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Airline strategies during the pandemic: What worked?

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ABSTRACT

An examination is conducted of airline strategies during the covid-19 pandemic using data from the United States. Our findings show that airlines pursued diverse strategies in terms of route entry and retention, pricing, and load factors. At the route level, a more detailed examination is conducted of the performance of a middle-seat blocking strategy designed to increase the safety of air travel. We show that this strategy (i.e., not making middle seats available to passengers) likely resulted in revenue losses for carriers, an estimated US $3,300 per flight. This revenue loss provides an indication as to why the middle seat blocking strategy was discontinued by all US airlines despite ongoing safety concerns.

1. Introduction

Although it has become a cliché to describe events during the covid-19 pandemic as "unprecedented", the term may aptly be applied to the collapse in traffic realized by airlines and the resultant loss in revenues. U.S. airlines experienced an expected loss of $35 Billion in 2020,[1] while worldwide airlines were expected to lose $157 Billion.[2] According to estimates from the U.S. Federal Aviation Administration (FAA),[3] total passenger enplanements across all the 446 commercial service airports in the U.S. dropped by more than 60% from 935 million in 2019 to 368 million in 2020. The decline in passenger demand caused airlines to discount airline tickets. On U.S. domestic routes, average airfares fell by more than 18% from $359 in 2019 to $292 in 2020, the lowest level since 1995 after adjusting for inflation.[4]

To improve their cash positions, airlines engaged in strategies to reduce costs and increase cash flow. To reduce costs, airlines grounded aircraft, retired older fleets, lobbied governments for tax relief and labor subsidies, laid off staff and provided employees with incentives for early retirements. To generate cash, airlines repositioned aircraft from business-oriented routes to (the less impacted) leisure routes, cut prices, converted aircraft to cargo operations, offered promotional deals including complementary covid-19 travel insurance, and lobbied governments for loans, equity investments, and direct aid (Adrienne et al., 2020; Albers and Rundshagen, 2020; Bombelli, 2020; Czerny et al., 2021; Wenzel et al., 2020; Tay et al., 2020). In addition, airlines sought to generate

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[1] https://www.cnbc.com/2021/01/01/us-airline-2-losses-expected-to-top-35-billion-in-dismal-2020-from-pandemic.html, accessed June 7, 2021.
[2] https://www.cnn.com/2020/11/24/business/iata-airlines-coronavirus/index.html, accessed June 7, 2021.
[3] https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/, accessed October 4, 2021.
[4] https://www.bts.gov/newsroom/average-air-fares-dropped-all-time-low-2020, accessed October 4, 2021.

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demand by reassuring passengers of increased safety-related procedures; for example, by changing boarding processes (e.g., boarding from back to front of aircraft), improving the cleaning regimen between flights, mandating facemasks, and leaving the middle seats open to increase social distances (Barnett and Fleming, 2020; Dube et al., 2021; Li, 2020; Milne et al., 2021). Moreover, when the covid-19 vaccine became available, many airlines required staff to be vaccinated and proof of vaccine to be provided by the traveling public.[5]

Did the pandemic-induced strategies work? For this paper, we use U.S. data to assess the impact of the strategies on airline performance. We review several of the pandemic strategies at the airline level and then examine the middle seat blocking strategy at the more micro, route level. Blocking middle seats may decrease passenger load factors but should be offset by higher yields. If both load factors and yields fall for the airlines with middle seats blocked, this would be an indication that the strategy is not successful from the financial consideration. However, if the higher yields produce sufficient revenues to offset the lower load factors, then the strategy may be considered successful.

In conducting this research, we make use of the differences in strategies undertaken by U.S. airlines. Most notably, airlines exhibited considerable variation in their middle-seat blocking strategies. Delta Air Lines made the greatest use of this strategy, blocking middle seats from April 2020 to April 2021, when it finally rescinded the policy. On the other hand, United Airlines never implemented the policy, while American Airlines implemented the policy for a shorter period, from April 2020 through June 2020. We examine how the middle-seat blocking policy may have benefited or cost Delta, along with the other U.S. airlines that engaged in this strategy.

Our major results show that the middle seat blocking strategy did lead to lower load factors, with a decrease of about 4.75 percentage points when middle seats were blocked (although, if the blocked middle seats are excluded from the seat total, the "effective load factor" actually increased by 12.28 percentage points). The middle seat blocking strategy also did not contribute to higher yields suggesting that the strategy may not have been effective at getting passengers to pay extra for the safety associated with the blocked middle seat. Yields were lower by $0.026 per revenue-passenger mile when the middle seats were blocked. Finally, airlines blocking middle seats operated routes with higher seat shares of about 2.1% and higher passenger shares of 7.93%.

Based on a mean plane size of 168 seats, a mean load factor of 53%, a mean yield of $0.12/revenue-passenger mile, and a mean route distance of 1,119 miles, the blocking of the middle seat on average resulted in decreased revenues of about $3,300 per flight.[6] Although the middle seat-blocking strategy may have conferred longer-term benefits to airlines, such as the perception of better safety or quality, in the short run, the strategy appears to have resulted in revenue losses. Therefore, it is not surprising that some airlines never instituted the policy, while others quickly rescinded the policy after implementation.[7]

This paper contributes to the growing literature on how the covid-19 pandemic impacted airline operations. Prior research describes how the pandemic has negatively affected the airline industry through decreased demand and lower revenues (e.g., Czerny et al., 2021; Iacus et al., 2020; Suau-Sancheza et al., 2020; Tay et al., 2020), led to various "pivot" strategies undertaken by the airlines to respond to the pandemic (Adrienne et al., 2020; Amankwah-Amoah, 2020; Bauer et al., 2020; Czerny et al., 2021), and resulted in measures undertaken by the airlines to reassure passengers and increase the safety of operations (Barnett and Fleming, 2020; Dube et al., 2021; Milne et al., 2021; Bielecki et al., 2021). Moreover, Hyman and Savage (2021 & 2022) have examined the impact of the middle seat blocking strategy used by Delta Air Lines and Li (2020) has undertaken a SWOT (strengths, weaknesses, opportunities, and threats) analysis of the middle seat blocking strategy. We add to this literature by demonstrating the variations in strategies undertaken by U.S. carriers in response to the covid-19 pandemic, and then by using a wide sample of routes and carriers to analyze the impact on carrier operations of the blocking of middle seats.

The rest of the paper is organized as follows. Section 2 reviews the aviation-related pandemic literature. Section 3 presents an industry-level descriptive analysis of U.S. airline operations during the pandemic period. Section 4 describes our econometric model and the data used to assess the performance impact of the middle-seat blocking strategy. Section 5 presents our results. We conclude with a discussion of our results, the limitations of this research and suggestions for future research projects.

2. Literature review

2.1. Covid-19 impact on airlines[8]

The covid-19 pandemic was first reported in China in January 2020. By April 2020, 17,000 aircraft had been grounded,

[5] See Bielecki et al. (2021) for a full review of preflight and in-flight measures taken by the major airlines worldwide to mitigate the potential virus transmission among passengers traveling during the pandemic period.

[6] These means are based on operations without middle seats blocked. As noted, load factors fell, and yields increased when middle seats were blocked.Calculations are as follows:WITHOUT MIDDLE SEAT BLOCKING:168 seats X 0.53 pax/seat = 89 pax/flight$0.115/m X 1,119 m = $129/paxRevenue = 89 pax/flight X $129/pax = $11,481/flightWITH MIDDLE SEAT BLOCKING:168 seats X 0.48 pax/seat = 81 pax/flight$0.09/m X 1,119 m = $101/paxRevenue = 81pax X $101/pax = $8,181/flightNET REVENUE from MIDDLE SEAT BLOCKING = $8,181– $11,481 = -$3,300/flight.

[7] Our results are consistent with Hyman and Savage (2021 & 2022) who examined the airfare and market share effects of the middle seat-blocking strategy adopted by Delta Air Lines. Hyman and Savage (2021 & 2022) do find that there is a positive willingness to pay from passengers for the blocking of middle seats; that is, yields are higher when middle seats are blocked. We find lower yields when middle seats are blocked and when airline-fixed effects are included in the estimation. When we estimate our yield equation without airline-fixed effects, our results are consistent with Hyman and Savage (2021 & 2022).

[8] An excellent summary of the impact of the pandemic on airlines is provided in Sun, et al. (2021).

representing 64% of the world's fleet. Airlines were projected to lose hundreds of billions of dollars in revenues during the pandemic as governments issued stay-at-home directives and restricted international travel (Adrienne et al., 2020). Between March 2020 and July 2020, 19 airlines had declared bankruptcy, including larger, well-established airlines, such as the South American-based carrier, LATAM, with a fleet of 315 aircraft (Czerny et al., 2021).

Tay et al. (2020) note that airlines have been differentially impacted by the pandemic. Airlines that have done better (than average) tended to have had stronger pre-pandemic balance sheets, operate in countries with large domestic markets (that have been subject to fewer travel restrictions than international markets), and have benefitted from direct governmental support, such as labor subsidies, loans and capital injections and/or indirect governmental support, such as the waiving of "use-it-or-lose-it" requirements for airport slots. Airlines specializing in freight transport fared better than (mainly) passenger airlines. With surging demand for protective equipment, medical devices, and accelerated online shopping, integrators, such as FedEx and DHL, were able to perform relatively better than carriers with limited cargo operations during the pandemic. According to a report by Boeing (2020),[9] integrators experienced an increase in air cargo traffic of 14% in the first nine months of 2020 compared to the same period in 2019. Similarly, cargo-only airlines carried 6% more air cargo from January to September in 2020, compared to the same period a year earlier. Moreover, as suggested by Bombelli (2020), the global route networks of air cargo operators were more resilient and recovered more quickly than the (mainly) passenger networks, leading to better performance results.

Iacus et al. (2020) and Suau-Sancheza et al. (2020) compare the impact of covid-19 on air transport to the impacts from previous pandemics, including SARS in 2003, the Avian Flu in 2005 and 2013 and MERS in 2015. The authors find that the 2003 SARS pandemic previously had the most serious effect on aviation. Its impact was mainly in the Asia-Pacific region, with traffic volumes in that region down about 35% at the peak of the pandemic. Recovery from the pandemic to pre-outbreak levels took about 6 months. Gudmundsson et al. (2021) estimated that it would take 2.4 years for the global air passenger traffic to recover from covid-19 to pre-pandemic levels, with the forecasted recovery time varying by region.

2.2. *Impact of air mobility on viral spread*

The main rationale for direct governmental restrictions on aviation, such as bans on international flights, is that air travel is believed to contribute to viral transmission. Gössling (2020) and Christidis and Christodoulou (2020), for example, state that air travel is a vector for the spread of pathogens and diseases, including covid-19. The risks of viral spread facilitated by air transport have been identified and quantified for previous epidemics; for example, with respect to the MERS epidemic in 2015 (Poletto et al., 2016), the Ebola epidemic in 2014 (Bogoch et al., 2015), and the SARS epidemic in 2003 (Bowen and Laroe, 2006; Gardner et al., 2016). Hosseini et al., (2010) provide empirical evidence that the high connectivity of global air travel network was a critical factor facilitating the rapid global spread of the A/H1NA influenza in 2009 and 2010, leading to the first pandemic in the 21st century. Moreover, air transport may contribute to higher mortality rates since it may help spread lethal viral mutations from country to country. Instead of using the traditional geographic distance between nodes (cities/countries), Brockmann and Helbling (2013) develop a unique measure called effective distance, which is based on the most probable path between two nodes in a given air mobility network. The use of effective distance measurement enables the calculation of arrival times of a contagion, even without considering epidemiological parameters such as viral reproduction rate and recovery rate. The authors use their effective distance measure to simulate the diffusion of the 2009 H1N1 influenza virus and 2003 SARS infections and find that this measure can successfully predict viral spread and arrival times in the context of a global, air transport mobility network.

Air travel may be restricted by governments during a pandemic because the travel mode, itself, may be unsafe due to the transmission of viruses within the closed quarters of aircraft cabins and airport facilities. Aircrafts have been described as incubators of respiratory pathogens due to the density of passengers in cabins (Gössling 2020). Barnett and Fleming (2020) seek to determine the increased risks for infections and mortality due to viral transmissions among passengers while flying. The authors use stated infection and mortality data from covid-19 and a probabilistic model to estimate the viral risks to a passenger traveling on a two-hour flight. The authors calculate the chance of catching the coronavirus at about 1 in 3,900 if the flight is full and 1 in 6,400 if the middle seats are left empty.[10] Given mortality rates from the virus, 1 in 710,000 air passengers could expect to encounter a fatal exposure to the coronavirus on a full flight. If the middle seat is left empty, the fatality rate from the coronavirus is predicted to fall to 1 in 920,000 passengers.

In summary, aviation may increase the transmission of covid-19 in two ways – through the actual process of traveling, including transmission while in aircraft, and by spreading the virus to the populations in cities across the route networks operated by airlines. Although the possibilities of contacting covid-19 or dying from the virus that is caught while flying are likely small, researchers have found that they can be made even less likely by leaving middle seats empty (Barnett and Fleming 2020).

2.3. *Airline strategies to combat Covid-19*

Airlines have engaged in a diverse array of strategies to respond to the decline in passenger demand due to the pandemic. These strategies can be divided into three categories: (1) cost reduction; (2) cash flow enhancement; and (3) safety improvement. The cost reduction strategies include, the grounding of aircraft, the retirement of entire fleets (of mainly older, less efficient aircraft) (Adrienne

[9] See Boeing's World Air Cargo Forecast 2020–2039 at https://www.boeing.com/resources/boeingdotcom/market/assets/downloads/2020_WACF_PDF_Download.pdf, accessed in Oct. 26, 2021.

[10] Calculations do not assume passengers are vaccinated against the coronavirus.

et al., 2020) and workforce layoffs and salary cuts (Amankwah-Amoah, 2020). Cash flow-enhancing strategies include, reducing fares to stimulate demand, lobbying governments for loans, equity investments, wage subsidies (Amankwah-Amoah, 2020) and repositioning aircraft to better respond to changing demand, such as shifting aircraft to service increased cargo flows, better serve leisure passengers, or to provide increased non-stop routings (Bauer et al., 2020). Safety measures implemented by airlines include the blocking of middle seats to increase social distancing (Barnett and Fleming, 2020; Li, 2020), the installation of better cabin air filtration systems, the improvement in cleaning procedures on aircraft (Dube et al., 2021), the enhancement of passenger screening measures, including temperature checks and covid testing, the mandating of facemasks on aircraft (Dube et al., 2021), improved protective equipment for cabin crews (Dube et al., 2021), and safer boarding procedures (Milne et al., 2021).

For this paper, we expand research on pandemic aviation strategies by examining the impacts of key strategies on airline performance. We then use an airline-route-level dataset to analyze, in greater detail, the impact of a middle-seat blocking strategy on three measures of airline performance – load factors, yields and seats shares. The airfare and market share effects of blocking middle seats are also studied in Hyman and Savage (2021 & 2022). Focusing on non-stop routes with the presence of Delta Air Lines, United Airlines, and American Airlines, and a subset of those routes where Delta directly competes with at least one of the two rivals, Hyman and Savage (2021 & 2022) find that Delta's middle-seat blocking strategy is associated with higher yields and market shares. In our study, we use a wider data sample to investigate the adoption of middle-seat blocking strategies by a larger number of U.S. carriers and estimate performance effects using a broad set of origin-and-destination routes, including direct and connecting routings. Our findings provide direct evidence that the strategy, on average, results in revenue losses for carriers, likely contributing to the decision by airlines to either forego the middle seat blocking strategy or terminate the strategy after implementation.

3. Airline pandemic strategies

In this section, we analyze the operational strategies of the four largest U.S. airlines, American, Delta, United and Southwest, describing how they adapted during the first year (2020) of the covid-19 pandemic. The strategies undertaken by the airlines varied considerably. While all four airlines dramatically reduced their flight operations after the onset of the pandemic to save operating expenses, our analysis shows that their pre-pandemic strategies and route network structures influenced their operational responses to the pandemic.

As shown in Table 1, Southwest was the largest airline in the U.S. by passenger enplanements in 2019. However, as opposed to the other three airlines, it had a greater focus on domestic routes, with international traffic accounting for only 3% of its total passenger traffic. In comparison, the share of international traffic ranged from 16% to 25% for the other three airlines. The focus on domestic markets, with fewer international destinations, made Southwest less vulnerable to the closing of international markets during the pandemic since it was less reliant on international traffic to feed its domestic routes. As a result, Southwest was in a better position to maintain its domestic route structure following the onset of the pandemic, compared to American, United and Delta.

Fig. 1 compares the number of origin-and-destination (O&D) routes offered by the four airlines in 2020 to the corresponding quarter in 2019. The figure shows that Southwest was the least aggressive of the four airlines in cutting routes during the pandemic, maintaining over 70% of its route total during the lowest point for airlines during the pandemic – the second quarter of 2020. The other three airlines reduced their route offerings by 60–65%, thus retaining only about half the routes (in percentage terms) as Southwest. Although the three network carriers all brought back routes during the third and fourth quarters of 2020, a gap in routes offered (compared to 2019) between Southwest and the three network carriers remained throughout the year.

The network structure of Southwest is distinct from the structures of the other three airlines, with a higher value for network density of 0.159, compared to 0.030 for American Airlines, 0.029 for United, and 0.024 for Delta Air Lines. Network density is defined as the ratio of the number of non-stop flight segments relative to all potential origin-and-destination connections within an airline's route network.[11] Therefore, an airline that operates a hub-and-spoke system has a lower density measure, since most passengers only have indirect connections through the hub, while an airline that operates a point-to-point network has a higher density measure, since the network offers a greater percent of nonstop origin-and-destination flights. Compared to a hub-and-spoke route structure, a point-to-point route structure could give an airline more flexibility to withdraw from routes or add new destinations with less disruption to the rest of the route network.[12]

As noted by Gary Kelly, the CEO of Southwest, the ability of Southwest to rapidly add vacation destinations to target leisure travelers during the pandemic enabled the airline to turn the pandemic crisis into an opportunity to outcompete its rivals.[13] After cutting its domestic routes from 1,404 in the second quarter of 2020 to 1,094 in the third quarter of 2020, Southwest quickly reversed this trend, adding 204 new routes into its network in the fourth quarter of the year, flying to several new destinations in Florida, Colorado, California, and Georgia that appealed primarily to vacation travelers.

Another factor that could impact the ability of an airline to maintain its network is its relationship with regional carriers since regional carriers provide traffic feed for network carriers, such as American, Delta and United. Of the three network airlines, Delta reported about 15% of its passenger revenue was derived from traffic feed provided by its regional carriers under capacity purchasing

[11] Network density values are calculated using monthly schedule data for the four airlines on domestic routes in 2019.

[12] With a hub-and-spoke network, withdrawing from a route impacts all other routes, since the network depends on traffic feed from all routes into the hub. Withdrawing from too many routes can impact the viability of the network.

[13] See the article "A strategy session at 40,000 feet: how Southwest Airlines used the pandemic to outmaneuver the majors" by Shawn Tully, published on Fortune.com, June 18, 2021.

Table 1
Passenger Enplanements of the Four Largest U.S. Airlines in 2019.

Airline (Rank)	Total Pax. In Mln.	Domestic Pax. In Mln. (% of Total)	International Pax. in Mln. (% of Total)
Southwest Airlines (1)	162.681	158.419 (97.4%)	4.263 (2.62%)
Delta Air Lines (2)	162.494	136.241 (83.8%)	26.280 (16.2%)
American Airlines (3)	155.785	126.031 (80.9%)	29.754 (19.1%)
United Airlines (4)	116.256	87.472 (75.2%)	28.784 (24.8%)
Total Scheduled Pax. Traffic	1,052.8	811.5 (77.1%)	241.3 (22.9%)

Data Source: The U.S. Bureau of Economic Analysis.

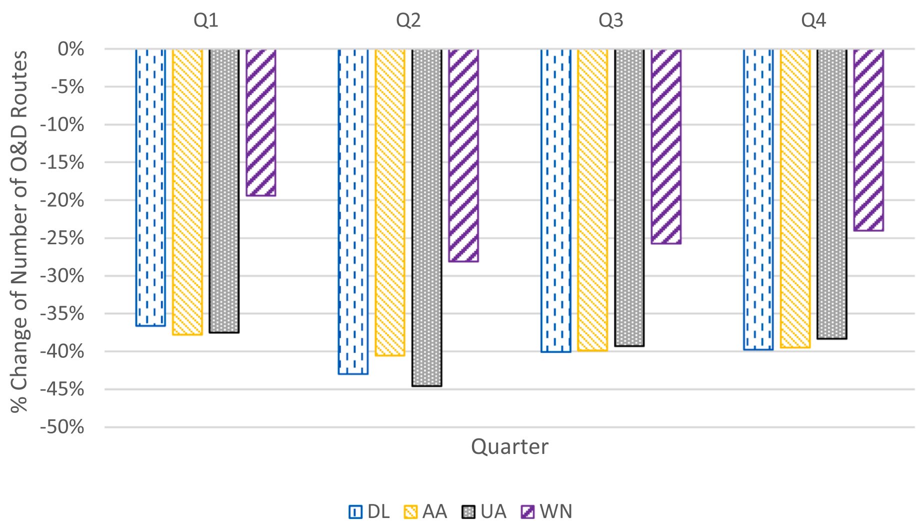

Fig. 1. The % Change of Number of O&D Routes in 2020 vs. 2019 Data Source: U.S. DOT O&D Data Collected from Cirium Diio Mi.

agreements in 2019.[14] In comparison, United Airlines reported about 11% of its capacity was operated by regional carriers that year, while American Airline reported that about 27% of its passenger enplanements were provided by its regional affiliates (owned or contracted) in 2019.

The relatively high use by American Airlines of regional carriers may have helped it maintain its network during the pandemic, since the regional services can be operated with fewer passengers. Network carriers, such as American, Delta and United, may act to maintain the centralized structure of their hub-and-spoke networks to run feed through their hubs. As shown in Fig. 2, the average degree of centrality[15] across all the airports in American's domestic route network dropped by only 0.43% (from 0.257 to 0.256), while it dropped by 11.29% for United (from 0.261 to 0.232), by 8.77% for Delta (from 0.232 to 0.211), and by 6% for Southwest (from 0.378 to 0.356) in the 2nd quarter of 2020, as compared to the same quarter of 2019. Similarly, Fig. 3 shows that the average degree of closeness centrality for American Airlines across all the airports in its domestic route network remained almost unchanged (i.e., 0.57735 vs. 0.57744) in the 2nd quarter of 2020, as compared to the same quarter of 2019, while the average degree of closeness centrality decreased by 3.62% for United (from 0.575 to 0.554), by 2.48% for Delta (from 0.561 to 0.547), and by 2.34% for Southwest (from 0.617 to 0.603).

American's ability to rely on its regional carriers may have also allowed the airline to limit its capacity and route reduction after the onset of the pandemic. To save operating expenses, all four airlines substantially reduced their flight operations during the pandemic. United Airlines cut its flights on domestic routes by 54.4% in 2020 relative to 2019 and Delta by 44.3%. However, American only reduced its flights by 42.4%, and Southwest's reduction of 33.6% was even lower. Seat capacity reductions were of similar magnitudes – 54.4% by United, 44.2% by Delta, 41.5% by American, and 32.6% by Southwest.

As shown in Figs. 4 and 5, all the four major carriers started trimming their domestic flight operations in March 2020, with the greatest reductions in May 2020. Compared to United and Delta, American made a smaller reduction in flight and seat capacity,

[14] Data are based on the airlines' 2019 10-K filings to the U.S. Securities and Exchange Commission.
[15] See Cheung et al. (2020) for definitions of these centrality measures.

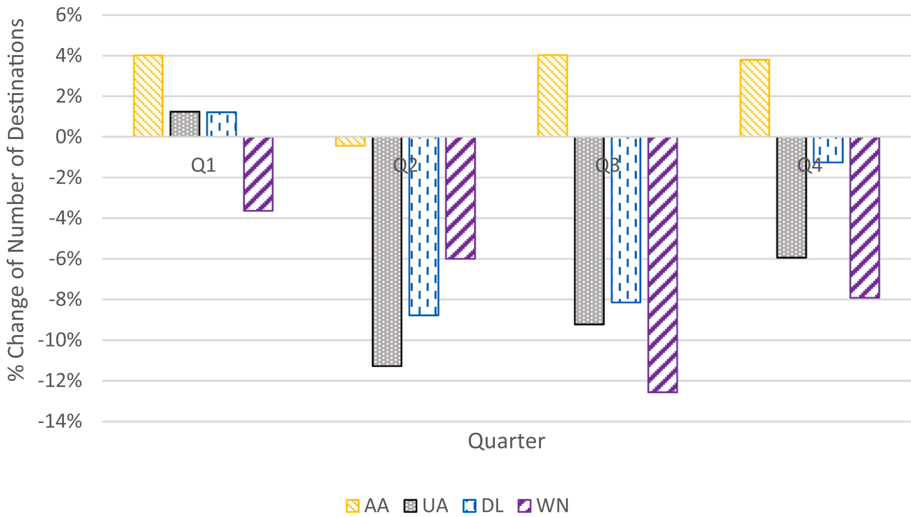

Fig. 2. The % Change of the Average Degree of Centrality in 2020 vs. 2019 Data Source: Cirium Diio Mi Schedule Report.

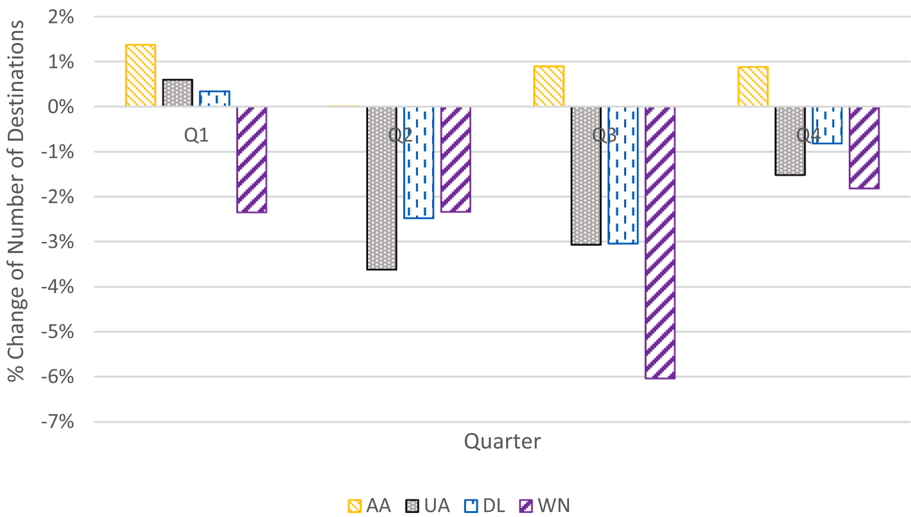

Fig. 3. The % Change of the Average Degree of Closeness Centrality in 2020 vs. 2019 Data Source: Cirium Diio Mi Schedule Report.

especially during the worst months of the pandemic. As shown in Fig. 4, in May 2020, American Airlines kept 49% of its flights compared to the same month in 2019 compared to 41% for Delta Air Lines and only 22% for United Airlines. Similar findings based on seat capacity are illustrated in Fig. 5.

In addition to downsizing operation capacity to adjust for falling passenger demand, airlines also used a variety of measures to enhance safety standards. Notable among these strategies was the blocking of middle seats to increase social distancing among passengers. Delta began blocking middle seats in April 2020 and kept the policy for the remainder of the year (only rescinding the policy in May 2021). American blocked middle seats only during the 2nd quarter of 2020, Southwest blocked middle seats from May 2020 until November 2020 while United never blocked middle seats, booking them throughout the pandemic.

Summarizing its commitment to both safety and financial measures during the pandemic, Edward Bastian, the CEO of Delta Air Lines, stated the following: "*Our response has been focused on three priorities. First, protecting the health and the safety of our employees and our customers. Second, preserving our financial liquidity to work through this crisis. And third, ensuring we are well-positioned to recover once the virus is contained and building a plan to accelerate our progress through this period of recovery*."[16].

Although the decision to block middle seats may have been primarily driven by safety concerns, the financial implications of middle seat blocking varied among airlines depending on their fleet composition. Importantly, the mix of narrow-body, wide-body and regional jets impact the percentage of middle seats in the total seat capacity of a fleet. For example, the fleet of Southwest consists of

[16] See "Delta Air Lines: Navigating the Covid-19 Storm" by Ted Berk and Ryan Flamerich, HBS Case (9–221-063), May 14, 2021.

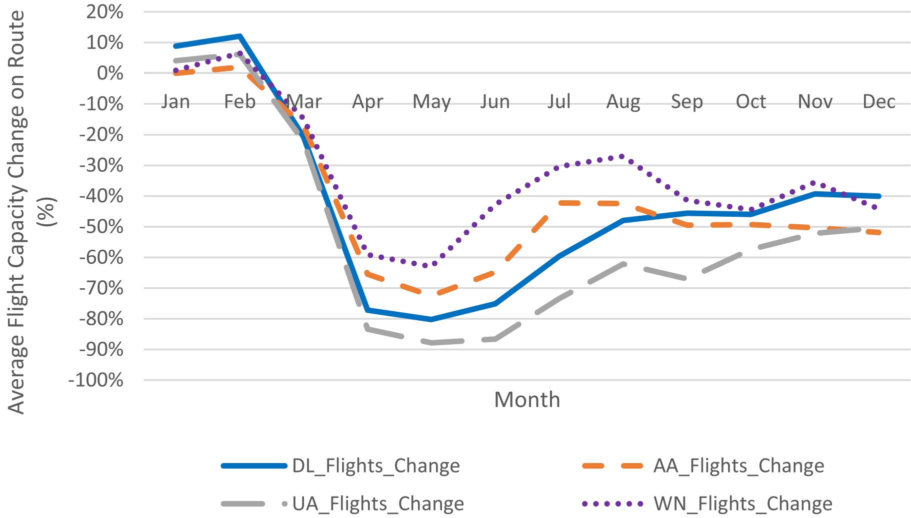

Fig. 4. The Comparison of Flights Capacity Change (%) in 2020 vs. 2019 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

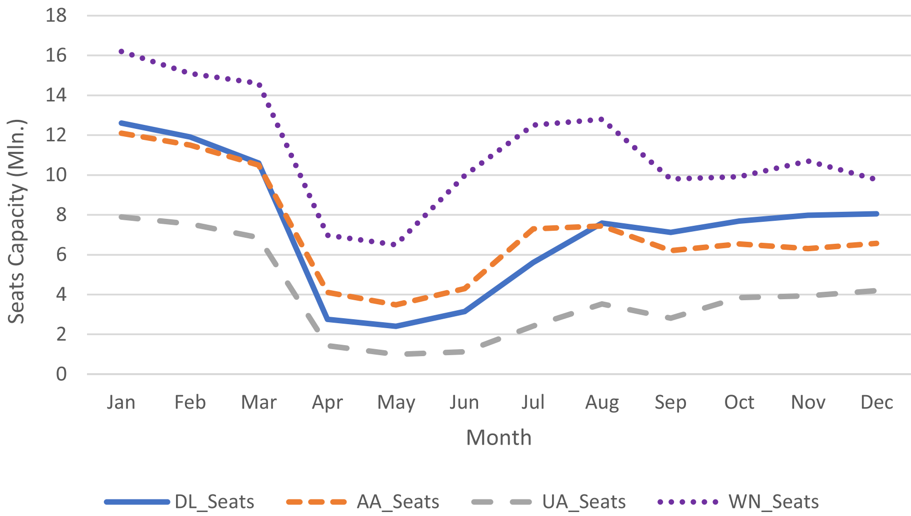

Fig. 5. The Comparison of Monthly Seat Capacity in 2020 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

B737-700, B737-800, and B737-Max 800 aircraft,[17] and middle seats account for more than 32% of the aircraft seat capacity across all three aircraft types. In contrast, the fleet of Delta Air Lines consists of 22 aircraft types with only 5 operating in domestic markets having middle seats.[18] As a result, middle seats account for only 30% of Delta's aircraft seat capacity. Therefore, middle seat blocking may have a lower impact on Delta compared to Southwest.

Figs. 6.1-6.3 show how daily flight frequencies on domestic routes evolved for the four major airlines between 2019 and 2020. As shown in Fig. 6.1, average daily flight frequencies per route were higher for American and Delta than for Southwest and United in 2019, prior to the pandemic. Fig. 6.2 shows that all four airlines cut their frequencies significantly beginning March 2020. By April 2020, frequencies had been reduced by their maximum compared to the corresponding month in 2019. 73.1% by United; 62.9% by American; 61.4% by Delta and 56.9% by Southwest. Fig. 6.3 indicates that the frequency reduction pattern varied by airline. In general, Delta and Southwest cut frequencies by the least amount, while United cut frequencies by the greatest amount.

Fig. 7 compares the four major airlines in terms of the change in average aircraft size on their domestic flight segments between 2019 and 2020. In contrast to the other three airlines, Southwest operated with larger aircraft in 2020 (compared to 2019) in each of the 2nd, 3rd, and 4th quarters of the year. United Airlines downsized its average aircraft size in each of these quarters, while Delta

[17] B737-Max 800 was not in operation during 2020.
[18] These 5 aircraft types are A319, A320-100/200, A321, B737-800, and B757-200.

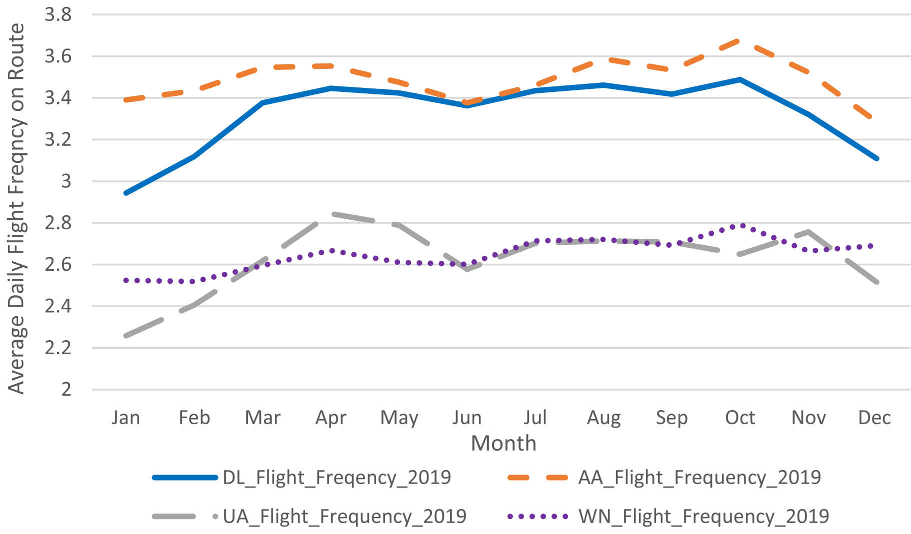

Fig. 6.1. Average Daily Flight Frequency on Route in 2019 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

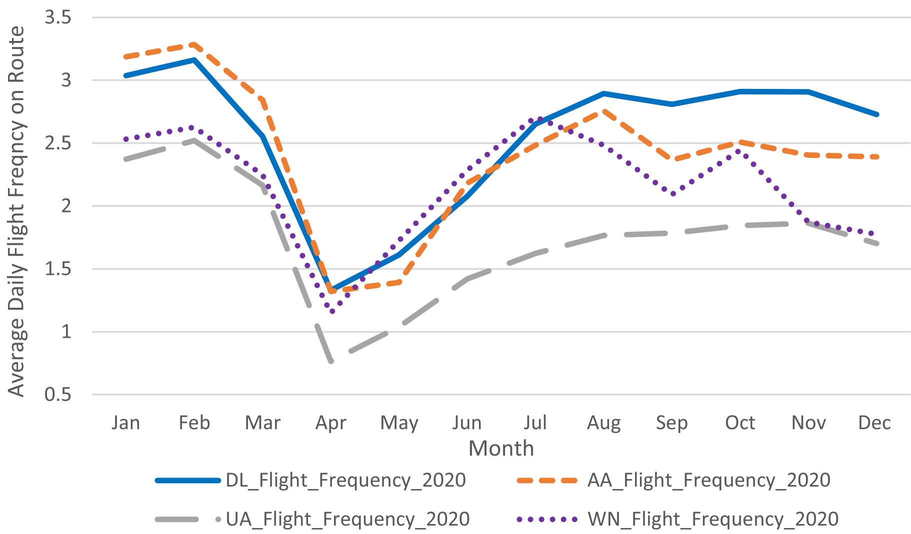

Fig. 6.2. Average Daily Flight Frequency on Route in 2020 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

Airlines downsized its average aircraft size in the 2nd quarter but increased average aircraft size in the 4th quarter. Finally, American held its aircraft size fairly steady in the 2nd and 3rd quarters, before increasing its aircraft size in the 4th quarter.

The strategies undertaken by the carriers, including capacity adjustments, fleet size adjustments and safety strategies such as the blocking of middle seats, likely affected performance outcomes. Fig. 8 shows that yields dropped for all airlines in 2020 compared to the pre-pandemic year, 2019. Yields in the industry may have declined for several reasons, notably due to a drop in demand as potential passengers stayed home due to personal choice and to government lockdown restrictions, and to the relatively larger decline in higher-yield business travelers compared to lower-yield leisure travelers. However, Fig. 8 shows that the decline in yields was not uniform across the four largest U.S. carriers. Yields dropped the most for American Airlines, which only blocked middle seats during the second quarter of 2020. During the last quarter of 2020, United experienced the second greatest drop in yields, while yields fell the least for Delta, providing some indication that the middle seat strategy may have been successful at stemming the decline in yields in agreement with Hyman and Savage (2021 & 2022).

Fig. 9 compares the load factors of the three airlines in 2020 relative to 2019. It can be seen that prior to the onset of the pandemic in the U.S. in March 2020, the four major carriers were filling about the same percentage of seats as in 2019. The onset of the pandemic reduced load factors, initially, for all four airlines by about 70%. The airlines responded by reducing capacity, thus increasing their load factors. The figure shows that during the latter half of 2020, load factors were lowest for Delta, reflecting, perhaps, its decision to keep middle seats open and highest for American and United, both of which did not block middle seats during the latter half of 2020.

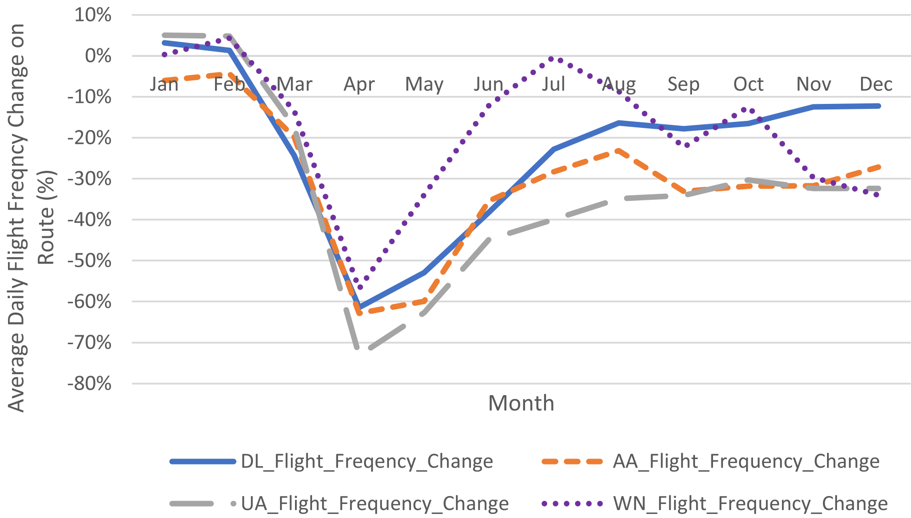

Fig. 6.3. The % Change in Average Daily Flight Frequency per Route in 2020 vs. 2019 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

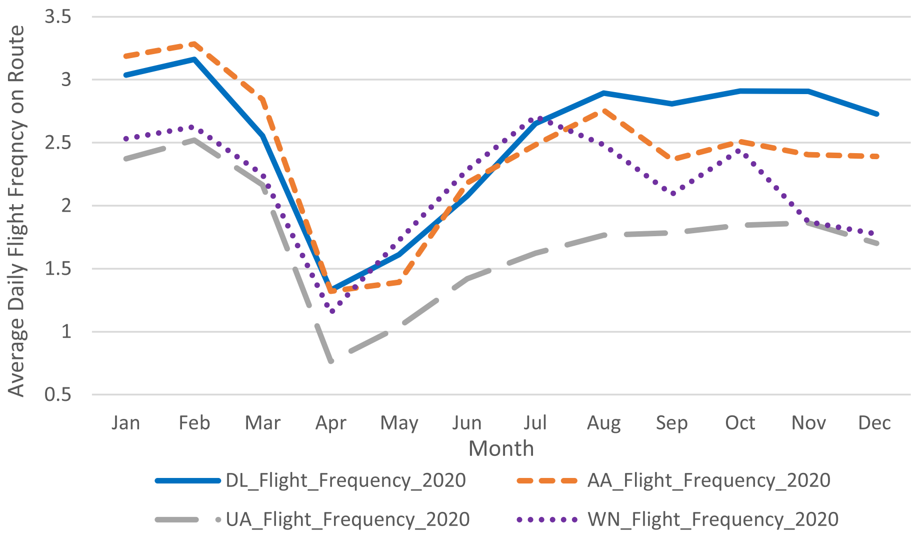

Fig. 7. The % Change of Average Aircraft Size on Route in 2019 vs. 2020 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

Southwest continued blocking middle seats until November, when it rescinded this policy and saw an uptick in its load factor, approaching the load factors of United and American.

In summary, the airlines adopted very different strategies to compete during the pandemic. Delta kept higher yields by allowing for lower load factors than its competitors, Southwest was aggressive at reconfiguring its routes, while American and United tolerated lower yields while keeping load factors higher. In the next section, we examine how performance outcomes may be more closely tied to the blocking of middles seats during the pandemic.

4. Models and data

4.1. Middle seat blocking profiles

In this section, we analyze at the airline-route level, the impact on airline performance of the middle seat blocking strategy. Table 2 shows the airlines included in our dataset and the periods of time in which they pursued middle seat blocking strategies. According to the Bureau of Transportation Statistics, by including the top ten airlines by revenue-passenger miles (RPMs), our dataset describes over

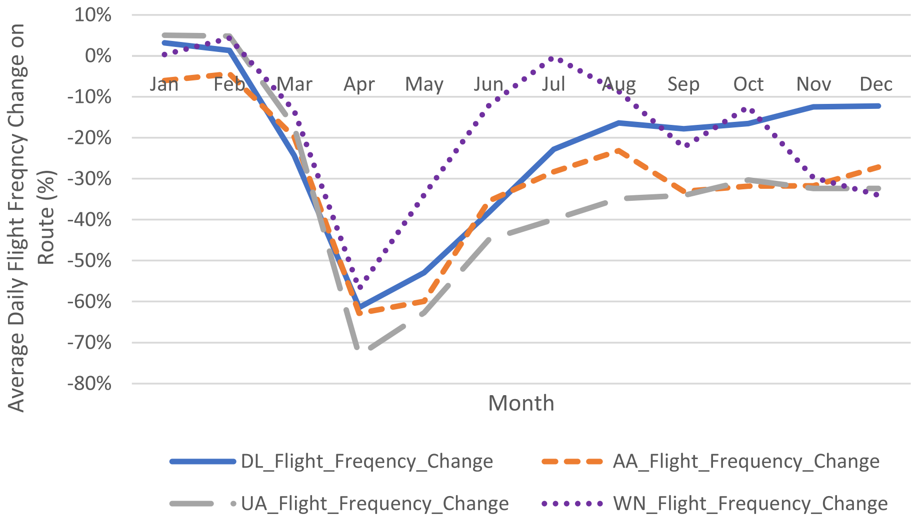

Fig. 8. Comparison of Average Yield Change from 2019 to 2020 among DL, AA, UA and WN Data Source: U.S. DOT O&D DB1B Data Collected from Cirium Diio Mi.

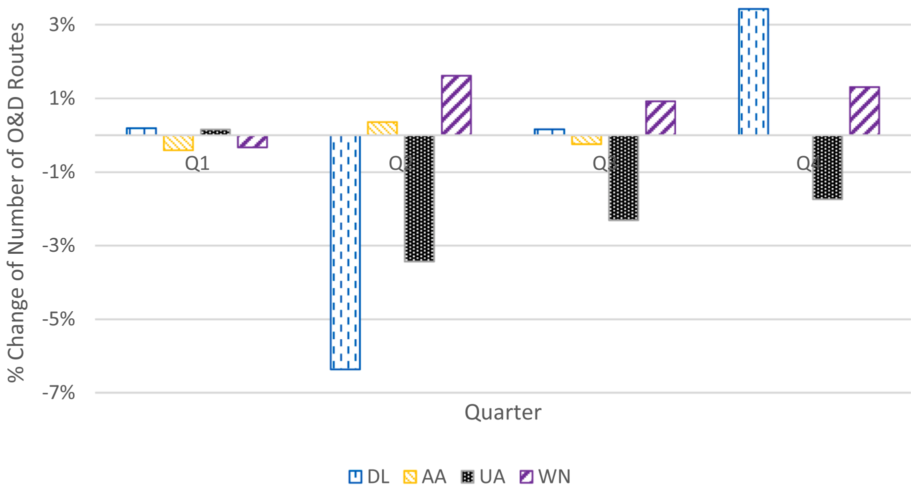

Fig. 9. Average Route LF Change in 2020 vs. 2019 Data Source: U.S. DOT T-100 Data Collected from Cirium Diio Mi.

Table 2
Airlines in Dataset and Middle Seat Blocking Time Periods in 2020.[30]

Airline Code	Airline Name	Jan (Q5)	Feb (Q5)	Mar (Q5)	Apr (Q6)	May (Q6)	Jun (Q6)	Jul (Q7)	Aug (Q7)	Sep (Q7)	Oct (Q8)	Nov (Q8)	Dec (Q8)
AA	American Airlines	0	0	0	1	1	1	0	0	0	0	0	0
DL	Delta Air Lines	0	0	0	1	1	1	1	1	1	1	1	1
UA	United Airlines	0	0	0	0	0	0	0	0	0	0	0	0
AS	Alaska Airlines	0	0	0	0	1	1	1	1	1	1	1	1
B6	JetBlue Airways	0	0	0	0	1	1	1	1	1	1	1	0
F9	Frontier Airlines	0	0	0	0	1	0	0	0	0	0	0	0
G4	Allegiant Air	0	0	0	0	0	0	0	0	0	0	0	0
HA	Hawaiian Airline	0	0	0	0	1	1	1	1	1	1	1	0
NK	Spirit Airlines	0	0	0	0	0	0	0	0	0	0	0	0
WN	Southwest Airlines	0	0	0	0	1	1	1	1	1	1	1	0

[30] Data are collected from the airlines' websites.

90 percent of the available seat miles (ASMs) in the US domestic market.[19]

In examining the three major network carriers in the U.S. domestic market (American, Delta and United), strong variations in the use of middle seat blocking are evident, as shown in Table 2. United never blocked middle seats, American only blocked middle seats during the first wave of the pandemic (April 2020 to June 2020), while Delta initially blocked middle seats during the first pandemic wave and then continued with this strategy throughout the year. Variations in middle seat blocking strategies also appear among the other seven carriers in the dataset. Notably, three airlines. JetBlue, Hawaiian and Southwest, blocked middle seats from May to November 2020, while Alaska continued middle seat blocking to December 2020. At the other end of the spectrum, Spirit and Allegiant joined United in never blocking middle seats, while Frontier blocked middle seats in only one month, May 2020.

4.2. Data Source

We collected 2019 and 2020 monthly segment-level operating data for the ten airlines' domestic routes from the U.S. Department of Transportation (DOT) T-100 reports, and quarterly origin and destination (O&D) airfare, itinerary and passenger data from U.S. DOT DB1B reports. Both the T-100 and DB1B reports are retrieved from the Cirium Diio Mi Market Intelligence data portal. In total, we gathered 313,492 observations from the T-100 dataset. After excluding carrier routes with<16 flights per month, we were left with 234,578 observations across 5,042 airport directional pairs.

The quarterly airfare dataset (DB1B) is larger, containing 1,624,120 itinerary-level observations for the ten airlines across 12,340 origin and destination (O&D) markets (with a minimum of 10 passengers per day). These itineraries include non-stop (5%), one-stop (54%) and two-stop (41%) connections.[20] The DB1B dataset is used to access passenger fare data. Fares are presented in the dataset net of applicable federal taxes and fees, such as security and passenger facility charges.[21] To convert fares into yields, fares are divided by route distance. The distance used for these calculations is the great circle distance between the O&D airports.

We include in our model a social distancing index to control for decreases in mobility due to the spread of covid-19. The index is compiled by the University of Maryland Transportation Institute at the state level, based on several factors, such as percent of people staying at home, the percent of individuals traveling to work, and the number of reported covid cases.[22] For each of our sample airlines, we also collect aircraft seat layout data primarily from seatguru.com, supplemented by the airlines' own fleet information webpages. For those aircraft models that have multiple layout designs, we use the number of seats per flight departure of an airline on a given route as a reference and select the layout design that provides the seat capacity closest to the reference.

4.3. Variables

Table 3 provides a description of variables in our models. We estimate our models with five dependent variables: passenger share, load factor, effective load factor, seat share, and yield. Passenger shares are computed using T-100 flight segment data for each carrier-specific route. Shares are based on the percentage of passengers carried during a period on a route by a specific carrier to the total number of passengers on the route during the time period. Load factors are computed for each carrier-specific route as passengers divided by seats on the route during the period. Seat shares are computed using the same data, based on seats offered by a carrier during a period on a route. In addition to computing the load factor for airline i on route j a given month, we also calculate the "effective load factor" after excluding the number of middle seats that are blocked by an airline in a period. Similarly, we develop "effective seat share" as a modified seat share measure. Given that passengers can use several itineraries to fly an O&D route, we calculate O&D yield based on the shares of the various itineraries for a route. Specifically, for airline i on route j in quarter t, we develop the variable $Yield_{ijt}$ based on the airline's itinerary-specific yield and the share of daily passenger numbers on itinerary m for airline i on route j in quarter t:

$$Yield_{ijt} = \sum_{m=1}^{N} Share \quad of \quad Passengers \quad per \quad day \quad by \quad Itineary \quad m_{ijt} \times Yield_{ijmt}$$

We also compute two measures that will be used in first-stage equations in our model, estimated to address potential econometric concerns (see Section 4.5). First, to measure the importance of origin and destination airports for an airline in terms of the connectivity in the airline's route network, we calculate an airport-specific network metric in period t, and then take the maximum of the network metric between the two endpoint airports on a given route j. The closeness centrality index is calculated as follows:

[19] See https://www.transtats.bts.gov/ accessed in October 2020. We did not include the regional connector airline, SkyWest, in our dataset since it operates under capacity purchasing agreements with the major carriers. Allegiant Air, the next largest carrier, was added to replace SkyWest.

[20] We exclude itineraries with more than two stops. Note that the itinerary percentages do not reflect passenger totals. Nonstop itineraries attract greater numbers of passengers than connecting itineraries.

[21] To exclude likely data errors from our dataset, as well as employee tickets, we drop records with fares below $10. This choice is arbitrary but is supported in the literature. For example, studying the same markets, Brueckner et al. (2013), set the threshold at $25. Given the nature of our research objective, we cautiously chose a less stringent level, but we also impose a percentile restriction by excluding those observations belonging to the first or the last percentile of the yield distribution. By doing so we exclude a total of about 0.4% of the records.

[22] https://data.covid.umd.edu/, last accessed January 28, 2022. Demographic data also come from this source.

Table 3
Variable Descriptions.

Variable	Description
PAXSHR	The passenger share of each airline *i* on route *j* at time *t*
LOADFACTOR	The average (absolute) load factor of each airline *i* on route *j* at time *t*
EFFLOADFACTOR	The average (effective) load factor of each airline *i* on route *j* at time *t*
SEATSHR	The seat share of each airline *i* on route *j* at time *t*
YIELD	The average fare per mile flown by each airline *i* on route *j* at time *t* (US dollars/mile)
MSB	A dummy variable equal to 1 if airline *i* applies middle seat blocking in period *t* (see Table 1)
RESROUTE	A dummy variable equal to 1 if airline *i* operates route *j* in the same period *t* of 2019 and 2020
SDI	The product of the endpoints state-based social distancing index
TOTCOMP	The number of competitors at the city pair level
LCC	A dummy variable equal to 1 if the airline *i* is a Low-Cost Carrier
DIST	Average route distance (miles)
SUNBELT	A dummy variable equal to 1 if one or both the endpoints are southern belt states
POP	Product of the two endpoints' population (trillion)
INC	Product of the two endpoints' income per capita (US dollars - million)
FREQ	The monthly frequency of operations of airline *i* on route *j* at time *t*
FLEETMIX	The number of different aircraft types employed by airline *i* at time *t*
AIRCRAFTSIZE	The average number of seats offered by airline *i* at time *t*
TOTROUTE	The total number of routes operated by airline *i* at time *t*
ONESTOP	The percentage of passengers flying one-stop on route *j* at time *t*
TWOSTOP	The percentage of passengers flying two-stop on route *j* at time *t*
EFFSEATSHR	The (effective) seat share of each airline *i* on route *j* at time *t*
CENTRALITY19	The maximum centrality at the endpoint airports of route *j* for airline *i* at time *t* in 2019
MIDDLESEATSHR19	The percentage of middle seats in the number of seats of airline *i* on route *j* at time *t* in 2019

$$Closeness\ \ Centrality_{ivt} = \frac{N_{it} - 1}{\sum_{w=1}^{N_{it}-1} S_{vwt}}$$

where S_{vwt} represents the length of the shortest paths from airport v to w in airline i's domestic route network in period t and N_{it} represents the number of airports in airline i's domestic route network in period t. The length of the shortest paths indicates the minimum number of connections needed for traveling from airport v to w, based on airline i's domestic route network in period t. The shorter the length, the greater the value of closeness centrality. This network metric has been applied in recent aviation research (e.g., Malighetti et al., 2019, Cheung et al., 2020, Sun et al., 2020; Reynolds-Feighan et al., 2022). We select this variable and incorporate its 2019 values into the estimation of an airline's resilient route selection (i.e., routes maintained in both 2019 and 2020) during the pandemic. Second, we compute the percentage of middle seats to the total number of seats provided by airline i on route j in period t. We incorporate values for 2019 to estimate the likelihood of an airline blocking a middle seat in a given period. The variable is computed as follows:

$$Middle\ \ Seat\ \ Share_{ijt} = \frac{NumberofMiddleSeats_{ijt}}{TotalNumberofSeats_{ijt}}$$

4.4. Models

To examine the impact of the middle seat blocking strategy, we use data from 2019 (pre-pandemic period) and 2020 (pandemic period, beginning March 2020) to estimate our models. The data are at the airline-route-month level or at the airline-route-quarter level, depending on the model employed. We define a route as the directional combination of a departing airport O and an arrival airport D (i.e., A-B is a different route from B-A). Dependent variables include airline passenger share, load factor (absolute and effective), seat share, and yield. An effective middle seat blocking strategy can be expected to attract passengers because of higher perceived travel safety, and to lead to higher yields, while, potentially, depressing load factors. Moreover, the strategy could cause airlines to adjust the number of seats offered on a route.

From the T-100 and DB1B data sources, two datasets are constructed. In each case, we confine our dataset to competitive routes, where airlines adopting the middle seat blocking strategy were competing with airlines that did not use this strategy. Monopolistic routes and routes where all airlines were blocking middle seats, or all airlines were not blocking middle seats are excluded from the datasets. This leaves the T-100 dataset and the DB1B dataset with 730 and 946 directional route pairs, respectively.

We present the results of the five models in Table 5 in Section 5. As robustness checks, we estimate several alternate econometric specifications. First, we run the five models without including airline fixed effects. These estimations allow us to compare our results with references in the existing literature (Hyman and Savage, 2021 & 2022). Second, we add route-time fixed effects to our main specification, hence adding an extra level of fixed effects and capturing the time variant characteristics of a given route. Results from these estimations are reported in Table A2 and Table A3 in the Appendix. Third, we run our models based on year-over-year changes to

Table 4
Descriptive Statistics.[32]

Variable	Obs.	Mean	Std. dev.	Min	Max
PAXSHR	7,135	22.54	15.31	0.99	93.35
LOADFACTOR	7,135	52.95	19.29	2.63	94.76
EFFLOADFACTOR	7,135	62.35	20.23	2.90	99.96
SEATSHR	7,135	22.56	15.22	2.06	90.86
YIELD	4,554	0.12	0.09	0.02	0.71
MSB	7,135	0.48	0.50	0.00	1.00
RESROUTE	7,135	0.91	0.28	0.00	1.00
SDI	7,135	1240.10	627.80	0.00	4683.50
TOTCOMP	7,135	3.00	0.92	2.00	6.00
LCC	7,135	0.54	0.50	0.00	1.00
DIST	7,135	1118.90	608.66	153.00	2918.00
SUNBELT	7,135	0.46	0.50	0.00	1.00
POP	7,135	186.00	241.00	4.00	1,560.00
INC	7,135	4,040.00	946.00	1,090.00	6,660.00
FLEETMIX	7,135	1.96	0.97	1.00	11.00
TOTROUTE	7,135	461.72	282.06	13.00	1,004.00
FREQ	7,135	66.61	55.39	16.00	1,080.00
AIRCRAFTSIZE	7,135	167.76	25.40	100.00	364.00
EFFSEATSHR	7,135	22.39	14.45	2.03	93.58
ONESTOP	4,554	0.11	0.20	0.00	1.00
TWOSTOP	4,554	0.00	0.01	0.00	0.15
CENTRALITY19	7,135	65.54	11.26	28.67	100.00
MIDDLESEATSHR19	7,209	30.07	4.91	0.00	45.10

[32] Data refers to the T-100 report, except for the *YIELD*, *ONESTOP*, and *TWOSTOP* variables.

the dependent variables (from 2019 to 2020).[23] Finally, we restrict our analysis to Delta Air Lines' middle seat blocking strategy and estimate our yield equation using the subset of data focusing on those routes where Delta Air Lines competed with the other two legacy airlines, that is, American Airlines and United Airlines. As with Hyman and Savage (2021, 2022) we find that blocking middle seats has a positive effect on yields, when examining this restricted database. This last result is reported in Table A4 in the Appendix.

The baseline models for the *PAXSHR* equation (Eq. (2)), *LOADFACTOR* equation (Eq. (3)), and *SEATSHR* equation (Eq. (4)), are generalized in Eq. (1) as follows:

$$Y_{ijt} = \alpha_0 + \boldsymbol{X}_{1\,ijt}{}^{*}\boldsymbol{\alpha}_1^{'} + \alpha_2{}^{*}MSB + \eta_i + \vartheta_j + \varkappa_t + e \tag{1}$$

The dependent variable, Y_{ijt}, is the average monthly passenger share (load factor, seat share) for airline *i* on route *j* in period *t*. The dependent variable is a function of a matrix X_1 of exogenous explanatory variables, and of a variable capturing the middle seat blocking strategy of each airline *i*. $\boldsymbol{\alpha}_1^{'}$ is a column vector of coefficients for the exogenous explanatory variables and α_2 the coefficient for the *MSB* dummy variable. Finally, η_i identifies airline fixed effects, ϑ_j captures airport pair fixed effects, κ_t month fixed effects, while *e* is the error term which is assumed to be normally distributed with zero mean and constant variance σ_e^2. The inclusion of airline fixed effects allows us to better identify the middle seat blocking effect as they capture the time invariant characteristics of each carrier. Similarly, airport pair fixed effects are included to control for route unobserved heterogeneity. Finally, month fixed effects are used to eliminate biases from unobservable factors that change over time and not across entities. In this way it is possible to exploit the variations within each carrier, route, and month.

Among the exogenous explanatory variables, we include regressors for market and airline characteristics such as pandemic intensity measures, sociodemographic data, a city pair-specific measure of competition (*TOTCOMP*), a dummy variable capturing the business model type of each airline (*LCC*) and other supply and demand shifters. As an additional regressor in the *PAXSHR* model, we include the effective share of seats each carrier offered during a period on a given route[24].

The extended formulations of Eq. (1) are reported in Eq. (2), (3), and (4) as follows:

$$\begin{aligned} PAXSHR_{ijt} = {} & \gamma_0 + \gamma_1{}^{*}MSB_{it} + \gamma_2{}^{*}IMR1_{it} + \gamma_3{}^{*}RESROUTE_{ijt} + \gamma_4{}^{*}IMR2_{ijt} + \gamma_5{}^{*}log(SDI)_{jt} \\ & + \gamma_6{}^{*}TOTCOMP_{jt} + \gamma_7{}^{*}LCC_{ijt} + \gamma_8{}^{*}log(DIST)_{ijt} + \gamma_9{}^{*}SUNBELT_j + \gamma_{10}{}^{*}log(POP)_{jt} \\ & + \gamma_{11}{}^{*}log(INC)_{jt} + \gamma_{12}{}^{*}FLEETMIX_{it} + \gamma_{13}{}^{*}TOTROUTE_{it} + \gamma_{14}{}^{*}FREQ_{ijt} + \gamma_{15}{}^{*}AIRCRAFTSIZE_{it} \\ & + \gamma_{16}{}^{*}EFFSEATSHR_{ijt} + \eta_i + \vartheta_j + \varkappa_t + h \end{aligned} \tag{2}$$

[23] We use the subset of routes that were operated both in 2019 and 2020 to estimate the change models at the month or quarter level. Results are very similar to the ones in Table 5 and are available upon request.

[24] Effective seat shares are based on the seat share computation considering the actual capacity available (discounted by the number of seats blocked).

$$\begin{aligned} LOADFACTOR_{ijt} = \delta_0 + \delta_1{*}MSB_{it} + \delta_2{*}IMR1_{it} + \delta_3{*}RESROUTE_{ijt} + \delta_4{*}IMR2_{ijt} \\ +\delta_5{*}log(SDI)_{jt} + \delta_6{*}TOTCOMP_{jt} + \delta_7{*}LCC_{ijt} + \delta_8{*}log(DIST)_{ijt} + \delta_9{*}SUNBELT_j \\ +\delta_{10}{*}log(POP)_{jt} + \delta_{11}{*}log(INC)_{jt} + \delta_{12}{*}FLEETMIX_{it} + \delta_{13}{*}TOTROUTE_{it} \\ +\delta_{14}{*}FREQ_{ijt} + \delta_{15}{*}AIRCRAFTSIZE_{it} + \eta_i + \vartheta_j + \varkappa_t + \mathrm{k} \end{aligned} \tag{3}$$

$$\begin{aligned} SEATSHR_{ijt} = \varepsilon_0 + \varepsilon_1{*}MSB_{it} + \varepsilon_2{*}IMR1_{it} + \varepsilon_3{*}RESROUTE_{ijt} + \varepsilon_4{*}IMR2_{ijt} \\ +\varepsilon_5{*}log(SDI)_{jt} + \varepsilon_6{*}TOTCOMP_{jt} + \varepsilon_7{*}LCC_{ijt} + \varepsilon_8{*}log(DIST)_{ijt} \\ +\varepsilon_9{*}SUNBELT_j + \varepsilon_{10}{*}log(POP)_{jt} + \varepsilon_{11}{*}log(INC)_{jt} + \varepsilon_{12}{*}FLEETMIX_{it} + \varepsilon_{13}{*}TOTROUTE_{it} \\ +\varepsilon_{14}{*}FREQ_{ijt} + \varepsilon_{15}{*}AIRCRAFTSIZE_{it} + \eta_i + \vartheta_j + x_t + r \end{aligned} \tag{4}$$

As shown in Eq. (5), the baseline general model for the *YIELD* equation is estimated with a different formulation from the previous baseline model, as this estimation relies on a separate dataset (O&D data):

$$YIELD_{ijt} = \beta_0 + \boldsymbol{X}_{2ijt}{*}\boldsymbol{\beta}_1^{'} + \beta_2{*}MSB + \lambda_i + \mu_j + \xi_t + u \tag{5}$$

where $YIELD_{ijt}$ is the average quarterly yield of each airline *i* on a route *j* in period *t*. The dependent variable is a function of a matrix $\boldsymbol{X}_2$ of exogenous explanatory variables and of a variable capturing the middle seat blocking strategy for each airline *i*. $\boldsymbol{\beta}_1^{'}$ is a column vector of coefficients for the exogenous explanatory variables and α_2 the coefficient for the *MSB* dummy variable. The airline fixed effects are identified by λ_i, while μ_j captures airport pair fixed effects and ξ_t refers to quarter fixed effects. Finally, u is the error term that is assumed to be normally distributed with zero mean and constant variance σ_u^2.

Among the exogenous explanatory variables are regressors identifying market and airline characteristics, including the percentage of passengers on a route flying on a connecting (rather than nonstop) itinerary (*ONESTOP*, *TWOSTOP*). The extended formulation of Eq. (4) is reported in Eq. (5) as follows:

$$\begin{aligned} YIELD_{ijt} = \pi_0 + \pi_1{*}MSB_{it} + \pi_2{*}IMR1_{ijt} + \pi_3{*}RESROUTE_{ijt} + \pi_4{*}IMR2_{ijt} + \pi_5{*} \\ log(SDI)_{jt} + \pi_6{*}TOTCOMP_{jt} + \pi_7{*}LCC_{ijt} + \pi_8{*}log(DIST)_{ijt} + \pi_9{*}SUNBELT + \pi_{10}{*} \\ log(POP)_{jt} + \pi_{11}{*}log(INC)_{jt} + \pi_{12}{*}FLEETMIX_{ijt} + \pi_{13}{*}TOTROUTE_{it} + \pi_{14}{*} \\ ONESTOP_{ijt} + \pi_{15}{*}TWOSTOP_{ijt} + \lambda_i + \mu_j + \xi_t + w \end{aligned} \tag{6}$$

4.5. Econometric concerns

Eq. (6) is characterized by possible econometric concerns related to potential endogeneity between *TOTCOMP* and *YIELD* (i.e., higher yields may produce a feedback effect attracting more competitors onto a route). However, following Brueckner and Singer (2019) and Brueckner et al. (2013), we do not specifically control for endogeneity for several reasons: First, by explicitly including fixed effects and market characteristics in our model, we already capture much of the unobserved heterogeneity among observations, hence limiting potential bias; second, there is evidence in the literature (i.e., Gayle and Wu (2013)) showing that directly addressing endogeneity of carrier competition via a structural model has little impact on the final estimates; third, the potential endogeneity between *TOTCOMP* and *YIELD* is mainly an issue with nonstop routes. In our final sample, 82% of itineraries involve connections; therefore, the feedback effect from passengers to number of competitors may be limited. Finally, in this work we do not attempt to obtain the best linear unbiased estimator (BLUE) for *TOTCOMP* or use its coefficient to interpret the causal impact on the dependent variable. *TOTCOMP* only serves as a control variable. Therefore, potential endogeneity between *TOTCOMP* and our dependent variables will not influence the main results measuring the influence of *MSB* on the dependent variables. For these reasons, we do not specifically control for the potential endogeneity of *TOTCOMP*.[25]

A second econometric concern is the selection problem for our observations. With the advent of the pandemic, carriers dropped many of their routes. However, the decrease in routes was likely systematic, rather than random. Therefore, we estimate Eq. (7) through a probit regression to generate the Inverse Mills Ratio (*IMR1*) to correct for route selection bias in Eqs. (2), (3), (4) and (6).

$$\begin{aligned} RESROUTE_{ijt} = \varphi_0 + \varphi_1{*}CENTRALITY19_{ijt} + \varphi_2{*}log(SDI) + \varphi_3{*}log(DIST)_{ijt} + \varphi_4{*}TOTCOMP_{jt} + \varphi_5{*}SUNBELT_j + \varphi_6{*}log(POP)_{jt} \\ + \varphi_7{*}log(INC)_{jt} + \varphi_8{*}TOTROUTE_{it} + \nu_t + z \end{aligned} \tag{7}$$

In Eq. (7), $RESROUTE_{ijt}$ is a binary outcome variable indicating whether a route is operated by a carrier in both 2019 and 2020. It is estimated as a function of the intensity of the pandemic at the state level, route cost and demand shifters and route market and origin and destination characteristics. Seasonal trends are captured by ν_t while z is the error term with 0 mean and, for identification purposes, variance ${\sigma_z}^2$ set equal to unity.

In Eq. (7) we also include the network variable *CENTRALITY19* that serves as an instrumental variable to tackle the route selection

[25] To check for the robustness of the estimates presented in Table 5 we also run the models including fixed effects at the *ROUTE-TIME* level. In this way we capture all the time-varying characteristics of each route across time, implicitly excluding some of the variables from the models (i.e., *TOTCOMP*).

bias in the main equations. This variable is included in the selection equation, but not in the equations of interest. We believe that an airline is more likely to keep a route if it is important in terms of connectivity for its network. To save operating expenses while minimizing the disruption to overall route network connectivity, an airline is more likely to cut routes involving endpoint airports that have low centrality values. This intuition is indeed supported by the probit results in Table A1 in the Appendix.

Since the connectivity of a route network is important for passengers (as well as for airlines), the centrality index may also impact passenger share, load factor, seat share, and yield. Given the exclusion restriction (i.e., the instrumental variable should not directly impact the dependent variables), we base our centrality measure on (pre-pandemic) 2019 data.

A third econometric concern rises because the adoption of a middle-seat blocking strategy may be due to self-selection by an airline. Systematic differences between airlines that did or did not adopt the strategy might yield biased measures of the effects of the middle-seat blocking strategy, even after correcting for route selection bias (i.e., due to carrier-specific characteristics). Therefore, we estimate Eq. (8) through a probit regression to generate the Inverse Mills Ratio (*IMR2*) to correct for airlines' self-selection bias in Eqs. (2), (3), (4) and (6).

We include the variable *MIDDLESEATSHR19* in Eq. (8). It measures the percentage of middle seats to total seats operated by airlines in 2019 (lagged to limit endogeneity concerns), and serves as an instrumental variable to address self-selection bias in the main equations. The percentage of middle seats on an airline's network may be linked to the likelihood that the airline will adopt a middle-seat blocking strategy. For example, the percentage of middle seats is higher for wide-body aircraft than for narrow-body aircraft; therefore, airlines that operate a high percentage of wide-bodied aircraft may be less likely to block middle seats.[26] The lagging of the variable allows us to exclude *MIDDLESEATSHR19* from the estimation of the performance variables, passenger share, load factor, seat share, and yield, since passenger choices are based on current, rather than on lagged, seat configurations.

$$\begin{aligned} MSB_{it} =& \zeta_0 + \zeta_1 {*} MIDDLESEATSHR19_{ijt} + \zeta_2 {*} log(SDI)_{jt} + \zeta_3 {*} log(DIST)_{ijt} + \zeta_4 {*} TOTCOMP_{jt} + \zeta_5 {*} SUNBELT_j + \zeta_6 {*} log(POP)_{jt} \\ & + \zeta_7 {*} log(INC)_{jt} + \zeta_8 {*} TOTROUTE_{it} + \tau_t + \omega \end{aligned} \quad (8)$$

Given the multi-step estimation procedure leading to our final estimates, standard errors may be underestimated, leading to inflated *t*-statistics. To adjust for potentially inflated standard errors, we employ a bootstrap procedure with 1,000 replications. Given the nature of our data, we implement the procedure by time blocks, resampling on the airline-route dimension (without resampling months or airline-route-months) to keep the time series properties of the observations (Dresner et al., 2021).[27] Moreover, Eqs. (2), (3), (4) and (6) are estimated using high dimensional fixed effects regressions. For identification reasons we include route, airline, and time dummies. Finally, standard errors are always clustered at the airline-route level.[28]

4.6. Descriptive statistics

Table 4 presents descriptive statistics for the variables in our models. The statistics for our five dependent variables show that, on average, a US carrier averaged about 23% of the market in terms of both seat share and passenger share. Airlines filled about 53% of seats on a route during the time of our dataset. Average load factors were, thus, quite low, during the first year of the covid-19 pandemic.[29] Yields averaged $0.12 per revenue-passenger mile. Data from the table indicate that the middle seat was blocked in 48% of our observations, about 91% of our observations are for routes operated both in 2019 and 2020 (the remaining 9% are new routes, introduced in 2020). There was an average of just over three carriers operating a route segment. Airlines employed about two different aircraft types on a route on average and the average aircraft size was 168 seats and the average route distance 1,119 miles.

5. Results

Results from our main estimations are presented in Table 5, while the probit route selection results[30] are shown in Table A1 in the Appendix. The main results show that blocking the middle seat contributes to higher passenger shares on a route, to lower absolute load factors, but to higher "effective" load factors (assuming that the seat capacity of an aircraft with middle seats blocked is lower by the number of blocked middle seats), to higher seat shares on a route, but, surprisingly to lower yields (after controlling for airline fixed effects). Based on a mean plane size of 168 seats, a mean load factor of 53%, a mean yield of $0.12/revenue-passenger mile, and a mean route distance of 1,119 miles, the blocking of the middle seat on average results in decreased revenues of more than $3,000 per flight.

Note that when fixed effects are not included in the model, the middle seat blocking strategy is associated with higher yields (see Appendix table, A2). This result indicates that there may be systematic decisions related to the blocking of middle seats, likely

[26] This result is supported in our probit analysis. We find that middle seat share is negatively associated with the middle seat blocking strategy. See results in Table A1 in the Appendix.

[27] In Stata the *bootstrap procedure* combined with the use of the *cluster* and *clusterid* options can account for the specific characteristics of the panel data and bootstrap by time blocks.

[28] According to Stock and Watson (2008), the use of the conventional heteroskedasticity-robust variance matrix estimator would produce inconsistent results.

[29] In our dataset average load factors per route fell to 11.4% in April 2020.

[30] The probit estimation results suggest that an airline is more likely to keep a route if the route involves the endpoint airports that are most connected to other airports in its network, and an airline is less likely to block middle seats when its fleet aircraft configuration consists of a greater share of middle seats.

Table 5
Estimates of the five models.

Variables	(1) *PAXSHR*	(2) *LOADFACTOR*	(3) *EFFLOADFACTOR*	(4) *SEATSHR*	(5) *YIELD*
MSB	7.925***	−4.751***	12.279***	2.098***	−0.026***
	(21.823)	(−9.784)	(20.141)	(4.328)	(−6.155)
IMR1	2.668***	−3.432*	6.965***	7.756***	−0.170***
	(2.884)	(−1.809)	(3.100)	(4.402)	(−6.162)
RESROUTE	−1.498***	−0.955	−2.590***	0.419	0.113***
	(−5.755)	(−1.499)	(−3.689)	(0.785)	(20.596)
IMR2	−2.829***	−10.638***	−13.506***	−4.376***	−0.082**
	(−4.235)	(−8.208)	(−8.912)	(−3.264)	(−2.575)
SDI	0.718**	−14.856***	−17.122***	6.773***	0.029***
	(2.415)	(−8.682)	(−8.803)	(6.033)	(4.337)
TOTCOMP	0.445***	−0.417	−0.218	−3.760***	−0.003**
	(5.530)	(−0.989)	(−0.431)	(−11.295)	(−2.491)
FLEETMIX	0.146	0.086	−0.150	−8.712***	−0.000
	(1.456)	(0.448)	(−0.720)	(−21.488)	(−1.438)
TOTROUTE	−0.009***	−0.017***	−0.007	−0.001	−0.000***
	(−4.521)	(−4.320)	(−1.602)	(−0.276)	(−7.242)
FREQ	−0.004	−0.017***	−0.007	0.177***	
	(−1.437)	(−3.963)	(−1.413)	(20.929)	
AIRCRAFTSIZE	−0.000	−0.003	0.018*	0.130***	
	(−0.010)	(−0.318)	(1.846)	(13.121)	
EFFSEATSHR	1.040***				
	(101.207)				
ONESTOP					−0.018***
					(−4.616)
TWOSTOP					−0.143*
					(−1.950)
AA	7.609***	16.820***	17.117***	−1.175	−0.011*
	(16.337)	(19.284)	(16.167)	(−1.212)	(−1.749)
AS	−1.387**	2.136	3.856**	−12.584***	−0.047***
	(−2.002)	(1.616)	(2.362)	(−8.208)	(−10.078)
B6	1.499**	7.407***	11.880***	−7.920***	−0.084***
	(2.005)	(5.534)	(7.238)	(−5.555)	(−6.572)
F9	3.426***	13.924***	9.070***	−14.042***	−0.179***
	(4.480)	(8.286)	(4.319)	(−9.815)	(−14.833)
G4	1.998	9.081**	4.681	−12.884***	−0.167***
	(1.123)	(2.291)	(1.135)	(−3.913)	(−11.463)
HA	−6.505***	−1.700	−2.365	−9.604***	−0.044***
	(−3.206)	(−0.758)	(−0.726)	(−4.134)	(−7.714)
NK	6.820***	22.791***	19.447***	−10.345***	−0.169***
	(10.448)	(16.666)	(11.302)	(−7.824)	(−12.542)
UA	4.701***	8.791***	9.641***	−3.681***	−0.037***
	(8.710)	(7.428)	(7.136)	(−3.969)	(−7.255)
WN	7.436***	10.698***	17.728***	1.206	−0.032***
	(10.940)	(7.171)	(10.549)	(0.779)	(−6.610)
Constant	−11.767***	162.964***	162.255***	−32.177***	0.197***
	(−4.668)	(13.446)	(11.682)	(−3.872)	(2.841)
Observations	7,135	7,135	7,135	7,135	4,554
Adj. $R-$squared	0.94	0.83	0.79	0.74	0.87
MONTH FEs	YES	YES	YES	YES	YES
ROUTE FEs	YES	YES	YES	YES	YES
AIRLINE FEs	YES	YES	YES	YES	YES
ROUTETIME FEs	NO	NO	NO	NO	NO

Robust $t-$statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The use of route fixed effects does not allow us to identify *LCC*, *DIST*, *SUNBELT*, *POP*, and *INC*. For this reason, those rows have not been included in the table.

associated with the yields airlines, on average, are able to achieve. Importantly, Delta Airlines, a carrier that blocked middle seats from April-December 2020, is associated with higher yields than most of its competitors. On the other hands, ultra-low-cost carriers Allegiant and Spirit never blocked middle seats. Therefore, accounting for systematic difference among airlines using fixed effects may be necessary to isolate the impact of the middle seat blocking strategy.[31]

[31] Although attempts are made to account for systematic differences by including the Inverse Mills Ratio in the estimations, this inclusion likely only partially accounts for these differences.

Other results in Table 5 from our estimations seem reasonable: increased social distancing at the endpoints of a route (*SDI*) reduces load factors. The significant coefficients for the Inverse Mills Ratios show that there is selection bias in both choosing whether to block middle seats and which routes to operate. As expected, connecting flights have lower yields.

The results from our estimations to demonstrate the robustness of our results are presented in the Appendix (Tables A2, A3 and A4). As noted above, when airline fixed effects are not included in the model, the impact of the middle seat blocking strategy on yields changes from negative to positive (Table A2, Column 4). Results for the other performance variables (load factor, effective load factor, seat share and passenger share) are reasonably consistent with our base results. When we include a different set of fixed effects (route-time fixed effects) in our estimations, we also get results consistent with our base results (Table A3). Finally, when we use a database similar to Hyman and Savage (2021 & 2022), confining our analysis to Delta and its network carrier competitors (American and United) and using a model without fixed airline effects, we obtain results similar to Hyman and Savage (2021 & 2022); that is with this limited dataset, the middle seat blocking strategy is associated with about 12% higher yields.

It should be noted, that even if yields are marginally higher with the middle seats blocked as per our results in Tables A2 and A4, the revenue losses from the decrease in load factors associated with the strategy outweigh the revenue gains from the higher yields. Thus, based on the coefficients from any of our models (base model and robustness check models), there will be net revenue losses for airlines undertaking a middle seat blocking strategy. This result likely indicates why airlines either did not implement the strategy or ceased implementing the strategy, despite continued safety concerns.

6. Conclusions, implications, limitations and future research

For this paper, we first provide a general analysis of strategies undertaken by the four largest U.S. airlines and then provide a more detailed analysis on a route-level basis of one of the key safety-related strategies, the blocking of middle seats. Our airline-level analysis shows distinct differences among the largest airlines in terms of their strategies undertaken during the pandemic. In particular, strategic decisions may be closely tied to pre-pandemic operations. Southwest Airlines, notably, without an extensive international route network, was best able to maintain domestic routes during the pandemic. Moreover, American Airlines, with its greater reliance on regional carriers, was able to keep a higher percent of flights and seats in operation during the pandemic compared to its network carrier rivals. The regional carriers were especially suited to operating routes when passenger demand declined early in the pandemic.

The strategies undertaken by the carriers likely resulted in variations in performance outcomes. Although American Airlines maintained a higher percentage of flights and seats than its rivals, it also had a higher decline in yields during the pandemic, compared to the previous year. Therefore, American's decision to maintain its capacity may have had a cost, with the higher capacity resulting in lower yields.

Our analysis of the middle seat blocking strategy reveals revenue losses for airlines engaging in this strategy. Although there may be a positive long-term rationale for blocking the seats; for example, enhancing the safety image of an airline, in the short run, we calculated an airline lost over $3,000 per flight due to the blocking of middle seats. Much of the revenue loss can be attributed to lower load factors. With the middle seats blocked, fewer passengers could be accommodated by airlines undertaking a middle seat blocking strategy. To offset at least part of the loss in capacity resulting from the blocking of middle-seats, airlines that instituted this policy also had a greater share of seats on a route. Airlines that blocked middle seat increased flight frequencies or operated with larger aircraft to, at least partially, compensate for the lost capacity. However, this offset was not sufficient to overcome the revenue losses due to the lower load factors.

Even though load factors were significantly lower when blocking the middle seats, effective load factors were higher. This result indicates that airlines blocking middle seats were able to fill a larger percent of available seats. This may be an indication that there were passengers that were attracted to airlines using this strategy. Further evidence of the ability of the strategy to attract passengers is that passenger shares were higher when the strategy was employed, even after controlling for an airline's capacity on a route (through seat share).

Finally, we find that yields were lower when the middle seat was blocked, contributing to an airline's revenue loss. This result was related to the inclusion of fixed airline effects in our model. When fixed effects were excluded, the middle seat blocking strategy contributed to higher yields. These mixed findings indicate that the middle seat blocking strategy was related to systematic differences in airline strategies and operations.

The major implication of this research is that strategy matters. Although some passengers may view airline travel as a commodity and the services offered by airlines to be largely undifferentiated, airlines do attempt to differentiate their services. This was evident with the various strategies undertaken by U.S. carriers during the pandemic, especially with respect to blocking middle seats. The fact that it appeared to be a "losing" strategy may be indicative of the faith passengers put into the other efforts airlines took to increase the safety levels in their aircraft.

A limitation of this paper is in its scope. We examine only the short run implications of blocking middle seats. Clearly some of the airlines that maintained this strategy for several months (e.g., Delta) must have seen some benefits to continuing to block middle seats. We do not assess these spillover effects from the middle seat blocking strategy. Furthermore, we only estimate a dataset for U.S. airlines. Since the viral levels differed across countries and since people's perception of air safety will vary across cultures, then our results may not be fully generalizable to other aviation markets.

We believe that there is future work that can be conducted on the blocking of middle seats as well as on other pandemic-related aviation strategies. As noted above, it would be useful to see if our results hold in other markets. Furthermore, other safety-related strategies, including face mask requirements, may contribute to passenger traffic or to yields. Therefore, conducting further analysis of pandemic airline strategies may produce more insights into how airlines can best survive pandemics.

CRediT authorship contribution statement

Andrea Gualini: Data curation, Methodology, Writing – review & editing. **Li Zou:** Investigation, Visualization, Writing – review & editing. **Martin Dresner:** Supervision, Validation, 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.

Appendix

Table A1
Estimates of the selection probit models.

Variables	(1) *RESROUTE*	(2) *MSB*
CENTRALITY19	0.037***	
	(10.290)	
MIDDLESEATSHR19		−0.041***
		(-5.711)
DIST	−0.013	0.358***
	(-0.223)	(9.903)
TOTCOMP	−0.022	0.045**
	(-0.718)	(2.123)
TOTROUTE	0.002***	0.003***
	(13.043)	(24.046)
SUNBELT	0.108*	0.014
	(1.700)	(0.336)
LCC	−1.122***	−0.239***
	(-10.220)	(-3.083)
POP	0.035	0.049**
	(1.132)	(2.489)
INC	0.073	−0.083
	(0.613)	(-0.954)
Constant	−3.104	−2.531
	(-1.164)	(-1.240)
Observations	7,135	7,209
MONTH FEs	YES	YES
ROUTE FEs	NO	NO
AIRLINE FEs	NO	NO
ROUTETIME FEs	NO	NO

Robust *t*-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A2
Estimates from the main model. without airline fixed effects.

Variables	(1) *PAXSHR*	(2) *LOADFACTOR*	(3) *EFFLOADFACTOR*	(4) *SEATSHR*	(5) *YIELD*
MSB	3.866***	−12.905***	5.571***	2.298***	0.029***
	(13.688)	(−25.644)	(10.403)	(4.556)	(16.555)
IMR1	3.044***	−2.500	6.967***	3.544**	−0.117***
	(2.940)	(−1.145)	(2.746)	(2.207)	(−6.275)
RESROUTE	−1.712***	−3.812***	−3.627***	2.210***	0.120***
	(−6.299)	(−5.559)	(−4.836)	(4.395)	(38.184)
IMR2	−2.961***	−11.563***	−14.396***	−2.983**	−0.114***
	(−4.234)	(−7.487)	(−8.213)	(−2.208)	(−4.185)
SDI	0.719***	−15.904***	−18.196***	6.820***	0.022***
	(2.753)	(−9.258)	(−9.237)	(6.073)	(3.047)
TOTCOMP	0.488***	0.075	0.474	−3.948***	−0.003**
	(6.228)	(0.176)	(0.902)	(−12.133)	(−2.212)
LCC	1.263***	5.909***	7.614***	−4.131***	−0.085***
	(2.662)	(6.097)	(6.672)	(−5.302)	(−18.862)
FLEETMIX	0.336***	1.223***	1.375***	−8.720***	−0.000
	(3.106)	(4.154)	(4.387)	(−19.277)	(−1.420)
TOTROUTE	−0.000	−0.013***	0.004	0.009***	−0.000***
	(−0.096)	(−3.531)	(0.970)	(3.518)	(−5.220)
FREQ	−0.009***	−0.051***	−0.039***	0.182***	
	(−2.948)	(−8.096)	(−5.707)	(20.876)	
AIRCRAFTSIZE	−0.003	0.004	−0.017	0.111***	
	(−0.510)	(0.520)	(−1.598)	(11.571)	
EFFSEATSHR	1.049***	0.135***	0.148***		
	(88.724)	(7.137)	(6.947)		
ONESTOP					−0.005
					(−1.163)
TWOSTOP					0.039
					(0.529)
Constant	−10.084***	176.377***	176.388***	−34.219***	0.049
	(−4.262)	(14.499)	(12.460)	(−4.237)	(0.822)
Observations	7,135	7,135	7,135	7,135	4,554
Adj. $R-$squared	0.93	0.79	0.77	0.73	0.84
MONTH FEs	YES	YES	YES	YES	YES
ROUTE FEs	YES	YES	YES	YES	YES
AIRLINE FEs	NO	NO	NO	NO	NO
ROUTETIME FEs	NO	NO	NO	NO	NO

Robust $t-$statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3
Estimates from the main model. with route-time fixed effects.

Variables	(1) *PAXSHR*	(2) *LOADFACTOR*	(3) *EFFLOADFACTOR*	(4) *SEATSHR*	(5) *YIELD*
MSB	8.812***	−3.687***	12.774***	8.051***	−0.031***
	(22.020)	(−7.448)	(20.131)	(41.192)	(−6.541)
IMR1	3.126***	−3.506*	7.115***	3.865***	−0.161***
	(3.281)	(−1.849)	(3.206)	(5.222)	(−5.642)
RESROUTE	−2.017***	−1.059	−3.042***	−0.353*	0.110***
	(−6.361)	(−1.613)	(−3.994)	(−1.906)	(16.281)
IMR2	−3.730***	−8.154***	−10.337***	0.194	−0.102***
	(−4.567)	(−5.405)	(−5.698)	(0.366)	(−3.272)
FLEETMIX	0.223*	0.646**	0.226	0.142**	−0.000**
	(1.725)	(2.544)	(0.815)	(2.037)	(−2.239)
TOTROUTE	−0.012***	−0.013***	−0.001	0.002	−0.000***
	(−5.072)	(−3.125)	(−0.253)	(1.603)	(−5.826)
FREQ	−0.008**	−0.025***	−0.008	−0.009***	
	(−2.459)	(−4.312)	(−1.376)	(−3.822)	
AIRCRAFTSIZE	−0.001	−0.008	0.016	0.013***	
	(−0.205)	(−0.820)	(1.347)	(3.618)	
EFFSEATSHR	1.057***	0.094***	0.086***	0.997***	
	(80.556)	(5.167)	(4.120)	(143.100)	
ONESTOP					−0.023***
					(−4.896)
TWOSTOP					−0.082
					(−1.026)
Constant	0.119	65.910***	50.424***	−9.747***	0.286***
	(0.060)	(18.571)	(12.050)	(−7.687)	(5.991)
Observations	7,135	7,135	7,135	7,135	4,554
Adj. $R-$squared	0.95	0.89	0.88	0.99	0.89
MONTH FEs	YES	YES	YES	YES	YES
ROUTE FEs	YES	YES	YES	YES	YES
AIRLINE FEs	YES	YES	YES	YES	YES
ROUTETIME FEs	YES	YES	YES	YES	YES

Robust $t-$statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4
Results based on a subsample where DL is always competing with AA, UA, or both.

Variables	*(1)* YIELD
MSB	0.017***
	(5.646)
IMR1	−0.008
	(−0.905)
IMR2	0.040***
	(3.648)
SDI	−0.029***
	(−3.272)
TOTCOMP	−0.000
	(−0.106)
FLEETMIX	0.000
	(0.087)
TOTROUTE	−0.000
	(−0.573)
ONESTOP	−0.020**
	(−2.420)
TWOSTOP	0.096
	(0.956)
Constant	0.353***
	(5.564)
Observations	544
Adj. R−squared	0.95
MONTH FEs	YES
ROUTE FEs	YES
AIRLINE FEs	NO
ROUTETIME FEs	NO

Robust t−statistics in parentheses
Legend: * = $p < 0.1$; ** = $p < 0.05$; *** = $p < 0.01$

We excluded Q2 of 2020 as AA was blocking the middle seat as well.
In this subsample the average yield is 0.14 and the airport pairs are 144.

References

Adrienne, N., Budd, L., Ison, S., 2020. Grounded aircraft: An airfield operations perspective of the challenges of resuming flights post COVID. J. Air Transp. Manag. 89 https://doi.org/10.1016/j.jairtraman.2020.101921.

Albers, S., Rundshagen, V. 2020. European airlines' strategic responses to the COVID-19 pandemic (January-May, 2020). Journal of Air Transport Management, Vol. 87. DOI: https://doi.org/10.1016/j.jairtraman.2020.101863.

Amankwah-Amoah, J., 2020. Note: Mayday, Mayday, Mayday! Responding to environmental shocks: Insights on global airlines' responses to COVID-19. Transp. Res. E 143. https://doi.org/10.1016/j.tre.2020.102098.

Barnett, A., Fleming, K., 2020. Covid-19 Risk Among Airline Passengers: Should the Middle Seat Stay Empty? MedRxiv, preprint 2021. https://doi.org/10.1101/2020.07.02.20143826, accessed, May 21.

Bauer, L.B., Bloch, D., Merkert, R., 2020. Ultra Long-Haul: An emerging business model accelerated by COVID-19. J. Air Transp. Manag. 89 https://doi.org/10.1016/j.jairtraman.2020.101901.

Bielecki, M., Patel, D., Hinkelbein, J., Komorowski, M., Kester, J., Ebrahim, S., Rodriguez-Morales, A.J., Memish, Z.A., Schlagenhauf, P., 2021. Air travel and COVID-19 prevention in the pandemic and peri-pandemic period: A narrative review. Travel Med. Infect. Dis. 39, 101915 https://doi.org/10.1016/j.tmaid.2020.101915.

Bogoch, I. I., MD, Creatore, M. I., PhD, Cetron, M. S., MD, Brownstein, J. S., PhD, Pesik, N., MD, Miniota, J., MSc, Tam, T., MD, Hu, W., MSA, Nicolucci, A., MSA, Ahmed, S., BSc, Yoon, J. W., MISt, Berry, I., Hay, S. I., Prof, Anema, A., PhD, Tatem, A. J., PhD, MacFadden, D., MD, German, M., MSc, & Khan, K., Dr. (2015). Assessment of the potential for international dissemination of ebola virus via commercial air travel during the 2014 west african outbreak. The Lancet (British Edition), 385(9962), 29-35. DOI: https://doi.org/10.1016/S0140-6736(14)61828-6.

Bombelli, A., 2020. Integrators' global networks: A topology analysis with insights into the effect of the COVID-19 pandemic. J. Transp. Geogr. 87 https://doi.org/10.1016/j.jtrangeo.2020.102815.

Brockmann, D., Helbling, D., 2013. The hidden geometry of complex, network-driven contagion phenomena. Science (American Association for the Advancement of Science) 342 (6164), 1337–1342. https://doi.org/10.1126/science.1245200.

Brueckner, J.K., Lee, D., Singer, E.S., 2013. Airline competition and domestic US airfares: A comprehensive reappraisal. Econ. Transp. 2 (1), 1–17. https://doi.org/10.1016/j.ecotra.2012.06.001.

Brueckner, J.K., Singer, E., 2019. Pricing by International Airline Alliances: A Retrospective Study Using Supplementary Foreign-Carrier Fare Data. Econ. Transp. 20 https://doi.org/10.1016/j.ecotra.2019.100139.

Cheung, Wong, C. W. H., & Zhang, A. (2020). The evolution of aviation network: Global airport connectivity index 2006–2016. Transportation Research. Part E, Logistics and Transportation Review, 133, 101826–. https://doi.org/10.1016/j.tre.2019.101826.

Christidis, P., Christodoulou, A., 2020. The predictive capacity of air travel patterns during the global spread of the COVID-19 pandemic: Risk, uncertainty and randomness. Int. J. Environ. Res. Public Health 17 (10), 3356. https://doi.org/10.3390/ijerph17103356.

Czerny, A.I., Fu, X., Lei, Z., Oum, T.H., 2021. Post pandemic aviation market recovery: Experience and lessons from China. J. Air Transp. Manag. 90, 1–10. https://doi.org/10.1016/j.jairtraman.2020.101971.

Dube, K., Nhamo, G., Chikodzi, D., 2021. COVID-19 pandemic and prospects for recovery of the global aviation industry. J. Air Transp. Manag. 92, 1–12. https://doi.org/10.1016/j.jairtraman.2021.102022.

Dresner, M., Gualini, A., Martini, G., Valli, M., 2021. Airline competition and LCCs in the North Atlantic market. J. Transport Econ. Policy (JTEP) 55 (4), 261–282.

Gardner, L.M., Chughtai, A.A., MacIntyre, C.R., 2016. Risk of global spread of Middle East respiratory syndrome coronavirus (MERS-CoV) via the air transport network. J. Travel Med. 23 (6) https://doi.org/10.1093/jtm/taw063.

Gayle, P.G., Wu, C.Y., 2013. A re-examination of incumbents' response to the threat of entry: Evidence from the airline industry. Econ. Transp. 2 (4), 119–130. https://doi.org/10.1016/j.ecotra.2014.01.001.

Gössling, S., 2020. Risks, resilience, and pathways to sustainable aviation: A COVID-19 perspective. J. Air Transp. Manag. 89 https://doi.org/10.1016/j.jairtraman.2020.101933.

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. J. Air Transp. Manag. 91 https://doi.org/10.1016/j.jairtraman.2020.102007.

Hosseini, P., Sokolow, S.H., Vandegrift, K.J., Kilpatrick, A.M., Daszak, P., 2010. Predictive power of air travel and socio-economic data for early pandemic spread. PLoS One 5 (9). https://doi.org/10.1371/journal.pone.0012763.

Hyman, & Savage, I. (2021). The value of space during a pandemic. Economics Letters, 207, 110039–10.1016/j.econlet.2021.110039.

Hyman, & Savage, I. (2022). The effect of vertical product differentiation on fare and market share: Evidence from Delta Air Lines' middle seat policy. Economics of Transportation (England), 31. https://doi.org/10.1016/j.ecotra.2022.100274.

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. Saf. Sci. 129 https://doi.org/10.1016/j.ssci.2020.104791.

Li, X., 2020. Analysis of Blocking Middle Seat Policy of Delta Airline. E3S Web of Conferences 218. https://doi.org/10.1051/e3sconf/202021803005.

Malighetti, Martini, G., Redondi, R., Scotti, D. (2019). Air transport networks of global integrators in the more liberalized Asian air cargo industry. Transport Policy, 80, 12–23. https://doi.org/10.1016/j.tranpol.2019.04.021.

Milne, R.J., Delcea, C., Cotfas, L.-A., 2021. Airplane boarding methods that reduce risk from COVID-19. Saf. Sci. 134, 1–13. https://doi.org/10.1016/j.ssci.2020.105061.

Reynolds-Feighan, Zou, L., Yu, C. (2022). Seasonality in European and North American Air Transport Markets: Network Structures and Implications for Airline Performance and Recovery. Transport. J., 61(3), 284–304. https://doi.org/10.5325/transportationj.61.3.0284.

Stock and Watson, 2008. Heteroskedasticity-robust standard errors for fixed-effects panel-data regression. Econometrica 76: 155-174. DOI: https://doi.org/10.1111/j.0012-9682.2008.00821.x.

Poletto, C., Boëlle, P.Y., Colizza, V., 2016. Risk of MERS importation and onward transmission: a systematic review and analysis of cases reported to WHO. BMC Infect. Dis. 16 (1), 448. https://doi.org/10.1186/s12879-016-1787-5.

Suau-Sancheza, P., Voltes-Dortac, A., Cugueró-Escofeta, 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? J. Transp. Geogr. 86 https://doi.org/10.1016/j.jtrangeo.2020.102749.

Sun, X., Wandelt, S, Zhang, A., 2020. On the degree of synchronization between air transport connectivity and COVID-19 cases at worldwide level, Physics and Society, arXiv:2007.08412. DOI: https://doi.org/10.1016/j.tranpol.2021.03.005.

Sun, X., Wandelt, S., Zheng, C., Zhang, A., 2021. COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. J. Air Transp. Manag. 94 https://doi.org/10.1016/j.jairtraman.2021.102062.

Tay, D., Du, K., Ho, J. Liu, Feng, Chan, C., Cao, C., 2020. The Aviation Industry: Tackling the turbulence caused by COVID-19. TEM, Vol. 1(1): 44-56. DOI: https://doi.org/10.6897/IETITEM.202007_1(1).0004.

Wenzel, M., Stanske, S., Lieberman, M.B., 2020. Strategic responses to crisis. Strateg. Manag. J. https://doi.org/10.1002/smj.3161.