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Aviation under the COVID-19 pandemic: A synopsis from normalcy to chaos and back

Xiaoqian Sun[1], Sebastian Wandelt[1], and Anming Zhang[2]

[1]*National Key Laboratory of CNS/ATM, School of Electronic and Information Engineering, Beihang University, Beijing, China*
[2]*Sauder School of Business, University of British Columbia, Vancouver, BC, Canada*

Abstract: Since the outbreak of the COVID-19 pandemic early in the year 2020, the aviation system has been under extreme pressure for more than two years, with many stakeholders anticipating the moment of recovery. In Summer 2022, eventually, many airlines reached profit margins again. Several airlines even reported to outperform pre-pandemic indicators, including the number of passengers and quarterly revenues. Accordingly, one could say that 2022 is part of the new normalcy in our global aviation system. In this study, we investigate the changes in the global aviation, comparing the year 2019 as a pre-pandemic baseline with the aviation system throughout the year 2022. The connectivity of nearly 8,000 cities worldwide is compared and underlying drivers identified through the design of adequate econometric models. We find that the largest extent of recovery has taken place in secondary cities. We find a rather heterogeneous spatial recovery pattern, which indicates the necessity to better understand the differences in the current aviation system. Moreover, changes of global connectivity indicators, e.g., betweenness centrality, seem to be of rather complex nature. Our study contributes towards a better understanding of the post-pandemic global aviation system and concludes with a set of future research directions, which can hopefully guide other researchers to identify open challenges for the new normalcy.
Keywords: *COVID-19 pandemic;Aviation;Review;Data-driven analysis*
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1. Introduction

After a decades-long steady growth, the aviation system came to an almost complete halt in the year 2020 due to the outbreak of the COVID-19 pandemic. The ramifications and implications of the pandemic and the aviation system has been rather well documented in the existing literature, see Abu-Rayash & Dincer (2020), Sun, Wandelt, Zheng & Zhang (2021), Shortall et al. (2022), Sun et al. (2022) for recent surveys on the subject. Throughout the pandemic, many stakeholders have expressed the desire to return to normalcy as soon as possible, while researchers have pointed out the huge potential for renewal of the aviation system (Budd et al. 2020, Macilree & Duval 2020, Serrano & Kazda 2020, Linden 2021, Tisdall et al. 2021, Sun, Wandelt & Zhang 2021, Dube et al. 2021, Dube 2022, Rizzi et al. 2022). Throughout the year 2021, while aviation was still largely impacted by the COVID-19 pandemic, particularly flight bans and uncertain demands, massive vaccine roll-outs took place with doses delivered and administered across continents. The roll-out came with significant inequities, e.g., almost 85% of vaccines had been administered in high- and upper-middle-income countries at that time[1]. Towards the end of 2021, many populations with strong travel desires and histories had been successfully vaccinated. Accordingly, throughout the year 2022, the global aviation system saw an impressive return. Various stakeholders returned to profits in the first half of 2022 and some airlines even reportedly outperforming pre-pandemic passenger and revenue records.

Figure 1 visualizes this return to (new) normalcy with two time series, highlighting the monthly evolution of passenger numbers (left) and airline revenues (right) throughout the period from January 2019 to December 2022. For the year 2019, we can see a strong seasonal development, with peaks of passengers and revenue being located around July. In April 2020, shortly after the World Health Organization declared COVID-19 a pandemic, the global aviation system came to a standstill. Afterwards, the system underwent several gradual recovery steps, most visible in plateaus following the Summer peak in 2020 and 2021, respectively. Finally, in the year 2022, we can see a similar highly seasonal signal as in the year 2019.

[1] According to the WHO: https://www.who.int/news-room/spotlight/history-of-vaccination/a-brief-history-of-vaccination

Overall, it can be seen that - at the global scale - the number of passengers is still lacking behind about 15% compared to the pre-pandemic reference from the year 2019. The total revenues (in USD) have already reached pre-pandemic levels in the year. Accordingly, the year 2022 can be considered the first year back to normalcy, following the COVID-19-induced chaos. The extent to which the subsystems are recovered, and the existence of heterogeneities and their drivers are yet to be explored in the scientific literature, given that existing studies have largely focused on describing the singleton-like impact of the pandemic on the system, throughout the years 2020 and 2021.

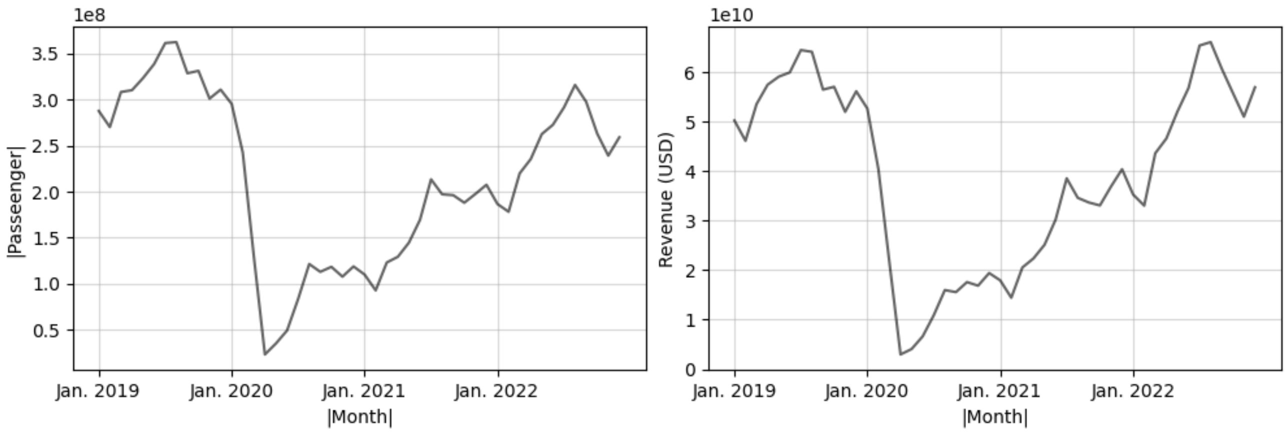

Figure 1: *Evolution of global airlines passengers (left) and revenue (right) for the years 2019 to 2022.*

In this study, we investigate the difference of the global aviation system, comparing pre-pandemic status and new normalcy. The former period is represented by data for the year 2019 and the latter by data for the year 2022. Specifically, we are interested in the analysis of a geographical and connectivity-based perspective, which emphasizes the roles of worldwide cities (and their changes) in the focus of interest. We think that the role of cities has been under-explored in the exiting literature, focusing very much on the role of individual airports or groups thereof. Moreover, the emphasis on cities hides the role of individual airport's success/failure strategies in multiple airport regions, focusing rather on the development of cities and regions. Our study analyzes the evolution of 7,996 cities worldwide in terms of three indicators: the number of departures, the local connectivity in terms of degree centrality, and the global connectivity in terms of betweenness centrality. In addition to analyzing the properties of specific cities, we further zoom into the role of specific markets (city pairs) and see which ones have recovered, rather well throughout the year 2022. For each analysis, we have designed an appropriate econometric model, which explains the changes in connectivity through a range of explanatory variables related to city size, geographical factors, and development indicators. Using Ordinary Least Squares regression, we identify a subset of significant variables and describe how these are possibly related to the observed recovery status.

The remainder of this study is structured as follows. Section 2 summarizes the existing literature on the subject, with a strong focus on studies concerned with COVID-19 and aviation. Section 3 introduces the analysis methodology / data and provides the description of various analysis experiments for the recovery of worldwide cities in the year 2022. Section 4 summarizes the findings in this study, provides an overview on relevant policy implications, and suggests a set of interesting directions for future work.

2. Literature Review

In this section, we review the extant literature on city connectivity and aviation during the COVID-19 pandemic. The latter topic, however, has caused what could be best described as a hurricane to the aviation literature and accordingly we refer readers for more details to specialized surveys, e.g., Abu-Rayash & Dincer (2020), Sun, Wandelt, Zheng & Zhang (2021), Shortall et al. (2022), Sun et al. (2022). Section 2.1 summarizes existing studies which have investigated the connectivity of airports and cities with a focus on pre-pandemic time periods. Section 2.2 provides a broad overview on studies that have discussed the early impact of COVID-19 on the global aviation system. Section 2.3 discusses extant work which focused on the early and late recovery phase of aviation from the pandemic impacts. Section 2.4 summarizes our main novel contributions considering the established state of the art.

2.1. Pre-pandemic connectivity analysis

Guimera & Amaral (2004) was among the first to develop a model for the worldwide airport. This model is based on the notion of complex networks, where nodes represent airports and links represent direct flights between airports. Various statistical properties have been analyzed, including the node degree distributions, network classification based on shortest path lengths, and the resilience of such systems. The number of similar follow-up studies is tremendous, especially when including the analysis of sub-networks. Accordingly, we refer the interested read to a empirical survey which compares various network snapshots concerning time and space domain, deriving a set of unifying properties, see Wandelt et al. (2019). Another related work on airports, but with a much stronger focus on connectivity, was conducted by Cheung et al. (2020). The authors proposed a set of five centrality indicators, coined the Global Airport Connectivity Index (GACI), in order to identify connectivity positions and development paths of airports in the global aviation system. It is shown that an increased GACI is an indicator for improved airport connectivity. While much of the related work in the literature focuses on individual airports, various aggregation schemes can be implemented for an improved analysis. The most natural aggregation in the aviation domain is presumably a so-called multiple-airport region, in which airports within a specific (spatial or temporal) distance are treated as a single entity. Beyond that, there is wide range of possible aggregations and fractality analysis, see Sun, Wandelt & Zanin (2017) for an overview. Cities maybe the most natural adaption of multiple-airport regions, by focusing less on the competition of airports and more on the location of populations agglomerations. Derudder & Witlox (2016) provided a comprehensive overview and highlighted that diverse connectivity through aviation is a vital component for the development of major cities' economies, mainly due to the fast access to markets and entities. Accordingly, the analysis of aviation city networks has gained an increased interest in recent years. Fan (2006) analyzed the evolution and improvements of inter-city flight connectivity in Europe for the period 1996–2004. Suau-Sanchez et al. (2016) reported in the dependence of a city and its neighborhood on selected airports within the catchment area and how bypassing some of these airports can lead to new market opportunities. Wang et al. (2020) analyzed the evolution of major city clusters in China, in presence of rail connectivity. Sun et al. (2020*b*) investigated the resilience of the global aviation city network under various disruption scenarios.

2.2. COVID-19 Phase 1: Unprecedented Shock

Concerning the first phase with COVID-19, which can be best described as the period from January 2020 to May 2020, a set of studies have been published which reported on the direct impact of COVID-19 on aviation. These studies have mostly focused on the excessive reduction in demand / mobility and sometimes provided an outlook based on possible future travel scenarios. Reviewing all these extant works is beyond the scope of this study; we refer to a few selected and influential papers only. Abu-Rayash & Dincer (2020) analyzed the effect of COVID-19 on global mobility trends, with an emphasis aviation and travel in selected cities. Nhamo et al. (2020), based on a network representation of global airports, identified negative impact of the pandemic on airport operations and revenue streams, raising concerns for an increased financial support of the aviation system and its stakeholders. Abu-Rayash & Dincer (2020) developed and evaluated a mobility index in the context of COVID-19-impact. In addition, the authors provide several complementary statistics at the city level for selected cities in the world. Suau-Sanchez et al. (2020) investigated the evolution of various economic aviation indicators, specifically focusing on airline revenues, and discussed the relationship to air travel restrictions gradually implemented throughout the year 2020. Iacus et al. (2020) reported on the significantly reduced passenger numbers during the early phase with COVID-19 and suggested various projections on the future passenger demands and the socio-economic impact of the pandemic. Sun et al. (2020*a*) took the complex network representation of the worldwide airport system and investigated how various indicators changed during the first few months of the COVID-19 pandemic. It was found that all indicators underwent strong fluctuations, indicating the instability of the overall system at that time. Chu et al. (2020) analyzed the impact of implemented travel restrictions in Latin America through the means of network connectedness, highlighting the importance of timely air travel restrictions, especially in cities and countries which serve as air transportation hubs. A few studies were more generic by their research question. For instance, Nižetić (2020) performed a wider case study on the early impact of COVID-19, including effects on air transport, the energy sector, and the environment. Similarly, Mhalla (2020) investigated the early impact of COVID-19 on the global oil and aviation markets.

2.3. COVID-19 Phase 2: Recovery and endemic normality

Research on the recovery of aviation is much scarcer than work on the negative impact. We discuss the relevant studies for air transportation recovery below. Sharma et al. (2021) used an agent-based model and developed a simulation of different recovery patterns. It was found that injecting money into the system at various places is likely to mitigate some of the negative impacts. Michelmann et al. (2022) developed three scenarios for aviation recovery, including interactions among economic, environmental, and pandemic factors, emphasizing the need to anticipate plausible development paths early. Gudmundsson et al. (2021) proposed a forecasting model based on auto regressive integrated moving average, highlighting different recovery scenarios. Overall, recovery times around two years were anticipated, with air freight recovering slightly faster than passenger air transport. Hanson et al. (2022) used two distinct elasticity models to predict the recovery of aviation inside the United States, predicting a recovery in the year 2022. Kaffash & Khezrimotlagh (2022) provided a comparison of recovery developments between full-service carriers and low-cost carriers, identifying trade-offs between efficiency and cancellations / flight reductions.

2.4. Major contributions of our study

Various extant studies have evaluated the connectivity of airports and cities before the onset of COVID-19 (Section 2.1). During the COVID-19 pandemic, existing studies have put a strong focus on the dissection of impacts according to various indicators (Section 2.2) derived a set of predictive models in order to forecast recovery periods of the global aviation system and its subsystems (Section 2.3). In this study, we make the following major contributions:

1. We perform a data-driven analysis of the aviation system recovery from COVID-19 at the city level, comparing selected connectivity indicators of the year 2019 with the year 2022. These connectivity indicators include the number of departures as well as local network connectivity (degree) and global network connectivity (betweenness).

2. The connectivity indicators are evaluated for two types of entities. First, we identify the importance of nearly 8,000 individual cities (and changes thereof) in the global aviation system. Second, we also look at specific markets (city pairs) and see how their connectivity has changed in the recovery compared to pre-pandemic levels.

3. The experiments in our study are not only performed by visual exploration, but we also develop a set of econometric models which aim to explain the underlying changes in connectivity at the city and market level. Through ordinary least squares regression, we identify a set of key variables which are significant for explaining system changes.

3. Data-driven analysis between 2019 and 2022

3.1. Preliminaries

The aviation-related data used in our study is from Sabre AirVision Market Intelligence[2], an aviation passenger flow analysis system for the collection and dissemination of historical passenger booking data, among others. The Sabre database contains comprehensive data items, including schedules and ticket data with origin, destination, intermediate stops, and fare data. For the purpose of this study, we have used data at city level, airports have been assigned to each city using the methodology proposed in Sun, Wandelt, Hansen & Li (2017). Figure 2 provides an overview on the cities in our study. In total, we have 7,996 cities across all continents. The top-10 cities according to population size (data for the year 2019) are highlighted with name and three-digit city code. A list of all cities referenced in our manuscript and their abbreviations mentioned in this study are provided in Table 6.

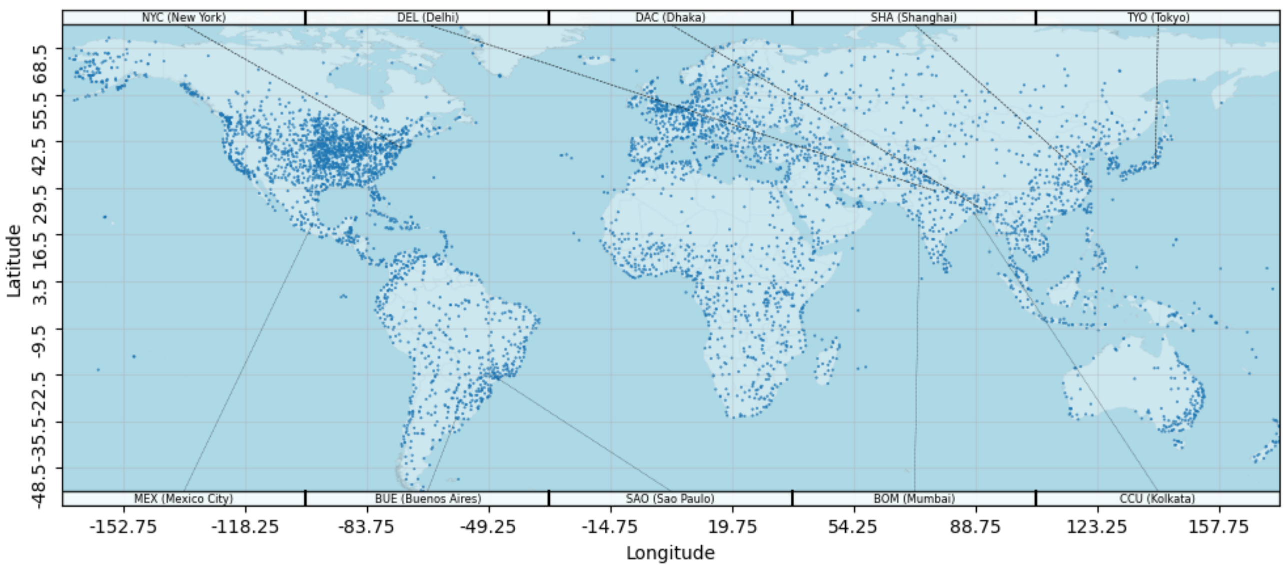

Figure 2: *Overview on 7,996 cities in our study.*

Throughout this study, we make use of a few connectivity indicators as defined below. Let $G = (N, E)$ be a network with nodes N and a set of edges E. The degree centrality of a node $n \in N$ is defined as:

$$deg(n) = \frac{|\{(x, y) \in E \mid x = n \vee y = n\}|}{N} \tag{1}$$

The betweenness centrality of a node $n \in N$ is defined as:

$$betw(n) = \sum_{(i,j) \in N \times N, i \neq j \neq n} \frac{\sigma_{ij}(n)}{\sigma_{ij}} \tag{2}$$

[2] https://www.sabre.com/products/market-intelligence/

, where σ_{ij} represents the number of shortest paths from i to j and $\sigma_{ij}(v)$ is the number of shortest paths that go through v from i to j. The betweenness centrality of an edge $(n, m) \in E$ is defined as:

$$edgebetw(m,n) = \sum_{i,j \in N \times N, i \neq j} \frac{\sigma_{ij}(m,n)}{\sigma_{ij}} \tag{3}$$

, where σ_{ij} represents the number of shortest paths from i to j and $\sigma_{ij}(m, n)$ is the number of shortest paths that go through edge (m, n) from i to j.

3.2. Analysis of global city connectivity changes

The following variables are used for regression analysis:

1. POP^c: The total population of a city c in the year 2019. This variable is log-scaled.
2. CAP^c: Whether a city c is a capital city (1.0) or not (0.0).
3. DNS^c: The population density of a city c in the year 2019. This variable is log-scaled.
4. APS^c: The number of airports associated to a city c in the year 2019; based on inter-airport temporal distances multiple-airport regions defined by Sun, Wandelt, Hansen & Li (2017). This variable is log-scaled.
5. HDI^c: The Human Development Index in the year 2019 of the country city c belongs to. Value 1.0 represents *very high / high* and value 0.0 represents *Low / very low*.
6. CHN^c: A dummy variable indicating whether city c is located in China (1.0) or not (0.0).
7. IND^c: A dummy variable indicating whether city c is located in India (1.0) or not (0.0).
8. AS^c: A dummy variable indicating whether city c is located in Asia (1.0) or not (0.0).
9. EU^c: A dummy variable indicating whether city c is located in Europe (1.0) or not (0.0).
10. AM^c: A dummy variable indicating whether city c is located in Americas, including North America and South America, (1.0) or not (0.0).

In Figure 3, we visually report an overview on the extent of correlation between the variables in our study. While several variables are binary in our study, we cannot observe a strong correlation between either pair of variables. Figure 4 visualizes the correlation between departures of each city concerning the years 2019 (x-axis) and 2022 (y-axis). Cities which have an unchanged number of departures can be found along the diagonal (red, dashed) line. The best linear fit for the city departure data is visualized with a blue solid line. Several selected cities are highlighted with their city codes and names, based on their distance from the diagonal line, highlighting interesting cases. Overall, the number of departures in 2022 is still smaller than in 2019 for most cities, also indicated by the slope and intercept of the blue line, compared to the diagonal. The two cities with the largest number of departures and gains in departures are both located in the United States: Miami (MIA) and Las Vegas (LAS). Both of these cities have a high domestic attractiveness, particularly in times of recovery from COVID-19 restrictions. Miami is a popular tourist destination in Summer / Winter and Las Vegas is infamous for its gambling industry. Accordingly, we presume that these two cities successfully recovered due to high domestic tourism interest. In addition, there is a larger number of cities with less than 100,000 departures per year, which were also able to recover beyond pre-pandemic levels. New York (NYC) had the largest number of departures in the year 2019 and has recovered nearly to pre-pandemic levels as well. Cities which are still far away from a complete recovery include Hong Kong (HKG), Bangkok (BKK), Moscow (MOW), Chicago (CHI), and London (LON).

Figure 5 visualizes the changes in departures on a map, highlighting the extent of changes by color, from red (reduction of departures) to blue (gains in departures). It can be seen that the vast number of cities has yet to recover completely. The locations of recovered cities do not reveal a strong pattern visually, with cities from major countries in the world being colored in blue.

To better understand the drivers behind departure-wise recovery, we develop a simple regression model. We have computed the Ordinary Least Squares regarding the following equation with coefficients β_1 to β_{10} and error term ϵ:

$$\begin{aligned} DEPchange^c =& \beta_1 * POP^c + \beta_2 * CAP^c + \beta_3 * DNS^c + \beta_4 * APS^c + \beta_5 * HDI^c + \beta_6 * CHN^c + \\ & \beta_7 * IND^c + \beta_8 * AS^c + \beta_9 * EU^c + \beta_{10} * AM^c + \epsilon \end{aligned}$$

Table 1 reports the results of the regression. The regression results were obtained by computation over all cities, i.e., one overall regression. Note that we have not clustered standard errors. We can identify seven statistically relevant variables which contribute to the explanation for departure changes of cities from 2019 to 2022. A higher population density reduces the likelihood for a recovery in departures. We believe that this observation is mainly related to the fact that there are various cities with a smaller number of departures in 2019 (secondary cities), which were able to increase their departures - contrary to other major aviation hubs. Similarly, we find the that capitals have less recovered in terms of departures,

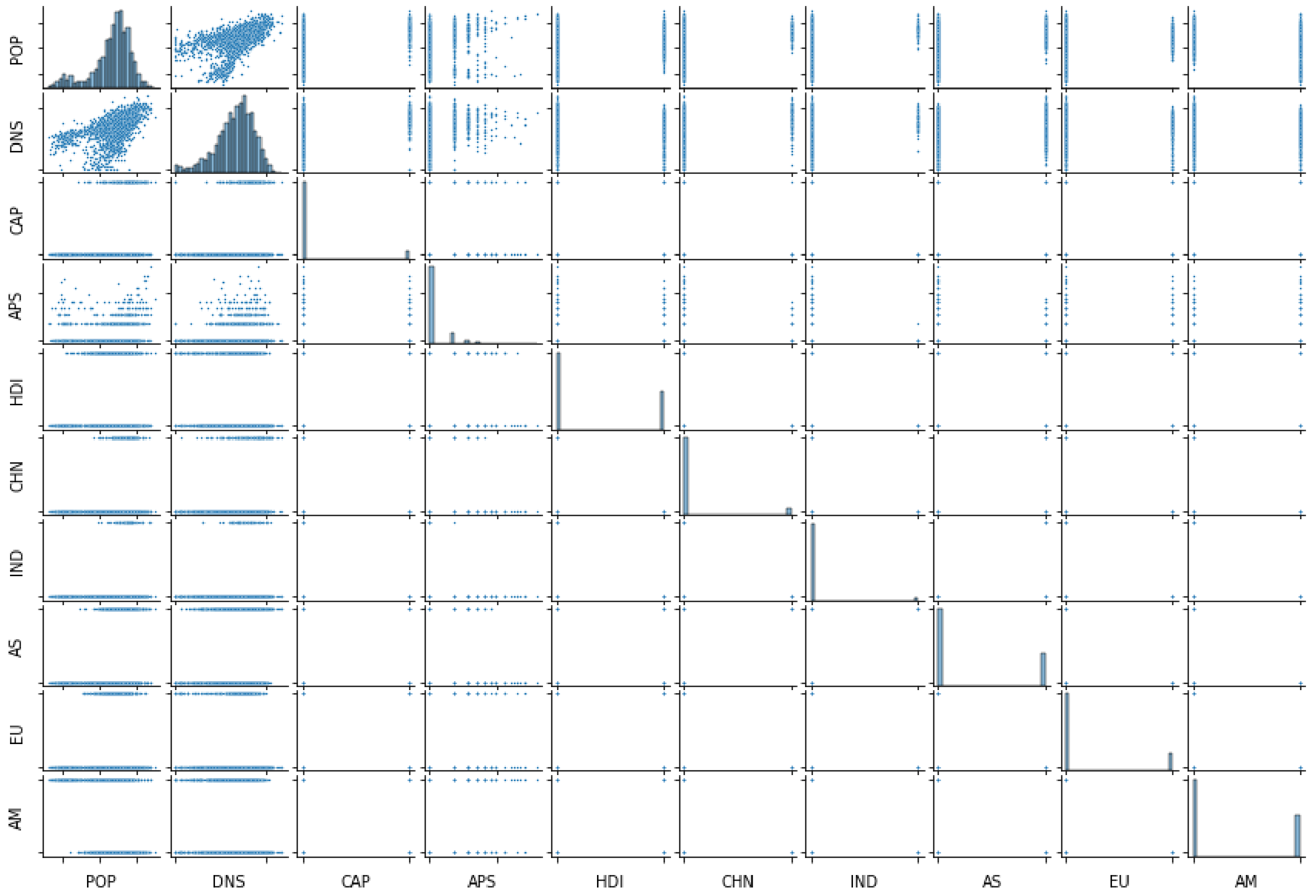

Figure 3: *Pairwise correlation between city-level regression variables in this study.*

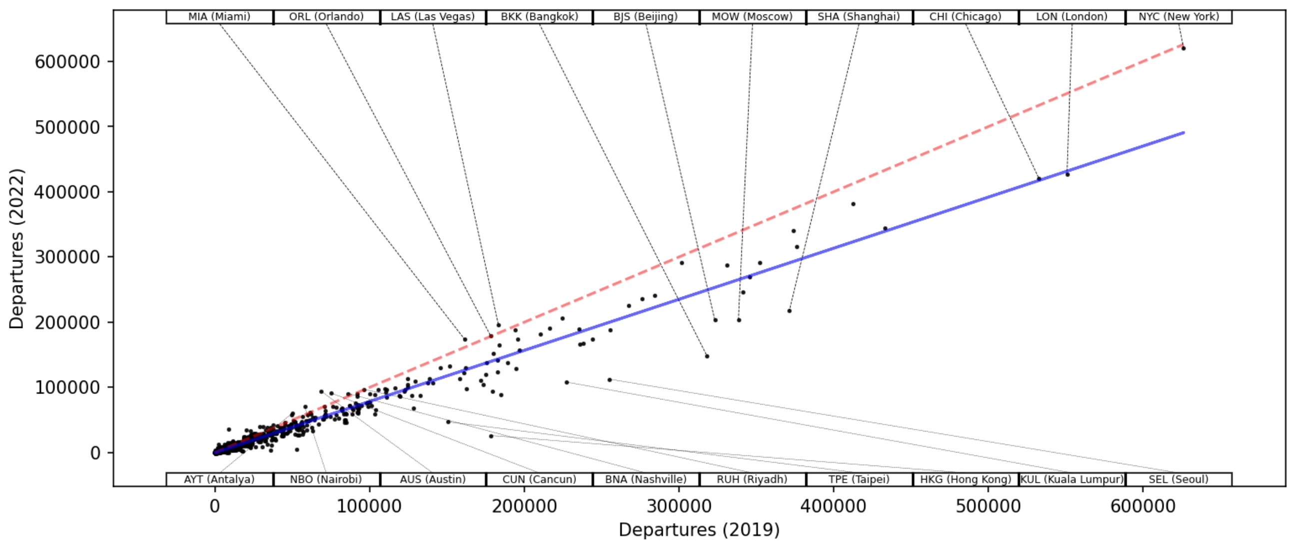

Figure 4: *Scatter plot of city departures comparing 2019 and 2022.*

compared to non-capitals, which can presumably be explained with a similar rationale as DNS. Other variables with a negative coefficient include APS, HDI, AS and AM, indicating that smaller cities with less airports from non-Asian and non-American countries might have a higher likelihood for recovery. Interestingly, IND has a positive impact on the departure recovery, indicating that Indian cities recovered rather well, possibly under influence of increased domestic traffic.

Figure 6 explores on the evolution of a complex network measure for each city concerning the years 2019 (x-axis) and 2022 (y-axis): The degree of each city. In network science, the degree of a node is a local node centrality which counts

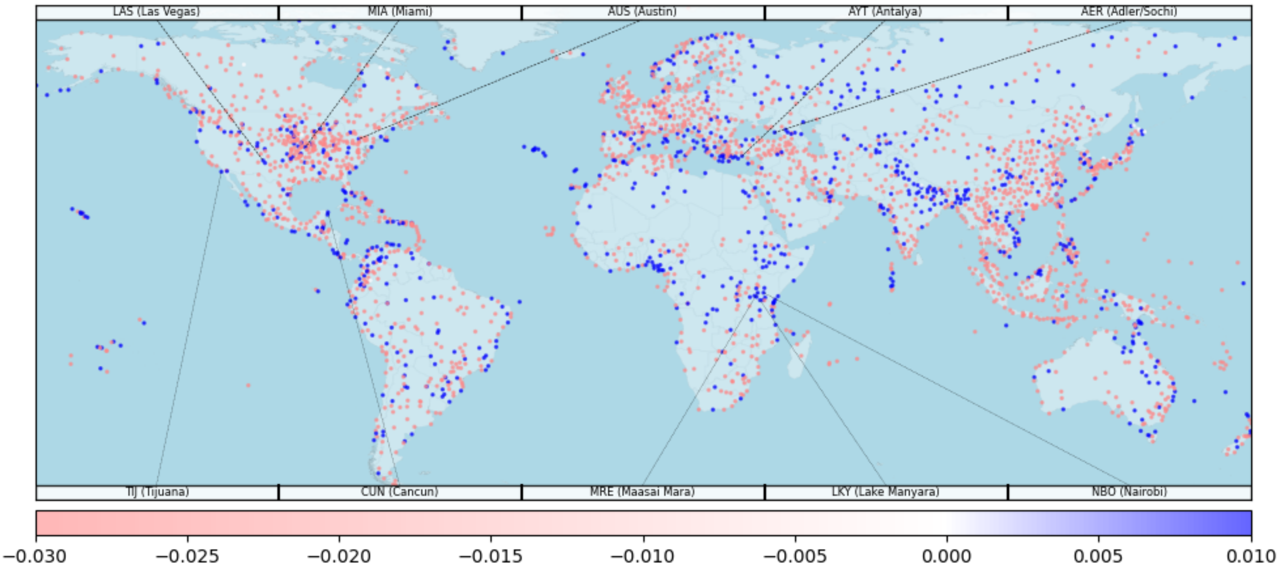

Figure 5: *Map visualization of city departures comparing 2019 and 2022.*

Table 1: *Regression results for the change in departures of a city.*

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.3454	0.660	-0.524	0.601	-1.639	0.948
POP	0.0047	0.058	0.081	0.936	-0.110	0.119
DNS	-0.1849	0.064	-2.867	**0.004****	-0.311	-0.058
CAP	-2.2123	0.425	-5.211	**0.000*****	-3.045	-1.380
APS	-3.1549	0.279	-11.328	**0.000*****	-3.701	-2.609
HDI	-0.7747	0.297	-2.605	**0.009****	-1.358	-0.191
CHN	-0.8572	0.501	-1.712	0.087	-1.839	0.125
IND	2.8324	0.674	4.204	**0.000*****	1.511	4.154
AS	-2.4701	0.387	-6.379	**0.000*****	-3.230	-1.711
EU	-0.1406	0.431	-0.326	0.744	-0.986	0.705
AM	-1.3844	0.354	-3.906	**0.000*****	-2.079	-0.689

the number of neighbors. Accordingly, in our context the degree measures the number of city destinations which can be reached by direct flights. The diagonal is indicated by a red, dashed line and the best linear fit is visualized with a blue solid line. Contrary to the departures, we can see that the degree of cities seems to have recovered more, with many of the well-connected cities having achieved or even outperformed pre-pandemic connectivity. The latter cities can be mostly found in Europe, North America, and the Middle East. Cities which are still significantly behind pre-pandemic degrees can be found mostly in Asia, such as Beijing (BJS), Bangkok (BKK), Seoul (SEL), and Moscow (MOW).

Figure 7 visualizes the results for the changes in degree centrality (which is the degree divided by the number of nodes) comparing the year 2019 with 2022. In line with the observations from Figure 6, we can see that the majority of cities with an increased degree can be found in the Northern hemisphere mostly (blue color). However, for most of the cities we do not find a significant change in degree centrality. The cities with significant lack of recovery (colored in red) can be found mostly in Asia and Europe.

To better understand the drivers behind degree-wise recovery, we develop a simple regression model. We have computed the Ordinary Least Squares regarding the following equation with coefficients β_1 to β_{10} and error term ϵ:

$$DEGchange^c = \beta_1 * POP^c + \beta_2 * CAP^c + \beta_3 * DNS^c + \beta_4 * APS^c + \beta_5 * HDI^c + \beta_6 * CHN^c + \beta_7 * IND^c + \beta_8 * AS^c + \beta_9 * EU^c + \beta_{10} * AM^c + \epsilon$$

Table 2 reports the results of the regression. The regression results were obtained by computation over all cities, i.e., one overall regression. Note that we have not clustered standard errors. We can identify six statistically relevant variables which contribute to the explanation for degree centrality changes of cities from 2019 to 2022. Three size-related variables for cities

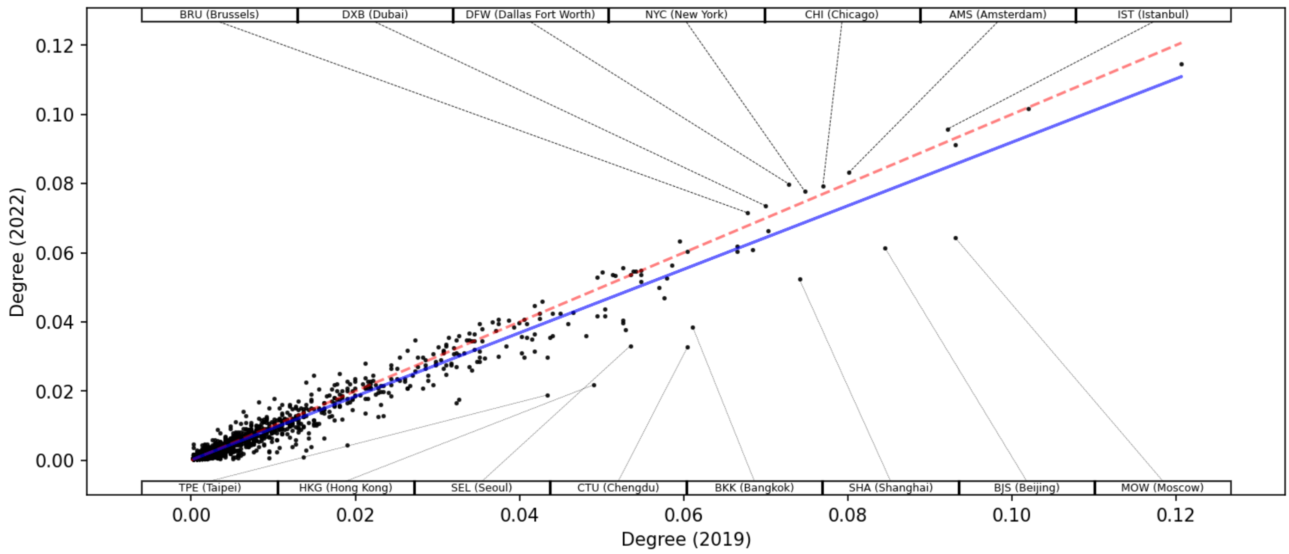

Figure 6: Scatter plot of city degree centrality comparing 2019 and 2022.

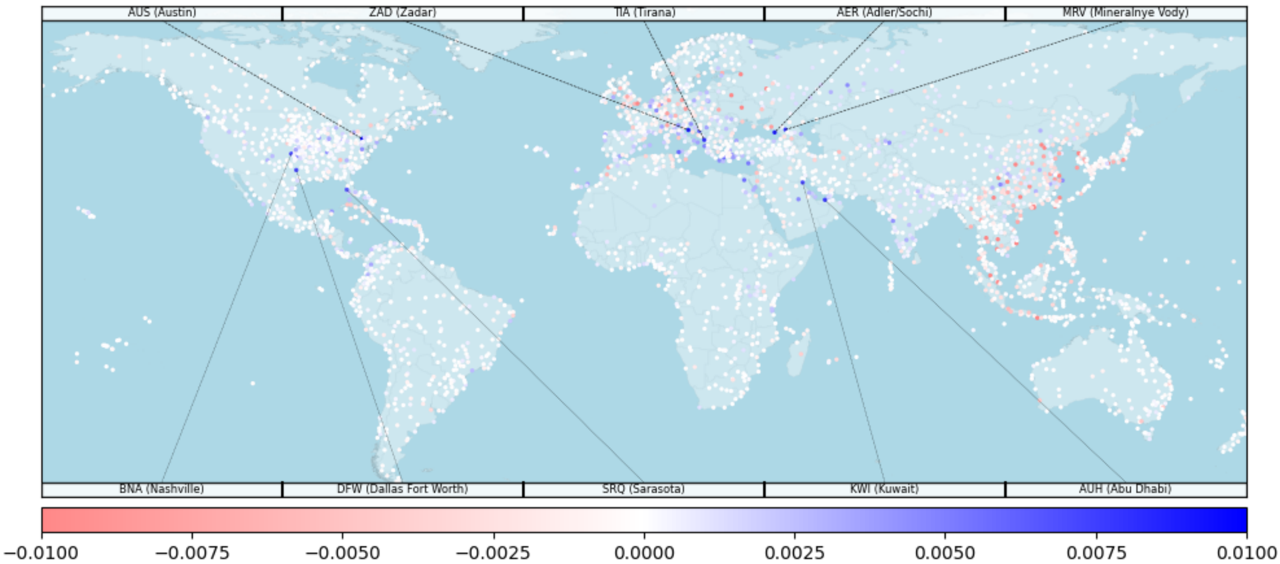

Figure 7: Map visualization of city degree centrality comparing 2019 and 2022.

have again a negative coefficient (POP, CAP, APS), indicating that the recovery is more prevalent across secondary cities. The coefficient for China (CHN) is negative and the coefficient for India (IND) positive, indicating the complementary evolution of both countries during the recovery in 2022. Finally, the variable for Asia (AS) have a negative coefficient as well, highlighting that Asia is lacking behind in recovery concerning the degree centrality.

In Figure 8, we investigate the relationship among betweenness centrality values of cities. Each data point corresponds to a city with 2019 betweenness values on the x-axis and 2022 betweenness values on the y-axis. In network science, the betweenness of a node is a global node centrality which counts the number of times a node appears on all-pairs shortest paths in the network. In our context the betweenness measures the probability that a random traveler uses a specific city as a hub. The diagonal is indicated by a red, dashed line and the best linear fit is visualized with a blue solid line. We can see that the trend line - contrary to the number of departures and the degree centrality - has a larger slope than the diagonal line, indicating that cities with a high initial betweenness (in the year 2019) have a slightly larger growth in betweenness than the other cities. Some of the betweenness increases are rather significant (considering the difficulty to change this global network centrality by local changes only under capacity constraints): Istanbul (IST), Dubai (DXB), Doha (DOH), and Guangzhou (CAN). These cities are located in the Middle East / Asia. Other cities gained betweenness centrality values as well: Amsterdam (AMS), Sao Paolo (SAO), and New York (NYC).

Figure 9 visualizes the changes in betweenness centrality on a map. We can see that the cities which gained betweenness

Table 2: *Regression results for the change in degree centrality of a city.*

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.001400	0.000000	5.138	0.000	0.001	0.002000
POP	-0.000081	0.000025	-3.269	**0.001*****	-0.000	-0.000032
DNS	-0.000062	0.000027	-2.276	0.023	-0.000	-0.000009
CAP	-0.000500	0.000000	-3.008	**0.003****	-0.001	-0.000000
APS	-0.001300	0.000000	-10.703	**0.000*****	-0.001	-0.001000
HDI	-0.000017	0.000000	-0.131	0.896	-0.000	0.000000
CHN	-0.000700	0.000000	-3.076	**0.002****	-0.001	-0.000000
IND	0.001500	0.000000	5.226	**0.000*****	0.001	0.002000
AS	-0.000800	0.000000	-4.866	**0.000*****	-0.001	-0.000000
EU	0.000200	0.000000	1.171	0.242	-0.000	0.001000
AM	0.000200	0.000000	1.207	0.228	-0.000	0.000000

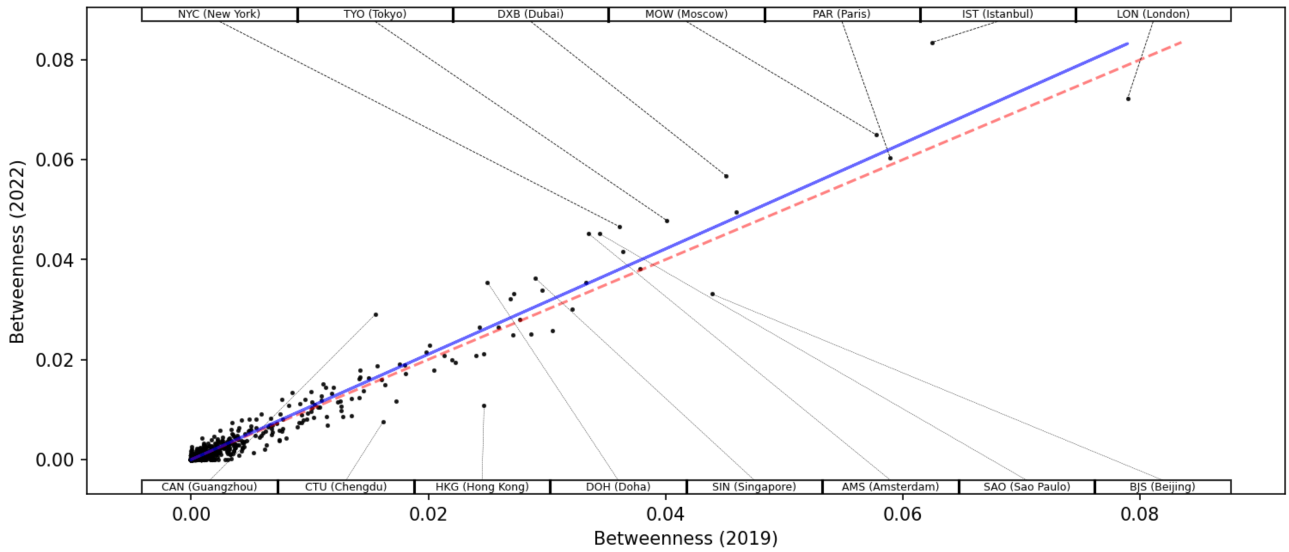

Figure 8: *Scatter plot of city betweenness centrality comparing 2019 and 2022.*

centrality are located well distributed on the map. The cities which have lost betweenness centrality, however, are mostly located in China: Beijing (BJS), Chengdu (CTU), and Hongkong (HKG).

To better understand the drivers behind betweenness-wise recovery, we develop a simple regression model. We have computed the Ordinary Least Squares regarding the following equation with coefficients β_1 to β_{10} and error term ϵ:

$$\begin{aligned} BETWchange^c =& \beta_1 * POP^c + \beta_2 * CAP^c + \beta_3 * DNS^c + \beta_4 * APS^c + \beta_5 * HDI^c + \beta_6 * CHN^c + \\ & \beta_7 * IND^c + \beta_8 * AS^c + \beta_9 * EU^c + \beta_{10} * AM^c + \epsilon \end{aligned}$$

Table 3 reports the results of the regression. The regression results were obtained by computation over all cities, i.e., one overall regression. Note that we have not clustered standard errors. It is striking that we only identify one statistically significant variable: the number of airports in a city (APS), which is related slightly positively with the gain in betweenness centrality. Beyond this, the drivers behind the change are rather difficult to identify. Moreover, it should be noted that the number of cities with extreme changes is rather small; most of the cities in Figure 9 were colored in white, indicating changes in betweenness centrality are rather minor.

3.3. Analysis of markets

The following variables are used for regression analysis:

1. $GRV^{c1,c2}$: The gravity model-based demand for the two cities $c1$ and $c2$ based on population data for the year 2019: $\frac{p_{c1} * p_{c2}}{d_{c1,c2}}$, where p_c is the population of city c and $d_{c1,c2}$ is the Haversine distance between the city centers of $c1$ and $c2$. This variable is log-scaled.

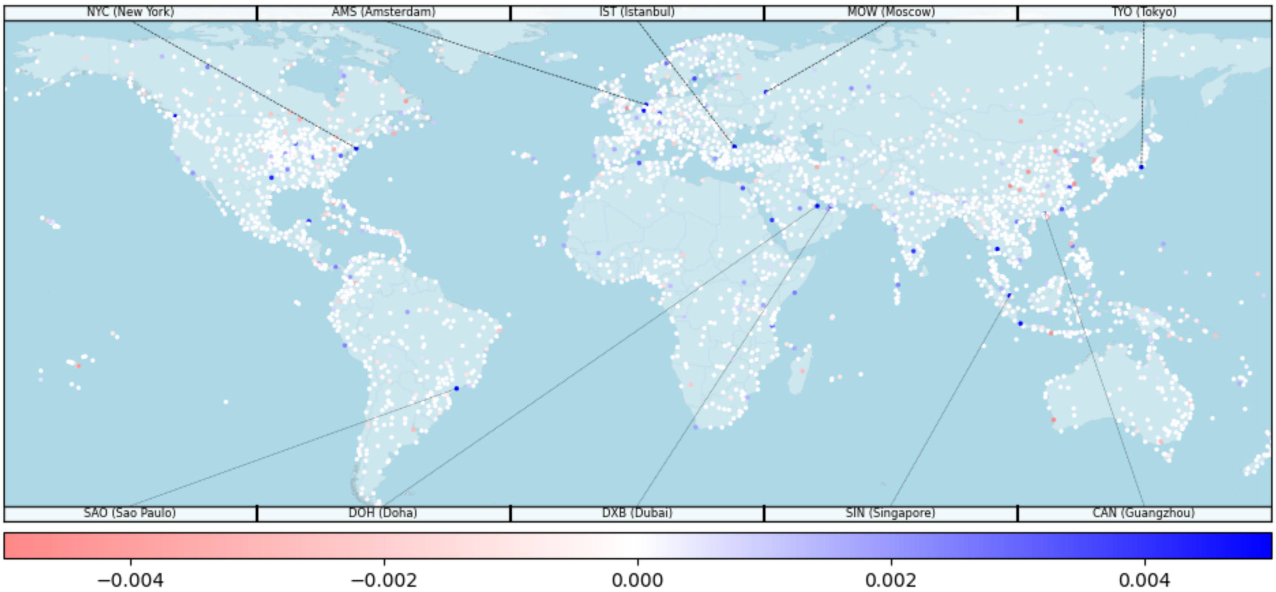

Figure 9: *Map visualization of city betweenness centrality comparing 2019 and 2022.*

Table 3: *Regression results for the change in betweenness centrality of a city.*

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.000300	0.000000	-1.325	0.185	-0.001000	0.000000
POP	0.000013	0.000022	0.607	0.544	-0.000030	0.000057
DNS	-0.000006	0.000024	-0.262	0.794	-0.000054	0.000042
CAP	0.000200	0.000000	1.442	0.150	-0.000068	0.000000
APS	0.000300	0.000087	3.219	**0.001*****	0.000000	0.000000
HDI	0.000089	0.000000	0.809	0.419	-0.000000	0.000000
CHN	-0.000300	0.000000	-1.978	0.048	-0.001000	-0.000003
IND	-0.000023	0.000000	-0.103	0.918	-0.000000	0.000000
AS	0.000300	0.000000	2.264	0.024	0.000045	0.001000
EU	0.000064	0.000000	0.395	0.693	-0.000000	0.000000
AM	0.000100	0.000000	0.913	0.362	-0.000000	0.000000

2. $DNSP^{c1,c2}$: Product of population density for the two cities. This variable is log-scaled.
3. $CAPP^{c1,c2}$: Product of CAP^{c1} and CAP^{c2}.
4. $CAPM^{c1,c2}$: Maximum of CAP^{c1} and CAP^{c2}.
5. $DOM^{c1,c2}$: Indicates whether the two cities are located in the same country (1.0) or not (0.0).

Figure 10 visualizes the correlation between departures in each market (city pair) concerning the years 2019 (x-axis) and 2022 (y-axis). Markets which have an unchanged number of departures can be found along the diagonal (red, dashed) line. The best linear fit for the city departure data is visualized with a blue solid line. Well-performing markets are highlighted with their city codes, please refer to the Appendix (Table 6) for a full list of used city abbreviations. We can identify a few markets which have recovery to an outstanding extent - even much beyond pre-pandemic levels: Maasai Mara (MRE) - Nairobi (NBO) and New York City (NYC) - Washington (WAS). Apart from that it seems like most markets are on the way of recovering well. The major exceptions, which are still lagging significantly behind in terms of departures, are mostly located in South-East Asia.

Figure 11 supports the spatial analysis further, by presenting the city pairs and their recovery on a map. The outperforming markets can be found mostly inside the three major aviation regions worldwide: North America, Europe, and Asia. This confirms earlier findings, that domestic connections have indeed recovered much faster and more sustainable than the international counterparts. Nevertheless, we can also identify a few cross-continental connections, which have exceeded pre-pandemic baselines.

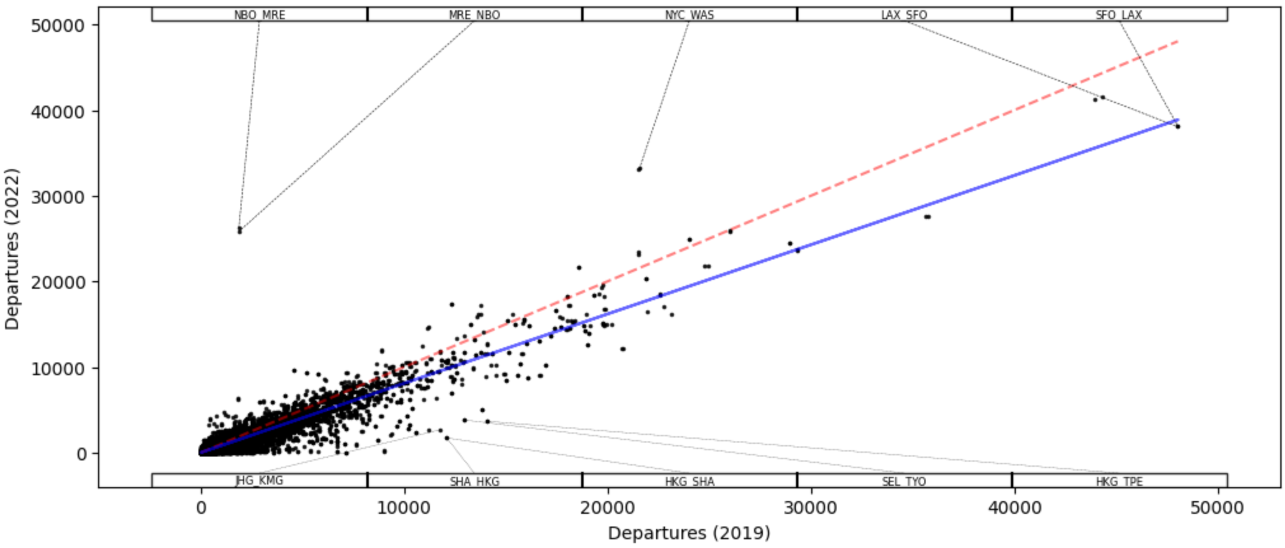

Figure 10: *Scatter plot of market departures comparing 2019 and 2022.*

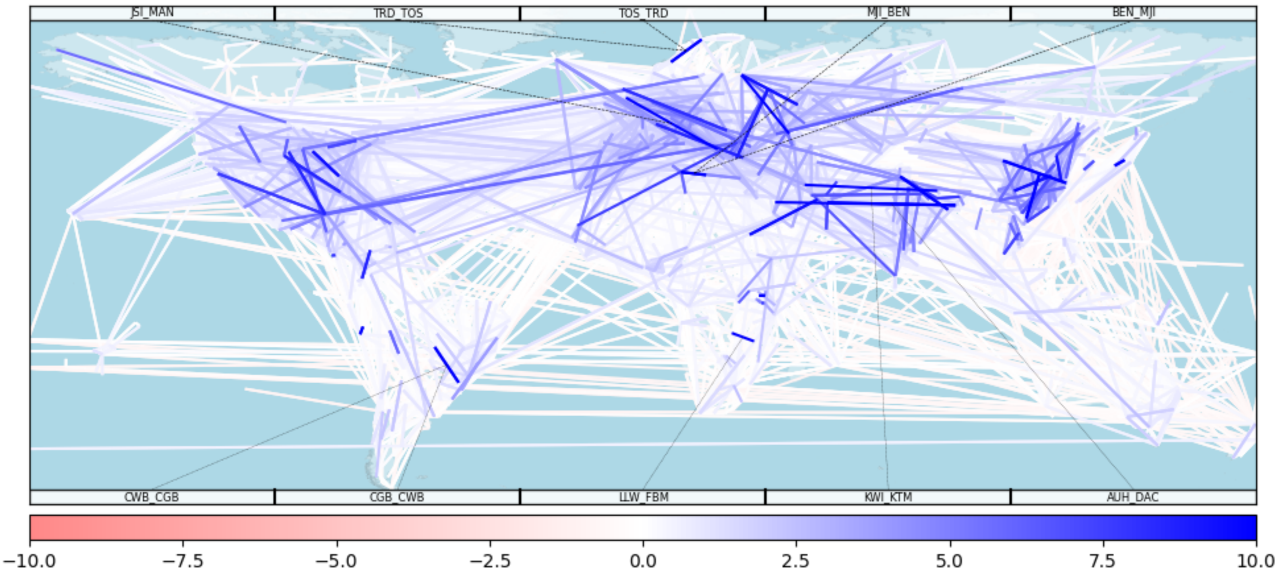

Figure 11: *Map visualization of market departures comparing 2019 and 2022.*

To better understand the drivers behind departure recovery across markets, we develop a simple regression model. We have computed the Ordinary Least Squares regarding the following equation with coefficients β_1 to β_5 and error term ϵ:

$$DEPchange^{c1,c2} = \beta_1 * GRV^{c1,c2} + \beta_2 * DNSP^{c1,c2} + \beta_3 * CAPP^{c1,c2} + \beta_4 * CAPM^{c1,c2} + \beta_5 * DOM^{c1,c2} + \epsilon$$

Table 4 reports the results of the regression. The regression results were obtained by computation over all markets, i.e., one overall regression. We can identify four statistically significant variables. The only positively related variable is GRV, meaning that cities with a higher gravity-induced demand indeed recovery better. Variable DNSP is negatively related to the departure recovery, indicating that connections between cities with dense population were slightly less likely to recover well. The variables with the largest absolute coefficients are $CAPP$ and $CAPM$, which indicates that connections involving capitals were less likely to recover well in the year 2022. Finally, it is interesting to note that variable DOM is not statistically significant. We presume that this is because some domestic markets recover rather well (e.g., markets involving tourism attractions), while other markets did not.

Figure 12 visualizes the correlation between edge betweenness centrality in each market (city pair) concerning the years 2019 (x-axis) and 2022 (y-axis). Outstanding markets are highlighted with their city codes, please again refer to the Appendix (Table 6) for a full list of used city abbreviations. The results in this chart are the most diverse in our study, with many markets having changed their betweenness between the years 2019 and 2022. It is rather difficult to get a sense

Table 4: *Regression results for the change in the number of departures of a market.*

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0691	0.021	3.336	0.001	0.029	0.110
GRV	0.0027	0.001	2.757	**0.006****	0.001	0.005
DNSP	-0.0020	0.000	-9.169	**0.000*****	-0.002	-0.002
CAPP	-0.0623	0.021	-2.955	**0.003****	-0.104	-0.021
CAPM	-0.0881	0.013	-6.862	**0.000*****	-0.113	-0.063
DOM	0.0166	0.012	1.388	0.165	-0.007	0.040

of any underlying patterns and therefore we visualize the changes on a map in Figure 13. Many of the well-performing markets serve exactly one airport in South-East Asia or Oceania. We conjecture that this observation is due to the loss of international connectivity for Chinese aviation hubs and also Hong Kong, due to significantly longer implementations of restrictions against COVID-19. Accordingly, it seems like not a single new hub is emerging, but airlines try to provide connections to destinations directly, without going through one of the popular hubs used earlier. Future research could aim to further elaborate on this possibility.

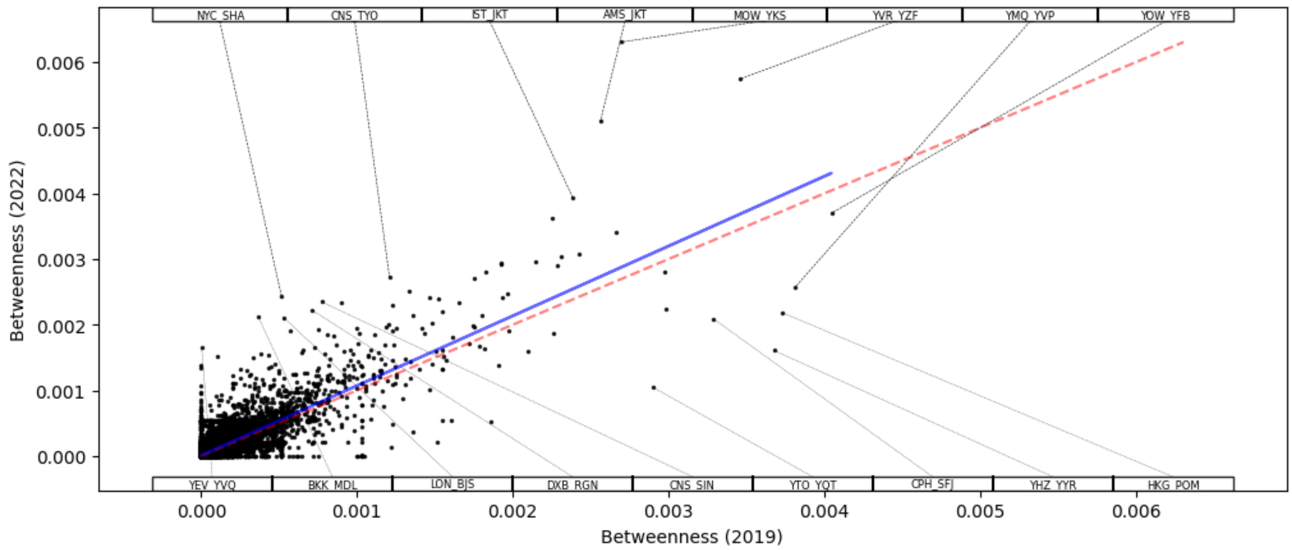

Figure 12: *Scatter plot of market edge betweenness centrality comparing 2019 and 2022.*

In order to understand the drivers behind betweenness recovery across markets, we develop a simple regression model. We have computed the Ordinary Least Squares regarding the following equation with coefficients β_1 to β_5 and error term ϵ:

$$BETWchange^{c1,c2} = \beta_1 * GRV^{c1,c2} + \beta_2 * DNSP^{c1,c2} + \beta_3 * CAPP^{c1,c2} + \beta_4 * CAPM^{c1,c2} + \beta_5 * DOM^{c1,c2} + \epsilon$$

Table 5 reports the results of the regression. The regression results were obtained by computation over all markets, i.e., one overall regression. Our results reveal two statistically relevant variables, both with a positive coefficient: GRV and CAPM. Accordingly, markets with a high demand, on which one of them is a capital, have increased their betweenness centrality value most. It should be noted that these findings are not in contradiction with the results for departures above: While markets involving one or more capitals have lost in departures, then network was apparently extended by adding (possibly low-frequency) connections between capitals and secondary cities.

4. Discussion

The overall takeaway for most aviation stakeholders from the year 2022 is that COVID-19 seems to have become history eventually and that the industry has returned to normalcy regarding a wide range of performance indicators. In this study, we have explored the return to normalcy at the city level, with a focus on analyzing the connectivity changes across cities and markets. Particularly, using aviation market data for the years 2019 and 2022, we have compared the number of departures, the degree (for cities), and the betweenness of entities in the global aviation system. Our major findings are summarized below.

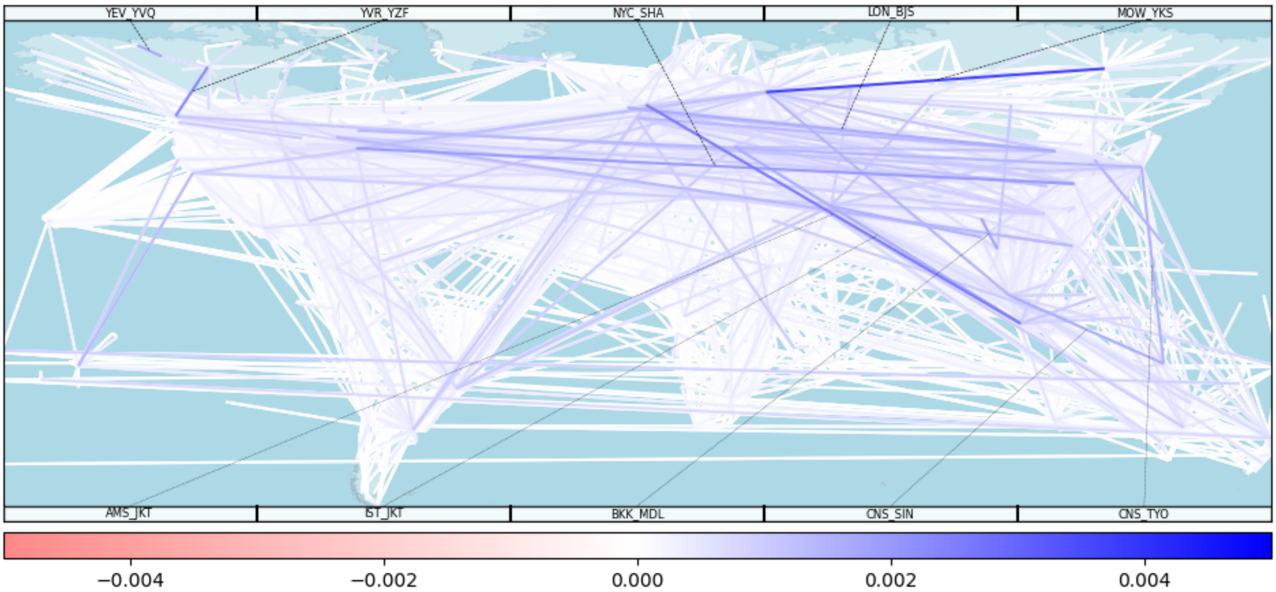

Figure 13: *Map visualization of market edge betweenness centrality comparing 2019 and 2022.*

Table 5: *Regression results for the change in the edge betweenness centrality of a market.*

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-8.685000e-06	4.290000e-06	-2.023	0.043	-1.710000e-05	-2.710000e-07
GRV	9.481000e-07	2.300000e-07	4.125	**0.000*****	4.980000e-07	1.400000e-06
DNSP	1.044000e-07	5.030000e-08	2.076	0.038	5.810000e-09	2.030000e-07
CAPP	-3.997000e-06	4.020000e-06	-0.995	0.320	-1.190000e-05	3.880000e-06
CAPM	2.573000e-05	2.510000e-06	10.249	**0.000*****	2.080000e-05	3.060000e-05
DOM	-3.208000e-06	2.370000e-06	-1.354	0.176	-7.850000e-06	1.440000e-06

First, we find that the recovery from COVID-19 preferably took place across secondary markets. This observation is consistent across all connectivity indicators and re-appeared through different regression variables. The observation that domestic markets did start to recover earlier than international markets has been made in the literature. And the rationale for such an observation is clear: In most countries, domestic travel is not susceptible to the uncertainty and impossibility inherent to travel restrictions. Accordingly, we complement the existing research by showing that the head start of domestic recovery has turned into a recovery of secondary markets. Further research is necessary to better understand the drivers behind this evolution. It could be related to changes in passenger travel behavior as well as operational / strategic changes of aviation stakeholders, most notably airlines.

Second, it appears that the connectivity inside Asia has significantly changed. One major driver for such changes is clearly the special path China and India took throughout the past three years when handling the ramifications of the COVID-19 pandemic. Particularly, Chinese airports were successfully established as aviation hubs for large parts in South-East Asia. With the disappearance of these hubs, it is natural that the demand (which did not involve China in the first place), aims to find different routes through the recovering aviation system. It will be interesting to see how recent changes in epidemic regulations of China (including Hong Kong) will lead to a competition between new routes and hubs, compared with the previous ones.

Third, explaining changes in betweenness seems to be rather difficult, compared to the indicators based on the number of departures and the degree centrality. The reasons for this observation are not entirely clear. It should be noted that - compared to degree centrality - betweenness centrality is a global network indicator. Accordingly, changes of one node (or its neighborhood alone) are most certainly not sufficient for explanation of all changes in the system. In fact, the loss of betweenness centrality for one set of nodes, e.g., the former Chinese international aviation hubs, can increase the betweenness centrality of other cities without actual action taken by the latter. Such effects need to be considered, when interpreting our results. Future research could try to include more regression variables and possibly consider network-aggregated information to better capture global changes.

This study comes with a set of limitations, addressing these limitations directly leads to several interesting avenues for future work. Our analysis did not consider the role of individual airlines and their strategic behavior (and changes thereof) during the COVID-19 pandemic. Especially in market with airline domination, an analysis at airline level will presumably lead to a set of additional insights. Moreover, it is conceivable that additional regression variables can lead to novel insights. Here, the major problem is to obtain consistent data for all cities at a global scale. Especially tourism-related data and information about the extent of travel restrictions and their duration are promising indicators which could be included in future studies. Finally, it will be interesting to see how the apparent recovery continues to develop throughout the next months and whether there exist other significant long-term changes to the global aviation system. This question will be particularly relevant in context of newly emerging contagions and how they interact with global air transportation.

Acknowledgement

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References

Abu-Rayash, A. & Dincer, I. (2020), 'Analysis of mobility trends during the covid-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities', *Energy research & social science* **68**, 101693.

Budd, L., Ison, S. & Adrienne, N. (2020), 'European airline response to the covid-19 pandemic–contraction, consolidation and future considerations for airline business and management', *Research in Transportation Business & Management* **37**, 100578.

Cheung, T. K., Wong, C. W. & Zhang, A. (2020), 'The evolution of aviation network: Global airport connectivity index 2006–2016', *Transportation Research Part E: Logistics and Transportation Review* **133**, 101826.

Chu, A. M., Tsang, J. T., Chan, J. N., Tiwari, A. & So, M. K. (2020), 'Analysis of travel restrictions for covid-19 control in latin america through network connectedness', *Journal of travel medicine* **27**(8), taaa176.

Derudder, B. & Witlox, F. (2016), Global cities and air transport, *in* 'The geographies of air transport', Routledge, pp. 119–140.

Dube, K. (2022), 'Emerging from the covid-19 pandemic: Aviation recovery, challenges and opportunities', *Aerospace* **10**(1), 19.

Dube, K., Nhamo, G. & Chikodzi, D. (2021), 'Covid-19 pandemic and prospects for recovery of the global aviation industry', *Journal of Air Transport Management* **92**, 102022.

Fan, T. (2006), 'Improvements in intra-european inter-city flight connectivity: 1996–2004', *Journal of Transport Geography* **14**(4), 273–286.

Gudmundsson, S. V., Cattaneo, M. & Redondi, R. (2021), 'Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19', *Journal of Air Transport Management* **91**, 102007.

Guimera, R. & Amaral, L. A. N. (2004), 'Modeling the world-wide airport network', *The European Physical Journal B* **38**, 381–385.

Hanson, D., Delibasi, T. T., Gatti, M. & Cohen, S. (2022), 'How do changes in economic activity affect air passenger traffic? The use of state-dependent income elasticities to improve aviation forecasts', *Journal of Air Transport Management* **98**, 102147.

Iacus, S. M., Natale, F., Santamaria, C., Spyratos, S. & Vespe, M. (2020), 'Estimating and projecting air passenger traffic during the covid-19 coronavirus outbreak and its socio-economic impact', *Safety Science* **129**, 104791.

Kaffash, S. & Khezrimotlagh, D. (2022), 'US network and low-cost carriers' performance in response to COVID-19: Strictness of government policies and passengers' panic', *Research in Transportation Business & Management* p. 100835.

Linden, E. (2021), 'Pandemics and environmental shocks: What aviation managers should learn from covid-19 for long-term planning', *Journal of Air Transport Management* **90**, 101944.

Macilree, J. & Duval, D. T. (2020), 'Aeropolitics in a post-covid-19 world', *Journal of Air Transport Management* **88**, 101864.

Mhalla, M. (2020), 'The impact of novel coronavirus (covid-19) on the global oil and aviation markets', *Journal of Asian Scientific Research* **10**(2), 96–104.

Michelmann, J., Schmalz, U., Becker, A., Stroh, F., Behnke, S. & Hornung, M. (2022), 'Influence of covid-19 on air travel - a scenario study toward future trusted aviation', *Journal of Air Transport Management* p. 102325.
URL: *https://www.sciencedirect.com/science/article/pii/S0969699722001442*

Nhamo, G., Dube, K., Chikodzi, D., Nhamo, G., Dube, K. & Chikodzi, D. (2020), 'Impact of covid-19 on the global network of airports', *Counting the Cost of COVID-19 on the Global Tourism Industry* pp. 109–133.

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.

Rizzi, C., Tettamanti, M. & Rizzi, P. (2022), 'Impact of covid-19 on world aviation industry, the: Challenges and opportunities'.

Serrano, F. & Kazda, A. (2020), 'The future of airports post covid-19', *Journal of Air Transport Management* **89**, 101900.

Sharma, D., Bouchaud, J.-P., Gualdi, S., Tarzia, M. & Zamponi, F. (2021), 'V–, u–, l– or w–shaped economic recovery after covid-19: Insights from an agent based model', *PLOS ONE* **16**(3), 1–22.
URL: *https://doi.org/10.1371/journal.pone.0247823*

Shortall, R., Mouter, N. & Van Wee, B. (2022), 'Covid-19 passenger transport measures and their impacts', *Transport Reviews* **42**(4), 441–466.

Suau-Sanchez, P., Voltes-Dorta, A. & Cugueró-Escofet, N. (2020), 'An early assessment of the impact of covid-19 on air transport: Just another crisis or the end of aviation as we know it?', *Journal of Transport Geography* **86**, 102749.

Suau-Sanchez, P., Voltes-Dorta, A. & Rodríguez-Déniz, H. (2016), 'The role of london airports in providing connectivity for the uk: regional dependence on foreign hubs', *Journal of Transport Geography* **50**, 94–104.

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. & Zanin, M. (2017), 'Worldwide air transportation networks: a matter of scale and fractality?', *Transportmetrica A: Transport Science* **13**(7), 607–630.

Sun, X., Wandelt, S. & Zhang, A. (2020*a*), '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. (2020*b*), 'Resilience of cities towards airport disruptions at global scale', *Research in Transportation Business & Management* **34**, 100452.

Sun, X., Wandelt, S. & Zhang, A. (2021), 'Technological and educational challenges towards pandemic-resilient aviation', *Transport Policy* **114**, 104–115.

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.
URL: *https://www.sciencedirect.com/science/article/pii/S2590198222001786*

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

Tisdall, L., Zhang, Y. & Zhang, A. (2021), 'Covid-19 impacts on general aviation–comparative experiences, governmental responses and policy imperatives', *Transport Policy* **110**, 273–280.

Wandelt, S., Sun, X. & Zhang, J. (2019), 'Evolution of domestic airport networks: a review and comparative analysis', *Transportmetrica B: Transport Dynamics* **7**(1), 1–17.

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

Appendix

Table 6: *Overview on city abbreviations used in this study*

cityid	cityname	country
AMS	Amsterdam	Netherlands
AUH	Abu Dhabi	United Arab Emirates
AUS	Austin	United States of America
AYT	Antalya	Turkey
BEN	Benghazi	Libya
BJS	Beijing	China
BKK	Bangkok	Thailand
BNA	Nashville	United States of America
CAN	Guangzhou	China
CGB	Cuiaba	Brazil
CHI	Chicago	United States of America
CNS	Cairns	Australia
CTU	Chengdu	China
CUN	Cancun	Mexico
CWB	Curitiba	Brazil
DAC	Dhaka	Bangladesh
DOH	Doha	Qatar
DXB	Dubai	United Arab Emirates
FBM	Lubumbashi	Congo, Democratic Republic of the
HKG	Hong Kong	Hong Kong
IST	Istanbul	Turkey
JKT	Jakarta	Indonesia
JSI	Skiathos	Greece
KTM	Kathmandu	Nepal
KUL	Kuala Lumpur	Malaysia
KWI	Kuwait	Kuwait
LAS	Las Vegas	United States of America
LLW	Lilongwe	Malawi
LON	London	Great Britain
MAN	Manchester	Great Britain
MDL	Mandalay	Myanmar
MIA	Miami	United States of America
MJI	Mitiga	Libya
MOW	Moscow	Russian Federation
NBO	Nairobi	Kenya
NYC	New York	United States of America
ORL	Orlando	United States of America
PAR	Paris	France
RUH	Riyadh	Saudi Arabia
SAO	Sao Paulo	Brazil
SEL	Seoul	Korea, Republic of
SHA	Shanghai	China
SIN	Singapore	Singapore
TOS	Tromso	Norway
TPE	Taipei	Taiwan, Province of China
TRD	Trondheim	Norway
TYO	Tokyo	Japan
YEV	Inuvik	Canada
YKS	Yakutsk	Russian Federation
YVQ	Norman Wells	Canada
YVR	Vancouver	Canada
YZF	Yellowknife	Canada