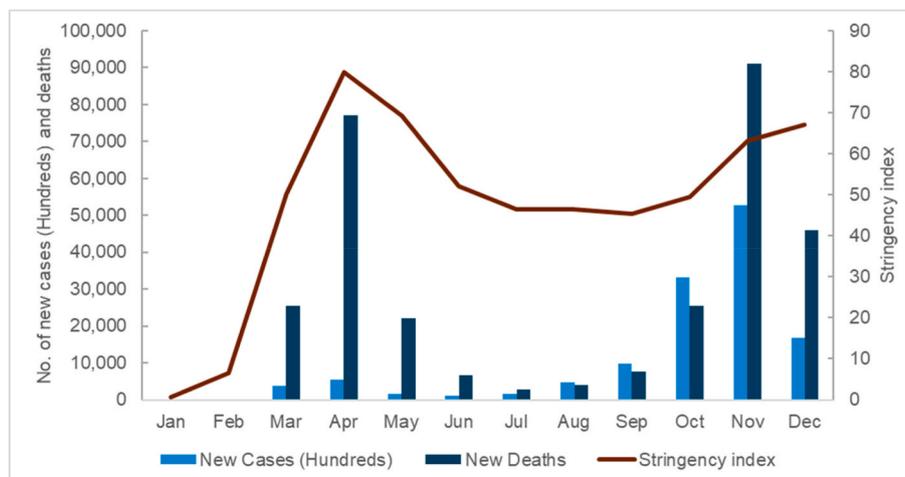


Fig. 1. Spread of COVID-19 and average stringency index in European Union (based on Hale et al. (2021) and ECDC (2020)).

by pre-existing conditions of transportation infrastructure. The crucial role of transportation infrastructure on trade volume has been agreed widely by economists (Francois & Manchin, 2013; Portugal-Perez & Wilson, 2012). Liu and Xin (2011) suggested that transportation improvement has a substantial impact on trade volume and argued that the contribution of transportation improvements to trade growth might have been underestimated in the trade literature. Thus, an inclusion of TIC reduces omitted variable bias and consequently improves the estimation of the impact of the spread of COVID-19. Consequently, we posit the following:

Hypothesis 7. (H7): A country's TIC has a positive impact on TradeQ.

On the other side, the improvement in transportation and enhanced connectivity are already a double-edged sword: the rising international connectivity (Castells, 2011; Colizza et al., 2006; Sigler et al., 2021) and globalization (Barua, 2020) are also considered responsible for the diffusion of infectious diseases.

Previous studies have confirmed the strong connection of transportation networks in the spread of the pandemic and seasonal influenza viruses, including the airline network (Colizza et al., 2006; Nakamura & Managi, 2020) and also public transit system. For example, Cai et al. (2019) found air, rail, and road travel all play significant impacts on the transmission of the influenza A (H1N1) pandemic in mainland China. Gaskin et al. (2021) found COVID-19 case and death numbers were positively correlated with nearby airway and railway facilities, measured by distance, numbers, and passenger volume. Zhang et al. (2020) found a strong relationship between the frequencies of air and train connections from Wuhan to other cities in China and COVID-19 case numbers in those cities. Accordingly, we hypothesize the following:

Hypothesis 8. (H8): TIC positively affects COVID.

The construct TIC is a country's transportation infrastructure connectivity evaluated with seven quantity and quality infrastructure indicators suggested by Wessel (2019): (1) distance, (2) liner shipping connectivity index, (3) The International Air Transport Association (IATA) airport connectivity indicator, (4) density of railroad, and (5–7) the number of commercial airports, seaports, and rail hubs connected with China.

3. Methodology

3.1. Data

First, we detect the structural breaking points of the COVID-19 pandemic (from January 2020 to July 2021) by estimating the F statistic and the CUSUM statistic for the number of COVID-19 new cases per month in EU (ECDC, 2020) using the R package "strucchange" (Kleiber et al., 2002). The significance values for a structural break of the Quandt Likelihood Ratio (QLR) statistic suggest that the data contain at least one structural break (sup.F = 173.32, p-value < 2.2e-16). And the one break F statistic result suggests that the break date is 2020.10 for EU (the sums

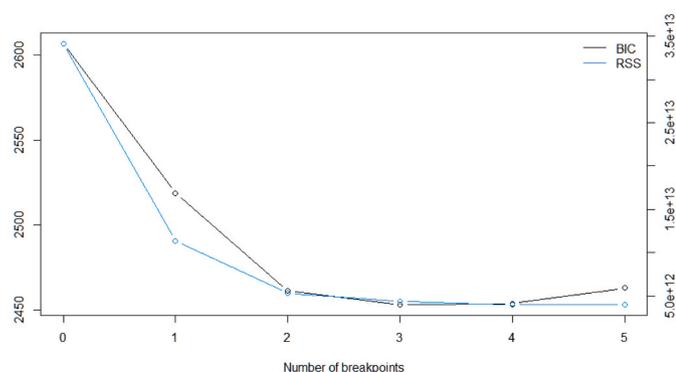


Fig. 2. RSS and BIC for models with up to five breaks.

of squares (RSS): 1.13×10^{13}). Fig. 2 presents the residual sum of squares and the BIC for all models with up to five breaks, which show that a three-break model has the minimum BIC. The break dates are 2020.10, 2021.01 and 2021.04. Thus, we define the first wave of the COVID-19 pandemic for EU as 2020.01 to 2020.10.

For this study, CovMeasure was measured by monthly averages stringency index for each country in EU (Hale et al., 2021). The construct TranspMkt represents the international freight transportation market supply condition and is measured by the inverse of idle container ship capacity (i.e., reSC), container freight rate (i.e., reSF), air freight capacity, and air freight rate (i.e., reAF). The trans-Eurasia railway monthly data for the study period is not included because the China-Europe rail freight rates and capacity remained stable during the study period (ColliCare Logistics UAB, 2020; Crane Worldwide Logistics, 2021).

Monthly data for all the measured variables for 27-EU member states from January 2020 to October 2020 are collected from various data sources as shown in Table 1, except transportation connectivity data, which has annual values for each country through the research period. Trade flows from 27 EU partners to China differentiated by transportation modes are taken from Eurostat database, which has often been used before for trade analysis, for example, the trade effects of transport-mode-specific infrastructure (Wessel, 2019). Additionally, the numbers of rail hubs, airports, and seaports are counted based on service plans published by the carriers (see Table 2).

Table 1
Source and descriptions of variables.

Construct	Description	Source
COVID		
COVID new cases	Number of COVID-19 new deaths per month	ECDC (2020)
COVID new death	Number of COVID-19 new cases per month	ECDC (2020)
death rate 14 day	Monthly average 14-day notification rate of new deaths per 100 000 inhabitants	ECDC (2020)
confirmed rate 14 day	Monthly average 14-day notification rate of new cases per 100 000 inhabitants	ECDC (2020)
CovMeasure		
CovMeasure	OXFORD COVID-19 Government Response Stringency index	Hale et al. (2021)
TIC		
Distance	Geodesic distances calculated following the great circle formula	Mayer and Zignago (2006)
Liner shipping connectivity	Liner Shipping Connectivity Index	World Economic Forum, 2019
Airport connectivity	IATA airport connectivity indicator	World Economic Forum, 2019
Railroad density	Railroad length in kilometers per 1000 square kilometers of land	World Economic Forum, 2019
Rail-hub number	Number of commercial rail hubs connected with China	Own calculation
Airport number	Number of commercial airports connected with China	Own calculation
Seaport number	Number of commercial seaports connected with China	Own calculation
TranspMkt		
Sea Idled Capacity	Monthly percentage of idled containership capacity	Clarksons Research, 2021
Sea Freightrate	Monthly Shanghai Containerized Freight Index (European base port)	Clarksons Research, 2021
Air Capacity	Monthly year-on-year growth rate in ACTKs	IATA (2020b)
Air Freightrate	Monthly TAC Index from Shanghai to Europe in Actual Net Price (the per Kg rate (dollars) achieved using all-in cost and actual weight declared on the Master Air Waybill)	TAC Index (2020)
TradeQ		
TradeQ	Monthly imports volume in 100 KG of the European Union from China by different transportation modes	Eurostat (2020b)

Table 2
Descriptive statistics for measure variables.

	Mean	Std.Dev	Skewness	Kurtosis	Shapiro-Wilk test
COVID new cases	24669.64	75489.71	5.89	44.82	0.3455***
COVID new death confirmed rate 14 day	686.26	2303.51	5.85	39.05	0.3149***
death rate 14 day	93.13	220.15	3.82	16.14	0.4582***
Stringency index	16.26	35.45	3.63	15.45	0.5034***
Distance	44.05	24.78	-0.38	-0.60	0.9383***
Liner shipping connectivity	7507.35	783.17	0.87	0.97	0.9181***
Airport connectivity	40.67	34.40	0.27	-1.38	0.8834***
Railroad density	184449.99	249519.20	1.79	1.83	0.67***
Railhubs Number	54.81	32.68	0.58	-0.56	0.9304***
Airports Number	0.48	0.90	2.52	6.70	0.5688***
Seaports Number	5.56	5.01	1.30	0.79	0.8074***
reSC	0.52	0.90	1.74	1.96	0.616***
reSF	-7.00	1.92	-0.89	0.08	0.8881***
Air Capacity	-914.48	122.17	-0.35	-1.15	0.9112***
reAF	-0.29	0.14	0.92	-0.42	0.8187***
Import Volume (100 KG)	-3.73	1.01	0.89	-0.37	0.8589***
	1855886.64	2670414.00	2.01	3.48	0.6799***

*: $p < .05$, **: $p < .01$, ***: $p < .001$.

After data cleaning, 250 observations are obtained. Table 2 lists the overall descriptive statistics for all variables. The standard deviation and mean of all measured variables are reported to show that the variables have sufficient variance for a better analysis. All the individual variables have significant p-values ($p < .05$) for Shapiro-Wilk test, and the absolute values of the Skewness and Kurtosis of several of the individual variables (seven out of 17) are not within the acceptable range of <2 and <7 , respectively (Hair et al., 2009), indicating that multivariate normality and univariate normality could not be established in the study.

In order to address the non-normality for SEM estimation, as suggested by Kline (2015) and Rosseel (2012), the Satorra-Bentler rescaling method (Satorra & Bentler, 2001), also known as the maximum likelihood estimation with robust standard errors (MLR), is applied in this study. This method is proposed to adjust for bias in Chi-square estimation due to non-normality (Bryant & Satorra, 2012).

3.2. Conceptual framework

In order to test the proposed eight hypotheses, this study employs SEM to examine the cause-and-effect relationships among the constructs. Although linear regression can also conduct the cause-and-effect relationships analysis (e.g., Chang and Thai (2016)), SEM has the advantages of examining all relationships of the whole model simultaneously, as well as being able to check the mediation effect between dimensions (Kao et al., 2009). In addition, SEM can also be used to analyze the relationships among conceptual variables that are normally not directly measurable (Kline, 2015; Ülengin et al., 2010).

As a commonly used method for social economics studies, SEM is also widely applied to transportation studies, including travel behaviour research (Ma et al., 2017; Shiftan et al., 2008; Weis & Axhausen, 2009), analysis of transportation policy and investment decisions (Caldeirinha et al., 2020; Setthasuravich & Kato, 2020; Xiao & Lam, 2020; Ülengin et al., 2010), and transportation infrastructure relation with regional economic developments (Chen & De Abreu E Silva, 2013; Deng et al., 2013; Jiang et al., 2017; Li et al., 2018). Additionally, multiple indicator variables can be used to represent conceptual variables as latent constructs that refer to hypothetical or theoretical constructs and cannot be observed or measured directly (Kline, 2015; Ülengin et al., 2010). In order to measure latent constructs, several measured variables under the latent construct will be used.

Our model aims to explore the early influence of COVID-19 and related government restriction measures on the supply and demand of international transportation (Fig. 3). The TIC, COIVD and TranspMkt are the latent constructs (presented by ovals in Fig. 3) and each of them includes several observed variables (see Table 1); whereas CovMeasure

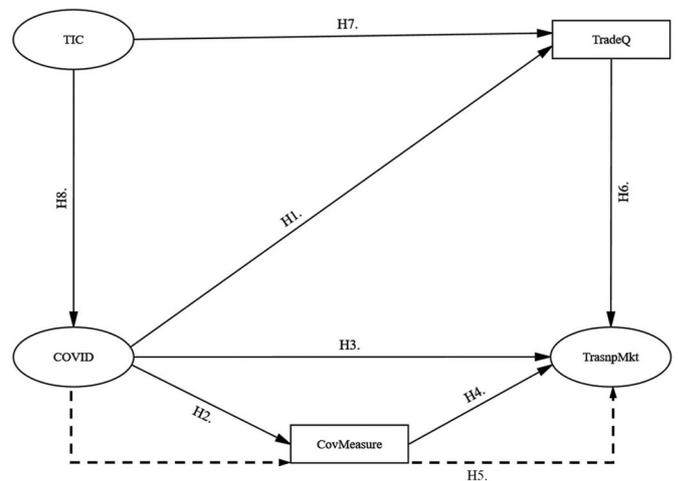


Fig. 3. Proposed model framework.

and TradeQ are measured variables (presented by rectangles in Fig. 3). Arrows connecting the variables represent the causal flow of relationships (Stein et al., 2017).

Several common indices are adapted to evaluate the model fit, including the Chi-square to degrees of freedom ratio (χ^2/df) (recommended to less than 3.000), the comparative fit index (CFI) (recommended to larger than 0.900), the goodness of fit index (GFI) (recommended to larger than 0.900), the adjusted goodness of fit index (AGFI) (recommended to larger than 0.900), the Tucker–Lewis index (TLI) (recommended to larger than 0.900), and the root mean squared error of approximation (RMSEA) (recommended to less than 0.080) (Hooper et al., 2008, pp. 195–200).

4. Results

After the measurement model is developed, confirmatory factor analysis (CFA) is conducted to test its reliability, whereas the proposed structural model and hypotheses are then tested via SEM. As previously mentioned that the normality assumption is not satisfied, this study adopts MLR to address the non-normality for SEM estimation, and the Satorra-Bentler Chi-square (χ^2), rather than the normal Chi-square from maximum likelihood estimation, will be presented hereafter. Both the measurement model and the structural model are assessed by MLR and a Satorra-Bentler scaled test statistic using the lavaan package in R program.

4.1. Measurement model

Before evaluating the model, each latent construct is evaluated separately by examining the factor loading (λ) to evaluate the convergent validity, composite reliability, and discriminant validity (Hair et al., 2009). Convergent validity is assessed through the factor loading of the item onto the latent construct and composite reliability tests an individual construct's internal consistency and homogeneity (Xiao & Lam, 2020). As suggested by Hair et al. (2009), $\lambda > 0.4$ should be considered significant for a sample size large than 200, and the composite reliability of the latent constructs measured by Cronbach's alpha (α), which should be larger than 0.70. A value of Average variance extracted (AVE), calculated according to Equation (1), larger than 0.50 indicates adequate convergent validity (Chang et al., 2021; Fornell & Larcker, 1981).

$$AVE = \frac{\sum_1^n \lambda^2}{\sum_1^n \lambda^2 + \sum_1^n (1 - \lambda^2)} \quad (1)$$

where n is the number of items under each construct.

The discriminant validity is used to assess the relationships between latent variables (Henseler et al., 2015). It is determined when the square root of the AVE drawn from each latent construct is larger than the value of the correlation coefficient between the two latent constructs (Fornell & Larcker, 1981).

Measure variables that have a low correlation with the related latent construct and a high cross-loadings with several other latent constructs are removed iteratively from the initial measurement model ($\chi^2/df = 8.206$; CFI = 0.732, GFI = 0.745, AGFI = 0.644, TLI = 0.673, and RMSEA = 0.170) to increase the reliability of the measurement model. The revised measurement model presented in Fig. 4 shows the existence of a relationship between the latent variables and their measure variables. The six indices achieve the acceptable level ($\chi^2/df = 2.403$; CFI = 0.968, GFI = 0.964, AGFI = 0.901, TLI = 0.945, and RMSEA = 0.075), which indicates a reasonable overall fit between the measurement model and the observed data. Table 3 shows that all λ , AVE and α meet the recommended levels, indicating that the structure passes the reliability and validity test.

The sea transportation capacity and freight rate variables are both found insignificant and therefore, removed from the model. This confirms that the sea transportation supply remained largely unaffected

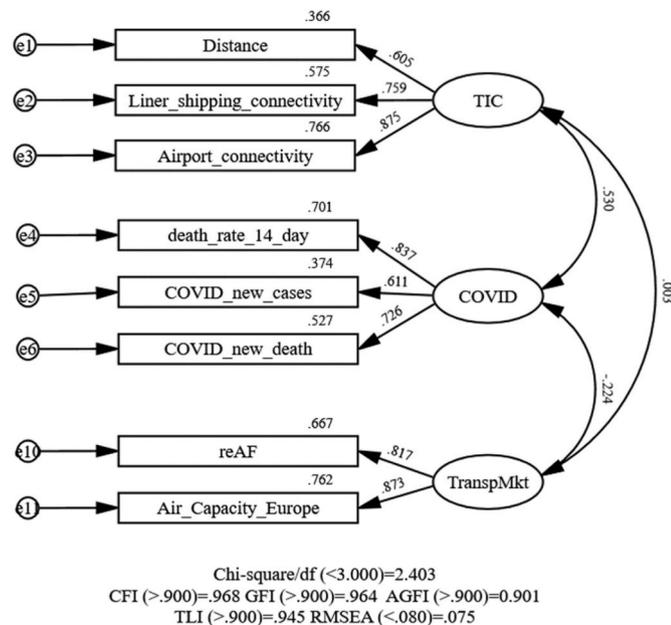


Fig. 4. The measurement model (standardized).

Table 3
 Results of convergent validity and discriminant validity test.

	α (>.70)	AVE (>.50)	COVID	TIC	TranspMkt
COVID	.742	.537	.733		
TIC	.806	.564	.530	.751	
TranspMkt	.832	.713	.220	-.003	.844

Note: The diagonal of this table has $\sqrt{(AVE)}$.

during the study period. Furthermore, the number of new deaths and the death rate are found to be better approximations of the severity of the pandemic compared to the number of cases and confirmed rate. This probably indicates the data of new cases are unreliable as testing and reporting become erratic in a crisis, whereas the count of deaths allows for better tracking of the pandemic, which is also concluded by other studies such as Courtney (2020).

4.2. Structural model

The acceptance of the measurement model indicates that the proposed structural model could be used to examine the hypotheses. Fig. 5 illustrates the path diagram from the structural model. The values on the arrows show the standard path coefficient (Std.Coeff.) and errors variance for each indicator.

The results show a $\chi^2/df = 2.506$, indicating a good fit for the model. A good fit of the model is also shown by the following metrics: RMSEA (0.078) CFI (0.971), GFI (0.951), AGFI (0.883), and TLI (0.952). Table 4 summarizes the results with estimated Std.Coeff. and the significance of the hypothesized relationships. All the path coefficients are standardized to the value range (-1, 1). The exception of -1.007 for the path from CovMeasure to TranspMkt occurs as a result of multicollinearity, which is a common phenomenon in SEM. Based on the estimation of the tolerance index (with a value of 0.993 > 0.2) and variance inflation factor (VIF = 1.007 < 5), we conclude that multicollinearity is not a serious concern for the model (Kenny, 2015).

H2, H3, H4, and H5 attempt to examine the interrelationship among COVID, CovMeasure, and TranspMkt. According to the results, COVID contributes to CovMeasure positively (supporting H2) and CovMeasure is found to influence TranspMkt negatively (supporting H4). In other words, more infection and death cases, and higher death rate lead to higher measure stringency, and higher measure stringency does disrupt the supply of international freight transportation service, that is, capacity reduction and price increase.

Direct effect (DE) refers to the relationship directly linking two constructs, indirect effect (IE) denotes the relationship between two constructs via a third (e.g., mediator) construct, and the total effect (TE) is the sum of the direct and indirect effect (Bollen, 1987). As reported in Table 4, the direct effect of CovMeasure on TranspMkt has the largest magnitude (with a Std.Coeff. of -1.007), followed by the direct effect of TIC on TradeQ (with a Std.Coeff of 0.907). Significant negative relationships are detected between COVID and TradeQ and between COVID and TranspMkt, supporting H1 and H3. For the total effects, COVID has greater negative influences on TranspMkt compared with TradeQ.

This mediation effect of CovMeasure on the negative relationship between COVID and TranspMkt (i.e., H5) is further tested with the suggestion of Little et al. (2012):

- 1) First, the direct effect (denoted c) of COVID on TranspMkt without the variable CovMeasure (i.e., the unmediated model as shown in Fig. 6 (A)) is examined, which is negative and significant ($c = -0.240, p = .007$).
- 2) Next, a bootstrap analysis with a 95% Bias-corrected bootstrap confidence interval based on 5000 bootstrap samples is conducted to examine the mediated model with the variable CovMeasure shown in Fig. 6 (B). The direct effects of COVID on CovMeasure (denoted a),

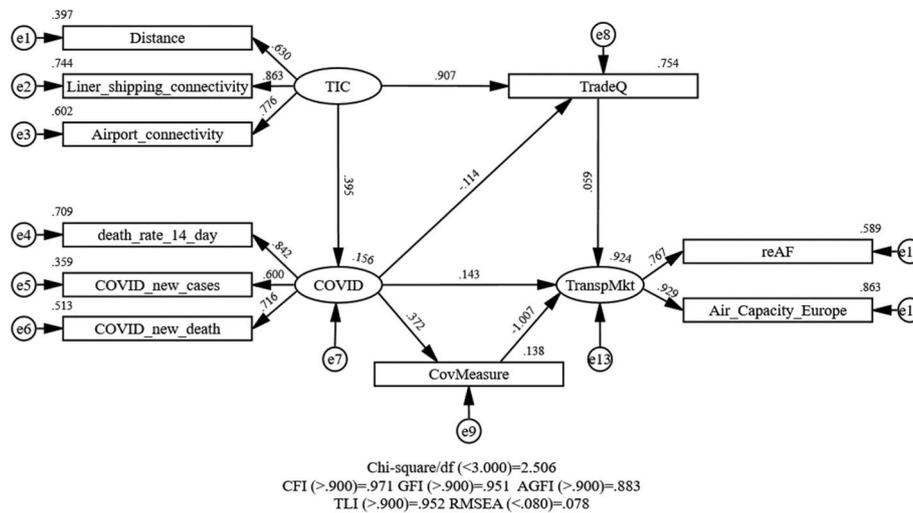


Fig. 5. Structural Equation model (standardized).

Table 4
 Results of the structure model.

Hypothesis		S.E.	t-value	p	Std.Coeff. (DE)	TE	IE
H1.	COVID→TradeQ	4597.794	-2.218	**	-.114	-.114	
H2.	COVID→CovMeasure	.058	5.368	***	.372	.372	
H3.	COVID→TranspMkt	.001	-3.769	***	.143	-.238	-.382
H4.	CovMeasure→TranspMkt	.002	16.936	***	-1.007	-1.007	
H6.	TradeQ→TranspMkt	.000	-1.937	.053	.059	.059	
H7.	TIC→TradeQ	558.766	8.773	***	.907	.864	-.045
H8.	TIC→COVID	.005	4.887	***	.396	.396	

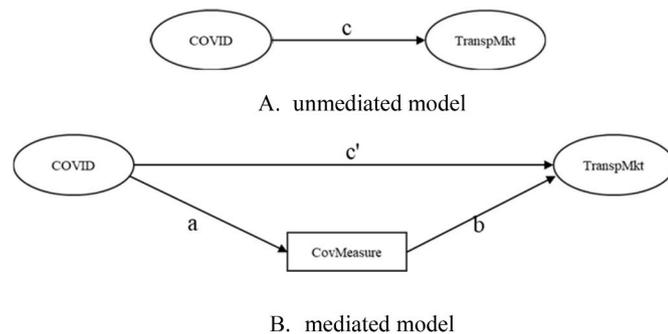


Fig. 6. The structures of unmediated model and mediated model.

CovMeasure on TranspMkt (denoted b), and COVID on TranspMkt (denoted c') are found significant ($a = 0.372$, $b = -1.007$, $c' = 0.143$), confirming that the mediation effect exists.

In addition, due to the introduction of CovMeasure, the magnitude of the direct effect of COVID on TranspMkt has changed in sign and decreased (from $c = -0.240$ to $c' = 0.143$), but the path was still significant in the presence of CovMeasure. Therefore, CovMeasure acts as a partial mediator in the relationship between COVID and TranspMkt, which supports H5. This phenomenon is also known as the suppression effect, that is, the direct and mediation effect have opposite signs (Little et al., 2012). The negative relationship between COVID and TranspMkt is suppressed by the indirect mediation through CovMeasure.

TIC is positively related to TradeQ and COVID, supporting H7 and H8. Contrary to what has been previously hypothesized, the influence of TradeQ on TranspMkt (i.e., H6) is not significant, with weak direct effects.

4.3. Transportation mode comparison

Previous results have explored the influence of COVID-19 pandemic on the aggregated tradeQ. To investigate the impacts of COVID-19 on demand for different transportation modes, the models are further estimated using mode-specific data. Import volumes by air, railway, and maritime transportation from China to all 27 EU partner countries (Eurostat, 2020b) are tested.

The results of the three transportation modes are reported in Table 5. All statistical fit indices are accepted, indicating a good fit of the proposed models. The mediation effect of CovMeasure works between COVID and TranspMkt does not change from the previous results of the aggregate model. Some findings also remain the same as in the aggregate model. For example, the transportation infrastructure is still found to have a similarly positive effect on mode-related imports and COVID spread.

Although all mode imports are negatively affected by COVID, the effect is only significant for sea imports. The average impacts on air and railway transportation flow are not significant for the study period, because both modes experienced quick output reduction and then resumption during the first wave of the pandemic. In comparison, the sea imports have been consistently lower than before.

5. Discussions

5.1. Conceptual and theoretical implications

The presented analysis is based on a series of SEM models using the dataset of Eurostat, ECDC and OxCGRT with the aim of understanding the impact of the first wave of COVID-19 pandemic on the international transportation market, taking China-Europe trade as an example. Based on the results of the eight developed hypotheses, several key findings are discussed as follows.

Table 5
Comparison of path coefficients by transportation mode.

Hypothesis		Air		Rail		Sea	
		Std.Coef.	t-value	Std.Coef.	t-value	Std.Coef.	t-value
H1.	COVID→TradeQ	-.005	-.077	-.031	-.298	-0.133**	-2.769
H2.	COVID→CovMeasure	0.381***	7.548	0.408***	7.715	0.372***	7.452
H3.	COVID→TranspMkt	0.152***	3.764	0.189***	4.096	0.142***	3.559
H4.	CovMeasure→TranspMkt	-1.008***	-6.323	-1.020***	-5.913	-1.007***	-5.967
H6.	TradeQ→TranspMkt	.021	.952	-.027	-.858	.066*	2.556
H7.	TIC→TradeQ	0.740***	9.552	0.227*	2.251	0.946***	14.025
H8.	TIC→COVID	0.402***	5.241	0.409***	4.992	0.396***	4.976
Observations		250		231		250	
χ^2/df (<.000) =		2.644		2.617		2.516	
CFI (>.900) =		.967		.960		.972	
GFI (>.900) =		.998		.991		.957	
AGFI (>.900) =		.994		.977		.896	
TLI (>.900) =		.945		.933		.953	
RMSEA (<.080) =		.081		.084		.078	

*: $p < .05$, **: $p < .01$, ***: $p < .001$.

First, confirmed by H1 and H3, the COVID-19 pandemic has significant negative effects on the demand and supply of international transportation services. And supply is more heavily influenced by the pandemic than the demand side, as the standard total effects of COVID on TranspMkt outweigh that of TradeQ.

Moreover, the model outcomes show that the relationship between COVID and TranspMkt is rather indirect, with CovMeasure acting as a mediator. With H2, H3, and H5, CovMeasure is found to be a partially mediating variable influencing the impact of the pandemic on the transportation services market. More specifically, the negative effects of the COVID-19 pandemic on transportation services are suppressed by indirect mediation through government restriction measures. The suppression effect of CovMeasure suggests that effective government restriction measures help to reduce the negative impact of COVID and ultimately promote the transportation service market.

The results from mode-specific models show that the pandemic did not impact evenly on the transportation modes. From the demand side, seaborne import volume is more severely affected than air and rail. This conflicts with the findings of Cui et al. (2021), that the air freight transportation will be most negatively affected measured in output decline percentage while waterway is the least. This again proves that the impact of the pandemic on the domestic trade and market in China and the international trade and transportation market are very different.

This can be further explained by the fact that the high severity of the pandemic in Europe has led to quickly-increasing demand for COVID-19 related products, especially medical products such as ventilators and face masks (Eurostat, 2020a), which are mainly imported from China and largely rely on air transportation (Bombelli, 2020). At the same time, the pandemic has also accelerated a global transition to e-commerce which is destined to benefit air cargo transportation demand (Rooley, 2021). Therefore, despite service supply reduction and price soaring, the air trade volume quickly picked up. On the other hand, skyrocketing air freight rates and longer transit times and harder restrictions in both air and sea transportation have made the 15-day trans-Eurasia railway services an ideal alternative for COVID-19 related products transportation and other intermediate goods (Zhang, 2021), and experienced a record peak in demand during the later time in 2020. As a result, sea service experienced the most demand reduction.

From the supply side, the maritime market shows higher stability than the air market during the first ten months of the pandemic, with consistent capacity and price control. Actions taken by liner companies, particularly blank sailing, slower speeds and longer routes have maintained freight rates at an impressively stable level (Cullinane & Haralambides, 2021). In other words, the COVID-19 shock did not dismantle the existing established liner shipping services during the first ten months (Rivera, 2020).

In contrast, the negative impacts on air freight capacity (and price) were much more significant than on liner shipping capacity (and price) during the first wave of the pandemic, which is in line with previous literature, although airlines are deploying grounded passenger aircraft in cargo-carrying roles to provide extra freight capacity, the capacity crunch driven by the lack of international passenger traffic is still ongoing (IATA, 2020c).

With respect to H7 and H8, this study confirms that international transportation infrastructure positively affects a country's import performance, and countries with intensive transportation connections are more prone to the threat of disease spread.

5.2. Policy and managerial implications

The findings of the study also have significant implications for government departments and industry managers.

Taking the demand and supply sides together, the three transportation modes clearly play different roles in international trade and compensate each other as a sustainable logistic network for a country. We believe the difference of the transportation modes' performance is due to two main reasons: first, the market control power wielded by the global liner alliances and the leading companies is highly effective, compared to the much more scattered airline market, and second, the human-involvement level of the different markets plays a critical role. An industry is more prone to disruptions caused by human-illness crises if it requires higher levels of human involvement. The China-Europe railway service, although not tested in the model due to lack of data, is an even more concentrated market (with China Express Railway as the main provider) and less human involvement than the airline system. Rail is the least affected mode during the pandemic time in terms of supply, and even experienced continuous growth in terms of demand.

Because of their different operating characteristics, they are impacted differently by external shocks. Since the extreme shocks are highly unpredictable, exemplified by the Covid-19 pandemic as well as the recent Russia-Ukraine war, a resilient multimodal transportation system with different characteristics and capacity buffers is strategically important for a country. Meanwhile, the development of intelligent transportation systems to improve transportation services with innovative technologies that can replace human handling, build agility and flexibility in transportation, and facilitate better recovery from disruptions is more prominent in the post COVID-19 era, as also mentioned in Zhao et al. (2022).

Furthermore, the suppression effect of European governments' restriction measures is confirmed in our study, as we found the negative relationship between COVID and TranspMkt is suppressed by the indirect mediation through CovMeasure, which supports that governments'

restriction measures are necessary for the first-wave period of the pandemic. Opposite to the public's perception that government controls harm the market, our model has shown that at least in the initial period, the harm to the market is mostly from the pandemic itself, i.e., human sickness and deaths. Both the demand and supply were strongly negatively affected by the pandemic.

As also pointed out by Xu, Shi, et al. (2021), even though the government's restriction measures led to a decline in shipping trade, they at the same time helped reduce the spread of the pandemic, which will help bring recovery to the economy and indirectly benefit shipping trade. Government controls not only save human lives but also help to reduce the negative impact of COVID on the general market and ultimately promote the transportation service market. However, we must point out that this conclusion is limited to only the first-wave period and only to Europe, during which time the harm of the disease to human health was much severer than later and in which areas the government interventions were quite milder compared to other regions of the world, such as Asia.

6. Conclusion

This study aims to understand the early disruptive impacts that the COVID-19 pandemic had on the international freight transportation market. To do this, a series of SEM models are applied to analyze EU-27's imports from China and the international transportation market for the first ten months of 2020, i.e., the first wave of the COVID-19 pandemic detected by structural breaking point method. The SEM allows to analyze cause-and-effect relationships among the constructs simultaneously and check the mediation effect. In this way it is possible to explore the interrelationships among the COVID-19 pandemic, government restriction measures, international trades, the transportation market performances, and transportation infrastructure pre-condition.

Our results show that the COVID-19 crisis had a negative impact on both the demand and supply of international transportation services as expected, and the impacts are different on different transportation modes. It is also found that the negative impact of the pandemic on transportation services is suppressed by indirect mediation through government restriction measures.

Our study is the first attempt in literature to understand the early impact of the pandemic on the international transportation market which has not been fully understood. By using SEM to test transportation market relationships in the pandemic, the study provides a picture of the impact of pandemics on international transportation, especially in respect to different transportation modes. Furthermore, this study is also among the first to explore the effect of government restriction measures on transportation service. The mediation effect of government restriction measures on the negative relationship between the pandemic and transportation service supply is identified. Although many studies on passenger travel behavior have examined the impacts of the pandemic and government restriction measures, we extend the analysis to freight transportation.

Our findings provide important guidance for transportation industry players and governments in their decision-making process facing with global market shocks such as pandemics. For example, the strictness of governments' restriction measures negatively influences the transportation market in the beginning of the pandemic. Policymakers should be aware of the impact of the disease control measures on freight movement and thus try to find the balance between disease control and the economy.

Furthermore, different transportation modes have been found to react differently facing the pandemic shock. This indicates that different modes play different roles in international trade and form a reliable and sustainable logistic network jointly for a country. To better cope with future potential disruptions, higher automation to reduce the vulnerability to human-caused crisis and higher market control levels to better align reactions could be helpful for a resilient transportation system.

This study is subject to some limitations. First, the current model does not consider the possible time-lagged effect of CovMeasure on COVID. Thus, the direct effect of CovMeasure on COVID could have been missed. Similarly, this study only focuses on the first wave of the pandemic, as limited by the available data at the time of writing. A worthwhile direction for future research is to analyze the impacts of all COVID-19 pandemic waves and the trade and transportation development alongside. The right extent of government measures in different situations were not investigated, which could bring more insightful guidance to policymakers. Finally, to fully explore the causes of COVID development and trade, future research could include other critical factors, such as the local economy and medical testing capacity.

CRedit authorship contribution statement

Yang Yang: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Qing Liu:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Chia-Hsun Chang:** Formal analysis, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- Ariane, D., Jacques, L., & Davide, P. (2022). *Research for TRAN Committee: Relaunching transport and tourism in the EU after COVID-19-Part V-Freight transport*.
- Bai, X., & Lam, J. S. L. (2019). An integrated analysis of interrelationships within the very large gas carrier (VLGC) shipping market. *Maritime Economics & Logistics*, 21(3), 372–389. <https://doi.org/10.1057/s41278-017-0087-3>
- Barua, S. (2020). *COVID-19 pandemic and world trade: Some analytical notes*. Available at SSRN 3577627.
- Bensassi, S., Martinez-Zarzoso, I., & Suárez, C. (2014). The effect of maritime transport costs on the extensive and intensive margins: Evidence from the Europe-Asia trade. *Maritime Economics & Logistics*, 16(3), 276–297. <https://doi.org/10.1057/mel.2014.3>
- Bollen, K. A. (1987). Total, direct, and indirect effects in structural equation models. *Sociological Methodology*, 37–69.
- Bombelli, A. (2020). Integrators' global networks: A topology analysis with insights into the effect of the COVID-19 pandemic. *Journal of Transport Geography*, 87(August), Article 102815. <https://doi.org/10.1016/j.jtrangeo.2020.102815>
- Bryant, F. B., & Satorra, A. (2012). Principles and practice of scaled difference chi-square testing. *Structural Equation Modeling: A Multidisciplinary Journal*, 19(3), 372–398.
- Cai, J., Xu, B., Chan, K. K. Y., Zhang, X., Zhang, B., Chen, Z., & Xu, B. (2019). Roles of different transport modes in the spatial spread of the 2009 influenza A(H1N1) pandemic in mainland China. *International Journal of Environmental Research and Public Health*, 16(2), 222. <https://doi.org/10.3390/ijerph16020222>
- Caldeirinha, V., Felcicio, J. A., Salvador, A. S., Nabais, J., & Pinho, T. (2020). The impact of port community systems (PCS) characteristics on performance. *Research in Transportation Economics*, 80, Article 100818.
- Castells, M. (2011). *The rise of the network society* (Vol. 12). John Wiley & Sons.
- Chang, C.-H., Lu, C.-S., & Lai, P.-L. (2021). Examining the drivers of competitive advantage of the international logistics industry, 0(0 *International Journal of Logistics Research and Applications*, 1–19. <https://doi.org/10.1080/13675567.2021.1915263>.
- Chang, C.-H., & Thai, V. V. (2016). Do port security quality and service quality influence customer satisfaction and loyalty? *Maritime Policy & Management*, 43(6), 720–736.
- Chen, G., & De Abreu E Silva, J. (2013). Regional impacts of high-speed rail: A review of methods and models. *Transportation Letters*, 5(3), 131–143. <https://doi.org/10.1179/1942786713Z.000000000018>
- Chung, H. W., Apio, C., Goo, T., Heo, G., Han, K., Kim, T., ... Park, T. (2021). Effects of government policies on the spread of COVID-19 worldwide. *Scientific Reports*, 11(1), 1–10. <https://doi.org/10.1038/s41598-021-99368-9>
- Clarksons Research. (2021). *Shanghai containerized freight index*. Retrieved from <https://www.clarksons.com/>. (Accessed 10 August 2021).

- Colizza, V., Barrat, A., Barthélemy, M., & Vespignani, A. (2006). The role of the airline transportation network in the prediction and predictability of global epidemics. *Proceedings of the National Academy of Sciences*, 103(7), 2015–2020.
- ColliCare Logistics UAB. (2020). Coronavirus update. Retrieved from <https://www.collicare.it/apie-collicare/nauijenos/coronavirus-update>. (Accessed 30 December 2020).
- Courtney, J. (2020). *COVID-19: Tracking the pandemic with A simple curve approximation tool (SCAT)*. Available at SSRN 3592504.
- Crane Worldwide Logistics. (2021). *Railfreight update - China to Europe*. Retrieved from <https://craneworld.com/knowledge-center/latest-news-and-info/rail-freight-china/>. (Accessed 29 April 2021).
- Cui, Q., He, L., Liu, Y., Zheng, Y., Wei, W., Yang, B., & Zhou, M. (2021). The impacts of COVID-19 pandemic on China's transport sectors based on the CGE model coupled with a decomposition analysis approach. *Transport Policy*, 103(February), 103–115. <https://doi.org/10.1016/j.tranpol.2021.01.017>
- Cullinane, K., & Haralambides, H. (2021). Global trends in maritime and port economics: The COVID-19 pandemic and beyond. *Maritime Economics & Logistics*, 23(3), 369–380. <https://doi.org/10.1057/s41278-021-00196-5>
- Deng, P., Lu, S., & Xiao, H. (2013). Evaluation of the relevance measure between ports and regional economy using structural equation modeling. *Transport Policy*, 27, 123–133. <https://doi.org/10.1016/j.tranpol.2013.01.008>
- Dube, K., Nhamo, G., & Chikodzi, D. (2021). COVID-19 pandemic and prospects for recovery of the global aviation industry. *Journal of Air Transport Management*, 92, Article 102022. <https://doi.org/10.1016/j.jairtraman.2021.102022>. July 2020.
- ECDC. (2020). COVID-19 situation update worldwide, as of 4 December 2020. Retrieved December 22, 2020, from Cdc Europe website: <https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases>.
- European Commission. (2020). *European economic forecast summer 2020 (interim)* (Vol. 8014). Publications Office of the European Union. <https://doi.org/10.2765/828014>
- Eurostat. (2020a). EU trade since 2015 of COVID-19 medical supplies. Retrieved from https://appsso.eurostat.ec.europa.eu/nui/show.do?query=BOOKMARK_DS-1180622_QID_-B1BCB1E_UID_-3F171EB0&layout=PERIOD,L,X,0;REPORTER,L,Y,0;PARTNER,C,Z,0;PRODUCT,L,Z,1;FLOW,L,Z,2;INDICATORS,C,Z,3;&zSelection=DS-1180622PARTNER,EU27_2020_EXTRA;DS-1180622FLOW,1. (Accessed 9 December 2020).
- Eurostat. (2020b). EXTRA EU trade since 2000 by mode of transport (HS2-HS4). Retrieved from <https://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do>. (Accessed 5 December 2020).
- Eurostat. (2021). China-EU - international trade in goods statistics. Retrieved October 3, 2021, from Eurostat website https://ec.europa.eu/eurostat/statistics-explained/index.php/China-EU_-_international_trade_in_goods_statistics#EU_and_China_in_world_trade_in_goods.
- Fang, D., & Guo, Y. (2022). Flow of goods to the shock of COVID-19 and toll-free highway policy: Evidence from logistics data in China. *Research in Transportation Economics*, Article 101185.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
- Francois, J., & Manchin, M. (2013). Institutions, infrastructure, and trade. *World Development*, 46, 165–175.
- Gaskin, D. J., Zare, H., & Delarmente, B. A. (2021). Geographic disparities in COVID-19 infections and deaths: The role of transportation. *Transport Policy*, 102, 35–46. <https://doi.org/10.1016/j.tranpol.2020.12.001>
- Gavalas, D., Syriopoulos, T., & Tsatsaronis, M. (2022). COVID-19 impact on the shipping industry: An event study approach. *Transport Policy*, 116(November 2021), 157–164. <https://doi.org/10.1016/j.tranpol.2021.11.016>
- Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., & Gong, P. (2020). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour*, 4(6), 577–587. <https://doi.org/10.1038/s41562-020-0896-8>
- Gudmundsson, S. V., Cattaneo, M., & Redondi, R. (2021). Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. *Journal of Air Transport Management*, 91, Article 102007. <https://doi.org/10.1016/j.jairtraman.2020.102007>. June 2020.
- Hair, J. F., Black, W. C., Anderson, R. E., & Tatham, R. L. (2009). *Multivariate data analysis*. Prentice-Hall.
- Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., ... Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*. <https://doi.org/10.1038/s41562-021-01079-8>
- Hayakawa, K., & Mukunoki, H. (2021). The impact of COVID-19 on international trade: Evidence from the first shock. *Journal of the Japanese and International Economies*, 60 (March), Article 101135. <https://doi.org/10.1016/j.jjie.2021.101135>
- Heiland, I., & Ulltveit-Moe, K. (2020). An unintended crisis: COVID-19 restrictions hit sea transportation. <https://voxeu.org/article/covid-19-restrictions-hit-sea-transportati-on>.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
- Hooper, D., Coughlan, J., & Mullen, M. (2008). *Evaluating model fit: A synthesis of the structural equation modelling literature* (pp. 195–200). 7th European Conference on Research Methodology for Business and Management Studies.
- IATA. (2020a). Air cargo market analysis: Robust end to 2020 for air cargo. <https://www.iata.org/en/iata-repository/publications/economic-reports/air-freight-monthly-analysis-december-2020/>.
- IATA. (2020b). *Air freight market analysis*. Retrieved from <https://www.iata.org/economics/>. (Accessed 1 December 2020).
- IATA. (2020c). *IATA: Air cargo recovery continues in June but at a slow pace*. Retrieved from <https://www.atc-network.com/atc-news/iata/iata-air-cargo-recovery-continue-s-in-june-but-at-a-slow-pace>. (Accessed 22 October 2020).
- ICAO. (2021). 2020 passenger totals drop 60 percent as COVID-19 assault on international mobility continues. <https://www.icao.int/Newsroom/Pages/2020-passenger-totals-drop-60-percent-as-COVID19-assault-on-international-mobility-continues.aspx>.
- Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136(March), Article 101922. <https://doi.org/10.1016/j.trre.2020.101922>
- Jiang, X., He, X., Zhang, L., Qin, H., & Shao, F. (2017). Multimodal transportation infrastructure investment and regional economic development: A structural equation modeling empirical analysis in China from 1986 to 2011. *Transport Policy*, 54, 43–52. <https://doi.org/10.1016/j.tranpol.2016.11.004>. November 2014.
- Kao, L.-H., Stewart, M., & Lee, K.-H. (2009). Using structural equation modeling to predict cabin safety outcomes among Taiwanese airlines. *Transportation Research Part E: Logistics and Transportation Review*, 45(2), 357–365.
- Kenny, D. A. (2015). Multiple regression. Retrieved March 2, 2021, from Online Tutorial website: <http://davidakenny.net/cm/mr.htm>.
- Kim, Y.-R., Lim, J.-H., & Choi, Y.-C. (2020). Analysis and prospect of export trend of air cargo market before and after COVID-19. *Journal of the Korean Society for Aviation and Aeronautics*, 28(4), 164–170. <https://doi.org/10.12985/ksaa.2020.28.4.164>
- Kleiber, C., Hornik, K., Leisch, F., & Zeileis, A. (2002). strucchange: An R package for testing for structural change in linear regression models. *Journal of Statistical Software*, 7(2), 1–38.
- Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
- Knowler, G. (2020). Lack of options has low-value air cargo moving at high-value rates. Retrieved October 6, 2020, from Journal of Commerce website <https://search.proquest.com/docview/2399595993?accountid=26658>.
- Korinek, J., & Sourdin, P. (2009). *Maritime transport costs and their impact on trade*, 2009 (p. 7). Organization for Economic Co-Operation and Development TAD/TC/WP.
- Koyuncu, K., Tavacioglu, L., Gökmen, N., & Arican, U.Ç. (2021). Forecasting COVID-19 impact on RWI/ISL container throughput index by using SARIMA models, 00(00) *Maritime Policy & Management*, 1–13. <https://doi.org/10.1080/03088839.2021.1876937>.
- Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Ichii, H., Zacharski, M., ... Khosrawipour, T. (2020). The association between international and domestic air traffic and the coronavirus (COVID-19) outbreak. *Journal of Microbiology, Immunology, and Infection*, 53(3), 467–472. <https://doi.org/10.1016/j.jmii.2020.03.026>
- Li, T. (2020). A SWOT analysis of China's air cargo sector in the context of COVID-19 pandemic. *Journal of Air Transport Management*, 88(July), Article 101875. <https://doi.org/10.1016/j.jairtraman.2020.101875>
- Li, H., Liu, Y., & Peng, K. (2018). Characterizing the relationship between road infrastructure and local economy using structural equation modeling. *Transport Policy*, 61(1), 17–25. <https://doi.org/10.1016/j.tranpol.2017.10.002>
- Little, T. D., Card, N. A., Bovaird, J. A., Preacher, K. J., & Crandall, C. S. (2012). Structural equation modeling of mediation and moderation with contextual factors. *Modeling Contextual Effects in Longitudinal Studies*, 207–230. <https://doi.org/10.4324/9780203936825>
- Liu, X., & Xin, X. (2011). Transportation uncertainty and international trade. *Transport Policy*, 18(1), 156–162.
- Ma, T.-Y., Chow, J. Y. J., & Xu, J. (2017). Causal structure learning for travel mode choice using structural restrictions and model averaging algorithm. *Transportmetrica: Transport Science*, 13(4), 299–325.
- Mayer, T., & Zignago, S. (2006). *GeoDist: The CEPII's distances and geographical database*.
- McKibbin, W., & Fernando, R. (2020). The global macroeconomic impacts of COVID-19: Seven scenarios. *Asian Economic Papers*, 1–55.
- Menhat, M. N. S., Mohd Zaideen, I. M., Yusuf, Y., Salleh, N. H. M., Zamri, M. A., & Jeevan, J. (2021). *The impact of covid-19 pandemic: A review on maritime sectors in Malaysia* (Vol. 105638). Ocean & Coastal Management. <https://doi.org/10.1016/j.ocecoaman.2021.105638>
- Nakamura, H., & Managi, S. (2020). Airport risk of importation and exportation of the COVID-19 pandemic. *Transport Policy*, 96(June), 40–47. <https://doi.org/10.1016/j.tranpol.2020.06.018>
- Notteboom, T. E., & Haralambides, H. E. (2020). Port management and governance in a post-COVID-19 era: Quo vadis? *Maritime Economics & Logistics*, 22(3), 329–352. <https://doi.org/10.1057/s41278-020-00162-7>
- Notteboom, T., Pallis, T., & Rodrigue, J. P. (2021). *Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic versus the 2008–2009 financial crisis*. *Maritime Economics and Logistics*, Article 0123456789. <https://doi.org/10.1057/s41278-020-00180-5>
- Portugal-Perez, A., & Wilson, J. S. (2012). Export performance and trade facilitation reform: Hard and soft infrastructure. *World Development*, 40(7), 1295–1307.
- Rivera, A. (2020). *The impact of COVID-19 on transport and logistics connectivity in the landlocked countries of South America*.
- Rodrigues, M., Teoh, T., Ramos, C., Winter, T.de, Knezevic, L., Marcucci, E., & Cutrufo, N. (2021). *Relaunching Transport and Tourism in the EU after COVID-19: Part I: Overview*.
- Rooley, J. (2021). *COVID-19 impact on the air cargo industry*. Retrieved from <http://www.willstowerswatson.com/en-US/Insights/2021/01/covid-19-impact-on-the-air-cargo-industry>. (Accessed 5 February 2021).
- Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *Journal of Statistical Software*, 48(2), 1–36.

- Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, 66(4), 507–514.
- Setthasuravich, P., & Kato, H. (2020). The mediating role of the digital divide in outcomes of short-term transportation policy in Thailand. *Transport Policy*, 97 (March), 161–171. <https://doi.org/10.1016/j.tranpol.2020.07.008>
- Shifan, Y., Outwater, M. L., & Zhou, Y. (2008). Transit market research using structural equation modeling and attitudinal market segmentation. *Transport Policy*, 15(3), 186–195. <https://doi.org/10.1016/j.tranpol.2008.03.002>
- Sigler, T., Mahmuda, S., Kimpton, A., Loginova, J., Wohland, P., Charles-Edwards, E., & Corcoran, J. (2021). The socio-spatial determinants of COVID-19 diffusion: The impact of globalisation, settlement characteristics and population. *Globalization and Health*, 17(1), 1–14. <https://doi.org/10.1186/s12992-021-00707-2>
- Stein, C. M., Morris, N. J., Hall, N. B., & Nock, N. L. (2017). Structural equation modeling. *Methods in Molecular Biology*, 1666, 557–580. https://doi.org/10.1007/978-1-4939-7274-6_28
- Suau-Sanchez, P., Voltes-Dorta, A., & Cugueró-Escofet, N. (2020). An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it? *Journal of Transport Geography*, 86(June), 39–43. <https://doi.org/10.1016/j.jtrangeo.2020.102749>
- TAC Index. (2020). *TAC Index monthly airfreight rates*. Retrieved from <https://www.aircargonews.net/data-hub/airfreight-rates-tac-index/>. (Accessed 5 December 2020).
- Tardivo, A., Sánchez Martín, C., & Carrillo Zanuy, A. (2020). COVID-19 impact in transport, an essay from the railways' systems research perspective. <https://doi.org/10.31124/advance.12204836>.
- Ülengin, F., Kabak, Ö., Önsel, Ş., Ülengin, B., & Aktaş, E. (2010). A problem-structuring model for analyzing transportation-environment relationships. *European Journal of Operational Research*, 200(3), 844–859. <https://doi.org/10.1016/j.ejor.2009.01.023>
- UNCTAD. (2020). COVID-19 and maritime transport: Impact and responses. *Report No UNCTAD/DTL/TLB/INF/2020/1* https://unctad.org/en/PublicationsLibrary/dtlb_inf2020d1_en.pdf.
- UNCTAD. (2021). *KEY statistics and trends, trade trends under the COVID-19 pandemic in international trade 2020 trade trends under the COVID-19 pandemic*. In United Nations Conference on Trade and Development. https://unctad.org/system/files/official-document/ditctab2020d4_en.pdf.
- Verschuur, J., Koks, E. E., & Hall, J. W. (2021). Erratum to: Global supply-chain effects of COVID-19 control measures, 2020 *Nature Human Behaviour*, 4(6), 577–587. <https://doi.org/10.1038/s41562-020-0896-8>. *Nature Human Behaviour*, 5(March). <https://doi.org/10.1038/s41562-021-01060-5>.
- Weis, C., & Axhausen, K. W. (2009). Induced travel demand: Evidence from a pseudo panel data based structural equations model. *Research in Transportation Economics*, 25(1), 8–18.
- Wessel, J. (2019). Evaluating the transport-mode-specific trade effects of different transport infrastructure types. *Transport Policy*, 78(February), 42–57. <https://doi.org/10.1016/j.tranpol.2019.04.002>
- World Bank. (2020). *COVID-19 to plunge global economy into worst recession since World War II*. World Bank. Retrieved from World Bank website: <https://www.worldbank.org/en/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii>.
- World Economic Forum. (2019). *The global competitiveness report 2019*.
- WTO. (2020). Trade costs in the time of global pandemic. <https://doi.org/10.30875/e29b9dca-en>.
- Xiao, Z., & Lam, J. S. L. (2020). The impact of institutional conditions on willingness to take contractual risk in port public-private partnerships of developing countries. *Transportation Research Part A: Policy and Practice*, 133(August 2018), 12–26. <https://doi.org/10.1016/j.tra.2019.12.023>
- Xu, L., Shi, J., Chen, J., & Li, L. (2021). Estimating the effect of COVID-19 epidemic on shipping trade: An empirical analysis using panel data. *Marine Policy*, 133 (September). <https://doi.org/10.1016/j.marpol.2021.104768>
- Xu, L., Yang, S., Chen, J., & Shi, J. (2021). The effect of COVID-19 pandemic on port performance: Evidence from China. *Ocean & Coastal Management*, 209(October 2020), Article 105660. <https://doi.org/10.1016/j.ocecoaman.2021.105660>
- Zhang, Y., Zhang, A., & Wang, J. (2020). Exploring the roles of high-speed train, air and coach services in the spread of COVID-19 in China. *Transport Policy*, 94(May), 34–42. <https://doi.org/10.1016/j.tranpol.2020.05.012>
- Zhang, Y. (2021). Alternative transport mode: China-EU trade on rail. <https://ihsmarkit.com/research-analysis/alternative-transport-mode-china-eu-trade-on-rail.html>. (Accessed 23 June 2021).
- Zhao, H.-M., He, H.-D., Lu, K.-F., Han, X.-L., Ding, Y., & Peng, Z.-R. (2022). Measuring the impact of an exogenous factor: An exponential smoothing model of the response of shipping to COVID-19. *Transport Policy*, 118, 91–100.