ISSN: 2941-198X
JATRS
Journal of the Air Transport Research Society Volume 1, Issue 1, June 2023

Impact of the COVID-19 Pandemic on Multi-airport Systems Worldwide

Xiangru Wu[1], Xiaowen Fu[1], Zheng Lei[2], and Kun Wang[1]

[1]*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, China*
[2]*Department of Aviation, Swinburne University of Technology, Australia*

Abstract: This study examines the impacts of the COVID-19 pandemic on multi-airport systems (MASs) worldwide. First, the recent literature on MASs is reviewed to identify emerging research topics and development patterns. Then, airline schedule data are collected for 53 sample MASs and used to analyse three dimensions of MAS structures before and during the late stage of the pandemic: (i) traffic and degree centrality distribution within MASs, (ii) intra-MAS airport competition; and (iii) airline competition intensity within MASs. The empirical findings reveal that MAS structures in Europe and the US have remained relatively stable despite the recent pandemic, partly because compared with Asia Pacific, air travel bans in these markets were lifted earlier, and domestic and international airline markets have largely returned to pre-pandemic levels. In comparison, significant changes have been observed in Asia-Pacific MASs due to restrictive bans on international travel and airline operations. As major airlines shifted capacity to domestic markets, in Asia Pacific intra-MAS airport traffic distribution became more balanced, intra-MAS airport competition intensified, smaller airlines dropped out, and airline concentration levels increased. In addition, with more under-utilized slots available, Chinese low-cost carriers increasingly consolidated their operations to selected airports within MASs which would allow them to achieve economies of scale. Overall, this study provides insights into the adaptability of MAS structures in the face of a global crisis.
Keywords: *Multi-airport system (MAS);COVID-19 pandemic;Full-service carrier (FSC);Low-cost carrier (LCC)*
Citation: *Wu, X., Fu, X., Lei, Z., and Wang, K. (2023). Impact of the COVID-19 Pandemic on Multi-airport Systems Worldwide. Journal of the Air Transport Research Society 1(1): 117-135*
DOI: https://dx.doi.org/10.59521/225FA3D62802E847

1. Introduction

The air transport industry's rapid growth in recent decades has led to the fast development of multi-airport systems (MASs) around the world. In addition to well-known systems in London, New York, Tokyo, and Paris, emerging countries with booming airline markets, particularly China, have also developed MASs (Hou et al., 2022). MASs not only alleviate airport capacity constraints but also optimize airline services and connectivity for metropolitan areas. Some MASs have airports serving distinct market positions to diversify the airline services in one metropolitan area. At the same time, the inter-airport competition within MASs can reduce airfares and increase flight frequencies, benefiting passengers and regional economies (Winston and Yan, 2011). A well-functioning MAS thus stimulates air traffic and coordinates economic development within and across regions (Brueckner, 2003; Sheard, 2014). The strategic interactions among airports and airlines are more complex in the presence of MASs, involving decisions about flight frequency, airfares, airport entries, and network development. Passengers' airport choices depend on factors such as ground access, flight networks, schedules, and airfares. Previous studies have documented these issues through theoretical and empirical approaches, as summarized and discussed in Section 2 of this paper.

The COVID-19 pandemic (hereafter referred to as "the pandemic") has had unprecedented impacts on the entire airline industry, and extensive research has been conducted to understand its effects from different perspectives (Sun et al., 2020; Nižetić, 2020; Suzumura et al., 2020; Zhang et al.,2021; Czerny et al. 2021). Existing studies of the pandemic's impact on airport operations have mainly focused on individual airports of different sizes and regions. Travel restrictions have severely damaged international connectivity for major regional gateway airports worldwide, while domestic aviation markets have generally recovered as outbreaks have been contained domestically, despite several waves of local outbreaks. The pandemic's impact on airports may also depend on their network structure, such as hub-and-spoke vs. point-to-point, as well as the type of airlines (full-service carriers (FSCs) vs. low-cost carriers (LCCs)) and airline dominance at a particular airport, because such factors are likely to moderate the pandemic's effect on airport operations, airline competition and dominance, and network configuration (Fu et al. 2015a, 2019).

Despite extensive research on the impacts of the pandemic on the air transport industry, there has been relatively little investigation into how MASs have been affected. Many questions remain unanswered in this area. First, the pandemic could have affected different airports in the same MAS differently, causing changes in traffic and connectivity distributions among individual airports. Second, inter-airport competition within MASs might have been affected, with market coverage converging (serving more common destinations) or diverging (serving fewer common destinations) during the pandemic. Last, the pandemic could have caused variations in airline competition (including that among airlines providing differentiated services, such as FSCs vs. LCCs (Fu et al. 2011)) and their dominance among different airports (such as an airport's hub status). For example, London's metropolitan area is served by six international airports, with Heathrow (LHR) dominated by British Airways and Gatwick (LGW) as a main base for Easyjet, a low-cost carrier. The pandemic is likely to have imposed heterogeneous impacts on these airports within the London MAS, which could have significant implications on airline competition, airport capacity/slot use, and airport connectivity. The pattern and magnitudes of such impacts nevertheless remain unclear to industry and policy makers. This study aims to address these gaps in the literature by examining the impacts of the pandemic on MASs worldwide, shedding light on the changes and development patterns of these systems.

To address the research questions outlined above, we collected airline scheduled seat data for 53 MASs worldwide over the 2018-2022 period. Several statistics and indices were calculated and benchmarked before and during the late stage of the pandemic, with a focus on the relatively long-term impact of the pandemic. We conducted an intra-MAS analysis to examine the heterogeneous impacts of the pandemic on the traffic and network size of airports within the same MAS, calculating the Gini index of scheduled capacity and the degree of centrality for each MAS. Additionally, we constructed a Herfindahl-Hirschman Index (HHI) using the capacity share of flights with the same destination but originating from different airports within an MAS, to measure the level of intra-MAS airport competition. We were also interested in checking the change in this index during the pandemic. To examine inter-airline competition, particularly between FSCs and LCCs within an MAS, we calculated and compared the Gini index of the airlines' market shares in each MAS before and during the late stage of the pandemic. We conducted these analyses for each sample MAS and conducted cross-regional comparisons to shed light on heterogeneous patterns among different regions worldwide, including the US, Europe, and the Asia-Pacific.

The remainder of this paper is structured as follows. Section 2 provides a review of the relevant literature on MAS published in recent years, revealing recent MAS developments and relevant research hotspots worldwide. Section 3 describes the data used in this research, including the definition and selection of sample MASs for this study. In Section 4, we conduct a series of calculations based on the statistics and indices described in the previous paragraph and provide a discussion and interpretation of the results. Finally, Section 5 provides concluding remarks for this study.

2. Literature Review

This section presents a review and summary of the recent literature on MAS development, with a focus on academic publications in the past decade (since 2013) related to MAS management and economic issues. Relevant studies can be broadly categorized into two categories: those investigating passengers' airport choices within an MAS and those examining airline/airport competition within an MAS. Additionally, we review recent studies of the impacts of the pandemic on airport operations, which should provide useful insights into the impacts on MASs.

2.1. Passengers' airport choices in MASs

Since the 1980s, it has been a common research strategy to examine passengers' airport choices within an MAS. Analytical and empirical research has explored the factors influencing passengers' airport choices, with a focus on some major MASs in the US and Europe, particularly San Francisco, New York, and London (Harvey, 1987; Pels et al., 2000, 2001, 2003; Hess et al., 2006; Marcucci and Gatta, 2011, 2012; Murça et al., 2013). These studies suggest that the ground access time and cost, flight frequency, and flight time play important roles in determining passengers' airport choices, with passengers exhibiting heterogeneous preferences for different factors.

In recent years, an increasing number of researchers have paid attention to MASs in developing countries, such as China, Iran, Slovenia, and Brazil. Table 1 summarizes papers on this topic published in the last decade, which focused on different factors that shape passengers' airport choices. In addition to the aforementioned influencing factors, recent studies have also considered new factors related to passengers' perceptions of service quality, such as safety and punctuality, which also contribute significantly to passengers' choice decisions. Some studies investigate air-rail intermodal transport for MAS connectivity and its influence on passengers' airport choices. Both theoretical and empirical studies have suggested that passengers choose air-rail intermodal transport if one airport has better integration with high-speed rail (HSR) service, such as Hongqiao Airport in Shanghai MAS and Daxing Airport in Beijing MAS, due to considerations related to the contingency arrangement in case of delays and regarding checking-in, comfort, and luggage deposits (Chiambaretto et al., 2013; Li et al., 2020; Wang et al., 2020a; Babić et al., 2022).

Table 1: *Recent literature on passenger airport choice in MAS*

Author/Year	Studied MAS	Model Specifications/Findings
Fuellhart et al. (2013)	Boston, Washington, and San Francisco, the US	Higher route-level airfares and longer route distance lead to an apparent switching of passengers' airport choices. This means passengers may be willing to make changes to a preferred airport for longer distance trips.
Mamdoohi et al. (2014)	Tehran MAS, Iran	Binary Logit model; Focus on the difference of airport choice between resident and non-resident and find that public access, flight frequency, and airport tax are more important for non-resident air travelers when choose their origin airport.
Paliska et al. (2016)	Upper Adriatic region, Slovenia	Mixed logit model; Access time to airport is the most important determinant in airport choice for all kinds travelers (business/leisure and cross-border/domestic) and borders have an influence on airport choice.
Jung and Yoo (2016)	Seoul MAS, South Korea	Two-level Nested Logit model; The results show that fare, flight time, frequency, access time, access cost and airport access convenience latent variables are significantly affecting passenger's airport choice behavior.
Bezerra and Gomes, (2019)	São Paulo MAS, Brazil	Partial least squares–structural equation model; Support airport service quality as a determinant of passenger loyalty. Marketing and operational strategies based on customer segmentation help to strengthen the passenger loyalty to the airport.
Tiglao (2020)	Aklan MAS, Philippines	Discrete choice model; Tourist passenger do put high premium in air safety.
Teixeira and Derudder (2021)	New York MAS, the US	Huff models; Consider the spatio-temporal dynamics in airport catchment areas and calculate airport attractiveness to passengers in different census block groups.
Liao et al. (2022)	Guangdong-Hong Kong-Macao Greater Bay Area (GBA), China	Partial least squares structural equation model; Confirm positive relationships between airport service quality and passengers' intention to reuse an airport.

2.2. Airline or airport competition in MASs

As mentioned in the introduction, the presence of an MAS enhances strategic interactions among airports in a region and intensifies both inter- and intra-airport airline competition. In recent years, researchers have paid increasing attention to the privatization of one or more airports within an MAS, following the global trend towards airport corporatization. This trend has been particularly notable in China, where several airports have consolidated to form airport group companies to improve profitability and achieve better coordination. Furthermore, the prevalence of HSR has significantly reshaped the intercity transport market, particularly in China. The integration of air and HSR transport with some airports within an MAS can significantly affect airport and airline competition and coordination behaviour. Recent studies have investigated the impacts of these developments on MASs and their implications for airport and airline operations and competition. Table 2 provides a summary of these studies published over the past decade.

2.3. The impact of the pandemic on the airport

The pandemic has had an unprecedented impact on the aviation industry, as evidenced by recent studies (Zhang et al., 2020; Sun et al., 2020; Monmousseau et al., 2020; Czerny et al., 2021; Sun et al., 2021a; Salesi et al., 2022). Researchers have conducted numerous investigations into the pandemic's effects on airport connectivity and operations and its heterogeneous impacts across different airports and regions. Sun et al. (2022) provided a comprehensive review of the research on the pandemic and air transport. Specifically, regarding the impact on airport operations, many studies have focused on the passenger travel experience during the pandemic. For example, Li et al. (2022) used a data-driven crowd-sourcing approach to study airport service quality during the pandemic. Ma et al. (2022) built a structural equation model to investigate the influences of four attributes of the airport physical environment on passengers' perceived safety, satisfaction, and travel intentions during the pandemic. Zhang et al. (2021) used passengers' air ticket booking transaction data and airport arrival data to empirically examine passengers' travel behaviours during the pandemic and found that passengers arrived at the airport earlier to undergo health check procedures, despite having fewer opportunities to shop and dine at airports. Chen (2022a, b) also found very obvious empirical evidence for the substitutability of online meetings for air travel among heterogeneous traveller, which could also cause changes in passenger composition and air travel behaviour during and after

Table 2: *Recent literature on inter-airport and airline competition in MAS*

Author/Year	Studied MAS	Model Specifications/Findings
Yan and Winston (2014)	San Francisco Bay area, the US	Focus on the private airport competition and find that private airport competition could increase commercial travelers' welfare and airlines' profits and enable the airports to be profitable.
Liao et al. (2019)	Guangdong-Hong Kong-Macao Greater Bay Area (GBA), China	Three liner models; Focus on the route level competition between airports in GBA-MAS and its impact on passenger airport choice.
Wong et al. (2019a)	MAC around world	With the competition of FSCs, LCC shift focus from smaller airports in MAR to non-MAR airports.
Wong et al. (2019b)	MAC around world	Discuss the competition for passengers among hubs and secondary airports in multi-airport cities.
Cheung et al. (2020)	Guangdong-Hong Kong-Macao Great Bay Area MAS, China	Dynamic spatial panel regression model, the model provides a new tool in airport competition study. This paper focus on the spatial interactions and spillover effects in the presence of airport competition.
Hou et al. (2022)	Beijing MAS, China	Multi-stage game-theoretical model; Focus on the impact of government intervention on airport competition. Find that without government intervention in airline allocation between the two airports, airlines would always prefer to enter both airports in the MAS, leading to both an inter-airport and an intra-airport competition structure.
de Paula Balan et al. (2022)	São Paulo and Rio de Janeiro MAS, Brazil	Increased overlap routes in MASs were healthy for competition between airports and airlines over the years.
Li et al. (2022)	Theoretical analysis	Investigates the effects of air and high-speed rail (HSR) cooperation on airport competition in MAS and social welfare.

the pandemic.

Many researchers have focused on the impact of the pandemic on airport connectivity and have found that airport networks changed significantly during the pandemic. These changes include shifts in airport degree centrality, international connections, and network connectivity (Sun et al., 2020, 2021b; Li et al., 2021; Kuo et al., 2022). Several studies have concluded that the pandemic has had a greater impact on international flights than on domestic flights, and that the recovery speed of local connectivity has been faster than that of global connectivity (Sun et al., 2020, 2021b; Li et al., 2021; Zhang et al., 2022). For example, researchers studying Incheon International Airport discovered that although the airport's efficiency decreased during the pandemic, the increase in connectivity between Incheon and other airports could improve the airport's efficiency (Shamohammadi et al., 2022).

Some studies have shed light on the heterogeneous impact of the pandemic on different types of airports, including hub and nonhub airports. For example, Mueller (2022) found that non-hub airports in Europe experienced more negative impacts than hub airports. Airports primarily served by LCCs were more likely to be cut off from the network during extensive network shrinkage than those served by FSCs. Other studies have examined the heterogeneous impacts of the pandemic across different regions and countries. Sun et al. (2020) reported that Europe has undergone more significant changes in network connectivity than North America. Many countries in North America, such as the United States, Canada, and Mexico, remained highly connected with other countries during the pandemic. Sun et al. (2021b) also found that, compared to other countries, the impact of the pandemic on airports in the United States was relatively homogeneous, with most airports only partially affected. Although there have been many studies that have explored the impacts of the pandemic on airports from different aspects, there are still no papers dedicated to examining the impact on MASs. For the characteristics of MASs, this study aims to investigate this topic to fill this research gap.

3. Data and MAS Samples

An MAS is defined as a set of two or more commercial airports that serve air traffic within a metropolitan region (Bonnefoy et al., 2010), regardless of the ownership or political control of individual airports (de Neufville, 2004). In this paper, we adopt the definition of Bonnefoy et al. (2010) to select sample MASs. Bonnefoy et al. (2010) used worldwide airport passenger traffic data from the International Civil Aviation Organization (ICAO) (2008) and the Federal Aviation Administration (2007), including all airports with more than 500,000 passengers in 2005. A geographical cluster analysis was conducted to identify MASs. To identify all airports located within a 60-mile radius of the city centre, clusters of two or more significant airports within 120 miles of each other were first identified. Then, certain MASs were excluded based on geographical characteristics, such as the presence of islands and the criterion that the largest airport served fewer than two million passengers per year. Based on this analysis, they identified 59 MASs, which was updated to 60 in 2011 (de Neufville, 2016). Sun et al. (2017) also defined major commercial airports as those with at least two million passengers per year.

We retrieved our airline scheduled seat data from the Official Airline Guide (OAG) for the sampled MASs as identified in Bonnefoy et al. (2010). These data include departure and arrival airports and airline-specific scheduled seats on a quarterly basis for the 149 airports in the 60 sample MASs from Q1 2018 to Q4 2022, covering both the pre-pandemic and the pandemic periods. The OAG database also includes variables indicating whether a route is domestic or international, and whether an operating airline is an FSC or an LCC. However, during our study period, one airport in each of the Belo Horizonte, Gothenburg, Tel Aviv, and Berlin MASs closed, leading us to exclude these four systems. Additionally, Beijing was included in the MAS list by Bonnefoy (2010), since the city is served by two airports. However, Nanyuan Airport serves only regional routes out of Beijing under special approval granted to selected airlines only and is much smaller than Beijing Capital Airport. Therefore, we also excluded Beijing from our sample.[1] Similarly, Lübeck Airport in the Hamburg MAS only serves a limited number of regional routes, leading us to exclude Hamburg as well. In the end, we identified a total of 53 MAS in 24 countries for study, as shown in Table 3.

4. Statistics and Discussions

In this section, we calculate and discuss some statistics and indices to shed light on the impact of the pandemic on MASs worldwide. For concise discussions and clear insights, we concentrate on the major MASs in each region (i.e., North America, Europe and Asia Pacific) while reporting the statistics of all sample MASs in the appendix.

4.1. Traffic and network size distribution within MAS

Individual airports within an MAS may focus on different markets or be served by different types of airlines. For example, FSCs may utilize hub airports to develop extensive regional and inter-continental networks that enable them to leverage various cost and competitive advantages (Zhang 1996; Tu et al, 2020), whereas secondary airports may focus on regional destinations and serve many LCC flights (Wang et al. 2020b). Airlines' frequency choices depend significantly on traffic volume and slot availability, which in term further affect service equality and passenger demand (Wang et al. 2014). The pandemic cause significant yet non-uniform demand reduction, which are likely to have imposed heterogeneous impacts on different airports. To capture the degree of possible uneven or unequal distributions among various entities, we adopt the Gini index as a commonly used measure. We calculate the Gini index of traffic and degree centrality for the sampled MASs before and during the late stage of the pandemic, based on data from Q3 2019 and 2022. The degree centrality is defined as the total number of destinations linked with each airport via direct flights, and it helps to measure the network scope of a particular airport. The Gini index is calculated using the following equation, which measures the degree of inequality in the distribution of airport traffic within the same MAS:

$$G_M = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} |Y_{it} - Y_{jt}|}{2m^2\overline{Y_m}}, \tag{1}$$

where Y_i is the degree centrality or scheduled seats of airport i, and m is the number of airports in one MAS. The Gini coefficient is G_M and it can theoretically range from 0 (complete equality) to 1 (complete inequality). The larger that the coefficient is, the more unequal that the distribution of airport seats is within the MAS.

Tables 4 and 5 present the Gini indices of the degree centrality and traffic volume (measured by scheduled seats) for the top 10 MASs in the world, respectively. In the case of London, where international services control a lion's share of the market, our analysis primarily reflect the dynamics of its international market. The Gini indices of both degree centrality and traffic remained relatively stable before (Q3 2019) and during the pandemic (Q3 2022), mainly due to the lifting of travel bans across European countries (and North America) during 2022, which led to a recovery in the intra-European and cross-Atlantic markets. The Gini indices of the degree of centrality and traffic in major US MASs, including New York, Los Angeles, and Chicago, as of Q3 2022, did not change significantly compared with those in Q3 2019. This finding demonstrates that the network and traffic distributions of US MASs were relatively stable once the pandemic was contained and travel restrictions were lifted. This pattern also applies to MASs in Paris. However, for Istanbul, we observe a more unevenly distributed degree of centrality in the domestic market during the pandemic. Istanbul Ataturk Airport is the primary airport in this MAS, focusing on both international and domestic markets, while Sabiha Gokcen Airport mainly serves the domestic market through LCC services. Prior to the pandemic, 55% of domestic traffic was served by Sabiha Airport. However, with the pandemic's impact, Sabiha Gokcen Airport withdrew some domestic routes, resulting in a decrease in domestic traffic to a level close to that of Ataturk Airport.

[1]Furthermore, Beijing Daxing Airport, which is comparable in size to Beijing Capital Airport, had only recently opened before the pandemic and was almost closed during the pandemic.

Table 3: *Sample MASs in this study*

Region	MAS | Country	Airports	MAS | Country	Airports
Asia-Pacific	Melbourne | AU	Melbourne, Avalon	Hong Kong | CN	Hong Kong, Shenzhen
	Shanghai | CN	Pudong, Hongqiao	Taipei | CN	Taoyuan, Songshan
	Osaka | JP	Kansai, Itami, Kobe	Tokyo | JP	Haneda, Narita
	Seoul | KR	Incheon, Gimpo	Bangkok | TH	Suvarnabhumi, Don Mueang
Europe	Brussels | BE	Brussels, S. Charleroi, Liege	Paris | FR	de Gaulle, Orly, Beauvais-Tille, Chalons-Vatry,
	Dusseldorf | DE	Duesseldorf, Cologne-Bonn, Dortmund, Weeze	Frankfurt | DE	Frankfurt, Hahn
	Stuttgart | DE	Stuttgart, Baden	Milan | IT	Malpensa, Bergamo, Linate
	Pisa | IT	Pisa, Florence	Rome | IT	Fiumicino, Ciampino
	Venice | IT	Marco Polo, Treviso	Amsterdam | NL	Amsterdam, Eindhoven, Rotterdam
	Oslo | NO	Gardermoen, Sandefjord-Torp	Moscow | RU	Sheremetyevo, Domodedovo, Vnukovo
	Vienna | SK	Vienna, Bratislava	Barcelona | ES	Barcelona, Girona, Reus
	Copenhagen | SE	Copenhagen, Malmo	Stockholm | SE	Arlanda, Bromma, Skavsta
	Istanbul | TR	Istanbul, Sabiha Gokcen	Belfast | UK	Belfast, George Best
	Glasgow | UK	Edinburgh, Glasgow, Prestwick	London | UK	Heathrow, Gatwick, Stansted, Luton, London City
	Manchester | UK	Manchester, Liverpool, Leeds Bradford		
Latin America & Middle East	Buenos | AR	Newbery, Ministro Pistarini	Rio de Janeiro | BR	Rio de Janeiro, Santos Dumont
	Sao Paulo | BR	Guarulhos, Congonhas, Campinas	Tehran | IR	Mehrabad, Khomeini
	Mexico City | MX	Mexico City, Toluca	Dubai | AE	Dubai, Sharjah
North America	Toronto | CA	Pearson, Billy Bishop, Hamilton	Vancouver | CA	Vancouver, Abbotsford
	San Diego | US	San Diego, Tijuana	Boston | US	Logan, Providence, Manchester-Boston
	Chicago | US	O'Hare, Midway, Rockford	Cleveland | US	Hopkins, Akron
	Dallas | US	Dallas, Love Field	Detroit | US	Metropolitan Wayne, Flint
	Houston | US	George Bush, Hobby	Los Angeles | US	Los Angeles, Santa Ana, Burbank, Ontario, Long Beach
	Miami | US	Miami, Lauderdale	New York | US	Kennedy, Liberty, LaGuardia, Islip
	Norfolk | US	Norfolk, Williamsburg	Orlando | US	Orlando, Sanford
	Philadelphia | US	Philadelphia, Atlantic City	San Francisco | US	San Francisco, San Jose, Oakland
	Tampa | US	Tampa, St Pete-Clearwater, Sarasota	Washington | US	Baltimore, Dulles, Reagan

Conversely, the MASs in Asia have experienced significant changes in the Gini indices of degree centrality and traffic before and during the late stage of the pandemic. In the case of the Tokyo MAS, Tokyo Narita Airport primarily serves the international market, accounting for 67% of international traffic as of Q3 2019. Haneda Airport, in contrast, focuses mainly on the domestic market, serving 90% of domestic traffic in the same period. Japan adopted stricter travel bans than European and North American countries, with Narita Airport being affected particularly strongly, resulting in a significant decrease in its international degree centrality, from 120 in 2019 to 71 in 2022. Consequently, the difference in international degree centrality between Narita and Haneda decreased during the pandemic, leading to a 25% decrease in the Gini index of degree centrality in the international market. Although the number of international routes from Narita decreased significantly, the airport's dominance in the international market led to an increase in the proportion of international traffic served, resulting in a 10% increase in the Gini index of traffic. Such findings are consistent with the empirical evidence of Ng et al. (2022), who indicated that the Japanese airline market was heavily affected by the pandemic, with the two dominant airlines (All Nippon Airways and Japanese Airlines) strengthening their competition in the major domestic routes linking to Haneda and Narita airports.

In the case of Shanghai, both Pudong and Hongqiao airports serve a considerable number of domestic destinations.

Table 4: *Gini index of the degree centrality before (Q3 2019) and during late stage of pandemic (Q3 2022) for top 10 MASs*

			Domestic routes			**International routes**		
Rank	**MAS**	**Region**	**Before**	**Late stage**	**Diff%**	**Before**	**Late stage**	**Diff%**
1	London	Europe	0.105	0.17	61%	0.211	0.236	12%
2	New York	North America	0.28	0.252	-10%	0.524	0.524	0%
3	Tokyo	Asia-Pacific	0.181	0.204	13%	0.279	0.21	-25%
4	Hong Kong	Asia-Pacific	0.227	0.371	63%	0.174	0.3	72%
5	Shanghai	Asia-Pacific	0.131	0.198	51%	0.457	0.5	10%
6	Paris	Europe	0.5	0.47	-6%	0.497	0.426	-14%
7	Los Angeles	North America	0.39	0.326	-16%	0.771	0.708	-8%
8	Istanbul	Europe	0.049	0.063	28%	0.247	0.248	0%
9	Chicago	North America	0.459	0.438	5%	0.573	0.55	-4%
10	Bangkok	Asia-Pacific	0.141	0.119	-16%	0.167	0.223	34%

Notes:
1. The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Table 5: *Gini index of the traffic (scheduled seats) before (Q3 2019) and during late stage of the pandemic (Q3 2022) for top 10 MASs*

			Domestic			**International**		
Rank	**MAS**	**Region**	**Before**	**Late stage**	**Diff%**	**Before**	**Late stage**	**Diff%**
1	London	Europe	0.326	0.31	5%	0.406	0.402	-1%
2	New York	North America	0.259	0.252	-3%	0.568	0.564	-1%
3	Tokyo	Asia-Pacific	0.399	0.387	-3%	0.173	0.191	10%
4	Hong Kong*	Asia-Pacific	0.257	0.449	75%	0.403	0.469	16%
5	Shanghai	Asia-Pacific	0.025	0.01	-58%	0.422	0.5	19%
6	Paris	Europe	0.543	0.513	-5%	0.594	0.541	-9%
7	Los Angeles	North America	0.543	0.491	-9%	0.791	0.782	-1%
8	Istanbul	Europe	0.055	0.028	-49%	0.286	0.265	-8%
9	Chicago	North America	0.513	0.474	-8%	0.636	0.626	-1%
10	Bangkok	Asia-Pacific	0.158	0.043	-73%	0.238	0.37	56%

Notes:
1. The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.
3.*The Hong Kong MAS includes the airports in the two nearby cities of Hong Kong and Shenzhen.

However, Hongqiao Airport serves only a small number of international destinations, mainly short-haul flights to Japan and Southeast Asia, while almost all international flights are served by Pudong Airport. During the pandemic, Pudong Airport had more under-utilized slots due to China's implementation of strict bans on international airline services. As a result, Pudong added flights to more domestic destinations, further exceeding Hongqiao in degree centrality in the domestic market. Since Hongqiao previously dominated the domestic traffic volume, the rise of Pudong Airport in domestic services narrowed the domestic traffic imbalance during the pandemic, leading to a 58% reduction in the Gini index of domestic traffic. For Hong Kong, the Chinese government banned flights between Hong Kong and mainland China, resulting in a significant drop in the number of domestic routes and traffic at Hong Kong Airport, increasing the Gini indices of domestic degree centrality and traffic of the MAS by 63% and 75%, respectively. Shenzhen cut almost all international flights during the pandemic, while Hong Kong maintained more international flight services, further exacerbating the uneven distribution of international air services in this MAS.

The Gini indices of degree centrality and traffic for the other sampled MASs are compiled in Appendix Tables 8 and 9, respectively. Overall, the observations indicate that, for European and US airports, the overall inequality of traffic and degree centrality did not change significantly by the end of 2022 compared to pre-pandemic conditions, because domestic traffic and international traffic volumes recovered in a similar pattern. In contrast, for the Asian Pacific MASs, the stricter international air travel bans adopted by these countries were more strict and lasted for much longer periods, which led to a significant redistribution of traffic and networks in the international markets. As airports with more idle slots from international operations switched to domestic flight services, the intra-MAS distribution of domestic operations also underwent significant changes.

4.2. Intra-MAS airport competition and market overlap

In this subsection, we focus on the origin-destination (OD) level competition among different airports within one MAS. That is, the different airports in one MAS might offer direct flights to the same destination. The intra-MAS airport competition is fiercer when airports serve more overlapping destination markets. To more accurately capture such intra-MAS competition (degree of market overlap), we devise with the following Herfindahl-Hirschman (HHI) index on each route originating from one MAS:

$$OD\_HHI_{Mj} = \sum_{i=1}^{m} (\frac{q_{ij}}{Q_{Mj}})^2, \tag{2}$$

where Q_{Mj} is the total scheduled seats from MAS M to destination airport j; q_{ij} is the scheduled seats from airport i in the MAS to destination airport j; and m is the number of airports in MAS M. Then, for each sample MAS, we are able to calculate this HHI index for each OD market. A larger value of HHI suggests higher market concentration, or more dominance of the leading airport(s) within the MAS serving this OD market.

For our empirical investigation, we focus on the top 5 MASs worldwide, namely London, New York, Tokyo, Hong Kong, and Shanghai. These MASs are distributed in major regions around the world. In Figure 1 and Figure 2, we present the percentage distributions of the OD level HHIs, as calculated in Eq. (2). For the London MAS, the HHI index became more concentrated towards lower values, indicating more intense competition among different airports in the London MAS. As we discuss in more detail in the next subsection, British Airways dominated at London Heathrow Airport, while LCC Easyjet operated its base airport at London Gatwick Airport. During the pandemic, British Airways relocated its capacity from intercontinental routes to more intra-European routes at its Heathrow hub, leading to more head-to-head competition with Easyjet at London Gatwick. For the New York MAS, there was no significant change in the OD level HHI during the pandemic. This outcome can be attributed to the almost full recovery of the US aviation market in Q3 2022 compared with Q3 2019, with airlines returning service levels and network configurations to pre-pandemic levels. In other words, we did not observe any clear or long-term changes in the MAS structure caused by the pandemic in the US.

In the case of the Tokyo MAS, the intra-MAS competition between Narita and Haneda airports appeared to intensify, with an overall decrease in the OD level HHI. This result occurred primarily because, during the pandemic, both airports cut services in thin markets and focused on denser and more lucrative routes, enhancing their market overlap and head-to-head competition. For the Hong Kong MAS, both the Hong Kong and Shenzhen airports were heavily impacted during the pandemic. Before the pandemic, they served many common destinations in mainland China, as well as short- to medium-haul international routes. However, most of the flights from Hong Kong to mainland Chinese cities were suspended during the pandemic, and international flights from Shenzhen were also dramatically reduced. Consequently, the two airports' networks became very distinct during the pandemic. Last, in the case of the Shanghai MAS, the competition between the Hongqiao and Pudong airports became much more intense. As discussed in the previous subsection (4.1), to alleviate the adverse impact of the pandemic, Pudong Airport expanded its domestic market services, resulting in increased head-to-head competition with Hongqiao Airport in many domestic OD markets.

We also calculated the average OD level HHI for each MAS to provide an overall measure of changes in airport competition within the MAS (as illustrated in Figure 2). Except for the Hong Kong MAS, all four of the other systems experienced increased intra-MAS airport competition during the later stage of the pandemic, consistent with our earlier analysis.

Furthermore, we compiled the distribution of the OD level HHI and average OD level HHI before and during the late stage of the pandemic for other sampled MASs and we present the results for the top 30 MASs in Figures 3 and 4. Overall, the observations indicate that for US and European MASs, once travel bans were lifted, the intra-MAS airport competition structure returned to pre-pandemic levels. In contrast, for Asian Pacific MASs, intra-MAS airport competition could be significantly reshaped because relevant airports' operations had been significantly constrained by strict international air travel bans.

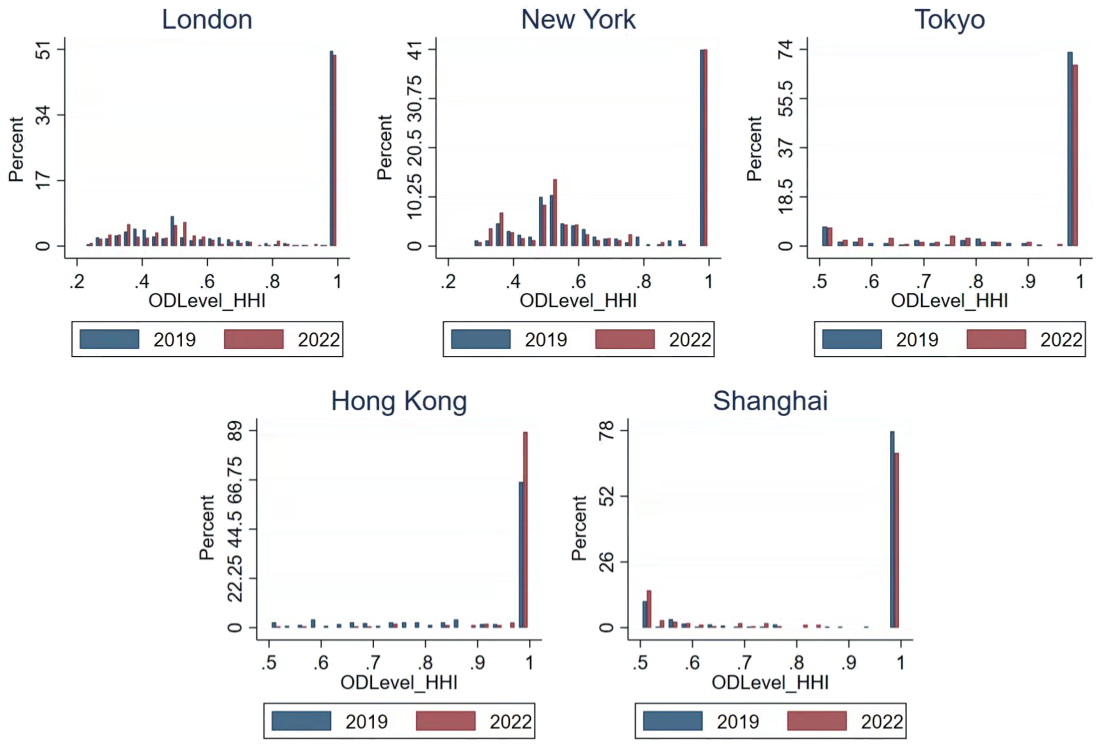

Figure 1: *The distribution of OD HHI for top 5 MAS before (Q3 2019) and during late stage of pandemic (Q3 2022).*

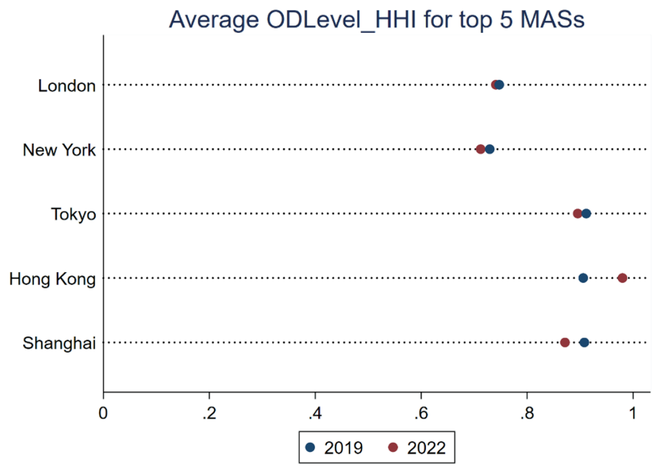

Figure 2: *The Average OD HHI for top 5 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022).*

4.3. Airline competition within the MAS

In this subsection, we examine the impact of the pandemic on airline-level competition within MASs. First, to measure the overall airline competition intensity, we calculate the airline HHI in each MAS using the following equation.

$$Airline\_HHI_M = \sum_{i=1}^{N} (\frac{q_{iM}}{Q_M})^2, \tag{3}$$

where q_{iM} is the scheduled seats of airline i in MAS M, regardless of airport; Q_M is the total scheduled seats in MAS M; and N is the number of airlines in MAS M. A larger value of airline HHI suggests more dominance of particular airlines within one MAS. Table 6 summarizes the airline HHIs for the top 10 MASs before and during the late stage of the pandemic. For US and European MASs, the airline HHI did not change significantly. This outcome suggests that there were no significant airline exits in these MASs during the pandemic. While some airlines might have exited the market in the early stages of the pandemic, once it was under control and most travel bans were lifted, airline services resumed quickly, leading to similar airline concentration levels. In contrast, for Asia-Pacific MASs, the concentration level of airlines increased significantly, with some airlines becoming much more dominant during the pandemic. One possible explanation is the crowding effect imposed by large-sized dominant airlines. Since international flight services were largely suspended, airlines that previously served international markets redeployed their capacity in domestic markets, intensifying competition and leading to exits by small airlines and LCCs. The MASs thus became more concentrated. We also compiled the airline HHI results for other MASs in Appendix Table 10. Notably, for small-scale MASs, such as Milan, Venice, and Bologna, their airline HHIs also increased significantly due to economies of scale. With air traffic dropping during the pandemic, it was difficult for all airlines to achieve efficient operations, and some inefficient airlines exited the market, leading to a higher airline HHI.

Table 6: *Airline HHI of top 10 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022)*

Rank	MAS	Before	Late stage	Diff%
1	London	0.118	0.115	-3%
2	New York	0.139	0.151	9%
3	Tokyo	0.183	0.235	28%
4	Hong Kong	0.079	0.123	55%
5	Shanghai	0.125	0.155	24%
6	Paris	0.176	0.177	0%
7	Los Angeles	0.118	0.124	5%
8	Istanbul	0.456	0.486	6%
9	Chicago	0.238	0.234	2%
10	Bangkok	0.080	0.080	0%

Notes:
1. The “before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

In addition to overall airline concentration, we also investigated competition between FSCs and LCCs in MASs. In some MASs, FSCs and LCCs prefer to have hubs at different airports. For example, in the London MAS, British Airways (FSC) has its hub at Heathrow Airport, while Easyjet has its main base at Gatwick Airport. In other MASs, FSCs and LCCs are not clearly distinguished in hub airports. For instance, in the Shanghai MAS, Spring Airlines (a LCC) and China Eastern Airlines (a FSC) claim hubs at both Hongqiao and Pudong airports. Spring Airlines aims to enter both airports to attract passengers with different airport preferences in the MAS, but doing so could hinder their achievement of economies of scale. The pandemic might have affected the incentives of FSCs and LCCs to choose airport entry and capacity distribution in the MAS. Thus, we calculated the Gini index of LCC capacity share, and the results for the top 10 MASs are shown in Table 7. First, for European and US MASs, the LCC capacity share became slightly more balanced during the pandemic, as indicated by an overall decrease in the Gini index. This outcome suggests that LCCs preferred to maintain the presence at multiple airports in MASs to serve passengers that have different airport preferences. This is probably due to LCCs' significant market shares and traffic volumes, which enable them to maintain sizeable operations at multiple airports. This is helped by the fact that LCCs offer simplified services (e.g. no connection nor complicated baggage handling, simple catering services), thus not too costly to maintain operations at multiple airports.

However, for Asia-Pacific MASs, particularly the Shanghai MAS, LCCs preferred to concentrate operations in a single airport, Pudong Airport, during the pandemic. There are two possible rationales for this choice. First, LCCs have a much smaller presence and market occupation in China and Japan, especially in China (no more than 15%). Therefore, it is crucial for them to have sufficient traffic to achieve economies of scale, especially when many input prices are beyond the control of LCCs (Fu et al. 2015b; Su et al. 2020). When the market is in a downturn and the traffic volume is low, LCCs must consolidate traffic into one airport in the MAS to maintain a certain level of operational scale. Our data show that China's largest LCC, Spring Airlines, increased its market share at Pudong Airport more than at Hongqiao Airport during the pandemic. When more idle slots are available for redistribution, LCCs can acquire them and expand services, in line with China's policy allowing LCCs to obtain new slots and open new routes from major hub airports (Shanghai and Beijing) during the pandemic as an indirect measure to support private LCCs in surviving the market downturn (e.g., Hou et al., 2021). Second, FSCs in the Asia-Pacific region faced more restrictive bans on operating international markets, forcing them to compete more aggressively in the domestic market to survive. They attempted to prevent LCC expansion in their hub airports by adopting more aggressive competition strategies, such as deep price discounts. The Gini index of LCC capacity share for other MASs is available in Appendix Table 11.

Table 7: *Gini index of LCC capacity share in top 10 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022)*

Rank	MAS	Before	Late stage	Diff%
1	London	0.461	0.437	-5%
2	New York	0.428	0.379	-11%
3	Tokyo	0.269	0.332	23%
4	Hong Kong	0.148	0.190	28%
5	Shanghai	0.026	0.069	169%
6	Paris	0.321	0.290	-10%
7	Los Angeles	0.247	0.209	-15%
8	Istanbul	0.467	0.489	5%
9	Chicago	0.309	0.296	-4%
10	Bangkok	0.385	0.282	-27%

Notes:
l. The “before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022. For Hong Kong MAS, it only constitutes Hong Kong and Shenzhen airports.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

5. Conclusions

This study first reviewed and summarized the recent literature on MASs, discussing the main research topics and development patterns. It is noted that the impacts of the pandemic on MASs have not been well explored in the literature. Therefore, we collected airport-airline-specific capacity data from OAG (before and during the late stage of the pandemic) to examine the pandemic's impact on different dimensions of MAS operations worldwide following the definitions used in previous studies for consistency. A total of 53 MASs are included in our sample, with a focus on the top MASs around the world. By calculating descriptive statistics and indices, we studied three dimensions of MAS structures before and during the late stage of the pandemic: i) traffic and degree centrality distributions within MASs; ii) intra-MAS airport competition (the degree of OD market overlap); and iii) airline competition intensity within MASs.

Our statistics suggest heterogeneous impacts of the pandemic on MASs in different regions when comparing market outcomes between Q3 2019 (before the pandemic) and Q3 2022 (during the pandemic). For MASs in the US and Europe, the distribution of traffic and degree centrality among airports remained largely unchanged. Both the domestic and international airline markets in these MASs have returned to pre-pandemic levels at similar paces. Until the end of 2022, intra-MAS airport competition and airline airport dominance and concentration (including between FSCs and LCCs) have also been similar to pre-pandemic levels at major European and US MASs. These results suggest the stability of MAS structures in the US and Europe after their airline markets recovered from the unprecedented shock of the pandemic.

In contrast, Asia-Pacific MASs experienced significant changes during the pandemic, mainly due to very restrictive bans on international travel. Since large-sized airlines could not serve international markets, they had to redeploy their capacity into domestic markets, leading to significant changes in the MAS structure. First, airport traffic could be more balanced within the MAS, and intra-MAS airport competition became much fiercer as airports focused on operations in similar domestic destinations. On the other hand, smaller airlines dropped quite a few markets, leading to higher airline concentration levels. The net effect (i.e. whether competition in an MAS increased and decreased) remains unclear. It is also noted that LCCs in Asia-Pacific seemed more likely to have a main base in a single airport in one MAS, either due to the incentive of achieving economies of scale or they were pushed out from other airports due to stronger competitive responses from FSCs who were forced to allocate more capacity to domestic markets.

In general, our study identified heterogeneous development and recovery patterns among MASs in different regions. Although some possible explanations are proposed, more in-depth analysis is required to go beyond simple statistics. Our study also raised some questions unanswered. For example, government interventions in the European and North American markets, where market largely returned to pre-pandemic conditions, are probably not necessary. Yet it is not clear whether the any government intervention should be considered to address the heterogeneous impacts caused by the pandemic, especially for “distortions” caused by previous regulations (e.g. ban on international services). Extension studies based on updated data can be helpful in addressing those important questions.

References

Babić, D., Kalić, M., Janić, M., Dožić, S., & Kukić, K. (2022). Integrated Door-to-Door Transport Services for Air Passengers: From Intermodality to Multimodality. Sustainability, 14(11), 6503.

Bezerra, G. C., & Gomes, C. F. (2019). Determinants of passenger loyalty in multi-airport regions: Implications for tourism destination. Tourism Management Perspectives, 31, 145-158.

Bonnefoy, P. A., de Neufville, R., & Hansman, R. J. (2010). Evolution and development of multiairport systems: Worldwide perspective. Journal of Transportation Engineering, 136(11), 1021-1029.

Brueckner, J. K. (2003). Airline traffic and urban economic development. Urban Studies, 40(8), 1455-1469.

Chen, T., Fu, X., Hensher, D. A., Li, Z. C., & Sze, N. N. (2022a). Air travel choice, online meeting and passenger heterogeneity–An international study on travellers' preference during a pandemic. Transportation Research Part A: Policy and Practice, 165, 439-453.

Chen, T., Fu, X., Hensher, D., Li, Z.C., Sze, N.N., (2022b), The effect of online meeting and health screening on business travel: a stated preference case study in Hong Kong, Transportation Research - Part E , 164, 102823.

Cheung, T. K.-Y., Wong, W.-h., Zhang, A., & Wu, Y. (2020). Spatial panel model for examining airport relationships within multi-airport regions. Transportation Research Part A: Policy and Practice, 133, 148-163.

Chiambaretto, P., Baudelaire, C., & Lavril, T. (2013). Measuring the willingness-to-pay of air-rail intermodal passengers. Journal of Air Transport Management, 26, 50-54.

Czerny, A. I., Fu, X., Lei, Z., & Oum, T. H. (2021). Post pandemic aviation market recovery: Experience and lessons from China. Journal of Air Transport Management, 90, 101971.

de Neufville, R. (2004). The Future of Secondary Airports: Nodes of a parallel air transport network?

de Neufville, R. (2016). Multi-Airport Systems. Istanbul Technical University. Air Transportation Management. Airport Planning and Management. Module 24.

de Paula Balan, B., da Cunha, M. C. F., da Cunha, R. C., & Halawi, L. (2022) Aviation supply and demand in the São Paulo and Rio de Janeiro systems evolution: An exploratory study. Journal of Economics and Management, 44(1), 393-419.

Fu, X., Dresner, M. & Oum, T.H. (2011), Effects of transport service differentiation in the U.S. domestic airline market, Transportation Research – Part E 47(3), 297-305.

Fu X., Lei Z., Wang K. and Yan J. (2015b), Low cost carrier competition and route entry in an emerging but regulated aviation market - the Case of China, Transportation Research - Part A, 79, 3-16.

Fu, X., Jin, H., Liu, S., Oum, T.H., & Yan, J. (2019) Exploring network effects of Point-to-Point networks: An investigation of the spatial patterns of Southwest airlines' network, Transport Policy, 76, 36-45.

Fu X., Oum T.H., Chen R. & Lei Z. (2015a), Dominant carrier performance and international liberalization – the case of North East Asia, Transport Policy, 43, 61–75.

Fuellhart, K., O'Connor, K., & Woltemade, C. (2013). Route-level passenger variation within three multi-airport regions in the USA. Journal of Transport Geography, 31, 171-180.

Harvey, G. (1987). Airport choice in a multiple airport region. Transportation Research Part A: General, 21(6), 439-449.

Hess, S., & Polak, J. W. (2006). Exploring the potential for cross-nesting structures in airport-choice analysis: a case-study of the Greater London area. Transportation Research Part E: Logistics and Transportation Review, 42(2), 63-81.

Hou, M., Wang, K., & Yang, H. (2021). Hub airport slot Re-allocation and subsidy policy to speed up air traffic recovery amid COVID-19 pandemic---case on the Chinese airline market. Journal of Air Transport Management, 93, 102047.

Hou, M., Wang, K., Yang, H., & Zhang, A. (2022). Airport-airline Relationship, Competition and Welfare in a Multi-airport System: The Case of New Beijing Daxing Airport. Journal of Transport Economics and Policy (JTEP), 56(2), 156-189.

Jung, S.-Y., & Yoo, K.-E. (2016). A study on passengers' airport choice behavior using hybrid choice model: A case study of Seoul metropolitan area, South Korea. Journal of Air Transport Management, 57, 70-79.

Kuo, P.-F., Putra, I. G. B., Setiawan, F. A., Wen, T.-H., Chiu, C.-S., & Sulistyah, U. D. (2022). The impact of the COVID-19 pandemic on OD flow and airport networks in the origin country and in Northeast Asia. Journal of Air Transport Management, 100, 102192.

Li, L. Y., Mao, Y. J., Wang, Y., & Ma, Z. H. (2022). How has airport service quality changed in the context of COVID-19: A data-driven crowdsourcing approach based on sentiment analysis. Journal of Air Transport Management, 105.

Li, S. P., Zhou, Y. M., Kundu, T., & Sheu, J. B. (2021). Spatiotemporal variation of the worldwide air transportation network induced by COVID-19 pandemic in 2020. Transport Policy, 111, 168-184.

Li, X., Tang, J., Hu, X., & Wang, W. (2020). Assessing intercity multimodal choice behavior in a Touristy City: A factor analysis. Journal of Transport Geography, 86, 102776.

Li, Z.-C., Tu, N., Fu, X., & Sheng, D. (2022). Modeling the effects of airline and high-speed rail cooperation on multi-airport systems: The implications on congestion, competition and social welfare. Transportation Research Part B-Methodological, 155, 448-478.

Liao, W., Cao, X., & Li, S. (2019). Competition and Sustainability Development of a Multi-Airport Region: A Case Study of the Guangdong-Hong Kong-Macao Greater Bay Area. Sustainability, 11(10).

Liao, W., Cao, X., Liu, Y., & Huang, Y. (2022). Investigating differential effects of airport service quality on behavioral intention in the multi-airport regions. Research in Transportation Business & Management, 45, 100877.

Ma, G. F., Ding, Y., & Ma, J. Y. (2022). The Impact of Airport Physical Environment on Perceived Safety and Domestic Travel Intention of Chinese Passengers during the COVID-19 Pandemic: The Mediating Role of Passenger Satisfaction. Sustainability, 14(9).

Mamdoohi, A. R., Yazdanpanah, M., Taherpour, A., & Saffarzadeh, M. (2014). An analysis of resident and Non-resident air passenger behaviour of origin airport choice. International Journal of Transportation Engineering, 2(1), 13-30.

Marcucci, E., & Gatta, V. (2011). Regional airport choice: Consumer behaviour and policy implications. Journal of Transport Geography, 19(1), 70-84.

Marcucci, E., & Gatta, V. (2012). Dissecting preference heterogeneity in consumer stated choices. Transportation Research Part E: Logistics and Transportation Review, 48(1), 331-339.

Monmousseau, P., Marzuoli, A., Feron, E., & Delahaye, D. (2020). Impact of Covid-19 on passengers and airlines from passenger measurements: Managing customer satisfaction while putting the US Air Transportation System to sleep. Transportation Research Interdisciplinary Perspectives, 7, 100179.

Mueller, F. (2022). Examining COVID-19-triggered changes in spatial connectivity patterns in the European air transport network up to June 2021. Research in Transportation Economics, 94, 101127.

Murça, M. C. R., & Correia, A. R. (2013). Análise da modelagem da escolha aeroportuária em regiões de múltiplos aeroportos. [Analysis of airport choice modeling in multi-airport regions]. Journal of Transport Literature, 7(4), 130-146.

Nižetić, S. (2020). Impact of coronavirus (COVID-19) pandemic on air transport mobility, energy, and environment: A case study. International Journal of Energy Research, 44(13), 10953-10961.

Noruzoliaee, M., Zou, B., & Zhang, A. (2015). Airport partial and full privatization in a multi-airport region: Focus on pricing and capacity. Transportation Research Part E: Logistics and Transportation Review, 77, 45-60.

Ng, K. T., Fu, X., Hanaoka, S., & Oum, T. H. (2022). Japanese aviation market performance during the COVID-19 pandemic-Analyzing airline yield and competition in the domestic market. Transport Policy, 116, 237-247.

Paliska, D., Drobne, S., Borruso, G., Gardina, M., & Fabjan, D. (2016). Passengers' airport choice and airports' catchment area analysis in cross-border Upper Adriatic multi-airport region. Journal of Air Transport Management, 57, 143-154.

Pels, E., Nijkamp, P., & Rietveld, P. (2000). Airport and airline competition for passengers departing from a large metropolitan area. Journal of Urban Economics, 48(1), 29-45.

Pels, E., Nijkamp, P., & Rietveld, P. (2001). Airport and airline choice in a multiple airport region: an empirical analysis for the San Francisco Bay Area. Regional Studies, 35(1), 1-9.

Pels, E., Nijkamp, P., & Rietveld, P. (2003). Access to and competition between airports: a case study for the San Francisco Bay area. Transportation Research Part A: Policy and Practice, 37(1), 71-83.

Salesi, V. K., Tsui, W. H. K., Fu, X., & Gilbey, A. (2022). Strategies for South Pacific Region to address future pandemics: Implications for the aviation and tourism sectors based on a systematic literature review (2010–2021). Transport Policy.

Shamohammadi, M., Park, Y., Choi, J. H., & Kwon, O. K. (2022). Exploring the Performance of International Airports in the Pre- and Post-COVID-19 Era: Evidence from Incheon International Airport. Sustainability, 14(7).

Sheard, N. (2014). Airports and urban sectoral employment. Journal of Urban Economics, 80, 133-152.

Su, M., Luan, W., Fu, X., Yang, Z., Zhang, R. (2020) The competition effects of low-cost carriers and high-speed rail on the Chinese aviation market, Transport Policy, 95, 37-46.

Sun, X., Wandelt, S., Hansen, M., & Li, A. (2017). Multiple airport regions based on inter-airport temporal distances. Transportation Research Part E: Logistics and Transportation Review, 101, 84-98.

Sun, X., Wandelt, S., & Zhang, A. (2020). How did COVID-19 impact air transportation? A first peek through the lens of complex networks. Journal of Air Transport Management, 89, 101928.

Sun, X., Wandelt, S., & Zhang, A. (2021b). On the degree of synchronization between air transport connectivity and COVID-19 cases at worldwide level. Transport Policy, 105, 115-123.

Sun, X., Wandelt, S., Zheng, C., & Zhang, A. (2021a). COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. Journal of Air Transport Management, 94, 102062.

Sun, X., Wandelt, S., & Zhang, A. (2022). COVID-19 pandemic and air transportation: Summary of Recent Research, Policy Consideration and Future Research Directions. Transportation Research Interdisciplinary Perspectives, 16, 100718.

Suzumura, T., Kanezashi, H., Dholakia, M., Ishii, E., Napagao, S. A., Pérez-Arnal, R., & Garcia-Gasulla, D. (2020). The impact of COVID-19 on flight networks. In 2020 IEEE International Conference on Big Data (Big Data) (pp. 2443-2452). IEEE.

Teixeira, F. M., & Derudder, B. (2021). Spatio-temporal dynamics in airport catchment areas: The case of the New York Multi Airport Region. Journal of Transport Geography, 90, 102916.

Tiglao, N. C. Investigating Tourists' Airport Choice in the Multi-Airport Region of Aklan, Philippines and Its Implications on Airport Capacity Expansion Decisions. Transport, 3(1).

Tu, N., Li, Z.C., Fu, X., Lei, Z. (2020). Airline network competition in inter-continental market. Transportation Research - Part E, 143, 102117.

Wang K., Gong Q., Fu X. and Fan X. (2014), Frequency and aircraft size dynamics in a concentrated growth market: The case of the Chinese domestic market, Journal of Air Transport Management, 36, 50–58.

Wang, K., Tsui, K., Li, L.B., Lei, Z., Fu, X. (2020b) Entry pattern of low-cost carriers in New Zealand - The impact of domestic and trans-Tasman market factors, Transport Policy, 93, 36-45.

Wang, K., Jiang, C., Ng, A. K., & Zhu, Z. (2020a). Air and rail connectivity patterns of major city clusters in China. Transportation Research Part A: Policy and Practice, 139, 35-53.

Wong, W. H., Cheung, T., Zhang, A., & Wang, Y. (2019a). Is spatial dispersal the dominant trend in air transport development? A global analysis for 2006-2015. Journal of Air Transport Management, 74, 1-12.

Wong, W.-H., Zhang, A., Cheung, T. K.-Y., & Chu, J. (2019b). Examination of low-cost carriers' development at secondary airports using a comprehensive world airport classification. Journal of Air Transport Management, 78, 96-105.

Winston, C., & Yan, J. (2011). Can privatization of US highways improve motorists' welfare?. Journal of Public Economics, 95(7-8), 993-1005.

Yan, J., & Winston, C. (2014). Can private airport competition improve runway pricing? The case of San Francisco Bay area airports. Journal of Public Economics, 115, 146-157.

Zhang, A. (1996) An analysis of fortress hubs in airline networks, Journal of Transport Economics and Policy, 30(3), 293-307.

Zhang, L., Hou, M., Liu, Y., Wang, K., & Yang, H. (2022). Measuring Beijing's international air connectivity and suggestions for improvement post COVID-19. Transport Policy, 116, 132-143.

Zhang, L., Yang, H., Wang, K., Bian, L., & Zhang, X. (2021). The impact of COVID-19 on airline passenger travel behavior: An exploratory analysis on the Chinese aviation market. Journal of Air Transport Management, 95, 102084.

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, 34-42.

Appendix

Table 8: *Gini index of the degree centrality before (Q3 2019) and during late stage of pandemic (Q3 2022) for MASs (other than top 10 MASs)*

			Domestic			International		
Rank	**MAS**	**Region**	**Before**	**Late stage**	**Diff%**	**Before**	**Late stage**	**Diff%**
11	Moscow	Europe	0.017	0.038	118%	0.116	0.08	-31%
12	Dubai	Latin America & Middle East	0	0	NA	0.223	0.224	0%
13	Seoul	Asia-Pacific	0.25	0.389	56%	0.464	0.48	3%
14	Dallas	North America	0.256	0.226	-12%	0.5	0.5	0%
15	San Francisco	North America	0.138	0.214	55%	0.387	0.437	13%
16	Amsterdam	Europe	0.133	0	-100%	0.389	0.345	-11%
17	Frankfurt	Europe	0.5	0.5	0%	0.395	0.38	-4%
18	Washington	North America	0.04	0.053	34%	0.438	0.433	-1%
19	Sao Paulo	Latin America & Middle East	0.106	0.164	55%	0.583	0.623	7%
20	Miami	North America	0.087	0.007	-92%	0.145	0.147	2%
21	Barcelona	Europe	0.667	0.586	-12%	0.403	0.426	6%
22	Houston	North America	0.18	0.15	-17%	0.359	0.361	1%
23	Rome	Europe	0.462	0.423	-8%	0.281	0.33	17%
24	Toronto	North America	0.381	0.292	-23%	0.603	0.604	0%
25	Taipei	Asia-Pacific	0.5	0.5	0%	0.407	0.442	9%
26	Osaka	Asia-Pacific	0.294	0.226	-23%	0.667	0.667	0%
27	Milan	Europe	0.026	0.062	137%	0.32	0.267	-17%
28	Mexico City	Latin America & Middle East	0.398	0.357	-10%	0.5	0.5	0%
29	Boston	North America	0.381	0.384	1%	0.642	0.667	4%
30	Dusseldorf	Europe	0.513	0.437	-15%	0.352	0.307	-13%
31	Orlando	North America	0.051	0.057	11%	0.312	0.438	40%
32	Manchester	Europe	0.292	0.232	-20%	0.278	0.271	-3%
33	Vienna	Europe	0.5	0.3	-40%	0.272	0.302	11%
34	Brussels	Europe	0	0	NA	0.383	0.319	-17%
35	Detroit	North America	0.451	0.394	-13%	0.5	0.433	-13%
36	Melbourne	Asia-Pacific	0.409	0.435	6%	0.477	0.5	5%
37	Copenhagen	Europe	0.167	0.125	-25%	0.405	0.377	-7%
38	San Diego	North America	0.142	0.132	-7%	0.318	0.5	57%
39	Philadelphia	North America	0.444	0.418	-6%	0.5	0.467	-7%
40	Oslo	Europe	0.372	0.353	-5%	0.309	0.284	-8%
41	Stockholm	Europe	0.419	0.396	-6%	0.484	0.59	22%
42	Vancouver	North America	0.304	0.394	29%	0.485	0.5	3%
43	Glasgow	Europe	0.346	0.349	1%	0.363	0.411	13%
44	Buenos Aires	Latin America & Middle East	0.255	0.11	-57%	0.456	0.125	-73%
45	Rio De Janeiro	Latin America & Middle East	0.095	0.056	-42%	0.5	0.5	0%
46	Tampa	North America	0.188	0.116	-38%	0.615	0.476	-23%
47	Tehran	Latin America & Middle East	0.5	0.5	0%	0.5	0.479	-4%
48	Stuttgart	Europe	0.357	0.389	9%	0.26	0.223	-14%
49	Venice	Europe	0.111	0.382	244%	0.23	0.142	-38%
50	Cleveland	North America	0.339	0.266	-21%	0.5	0.5	0%
51	Pisa	Europe	0.269	0.188	-30%	0.216	0.228	6%
52	Belfast	Europe	0.052	0.094	81%	0.438	0.469	7%
53	Norfolk	North America	0.403	0.474	18%	0	0	NA

Notes:
1.The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Table 9: *Gini index of the traffic before (Q3 2019) and during late stage of pandemic (Q3 2022) for MASs (other than top 10 MASs)*

			Domestic			International		
Rank	**MAS**	**Region**	**Before**	**Late stage**	**Diff%**	**Before**	**Late stage**	**Diff%**
11	Moscow	Europe	0.155	0.201	30%	0.276	0.034	-88%
12	Dubai	Latin America & Middle East	0	0	NA	0.384	0.359	-7%
13	Seoul	Asia-Pacific	0.465	0.5	8%	0.444	0.484	9%
14	Dallas	North America	0.287	0.288	0%	0.5	0.5	0%
15	San Francisco	North America	0.274	0.222	-19%	0.569	0.606	7%
16	Amsterdam	Europe	0.552	0.173	-69%	0.568	0.543	-4%
17	Frankfurt	Europe	0.5	0.5	0%	0.481	0.472	-2%
18	Washington	North America	0.108	0.128	19%	0.528	0.527	0%
19	Sao Paulo	Latin America & Middle East	0.198	0.151	-24%	0.618	0.612	-1%
20	Miami	North America	0.057	0.047	-17%	0.189	0.215	14%
21	Barcelona	Europe	0.667	0.662	-1%	0.574	0.571	-1%
22	Houston	North America	0.192	0.194	1%	0.438	0.418	-5%
23	Rome	Europe	0.486	0.473	-3%	0.382	0.4	5%
24	Toronto	North America	0.551	0.547	-1%	0.632	0.634	0%
25	Taipei	Asia-Pacific	0.5	0.5	0%	0.441	0.467	6%
26	Osaka	Asia-Pacific	0.317	0.298	-6%	0.667	0.667	0%
27	Milan	Europe	0.335	0.15	-55%	0.444	0.293	-34%
28	Mexico City	Latin America & Middle East	0.478	0.479	0%	0.5	0.5	0%
29	Boston	North America	0.542	0.543	0%	0.661	0.667	1%
30	Dusseldorf	Europe	0.524	0.567	8%	0.492	0.456	-7%
31	Orlando	North America	0.432	0.444	3%	0.467	0.494	6%
32	Manchester	Europe	0.385	0.279	-27%	0.447	0.454	2%
33	Vienna	Europe	0.5	0.497	-1%	0.428	0.431	1%
34	Brussels	Europe	0	0	NA	0.511	0.466	-9%
35	Detroit	North America	0.484	0.482	0%	0.5	0.499	0%
36	Melbourne	Asia-Pacific	0.471	0.48	2%	0.462	0.5	8%
37	Copenhagen	Europe	0.116	0.193	67%	0.47	0.468	0%
38	San Diego	North America	0.241	0.152	-37%	0.416	0.5	20%
39	Philadelphia	North America	0.472	0.459	-3%	0.5	0.494	-1%
40	Oslo	Europe	0.466	0.468	1%	0.411	0.403	-2%
41	Stockholm	Europe	0.473	0.51	8%	0.586	0.631	8%
42	Vancouver	North America	0.424	0.414	-2%	0.498	0.5	0%
43	Glasgow	Europe	0.384	0.341	-11%	0.371	0.415	12%
44	Buenos Aires	Latin America & Middle East	0.414	0.329	-21%	0.471	0.172	-63%
45	Rio De Janeiro	Latin America & Middle East	0.102	0.315	208%	0.5	0.5	0%
46	Tampa	North America	0.508	0.458	-10%	0.666	0.654	-2%
47	Tehran	Latin America & Middle East	0.5	0.5	0%	0.5	0.5	0%
48	Stuttgart	Europe	0.463	0.48	4%	0.391	0.347	-11%
49	Venice	Europe	0.172	0.426	148%	0.355	0.282	-21%
50	Cleveland	North America	0.426	0.448	5%	0.5	0.5	0%
51	Pisa	Europe	0.265	0.32	21%	0.128	0.102	-21%
52	Belfast	Europe	0.09	0.091	1%	0.437	0.457	5%
53	Norfolk	North America	0.405	0.467	15%	0	0	NA

Notes:
1.The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

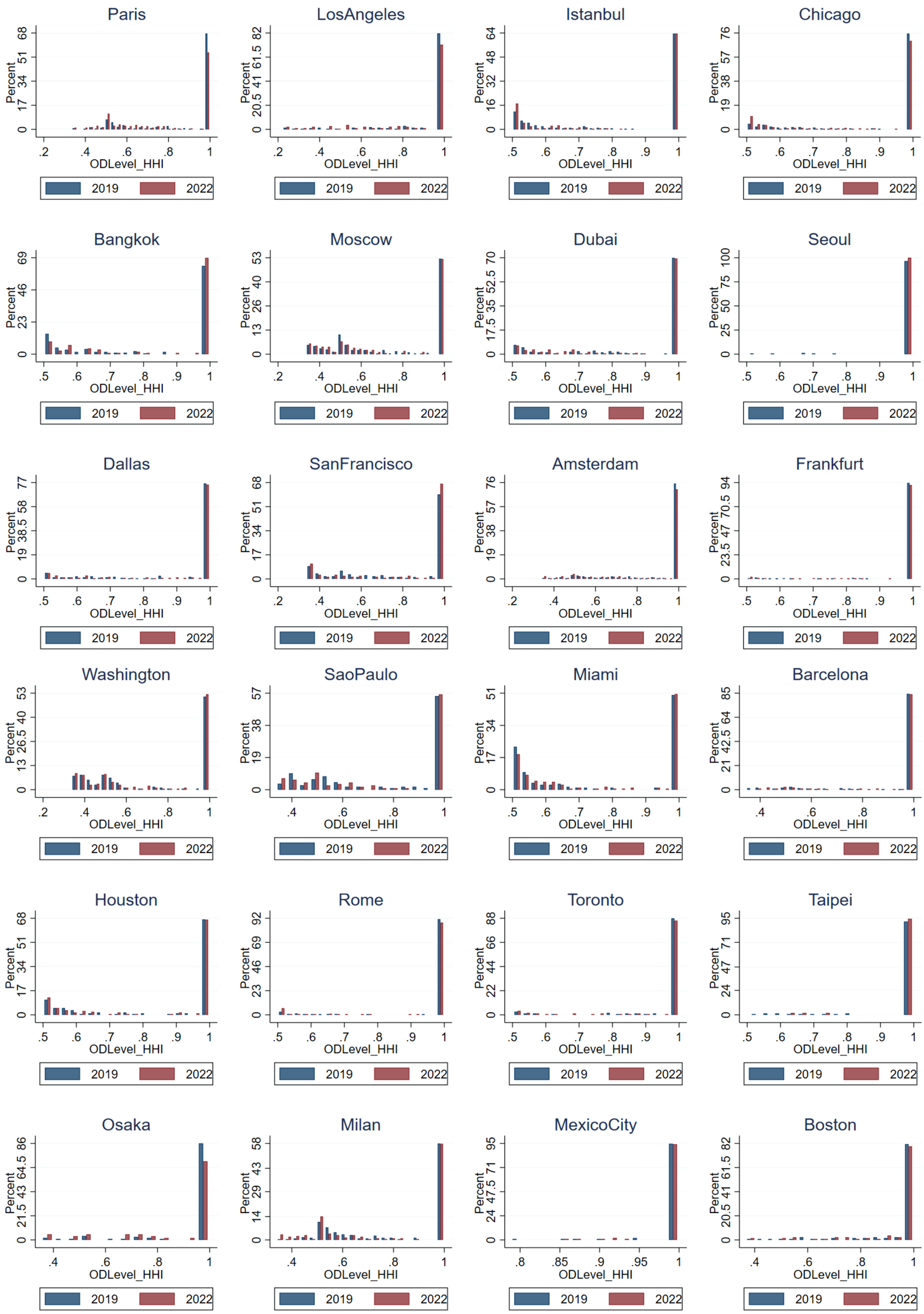

Figure 3: *The distribution of OD HHI in top 29 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 5 MASs)*

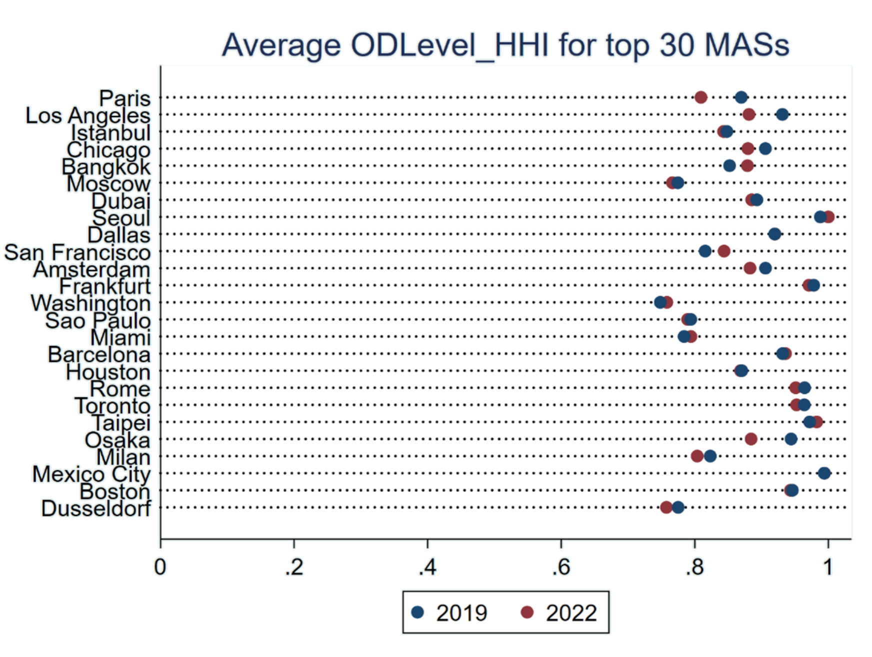

Figure 4: *The Average OD level HHI for top 30 MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 5 MASs)*

Table 10: *Airline HHI of MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 10 MASs)*

Rank	MAS	Region	Before	Late stage	Diff%
11	Moscow	Europe	0.205	0.2	-3%
12	Dubai	Latin America & Middle East	0.372	0.282	-24%
13	Seoul	Asia-Pacific	0.119	0.126	6%
14	Dallas	North America	0.504	0.491	-2%
15	San Francisco	North America	0.18	0.196	9%
16	Amsterdam	Europe	0.201	0.203	1%
17	Frankfurt	Europe	0.362	0.334	-8%
18	Washington	North America	0.19	0.197	4%
19	Sao Paulo	Latin America & Middle East	0.274	0.28	2%
20	Miami	North America	0.198	0.211	6%
21	Barcelona	Europe	0.177	0.206	16%
22	Houston	North America	0.372	0.353	-5%
23	Rome	Europe	0.155	0.126	-19%
24	Toronto	North America	0.316	0.267	-15%
25	Taipei	Asia-Pacific	0.108	0.2	84%
26	Osaka	Asia-Pacific	0.095	0.204	115%
27	Milan	Europe	0.107	0.143	35%
28	Mexico City	Latin America & Middle East	0.217	0.283	30%
29	Boston	North America	0.14	0.158	13%
30	Dusseldorf	Europe	0.154	0.15	-3%
31	Orlando	North America	0.106	0.113	7%
32	Manchester	Europe	0.116	0.146	26%
33	Vienna	Europe	0.194	0.264	36%
34	Brussels	Europe	0.156	0.153	-2%
35	Detroit	North America	0.553	0.531	-4%
36	Melbourne	Asia-Pacific	0.187	0.22	18%
37	Copenhagen	Europe	0.147	0.121	-17%
38	San Diego	North America	0.151	0.159	6%
39	Philadelphia	North America	0.46	0.398	-13%
40	Oslo	Europe	0.243	0.217	-11%
41	Stockholm	Europe	0.154	0.127	-18%
42	Vancouver	North America	0.255	0.247	-3%
43	Glasgow	Europe	0.117	0.16	37%
44	Buenos Aires	Latin America & Middle East	0.282	0.301	7%
45	Rio De Janeiro	Latin America & Middle East	0.319	0.273	-15%
46	Tampa	North America	0.155	0.155	0%
47	Tehran	Latin America & Middle East	0.129	0.114	-12%
48	Stuttgart	Europe	0.154	0.181	17%
49	Venice	Europe	0.086	0.143	66%
50	Cleveland	North America	0.164	0.159	-4%
51	Pisa	Europe	0.153	0.201	31%
52	Belfast	Europe	0.298	0.405	36%
53	Norfolk	North America	0.258	0.227	-12%

Notes:
1.The “before” represents the Q3 of 2019, and “late stage” represents Q3 of 2022.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.

Table 11: *Gini index of LCC capacity share in MASs before (Q3 2019) and during late stage of pandemic (Q3 2022) (other than top 10 MASs)*

Rank	MAS	Region	Before	Late stage	Diff%
11	Moscow	Europe	0.648	0.608	-6%
12	Dubai	Latin America & Middle East	0.341	0.271	-20%
13	Seoul	Asia-Pacific	0.031	0.114	264%
14	Dallas	North America	0.44	0.428	-3%
15	San Francisco	North America	0.329	0.309	-6%
16	Amsterdam	Europe	0.252	0.257	2%
17	Frankfurt	Europe	0.435	0.465	7%
18	Washington	North America	0.467	0.492	5%
19	Sao Paulo	Latin America & Middle East	0.207	0.244	18%
20	Miami	North America	0.464	0.341	-27%
21	Barcelona	Europe	0.084	0.044	-47%
22	Houston	North America	0.42	0.373	-11%
23	Rome	Europe	0.306	0.191	-37%
24	Toronto	North America	0.56	0.58	4%
25	Taipei	Asia-Pacific	0.42	0.5	19%
26	Osaka	Asia-Pacific	0.462	0.407	-12%
27	Milan	Europe	0.412	0.248	-40%
28	Mexico City	Latin America & Middle East	0.172	0.214	24%
29	Boston	North America	0.073	0.148	104%
30	Dusseldorf	Europe	0.15	0.16	6%
31	Orlando	North America	0.103	0.122	18%
32	Manchester	Europe	0.152	0.095	-37%
33	Vienna	Europe	0.238	0.107	-55%
34	Brussels	Europe	0.563	0.564	0%
35	Detroit	North America	0.098	0.299	205%
36	Melbourne	Asia-Pacific	0.204	0.163	-20%
37	Copenhagen	Europe	0.115	0.1	-13%
38	San Diego	North America	0.155	0.152	-2%
39	Philadelphia	North America	0.349	0.305	-12%
40	Oslo	Europe	0.069	0.14	102%
41	Stockholm	Europe	0.515	0.494	-4%
42	Vancouver	North America	0.461	0.432	-6%
43	Glasgow	Europe	0.195	0.123	-37%
44	Buenos Aires	Latin America & Middle East	0.076	0.065	-15%
45	Rio De Janeiro	Latin America & Middle East	0.033	0.122	266%
46	Tampa	North America	0.239	0.155	-35%
47	Tehran	Latin America & Middle East	0.5	0.5	0%
48	Stuttgart	Europe	0.135	0.135	0%
49	Venice	Europe	0.172	0.124	-28%
50	Cleveland	North America	0.278	0.116	-58%
51	Pisa	Europe	0.261	0.174	-33%
52	Belfast	Europe	0.5	0.404	-19%
53	Norfolk	North America	0.5	0.5	0%

Notes:
1.The "before" represents the Q3 of 2019, and "late stage" represents Q3 of 2022.
2.The rank of the airports are defined by the total scheduled seats of the MAS at Q3, 2019.