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Benchmarking the recovery of air travel demands for US airports during the COVID-19 Pandemic

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ABSTRACT

The aviation industry has gone through numerous ups and downs in the past decades. Despite the devastating damage caused by the COVID-19 Pandemic, the aviation industry worldwide still manages to bounce back from the abyss of Q2, 2020, though the speed of recovery is less than satisfactory for most regions. Being aware of the existing literature on air travel demands published since March 2020, this study aims to provide US Primary Hub airports with benchmarks that can help airports predict the recovery of air travel demand during the COVID-19 Pandemic. This study uses the passenger numbers going through airport security checkpoints as the input data and the k-shape clustering algorithm to group airports by their travel demand recovery patterns. The clustering analysis results are presented in a circular dendrogram so that any of the 118 subject airports can quickly locate their benchmarking airports. In this process, the geographic location and hub category of an airport are found to play important roles in determining how local outbound traffic recovers during the Pandemic. We also test if state political preference in the 2020 Presidential Election affects local airport traffic but cannot find any convincing results. The method used by this study can be fed with up-to-date data to produce more timely and reliable results to guide airports and other stakeholders through the recovery journey.

1. Introduction

The COVID-19 Pandemic has caused unprecedented turmoil to the global economy since the beginning of 2020. To slow down the spread of SARS-CoV-2 and combat its potentially fatal health consequences, national, state, and local governments worldwide have since introduced various strict stay-at-home orders or lockdown restrictions at different stages of the Pandemic. While the intentional mobility control may have contributed to ‘flatten the curve’ during the early stages of the Pandemic, it has caused the aviation industry across the world to a complete stall that was rarely seen before. Using the United States as an example, during mid-April 2020, the number of passengers who went through TSA airport security checkpoints to access commercial aviation was less than 5% of the number reported from the same period in 2019 (Transportation Security Administration, 2021). Measured by the speed and magnitude of air traffic volume contraction, the devastating impact of the COVID-19 Pandemic overwhelmingly tops those caused by other economic or public health crises in living memories.

Despite the ongoing public health threats created by new variants of SARS-CoV-2, the aviation industry has started to recover from the abyss of Q2, 2020. Aggressive quarantine policies and the rolling out of vaccines have partially restored the public’s confidence in air travel, at least for countries and regions where the domestic market size is decent (Chokshi, 2021; Harper, 2021), though frictionless travel across national borders still appears to be less likely in the near future. While the slowly climbing traffic numbers are bringing back some hopes, the aviation industry is now facing a novel challenge: How could the aviation industry predict the recovery of air travel demand during the COVID-19 Pandemic?

Traditionally, commercial airlines rely on the historical data accumulated over the years as the baseline to project future travel demands. External information, such as macro-economic data and destination-specific event schedules, is used to fine-tune the forecasting results for more accurate predictions. However, the shock caused by the COVID-19 Pandemic has dismantled this approach. Airlines quickly realize that one of their most valuable assets, the historical data, has suddenly lost its relevance at least before this Pandemic ends. Neither the pre-COVID data nor the 2020 figures seem appropriate references to forecast what will occur in 2021. And this struggle is likely to continue in 2022 and beyond, given how lingering the Pandemic is when this manuscript was drafted in mid-2021 and subsequently revised in late 2021.

The airline industry and aviation research community are looking for...
alternative signals and approaches to help forecast future travel demands. For instance, Sabre, a Texas-based travel technology company and one of the largest Global Distribution Systems (GDS) providers in the world, reports that airlines are “utilizing(ing) shopping data at an O&K level to get a picture of demand in short to medium-term” (Tanyel and Newell, 2021, p. 13). In academia, scholars are also exploring various new data sources and ways to analyze travel demands. These efforts are summarized in Section 2 of this paper.

This paper aims to help the aviation industry estimate the travel demands during volatile times. Unlike many existing studies that often build complex econometric models to link exogenous explanatory variables with the response variable – travel demands, this paper uses the passenger numbers at the airport level and a robust time-series clustering algorithm, k-shape, to classify airports into various groups based on the patterns of air travel demand recovery during the Pandemic. Potential users of this study are expected to refer to our approach and identify benchmark airports that share a similar recovery pattern to the airport of interest. The additional exogenous factors and the traffic patterns of benchmark airports may help improve the estimation of travel demand recovery for the airport of interest.

The specific research question that this study attempts to answer is: Which airport(s) can be used by a Primary Hub airport of the US as the benchmark to help predict the recovery of air travel demand during the COVID-19 Pandemic?

The rest of this article is organized as follows: Section 2 reviews recent scholarly efforts in analyzing or estimating travel demands since the beginning of the COVID-19 Pandemic. Section 3 documents the procedure of data collection, processing, analysis, and results visualization. In Section 4, we present the research results in the form of a full circular dendrogram and several highlighted airport clusters. Finally, in Section 5, we summarize the primary findings, review the impact of some potential factors, and discuss the implications of this study.

2. Literature review

To fight the most severe public health crisis of the century, researchers of almost all fields have contributed their expertise to SARS-CoV-2 and its impacts, leading to a plethora of COVID-19 related studies published in a relatively short period. In air transportation and tourism research, many scholarly efforts have concentrated on analyzing or predicting the change of travel demands. As this paper was drafted in 2021, the selection of literature includes studies about the demand for air travel or tourism published between early 2020 and mid-2021. Our review focuses on the research subjects, input data, analytical models, and key findings of the selected studies.

With regard to the research subjects, several studies attempt to analyze the global travel demands and compare the performance of major regions (Dube et al., 2021; Gallego and Font, 2021; Gudmundsson et al., 2021; Iacus et al., 2020; Sun et al., 2020). Among studies that target individual countries, China as the region where SARS-CoV-2 was first confirmed has been closely examined, both in terms of its domestic tourism market (Czerny et al., 2021; Warnock-Smith et al., 2021; Yang et al., 2021) and its outbound passengers to overseas destinations (Polyzos et al., 2021). Other countries or regions that appear in the literature include Brazil (Bazzo et al., 2021; Santos et al., 2021), Europe (A. Liu et al., 2021), Germany (Wolle, 2021), Singapore (Li Long et al., 2021), South Africa (Dube, 2021), Turkey (Günay et al., 2020), and the United States (Hotle and Mumbower, 2021; Liu et al., 2020). This limited sample of literature has so far demonstrated diverse and balanced research attention in terms of the selection of research subjects.

Studies analyzing travel demands are data intensive. High-quality input data from credible sources are prerequisites to produce reliable analytical results. Among the reviewed literature, various government agencies and large international organizations are the preferred sources for tourism statistics (Dube, 2021; Gudmundsson et al., 2021; Günay et al., 2020; Zhang et al., 2021) and economic indicators (Santos et al., 2020; Zhang et al., 2021). In terms of historical air travel demands or flight capacity data, conventional sources such as the US Department of Transportation (Hotle and Mumbower, 2021), OAG (Warnock-Smith et al., 2021), Sabre (Iacus et al., 2020; Warnock-Smith et al., 2021), and Cirium (Gallego and Font, 2021) remain as popular choices. Meanwhile, flight tracking websites such as Flightradar24 (Dube et al., 2021; Sun et al., 2020; Wolle, 2021) and OpenSky Network (Iacus et al., 2020) are becoming increasingly popular due to their conveniences and availability in supplying flight level statistics. Researchers are also exploring new sources for informative signals to predict travel demands. For instance, Li Long et al. (2021) investigate more than 1000 Google trend queries to identify queries that can be used to forecast monthly passenger arrivals at Singapore Changi Airport. Similarly, Yang et al. (2021) use the Baidu Index provided by the largest search engine of China to measure tourism demand for 257 5A-level scenic destinations of China. Like what is introduced by Sabre in its recently published whitepaper (Tanyel and Newell, 2021) on the application of shopping data by airlines, Gallego and Font (2021) use Skyscanner data of air passenger searches and picks (purchases) to predict passenger demand recovery.

In terms of the analytical framework, several studies are of a descriptive nature, documenting the destructive effect of the Pandemic in sinking the travel demands and other related tourism indicators (Czerny et al., 2021; Dube, 2021; Dube et al., 2021; Gallego and Font, 2021; Hotle and Mumbower, 2021; Sun et al., 2020; Warnock-Smith et al., 2021). As the purposes of some reviewed studies are to estimate how long and how severe the COVID-19 Pandemic will affect air transportation or the broad tourism sector, econometric methods naturally fit such studies well. These methods include non-homogeneous Poisson process (Iacus et al., 2020), Multivariate Auto-Regression Integrated Moving Average (ARIMA) models with structural changes (Gudmundsson et al., 2021), Autoregressive Distributed Lag (ARDL) – Error Correction Model (ECM) (Zhang et al., 2021), logistic function (Liu et al., 2021), stochastic equations with Gaussian white noise (Wolle, 2021), two-step regression (Santos et al., 2021), and Bayesian structural time-series model (BSTS) (Bazzo et al., 2021). In addition, several studies have adopted various artificial intelligence (AI) based methods, including Long Short Term Memory (LSTM) (Polyzos et al., 2021), and the Neural Granger Causality model (Li Long et al., 2021). In particular, Liu et al. (2021) utilize three frequently adapted AI models, which are neutral network (NN), random forest (RF), and support vector machine (SVM). Another group of methods used by the reviewed studies is scenario-based analysis, where researchers would refer to similar historical events such as SARS (2003), Avian Flu (2005 & 2013), and MERS (2015) and estimate a few different scenarios to predict the likely trajectory of demand recovery during the COVID-19 Pandemic (Günay et al., 2020; Iacus et al., 2020; Liu et al., 2021; Zhang et al., 2021). And the last theoretical framework used by the reviewed literature is spatial analyses conducted by Yang et al. (2021).

The current literature mainly contributes to our understanding of how the COVID-19 Pandemic affects the aviation or tourism industry in three major categories. In the first category, these studies (Gudmundsson et al., 2021; Günay et al., 2020; Iacus et al., 2020; Polyzos et al., 2021; Wolle, 2021) attempt to forecast the likely course of COVID-19 and its potential impact based on historical epidemics, such as SARS, MERS, and Avian Flu. These papers were primarily drafted in 2020, despite their publication years being 2020 or 2021. They usually provide several scenarios and discuss how long the Pandemic will last and when the travel demand is likely to recover to the pre-COVID level. Among these studies, Gudmundsson et al. (2021) provide detailed recovery estimations for different regions of the world, suggesting the impact of the Pandemic on travel demand and the speed of recovery will vary by region.

The second category discusses or advises policies related to COVID-19, including the implication of government policies (Czerny et al., 2021), the importance of virus testing (Dube et al., 2021), financial aids...
and tax breaks for the tourism sector, and vaccinations (Dube, 2021).

The third category of literature analyzes the impact of the COVID-19 Pandemic on travel demand and further breaks down such impact in a disaggregated approach. In their study addressing the impact of COVID-19 on the Chinese airport passenger market, Warnock-Smith et al. (2021) observe the direct link between the infection rate and the disruption of air services. Areas less exposed to the Pandemic, served by stronger air carriers, have been impacted least and are likely to rebound first. Regarding tourism demands to 5A-level scenic destinations in China, Yang et al. (2021) find that cities with developed economies and mature tourism sectors are more severely affected. In addition, cultural scenic destinations or well-known attractions have experienced more severe impacts than natural and religious ones. Sun et al. (2020) notice that international trips have declined more globally compared with domestic operations. In the United States, Hotelel and Mumberier (2021) conclude that due to the CARES Act, which requires airlines to maintain service to domestic destinations served before the Pandemic, airlines generally cut more flights serving larger airports than they do for smaller airports. And airports located in Multiple Airport Regions (MARs) experience a more significant air service decline than airports from Single Airport Regions (SARs). In Brazil, both Santos et al. (2021) and Buzo et al. (2021) observe that shorter routes connecting to local and regional airports are more affected by the Pandemic. In particular, Santos et al. (2021) find that markets that had benefited from the greater social inclusion and recorded high air traffic growth in past years are being hit harder by the Pandemic.

Through the review of existing literature addressing the impact of the COVID-19 Pandemic on air travel or tourism demands, we notice that the air transportation and tourism research community has intensively analyzed the effect of the COVID-19 Pandemic on travel demand, using both aggregated and disaggregated approaches. They have estimated the likely course of how travel demand will react to the development of the Pandemic around the world. Several studies have explored the possibility of using new data and new methods to help predict the recovery of travel demands when traditional reference data and methods may not work well due to the severe disruptions caused by the COVID-19 Pandemic. In light of the contribution made by the existing literature so far, this study aims to provide stakeholders of the air transportation and the tourism sectors a new perspective of benchmarking the recovery of air travel demands at the airport level in the US.

3. Methodology

3.1. Data selection and collection

This study uses the number of passengers going through airport security checkpoints as the target variable to measure and benchmark travel demands at US airports. These passenger numbers (hereafter termed as “TSA numbers”) are collected by the Transportation Security Administration (2021) for each airport that provides commercial aviation and are shared daily with the public. Due to the security check requirements of accessing commercial air transportation in the US, the TSA numbers are a more accurate measure of local travel demands than the passenger enplanement data, the sum of local passenger traffic and connecting passenger traffic. The TSA numbers have been widely used by media and the public of the US since the onset of the COVID-19 Pandemic to measure air travel activities (Politico, 2021; The Hill, 2021; USA Today, 2021).

To measure the disruption caused by the COVID-19 Pandemic to air travel and the recovery of travel demands, we plan to use the TSA numbers before and during the Pandemic to construct a travel demand recovery ratio (noted as r). On March 11, 2020, the World Health Organization (WHO) officially declared the COVID-19 Pandemic (WHO, 2020). However, the significant decline of air traffic in the US started a few days before that. Only for the purpose of this study, we select March 2, 2020 (Monday) as the reference date to divide the pre-COVID period with the COVID period. To build a time-series measuring travel demand recovery ratio, this study uses the 52 weeks before March 2, 2020 (March 4, 2019 – March 1, 2020) as the pre-COVID period. We assume the demand for air travel during the pre-COVID period follows normal patterns that are primarily affected by seasonal effects, economic activities, and operational factors. As of the COVID period, we collect the TSA numbers from March 2, 2020, to the Thanksgiving week of 2021, the latest data available when we revise this manuscript.

To focus on airports where most of the public access commercial aviation in the US, we delimit the scope of airports to Primary Hub airports only. As of 2019, 136 airports are considered by the Federal Aviation Administration (FAA) as Large, Medium, and Small Hubs in the Primary airport category (FAA, 2019). However, the TSA data during the pre-COVID and COVID periods defined by this study contain missing numbers for 18 Primary Hub airports. Therefore, these 18 airports need to be removed to ensure that the length of the time-series representing different airports’ recovery ratios is identical, as the clustering algorithm requires. The final number of airports included in this study for subsequent analysis is 118.

3.2. Data processing and analysis

We aggregate the raw TSA numbers reported hourly on the security checkpoint level to construct practical measures. Large airports like Atlanta Hartsfield-Jackson International Airport (ATL) or Chicago O’Hare International Airport (ORD) typically have multiple security checkpoints. As we are only interested in addressing travel demands at the airport level, reported passenger numbers for checkpoints of the same airports are firstly aggregated to generate the airport data. In addition, the raw TSA numbers are recorded for each hour with actual passenger throughput. These hourly passenger numbers are also aggregated to create daily TSA numbers. After these two aggregation steps, the raw TSA numbers are now converted to time-series representing daily numbers of passengers going through all the security checkpoints of an airport.

TSA numbers for pre-COVID and COVID periods need to be carefully matched to construct a meaningful recovery ratio. As air travel activities are closely related to work/vacation schedules and holidays, we first match weekdays and weekends for the pre-COVID and COVID periods (Refer to Table 1). By doing so, we can reduce the impact of demand variations caused by weekly travel patterns in creating a meaningful recovery ratio time-series. In this case, the travel demand recovery ratio for an airport on any given day during the COVID period could be calculated using the TSA number of that day divided by the TSA number of the matched day during the pre-COVID period.

Matching weekdays and weeks for the pre-COVID period and the COVID period only solve the calendar effect partially. There are still several major holidays that are scheduled based on dates rather than on certain days in a given week, for instance, Independence Day (July 4), Christmas (December 25), and New Year (January 1). When using the matching scheme listed in Table 1, these holidays will be misaligned, thus creating unintended sudden peaks or dips in the recovery ratio time-series. To mitigate this effect of unmatched holidays, we introduce a centered 7-day simple moving average (7-SMA) to smooth the raw TSA numbers. To calculate the 7-SMA for every day from March 4, 2019 to November 28, 2021, we need to expand the time horizon of raw data by three more days on both ends. After this step, the extended time horizon for data collection starts on March 1, 2019, and completes on December 1, 2021.

See Fig. 1 for the comparison of raw TSA numbers (daily aggregated) and the 7-SMA at Atlanta Hartsfield-Jackson International Airport (ATL).

For each airport, the travel demand recovery ratio, r, can be easily computed using the 7-SMA of the COVID period divided by the pre-COVID period. The length of the travel demand recovery ratio time-series is 637 days (March 2, 2020 – November 28, 2021). To enable
the subsequent clustering analysis, we apply z-normalization to all the time-series representing recovery ratios of the 118 selected airports. Normalized recovery ratio is noted as $r_{\text{normal}}$. See Fig. 2 for both the original and normalized recovery ratio time-series of ATL airport.

Prior studies have shown that air transportation correlates closely to the airport hub category and its geographic location (Gao and Sobieralski, 2021; Tan and Samuel, 2016; Zhang et al., 2013). We intend to test if the travel demand recovery at the airport level also correlates to these factors. In this study, travel demand recoveries of airports from the same hub category and region are to be plotted in the same chart to visually examine if they follow similar patterns and are closely clustered together. Such examinations could provide insights to understand factors behind travel demand recoveries at national airports.

In the US, the analysis of COVID-19 related topics often involves examining the political preference of different regions (Ellis, 2021; Medina and Gebeloff, 2020; Migdon, 2021). The media and public seem to be obsessed by the divergence between “red states” and “blue states.” We, therefore, hypothesize the influence of political preference on the travel choices of local travelers. Intuitively, it would be more meaningful to examine such hypothetical relations within the airport catchment areas. However, in actual practice, most hub airports analyzed in this study are in metropolitan areas, where residents predominantly voted for the Democratic candidates in recent Presidential Elections. Therefore, we are unable to test the impact of political factors on the airport catchment area level but have to compare this effect on the state level. The state political preferences are plotted along with the clustering

| Table 1 | Pre-COVID and COVID periods. |
|---------|-----------------------------|
|         | Monday | Thursday | Sunday | Sunday |
| **pre-COVID period** | | | | |
| (3/4/2019 – 3/1/2020) | 3/4/19 | … | 11/28/19 (Thanksgiving) | … |
| **COVID period** | | | | |
| (3/2/2020 – 2/28/2021) | 3/2/20 | … | 11/26/20 (Thanksgiving) | … |
| (Beginning) | (Beginning) |
| **COVID period (Continued)** | | | | |
| (3/1/2021 – 11/28/2021) | 3/1/21 | … | 11/25/21 | … |
| (Thanksgiving) | (Thanksgiving) | (Thanksgiving) |

Fig. 1. Comparing raw TSA numbers and 7-SMA at ATL.

Fig. 2. Original and normalized demand recovery ratios of ATL.
result to see if airports from states which voted for the same candidate in the 2020 US Presidential Elections display similar air travel recovery patterns.

To cluster recovery ratio time-series based on the timing and magnitude of data variations, we apply \textit{k-shape} clustering, an algorithm introduced by Paparrizos and Gravano (2015). \textit{k-shape} clustering uses Dynamic Time Warping (Berndt and Clifford, 1994) as the distance measure to compare two time-series and determine if they are similar. Compared with conventional distance measures such as Euclidean distance, Dynamic Time Warping is more robust in tolerating temporal distortion between different time series. In other words, Dynamic Time Warping is effective in finding time-series that are similar to each other in terms of their shapes but does not require different time-series to be identical. Gao (2021) uses \textit{k-shape} clustering and TSA passenger numbers to analyze passenger arrival patterns. In this study, we apply the \textit{dtwclust} package of R (Sarda-Espinosa, 2019) to implement the \textit{k-shape} clustering on travel demand recovery ratio time-series.

3.3. Results visualization

Due to the number of airports being analyzed, presenting the clustering results in a viewer-friendly format is challenging. Horizontal or vertical dendrogram, often used by clustering studies, packs a large amount of information sequentially in a confined space, making it challenging to identify subjects of interest. To improve this, we apply a circular dendrogram to display the clustering analysis results and other relevant background information, such as hub category, regional affiliation, and the electoral votes of the state that the airport is located in the 2020 US Presidential Election.

In addition to the circular dendrogram, certain airport clusters are selected for thorough analyses to help further understand the progress of travel demand recoveries. Data visualization showing the course of travel demand recovery could confirm the accuracy of clustering analysis and present crucial demand variations along the temporal scale.

4. Results

4.1. Demand recovery overview

The analysis results show that all hub airports in the US have experienced severe demand decline since the start of the COVID-19 Pandemic. Travel demands at most airports dropped to the bottom in April 2020 and have only started to recover slowly since. While air travel of several airports from mainly southern regions has recovered to their pre-COVID levels in late 2021, there are still quite several airports struggling to achieve so, for instance, airports from the Eastern, Great Lakes, and New England regions.

A visual inspection of how the recovery ratio fluctuates and if airports of the same region display similar patterns finds that the location of an airport plays a vital role in determining the travel demand recovery (Fig. 3). The travel demands of airports of Alaska, the Central region, the Eastern region, the Great Lakes region, the New England region, and the Southwest region show homogeneous patterns. Meanwhile, demand recoveries in the Northwest Mountain, Southern, and Western Pacific regions have wide variations.

Compared with the regional plot (Fig. 3), the travel demand recovery ratio plot by hub categories (Fig. 4.) shows greater variations between different airports. This is partially caused by the number of airports included in each hub category and shows that the hub category alone may not be a significant factor in determining how travel demand would recover. Large Hub airports present the lowest variations in recovery ratios within the three hub categories, and Small Hub airports show the highest variations. The persistently low recovery ratio line in the Small Hub category of Fig. 4 (and Western Pacific group of Fig. 3) is of Guam International Airport (GUM), where inbound traffic has suffered from restrictions imposed on international air travel since the beginning of the Pandemic.

4.2. Full dendrogram

The full results of the clustering analysis are illustrated in Fig. 5 in

![Comparing demand recovery ratios by regions](image-url)

**Fig. 3.** Travel demand recovery ratio plot by regions.
the form of a circular dendrogram. In addition to airports (using the FAA Location Identifier) and the similarities between different airports measured by the Dynamic Time Warping distances, this circular dendrogram also shows airports’ regional affiliation and the two-party preference in the 2020 Presidential Election of the state where the airport is located.

Judged by the information presented in Fig. 5 (the outer ring), the state political preference in the 2020 Presidential Election is not an influential factor in determining the clustering affiliation of an airport in the dendrogram, thus indicating the political factors alone are not effective in predicting the travel demand recovery pattern. The regional affiliation visualized by the inner ring shows spatial continuity between airports. However, several “outlier” airports are placed closely with distant airports. For instance, travel demand recoveries of Tampa International Airport (TPA) in Florida and Phoenix Sky Harbor International Airport (PHX) in Arizona are similar. Detailed analysis of different airport clusters is presented in Section 4.3.

4.3. Selected clusters

This section plots the raw travel demand recovery ratios by airport clusters. A total of 18 airport clusters are visually presented in Figs. 6–9. Airports that appear in the same chart resemble each other in terms of how travel demands recover. For the convenience of viewing, recovery ratio lines of the subject airports in each chart are color-coded. The rest of the airports are included (in grey) in each chart for referencing.

A thorough examination of airport clusters leads to the identification of several potential factors affecting the recovery of travel demands at the airport level. Firstly, the geographic location of an airport plays a decisive role in the recovery process. The majority of airports clusters contain mostly airports from the same region, for instance, Hawaii Airports (HNL, KOA, and OGG), Florida Small Hubs (ECP, VPS, RSW, SRQ), and South Atlantic Coast (MYR, ILM, CHS, and SAV) in Fig. 6, and various airport pairs in Fig. 9. Secondly, airports of the same hub category typically display similar travel demand recovery patterns, such as West Central Small Hubs (RNO, RDM, BOI, MFR) and South Small Hubs (HSV, XNA, CAE, GSO) in Fig. 7, and East Gateway Airports (EW, ORD, IAD, JFK) in Fig. 8. Thirdly, the traffic composition (business vs. leisure) at an airport largely dictates the level of travel demand recovery. Airports traditionally dominated by business travelers, e.g., IAD and JFK in Fig. 8 show much slower recovery than airports filled by leisure travelers, for instance, airports serving vacation destinations in Fig. 9. Finally, airports that had a higher percentage of long-haul traffic, such as GUM, SFO, LAX, EWR, JFK, before the COVID-19 Pandemic are showing a much slower recovery than airports with predominantly domestic traffic, largely due to the travel restrictions that still apply to several international markets as of late 2021.

5. Conclusions and discussions

The impact of the COVID-19 Pandemic on air travel demand is unprecedentedly devastating. It only took a few weeks for the passenger numbers across the US to drop from normal levels in early March 2020 to less than 10% of the pre-COVID levels a month later. Since then, the air travel demand has started to recover. However, the recovery is slow and coupled with frequent turbulences, clearly visible in Figs. 6–9. In March 2021, almost a year after entering the Pandemic, travel demands at most airports analyzed in this study had not recovered to 50% of the pre-COVID level. Followed by the rolling out of vaccines, the recovery speed started to pick up since April 2021. A more detailed examination of how travel demand changed at different airports reveals a diverse and complex landscape in which traffic at certain airports is more resilient. Travel demands at these airports bounced back quickly, showing an emerging trend of new travel patterns during the Pandemic.

This study investigates a few factors that may affect how travel demands recover at different airports. The clustering analysis results show that the geographical location of an airport plays a vital role in determining its air travel demand. Airports from the same region usually display similar patterns regarding the magnitude and timing of demand recovery. Hub status is another factor visible in the results of the travel demand recovery clustering analysis. Though not all the airports of the same hub category are closely clustered, a few large hubs display similar travel demand recovery patterns.

Air travel for business purposes has tumbled to historically low levels since the beginning of the COVID-19 Pandemic because of the health concerns and the widely adopted work-from-home (WFH) policies. This shift in travel behaviors produces evident outcomes at airports traditionally sustained by business travelers, e.g., Washington Dulles International Airport (IAD) and New York John F. Kennedy Airport (JFK). In addition, due to various nations’ uncoordinated approach and frequent border-closure decisions, airports that previously served as international gateways, e.g., East Gateway Airports and California Major Airports (Fig. 8), are still seeing weaker demand as of late 2021. Meanwhile, travel demands to leisure destinations, for instance, Florida airports and airports serving national parks, bounced back quickly and firmly (Robertson, 2020). This is visible in some airport clusters in Fig. 6.

As mentioned in previous sections, we test the potential impact of state political preference on residents’ travel behaviors. Results presented in Fig. 5 show that though certain airports from states of the same political preference are clustered, for instance, East Gateway Airports.
and Northeast Hubs (Fig. 8), there are also several clusters containing airports from states of distinctive voting preferences in the 2020 Presidential Election. Therefore, we conclude that the state political preference alone is not a good predictor of how the travel demand of an airport recovers during the COVID period defined in this study (March 2020–November 2021).

This study aims to identify airports where the travel demands recover in similar patterns so that these airports can be used as benchmarks for each other in helping predict future travel demands. We test and identify a few factors that shape travel demands at the airport level, namely geographical locations and hub categories. Behind these factors are the spatial continuity of local economic structures and residents’ travel behaviors. Also, travel demands are known to spill over from large hub airports to smaller airports in the vicinity (Gudmundson et al., 2014) and leak from smaller airports to large substation airports (Gao, 2020; Kim and Ryerson, 2018). Airport operators, therefore, should eye benchmark airports identified in this study to enrich the input information when predicting future travel demands. By doing so, they would expect more reliable prediction results than what is derived solely from complex statistical models. Such results could be invaluable when conventional indicators are less effective.

We do not test the effect of mobility restricting orders adopted by various states in the early stages of the Pandemic on travel demands due to several practical constraints. Data with regard to the start and end of lockdown orders are not available for all 50 states, and the enforcement of such orders varies significantly across different states. In addition, it is not uncommon for US airports to attract travelers residing in multiple neighboring states, especially for large hubs. Therefore, it is technically challenging to determine which state policy should be considered when assessing the impact of such policies on the travel demand of an airport. The omission of this analysis could be considered as a limitation of this study.

The analysis of this study is limited to March 2020–November 2021. For airports interested in identifying more timely benchmarks, they are recommended to plug in newer data and use the methods of this study to produce updated results. When doing so, airports need to decide if they...
Fig. 6. Travel demand recovery ratios – Plot 1.
Fig. 7. Travel demand recovery ratios – Plot 2.
Fig. 8. Travel demand recovery ratios – Plot 3.
Fig. 9. Travel demand recovery ratios – Plot 4.
should use the 2019 or 2020 data as the referencing travel demand. For the purpose of results continuity (in terms of travel demand recovery ratios), we recommend airports to use March 2019 – February 2020 as the baseline to construct longer time-series of travel demand recovery ratios. Meanwhile, it needs to be noted that the results of this study apply to passenger demands only. Airports dominated by cargo operations need to identify appropriate cargo-performance data as the target variable to replace the TSA data used in this study.

CRediT authorship contribution statement

Yi Gao: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

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