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Modelling Heterogeneous Capacity Response Strategies of Airlines in the Initial Stage of the COVID-19 Pandemic in the EU-US Market

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Abstract

This paper investigates the causal impact of the initial stage of the COVID-19 pandemic (i.e., 2020) on airlines' crisis response strategies from the supply perspective in the EU-US market. An analytical framework examining three strategies, namely market exit, capacity retrenchment, and route hierarchy persevering, is established by utilizing the difference-in-differences (DID) method, which jointly considers dynamics in pandemic severity, border control policies, and route structure. The results demonstrate that the COVID-19 pandemic led to the disappearance of diversity in the business models of the EU-US market in the short term. Analysis of individual airlines' capacity retrenchment strategies reveals heterogeneity in the impact of COVID-19. The route hierarchy persevering analysis exhibits three distinct strategies of airlines, i.e., connectivity-oriented, antitrust immunity joint venture-oriented, and market presence-oriented.

1 Introduction

The worldwide spread of the coronavirus disease 2019 (COVID-19) has significantly transformed the way international air transport is operated. In the initial stage of COVID-19 (i.e., 2020), both the demand and supply sides of the airline industry were hit hardest (Abate et al., 2020). Being one of the most liberalized and profitable markets, the Europe-United States (EU-US) market has undergone tremendous loss in terms of both supply and demand in the initial stage of COVID-19 (Budd et al., 2020; Iacus et al., 2020). However, little research has paid attention to examining the impact of the initial stage of COVID-19 on this market as compared to other markets in the literature (Sun et al., 2021), and how carriers respond to this unprecedented disturbance.

The difficulty in quantifying the pure impact of COVID-19 refers to the counterfactual assessment (Angelov & Waldenström, 2023), i.e., nearly no international market did not suffer from the pandemic. The existing studies utilizing before-and-after comparisons (Fontanet-Pérez et al., 2022), time series (Giouroukelis et al., 2022; Kallidoni et al., 2022; Maneenop & Kotcharin, 2020), or simulation methods (Ivanov, 2020; Li, Zhou, Kundu & Zhang, 2021; Truong, 2021) cannot accurately measure the net causal effect of COVID-19, in that the short-term decreases in supply/demand indicators may also be affected by other confounding factors. First, in the EU-US market, the stringency level of control measures varies across different European countries and the US (Shibayama et al., 2021; Unruh et al., 2021). Some countries also frequently changed their control policies in 2020 in response to different levels of pandemic severity. Second, researchers found that the route structure of the worldwide air transport network has changed, whereby the number of hub-and-spoke routes increased after the epidemic (Sun et al., 2020). In addition, carriers responded differently due to the variation in business models, ownerships (Brown & Kline, 2020), and passenger demand (Manca et al., 2021). A new method is thus needed to not only capture the direct impact of COVID-19 but also control for other factors, such as national control measures, the change of network structures, and the response strategies of carriers.

Researchers have shown that a difference-in-differences (DID) model is capable of dealing with the aforementioned issues by estimating the average treatment effect on the treated (ATT) (Karanki & Lim, 2023). The novelty is to set the time before the pandemic as the control group because there is no comparable international market unaffected by the pandemic.

Route capacity is a key focus in studies of airline crisis response strategies, as it directly influences an airline's ability to adjust to sudden demand fluctuations and minimize operational costs during a crisis. Capacity provides a comprehensive measure of an airline's available resources to respond to disruptive events like the COVID-19 pandemic. Given the fact that most of the research studies the changes in the number of routes (Ivanov, 2020) or available seat kilometres (ASK) (Truong, 2021), this paper will also focus on the capacity side, but choose flight frequency as the main dependent variable.

The objective of this paper is, therefore, to quantify the causal impact of the initial stage of COVID-19 on the EU-US capacity by exploring the heterogeneous response strategies of airlines. A DID modelling framework is applied to consider the severity of COVID-19, international travel control measures, as well as variables influencing the capacity of international markets.

2 Literature review

Traditional response strategies, such as competition schemes or acquisitions, cannot help carriers deal with this unprecedented crisis due to its long duration, broad geographical reach, and high level of uncertainty (Ivanov, 2020). To model the heterogeneous capacity response strategies of airlines to the pandemic, we adopt the concept framework proposed by Wenzel et al. (2020), namely retrenchment, persevering, and exit. These three strategies are dynamic adjustments of an airline's response strategy within the scope of its existing business in short and medium terms. The established DID models should allow accurate and fair comparisons between carriers serving the EU-US market to reveal the differences in the three strategies.

2.1 *Capacity retrenchment*

Capacity retrenchment strategy refers to an airline's decision to scale back operations to significantly reduce costs when exposed to the pandemic (Bruton et al., 2003). The challenges to depict the retrenchment strategy in a DID framework are: First, how to transform the characteristics of COVID-19 into independent variables? Second, how to represent the indirect impact of the pandemic that can also influence the EU-US capacity?

Existing research applies two methods to represent the characteristics of COVID-19. First, several key time points after the event are applied to show the temporal aspect (Angelov & Waldenström, 2023). Second, the number of confirmed infection cases is applied to explicitly describe the characteristics of COVID-19 (Li, Zhou, Kundu & Sheu, 2021). The case studies generally focus on one or several countries (Kim & Sohn, 2021; Kuo et al., 2022), but do not establish a relationship between the indicator and international air transport. The aforementioned literature that applied aggregated data will ignore the consecutive temporal evolution of the pandemic and its spatial impact on the EU-US market. In Europe, Italy was the first country to experience a significant outbreak in February 2020, and subsequently, the other countries followed within a month. The outbreak in the US did not start until late March. In this way, the time for countries to take control measures differs and may gradually change (Plümper & Neumayer, 2020). This paper applies disaggregated weekly time series and carrier-route-level data to accurately capture the COVID-19 impact. Both the occurrence time of the pandemic and the number of confirmed cases is used to represent the characteristics of COVID-19.

The pandemic-induced impact refers to different control policies enacted by European countries and the US. Countries like the UK published a "live with the virus" policy, while Italy and Spain implemented strict control measures to reduce infections in the short term. Truong (2021) found that relaxing border controls significantly increased the volume of international flights compared to strict travel bans under similar infection levels. Consequently, the stringency of control policies should be considered as an important factor influencing the EU-US capacity in the DID modelling.

2.2 *Route hierarchy persevering*

Persevering strategy is defined as an airline's effort to conserve its route network structure and subsequently maintain a market presence during the pandemic. Kuo et al. (2022) found that hub airports have been predominantly retained in the network and maintained their high centrality after COVID-19, and a trend toward a hub-and-spoke network structure was observed in 2020 by Li, Zhou, Kundu, and Sheu (2021). The findings applied to the Northeast Asian and worldwide networks. It is still unclear whether carriers serving the EU-US market raise or reduce the roles played by primary airports.

It is also uncertain whether the increased functions of the so-called secondary airports in the transatlantic market (Zhang et al., 2018; Zuidberg & de Wit, 2020) before the pandemic were dampened or maintained during the pandemic. For instance, British Airways and Virgin Atlantic announced a cessation of operations at Gatwick Airport in early 2020 (Abate et al., 2020). Airlines' persevering strategies may also be influenced by slot control policies. Due to the existence of the "use it or lose it" rule, some airlines continued to operate flights to coordinated airports at low load factors, even during the sharp decline in passenger demand, to maintain their slots. These flights are referred to as "ghost flights". A study by Sun et al. (2022a) has confirmed the existence of ghost flights in the European market during the pandemic despite the slot waiver programs. Moreover, there were significant differences between airlines in their decisions to operate these ghost flights. Since coordinated airports are typically busy hub airports, whether these differences affect capacity requires further investigation. Therefore, it is necessary to conduct a systematic analysis of the perseverance of airports serving the EU-US market and then examine whether the resulting route hierarchy still influences the capacity of carriers during the pandemic.

2.3 Market exit

Market exit strategy refers to scenarios when an airline enters into bankruptcy, undergoes acquisitions (Dube et al., 2021), or withdraws from a specific market due to limited resources. It is challenging for carriers to keep operating international routes due to high fixed costs and the shortage of cash flow during COVID-19. In Europe, traditional full-service carriers received substantial government support, while low-cost carriers and charter carriers struggled to acquire subsidies (Albers & Rundshagen, 2020). The US government provided more extensive aid to full-service, charter, and cargo carriers (Martin-Domingo & Martín, 2022). It is thus possible that some carriers cannot survive and fully disappear in the EU-US market, while others exited a large number of routes. To eliminate the impact of the unfairness in subsidy allocation among airlines with different business models during the pandemic, we will next analyse the response strategies of low-cost carriers and full-service carriers separately.

This paper will first perform a comprehensive analysis of carriers' exit strategies on the EU-US routes based on different business models.

3 Data and exploratory analysis

3.1 Data Sources

This study focuses on the nonstop intercontinental market between Europe and the US. European countries are limited to those that signed the European Common Aviation Area (ECAA) agreement before January 2019 and play significant roles in serving the EU-US market (e.g., Switzerland), totalling 20 countries.

The data on the market operation (e.g., origin and destination airport, operating carrier, and frequency) is primarily sourced from the Official Airlines Guide (OAG). The investigation focuses on the period from 2019 to 2020, with 2020 selected to represent the initial stage of the pandemic for two key reasons. First, the unprecedented demand collapse and control policies in 2020 forced airlines to implement immediate response strategies. Unlike later stages, where government interventions such as vaccines and demand recovery played a larger role, 2020 represents a unique period where airlines' strategic decisions were primarily driven by the direct impact of the shock itself. Second, during 2020, the dominant COVID-19 variant remained unchanged in Europe and the U.S., and widespread vaccinations had not yet been implemented (European Centre for Disease Prevention and Control [ECDC], 2021; Centers for Disease Control and Prevention [CDC], n.d.). This study seeks to explore the factors influencing airlines' crisis response strategies in the absence of vaccines while excluding the impact of virus variants.

The COVID-19-related data, i.e., severity of the pandemic and national-level control policies, are derived from the Center of Systems Science and Engineering at Johns Hopkins University (JHU) (Dong et al., 2020) and the Oxford COVID-19 Government Response Tracker (OxCGRT) database, respectively (Hale et al., 2021). All data are aggregated on a weekly basis.

3.2 Exit and survival of airlines in 2020

After the pandemic, notable disparities emerged among carriers regarding their operational sustainability. In 2019, 46 airlines provided services in the EU-US market. These carriers can be categorized into three groups based on the total number of weeks in operation in 2020, as displayed in Table 1.

Service continuation carriers refer to those that managed to maintain operations through all 52 weeks in 2020, which consist of 14 airlines. In 2020, a total of 18 carriers ceased operations. The reasons for a complete cease can be divided into bankruptcy and withdrawal from the EU-US market (Albers & Rundshagen, 2020). Among 18 carriers, three carriers (IG, DE, DI) declared bankruptcy in 2020, while the remaining 13 carriers merely opted to exit the EU-US market. 14 airlines are categorized into service interruption carriers. These carriers did not provide services during certain weeks of 2020, reflecting partial exits from the market.

Carriers that fall under the category of complete cessation or service interruption are considered to have adopted the market exit strategy, constituting approximately 70% of all airlines. All long-haul low-cost carriers (LCCs) and charter airlines implemented the strategy, while most full-service carriers (FSCs) continuously maintained their market presence. This implies that the pandemic has significantly impacted the diversity of business models in the EU-US market.

The reason non-FSCs chose to exit the market during the pandemic might be the lack of subsidies (Abate et al., 2020; Zhang & Zhang, 2021; Adler & Andreana, 2023). According to a survey on government subsidies by the Organisation for Economic Co-operation and Development (OECD) (OECD, 2021), among the sample carriers, all carriers except BA received government subsidies in 2020 (as shown in Table 1), all of which were FSCs. FSCs, especially flag carriers, might have exited the market without government subsidies. A typical case is Alitalia (AZ). Before the pandemic, AZ faced bankruptcy due to poor management, but after the pandemic, the Italian government took over and nationalized the airline, highlighting the role of government bailouts in ensuring airlines' survival in the absence of profitability.

Table 1. An overview of carriers' operational sustainability in 2020

Carrier Type		#of Carriers	Carrier Code [(1)]
Service continuation	FSCs	13	AA**, AF**, AZ**, BA, DL**, EI**, FI**, JU**, KL**, LH**, LO**, LX**, UA**
	Others [(2)]	1	ET
Complete cease	FSCs	1	SN
	Long-haul LCCs	5	D8*, WW*, DI, DY, EW
	Charter	8	MT*, SE*, LS, IG, OR, SS, WK, DE
	Others	4	KU*, NZ, SQ, TN
Service interruption	FSCs	5	AY, OS**, IB**, SK**, TP**
	Long-haul LCCs	2	LV, BF
	Charter	3	TOM, TB, S4
	Others	4	EK, B0, UX, VS

[(1)] The full names and countries of carriers are demonstrated in the Appendix.
[(2)] Other carriers refer to carriers registered outside Europe and the US.
* These carriers withdrew from the market before 2020.
** These carriers received a government subsidy in 2020.

Although some carriers preserved market presence in 2020, their capacity has been impacted by the pandemic and related factors. To further investigate COVID-19's impact on different carriers, 16 carriers are selected for empirical analysis as displayed in Table 2. The construction of the sample starts by excluding 18 complete cease carriers. From the remaining 25 airlines, we further narrow down the selection to include only FSCs with a market share exceeding 1% for the study period. Among the 16 sample airlines, the European carriers are all flag carriers. Eight airlines are part of three international airline groups, i.e., the International Airlines Group (IAG), Lufthansa Group, and Air France-KLM.

Table 2. Information for the sampled carriers, their alliances, and airline groups

Carrier Code	International Airline Group	Alliance	Weekly Average Route Frequency		
			2019	2020	2020 vs 2019 (%)
BA	IAG	Oneworld	11.16	7.57	-32.11%
IB	IAG	Oneworld	6.53	3.65	-44.03%
AA		Oneworld	8.76	6.77	-22.67%
AF	Air France-KLM	SkyTeam	9.64	6.07	-37.05%
KL	Air France-KLM	SkyTeam	7.61	5.52	-27.41%
AZ		SkyTeam	8.17	5.02	-38.47%
DL		SkyTeam	8.04	6.09	-24.24%
LX	Lufthansa Group	Star	8.84	4.47	-49.37%
OS	Lufthansa Group	Star	6.12	3.82	-37.60%
LH	Lufthansa Group	Star	7.54	4.41	-41.55%
LO		Star	4.35	3.28	-24.63%
SK		Star	6.41	4.20	-34.41%
TP		Star	5.73	3.23	-43.55%
UA		Star	8.52	6.35	-25.53%
EI	IAG		7.14	6.49	-9.17%
FI			6.51	3.49	-46.36%

Figure 1 displays the weekly frequency variations of the sample airlines from 2019 to 2020. Route frequency experienced a significant decline for all airlines in 2020. However, the extent of the decrease varied significantly. Specifically, European airlines exhibited a greater reduction in frequency compared to American airlines. Among them, SWISS (LX) experienced the most significant year-on-year decrease at 49.37%, followed by FI (Icelandair), Iberia (IB), TAP Air Portugal (TP), and Deutsche Lufthansa AG (LH), all of which exceeded 40%. The decreases of seven airlines were lower than the market average, including the three major American carriers United Airlines (UA), DL (Delta Air Lines), and American Airlines (AA), as well as LOT - Polish Airlines (LO), KLM-Royal Dutch Airlines (KL) under Air France-KLM, and the IAG-affiliated British Airways (BA) and Aer Lingus (EI), with EI experiencing the smallest decrease. This suggests that the extent of capacity reduction may be influenced by factors such as geographic regions and participation in international airline groups. Further modelling is needed to identify the net impact of COVID-19 on capacity retrenchments.

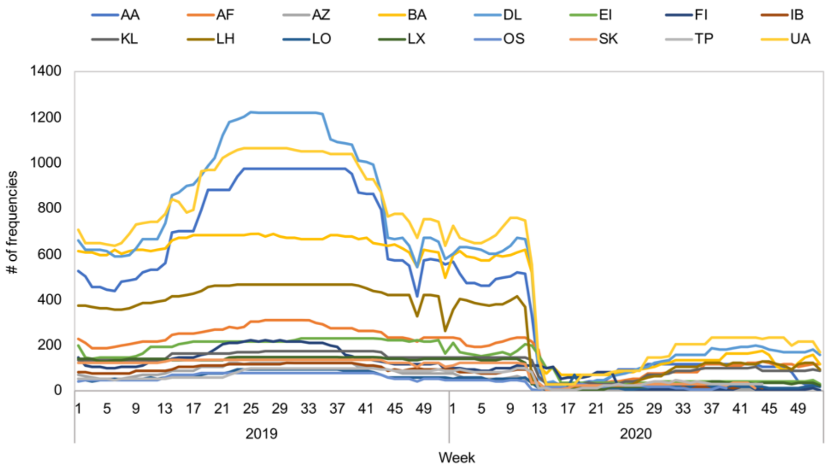

Figure 1. Weekly frequencies of sample carriers from 2019 to 2020

3.3 Exploratory analysis of factors influencing capacity

This section investigates the temporal evolution of factors potentially influencing route capacity after the pandemic, providing a foundation for designing quasi-natural experiments and setting variables in subsequent DID models.

Pandemic severity

The cumulative number of confirmed cases is chosen to characterize the severity of COVID-19. Figure 2 demonstrates the changes in the total frequency of all routes in the EU-US market and cumulative confirmed cases in all sample countries throughout 2020. A certain degree of negative correlation between the pandemic severity and route supply can be observed. Starting in March 2020, confirmed cases exhibited exponential growth, coinciding with a marked decrease in frequencies from that month. Given the differences in the magnitude of cumulative confirmed cases and frequency, careful consideration should be given to data configuration in subsequent modelling.

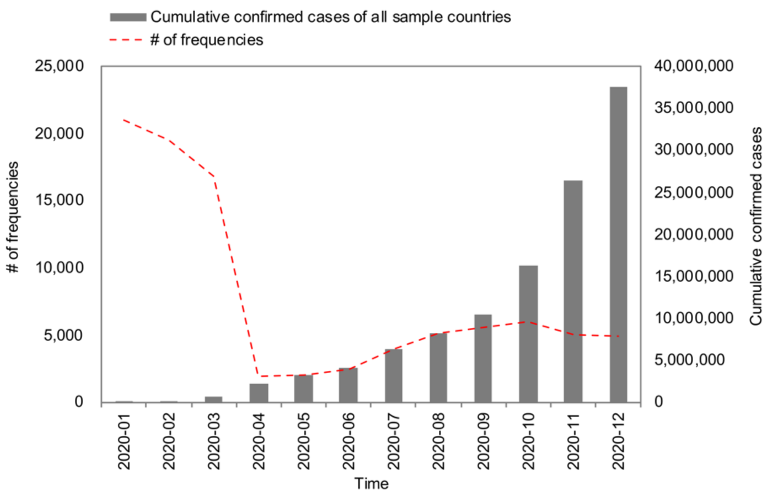

Figure 2. Weekly cumulative confirmed cases and frequency in the EU-US market in 2020

Control measure stringency

Governments worldwide implemented a series of control restrictions on international travel to slow down COVID-19 propagation. The OxCGRT database classifies policies relating to international travel restrictions into five distinct levels of severity. These levels range from the least stringent to the most stringent in the following order:

1. 0, which indicates that no restrictions are in place.
2. 1, which means that arrivals are being screened.
3. 2, which requires a quarantine for arrivals from some or all regions.
4. 3, which prohibits arrivals from some regions.
5. 4, which imposes a ban on all regions or total border closure.

Figure 3 displays fluctuations of control levels among sample countries throughout 2020. Significant differences in the level of stringency and frequencies of policy modifications can be observed. For example, the control policies in Czech, Norway, and Croatia experienced more than 5 adjustments, while countries such as the US, Netherlands, Italy, and France did not modify their policies once they were adjusted in the initial stages of the pandemic. The volatility of international travel policies intensified the uncertainty of the actual impact of COVID-19 on the international air transport market. Additionally, route-level analyses should account for policy adjustments on both ends. The effects of varying degrees of control measures by different countries on international route capacity remain unclear, requiring careful incorporation into the analytical models.

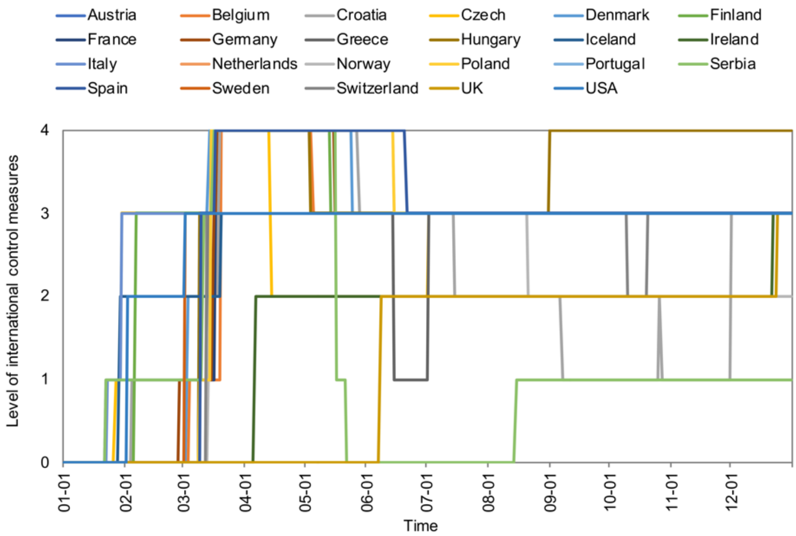

Figure 3. Restrictions on international travel in different countries in 2020

Route Hierarchy

The investigation of the airline's persevering strategy is conducted based on an examination of the route structure in the EU-US market. The categorization of airport hierarchy draws from Zhang et al.'s (2018) study of the transatlantic market, encompassing three classifications: primary airports, secondary airports, and non-hubs.

Table 3 displays a breakdown of airports according to their type and service duration between 2019 and 2020. These airports can be further categorized as complete exit airports, operation interruption airports, and full operation airports. Before the pandemic, a total of 108 airports operated in the market. The emergence and development of secondary hubs and non-hubs contributed to the connectivity of the market. 77% and 63% of secondary hubs and non-hub airports disappeared from the market, respectively after the pandemic. Fortunately, most primary airports survived, except HEL. Additionally, a few secondary airports and non-hubs were able to maintain operations. The integrity of the airport hierarchy was partly preserved.

The closure of airports may change the route hierarchy of the EU-US market and further influence the capacity. Figure 4 demonstrates the evolution of the market share (measured by frequency) structure from 2019 to 2020. Due to the substantial exits of secondary and non-hub airports post-COVID-19, the market share of primary-to-primary routes has seen an increase, while the market share for other types of routes has experienced a decline. Therefore, the key to identifying the airline's route hierarchy persevering strategy lies in studying how the reduced spatial scope and completeness of the route hierarchy affect its capacity. In other words, an investigation is needed into how airlines, while accounting for the impacts of control and policies, utilize their market presence and dominance at airports to maintain the connectivity of the EU-US market collectively.

Table 3. An overview of the operating airport in the EU-US market

Airport Type		Airport code	
		EU	US
Exit airport*	Primary hub	HEL (4)	N/A
	Secondary hub	VCE (1), BFS (1), GVA (4), OSL (4), ATH (4), DUS (4), EDI (4), ARN (5), BHX (6), GLA (6), MAN (6), LGW (6), NCE (8)	SAN (4), TPA (4), FLL (4), LAS (5), MCO (6), PDX (6), SFB (6), ANC (7), BWI (8)
	Non-hub	AGP (1), BLQ (1), DBV (1), EMA (1), LBA (1), LDE (1), NAP (1), PRG (1), TXL (4), RZE (5), BRS (6), DSA (6), NCL (6), TER (9)	CHS (1), FAI (1), STL (1), MCI (1), OAK (1), PVD (1), SWF (1), AUS (4), BNA (4), CVG (4), IND (4), MSY (4), PIT (4), RSW (4), SJC (4), SLC (4), BDL (4)
Operation interruption airport	Primary hub	BRU, CPH, LIS, MAD, MUC, VIE	CLT, DEN, IAH, MSP, PHL, SFO
	Secondary hub	BCN, MXP, SNN, STR	N/A
	Non-hub	BUD, KRK, OPO, ORY, PDL	PHX
Full operation airport	Primary hub	AMS, CDG, FCO, FRA, LHR, ZRH	ATL, DFW, DTW, EWR, IAD, JFK, LAX, ORD
	Secondary hub	DUB, KEF	BOS, MIA, SEA
	Non-hub	BEG, WAW	N/A

* The numbers in parentheses indicate the exit month of the airport in 2020.

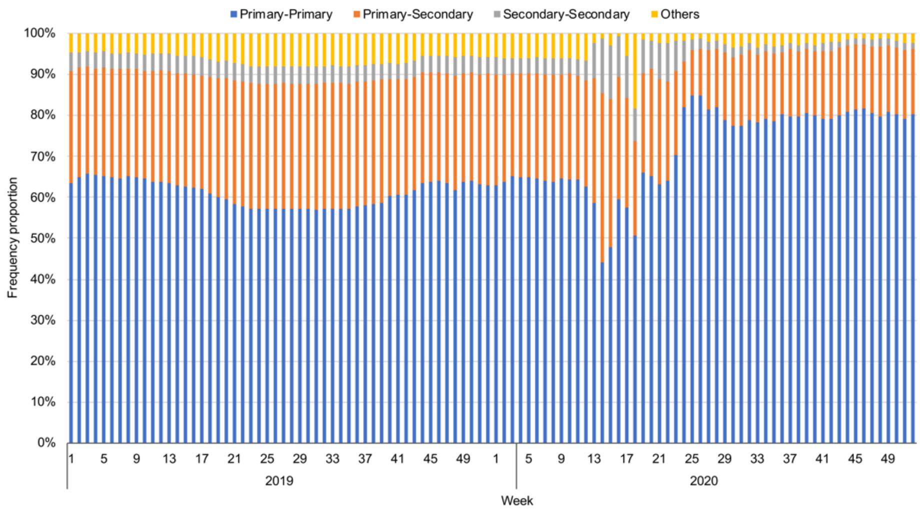

Figure 4. The evolution of the weekly market share structure over time from 2019 to 2020

Slot Policy

Besides being driven by the need to maintain network connectivity, carriers may also operate "ghost flights" to retain their slots at coordinated airports, which in turn affects their capacity. To examine this, we conduct a statistical analysis of the proportion of routes connected to coordinated airports (identified as Level 3 airports by IATA) for different airlines (Table 4).

A total of 10 airlines exclusively operated routes connecting coordinated airports before and after the pandemic. These include LH, OS, and LX from Lufthansa Group, Air France-KLM, BA, and IB from IAG, as well as three non-allianced airlines (i.e., AZ, FI, and SK). Five airlines increased their capacity on slot-controlled routes after the pandemic, including the three major US carriers. In contrast, only TP decreased its capacity on coordinated routes post-pandemic, suggesting a lower proportion of ghost flights. This finding aligns with Sun's study on the European market (Sun et al., 2022a).

During the pandemic, airlines preserved their capacity at coordinated airports not only to maintain network connectivity but also to protect their strategic positions at key hubs. International airline alliances, in particular, prioritized retaining their slot advantages to prevent competitors from seizing these valuable resources.

Table 4. Changes in the frequency of routes connecting coordinated airports of sample carriers

Carrier Code	The Proportion of Frequency of Routes* Connecting Coordinated Airports		
	2019	2020	2020 vs 2019
AA	95.08%	100.00%	5.18%
AF	100.00%	100.00%	0.00%
AZ	100.00%	100.00%	0.00%
BA	100.00%	100.00%	0.00%
DL	99.56%	100.00%	0.44%
EI	95.12%	96.23%	1.17%
FI	100.00%	100.00%	0.00%
IB	100.00%	100.00%	0.00%
KL	100.00%	100.00%	0.00%
LH	100.00%	100.00%	0.00%
LO	89.27%	98.12%	9.91%
LX	100.00%	100.00%	0.00%
OS	100.00%	100.00%	0.00%
SK	100.00%	100.00%	0.00%
TP	100.00%	96.12%	-3.88%
UA	94.81%	98.67%	4.07%

* Routes with at least one endpoint at a coordinated airport.

In summary, this study constructs an unbalanced panel data set of 581 two-way non-stop routes linking 20 European countries with the US over 2019 and 2020. It explores both the aggregated market and the markets disaggregated by airlines, analysing the impact of various factors on route capacity across carriers to uncover the diversity in their crisis response strategies.

4 Econometric analysis

We apply a DID method to capture the causal effect of COVID-19 on the EU-US capacity at the route level. Given the fact that finding routes unaffected in 2020 is not feasible due to the wide geographic coverage of COVID-19, we chose the year 2019 as the control group and the year 2020 as the treatment group. The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020. Therefore, the period after the 11th week of 2020 is defined as the post-treatment phase. In this way, the period of 2019-2020 is divided into four subgroups (Figure 5), i.e., control group 1 (The 1st week to the 11th week of 2019), control group 2 (The 12th week to the 52nd week of 2019), treatment group 1 (The 1st week to the 11th week of 2020), and treatment group 2 (The 12th week to the 52nd week of 2020).

As an econometric technique within the framework of the quasi-natural experiment, the causality identified by DID is interpreted by comparing the difference between the changes in a treatment group and the changes in a control group after the pandemic. In our model, instead of simply comparing the changes between 2020 and 2019, we first consider the average changes in a situation with (i.e., treatment group2) and without (treatment group1) the pandemic in 2020, and then reflect the same calculation in the previous year 2019 (i.e., control group2 versus control group1). The net effect of COVID-19 is finally realized by measuring the difference between the average changes in 2020 and 2019, respectively, i.e., the so-called average treatment effect (ATT). To put it more straightforwardly, ATT is calculated as *(treatment group 2 - treatment group1) - (control group 2- control group 1)*.

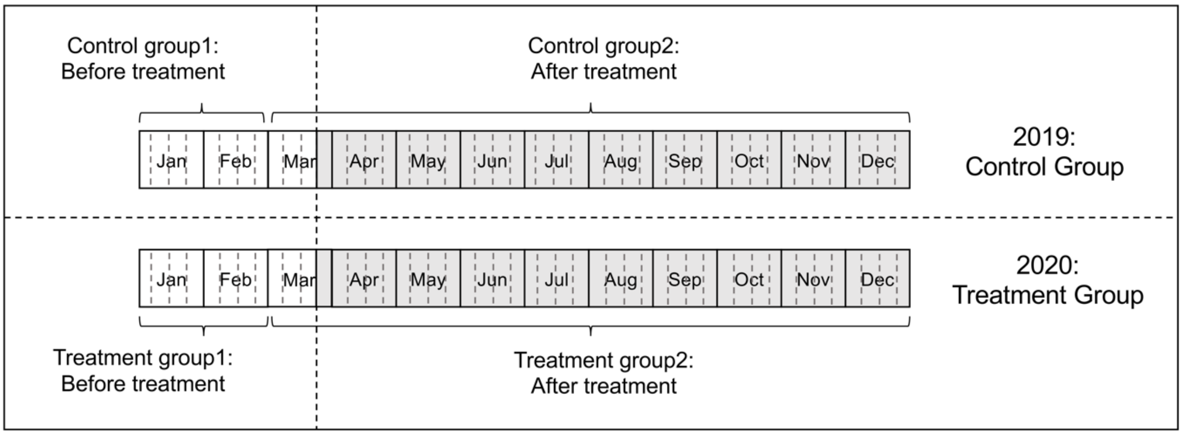

Figure 5. A demonstration of the DID setup

In addition to applying the treatment period to identify the impact of COVID-19 (Equation (1)), a separate model is established to use the cumulative confirmed cases to represent the severity of the pandemic (Equation (2)). Other factors, such as stringency level of control measures, route hierarchy persevering, demand and supply-related variables, are also incorporated into the models. The detailed specification of the DID model is presented as follows:

$$\begin{aligned} Frequency_{a,r,w,y} &= \gamma_0 + \gamma_1 Treatment_{a,r,y} * Period_{a,r,w} \\ &+\gamma_2 ControlEuro1_{c,w,y} + \gamma_3 ControlEuro2_{c,w,y} + \gamma_4 ControlEuro3_{c,w,y} \\ &+\gamma_5 ControlEuro4_{c,w,y} + \gamma_6 ControlUS2_{c,w,y} + \gamma_7 ControlUS3_{c,w,y} \\ &+\gamma_8 PP_r + \gamma_9 PS_r + \gamma_{10} SS_r + \gamma_{11} Business_{r,w,y} + \gamma_{12}\, ln(HHI)_{r,w,y} + \gamma_{13}\, ln(GCD)_r \\ &+\delta_w + \delta_c + \delta_a + \varepsilon_{a,r,w,y} \qquad (1) \end{aligned}$$

$$\begin{aligned} Frequency_{a,r,w,y} &= \beta_0 + \beta_1 Treatment_{a,r,y} * Period_{a,r,w} * Cases_{c,w,y} \\ &+\beta_2 ControlEuro1_{c,w,y} + \beta_3 ControlEuro2_{c,w,y} + \beta_4 ControlEuro3_{c,w,y} \\ &+\beta_5 ControlEuro4_{c,w,y} + \beta_6 ControlUS2_{c,w,y} + \beta_7 ControlUS3_{c,w,y} \\ &+\beta_8 PP_r + \beta_9 PS_r + \beta_{10} SS_r + \beta_{11} Business_{r,w,y} + \beta_{12} ln(HHI)_{r,w,y} + \beta_{13} ln(GCD)_r \\ &+\delta_w + \delta_c + \delta_a + \varepsilon_{a,r,w,y} \qquad (2) \end{aligned}$$

where: a denotes the airline. r denotes route, w denotes week, and y denotes year. c denotes the country pair connected by the route. A country-pair is considered directional since international flights are mainly affected by the control policies of the destination country. *Frequency* is the carrier-route level dependent variable and represents weekly flight frequency. γ_0- γ_{13} and β_0- β_{13} are the estimators. $\varepsilon_{a,r,w,y}$ is the error term clustered at the country-pair level to address possible heteroskedasticity problems.

COVID-19 directly related variables

$Treatment_{a,r,y}$ is the treatment group indicator. It is a binary variable that takes the value of 1 when carrier a operates on route r in 2020, indicating the observation belongs to the treatment group.

$Period_{a,r,w}$ is the post-treatment period indicator. It is a binary variable that takes the value of 1 when carrier a operates on route r from the 12th week onward.

$Cases_{c,y,w}$ is the pandemic severity indicator. Sourced from the JHU database, it is calculated by the arithmetic average of cumulative confirmed cases for countries at both ends of country-pair c. As seen in Figure 2, a significant difference in magnitude between route frequency and cumulative confirmed cases exists. Therefore, the logarithmic form of confirmed cases is used.

$Treatment_{a,r,y} * Period_{a,r,w}$ is the DID estimator. Its coefficient γ_1 is the primary interest in model (1). It measures the average net decline in flight frequency per carrier per route within the EU-US market in 2020 compared to a counterfactual scenario absent the pandemic's impact, while accounting for other factors.

$Treatment_{a,r,y} * Period_{a,r,w} * Cases_{c,w,y}$ is the interaction term of the DID estimator and the pandemic severity indicator. Its coefficient β_1 is the primary interest in model (2). It measures the net causal impact of the COVID-19 severity on capacity, while controlling for other influencing factors.

Stringency of international control measure variables

Six variables are devised to evaluate the impact of control policies implemented by countries under COVID-19, and are set separately for European countries and the US. The international entry restriction levels published by the OxCGRT database range from 0 to 4. Level 0 (no entry restrictions) serves as the baseline. As the US only implemented restrictions at levels 0, 2, and 3 in 2020, only two variables are established for the US.

$ControlEuro1_{c,w,y}$ is a binary variable and takes 1 when nucleic acid testing is required by a European country.

$ControlEuro2_{c,w,y}$ / $ControlUS2_{c,w,y}$ is a binary variable and takes 1 when quarantine for arrivals is required by a European country or the US.

$ControlEuro3_{c,w,y}$ / $ControlUS3_{c,w,y}$ is a binary variable and takes 1 when prohibiting arrivals from some regions is required by a European country or the US.

$ControlEuro4_{c,w,y}$ is a binary variable and takes 1 when closing the border is required by a European country.

Route hierarchy persevering variables

To evaluate whether carriers adjust their route network structure after COVID-19, we set three dummy variables. Routes connecting non-hubs are set as the baseline.

PP_r is a binary variable and represents whether route r is connected by two primary airports.

PS_r is a binary variable and represents whether route r is connected by a primary and a secondary airport.

SS_r is a binary variable and represents whether route r is connected by two secondary airports.

Demand and cost variables

$Business_{r,w,y}$ is the percentage of passenger bookings in business class on route r in week w of year y.

$ln(HHI)_{r,w,y}$ is the Herfindahl index, calculated based on frequency for route *r* in week *w* of year *y*. Log-transformed values are applied to accurately capture the linear relationship.

$ln(GCD)_r$ is the great circle distance of route *r*.

Fixed effect variables

δ_c is the country-pair fixed effect and controls for time-invariant unobserved characteristics specific to each country pair, such as demographic features, diplomatic relations, and the varying governmental policies in response to the pandemic concerning different nations, etc.

δ_a is the carrier fixed effect and controls for airline-specific characteristics such as government bailouts and subsidies during COVID-19.

δ_w is the week fixed effect and controls for temporal trends, such as the seasonal capacity adjustments.

Based on the two fundamental DID models established in Equations (1) and (2), the estimations are performed for both the aggregated market and the disaggregated dataset (i.e., individual airline routes). With the latter, nuanced variation comparisons across carriers can help identify different response strategies under COVID-19.

5 Results and discussion

We conduct a Hausman test, and the results confirm the existence of the fixed-effects. The estimation results of models (1) and (2) are presented in Tables 5 and 6, respectively. The first column in each table displays the estimations for the aggregated EU-US market. The remaining columns that present the results for the 16 survival carriers show the heterogeneous impact of the pandemic and other factors. For ease of presentation, results for country-pair, carrier, and time fixed effects are not reported but can be requested from the authors.

For the results, we first focus on the aggregated market by explaining how COVID-19 variables, control policy variables, and other demand and cost variables influence capacity. Overall, the estimation results of the two models correspond to each other for both the aggregated market and individual carriers. Exceptions are the control measure stringency variables. For individual carriers, we therefore just focus on elaborating the heterogeneity of the retrenchment and persevering strategy across carriers through the *TreatmentPeriod* variable and route hierarchy variables.

5.1 The impact of COVID-19 and control policies on the aggregated market

For the aggregated market, the pandemic has significantly reduced the EU-US capacity. In Table 5, the negative sign of the *TreatmentPeriod* variable demonstrates that the pandemic caused a 2.293 decrease in weekly frequency in 2020 at 1% significance level. In Table 6, with other things being equal, as the cumulative number of confirmed cases doubles, the average weekly route frequency decreases by 0.135 (ΔFrequency=-0.195×ln2≈-0.195×0.693≈-0.135) in the EU-US market.

The impact of control measure stringency adopted by European countries is greater than that for the US. In both models, *ControlEuro2* is significantly negative at a 1% significance level. This implies that quarantine measures taken by European countries significantly reduced route capacity compared to the no-control policy. The US implemented the entry quarantine measures only in February 2020 and shifted to partial border closures thereafter, which led to a positive effect of *ControlUS2* in model (1). Hence, the impact of national control policies is predominantly shaped by not only their intensity but also week-by-week adjustments within a short period.

Table 5. The estimated impact of the COVID-19 pandemic on capacity

Variables	Full Sample	Carriers															
		AA	AF	AZ	BA	DL	EI	FI	IB	KL	LH	LO	LX	OS	SK	TP	UA
Treatment Period	-2.293***	-2.279***	0.403**	-3.924***	-2.127***	-2.349***	-0.163**	-0.394**	-1.474*	0.503	-0.433*	-0.294	0.222	-0.776**	-2.089***	-1.834**	-3.034***
	(-0.342)	(-0.556)	(-0.025)	(-0.035)	(-0.200)	(-0.268)	(-0.022)	(-0.017)	(-0.179)	(-0.249)	(-0.057)	(-0.487)	(-0.090)	(-0.034)	(-0.342)	(-0.087)	(-0.684)
ControlEuro1	0.186	0.780***	0.149	0.065		-0.141					-0.171	-0.046					0.634*
	(-0.139)	(-0.191)	(-0.061)	(-0.048)		(-0.109)					(-0.050)	(-0.160)					(-0.350)
ControlEuro2	-2.229***	-4.417***			-1.980**	-2.172***	-0.510**	-4.372***					-6.736**		-0.240		-2.902***
	(-0.423)	(-0.693)			(-0.400)	(-0.488)	(-0.064)	(-0.019)					(-0.455)		(-0.167)		(-0.365)
ControlEuro3	0.659	2.765***	-2.430	-3.299***		-1.708**	-0.613	-4.488*	-1.667	-3.260**	-3.223**	-1.718	-5.970***	-2.218**	-1.315*	-2.136***	2.575**
	(-0.746)	(-0.889)	(-0.586)	(-0.005)		(-0.822)	(-0.419)	(-0.590)	(-0.415)	(-0.171)	(-0.071)	(-0.877)	(-0.002)	(-0.054)	(-0.613)	(-0.015)	(-1.092)
ControlEuro4	0.508	0.407				0.130			-0.060		-4.437***	-1.954*			-2.054***		1.944**
	(-0.617)	(-0.384)				(-0.305)			(-0.065)		(-0.067)	(-0.777)			(-0.327)		(-0.761)
ControlUS2	0.108	-0.314*	0.262***	2.905***	-0.836**	0.456**	0.408***	0.814*	0.598	0.653*	0.138***	0.363***	0.110	-0.229*	-0.015	0.336	-0.259*
	(-0.124)	(-0.170)	(-0.004)	(-0.005)	(-0.160)	(-0.186)	(-0.022)	(-0.088)	(-0.182)	(-0.061)	(-0.002)	(-0.026)	(-0.025)	(-0.021)	(-0.077)	(-0.114)	(-0.131)
ControlUS3	-1.040***	-1.978***	0.380		-1.009**	-0.568**		0.905	0.231	0.273		0.145	-1.079***	-0.197**	-0.603**	1.532	-1.626***
	(-0.221)	(-0.179)	(-0.242)		(-0.232)	(-0.215)		(-0.159)	(-0.159)	(-0.046)		(-0.268)	(-0.003)	(-0.008)	(-0.222)	(-0.301)	(-0.380)
PP	3.792***	7.450***	0.985	4.882***	0.368	3.604***			5.120**	6.258***	2.102**		0.212**	2.993***	6.288***	1.346**	1.931***
	(-0.685)	(-1.732)	(-0.180)	(-0.009)	(-0.394)	(-0.955)			(-0.230)	(-0.050)	(-0.039)		(-0.009)	(-0.037)	(-0.916)	(-0.056)	(-0.507)
PS	1.568***	3.155***	-3.654**		1.479**	0.020	3.105**	3.596**	2.539***	2.424	1.542**				2.633**	2.420**	-2.827
	(-0.427)	(-1.047)	(-0.124)		(-0.176)	(-0.435)	(-0.330)	(-0.187)	(-0.037)	(-0.785)	(-0.046)				(-0.958)	(-0.065)	(-1.995)
SS	0.289	5.407***			-3.125***	-2.014***	1.651**	3.906**							-1.218		
	(-0.512)	(-1.374)			(-0.303)	(-0.588)	(-0.217)	(-0.194)							(-0.763)		
Business	1.708*	4.254**	-1.298	-1.377	3.770	1.516	1.298	2.440*	11.690**	-6.003**	-1.149	-0.296	-5.427**	1.497**	-1.572**	4.454	4.366**
	(-0.921)	(-1.855)	(-2.785)	(-0.830)	(-2.644)	(-1.499)	(-0.507)	(-0.194)	(-0.639)	(-0.405)	(-0.245)	(-1.509)	(-0.226)	(-0.040)	(-0.602)	(-1.695)	(-1.600)
ln(HHI)	-2.505***	-1.839**	-6.932**	1.350***	-10.938***	-0.144	-1.651	-0.180**	-4.452**	-6.287**	-1.168***		-0.703		0.773**	-1.302**	-1.670**
	(-0.817)	(-0.680)	(-0.423)	(-0.018)	(-0.253)	(-0.819)	(-0.794)	(-0.009)	(-0.107)	(-0.321)	(-0.001)		(-0.123)		(-0.282)	(-0.051)	(-0.797)
ln(GCD)	-5.068***	2.129	-8.264***	-16.558***	-12.299***	-6.926**	-5.856***	-6.919***	-6.474**	3.341	-3.334***	-2.193*	-4.611*	-0.473**	-5.364***	-1.473***	-9.556*
	(-0.885)	(-2.112)	(-0.050)	(-0.146)	(-0.679)	(-2.839)	(-0.507)	(-0.004)	(-0.221)	(-0.627)	(-0.014)	(-0.706)	(-0.455)	(-0.014)	(-0.639)	(-0.002)	(-4.922)
Cons	75.869***	5.098	142.128**	143.107***	213.807***	68.034***	63.941***	61.309***	96.305**	27.741*	45.233***	23.814**	58.515**	6.774***	45.495***	28.614***	111.314**
	(-14.396)	(-22.440)	(-3.226)	(-0.940)	(-6.184)	(-18.471)	(-2.836)	(-0.473)	(-2.592)	(-3.274)	(-0.346)	(-6.831)	(-2.849)	(-0.056)	(-5.046)	(-0.245)	(-49.311)
Observations	45284	5640	2207	790	4365	7635	2113	1711	1151	1861	4304	1229	1298	782	1537	1216	7445
R-squared	0.352	0.566	0.383	0.389	0.432	0.499	0.299	0.433	0.727	0.484	0.413	0.177	0.494	0.783	0.731	0.612	0.462

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 6. The estimated impact of the COVID-19 confirmed cases on capacity

Variables	Full Sample	Carriers															
		AA	AF	AZ	BA	DL	EI	FI	IB	KL	LH	LO	LX	OS	SK	TP	UA
ln(Cases)* Treatment Period	-0.195***	-0.173**	0.118	-0.299**	-0.181*	-0.214***	0.040	-0.191***	-0.143	-0.018	0.275***	-0.117**	-0.284*	-0.100**	-0.197***	-0.187***	-0.211***
	(-0.029)	(-0.066)	(-0.139)	(-0.007)	(-0.048)	(-0.040)	(-0.023)	(-0.002)	(-0.032)	(-0.003)	(-0.002)	(-0.032)	(-0.033)	(-0.004)	(-0.024)	(0.000)	(-0.058)
ControlEuro1	0.114	0.777***	0.137	0.102		-0.200**					-0.169	0.169					0.581*
	(-0.109)	(-0.203)	(-0.068)	(-0.033)		(-0.089)					(-0.050)	(-0.094)					(-0.313)
ControlEuro2	-1.553***	-3.738***			-0.973	-1.167**	-0.686***	-2.543**					-1.018		-0.269		-2.181***
	(-0.351)	(-0.915)			(-0.626)	(-0.504)	(-0.014)	(-0.048)					(-0.233)		(-0.196)		(-0.544)
ControlEuro3	1.428*	3.268***	-4.067	-1.990**		-0.774	-1.461***	-2.115	-0.509**	-2.431**	-8.909***	0.191	-0.526	-1.136***	-0.122	-0.565*	3.282**
	(-0.837)	(-1.108)	(-1.792)	(-0.092)		(-0.552)	(-0.006)	(-0.552)	(-0.032)	(-0.137)	(-0.031)	(-0.303)	(-0.699)	(-0.003)	(-0.481)	(-0.056)	(-1.338)
ControlEuro4	0.637	0.491				0.166			0.342		-9.044***	-0.462			-2.101***		1.832**
	(-0.606)	(-0.514)				(-0.189)			(-0.269)		(-0.026)	(-0.288)			(-0.241)		(-0.820)
ControlUS2	-0.556**	-1.708***	0.416		-0.685*	-0.023		2.009*	0.259	0.271		0.140	-1.118***	-0.201**	-0.399	1.517	-1.457***
	(-0.237)	(-0.293)	(-0.278)		(-0.215)	(-0.174)		(-0.188)	(-0.172)	(-0.046)		(-0.268)	(-0.011)	(-0.008)	(-0.212)	(-0.286)	(-0.338)
ControlUS3	0.039	-0.375**	0.265***	1.628**	-0.850**	0.383**	0.584***	0.819*	0.615	0.655*	0.139***	0.363***	0.117	-0.221*	-0.023	0.369	-0.302**
	(-0.114)	(-0.158)	(0.000)	(-0.077)	(-0.132)	(-0.160)	(-0.057)	(-0.091)	(-0.191)	(-0.060)	(-0.002)	(-0.025)	(-0.029)	(-0.018)	(-0.085)	(-0.111)	(-0.130)
PP	3.834***	7.506***	0.895	4.892***	0.435	3.657***			5.189**	6.259***	2.097**		0.169**	2.995***	6.096***	1.332**	1.934***
	(-0.693)	(-1.764)	(-0.293)	(-0.005)	(-0.414)	(-0.964)			(-0.255)	(-0.050)	(-0.038)		(-0.005)	(-0.034)	(-0.705)	(-0.055)	(-0.511)
PS	1.588***	3.201***	-3.733**		1.507**	0.056	3.100**	3.584**	2.591***	2.425	1.526**				2.382**	2.412**	-2.852
	(-0.429)	(-1.067)	(-0.225)		(-0.184)	(-0.438)	(-0.335)	(-0.185)	(-0.022)	(-0.786)	(-0.045)				(-0.709)	(-0.061)	(-2.010)
SS	0.303	5.429***			-3.115***	-2.026***	1.646**	3.938**							-1.488**		
	(-0.519)	(-1.390)			(-0.295)	(-0.582)	(-0.221)	(-0.193)							(-0.544)		
Business	1.560	4.070**	-0.824	-0.510	3.663	1.271	1.347	2.442*	11.830**	-6.059**	-1.129	-0.407	-5.900**	1.381**	-2.192**	4.040	4.144**
	(-0.927)	(-1.836)	(-3.401)	(-0.665)	(-2.628)	(-1.566)	(-0.528)	(-0.214)	(-0.712)	(-0.391)	(-0.252)	(-1.572)	(-0.346)	(-0.060)	(-0.570)	(-1.687)	(-1.557)
ln(HHI)	-2.487***	-1.822**	-7.053*	1.370***	-10.883***	-0.112	-1.658	-0.215**	-4.401**	-6.285**	-1.152***		-0.694		0.737**	-1.262**	-1.672**
	(-0.813)	(-0.674)	(-0.572)	(-0.017)	(-0.274)	(-0.828)	(-0.802)	(-0.005)	(-0.095)	(-0.320)	(-0.001)		(-0.136)		(-0.260)	(-0.052)	(-0.794)
ln(GCD)	-5.081***	2.282	-8.248***	-16.792***	-12.316***	-6.976**	-5.849***	-6.978***	-6.526**	3.346	-3.354***	-2.242*	-4.552*	-0.532**	-5.359***	-1.602***	-9.571*
	(-0.884)	(-2.149)	(-0.040)	(-0.104)	(-0.668)	(-2.826)	(-0.517)	(-0.002)	(-0.240)	(-0.627)	(-0.014)	(-0.709)	(-0.493)	(-0.016)	(-0.634)	(-0.003)	(-4.921)
Cons	74.714***	2.473	143.126**	142.641***	212.427***	67.075***	63.865***	61.959***	95.454**	27.968*	45.050***	24.153**	58.289**	6.948***	45.120***	28.334***	109.991**
	(-14.199)	(-22.633)	(-4.279)	(-0.601)	(-6.262)	(-18.240)	(-2.813)	(-0.412)	(-2.520)	(-3.154)	(-0.323)	(-6.651)	(-3.170)	(-0.100)	(-5.494)	(-0.188)	(-48.973)
Observations	45284	5640	2207	790	4365	7635	2113	1711	1151	1861	4304	1229	1298	782	1537	1216	7445
R-squared	0.353	0.566	0.384	0.393	0.432	0.501	0.299	0.438	0.728	0.484	0.416	0.179	0.499	0.788	0.736	0.623	0.462

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

The impact of other factors, such as passenger demand, market competition, and cost, also shows significant results. The estimations for the *Business* variable in both models is significantly positive, suggesting that the EU-US route capacity was still driven by the percentage of business travellers in 2020. The negative sign of the *HHI* variable is caused by the withdrawal of LCCs and other types of carriers during COVID-19. The increased market concentration remarkably reduces the capacity. The negative sign of the *GCD* variable shows that the infection risks perceived by passengers on the long-haul market decreased their willingness to travel and further reduced their capacity.

5.2 Heterogeneity of the retrenchment strategy

As can be seen in Table 5, airlines broadly implemented the capacity retrenchment strategy. The cut magnitude varies across different international airline groups. In general, Lufthansa Group and IAG members reduce frequencies to a greater extent compared to Air France-KLM Group members. Among the 16 airlines, Alitalia (AZ) experienced the most significant capacity reduction, with weekly frequency being decreased by 3.924 on average. The estimations for all the other variables are the same as those for the aggregate market, except for the *ControlEU3* and *Business* variables. The capacity of AZ was notably impacted by border control policies, which can be attributed to Italy being one of the first European countries to implement lockdown measures. The negative sign of *Business* suggests that the capacity retrenchment strategies of AZ may be triggered mainly by the substantial losses in business travel demand.

Based on the pandemic stringency variable, Table 6 demonstrates that the route frequency of AZ is the most sensitive to the severity of the pandemic, followed by SWISS (LX). For IAG members, British Airways (BA) experienced the most significant capacity reduction. The significantly negative sign of *ControlUS2* reveals that BA’s capacity is impacted by policy adjustments implemented by the US compared to the absence of policy intervention.

An interesting observation is that not all airlines' capacity is negatively affected by pandemic severity. Specifically, for airlines within the Air France-KLM Group, the estimates for the confirmed cases variable are insignificant, while the estimates of KLM-Royal Dutch Airlines (KL) for *ControlEuro3* are significantly negative. A similar pattern can also be seen in the Lufthansa (LH) model, except that the pandemic severity variable for LH is significantly positive. Combined with the results in Table 4, the pandemic caused a greater reduction in LH's capacity than AF and KL.

5.3 Heterogeneity of the persevering strategy

The route hierarchy variables significantly influence the EU-US capacity during the pandemic. The variables *PP* and *PS* are significantly positive in both models, indicating that airlines allocated more capacity to hub-to-hub routes compared to routes connecting non-hub airports. A horizontal comparison is then conducted across airlines.

In the market connected by two primary airports, the estimations of *PP* are reported significantly positive in 11 airlines’ models. The coefficient for AA is the largest and surpasses the aggregated model by approximately 4 points. Overall, Oneworld, composed of IB and AA, possesses a significant primary-primary capacity advantage. Compared to the other two international airline groups, the Lufthansa Group is relatively disadvantaged.

The estimated coefficients of PS are significantly positive in 9 airlines’ models, while those for 3 airlines, namely Delta Air Lines (DL), KL, and United Airlines (UA), are insignificant. Oneworld, including BA, IB, and AA, demonstrates the largest primary-secondary capacity advantage. The capacity of the Air France-KLM Group is larger than that in the aggregated model. Within the Lufthansa Group, only LH allocated capacity in this market, with capacity estimates slightly lower than those in the aggregated model. Both EI and Icelandair (FI) have shown strong PS capacity performance, given that the base airports Dublin and Reykjavik are classified as secondary hubs.

Only 6 airlines provide services in the EU-US market, connected by two secondary airports. The coefficients of the three are significantly positive, among which AA puts the most capacity priority. An interesting phenomenon is that the *SS* coefficient for DL and BA is significantly negative, indicating that the capacity of their SS routes is lower than that of routes connected by non-hubs. Although the non-hub capacity of DL and BA was around 8% larger than that of the SS routes in 2019, the crisis forced them to shift their distinct expansion strategy by largely exiting secondary airports.

5.4 Discussion

Overall, the EU-US capacity is jointly affected by the severity of the pandemic, the stringency level, and capacity of changes in control policies, as well as passenger demand structure and cost in 2020. For some airlines, the impact of control measures implemented by governments (i.e., an indirect effect of COVID-19) is over that of the treatment period or confirmed cases (i.e., a direct effect of COVID-19).

Based on the analysis of the route hierarchy persevering across carriers, three strategy categories emerge, i.e., connectivity-oriented, antitrust immunity joint venture-oriented, and market presence-oriented. Airlines adopting the connectivity-oriented strategy (e.g., AA and BA) maintain the completeness of the route hierarchy to sustain network connectivity but with a larger extent of capacity retrenchment. Airlines following the antitrust immunity joint venture-oriented approach (e.g., DL, AF, and KL) give priority to routes connected by countries with well-established cooperation. The lack of a route type can be complemented by other partners. Airlines pursuing the market presence-oriented strategy (e.g., OS, AZ, and LO) aim to survive in the EU-US market with the lowest capacity, the largest reduction, and the fewest route types.

6 Conclusion

This paper proposes a difference-in-differences framework to investigate the short-term impact of the COVID-19 pandemic on EU-US route capacity. Three crisis response strategies employed by airlines are identified. The results contribute to the literature in both methodological and empirical aspects.

From the methodological perspective, the modelling integrates the direct and indirect impact of the pandemic, route hierarchy, as well as the demand and supply variables into one framework. In particular, including both the DID estimator and the number of confirmed cases into models can explain the COVID-19 impact in a parallel and straightforward way. A quantified relationship is also established between international control policies and the capacity through the stringency level variables. Therefore, the proposed method can be applied to investigate the pandemic impact on other international markets when countries' policies play significant and interactive roles.

From the empirical aspect, the results can help carriers consolidate their international route networks and business models in order to smoothly deal with extreme crises in the future. First, under COVID-19, the EU-US air transport network contracted from a hierarchical network with secondary airports emerging in the pre-pandemic period towards a more concentrated network dominated merely by primary airports. This is also because a significant number of LCCs and charter carriers were forced to completely exit the market. Given the vulnerability of the international market, we suggest that a cooperation partnership between LCCs/charter carriers and secondary airports should be established to minimize the failure risks, but under the condition of a deep policy negotiation with governments. Second, the variation of the retrenchment and preserving occurred not only among individual carriers within the same country/region but also among different alliances. Airlines adopting a connectivity-oriented or market-centric persevering approach tend to implement higher levels of capacity retrenchment. In contrast, those favouring anti-trust immunity joint ventures tend to pursue more conservative capacity reductions. As those carriers have shown their survival capability and sustainability of business models when facing external crises, the identified response strategies can be used as references by other carriers.

This paper has some limitations that can be addressed in future studies. It focuses solely on the early stages of the pandemic. However, the analysis would become more complex from 2021 to 2022. In 2021, Delta replaced Alpha as the dominant variant, followed by Omicron in 2022. These new variants exhibited higher transmissibility and immune evasion. The large-scale rollout of vaccines in 2021 effectively curbed viral transmission, leading to adjustments in national control policies (Sun et al., 2022b). If data on the proportion of different virus variants among confirmed cases and the vaccination rate among passengers were available, a more detailed analysis of their specific effects on capacity could be conducted. Meanwhile, the pandemic brought structural changes to air travel demand (Sun et al., 2023), particularly for business travellers, as the widespread adoption of remote work reduced the necessity of corporate travel. Airlines may have responded by shifting capacity toward leisure markets. Additionally, government subsidies played a crucial role in supporting airlines during the crisis, potentially influencing ownership structures and competition dynamics in the industry (Sun et al., 2021). Examining how these factors influenced airlines' recovery strategies would provide valuable insights for policymakers to develop more resilient and adaptive aviation policies in future crises. Another limitation of this study is the lack of load factor data, making it infeasible to directly identify "ghost flights". Future studies could employ a difference in difference in differences (DDD) approach to examine the heterogenous causal impact of the pandemic on coordinated airports versus others.

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Data/Software Access Statement

Data supporting this study cannot be made publicly available due to contractual restrictions and licensing agreements with the data provider.

Author and Contributor Statement

The authors confirm contribution to the paper as follows: Conceptualization: S. Zhang, L. Wang, X. Tang; Data Curation: L. Wang, S. Zhang; Methodology: L. Wang, S. Zhang; Formal Analysis: L. Wang, S. Zhang; Funding Acquisition: X. Tang, S. Zhang; Writing-Original Draft: L. Wang, S. Zhang; Writing-Review and Editing: F. Witlox. All authors reviewed the results and approved the final version of the manuscript.

Use of AI

During the preparation of this work, the author(s) did not use AI.

Conflict Of Interest (COI)

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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Appendix

Table 7. Information of carriers operating in the EU-US market in 2019-2020

Carrier Code	Carrier Name	Country	Carrier Code	Carrier Name	Country
OS	Austrian Airlines	Austria	DY	Norwegian Air Shuttle	Norway
SN	Brussels Airlines	Belgium	LO	LOT - Polish Airlines	Poland
TB	TUI fly Belgium	Belgium	TP	TAP Air Portugal	Portugal
AY	Finnair	Finland	S4	SATA International-Azores Airlines S.A.	Portugal
AF	Air France	France	JU	Air Serbia	Serbia
BF	French Bee	France	SQ	Singapore Airlines	Singapore
B0	La Compagnie	France	IB	Iberia	Spain
SS	Corsair	France	UX	Air Europa	Spain
SE	XL Airways France	France	SK	SAS Scandinavian Airlines	Sweden
TN	Air Tahiti Nui	French	D8	Norwegian	Sweden
LH	Deutsche Lufthansa AG	Germany	LX	SWISS	Switzerland
DE	Condor Flugdienst	Germany	WK	Edelweiss Air	Switzerland
EW	Eurowings	Germany	EK	Emirates	United Arab Emirates
FI	Icelandair	Iceland	ET	Etihad Airways	United Arab Emirates
WW	WOW Air	Iceland	BA	British Airways	the UK
EI	Aer Lingus	Ireland	LV	LEVEL operated by OpenSkies (LV)	the UK
AZ	ITA Airways	Italy	DI	Norwegian Air UK ltd	the UK
IG	Air Italy S.p.A.	Italy	TOM	TUI Airways	the UK
KU	Kuwait Airways	Kuwait	VS	Virgin Atlantic Airways	the UK
MT	Malta MedAir	Malta	LS	Jet2	the UK
KL	KLM-Royal Dutch Airlines	Netherlands	UA	United Airlines	the US
OR	TUI fly Netherlands	Netherlands	DL	Delta Air Lines	the US
NZ	Air New Zealand	New Zealand	AA	American Airlines	the US