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A data-driven analysis of the aviation recovery from the COVID-19 pandemic

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ABSTRACT

In Summer 2022, after a lean COVID-19 spell of almost three years, many airlines reported profits and some airlines even outperformed their pre-pandemic records. In context of the perceived recovery, it is interesting to understand how different markets have gone through the pandemic challenges. In this study, we perform a spatial and temporal dissection of the recovery process the global aviation system went through since May 2020. At the heart of this study, we investigate the patterns underlying market entry decisions during the recovery phase. We identify a rather heterogeneous type of recovery as well as its underlying drivers. We believe that our work is a timely contribution to the research on COVID-19 and aviation, complementary to the existing studies in the literature.

1. Introduction

The devastating impact of COVID-19 on the aviation system is hard to overstate. Many studies in the literature have been published with the goal to dissect the early impact of COVID-19 regarding specific airports, airlines, or passengers; see Sun et al. (2022a) for a recent literature survey. In Q2 2022 (the second quarter of the year 2022), however, the attitude in the aviation sector largely changed from bearish to bullish, with many stakeholders returning to profits and some airlines even reported outperforming pre-pandemic records (Clarke, 2023; Air, 2023). While the overall aviation system is still behind pre-pandemic references according to global, aggregated indicators, e.g., the total number of passengers, the developments in Q2 2022 show that the process of recovery is on the way and possibly heterogeneous in nature. Various earlier studies had predicted a long-term impact with (full) recoveries for the period 2022–2024 (EUROCONTROL, 2020; Gudmundsson et al., 2021; Hanson et al., 2022). Existing studies with an emphasis on recovery in the year 2022 are either spatially or temporally constrained, e.g., covering selected airlines in the United States (Kaffash and Khezrimotlagh, 2022), Chinese airlines (Liao et al., 2022), or cargo systems (Aydın and Ülengin, 2022; Tanrıverdi et al., 2022).

In this study, we analyze the recovery of the global aviation system. Based on ticket and flight data for the time period between January 2019 and June 2022, we perform a data-driven, exploratory analysis of all global passenger markets. Data for the year 2019 is mainly used as a baseline, while we focus on the later stages of COVID-19 recovery, with an emphasis on the second quarter of 2022, where many airlines turned to profits or even exceeded pre-pandemic records. Our study covers a range of 100,000 markets (airport pairs) over a set of 3500 airports worldwide, leading to a complete picture of aviation-induced mobility. Apart from reporting descriptive analysis of the temporal evolution, we also perform a regression analysis on the relevant variables identifying markets which have recovered successfully, in terms of passenger counts and load factors. The identification of these drivers provides important insights on how the system has recovered from the devastating impact of the COVID-19 pandemic and suggests ways to potentially improve the recovery process in terms of a future outbreak. Our study is complementary to the existing literature, which has largely focused on the negative impact of the COVID-19 pandemic on aviation. Overall, we believe that our results provide important novel managerial insights as well as relevant guidance to the aviation community.

The remainder of this study is structured as follows. Section 2 provides an overview on the existing literature with a strong focus on the recovery of the aviation system from the COVID-19 pandemic. Section 3 introduces the recovery analysis framework used throughout our study and also describes the underlying data sets as well as the research questions. Section 4 reports the results of our data-driven analysis of the global aviation system for the period of January 2019 to June 2022. Section 5 identifies the key drivers for the heterogeneous recovery of aviation markets through a simple regression model. Section 6 concludes this study, discusses managerial implications, and provides a set of recommendations for future work.

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2. Literature review

The general economic recovery as well as the aviation recovery in the post-COVID-19 era is closely intertwined. Using an agent-based model, the impact of COVID-19-like shock on the economy was assessed (Sharma et al., 2021), different types of recoveries (V-, U-, W-, L-shaped) were identified for various shock amplitudes and shock durations. They found that either giving easy credit to firms or injecting new money into households could moderate the impacts of the shock, and these two policies would be effective if strong enough. Taking into account the interdependencies among economic, environmental, and pandemic factors, three scenarios for the aviation industry's recovery from the COVID-19 pandemic until 2030 were developed, including post-COVID digivation (it refers to a fast economic and air traffic recovery and tech companies entering the aviation market, followed by extensive digitization efforts), clean restart (a strong customer focus on environmentally friendly means of transport after the pandemic is constrained), green and clean new normal (the slowest economic recovery and it deals longest with COVID-19-related hygiene measures) (Michelmann et al., 2022). A fast economic recovery was observed in many sectors, while aviation being one of the hardest hit.

Heterogeneity of revival paths from the COVID-19 pandemic hides in passenger and freight transportation, travel purposes, as well as in geographical regions and business models. The recovery time for the air transport sector based on historical aviation data and available epidemic data has been extensively discussed. EUROCONTROL issued a five-year (2020–2024) forecast of the European aviation at the end of 2020, mainly depending on the availability and effectiveness of COVID-19 vaccines, along with passenger confidence on air traffic (EUROCONTROL, 2020). Gudmundsson et al. (2021) developed the Auto Regressive Integrated Moving Average (ARIMAX) model and forecasted the time for aviation to reach pre-COVID-19 levels by this time series model. They found that global recovery of air passenger would take 2.4 years, varying from 2.2 years (Asia Pacific) to 2.7 years (Europe). Air freight would resume within 2.2 years on average, varying from 1.5 years (North America) to 2.2 years (Europe and Asia Pacific). Hanson et al. (2022) predicted the demand of air passenger in the US with two elasticity models: The constant elasticity model forecasted that air travel would rebound to its 2019 level around 2022, which was two years ahead of the estimation of the short-run elasticity model.

There were different opinions about the recovery of Low-Cost Carriers (LCCs) and Full-Service Carriers (FSCs). Suau-Sanchez et al. (2020) argued that the pandemic brought LCCs chances to enter hub airports, which would enable these airlines to be more competitive and resume operation quickly. On the other hand, Abate et al. (2020) raised concerns that LCCs would be at an unfair disadvantage in the recovery processes because financial supports from governments and investors might prioritize national carriers. LCCs in different countries showed distinct recovery patterns, depending on epidemic situations, travel demand, flight-related policies, slot allocation and other factors. Chinese LCCs experienced quick recoveries, where Spring Airlines outperformed others in term of network connectivity (Liao et al., 2022). The US LCCs showed a higher efficiency during the pandemic, while FSCs recovered moderately with more positive responses to COVID-19 regarding cancellations and reductions of scheduled flights (Kaffash and Khezrimotlagh, 2022).

Comparing with air passenger transportation, air freight has been less affected by the COVID-19 pandemic. Despite fluctuations in economic drivers such as disruptions in manufacturing and trade, labor shortages in airports and congestion (Aydın and Ülengin, 2022), the global air freight played an important role in ensuring the stability of the global supply chain during the COVID-19 pandemic. Integrators including FedEx, UPS, and DHL might be the great winners given their relatively robust networks, although airlines heavily relying on belly space of passenger aircraft for cargo business would be affected by sudden flight cancellations (Bombelli, 2020). Given rising air cargo demand and insufficient capacity supply, carriers should be cautious to deploy existing aircraft and select airports for scheduled and non-scheduled freight transportation on different routes (Tanrıverdi et al., 2022).

This study aims to explore the extent of – and drivers behind – the ongoing recovery process of our global aviation system. Global aviation market data, covering passenger numbers as well as load factors, together with a data-driven analysis facilitate us to answer a set of important and timely research questions. We are mainly concerned with discovering and better understanding the heterogeneity of the recovery process. We are seeking to provide explanations for deviations from normality, through selected geographical, economical, and operational variables. Ultimately, this study provides insights into differences between pre-COVID-19 structures and the situation of the global aviation system during the recovery from the pandemic. To the best of our knowledge, our study is the first to dissect the recovery status; and it is complementary to a rich set of studies which have put an emphasis on the disruptive aspect of COVID-19, mainly during the early phase of the outbreak (e.g., until May 2020).

3. Framework, data, and research questions

The recovery of complex socio-technological systems has been studied from various perspectives in recent decades (O 'Neill, 1998; Shang, 2016; Blackman et al., 2017; Clements et al., 2019). While being disrupted by an external shock, the functionality of the system is temporally affected. Fig. 1 summarizes the general evolution of a system under disruptions, in context of the global aviation system, measured by the total number of passengers transported over time. Here, the aviation system originally performs without loss of functionality (green area). Upon emergence of an external shock, e.g., COVID-19 or a financial crisis, the system performance is significantly degraded with less passengers transported (red area). The system's functionality reaches the minimum value before a response is taken. Afterwards, the functionality is gradually restored (blue area), until the aviation system reaches the pre-disruption number of passengers. Notably, the functionality extent of the recovered system can be lower or even higher than the original functionality before the onset of a disruption. This chart visualizes the performance of the entire system but hides information on sub-system performances. In the case of the aviation system under COVID-19, this means that while the overall system is on the way to recovery in the year 2022, there might be components (markets) which have a significant deviation from the overall recovery trend. Specifically, there might be markets which have been less disrupted than others throughout the entire phase of the COVID-19 pandemic.

In this study, we take the perspective of analyzing how distinct markets performed during the recovery of aviation from the COVID-19 pandemic. In our context, a market is an airport pair which is served by a direct flight. There are various other air transport markets used in the literature, e.g., with cities being constituting elements for an aggregated city-pair-based definition. Other market variants could focus on the analysis of origin–destination, i.e., including indirect flights. Finally, the notion of markets could also refer to the major subsets of the aviation system, such as induced by different airline business models, e.g., point-to-point versus hub-and-spoke systems (e.g., Oum et al. (1995)). Our focus on airport pairs enables the most fine-grained analysis for the investigation of aviation recovery. To better capture for heterogeneous effects, we investigate four distinct instances of system component recovery in Fig. 2. To derive these four instances, we disregard the timespan between shock and response, given that – in general – the system had come to an overall standstill at that time. In the context of COVID-19, the time between March 2020 and May 2020 was rather extreme, with most flights being canceled and the flights which have still been operated had significantly reduced load factors. Accordingly, we only consider the time pre-shock and post-response to derive four distinct market types. Please note that

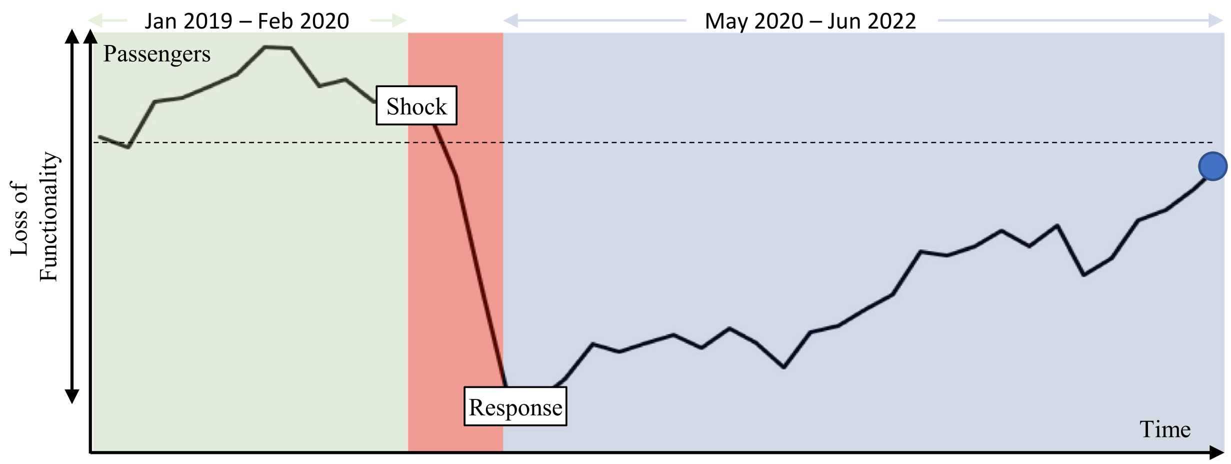

Fig. 1. Identification of distinct analysis periods based on the monthly number of passengers in the global aviation system. Three periods are highlighted: pre-pandemic normality in green (Jan 2019–Feb 2020), the time from shock to response in red (Mar 2020–Apr 2020), and recovery in blue (May 2020–Jun 2022). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

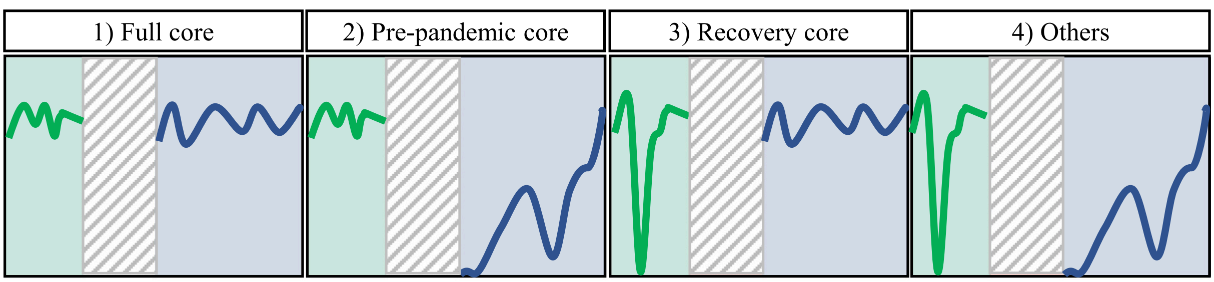

Fig. 2. Four distinct market types during pre-pandemic and recovery phase. The *y*-axis corresponds to the number of passengers on direct flights at the market and the *x*-axis visualizes time. The gray hatched area corresponds to the period between shock and response; since this study is concerned with recovery, we do not take into consideration the market evolution during that hatched period.

the discussion of disruption could be flight-based or passenger-based. Below, we continue to take the perspective of passenger served through direct flights across a market. These four classes are defined as follows:

1. **Full core**: This class contains markets which have been served continuously before the COVID-19 onset (January 2019 to February 2020) and after the peak of the impact (May 20202–June 2022). A market is considered as being continuously served, if it had at least four operated flights per month (about once per week). In essence, this class contains markets that have been highly connected before and throughout the COVID-10 pandemic, naturally at varying capacity and load factors. Therefore, we refer to these markets as the *Full core*.
2. **Pre-pandemic core**: The class *Pre-pandemic core* contains markets which have been served continuously before the COVID-19 onset but not continuously during the recovery phase, i.e., for some of the months in the recovery phase there was no flight for this market.
3. **Recovery core**: The class *Recovery core* contains markets which have been served partially before the COVID-19 onset, yet continuously during the recovery phase. While the existence of this class seems counter-intuitive at first, it mainly consists of pre-pandemic seasonal markets and emerging markets for previously unserved airports.
4. **Others**: The class *Others* contains markets which have been served partially before the COVID-19 onset as well as partially during the recovery phase. Again, seasonality can be a major driver, given that there exist pre-pandemic snapshots without passengers on direct flights.

Fig. 3 presents a toy example to better understand the four market types considered for recovery analysis. The example consists of five airport network snapshots (Month 1 to Month 5) over six German airports. We consider Month 1 and Month 2 as pre-pandemic normality, Month 3 as the peak of the shock, and Month 4 together with Month 5 as recovery snapshots. The connectivity among nodes changes during the evolution from Month 1 to Month 5. Market FRA-MUC is considered as full core, given that it was served in Month 1, Month 2, Month 4, and Month 5. Note that our definition does not force a service at Month 3 for full core, given that we want to focus on the recovery, instead of the peak impact. Market FRA-HAM is considered full core as well. Market FRA-DUS is categorized as pre-pandemic core, since it is not served in Month 4. Market MUC-DRS, on the other hand, is a recovery core, since it is not served in Month 1. Market FRA-BER is an example for the fourth category (others), given that it was not served in Month 1–4.

In addition to the continuity of service, we also take into consideration the recovery extent for specific markets. Naturally, there exist various possibilities to quantify the extent to which a market has recovered, for instance, based on the number of passengers, the number of departures, and load factors. More economics-oriented variables could include airline yields or profits. However, the limited availability of data at a global scale, makes an analysis of such airline-specific and often proprietary properties difficult, if not impossible. Accordingly, in our study we choose two indicators which – in combination – lead to a trade-off between simplicity and realism: Passenger counts and load factors. It should be noted that these two variables are nearly independent: We have computed the Pearson correlation coefficient between load factors and passenger counts across global markets from

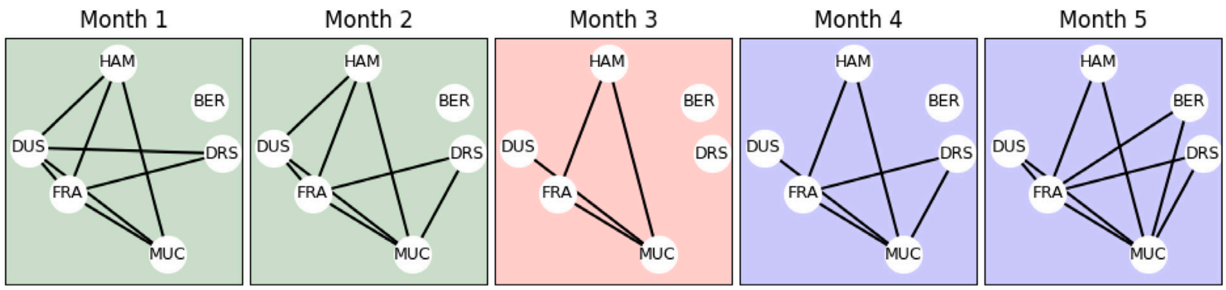

Fig. 3. Toy example for visualizing the four market classes for recovery analysis based on an example with five months (left to right). The third month (highlighted in pink) is considered the period between shock and recovery. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Sabre Market Intelligence for two years: 2019 and 2022. In these experiments, we obtained a Pearson correlation coefficient of 0.06 (0.12) with a 2-tailed p-value of 8.68e−157 (5.36e−50) for the year 2019 (2022), respectively. In fact, existing studies on the early impact of COVID-19 on the aviation system have often used the number of departures as the only variable. This, however, ignores the important effect of load factors; see Sun et al. (2022b) for an analysis of the ghost flight phenomenon in the European context. Therefore, this study investigates both variables, passengers and load factors, to define the extent of recovery for a given market. A potential concern regarding the evaluation of load factors would be an extensive change in seats per operations (mainly due to aircraft types). In Fig. 15 (Appendix), we show that there exists a rather strong correlation between seats per operations within the two considered time periods across all markets, with an observed R-squared value of 0.94. In addition, it is natural for airlines to maximize their load factors across markets; and load factors can therefore serve as an appropriate evaluation criterion.

Fig. 4 visualizes how these two variables induce four interesting classes for recovery. We compute the ratio of data points for April 2022–June 2022 (Q2 2022) over April 2019–June 2019 (Q2 2019) for both variables as follows. For each market, we divide the number of passengers (load factors) in Q2 2022 through the number of passengers (load factors) in Q2 2019. The resulting quotients can be interpreted as an indicator of recovery extent: A value larger than 1.0 shows that the number of passengers (load factors) have outperformed pre-pandemic levels during the recovery. In Fig. 4, the passenger ratio is shown along the x-axis and the load-factor ratio is reported along the y-axis. With the threshold 1.0 in mind, we obtain four classes according to the four quadrants:

- **Quadrant I: Recovered load factors** (only load factor ratio larger than or equal to 1.0)
- **Quadrant II: Fully recovered** (load factor and passenger ratio larger than or equal to 1.0)
- **Quadrant III: Recovered passengers** (only passenger ratio larger than or equal to 1.0)
- **Quadrant IV: Still disrupted** (neither ratio is larger than or equal to 1.0)

The data in this study comes from Sabre Market Intelligence (Sabre, 2023), a commercial provider for global airline and airport data. We have obtained aviation-related data for the period from January 2019 to June 2022, covering the entire COVID-19 pandemic impact cycle, with one year pre-shock reference data. Sabre provides data at market and airline level, mostly with monthly resolutions. The dataset includes information on the number of departures, the number of passengers, the load factors, and other variables for each market. Concerning data coverage and quality, it should be noted that SABRE is based on one of the largest global distribution system, besides Amadeus CRS. Based on our own experience with the dataset, the data is reliable and consistent with other aggregated data reports which have been published during the COVID-19 pandemic, e.g., by the International Air Transport Association in its annual reviews.[1]

4. Market type analysis

In total, data for more than 100,000 airport pairs worldwide can be accessed through Sabre Market Intelligence. For the purpose of this study, we have obtained markets with at least four flights per month, equaling to at least one weekly service. Fig. 5 provides an overview on the airport coverage in our study. In total, we have data for more than 3500 airports across all geographical areas. The marker size in Fig. 5 corresponds to the total number of distinct destinations served throughout the study period. The top-20 ranked airports are highlighted with their IATA codes.

The first part of this section analyzes the existing market structures in the global aviation system. In this study, as we do not analyze data at airline level, a market consists of an OD pair in a specific month. In total, our study covers a period of $3 * 12 + 6 = 42$ months, starting with data for January 2019 and ending with data in June 2022. This range is interesting to analyze, as it covers the entire pandemic disruption cycle, including pre-pandemic baselines (the year 2019), the excessive impact of COVID-19 on aviation when turning from an epidemic outbreak into a fully-blown pandemic (March and April 2020), towards a two-year long recovery process (May 2020 to June 2022).

In Fig. 6 we investigate the extent of service for these market types in the period between January 2019 and June 2022. While all markets faced a visible impact of the COVID-19 pandemic in March/April 2020, the extent of this impact is rather heterogeneous. The full core, for instance, has been affected to a significantly smaller extent than the other three markets: the number of served markets is reduced by about one third for full core only, while all other types face reduction by a half or more. Another interesting observation from this figure is the distinct recovery of pre-pandemic core and other partial markets, particularly regarding seasonality in Summer 2021. While for pre-pandemic core we can observe a rather slow, monotonic recovery over time, the other markets have a significant peak in Summer 2021. Presumably, airlines tried preferably to enter markets which have seasonal demands before the onset of the COVID-19 pandemic.

To better understand the composition of the four market types, we provide a set of statistical analysis below. Fig. 7 visualizes the relative frequency distribution of route sizes (number of pre-pandemic passengers, log) for the four market types in red color, with the frequency distribution across all types (gray color) as reference. The full core consists mainly of markets with a significantly larger route size, visible through the two orders of magnitude distribution shift to the right. This means that airlines have continuously served their most important markets with a large number of pre-pandemic passengers. The pre-pandemic core distribution is also shifted to the right — but to a smaller extent. Markets belonging to the other categories are just markets with

[1] https://www.iata.org/en/publications/annual-review/.

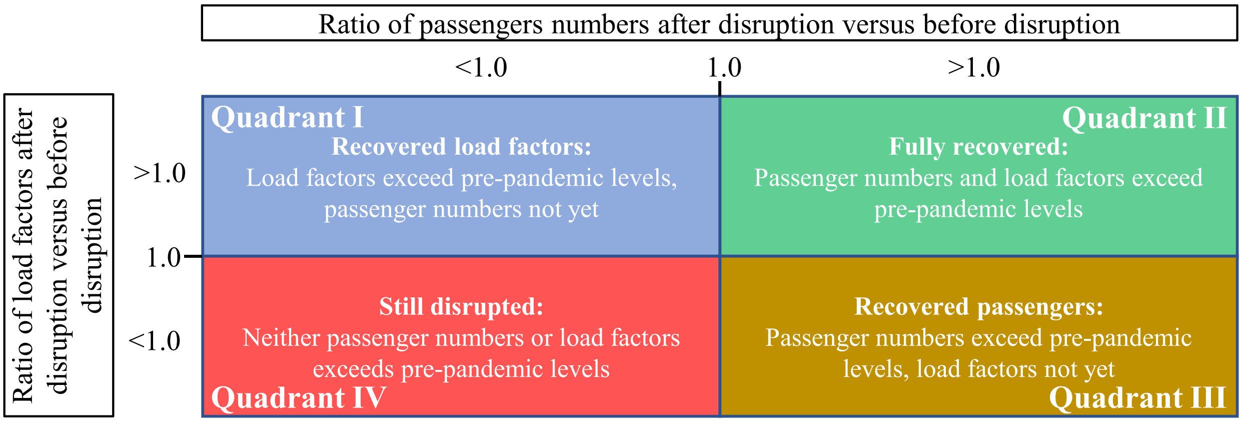

Fig. 4. Recovery quadrants based on passenger (x-axis) and load factor (y-axis) ratios.

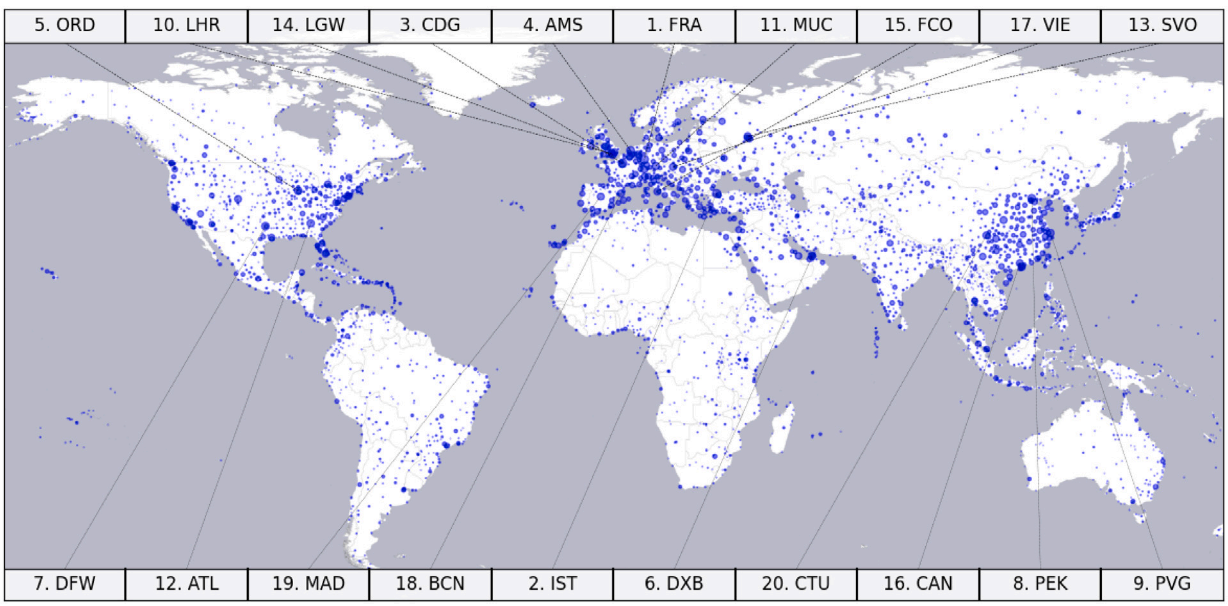

Fig. 5. Overview on airports in this study. Each circle corresponds to one airport and the size correlates with the number of destinations served. *Data Source:* Sabre (2023).

a significantly lower route size. The recovery core consists of too few data points to derive a clear judgment. Fig. 8 complements our market type analysis by revealing similar results for the distribution of the departure frequencies for markets in each type.

In Fig. 9, we investigate whether a significant difference in route length can be observed among the four market types. According to the visualization of distance (log) distribution, it seems like the distance played no important role — at least when being analyzed through the lens of the four market type categories, visible through the largely coinciding distributions for each market type, respectively.

Next, we investigate six additional properties of markets aggregated in the four market types. Fig. 10 reports these results with each subplot corresponding to one property. Within each subplot, we report the relative frequency of specific markets, where the dashed horizontal line represents the value over all markets as reference For instance, when considering the number of domestic markets in each market type (Fig. 10a), we can find that two types have a significantly increased fraction of domestic connections: full core and recovery core. This suggests that domestic markets have been served much more continuously during the COVID-19 pandemic. The contrary holds for intercontinental connects (Fig. 10b), which can be preferably found in the pre-pandemic core and the fourth market type (other). We can observe a slight preference of low-cost carrier-dominated markets in the fourth market type (Fig. 10c). The remaining three subplots report on the distribution of hub–hub, hub–spoke, and spoke–spoke connections, respectively. We find that the full core and pre-pandemic core have a significantly larger fraction of hub–hub and hub–spoke connections. Spoke–spoke connections, however, are more likely to be found in the other two market categories.

Fig. 11 further reports on the country of origins in each market type, distinguishing domestic and international connections. The domestic markets of all four types are dominated by China and the United States, given that these two countries are the two strongest powerhouses with the largest domestic markets — maybe in addition an aggregated variant of Europe. Notably, China is dominating the recovery core, with more than 60% of all markets. Concerning the international markets in our study, we can indeed discover significant differences across market types. The full core, pre-pandemic core, and other markets are all dominated by European countries and the United States. Among international flights in the recovery core, we can also find Japan and Australia, in addition to the United States and the Netherlands.

Next, we investigate whether there are significant differences in the recovery of load factors concerning the four market types in our study. Fig. 12 visualizes the load factors in two periods: the first year

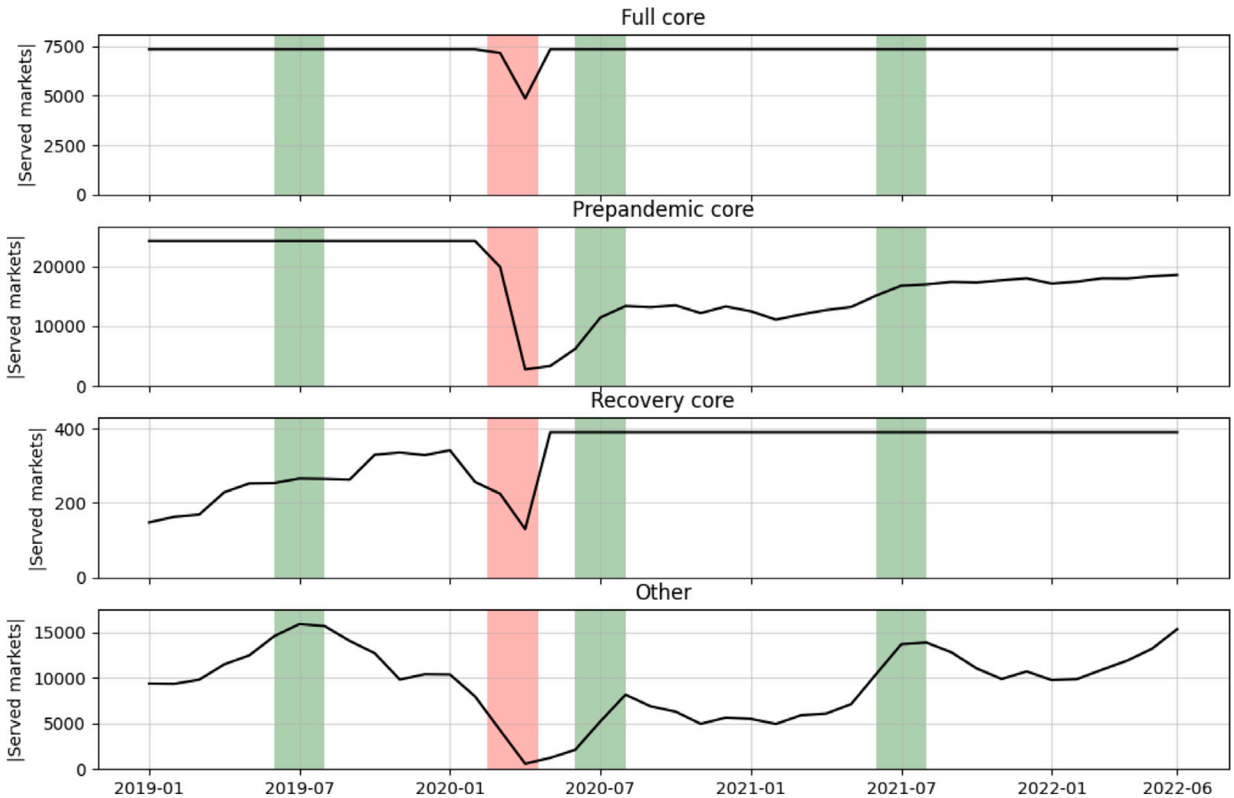

Fig. 6. Evolution of the number of served markets in the four market types. The green areas highlight the Summer cycle (June–August, respectively) and the red area emphasizes the peak impact of COVID-19 (March and April 2020). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

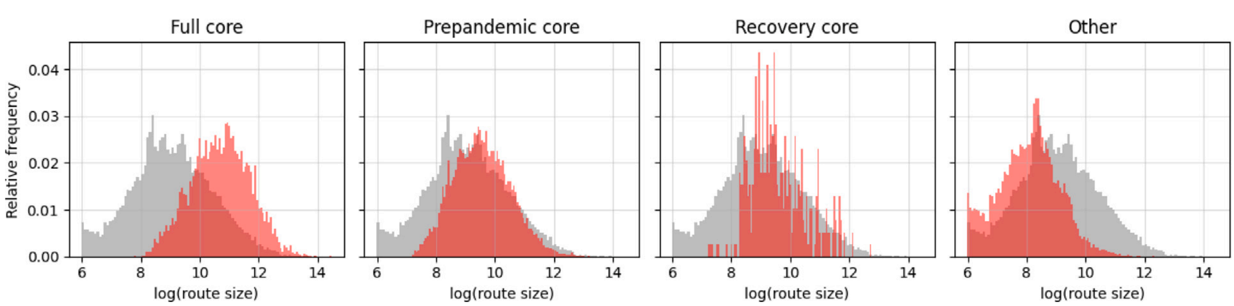

Fig. 7. Distribution of route size (log) across the four categories (red color) and over all markets (gray color) as reference. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

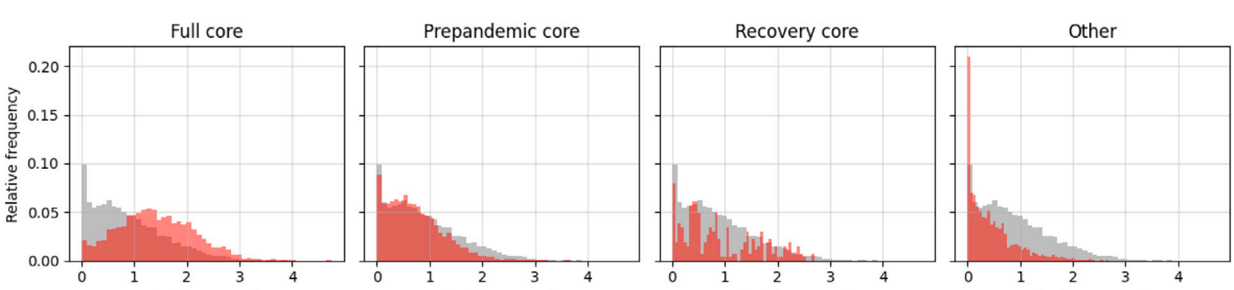

Fig. 8. Distribution of departure frequencies (log) across the four categories (red color) and over all markets (gray color) as reference. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

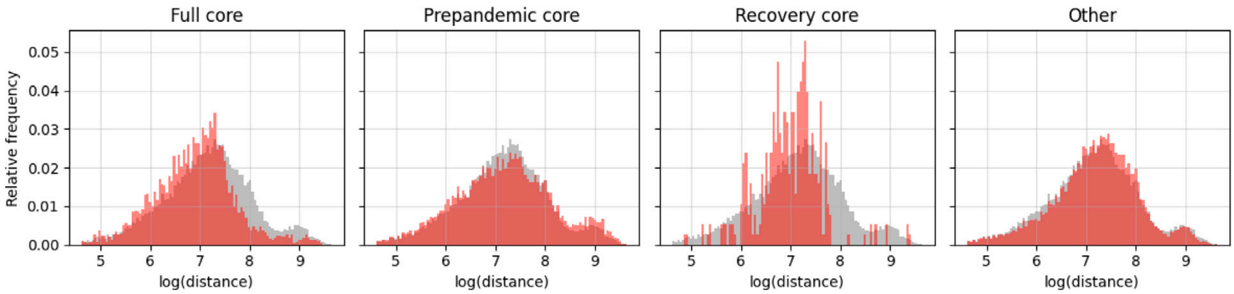

Fig. 9. Distribution of route length (log) across the four categories (red color) and over all markets (gray color) as reference. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

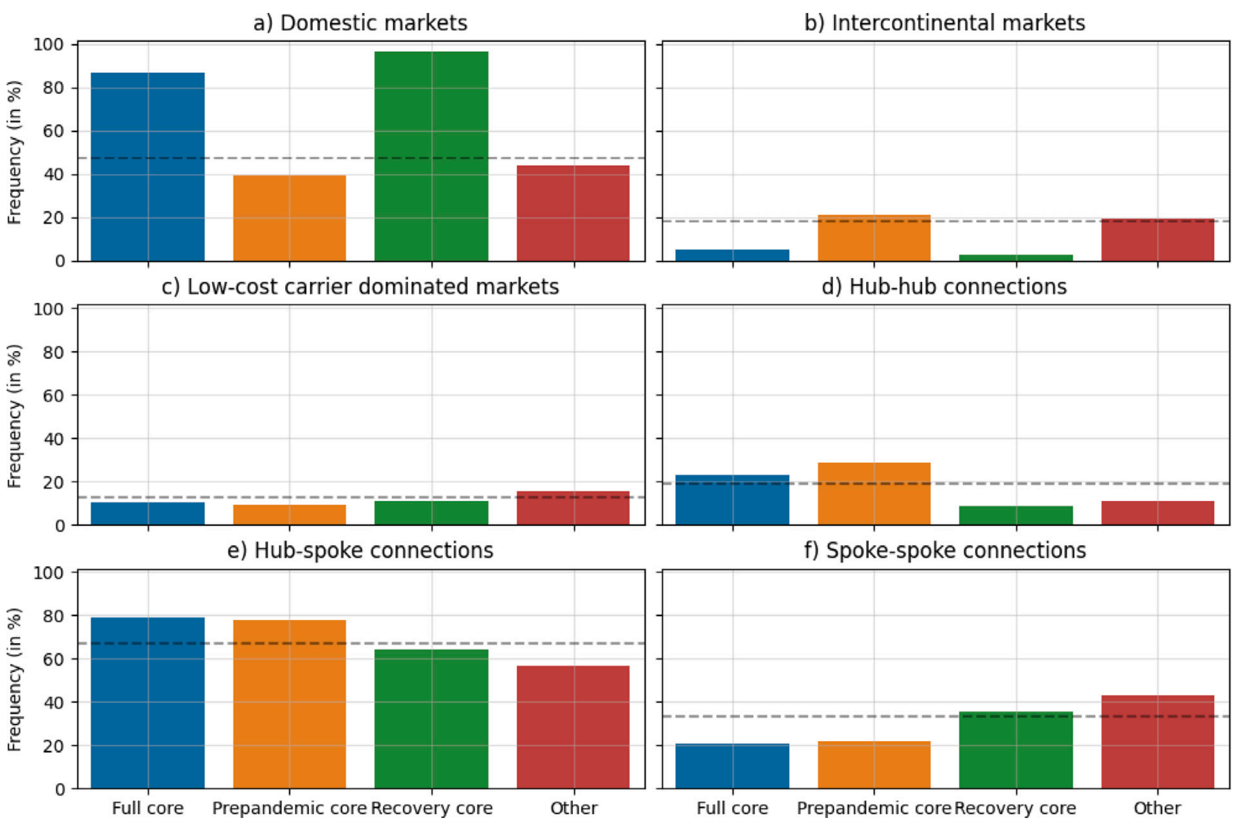

Fig. 10. Dissection of market types by six market criteria.
Data Source: Sabre (2023).

with COVID-19 (top) and the second year with COVID-19 (bottom). We can see that the load factors were significantly reduced throughout the initial impact of COVID-19. This is presumably caused by an interaction of two phenomena: (1) airlines trying to serve markets in fear of losing slots or market shares and (2) exploration of working alternatives for the at-that-time upcoming Summer 2020 cycle. In May 2020, the observed load factors in full core and category ‘Other’ are significantly higher than in the other two categories. In other months, this distinction is not strongly present anymore. Another observation is the rather gradual increase of load factors over time, with a few seasonal effects caused by Summer 2021.

In the next analysis, we take a combined perspective on passenger counts and load factors to investigate the transition from pandemic peak impact towards recovery. Fig. 13 presents a scatter plot of ratios (x-axis: ratio of passengers Q2 2022 vs. Q2 2019, y-axis: ratio of load factors Q2 2022 vs. Q2 2019). Each data point corresponds to one market. We can observe that the full core markets have a much smaller variation of ratios from the center, the latter indicating equivalent passenger numbers and load factors comparing pre-pandemic and post-pandemic quarters. This reduced variation concerns all directions, including larger as well as smaller ratios. Accordingly, we conclude that the full core seems to have been a much safer choice for airlines. This insight clearly has policy relevance, as discussed in Section 6.

5. Regression model for identifying drivers of recovery

To further analyze these results, Fig. 14 presents results on the data points located in one of the four quadrants. On the right-hand side, each colored data point corresponds to the transition of a market from the beginning of the recovery period (0 month) to the end of the recovery period in our study (25 months, starting from May 2020), see the color bar for reference. Each of the panels in the right-hand side corresponds to a quadrant of data on the left-hand side. Accordingly, we can observe that almost markets started in the lower left quadrant

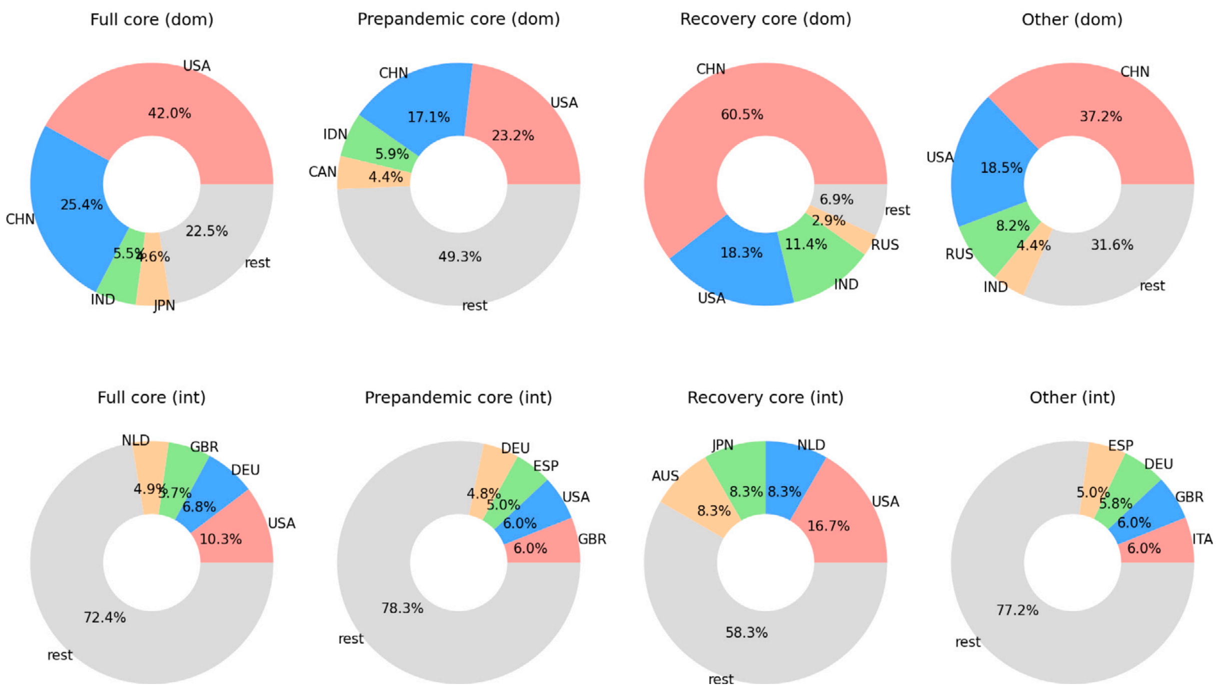

Fig. 11. Statistics at country level for domestic (top) and international (bottom) connections.
Data Source: Sabre (2023).

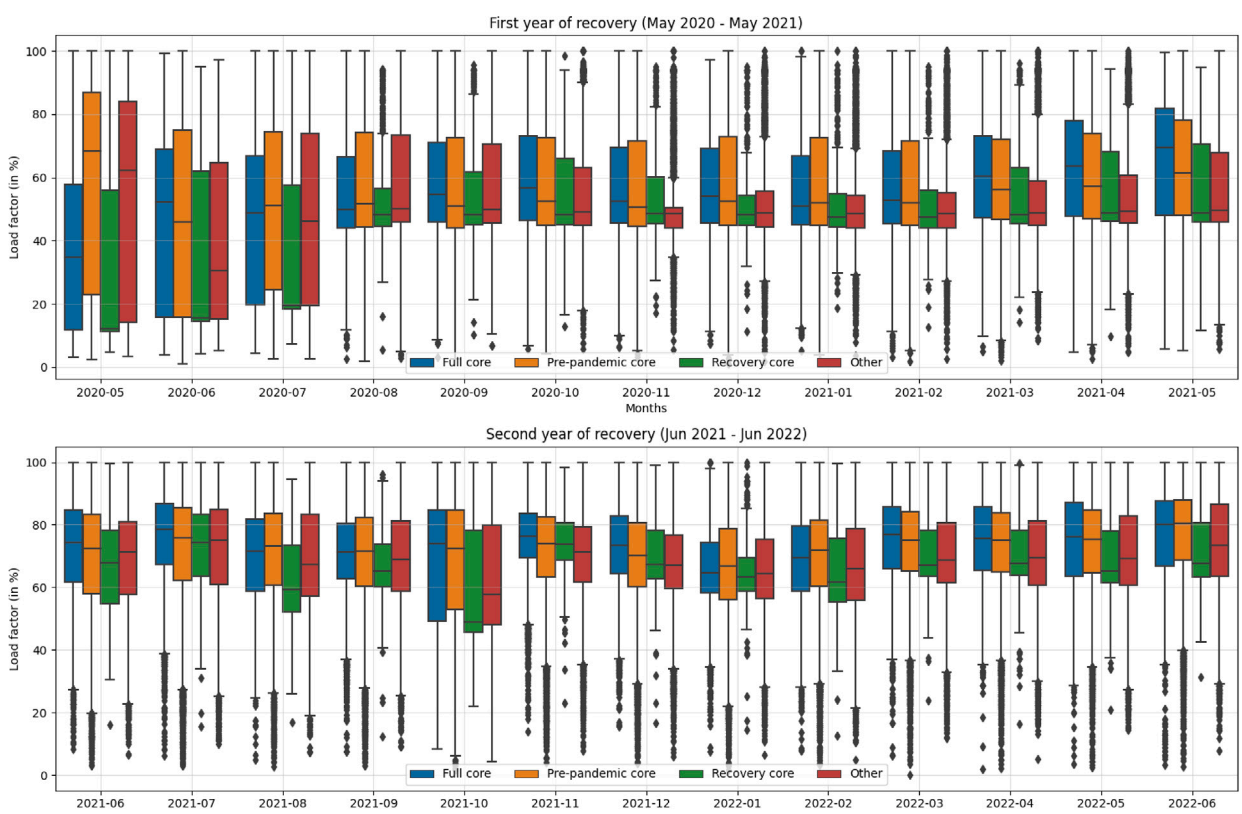

Fig. 12. Evolution of load factors across the four market types.
Data Source: Sabre (2023).

at the beginning of the recovery phase, representing reduced passenger ratios and reduced load factors. Following the recovery process (the color transition from red to yellow), we can observe that all data points do have a slight upward/right tendency, but the overall trajectory is rather different and rather continuous throughout the recovery period. In other words, those markets which made it to Quadrant 2 — which indicates a recovery beyond pre-pandemic cases, mostly had a continuous development to that region throughout the recovery phase.

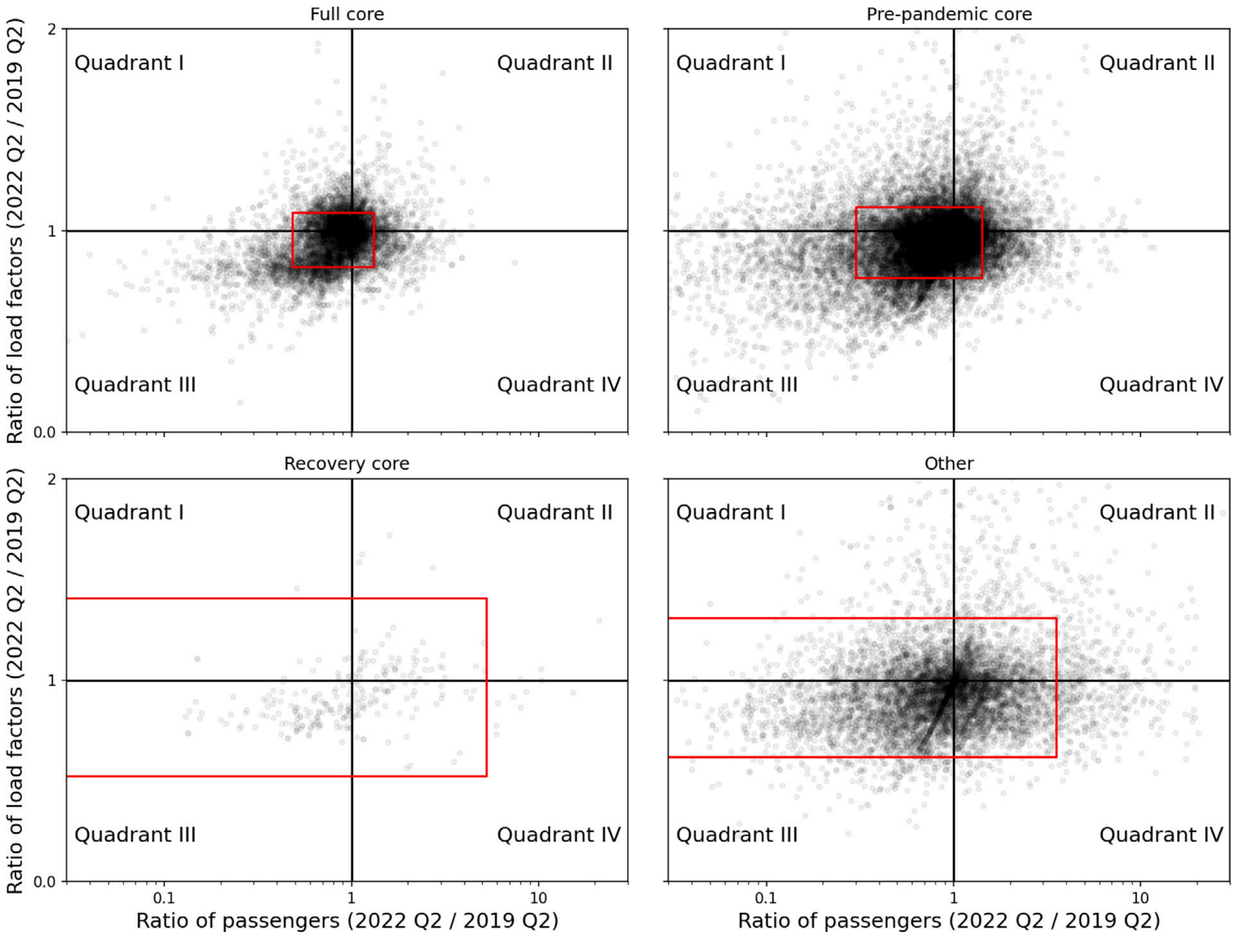

Fig. 13. Integrated comparison of passenger counts and load factors. The red box visualizes the area within standard deviation from the mean of both variables, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

There are, however, outliers which, for instance, end up in Quadrant 1 (increased load factors, reduced passenger counts), which went through Quadrant 2 (increased load factors, increased passenger counts) during the recovery process. In this context, it should also be noted that Fig. 13 (left) reports results based on data for three consecutive months (March 2022 to June 2022), while Fig. 13 (right) reports evolutionary results on a monthly resolution.

In the following, we develop a regression model which aims to explain the existing heterogeneity through a simple regression model. The response variable is whether a market can be found inside Quadrant II (Fig. 4), i.e., whether the market has successfully recovered regarding passenger numbers and load factors. The regressors used in this study consist of a set of geographical, economical, and operational variables which are based on pre-pandemic data and those obtained during the actual recovery process. We specify a simple linear regression model as follows:

$$\begin{aligned} Rec =& \alpha_0 + \alpha_1 * DOM + \alpha_2 * DIS + \alpha_3 * FC + \alpha_4 * PM \\ &+ \alpha_5 * PC + \alpha_6 * COC \\ &+ \alpha_7 * COV + \alpha_8 * HHI2019 + \alpha_9 * PAX2019 \end{aligned}$$

where Rec indicates whether the market was considered fully recovered (1.0) or not (0.0). Below, we explain the choice of regressors:

- DOM: Describes whether a market is domestic (1.0) or not (0.0).
- DIS: Denotes the great circle distance of the market's airport pairs (log-scaled), computed using the Haversine distance.
- FC: Whether a market belongs to the full core (1.0) or not (0.0).
- PM: Whether a market belongs to the pre-pandemic core (1.0) or not (0.0).
- PC: Whether a market belongs to the other markets (1.0) or not (0.0).
- COC: Denotes the minimum of the current COVID-19 confirmed cases rate (per 1,000,000 inhabitants) of the airport pair (log scaled) in June 2022. Data source: Our World in Data (2023).
- COV: Denotes the minimum of the current COVID-19 vaccination rate (per 100 inhabitants) of the airport pair (log scaled) in June 2022. Data source: Our World in Data (2023).
- $HHI2019$: The Herfindahl–Hirschman index computed based on the passenger distribution over airlines serving a market, indicating the extent of competition (larger numbers indicate less competition). Data source: Sabre (2023).
- $PAX2019$: The number of passengers for a market in the year 2019 (log-scaled). Data source: Sabre (2023).

We provide a few explanations regarding the choice of variables here. First, we have not included a variable for the recovery core as it leads to strong multicollinearity. Second, variable $PAX2019$ does not lead to simultaneity/endogeneity, since the response variable depends on the ratio of passenger counts — which by itself is not dependent of the base value. We have not included a variable for load factors in 2019, since a higher value of 2019 load factors will induce a smaller ratio of load factor, leading to potential endogeneity problems.

Table 1 reports the regression results. All variables are statistically significant with p-values smaller than 0.001, except for one variable: FC. Our visualization in Fig. 13 already highlighted the fact that the full

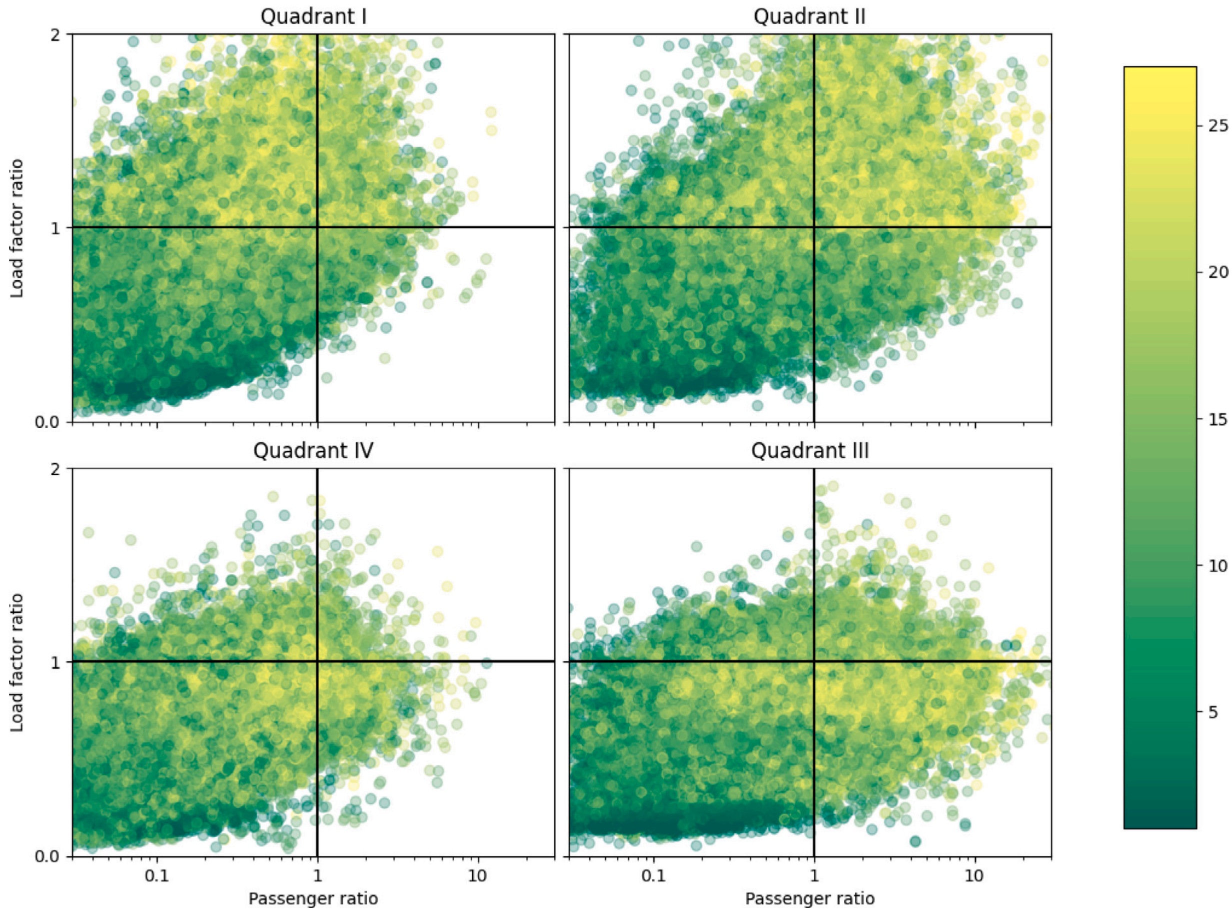

Fig. 14. Integrated comparison of passenger counts and load factors. For each market, the evolution of ratios is plotted using color, from the first month to the last month of the recovery. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Data Source: Sabre (2023).

Table 1
Summary of regression results.

	coef	std err	t	P > |t|	[0.025]	[0.975]
Intercept	0.6301	0.033	19.124	**0.000*****	0.566	0.695
DOM	0.0353	0.005	7.439	**0.000*****	0.026	0.045
DIS	0.0421	0.005	7.890	**0.000*****	0.032	0.053
FC	−0.0352	0.021	−1.662	0.097	−0.077	0.006
PM	−0.1259	0.021	−5.925	**0.000*****	−0.168	−0.084
PC	−0.1137	0.021	−5.429	**0.000*****	−0.155	−0.073
COC	−0.0839	0.008	−10.064	**0.000*****	−0.100	−0.068
COV	0.1370	0.011	12.979	**0.000*****	0.116	0.158
HHI2019	−0.0337	0.006	−5.895	**0.000*****	−0.045	−0.022
PAX2019	−0.1449	0.004	−32.477	**0.000*****	−0.154	−0.136

Note: The data shown is calculated based on yearly averages for the year 2017–2019, i.e., pre-COVID-19 levels.
***Variables which are statistically significant with p-values smaller than 0.001.

core markets have been less subjective to extreme values, but appeared more stable during the COVID-19 pandemic. With the major FC markets centered around (1.0,1.0) in Fig. 13, it is natural that this variable has no significant impact on the quadrant of a market. We discuss the remaining significant results variable-by-variable below.

The variable DOM has a positive coefficient indicating that domestic markets have recovered much better than international markets. This finding is in line with the existing literature, where it was reported that domestic markets were less sensitive to flight bans and it was also considered more important for stakeholders to keep the transportation system inside a country moving (Sun et al., 2020; Bauranov et al., 2021). The variable DIS has a positive coefficient as well, suggesting that markets with a longer line-by-sight distance are more likely to have recovered well. When interpreting this variable, one should note that DOM is already positive. Therefore, we presume that for short-distance markets passengers prefer to use other transportation modes during the recovery, compared to the period before COVID-19. This preference may be induced by remaining fears concerning the role of aviation in spreading the virus and social distancing restrictions. The variables PM and PC both have a negative coefficient in our model, suggesting that not serving continuously during the recovery phase will rather have a negative effect on the load factor or passenger counts. This could possibly be explained by passengers preferring stable travel itineraries; alternatively, it might suggest that stakeholders did not succeed to successfully disseminate information regarding such fluctuating markets. The variable COC is negative, which confirms that hypothesis that markets with a larger number of confirmed cases (per 1,000,000 inhabitants) have a smaller likelihood for successful recovery. In other words, markets with controlled COVID-19 outbreaks might attract passengers more effectively. In line with this result, the variable COV has a positive coefficient, indicating the markets with higher vaccination rates are more likely to recover well. The variable HHI2019 has a negative coefficient. This suggests that markets with a smaller extent of competition have a smaller likelihood to be recovered well. In terms of COVID-19, this could imply that airlines simply focusing on their traditional dominated markets, are less likely to see success. Instead, it was those markets that had a fiercer competition before COVID-19, which saw a better recovery. Presumably, a higher degree of competition also increases the likelihood that one of the airlines had entered the market with a successful strategy. Finally, variable PAX2019 has a negative coefficient as well, supporting a similar hypothesis: Markets with high demand pre-COVID-19 are not necessarily the ones which perform well after the COVID-19 recovery. Here, our results suggest that it is the biggest routes which are taking longest to return to earlier level. Accordingly, there is a need for future research to better understand the aviation system under COVID-19 recovery and where it is heading to.

6. Discussion, policy recommendations, and future work

This study has investigated the recovery process of the global aviation system from the COVID-19 pandemic. Specifically, using data for the years 2019 to 2022, we compare how specific markets have developed and identified spatio-temporal characteristics. In addition, we developed a regression for explaining the performance of better-than-average markets. Our major findings are summarized as follows.

First, our results confirm that the recovery, as of the second quarter in 2022, is rather heterogeneous across all markets. Some markets significantly outperform pre-pandemic baselines, while other markets are stuck at residual functionality. We also confirm that there exists a significant dominance of domestic markets among the successfully recovered markets, which can at least partially be attributed to the smaller impact of COVID-19 on these markets and the higher importance for domestic mobility. Overall, load factors have reached 60%–80% in most markets, with measurable seasonal improvements starting from August 2020. The region which has seen the least extent of recovery is Asia, mostly dominated by the Chinese dynamic COVID-zero policy and its Circuit Breaker mechanism (Wandelt et al., 2023); which have just been eliminated in towards the end of 2022. From these results, it can be concluded that there is not only an instrumental need for orchestrated reactions against emergent outbreaks, but also the necessity to develop common rules and policies for a synchronized and informed recovery. In this regard, one should explicitly mention the chaotic conditions in Summer 2022 with excessive cancellations and flight delays. The underlying drivers are complex, covering various aspects of the aviation system. There is a tremendous staff shortage in some parts of the industry, especially concerning ground handling, e.g., London Heathrow is reportedly at 70% of pre-pandemic resource capacities (Calder, 2022) and challenges for attracting staff back into aviation (Webb, 2022); see also Stewart (2022) for the potential of Brexit having reduced British airports' employment pools. Finally, Kazda et al. (2022) pointed out the contribution of time-consuming security background checks and specialized training leading to a bottleneck in airport staff recruitment. In the future, such problems should be anticipated and avoided — especially given the large amount of financial support provided to aviation stakeholders, which was explicitly requested by airlines for the purpose of keeping the aviation system alive and allowing a timely and coordinated recovery.[2]

Second, our analysis of core markets – induced by the continued service frequency pre-pandemic and during the recovery – showed that the full core market was most conservative in terms of recovery (measured by load factor ratios and passenger ratios). Here, conservative means that these markets did not see extreme failure or extreme success. The other types of markets seem to have provided more potential gains at the price of higher risks. This finding indicates that business-as-usual did not work out well for airlines during the recovery. The major problem here was that airlines did not know where the actual demand emerging, given their over-reliance on history-based prediction models. Especially the large traditional network carriers were reported to struggle hard when it comes to making fare decisions (Fontanet-Pérez et al., 2022). Smaller airlines and low-cost carriers were reported to have a much higher degree of flexibility, especially when it comes to the potential of innovation (Sun et al., 2022c). Policy makers and researchers should focus on these different recovery conditions, provide formal verifications of this phenomenon and come up with strategies to overcome these problems in future outbreaks and their recoveries. Along these lines, the development of new passenger choice and demand prediction models should be investigated, in order to better prepare airlines for such difficult situation. It would be unfortunate, if the aviation industry recovers from the COVID-19 pandemic without having learned appropriate lessons and incorporated into their operations.

Third, our study highlights the relevance of confirmed cases and vaccination rates for the success of a market. While we find that the rate of confirmed COVID-19 cases has a negative impact on market performance, the rate of COVID-19 vaccinations has a positive impact. This finding is important from various perspectives. It indicates that it is indeed beneficial for markets to push the envelope towards epidemic containment and population vaccination. Presumably, the perceived safety on such markets makes it more likely for passengers to fly. Moreover, it also encourages airlines to explicitly provide (and advertise) the existence of relative safer markets as part of their efforts to attract passengers.

Finally, we find that the system is quite different from pre-pandemic at various stages of our study. This has implications on research as well as policy making. Research-wise, this leads to an opportunity to revisit and re-evaluate various properties underlying our global mobility, e.g., based on complex network analysis. Given that most studies in the literature either focus on the pre-pandemic structure or the devastating impact, researchers need to find a transition into the new normal, only carefully publishing results which is based on pre-pandemic aviation data. Ideally, one would need to perform cross-experiments to confirm that found hypotheses still hold in the recovered aviation system. Similarly, existing policies need to be re-assessed according to the observations made for the pandemic recovery. Such policies particularly include those designed around the achievement of sustainable development goals and climate change, given that deviations from the pre-pandemic situation can impact the effectiveness of decisions based on the related policies.

Our study comes with a few limitations which lead to interesting directions for future work. First, while we have analyzed the temporal aspects from a data-driven perspective, focusing on the regression analysis on the second quarter of 2022, i.e., the first months with a broad recovery in the aviation system. This analysis was motivated by announcements of some airlines' record profits, indicating a strong recovery in this quarter. In addition, we do not have data available for the full year 2022 — the final data from Sabre Market Intelligence is published with a lag of around four months. Future studies could perform a finer temporal analysis of the drivers leading towards the recovery in the second quarter of 2022 and beyond. It should be noted that the overall aviation system is still behind pre-pandemic references according to global, aggregated indicators, e.g., the total number of passengers. Nevertheless, various markets have indeed recovered beyond pre-pandemic values (in terms of, e.g., passenger numbers, load factors, and profits). One contribution of our study is the dissection of which markets have recovered and up to what degree. In this context, a particularly interesting direction is to include airline data. Our study was largely market-focused, which neglects the specific actions of actors (airlines) in the system. Accordingly, it would be interesting to break down the results by airlines and see how their heterogeneous strategies played out on the way towards recovery. Also, it should be noted that our two-dimensional recovery analysis neglects information about aircraft sizes, which could underestimate the recovery in case of significant size modifications.

Another interesting direction for analysis in future work is the question to which extent the seasonality of markets has changed during the recovery from COVID-19, compared to pre-pandemic baselines. Moreover, since our analysis is based on direct flights, we do not accurately capture passenger choices for their itineraries, a limitation

[2] https://www.politico.com/news/2021/11/20/airlines-pandemic-bailout-cancellations-523100.

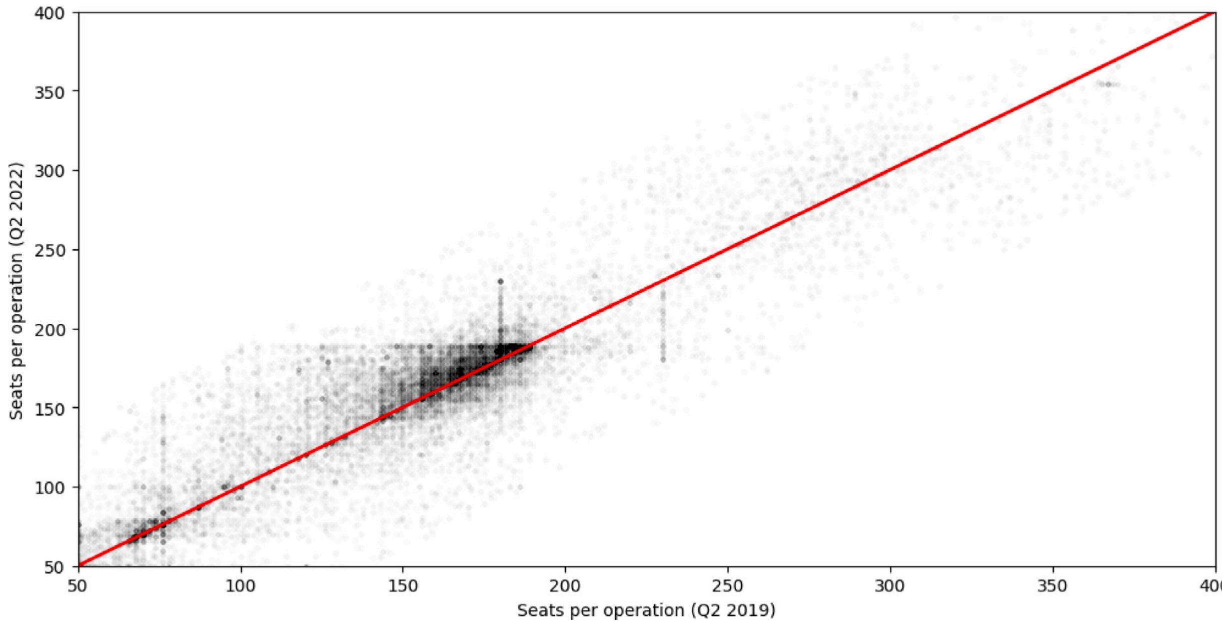

Fig. 15. Comparison of seats per operations.

which could be addressed in future work by investigating ticket data and origin–destination pairs. Finally, as discussed earlier, we see a need for studies which evaluate the pandemic preparedness of our aviation system – as part of the new normal – in anticipation of the next singularity – which will presumably come unless we change our mobility patterns significantly. Finally, while we have, in our regression model, independent variables such as HHI2019 and PAX2019 that are known prior to the pandemic, the four-market-types variables involve ex-post observations. As such, the model may not be relevant for predicting the effects of the next pandemic (or other similar shocks). In this sense, our model is retrospective in nature: it reviews the recovery experience and dissects which factors favor full recovery while others do not. Nonetheless, we can, through our earlier analyses of the major composition and characteristics of the four market types, substitute these variables with related observed proxies in the regression, which would give rise to similar insights. We consider this exercise as an avenue for future research.

CRediT authorship contribution statement

Xiaoqian Sun: Conceptualization, Methodology, Writing – original draft. **Sebastian Wandelt:** Conceptualization, Software, Writing – review & editing. **Anming Zhang:** Conceptualization, Validation, Writing – review & editing.

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Appendix

See Fig. 15.

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