Airline Strategies During the Pandemic: What Worked?

Andrea Gualini – University of Bergamo

Li Zou – Embry-Riddle Aeronautical University

Martin Dresner – University of Maryland

Abstract

The onset of the covid-19 pandemic significantly impacted the airline industry. Passenger demand plummeted due to government-imposed travel restrictions and general safety concerns. Airlines employed various strategies to generate revenues, reduce costs, and improve safety. Using data from the U.S. airline industry, we provide descriptive statistics at the airline level demonstrating the diverse strategies used by the airlines. Then, at the route level, we examine the middle seat blocking strategy in more depth. Our analysis shows that this strategy resulted in revenue losses for the airlines, as increased yields realized from the strategy did not fully compensate for lower load factors. Our results highlight why airlines ultimately abandoned this strategy.

Airline Strategies During the Pandemic: What Worked?

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; Stanske and Lieberman 2020; Tay et al. 2020). In addition, airlines sought to generate demand by reassuring

[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.

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; Dubeet 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. 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 Airlines 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.

[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.

Our major results show that the middle seat blocking strategy did lead to lower load factors, as well as to increased yields and an increase in seat share on a route. Load factors decreased by about 10.5 percentage points when middle seats were blocked, while yields increased by $0.014/revenue-passenger mile and seat share on a route increased by about 3.7%. However, the increased yields and seat share did not fully compensate for the lost revenues due to decreased load factor. Based on a mean plane size of 162 seats, a mean load factor of 72%, a mean yield of $0.19/revenue-passenger mile, and a mean route distance of 1,082 miles, the blocking of the middle seat on average resulted in decreased revenues of about $2,000 per flight.[6] The increased seat share reduces this revenue loss by about $74 per flight on an average route (i.e., assuming that, on average, each flight had 3.7% more seats. 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.

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

---

[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:
162 seats X 0.72 pax/seat = 117 pax/flight
$0.19/m X 1,082 m = $206/pax
Revenue=117pax X $206/pax = $24,102/flight

WITH MIDDLE SEAT BLOCKING:
162 seats X 0.62 pax/seat = 100 pax/flight
$0.204/m X 1,082 m = $221/pax
Revenue=100pax X $221/pax = $22,100/flight

NET REVENUE from MIDDLE SEAT BLOCKING = $22,100 – $24,100 = -$2,000/flight 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). Li (2020) has undertaken a SWOT (strengths, weaknesses, opportunities, and threats) analysis of the middle seat blocking strategy. A key finding is that there may be a reputational effect from the strategy, increasing the trust of passengers. We add to this literature by empirically examining the impact of key strategies on airline operations and by analyzing at the route level the performance of one of the most significant safety strategies, 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[7]

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

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

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 without cargo operations during the pandemic. According to a report by Boeing (2020)[8], 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

[8] 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.

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, 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 Helbing (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 spreading speed and arrival times of a contagious speed even without knowing some epidemiological parameters such as reproduction rate and recovery rate. They apply this method to simulate the diffusion of the 2009 H1N1 influenza virus and 2003 SARS infections, and find that the effective distance can be used to successfully predict the spreading speed and arrival time of these two contagious diseases in the context of global, air transport mobility network.

Air travel may also be restricted by governments during a pandemic because the travel mode, itself, may be unsafe due to the transmission of viruses within the close 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.[9] 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 small, researchers have found that they can be made even less likely by leaving middle seats empty (Bennet 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

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

aircraft, the retirement of entire fleets (of mainly older, less efficient aircraft) (Adrienne 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.

3. Airline Pandemic Strategies

In this section, we analyze strategies of the four largest U.S. airlines, American, Delta, United and Southwest, during the first year (2020) of the covid-19 pandemic. The strategies undertaken by the airlines varied considerably. Most notably, the airlines undertook different strategies with respect to the blocking of middle seats. Delta began blocking middle seats from 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 Nov. 2020 while

United never blocked middle seats, booking them throughout the pandemic. It is expected that this variation in strategy may have impacts on performance outcomes, such as yields, load factors and seats shares.

Figure 1 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 decline 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, Figure 1 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.

Figure 1. Comparison of Average Yield Change from 2019 to 2020 among DL, AA, UA and WN

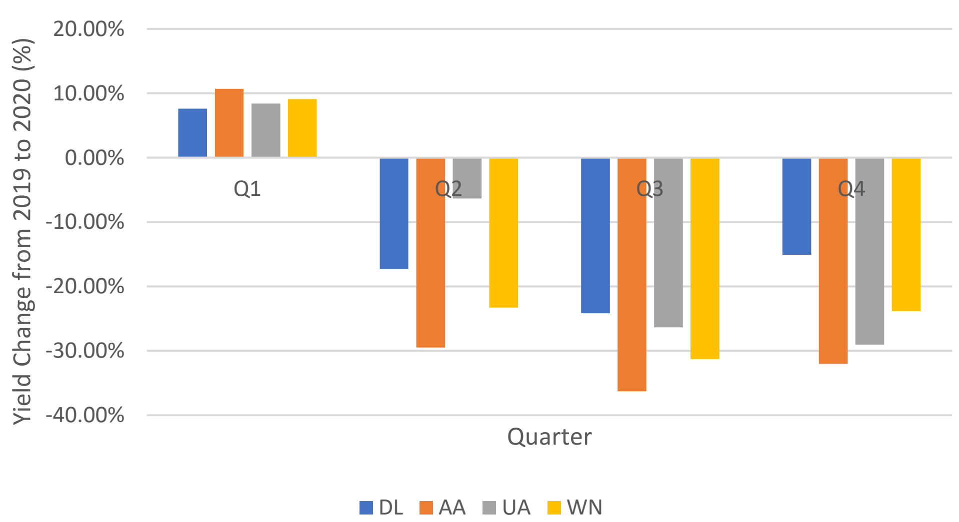
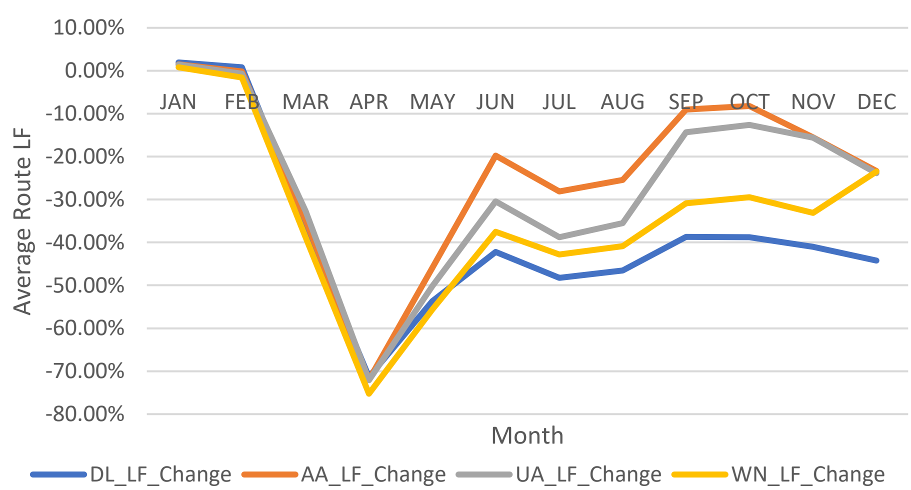


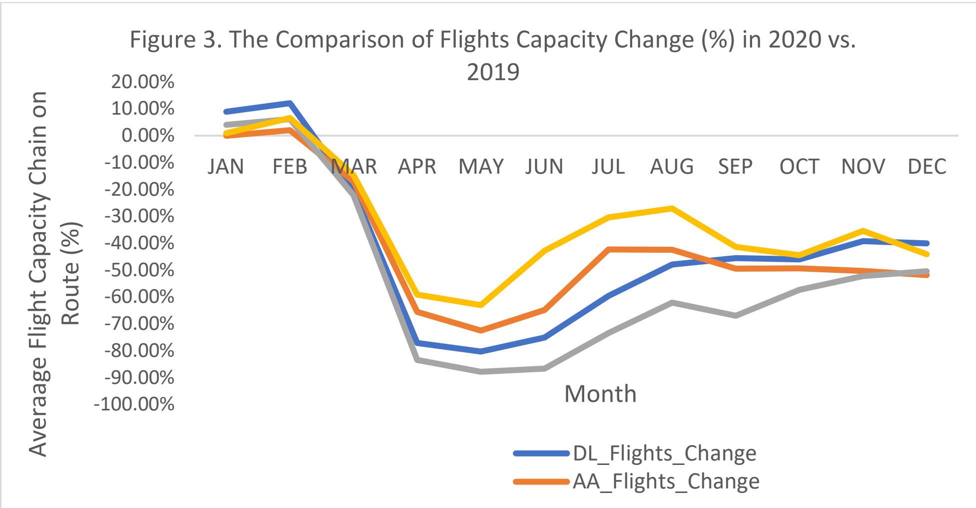
Figure 2 compares the load factors of the three airlines in 2020 relative to 2019. It can be seen that prior to the onset of the pandemic in the U.S. in March 2020, the four major carriers were filling about the same percentage of seats as in 2019. The onset of the pandemic reduced load factors, initially, 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. 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.

Figure 2. Average Route LF Change in 2020 vs. 2019



To save operating expenses, 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, Delta by 44.3%, American by 42.4%, and Southwest by 33.6%. 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 Figures 3 and 4, all the four major carriers started trimming their domestic flight operations in March 2020, with the greatest reductions in May 2020.

.



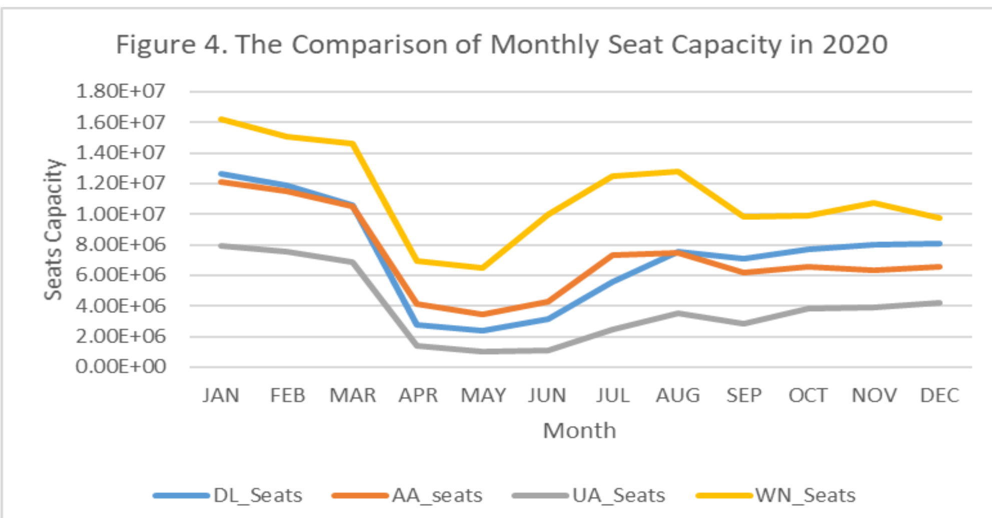


Figure 5 shows how daily flight frequencies on domestic routes evolved for the four major airlines between 2019 and 2020. As shown in Figure 5.1, average daily flight frequencies per route were higher for American and Delta than for Southwest and United in 2019, prior to the pandemic. Figure 5.2 shows 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. Figure 5.3 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.

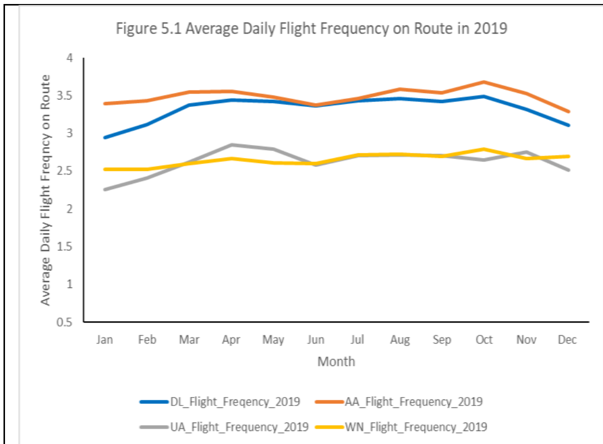


Figure 5.1 Average Daily Flight Frequency on Route in 2019

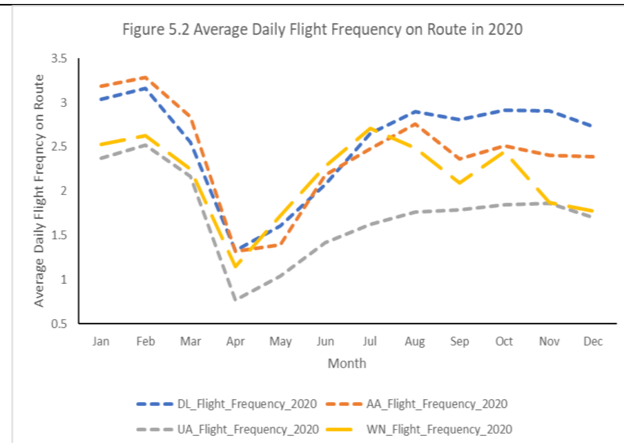


Figure 5.2 Average Daily Flight Frequency on Route in 2020

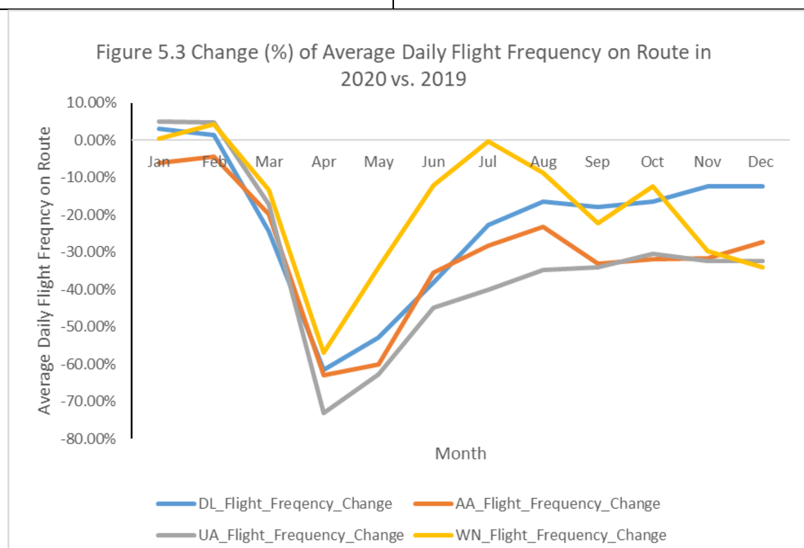


Figure 5.3 Change (%) of Average Daily Flight Frequency on Route in 2020 vs. 2019

Figure 6 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 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.

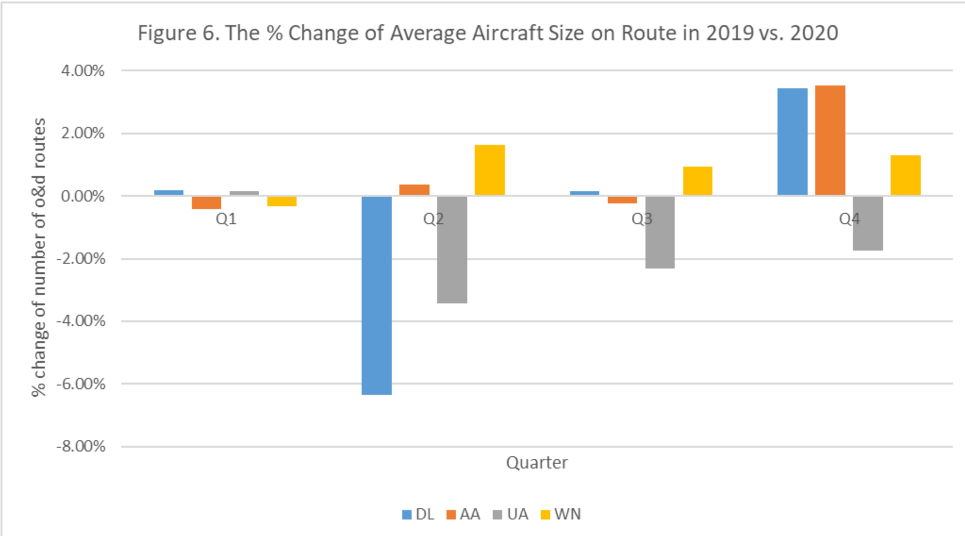
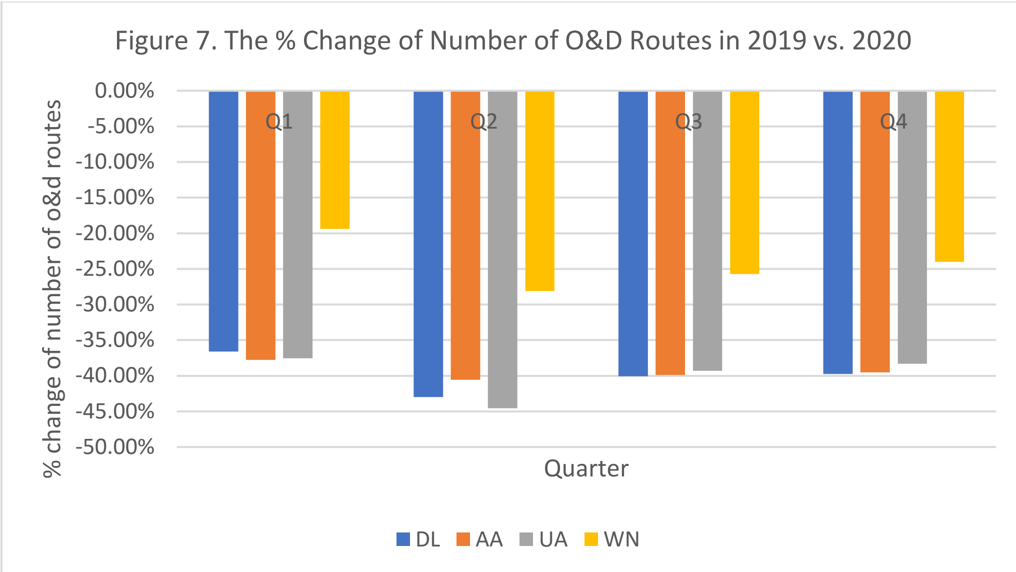
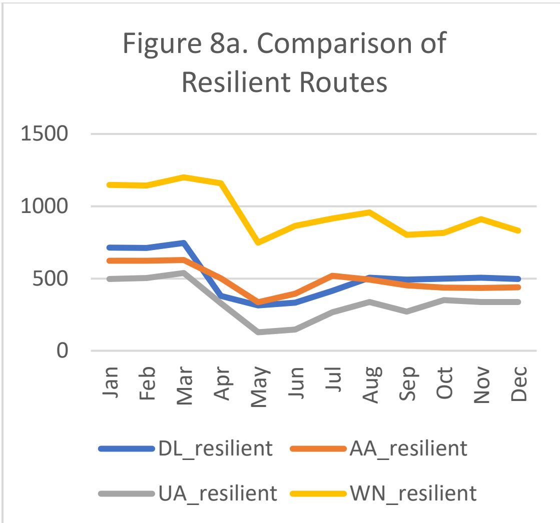
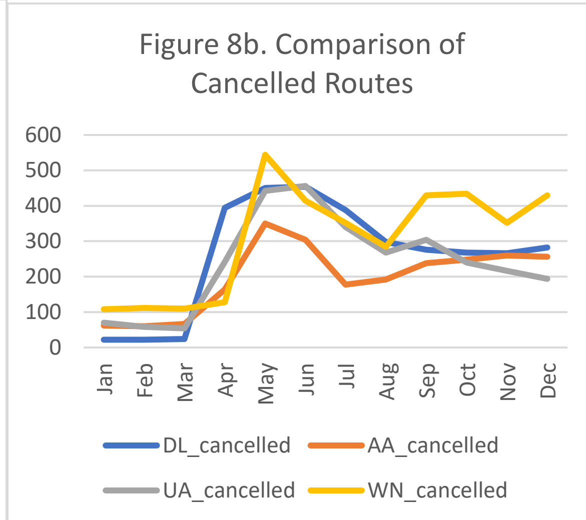


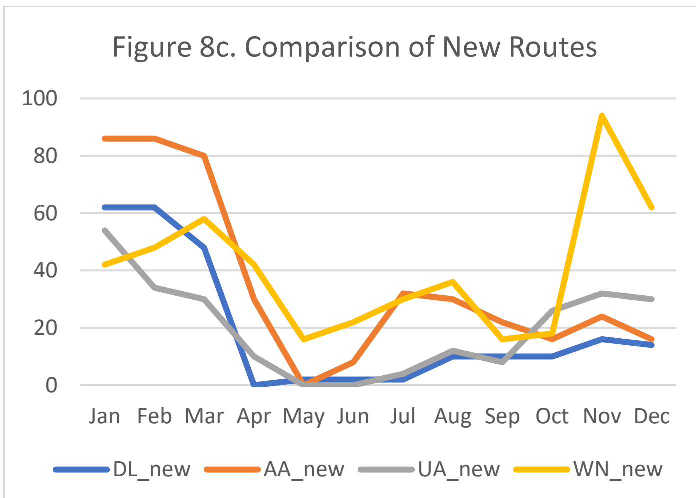
Figure 7 compares the number of origin-and-destination (O&D) routes offered by the four airlines in 2020 compared to the corresponding quarter in 2019. The figure shows that Southwest was least aggressive at cutting routes during the pandemic, maintaining over 70% of its routes during the worst point for airlines in the pandemic – the second quarter of 2020. The other three airlines reduced their route offerings by 60-65%, thus retaining only about half as many routes (in percentage terms) as Southwest. Although the three network carriers all brought back routes during the third and fourth quarters of 2020, the gap in routes offered (compared to 2019) between Southwest and the three network carriers remained.



Figures 8a, 8b, and 8c provide more detail on the route strategies pursued by the four largest U.S. carriers. Again, the figures contrast the strategy pursued by Southwest to the strategies of the other three carriers. The figures divide the routes into three categories: resilient routes – routes operated both in 2019 and 2020; cancelled routes – routes offered in 2019 but not in 2020; and new routes – routes operated in 2020 but not in 2019. Southwest was the most aggressive at adjusting its routes to meet changing demand, both canceling routes and adding new routes. In particular, during the 4th quarter of 2020, Southwest discontinued about 400 routes, while adding 60-100 routes (depending on the month). United, on the other hand, was the most aggressive airline at reducing routes. It maintained the fewest resilient routes, added comparatively few routes, and canceled a relatively large number of routes.







In summary, the airlines adopted very different strategies to compete during the pandemic. Delta maintained 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 1 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 90 percent of the available seat miles (ASMs) of the US domestic market.[10]

Table 1 reports the middle seat blocking profile for the 10 airlines included in the dataset. 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. 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.

Airline Code	**Airline Name**	**Jan 2020 (Q5)**	**Feb 2020 (Q5)**	**Mar 2020 (Q5)**	**Apr 2020 (Q6)**	**May 2020 (Q6)**	**Jun 2020 (Q6)**	**Jul 2020 (Q7)**	**Aug 2020 (Q7)**	**Sep 2020 (Q7)**	**Oct 2020 (Q8)**	**Nov 2020 (Q8)**	**Dec 2020 (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

[10] 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 code-sharing agreements with the major carriers. Allegiant Air, the next largest carrier, was added to replace SkyWest.

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

Table 1 – Airlines in Dataset and Middle Seat Blocking Time Periods[11]

4.2 Airline Operating and Yield Data

We collect 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 fewer than 16 flights per month, we are 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.[12] 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.[13] 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.

4.3 Variables

[11] Data are collected from the airlines' websites.
[12] 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.
[13] 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. (2014), set the threshold at $25. Given the nature of our research objective, we cautiously chose a less stringent level. By doing so we exclude about 0.2% of the records.

Table 2 provides a description of variables in our models. We estimate our models with three dependent variables: yield, load factor and seat share. 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*:

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

Load factors are computed for each carrier-specific route as passengers divided by seats on the route during the period, using the T-100 flight segment data. Seat shares are computed using the same data based on seats offered during a period on a route.

Table 2. Variable Descriptions

Dependent Variable	**Description**
LOADFACTOR	Average load factor of an airline on route *j* at time *t* (%)
SEATSHARE	Seat share of an airline on route *j* at time *t* (%)
YIELD	Average fare per mile flown by an airline on route *j* at time *t* (US dollars/mile)
Independent Variable	
ODSDI	Product of the endpoints state-based social distancing index
MIDDLESEAT	Dummy variable equal to 1 if an airline *i* applies middle seat blocking policy in period *t*
RESROUTE	Dummy variable equal to 1 if an airline *i* operates a route in both years (same period of 2019 and 2020)
IMR	Inverse Mills Ratio to correct for sample selection
TOTCOMP	Number of airlines competing at the city pair level
FREQ	Monthly frequency of operations of airline *i* on route *j* at time *t*
FLEETMIX	Number of different aircraft types employed by airline *i* at time *t*
AIRCRAFTSIZE	Average number of seats offered by airline *i* at time *t*

TOTROUTE	Total number of routes operated by airline *i* at time *t*
DIST	Average route distance (miles)
SUNBELT	Dummy variable equal to 1 if one or both the endpoints is in a southern belt state of the U.S.[14]
ODLINKS	Product of the nonstop routes at origin city and the destination city of a route
ODPOP	Product of the two endpoints' populations (bln. people)
ODINC	Product of the two endpoints' income per capita (mln. U.S. dollars)
LCC	Dummy variable equal to 1 if the airline *i* is a Low-Cost Carrier[15]
ONESTOP	Percentage of passengers flying one-stop with airline *i* on route *j* at time *t*
TWOSTOP	Percentage of passengers flying two-stop with airline *i* on route *j* at time *t*

4.4 Models

To examine the impact of the middle seat blocking strategy, we use data from 2019 (pre-pandemic) and 2020 (pandemic, 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. Dependent variables include airline yield, load factor and seat share. An effective middle seat blocking strategy can be expected to lead to higher yields and seat shares, while, potentially, depressing load factors. Finally, as robustness checks, we estimate all three models based on year-over-year changes to the dependent variables (from 2019 to 2020).[16]

The baseline model for the *LOADFACTOR* equation (Eq. (3)) and for the *SEATSHARE* equation (Eq. (4)) is generalized in Eq. (1) as follows:

[14] These states are Florida, California, Hawaii, Arizona, Texas, Nevada, New Mexico, Alabama, Louisiana, Mississippi, Puerto Rico, and Virgin Island.

[15] Our dataset includes the major ten airlines operating in the U.S. domestic market. We distinguish them by business model (Full-Service Carrier (FSC) vs Low-Cost Carrier (LCC)) and we code AA, DL, UA, AS, HA as FSCs, and B6, F9, G4, NK and WN as LCCs. However, given the actual intra-groups heterogeneity and the peculiarities of some airlines, we run some robustness check without any significant change.

[16] 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.

$$Y_{ijt} = \alpha_0 + \boldsymbol{\alpha_1} * \boldsymbol{X_1}_{ijt} + \alpha_2 * MIDDLESEAT + \eta_i + \vartheta_j + \varkappa_t + e \qquad (1)$$

The dependent variable, Y_{ijt}, is the average monthly passenger load factor (seat share) for airline *i* on route *j* in period t. The dependent variable is a function of a matrix $\boldsymbol{X_1}$ 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 *MIDDLESEAT* dummy variable. Finally, η_i identifies airline fixed effects, ϑ_j captures city pair fixed effects, κ_t time fixed effects, while e is the error term which is assumed to be normally distributed with zero mean and constant variance $\sigma_e{}^2$.

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.

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

$$LOADFACTOR_{ijt} = \gamma_0 + \gamma_1 * \ log(ODSDI)_{jt} + \gamma_2 * \ MIDDLESEAT_{it} + \gamma_3 * \ RESROUTE_{ijt} + \gamma_4 * IMR_{ijt} + \gamma_5 * \ TOTCOMP_{jt} + \gamma_6 * \ LCC_{ijt} + \gamma_7 * \ log(DIST)_{ijt} + \gamma_8 * \ log(ODPOP)_{jt} + \gamma_9 * log(ODINC)_{jt} + \gamma_{10} * \ FREQ_{ijt} + \gamma_{11} * \ FLEETMIX_{ijt} + \gamma_{12} * \ AIRCRAFTSIZE_{it} + \gamma_{13} * TOTROUTE_{it} + \pi_i + \rho_j + \sigma_t + h \qquad (2)$$

$$MKTSHARE_{ijt} = \delta_0 + \delta_1 * log(ODSDI)_{jt} + \delta_2 * MIDDLESEAT_{it} + \delta_3 * RESROUTE_{ijt} + \delta_4 * IMR_{ijt} + \delta_5 * \ TOTCOMP_{jt} + \delta_6 * LCC_{ijt} + \delta_7 * log(DIST)_{ijt} + \delta_8 * log(ODPOP)_{jt} + \delta_9 * log(ODINC)_{jt} + \delta_{10} * FREQ_{ijt} + \delta_{11} * FLEETMIX_{ijt} + \delta_{12} * AIRCRAFTSIZE_{it} + \delta_{13} * TOTROUTE_{it} + \tau_i + \varphi_j + \chi_t + \mathrm{r} \qquad (3)$$

As shown in Eq. (4), 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):

$$YIELD_{ijt} = \beta_0 + \boldsymbol{\beta_1} * \boldsymbol{X_2}_{ijt} + \beta_2 * MIDDLESEAT + \lambda_i + \mu_j + \xi_t + u \qquad (4)$$

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*. $\boldsymbol{\alpha_1}$ is a column vector of coefficients for the exogenous explanatory variables and α_2 the coefficient for the *MIDDLESEAT* dummy variable. The airline fixed effects are identified by λ_i, while μ_j captures city pair fixed effects and ξ_t refers to time fixed effects. Finally, u is the error term which is assumed to be normally distributed with zero mean and constant variance ${\sigma_u}^2$.

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:

$$YIELD_{ijt} = \varepsilon_0 + \varepsilon_1 * log(ODSDI)_{jt} + \varepsilon_2 * MIDDLESEAT_{it} + \varepsilon_3 * RESROUTE_{ijt} + \varepsilon_4 * IMR_{ijt} + \varepsilon_5 * TOTCOMP_{jt} + \varepsilon_6 * LCC_{ijt} + \varepsilon_7 * log(DIST)_{ijt} + \varepsilon_8 * log(ODPOP)_{jt} + \varepsilon_9 * log(ODINC)_{jt} + \varepsilon_{10} * FLEETMIX_{ijt} + \varepsilon_{11} * TOTROUTE_{it} + \varepsilon_{12} * ONESTOP_{ijt} + \varepsilon_{13} * TWOSTOP_{ijt} + \psi_i + \varsigma_j + \omega_t + \mathrm{w} \qquad (5)$$

4.5 Econometric Concerns

Eq. (5) 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 et al. (2019, 2013), we disregard this issue 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 more of 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 to 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 *MIDDLESEAT* on the dependent variables. For these reasons, we do not specifically control for the potential endogeneity of *TOTCOMP*.

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. (6) through a probit regression to generate the Inverse Mills Ratio to correct for route selection bias in Eqs. (2), (3) and (5).

$$RESROUTE_{ijt} = \zeta_0 + \zeta_1 * log(ODSDI)_{jt} + \zeta_2 * log(DIST)_{ijt} + \zeta_3 * TOTCOMP_{jt} + \zeta_4 * SUNBELT_j + \zeta_5 * log(ODPOP)_{jt} + \zeta_6 * log(ODINC)_{jt} + \zeta_7 * ODLINKS_{ijt} + \zeta_8 * TOTROUTE_{it} + \nu_t + z \quad (6)$$

In Eq. (6), $RESROUTE_{ijt}$ 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 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.

Given the two-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 10,000 replications. Given the nature of our data, we implement the procedure by time blocks, resampling routes (without resampling months or pairs of route-months) to keep the time series properties of the observations.[17] Moreover, Eqs. (2) (3) and (5) are estimated using a panel data approach. For identification reasons we apply a random effects specification, although we include route, airline, and time dummies. Finally, standard errors are always clustered at the airport pair level.

4.6 Descriptive Statistics

Table 3 presents descriptive statistics for the variables in our models. The statistics for our three dependent variables show that, on average, airlines fill about 72% of seats on a route, but that load factors could be very low, especially during the early months of the pandemic.[18] Yields average $0.19 per

[17] The Stata command *vce(bootstrap)* as well as the use of the option *cluster(route)* can account for the specific characteristics of the panel data and bootstrap by time blocks.
[18] Average load factors per route fell to 11.4% in April 2020.

revenue-passenger mile. Data from the table indicate that the middle seat is blocked in 14% of our observations, about 76% of our observations are for routes operated in the same periods of both 2019 and 2020, there is an average of just over two carriers operating a route segment, airlines employ about two different aircraft types on a route on average, the average aircraft size is 162 seats and the average route distance 1,082 miles.

Table 3 – Descriptive Statistics[19]

Variable	Mean	Std. Dev.	Min	Max
LOADFACTOR	71.82	20.10	1.62	98.60
SEATSHARE	41.61	30.27	1.09	100
YIELD	0.188	0.17	0.004	6.06
ODSDI	436	657	0	4784
MIDDLESEAT	0.14	0.35	0	1
RESROUTE	0.76	0.43	0	1
TOTCOMP	2.03	1.11	1	7
FREQ	77.21	69.95	16	844
FLEETMIX	2.04	1.08	1	11
AIRCRAFTSIZE	162	26	86	364
TOTROUTE	665	361	12	1310
DIST	1,082	682	31	5,095
SUNBELT	0.44	0.50	0	1
ODPOP	217,000	289,000	10	1,560,000
ODINC	4,010	953	324	6,790
ODLINKS	1,973	1,679	1	12,416
ONESTOP	0.78	0.38	0	1
TWOSTOP	0.04	0.15	0	1

5. Results

Results from our main estimations are presented in Table 4, while the probit route selection results are shown in the Appendix. The main results show that blocking the middle seat contributes to lower load factors, to higher seat shares and to higher yields. Based on a mean plane size of 162 seats, a mean load factor of 72%, a mean yield of $0.19/revenue-passenger mile, and a mean route distance of 1,082 miles,

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

the blocking of the middle seat on average results in decreased revenues of about $2,000 per flight or $1.23 per seat. If an airline increases its seat share on a route by 3.7% (the value of the middle seat coefficient in the seat share equation), then it can cut its revenue loss by about $74 on an average route (i.e., assuming each flight has, on average, 3.7% more seats).

Other results from the estimation seem reasonable: Increased social distancing at the endpoints of a route (LODSI) reduces load factors and yields. Resilient routes have higher load factors and yields, which is likely why they were retained in 2020. The significant coefficients for the Inverse Mills Ratio show that there is selection bias in choosing the routes to operate. Low-cost carriers have lower yields, lower load factors and lower seat shares. Perhaps a surprising result is that connecting flights have higher yields, but this result is obtained after controlling for other factors that may influence yields and could reflect the longer distance passengers must travel on connecting routes versus nonstop routes.

Table 4 - Estimates of the three models

Variables	*(1)* *LOADFACTOR*	*(2)* *SEATSHARE*	*(3)* *YIELD*
LODSDI	-2.269***	-0.004	-0.002***
	(-107.05)	(-0.18)	(-8.35)
MIDDLESEAT	-10.524***	3.714***	0.014***
	(-35.26)	(11.28)	(22.78)
RESROUTE	0.751***	-0.477***	0.014***
	(6.54)	(-3.20)	(3.68)
IMR	11.775***	-1.313***	-0.053***
	(27.76)	(-2.81)	(-14.12)
TOTCOMP	1.162***	-10.70***	-0.002***
	(12.20)	(-38.93)	(-8.47)
FLEETMIX	-0.661***	-15.132***	-0.001***
	(-10.90)	(-54.66)	(-17.94)
TOTROUTE	0.027***	-0.0003	0.000***

	(28.07)	(-0.20)	(42.92)
LCC	-14.394***	-7.730***	-0.051***
	(-27.75)	(-9.19)	(-31.48)
LDIST	5.630***	0.4150	-0.196***
	(33.13)	(1.07)	(-64.68)
LODPOP	0.293***	-1.404***	-0.004***
	(3.92)	(-8.07)	(-5.44)
LODINC	-2.939***	-3.262***	0.043***
	(-5.59)	(-3.52)	(9.65)
FREQ	0.030***	0.055***	
	(17.68)	(19.01)	
AIRCRAFTSIZE	-0.031***	-0.042***	
	(-8.57)	(-5.52)	
ONESTOP			0.031***
			(15.50)
TWOSTOP			0.104***
			(23.72)
Constant	80.334***	217.13***	0.719***
	(6.72)	(10.63)	(8.24)
Observations	96,686	96,686	307,574
Number of id	6,266	6,266	52,466
R^2 (within)	0.72	0.50	0.16
ROUTE FEs	YES	YES	YES
TIME FEs	YES	YES	YES
AIRLINE FEs	YES	YES	YES
SELECTION CORRECTION	YES	YES	YES

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

6. Conclusions, Implications, Limitations and Future Research

Blocking the middle seats likely resulted in revenue losses for airlines. 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 calculate an airline lost about $2,000 per flight due to the blocking of the middle seat. Although yields were higher when the middle seat was blocked, load factors were significantly lower contributing to the revenue loss. This loss was only slightly offset by the greater seat shares offered per route by carriers that engaged in the middle-seat blocking strategy.

Our other results, at the airline level, show how airlines engaged in quite different strategies to cope with the pandemic. Southwest appears to be among the most successful in coping with the pandemic. It was aggressive at shifting routes to respond to changing demand. United was the most aggressive in another way; that is through cutting routes and capacities to reduce operating costs and better balance supply and demand. Delta sacrificed load factors to maintain yields, while American kept aircraft size fairly steady and maintained frequencies on the routes it operated in 2020.

The major implication of this research is that strategy matters. Although some passengers may view airline travel as a commodity and the service 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 the middle seat blocking strategy. The fact that it appeared to be a “losing” strategy may be indicative of the faith passengers put into the other efforts airlines have taken 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 (and Delta, for a full year) 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 differ 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.

Clearly 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.

7. References

Adrienne, N., Budd, L., Ison, S. 2020. Grounded aircraft: An airfield operations perspective of the challenges of resuming flights post COVID. Journal of Air Transport Management, Vol. 89, DOI: 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: 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. Transportation Research Part E, Vol. 143, DOI: 10.1016/j.tre.2020.102098.

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

Bauer, L.B., Bloch, D., Merkert, R., 2020. Ultra Long-Haul: An emerging business model accelerated by COVID-19. Journal of Air Transport Management, Vol. 89, DOI: 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 medicine and infectious disease, *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. 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. Journal of Transport Geography, 87, 102815-102815. https://doi.org/10.1016/j.jtrangeo.2020.102815.

Brockmann, D., and 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. Economics of Transportation, *2*(1), 1-17.

Brueckner, J.K. and Singer, E. 2019. Pricing by International Airline Alliances: A Retrospective Study Using Supplementary Foreign-Carrier Fare Data. Economics of Transportation, 20, Article 100139.

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

Czerny, A.I., Fu, X., Lei, Z. and Oum, T.H., 2021. Post pandemic aviation market recovery: Experience and lessons from China. Journal of Air Transport Management, Vol. 90: 1-10.

Dube, K., Nhamo, G. and Chikodzi, D., 2021. COVID-19 pandemic and prospects for recovery of the global aviation industry. Journal of Air Transport Management, Vol. 92: 1-12.

Gardner, L.M., Chughtai, A.A. and MacIntyre, C.R. 2016. Risk of global spread of Middle East respiratory syndrome coronavirus (MERS-CoV) via the air transport network. Journal of Travel Medicine, Vol. 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. Economics of Transportation, *2*(4), 119-130.

Gössling, S. 2020. Risks, resilience, and pathways to sustainable aviation: A COVID-19 perspective. Journal of Air Transport Management, Vol. 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. Journal of Air Transport Management, 91, 102007. 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), e12763-e12763. https://doi.org/10.1371/journal.pone.0012763.

Iacus, S.M, Natale, F., Santamaria, C., Spyratos, S., Vespe, M., 2020. Estimating and projecting air passenger traffic during the COVID-19 coronavirus outbreak and its socio-economic impact. Safety Science, Vol. 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, Vol. 218, https://doi.org/10.1051/e3sconf/202021803005.

Linden, E., 2020. Pandemics and environmental shocks: What aviation managers should learn from COVID-19 for long-term planning. Journal of Air Transport Management, DOI: 10.1016/j.jairtraman.2020.101944.

McCartney, S, 2020a. The Middle Seat: The Devastated Travel Industry, by the Numbers, April 15, https://www.wsj.com/articles/the-devastated-travel-industry-by-the-numbers-11586959775, Accessed May 21, 2021.

McCartney, S., 2020b. The Middle Seat: How Coronavirus Ravaged Travel in 2020. Wall Street Journal, November 4, https://www.wsj.com/articles/how-coronavirus-ravaged-travel-in-2020-11604500952, Accessed May 20, 2021.

Milne, R.J., Delcea, C. and Cotfas, L.-A., 2021, Airplane boarding methods that reduce risk from COVID-19. Safety Science, Vol. 134: 1-13.

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? Journal of Transport Geography, Vol. 86, DOI: 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.

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

Wenzel, M., Stanske, S., Lieberman, M.B., 2020. Strategic responses to crisis, Strategic Management Journal, DOI: 10.1002/smj.3161.

8. Appendix

Table A1 - Estimates of the resilient route selection

Variables	*(1)* *RESROUTE*
LOD_SDI	-0.026*
	(-1.83)
LDIST	0.273***
	(12.92)
TOTCOMP	-0.085**
	(-8.74)
TOTROUTE	0.000***
	(32.19)
SUNBELT	-0.103***
	(-4.26)
LCC	-0.525***
	(-21.50)
ODLINKS	0.000***
	(13.38)
LOD_POP	-0.004
	(-0.43)
LOD_INC	-0.125**
	(-2.05)
Constant	2.917**
	(2.35)
Observations	119,064
Pseudo R^2	0.17

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

Quarterly dummies are controlled for, but estimates have been suppressed