Transport Policy 140 (2023) 42–53

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

# Assessing the impacts of northeast alliance between American airlines and JetBlue airways

Li Zou [a,*], Chunyan Yu [a], Daniel Friedenzohn [b]

[a] David B. O'Maley College of Business, Embry-Riddle Aeronautical University, Daytona Beach, FL, 32114, USA
[b] College of Aviation, Embry-Riddle Aeronautical University, Daytona Beach, FL, 32114, USA

ARTICLE INFO

*Keywords:*
Airline alliances
Codeshare agreements
Airfare
Market concentration

ABSTRACT

This paper investigates the impacts of Northeast Alliance (NEA) between American Airlines and JetBlue Airways on market concentration and airfares on routes to and from the four pertinent airports in Boston and New York regions. Using panel data covering quarterly domestic flight schedules and airfares for 11 U.S. airlines during the 2019–2021 period, we apply difference-in-difference method and find evidence for positive and significant NEA effect on market concentration on routes out of BOS, and negative and significant effect on routes out of EWR, but no significant effect for routes out of JFK and LGA. The overall NEA effects, including all four airports, are not significant. Furthermore, our airfare estimation results indicate that NEA has led to higher airfares on routes out of BOS, JFK and LGA, but not on routes out of EWR. These findings are valuable to supplement the recent antitrust investigation by the U.S. Department of Justice of this alliance.

## 1. Introduction

Over the past three decades, airlines have formed various codeshare partnerships[1] to overcome regulatory barriers in foreign countries, expand their route network, increase traffic density, provide better schedule options, improve connecting services, restrain competition as well as provide services to otherwise unprofitable destinations (Ito and Lee, 2007). Codeshare partnerships in the U.S. domestic markets started to flourish in the late 1990s and early 2000s. In 2002, after a failed attempt to merge (ABC News, 2001), United Airlines and U.S. Airways entered into a codeshare agreement giving each carrier the ability to sell seats on their partner's flights (Chicago Tribune, 2002). Continental Airlines, Northwest Airlines, and Delta Air Lines formed a similar codeshare partnership in 2003 (Ito and Lee, 2007). Alaska Airlines and American Airlines also entered into a codeshare relationship that provides Alaska and Horizon customers' access to more than 100 new destinations served by American Airlines (Alaska Airlines, 2004).

American Airlines merged with Trans World Airlines in 2001. Since then, there have been eight mergers involving U.S. mainline carriers (Pallini, 2020). This industry-wide consolidation has resulted in a smaller number of network carriers in the U.S. domestic market. According to the Airlines, 2004 compiled by the U.S. Bureau of Transportation Statistics, the four largest U.S. airlines, Southwest Airlines (WN), Delta Air Lines (DL), American Airlines (AA), and United Airlines (UA), operated 62.6% of the U.S. domestic passenger traffic, and 36.9% of the U.S. international passenger traffic, accounting for 70% of the total revenue passenger miles (RPMs), while earning 79% of the total scheduled passenger revenue in the U.S. airline industry.

The consolidation over the past two decades has lessened the need and desire for airlines to form codeshare and other forms of partnership (Sampaio and Urdanoz, 2022). Thus, it was somewhat surprising to many people when American Airlines and JetBlue Airways (B6) announced in July 2020 that they intended to form a Northeast Alliance (NEA) through "cooperative agreements" related to "code-sharing, frequent flyer, interline, revenue sharing, and asset sharing" on routes out of Boston Logan International Airport (BOS), John F. Kennedy

* Corresponding author. David B. O'Maley College of Business, Embry-Riddle Aeronautical University, 1 Aerospace Boulevard, Daytona Beach, FL, 32114, USA.
*E-mail address:* zoul@erau.edu (L. Zou).

[1] A fundamental characteristic of the U.S. domestic airline market is that mainline carriers reach capacity purchasing agreements with regional carriers, through which regional carriers operate flights under the mainline carriers' codes (Gillen et al., 2015). A regional airline may operate exclusively under the regional operations banner of one mainline carrier or may operate on behalf of several mainline carriers. In 2019, regional carriers operated 44.4% of domestic scheduled departures, accounting for 20.4% domestic passenger enplanement, and 10.9% revenue passenger miles (RAA, 2021). A key difference between such capacity purchasing agreements and other airline codeshare agreements is that the regional carriers do not market or operate any flight under their own code. Such capacity purchasing arrangements are not considered as code-sharing partnership in this paper.

https://doi.org/10.1016/j.tranpol.2023.06.011
Received 13 January 2023; Received in revised form 5 May 2023; Accepted 19 June 2023
Available online 20 June 2023
0967-070X/

International Airport (JFK), LaGuardia Airport (LGA) and Newark Liberty International Airport (EWR) (American Airlines, 2020). The agreement includes a commitment by both carriers to "pool revenues and coordinate 'on all aspects' of network planning at Boston Logan, JFK, LaGuardia, and Newark Liberty, including deciding together which routes to fly, when to fly them, who will fly them, and what size planes to use" (Complaint, U.S. v. American Airlines Group, Inc. and JetBlue Airways Corporation). The carriers "pool and apportion revenues earned on flights to and from the four airports such that each partner earns the same revenues regardless of whether a passenger flies on an American or a JetBlue plane" (Complaint, U.S. v. American Airlines Group, Inc. and JetBlue Airways Corporation, Sept. 2021).

The NEA partnership was approved by the U.S. Department of Transportation on January 10, 2021, and the two airlines started their first codeshare flights on February 18, 2021 (JetBlue, 2021). The two carriers stated that the partnership was to focus on providing "customers new flight options, with improved schedules, better connections, competitive fares and access to more domestic and international destinations" (Nasdaq, 2021). The carriers also emphasized that the NEA would provide more competition "especially on routes currently served by only one airline with high fares and poor service" (Nasdaq, 2021).

In the past, domestic codeshare agreements have generally allowed carriers to sell seats on their partner's flights (Ito and Lee, 2005; Armantier and Richard, 2008), and passengers to earn frequent flier benefits on flights operated by their codeshare partners as well as access to airport lounges (Burton, 2002). Such codeshare agreements, however, require the carriers to "separate sales, pricing and scheduling" (Burton, 2002). The NEA, however, is a much more integrated partnership with some characteristics of a joint venture relationship as the carriers "pool revenues and coordinate 'on all aspects' of network planning on flights operated to and from Boston Logan, JFK, LaGuardia, and Newark Liberty (Complaint, U.S. v. American Airlines Group, Inc. and JetBlue Airways Corporation). Furthermore, different from the previous airline codeshare partnerships, the NEA was formed during a very disruptive, abnormal year due to the Covid-19 pandemic, and it is also the first alliance between a full-service legacy airline and a low-cost carrier in the U.S. airline industry.

On September 21, 2021, the United States Department of Justice (DOJ) and six states plus the District of Columbia brought a cause of action against American Airlines and JetBlue Airways alleging that the Northeast Alliance "unreasonably restrains competition," and it is thus in violation of Section 1 of the Sherman Act (DOJ, 2021). The civil antitrust complaint alleges that the alliance restrains competition between the two carriers and reduces competition in the marketplace which would result in higher fares and a reduction in service on many routes (DOJ, 2021).

The DOJ also stated that the alliance "effectively operates like a merger in domestic markets that have either Boston or JFK/LaGuardia as an endpoint" (DOJ, 2021). To support their allegations, the DOJ examined and presented the competitive effects of the alliance by using the Herfindahl-Hirschman Index (HHI) as the market concentration indicator. The DOJ stated that "[t]he more concentrated a market, and the more a merger would increase concentration in a market, the more likely it is that a merger between competitors would result in a meaningful reduction in competition" (Complaint, U.S. v. American Airlines Group, Inc. and JetBlue Airways Corporation, Sept. 2021).

Using route-specific passenger revenue data in 2019, the DOJ calculated the HHI values based on the combined market share of AA and B6, as well as their respective individual market shares in 11 markets[2] to and from Boston and 17 markets[3] to and from JFK/LGA, respectively, where the two airlines provided competing, non-stop services prior to the pandemic. Furthermore, the DOJ investigated the 98 markets where B6 competed with AA through connections via BOS or JFK. The DOJ's analysis is based on two criteria. First, whether the difference of HHI values using the two sets of the calculations is greater than 0.02.[4] Second, whether the HHI values based on the joint market shares of AA and B6 are greater than 0.25. For all the markets under the DOJ's investigation, the HHI calculation results meet both criteria. Therefore, the DOJ asserted that the NEA alliance is "presumptively anticompetitive" in the markets with BOS, JFK, and LGA as endpoint airports.

The HHI is an important tool to measure market concentration. Nevertheless, the use of data covering a single year of 2019 for the HHI calculations would cause three limitations to the DOJ's analysis. First, it is not able to incorporate the potential interplay between the two partner airlines, and the varied strategies taken by the two partner airlines and potentially by their rival airlines in terms of pricing, flight frequency, seat capacity or route network. Those strategies could lead to multiple alternative market scenarios. For example, how many new markets will AA & B6 create? Will they stimulate more traffic than the diversion between each other? Will AA & B6 compete less vigorously to the extent that they may lose their joint market share to other formidable rival airlines? Considering B6 is a low-cost carrier, will AA use the codeshare flights operated by B6 to create a generic version of its brand-name product targeting price-sensitive passengers[5] so that it may further increase the airfares on its own flights targeting price-insensitive passengers? And whether and how will their rival airlines (e.g., DL) adapt its pricing strategy to defend their own market shares? Certainly, all these scenarios will have different implications on market share redistribution, which cannot be measured by using data in 2019 alone, the year prior to the NEA formation.

Second, the HHI values based on the joint market shares of AA and B6 will always be higher than the HHI values based on their individual market shares when both airlines have operations on a given route.[6] Thus, the first criterion used by DOJ does not measure the HHI increase as result of the NEA alliance, thereby limiting its anti-competition assertion to be a "presumptive" inference.

Finally, the threshold value of 0.25 selected for making HHI comparisons is too low to draw a solid, meaningful conclusion, especially considering that in the 2nd quarter of 2019, the mean market concentration (HHI) value on all the U.S. domestic routes out of the top 30 U.S. airports including the four airports concerned was 0.65, and more than 98% of those domestic routes had HHI values all being greater than 0.25.

To address the aforementioned limitations of the DOJ's analysis, we conduct a more rigorous analysis to investigate the effects of NEA not

[2] The destinations for these 11 markets are Charlotte, Washington DC, Philadelphia, Rochester, Phoenix, Dallas, Syracuse, Miami, Los Angeles, NYC, and Chicago.

[3] The destinations for these 17 markets are Nantucket, Martha's Vineyard, Phoenix, West Palm Beach, Los Angeles, Miami, Orlando, Boston, Raleigh-Durham, Savannah, Las Vegas, San Francisco, Austin, Sand Diego, Charleston, Portland, ME, and Chicago.

[4] The DOJ scales up the HHI value by a factor of 10,000 from the results based on the decimal form of the market share. Therefore, the threshold values as shown in the report are 200 for the 1st criterion, and 2500 for the 2nd criterion.

[5] Ito and Lee (2007) conjecture that airlines could use virtual code-shared flights as generic products while using its own pure online flights as premium products, targeting different market segments.

[6] The difference between these two sets of HHI values will be equal to the product of the individual market shares of the two airlines, and then multiplied by a factor of two.

only on market concentration, but also on airfare, which is important to be studied especially from the passenger welfare perspective. Specifically, we address two research questions. First, how does NEA impact market concentration on routes to and from the four pertinent airports (BOS, JFK, LGA and EWR)? Second, what are the overall NEA's airfare effects on those affected routes? Are the airfares effects of NEA different for different airlines – AA, B6, and their main rival airlines, on those concerned routes?

We apply difference-in-difference (DID) model to analyze the market concentration before and after the NEA formation across routes that originate from the top 30 airports in the U.S. Routes containing destinations that can be reached through direct and indirect flights originating from JFK, BOS, EWR and LGA are considered as NEA routes, while the others are non-NEA routes. We find a positive and significant NEA effect on market concentration on routes out of BOS, while the effect is negative and significant out of EWR, but not significant out of JFK and LGA. The overall NEA effects, including all four airports, are not significant. Moreover, we estimate the effect of NEA on airfares, measured by passenger yield, and the results provide evidence for a higher airfare effect at BOS than those at JFK and LGA, while there is no evidence for the increased airfare effect at EWR. The additional estimation results at the airline and route level suggest a higher airfare increasing effects for B6 than for AA at BOS and JFK, whereas the airfare effects are not statistically different for these two airlines at LGA. While the previous literature (e.g., Armantier and Richard, 2008) finds the mixed airfare effects of codesharing alliance between Continental and Northwest Airlines in 1999 on the U.S. domestic routes – the positive effect for connecting flights, and the negative effect for non-stop flights, our results show the heterogeneous airfare effects of the NEA that vary at different airports, and the presence of asymmetric positive airfare effects between AA and B6. These findings could be used to supplement the antitrust analysis by the DOJ in its NEA investigation, and are also valuable for regulators to consider in their review of future codesharing alliances on domestic routes, as previous studies either show no significant airfare increase following codesharing or significant airfare increase following the formation of joint ventures in transatlantic or transpacific markets.

The rest of the paper is organized as follows. Section 2 reviews the previous literature studying the competition effects of airline cooperative partnerships focusing on codesharing alliances and joint ventures. Section 3 presents an exploratory analysis of market concentration on routes out of the four airports concerned before and after the NEA. Section 4 describes our empirical model and the data collected for estimating the airfare effects of the NEA. The results for main models and robustness checks are presented in Section 5. We conclude our paper in Section 6 discussing policy implications, the limitations of the current paper, and future research.

## 2. Literature review

Airline codesharing has long been an interest of academic researchers, industry analysts, government policy makers and regulators. In a report to the U.S. Department of Transportation, Gellman Research Associates (1994) provides a very good discussion about different types of codesharing and a compendious analysis of codesharing effects on consumer welfare, employment, CRS screen, airline marketing, etc. European Commission (2007) reports a comprehensive study of the impact of codeshare agreements. The report provides a "typology" of airline codesharing as well as a full inventory of existing codeshare agreements involving EU airlines. The study found that routes with codeshared flights had shown increasing capacity and decreasing fares in many cases, but there was evidence suggesting that in some cases, codeshare partners on parallel operated routes did not compete as much as similar routes without codeshare arrangements.

Early studies of airline codesharing focus on international markets. These studies generally show that codesharing often led to reduced airfares and increased passenger volume. For example, Oum et al. (1996) measure the effects of a codesharing agreement between non-leader airlines on the market leader's price and passenger volume based on a panel data of 57 transpacific air routes during the 1982-92 period. The study shows that the codesharing between the non-leaders makes the market leader behave more competitively, reducing pricing and consequently increasing passenger traffic volume. Hassin and Shy (2004) show that no passenger is worse off and both airlines earn higher profits under a codesharing agreement when there are only two airlines operating in the market. Other studies that yielded similar findings include Brueckner (2001, 2003), Whalen (2007), Park and Zhang (1998), etc.

As stated in the introduction, there was a proliferation of codeshare partnerships in the U.S. domestic markets in the late 1990s and early 2000s. Researchers have applied different methodologies to analyze the impacts of such partnerships, starting with investigating the consequences of specific codesharing agreements. For example, Bamberger et al. (2004) estimate a series of regression models with airfares and traffic volumes as dependent variables, and find that the airfares were reduced by 7.5% by the Continental/America West codesharing and 3.9% by the Northwest/Alaska codesharing. Du et al. (2008) examine the complementary codesharing between Southwest and ATA. Their results show that the complementary codesharing arrangement decreased incumbent carriers' airfares on non-stop flights and increased their passenger volumes, increasing both producer and consumer surplus in the Denver market. Armantier and Richard (2008) apply a discrete choice model and find that the surplus of passengers on connecting flights increased significantly, whereas the surplus of passengers on non-stop flights declined sharply following the 1999 Continental/Northwest codesharing agreement.

Ito and Lee (2007) coined the term "virtual codesharing" to refer to the practice whereby one carrier sells tickets on flights solely operated by its codeshare partner to distinguish it from the "traditional codesharing" where the marketing carrier operates at least one segment of an interline itinerary. The data for their empirical analysis includes flights covered by 10 codesharing agreements that had formed between 1998 and 2003. They conduct a fixed-effects econometric analysis of the US domestic round trip coach class tickets in the 3rd quarter 2003 and find that the price of the virtual codesharing tickets are lower than those operated and marketed by a single carrier. Goetz and Shapiro (2012) estimate a set of within-flight segment, fixed-effects regressions based on a panel data of the US domestic Origin-Destination tickets during the 1998 to 2010 period, and show that when an incumbent carrier's segment is threatened by a low-cost competitor it is 25% more likely to be codeshared with its partner. Shen (2017) develops a structural model of codesharing among major U.S domestic airlines and illustrates that codesharing leads to reduction in partner airlines' marginal costs, and codeshared products have lower prices but with higher margin. Ivaldi et al. (2022) focus on the U.S. domestic markets where only two airlines operate, excluding markets with low-cost carriers (LCC) presence. They define airlines as alliance partners "if passengers on one of the alliance carriers can earn elite-qualifying frequent flyer miles on flights marketed or operated by the other alliance partner and vice versa", and distinguish the markets by with or without alliance presence. They include a codeshare dummy variable if at least one passenger use codeshared tickets between the carriers in a market. Based on third quarter data from 2008 to 2019, their results indicate that alliances are associated with both lower prices and lower price dispersion, although the *Codeshare* variable presents a positive effect on both reservation cost and ticket prices (transaction prices).

The aforesaid discussions appear to consistently indicate reduced airfare following airline codesharing in both international and U.S. domestic markets. Instead of investigating the impacts of codesharing on airfares, Gayle and Thomas (2015) provide evidence indicating that cooperation between international carriers is associated with an increase in carriers' routing quality. For United Airlines and American

Airlines, virtual codeshares led to the greatest relative routing quality increases. Yimga (2022) finds similar results associated with virtual codeshares, and further shows that in contrast to the virtual codeshares, traditional codeshare itineraries are associated with worse path quality. On-time performance is another service quality indicators for airlines, Yimga (2020) shows that codeshare itineraries are associated with less arrival delay relative to itineraries marketed and operated by a single carrier. Based on the perception of 547 airline passengers in Taiwan, Lu and Yang (2022) investigate how passengers feel about flying on code-shared flights and conclude that passengers may exhibit aversion behaviors caused by their concerns about inconsistent services. The study shows that the domicile of codeshare partner airlines, passengers' awareness of codeshare scheme and the perceived inconsistent services are the key drivers for passengers' feelings toward airline codesharing. de Jong et al. (2022) conduct a stated preference experiment in Australia covering two long haul non-stop destinations: Australia to Santiago (Chile) and Australia to San Francisco (USA). They find that an average passenger is willing to pay a premium of 4–5.5% of the ticket price when a flight by a foreign carrier is codeshared with Australian national carrier Qantas, and risk averse passengers are willing to pay a premium about two times higher than non-risk averse passengers when flying to a less familiar destination.

Different from the aforementioned studies that mostly consider the effects of airline codesharing on consumers in terms of airfare (price), passenger volume, service quality and passenger behavior, Zou and Chen (2017) investigate the joint benefits of codesharing partnerships and global alliances on airline profitability based on data for 81 airlines during the 2007–2012 period. Their results show that the number of codesharing partnerships has a positive association with an airline's profit margin, and the more of its codesharing partners in the same global alliance, the greater its profit margin gains. Chua et al. (2005) and Goh and Yong (2006) use trans-log cost functions to assess the effects of codesharing on partner airlines' costs. Both papers find that codesharing led to lower costs for major airline alliances. Kenan et al. (2018) consider codeshare agreements in integrated flight scheduling, fleet assignment and aircraft routing in an optimization context and show that codeshare can have a significant impact on the profits of an airline by enabling the scheduling of more flights while minimizing delays. Yimga and Gorjidooz (2019) estimate reduced form regressions of airline capacity utilization based on the monthly data of the US domestic non-stop flights during July–December of 2002 and 2004. They find evidence that codesharing improves the partner airlines' load factors relative to other carriers overall. Furthermore, they find that codesharing had negative effects on load factor in markets where the partners competed prior to codesharing, but positive effects on load factor in markets where partners did not compete.

NEA has some characteristics of joint venture beyond codesharing, although it does not include joint price-setting as in other airline joint ventures. Bilotkach (2019) provides a critical review of studies on the effects of airline partnerships on prices and other airline product characteristics, noting limited researchers' attention to airline joint ventures. The effects of joint ventures have since been examined by a number of studies. Based on the monthly segment data for European and the US "legacy' carriers in the Transatlantic markets during 2007–2013, Bilotkach and Hüschelrath (2019) find that joint ventures lead to 3–5% increase in seat capacity between the respective partner airlines' hub airports which is achieved at the expense of services elsewhere in the network. Fageda et al. (2019) define the degree of airline cooperation agreements in two dimensions: revenue sharing (scope of alliance) and cost sharing (scope of joint venture). Their analysis distinguishes interline versus interhub markets, and finds that deeper degrees of airline cooperation lead to more traffic in both interhub and interline markets. The study also finds that socially optimal cooperation agreement moves from full alliance to joint venture in interline market as economies of traffic density become stronger, whereas it moves from joint venture to merger in interhub markets. No anticompetitive effect associated with joint venture is observed in their empirical analysis. Brueckner and Singer (2019) examine the airfare effects of international airline alliances during the 1997–2016 period. Their results indicate that cooperation between alliance partners lead to lower airfares for connecting interline trips relative to the fares charged by nonaligned carriers, whereas airfares charged by carriers that enjoy antitrust immunity or in joint venture are indistinguishable from online fares. They further show that cooperation in fare-setting on gateway-to-gateway routes with overlapping services by alliance partners leads to higher economy fares, indicating airline partners with antitrust immunity or in a joint venture do not compete with one another in setting economy fares on overlapping routes. Focusing on the behind-to-gateway markets between a non-gateway U.S. city and a foreign gateway city, Tan and Zhang (2022) find that the Oneworld transatlantic joint venture increased airfares of online flights by 3–4% in the behind-to-gateway markets based on data from 2008 to 2013. Their results are consistent with the findings of Brueckner and Singer (2019).

A major concern associated with airline cooperation or partnership is market concentration. Market concentration in the airline industry is commonly measured by the Herfindahl-Hirschman Index (Alderighi et al., 2012; Greenfield, 2014; Lieshout et al., 2016, etc.), and has been studied at route level and at airports. Some recent studies include Grosche et al. (2020) and Bedford and Bilotkach (2022). Oliveira and Oliveira (2018) examine the evolution of concentration in the Brazilian airline markets during the 2002–2013 period. Their results indicate a negative association between market concentration and traffic density, suggesting the entry-attraction effect of market size more than offset the economies of density effect. They further find evidence that dominant carriers' strategic investment in capacity is a key driver of concentration, and airport privatization has resulted in higher concentration in the Brazilian airline market. Grosche et al. (2020) incorporate high-speed rail services and connecting flights as alternatives to non-stop flights in their assessment of market concentration in German air travel markets and find that concentration in domestic markets in Germany is higher than those for European and international destinations. Neither Oliveira and Oliveira (2018) nor Grosche et al. (2020) examine the effects of market concentration on airfare. Bedford and Bilotkach (2022) find significant positive relationship between market concentration and airfares in the UK-Asia and UK-Australasia markets during the 2014 to 2016 period.

Our literature review finds that codesharing alone does not appear to lead to higher airfares in both domestic and international markets. More integrated relationships like joint venture, are likely to lead to higher airfare in certain markets. Furthermore, almost all the previous studies are based on cooperation or partnership among full-service carriers (FSC). NEA is a cooperation agreement between a FSC and a low-cost carrier (LCC) with characteristics of joint venture in domestic markets, whereas joint venture relationship studied previously in the airline industry generally involves two or more carriers from different countries serving international markets.

Given the unprecedented nature of the Covid-19 pandemic and the resultant disruption it caused to air travel market, it is worthwhile conducting an empirical study to examine the effects of NEA, which was formed during the second year of the pandemic, on market concentration and airfare. On one hand, the codesharing partnership between a FSC (i.e., AA) and a LCC (i.e., B6) may enable AA to expand market segments through relying on the codeshare flights operated by B6 as a new generic version of product, thereby stimulating passenger traffic, and lowering airfare. On the other hand, it is also likely that the substantial traffic depression occurring during the pandemic may prompt AA and B6 to raise airfare as the two airlines are able to compete less vigorously through their NEA partnership. In the following section, we will empirically investigate the impacts of NEA on market concentration and airfare to find out which of the above two hypotheses holds true.

## 3. Overview of market concentration before and after the NEA

JetBlue Airways was established in 2000 as a low-cost carrier based at JFK operating flights in an all-economy class configuration. As it grew, the carrier has established hubs at Boston Logan, Fort Lauderdale-Hollywood International Airport (FLL), and Orlando International Airport (MCO). JetBlue's domestic network focuses on flights along the east coast of the United States with the carrier also operating trans-continental flights in a two-class cabin configuration. The carrier has also developed an important presence in the Caribbean, offering over 30,000 seats per week to various destinations in the Dominican Republic and Puerto Rico. While JetBlue is ranked as the fifth largest airline in the U.S., its overall market share by the number of passengers is only 4.6% in 2019 (BTS, 2019), lagging behind the four largest U.S. airlines – 12.5% for United Airlines, 16.8% for American Airline at 16.8%, 17.5% for Delta Air Lines at 17.5%, and 17.6% for Southwest Airlines.

American Airlines is one of the largest airlines in the world. In 2019, the carrier served over 20% of the passenger traffic transported by all U. S. carriers in terms of revenue passenger miles (BTS, 2019). The airline operates 6700 flights per day to close to 350 destinations (American Airlines, 2020). American operates hubs in Charlotte, Chicago, Dallas/Fort Worth, Los Angeles, Miami, New York, Philadelphia, Phoenix, and Washington DC (American Airlines, 2020). The carrier is a founding member of the Oneworld Alliance and has a large international network with flights to Europe, Asia, and South America. By international passenger traffic, American Airline is ranked as the largest U.S. airlines with more than 12% market share in 2019, according to data compiled from Bureau of Transportation Statistics.

To examine the potential NEA impact on market concentration, we develop two sets of market concentration, i.e., HHI values, based on scheduled quarterly seat capacity at the route level. In Set I, we use market share for each individual airline, considering AA and BA separately, as the pre-NEA basis for calculating HHI value, whereas the combined market share of AA and B6 is used for calculating the post-NEA HHI value in Set II. Considering the industry-wide, pandemic-induced traffic losses and THE abnormity of flight operations in 2020, we decide to use the four quarters in 2019 as the base period before the NEA, and the four quarters in 2021 as the post-NEA study period. Of the four pertinent airports (JFK, BOS, LGA, and EWR), the results show that market concentration across routes out of JFK is, on average, lower than the other three airports throughout the quarters in 2019 and 2021, and the results hold true when using the two sets of HHI values for comparison.[7]

Table 1 shows the percentage of overlapped routes between AA and B6 is higher at JFK and BOS than at LGA and EWR. Indeed, there were no overlapped routes between AA and B6 out of EWR in 2019, and the two airlines had only two overlapping routes out of EWR in 2021. The average market concentration on those overlapped routes between AA and B6 is found to be higher out of BOS than out of the other three airports.

The differences between the HHI values in Set II in 2021 (based on the combined market share of AA and B6) and the HHI values in Set I in 2019 (based on the individual market share of AA and B6 separately) are calculated in order to examine the change of market concentration associated with the NEA formation. As shown in Fig. 1, the increase of market concentration related to the NEA across all routes is the highest out of BOS, as compared to the other three airports. The average change on all the routes across the four quarters is 0.077 at BOS, 0.036 at JFK, 0.019 at LGA, and −0.043 at EWR. While JFK and BOS both had an increase of market concentration related to the NEA throughout the four quarters, EWR had a decrease of market concentration, and the change is positive for LGA in Q1 & Q2, but negative in Q3 & Q4. It is also notable that both BOS and JFK had a much greater increase of market concentration when considering the overlapped routes between AA and B6, as compared to all the routes out of these two airports. Specifically, the average increase of market concentration on the overlapped routes out of BOS across the four quarters is 0.250, as compared to 0.133 out of JFK. In contrast, the average market concentration on the overlapped routes between AA and B6 out of LGA had a slight decrease (i.e., −0.018) across the four quarters from 2019 to 2021. The results reflect the stronger market position held by both B6 and AA at BOS and JFK, as compared to at the other two airports.

Fig. 2 plots the two sets of HHI values over the 12 quarters during the 2019–2021 period, and shows that in 2021, the gap between these two sets of market concentration values out of BOS and JFK are quite large, while the difference is quite small on routes out of EWR and LGA. Overall, these results indicate that the joint market position of AA and B6 is much stronger at BOS and JFK, than at EWR and LGA.

Using the two sets of HHI values (Set II in 2021 vs. Set I in 2019), we conduct a difference-in-difference (DID) analysis to investigate if there is any significant NEA treatment effect, controlling for the total seat capacity on route, and quarterly time dummy variables. Table 2 summarizes the estimation results.

As shown in Table 2, there is a positive and highly significant treatment effect of NEA on the difference between the two sets of HHI, but only on the routes out of BOS. On the contrary, the effects are negative, and moderately significant on routes out of EWR, while the effects are not significant out of JFK and LGA. Overall, the market concentration analysis provides mixed evidence for the presence of anticompetition effects. Therefore, it is necessary to further investigate the airfare effects of NEA, as detailed in Section 4.

**Table 1**
The overlapped routes (%) between AA and B6 in the total number of routes.

| Airport | Q1 | | Q2 | | Q3 | | Q4 | |
|---|---|---|---|---|---|---|---|---|
| | 2021 | 2019 | 2021 | 2019 | 2021 | 2019 | 2021 | 2019 |
| JFK | 10% | 19% | 14% | 18% | 14% | 17% | 20% | 13% |
| BOS | 13% | 15% | 14% | 14% | 12% | 14% | 17% | 14% |
| LGA | 9% | 4% | 3% | 5% | 2% | 5% | 3% | 4% |
| EWR | 2% | 0% | 3% | 0% | 3% | 0% | 2% | 0% |

## 4. Data, variable development and empirical model

### 4.1. Data source

The quarterly flight schedule and DB1B airfare data for 11 U.S. airlines on domestic routes during the 2019–2021 period are collected from Cirium Diio MI Market Intelligence. We also retrieve the historical Covid-19 cases at the state level from the Centers for Disease Control and Prevention website. The annual population and per capita personal income data are collected from the U.S. Census Bureau.

Our data includes 237,776 quarterly flight schedule observations covering all domestic flights marketed by 11 U.S. airlines from 2019 to 2021. The DB1B airfare data contains a total of 1,586,184 O&D airport-paired, airline-itinerary airfare observations on all domestic routes marketed by the 11 airlines out of the top 30 airports during the 12

[7] The HHI values in 2020 are indeed higher than those in 2021 for both sets of HHI. The comparison between Set I in 2020 and Set II in 2021 leads to similar conclusion except for BOS, where the mean value of Set I (0.7396) over four quarters in 2020 is slightly lower than Set II (0.7435) in 2021. This result is consistent with the conclusion based on the DID analysis using data for 2019 and 2021 suggesting the positive and significant NEA effect on market concentration only on routes out of BOS.

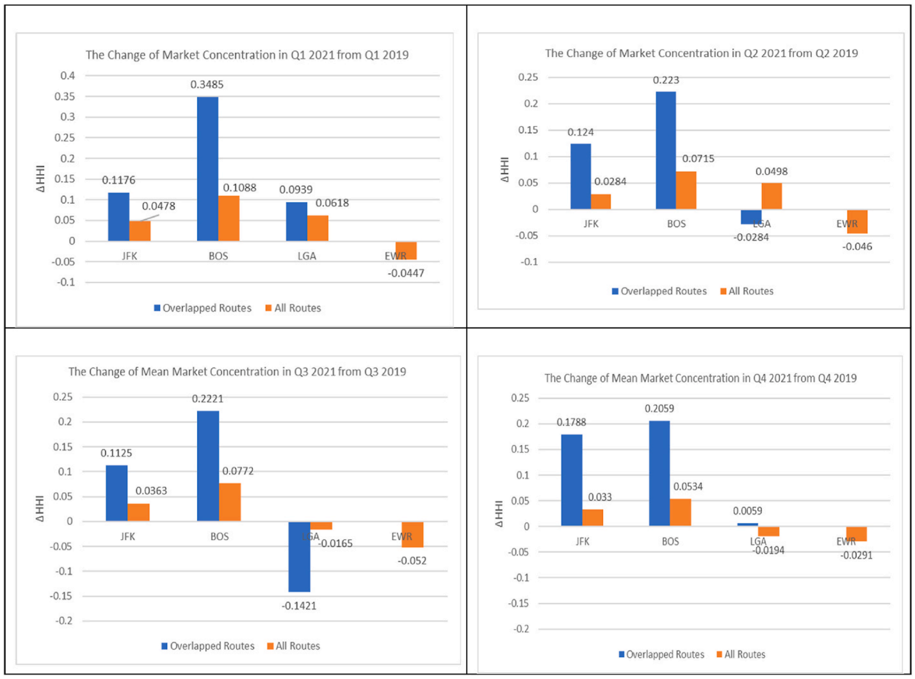


**Fig. 1.** The Change of Market Concentration (HHI) on Overlapped vs. All Routes.

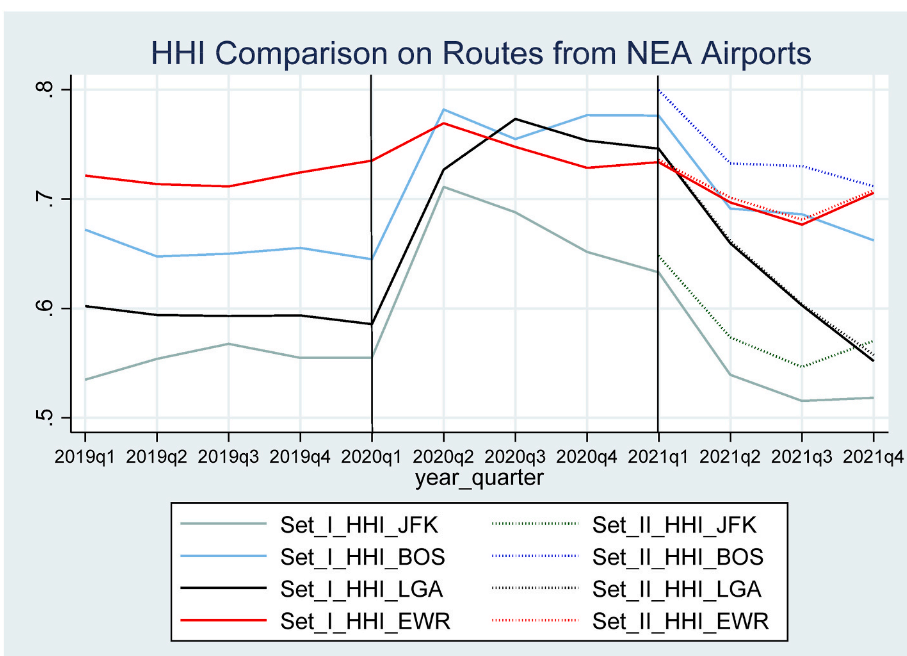


**Fig. 2.** The Comparison of pre-NEA vs. post-NEA HHI Values
Note: Set I HHI values are calculated using seat-based market share of each individual airlines and plotted over the 12 quarters, whereas Set II uses the combined seat share of AA and B6 in calculating HHI valued and plotted only for the four quarters of 2021.

**Table 2**
DID estimation results.

| HHI of Set II 2021 vs. HHI of Set I 2019 | NEA Airports | BOS | JFK | EWR | LGA |
|---|---|---|---|---|---|
| Treatment Effect | 0.0044 (0.0116) | 0.0517** (0.0227) | −0.0029 (0.0209) | −0.035* (0.0206) | −0.0038 (0.0214) |
| Ln (total seats) | −0.1065*** (0.0065) | −0.1058*** (0.0068) | −0.1023*** (0.0068) | −0.1026*** (0.0068) | −0.1054*** (0.0069) |
| # of obs. | 17,152 | 16,192 | 16,048 | 16,152 | 16,016 |

Note: *** significant at 0.01 level; ** significant at 0.05 level; *significant at 0.1 level.

quarters from 2019 to 2021. Of all the airline-route-itinerary airfare observations, 4.32% are for non-stop fare, 51.54% for one-stop connection, and 44.14% for two-stop connections. For Airline *i* on Route *j* in Quarter *t*, we calculate the overall airline-route yield[8] based on airline *i*'s itinerary-specific yield, weighted by the share of itinerary-specific passenger volume in the total number of passengers traveling with airline *i* on route *j* in quarter *t*. The aggregated airline-route airfare dataset contains 323,720 observations covering 11,959 O&D markets. The selection of balanced panel data provides 290,743 observations covering 7747 O&D markets for those 11 airlines across 12 quarters.

### 4.2. Measurements of airline yield and market yield

The NEA effects on airfares are examined at both the market and airline level. The airfares are approximated by passenger yields. Since an airline can provide multiple itineraries in an O&D market, we develop the variable $Airline\ Yield_{ijt}$ for Airline *i* on Route *j* in Quarter *t* using airline *i*'s itinerary-specific airfare on a route in a quarter, divided by the great circle distance between the origin and destination airports, and the calculated airline-route-itinerary yield is then weighed by the share of quarterly passenger number associated with itinerary *m* for airline *i* on route *j* in quarter *t*. The sum of the weighted yields is denoted as $Airline\ Yield_{ijt}$.

$$Airline\ Yield_{ijt} = \sum_{m=1}^{M} Share\ of\ passengers\ per\ \text{quarter of Airline } i \text{ by } itineary\ m_{ijt} \times Yield_{ijmt} \quad \text{Eq. (1)}$$

Then we aggregate the above airline-route-specific yields to calculate the market yield, $Market\ Yield_{jt}$ on route *j* in a given quarter *t*, using the shares of passengers carried by all marketing airlines on route *j* in quarter *t* as the corresponding weights. The formula is the following.

$$Market\ Yield_{jt} = \sum_{i=1}^{N} Share\ of\ passengers\ per\ \text{quarter by Airline } i \text{ on Route } j_{ijt} \times Airline\ Yield_{ijt} \quad \text{Eq. (2)}$$

### 4.3. Empirical model

To estimate the overall airfare impacts of NEA, and its potential different impacts for different airlines including not only the two allied airlines, i.e., B6 and AA, but also their main rival airlines out of the airports concerned including JFK, LGA, EWR, and BOS, we develop two empirical models. Specifically, Model I is illustrated by Eq. (3), with the O&D market yield, $Market\ Yield_{jt}$, as the dependent variable.

$$Market\ Yield_{jt} = \varphi_0 + NEA\ Airport\ \ Post\ Alliance_{jt} * \varphi_1' + X_{jt} * \varphi_2' + \mu_j + \theta_t + \tau_{ijt} \quad \text{Eq. (3)}$$

where the independent variables $NEA\ Airport\ \ Post\ Alliance_{jt}$ are dummy variables indicating whether the route observations include the four NEA airports as endpoint, and whether it is the post-alliance period (i.e., 2021). The vector $X_{jt}$ represents a set of control variables including market concentration, ticket characteristics, demand variables such as population, average income at endpoint cities. Among our selected control variables, market concentration, population and income, and presence of LCCs are commonly adopted variables in estimating the airfare effects of alliances (e.g., Ito and Lee, 2007; Bamberger et al., 2004; Brueckner and Singer, 2019). Following Gualini et al. (2023), we include the percentages of passengers traveling on itineraries with one-stop or two-stop connection as ticket characteristics, which also reflects the extent of competition for the non-stop flights. Our exploratory analysis of passengers bookings in the markets that are directly impacted by the NEA (i.e., non-stop domestic destinations out of the four NEA airports) show the presence of significant percentages of passengers traveling on itineraries with connections in 2019: 34% out of BOS, 15% out of JFK, 18% out of EWR, and 35% out of LGA, suggesting the competition effect of these alternative routings to the NEA non-stop flights. In addition, we include the average percentage of first and business class seats at endpoint airports of the route, which is expected to have a positive effect on yield (Armantier and Richard, 2008).

We also include Covid-19 situation, as measured by average cases per capita, to control for the traffic deterring effects inflicted by the pandemic. The presence of LCC and ultra-Low Cost Carrier (ULCC)[9] on a particular route is also considered as their presence is expected to decrease passenger yield on the route. Considering the potential endogeneity of market concentration in the yield regression, we use the lagged route HHI in the previous quarter as an instrumental variable, i.e., $Route\ HHI_{jt-1}$. The route fixed effect is represented by $\mu_j$, and time-fixed effect is $\theta_t$, while $\tau_{ijt}$ is the error term, which is assumed to be normally distributed with a zero mean and a constant variance. The log-linear form of Eq. (3) is written as follows.

$$\begin{aligned} Ln(Market\ Yield)_{jt} = {} & \gamma_0 + \sum_{i=1}^{4} \gamma_i * NEA\ Airport\ \ Post\ Alliance_{jt} + \gamma_5 \\ & * Route\ HHI_{jt-1} + \gamma_6\ First\ \&\ Business\ Class\ Seats\ \%_{jt} + \gamma_7 \\ & * Onestop\ \%\ Connections\ R_{jt} + \gamma_8 * Twostop\ \%\ Connections_{jt} + \gamma_9 \\ & * Ln(Avg.\ Pop)_{jt} + \gamma_{10} * Ln\ (Avg.\ Income)_{jt} + \gamma_{11} \\ & * Avg.\ Covid19\ Cases_{jt} + \gamma_{12} *\ ULCC\ Presence_{jt} + \gamma_{13} \\ & * LCC\ Pr\ esence_{jt} + \sum_{Qurater\ t} \gamma_{14-20} * Quarter_t + \mu_j + \theta_t + \tau_{ijt} \end{aligned} \quad \text{Eq. (4)}$$

Model II is specified by Eq. (5), in which the dependent variable is the airline yield on the route level, and the independent variables are $NEA\ Airport\ \ Post\ Alliance_{jt}$, and its interaction terms with different airlines including AA, B6, and their main rivals. Such interaction terms represent the potentially different NEA effects for different airlines from each of the four airports concerned. For B6 and AA, DL is their archrival airline across all those four airports, whereas UA, WN, and NK are their main rival airlines across the three, two and one airport, respectively.

$$\begin{aligned} Airline\ Yield_{ijt} = {} & \omega_0 + NEA\ Airport\ \ Post\ Alliance_{jt} * \omega_1' + NEA\ Airlines_{ijt} \\ & * NEA\ Airport\ Post\ Alliance_{jt} * \omega_2' + Rival\ Airlines_{ijt} \\ & * NEA\ Airport\ Post\ Alliance_{jt} * \omega_3' + X_{ijt} * \omega_4' + \rho_j + \sigma_t + \varepsilon_{ijt} \end{aligned} \quad \text{Eq. (5)}$$

The vector $X_{ijt}$ represents a set of exogenous variables that are determinants of the overall yield for Airline *i* on Route *j* in Quarter *t*. These variables include the lagged route HHI, ticket characteristics in terms of seat classes, number of connections, average population, per capita income, and Covid-19 cases per million population at endpoint states of the route, and the presence of ULCCs or other LCCs on the route. We also add a route-distance-adjusted unit cost as a new control variable, which

[8] We calculate yield by dividing airfare by route distance, and such yield measurement does not include any ancillary fees because airfare only represents ticket price.

[9] Ultra-low-cost carrier (ULCC) is considered to be a new business model in the U.S. (Bachwich and Wittman, 2017), being distinguished from the traditional low-cost carriers (LCC) such as Southwest and JetBlue. ULCCs offer bare-bone services and have more significant amount of add-on fees, such as Allegiant and Spirit. However, the U.S. ULCCs share many common characteristics with the European LCCs (Klophaus and Yu, 2023).

is expected to have a positive coefficient. Furthermore, we expect positive coefficients for market concentration, the percentage of first/business/premium economy seats, per capital income, but negative coefficient for Avg. Covid-19 Cases because of its demand-suppressing effect. Finally, $\rho_j$ represent route-specific effects, $\sigma_t$ measures quarter-fixed effect, and $\varepsilon_{ijt}$ is the normal error term which is assumed to have a constant variance and zero mean value. The log-linear form of Eq. (5) is the following.

$$\begin{aligned} Ln(Airline\ Yield)_{ijt} &= \alpha_0 + \sum_{i=1}^{4}\alpha_i * NEA\ Airport\ \ Post\ Alliance_{jt} + \sum_{i=5}^{12}\alpha_i \\ &* NEA\ Airline_{it} * NEA\ Airport\ Post\ Alliance_{jt} + \sum_{i=13}^{24}\alpha_i * Rival\ Airline_{it} \\ &* NEA\ Airport\ Post\ Alliance_{jt} + \alpha_{25} *\ Route\ HHI_{jt-1} + \alpha_{26} \\ &*\ First\ \&\ Business\ Class\ \%\ Seats_{ijt} + \alpha_{27} \\ &* Onestop\ \%\ Connections\ R_{ijt} + \alpha_{28} \\ &* Twostop\ \%\ Connections_{ijt} + \alpha_{29} * Ln\ (Adj.\ Unit\ Cost)_{ijt} + \alpha_{30} \\ &*\ Ln(Avg.\ Pop)_{jt} + \alpha_{31} * Ln\ (Avg.\ Income)_{jt} + \alpha_{32} \\ &*\ Avg.\ Covid19\ Cases_{jt} + \alpha_{33} *\ ULCC\ Presence_{jt} + \alpha_{34} \\ &*\ LCC\ Presence_{jt} + \sum_{Qurater\ t}\alpha_{35-41} * Quarter_t + \rho_j + \sigma_t + \varepsilon_{ijt} \end{aligned} \qquad \text{Eq. (6)}$$

To calculate the airline-route specific unit cost, we follow a two-step procedure. First, we estimate a log-linear regression model (see Eq. (7)), in which the dependent variable is unit cost per available seat-mile (CASM) for Airline $i$ in Quarter $t$, and the independent variable is its average stage length, while controlling for airline-fixed and time-fixed effects.

$$\ln CASM_{it} = \beta_0 + \beta_1 \ln Avg.\ Stage\ Length_{it} + \mu_i + \delta_t + \varepsilon_{it} \qquad \text{Eq. (7)}$$

Then we use the estimated value for $\beta_1$ to adjust for the effects of stage length on the unit cost of Airline $i$ on Route $j$ in Quarter $t$ through the following equation.

$$CASM^*_{ijt} = \overline{CASM}_{it} \times \left(\frac{D_{ijt}}{\overline{D}_{it}}\right)^{\widehat{\beta_1}} \qquad \text{Eq. (8)}$$

where $\overline{CASM}_{it}$ represents the system-wide unit cost per available seat-mile of Airline $i$ in quarter $t$, $\overline{D}_{it}$ is the network-wide stage length of Airline $i$ in quarter $t$, while the $D_{ijt}$ represents the flight distance for Airline $i$ on route $j$ in quarter $t$.

### 4.4. Descriptive statistics

We collect the quarterly CASM data from the U.S. DOT Form 41 report for the 11 sample airlines from Q1 2019 to Q4 2021. Eq. (7) is estimated using three different methods, namely the pooled OLS model, fixed-effects model, and random-effects model. The Hausman tests show the support for using fixed-effect, not random-effect estimation ($Prob > \chi^2 = 0.0026$). The fixed-effects estimation model provides the same results as a pooled OLS model including airline-specific effects and quarterly dummy variables for time-fixed effects. Table 3 presents the estimation results.

**Table 3**
The estimation results for CASM using the pooled OLS model.

| Variable | Coefficient | t-statistics |
|---|---|---|
| Avg. Stage Length | −0.9434*** | −4.63 |
| Constant | 9.5774*** | 6.62 |
| $R^2$ | 0.8946 | |
| Num. of Obs. | 132 | |

Note: *** Significant at 0.01 level; the airline-fixed effects and quarterly fixed effects are omitted but available upon request.

As expected, the estimated coefficient on average stage length is negative (−0.9434), and highly significant, implying that the higher stage length contributes to lower unit cost per available seat-mile, after controlling for a set of airline-specific, and time-specific effects. It is then used as the value for $\widehat{\beta_1}$ in Eq. (8) to calculate the distance-adjusted unit cost.

Table 4 presents the definitions for the variables employed in our models as well as a summary of descriptive statistics.

## 5. Estimation results

The estimation results for Model I using the fixed-effects model are presented in Table 5. As a robustness check, we also run the random-effects model, and the Hausman tests ($Prob > \chi^2 = 0.0000$) provide support for using fixed-effect model. The robust standard errors reported are adjusted for 7720 route clusters. In Model I, the dependent variable is Market Yield, and independent variables include dummy variables representing NEA alliances at JFK, LGA, EWR, and BOS, respectively. The estimated coefficients are positive and highly significant for the NEA alliance at JFK, LGA, and BOS, while it is negative but not significant at EWR. Moreover, we conduct the Wald test to see if the

**Table 4**
Variable definition and summary statistics.

| Variable | Descriptions | Mean(Std. Dev.) |
|---|---|---|
| Airline $Yield_{ijt}$ | Itinerary-based passenger yield by airline $i$ on route $j$ in quarter $t$, weighted by the percent of itinerary-specific passenger bookings in the total number of passengers traveling with airline $i$ on route $j$ in quarter $t$. | 0.1805 (0.1665) |
| Market $Yield_{jt}$ | Overall yield for airline $i$ on route $j$ in quarter $t$, weighted by the percent of airline-specific passenger bookings in the total number of passengers traveling on route $j$ in quarter $t$. | 0.1773 (0.1393) |
| Route $HHI_{jt-1}$ | Market concentration measure, based on passenger market share values across all airlines selling tickets on route $j$ in quarter $t-1$. | 0.6581 (0.2594) |
| % of First & Business Class $Seats_{ijt}$ | The average value of the percent of first & business class seats in the total number of seats operated by airline $i$ at origin and destination airports on route $j$ in quarter $t$, based on flight schedule data. | 0.0723 (0.0445) |
| % of One-stop $connections_{ijt}$ | The percent of passenger bookings on one-stop itineraries with airline $i$ on route $j$ in quarter $t$. | 0.7645 (0.3810) |
| % of Two-stop $connections_{ijt}$ | The percent of passenger bookings on a two-stop itinerary with airline $i$ on route $j$ in quarter $t$. | 0.0605 (0.1829) |
| Adjusted $CASM_{ijt}$ | The unit cost of airline $i$ in quarter $t$, adjusted by milage distance on route $j$ in quarter $t$. | 23.8992 (29.6657) |
| Avg. $Population_{jt}$ | The average population at the origin and destination states of route $j$ in quarter $t$. | 1.32e+07 (7,974,884) |
| Avg. Income per $Capita_{jt}$ | The average per capita personal income at the origin and destination states of route $j$ in quarter $t$. | $59,161.45 (6395.278) |
| Avg. Covid Cases per million $people_{jt}$ | The average Covid-19 cases per million population at the origin and destination states of route $j$ in quarter $t$. | 132,255 (150,980) |
| Presence of $ULCC_{jt}$ | Dummy variable equals 1 if at least one ULCC operates on route $j$ in quarter $t$, and 0 otherwise. | 0.2963 (0.4566) |
| Presence of $LCC_{jt}$ | Dummy variable equals 1 if at least one LCC (other than B6) operates on route $j$ in quarter $t$, and 0 otherwise. | 0.5934 (0.4912) |

**Table 5**
Estimation results of the NEA effects on Ln (market yield).

| Variable | Coefficient | Robust Standard Error |
|---|---|---|
| Ln (Lagged Route HHI) | 0.0722*** | 0.0061 |
| First & Business Class Seats (%) | 2.3686*** | 0.1254 |
| One-stop Connection (%) | 0.3051*** | 0.0133 |
| Two-stop Connection (%) | 0.5639*** | 0.0327 |
| ln (Avg. Population) | −0.3803 | 0.2917 |
| ln (Avg. Income) | 0.6194*** | 0.1792 |
| Covid-19 Cases per million population | −0.0232*** | 0.0013 |
| Post-NEA at JFK | 0.0470*** | 0.0116 |
| Post-NEA at LGA | 0.0326** | 0.0103 |
| Post-NEA at EWR | −0.0032 | 0.0111 |
| Post-NEA at BOS | 0.0725*** | 0.0090 |
| Presence of ULCC | −0.0359*** | 0.0065 |
| Presence of LCC | −0.0506*** | 0.0066 |
| 2019 Q3 | −0.0209*** | 0.0016 |
| 2019 Q4 | −0.0244*** | 0.0019 |
| 2021 Q1 | −0.3540*** | 0.0259 |
| 2021 Q2 | −0.2671*** | 0.0254 |
| 2021 Q3 | −0.1577*** | 0.0258 |
| 2021 Q4 | −0.1179*** | 0.0259 |
| Constant | −2.5532 | 6.2051 |
| Number of Obs. | 54,047 | |
| Number of Route Groups | 7720 | |
| *F (19, 7719)* and *Prob > F* | 751.05 and 0.0000 | |
| Within-$R^2$ | 0.4016 | |

Note: *p < 0.10, **p < 0.05, ***p < 0.001.

coefficients on the NEA alliances at different airports are different. The results show that the NEA effects are not statistically different between JFK and LGA ($F(1,7719) = 1.06$; $Prob > F = 0.3034$), while the effect of NEA alliance at BOS is statistically different from those at JFK ($F(1,7719) = 3.18; Prob > F = 0.0747$) and LGA ($F(1,7719) = 9.22$; $Prob > F = 0.0024$), at the 10% and 1% significance level, respectively.

The estimation results for control variables are summarized as follows. First, the lagged *Route HHI* has a positive and significant coefficient, supporting the expected positive effect of market concentration on yield. Second, the *percentage of first & business class seats* is found to have positive and significant impact on market yield, as compared to the % of economy seats, which is the default case in the estimation. Similarly, the *percentage of one-stop connection and two-step connection itineraries* is found to have positive and significant impact on yield, as compared to the % of non-stop bookings, which is the default case in the estimation. The positive yield effect of the connection itineraries potentially reflects the higher operating costs associated with the connection flights, as compared to non-stop flights (Ito and Lee, 2007). Third, *Avg. Income* has a positive and significant coefficient, suggesting the demand effect, as a higher income level would lead to a greater market demand, and thus a high yield on routes. In addition, the negative and significant coefficient on *Avg. Covid-19 Cases* suggests the demand-suppression effects inflicted by the pandemic[10]. Finally, the presence of LCC and ULCC, as expected, leads to lower yield on routes. The results on the quarterly time dummies indicate the persistent negative pandemic effects on yields throughout 2021 with 2019 Q2 as default.

Table 6 presents the estimation results of Model II, using the airline & route fixed-effect model. In Model II, the dependent variable is Airline Yield for an airline on a given route. As shown in Table 6, the coefficient for *Adjusted CASM* is positive, and significant, suggesting a higher yield is associated with a higher unit cost, adjusted by route distance. The negative and significant coefficient on *Avg. Population* suggests the presence of supply effect, as a greater market demand would lead to a higher seat capacity, and thus a lower yield. The estimation results for other control variables are all similar to those in Table 5.

**Table 6**
Estimation results of the NEA effects on Ln (airline yield).

| Variable | Coefficient | Robust Standard Error |
|---|---|---|
| Ln (Lagged Route HHI) | 0.0467*** | 0.0051 |
| First & Business Class Seats (%) | 1.1733*** | 0.0834 |
| One-stop Connection (%) | 0.2318*** | 0.0110 |
| Two-stop Connection (%) | 0.4257*** | 0.0192 |
| ln (Adjusted CASM) | 0.0259** | 0.0127 |
| ln (Avg. Population) | −0.6170** | 0.2676 |
| ln (Avg. Income) | 0.5544*** | 0.1694 |
| Covid-19 Cases per million population | −0.0303*** | 0.0013 |
| Post-NEA at JFK | −0.0222 | 0.0305 |
| Post-NEA at LGA | −0.1506*** | 0.0437 |
| Post-NEA at EWR | 0.0605 | 0.0433 |
| Post-NEA at BOS | −0.0382 | 0.0274 |
| Post-NEA by B6 at JFK | 0.1651*** | 0.0436 |
| Post-NEA by B6 at LGA | 0.2288*** | 0.0553 |
| Post-NEA by B6 at EWR | 0.0265 | 0.0532 |
| Post-NEA by B6 at BOS | 0.1847*** | 0.0349 |
| Post-NEA by AA at JFK | 0.0782** | 0.0338 |
| Post-NEA by AA at LGA | 0.1997*** | 0.0450 |
| Post-NEA by AA at EWR | −0.0199 | 0.0452 |
| Post-NEA by AA at BOS | 0.1119*** | 0.0293 |
| Post-NEA by DL at JFK | 0.1046*** | 0.0330 |
| Post-NEA by DL at LGA | 0.2008*** | 0.0456 |
| Post-NEA by DL at EWR | 0.0211 | 0.0447 |
| Post-NEA by DL at BOS | 0.1608*** | 0.0295 |
| Post-NEA by UA at LGA | 0.2456*** | 0.0469 |
| Post-NEA by UA at EWR | −0.0369 | 0.0445 |
| Post-NEA by UA at BOS | 0.1472*** | 0.0297 |
| Post-NEA by WN at LGA | 0.1322** | 0.0537 |
| Post-NEA by WN at BOS | 0.0343 | 0.0379 |
| Post-NEA by NK at EWR | −0.3015*** | 0.0663 |
| Presence of ULCC | −0.0161*** | 0.0048 |
| Presence of LCC | −0.0382*** | 0.0056 |
| 2019 Q3 | −0.0091*** | 0.0019 |
| 2019 Q4 | −0.0245*** | 0.0020 |
| 2021 Q1 | −0.3703*** | 0.0246 |
| 2021 Q2 | −0.2624*** | 0.0240 |
| 2021 Q3 | −0.1372*** | 0.0243 |
| 2021 Q4 | −0.0944** | 0.0245 |
| Constant | 1.8304 | 5.7728 |
| Number of Obs. | 175,554 | |
| Number of Route Groups | 30,139 | |
| *F (38, 30138)* and *Prob > F* | 633.11 and 0.0000 | |
| Within-$R^2$ | 0.2123 | |

Note: *p < 0.10, **p < 0.05, ***p < 0.001.

From Table 6, we can find the different yield effects of NEA for different airlines at different airports. Consistent with the findings from Model I, there is no NEA effects at EWR on the yield of B6, AA, and its main rivals such as DL and UA, except for NK, as suggested by the negative and significant coefficient for the dummy variable *Post-NEA by NK at EWR*. As for the BOS airport, its main effect is negative but not significant. However, for all the major airlines except for WN, the coefficients on the interaction terms between airline and post-NEA airports suggest the presence of positive and significant yield effects for B6, AA, DL, and UA at BOS in the post-alliance period. Specifically, the comparison of the coefficients among B6, AA, DL, and UA shows that the positive yield effects are not statistically different between B6 and DL ($F(1,30,138) = 0.96; Prob > F = 0.3275$), and between DL and UA ($F(1,30,138) = 0.71; Prob > F = 0.3998$), while the positive effect for B6 (i.e., 0.1847) is statistically different from that for AA (i.e., 0.1119) at the 5% significance level ($F(1,30,138) = 9.10; Prob > F = 0.0026$). The coefficient value for *Post-NEA by B6 at BOS* is 0.1847, more than the coefficient value for *Post-NEA by AA at BOS* by 65%.

Similarly, we find the positive and significant yield effects for B6, AA and DL at JFK in the post-alliance period. The comparison of the co-

[10] We also added the interaction terms between Covid-19 case per million population and the quarterly dummies in 2021 in the yield regression. The results show the negative effect in the fourth quarter of 2021 is smaller than those in the previous three quarters, suggesting the Covid-induced traffic reduction effect is diminishing over time as pandemic evolves to be less disruptive to air travel in its later stage than earlier. The results for other coefficients are similar to our base model, and available upon request.

 

efficients among these three airlines shows the highest yield effect for B6 at 0.1651, followed by the effect for DL at 0.1046, and then for AA at 0.0782. Moreover, the coefficients are found not to be significantly different between DL and AA (($F(1, 30, 138) = 1.71; Prob > F = 0.1910$), while they are significantly different between B6 and AA at the 5% significance level ($F(1, 30, 138) = 6.18; Prob > F = 0.0129$), and between B6 and DL at the 10% significance level ($F(1, 30, 138) = 3.13; Prob > F = 0.0767$)..

Since the main yield effects at the LGA airport is negative, and significant, while the airline-specific effects out of this airport in the post-alliance period are all positive and significant, we calculate the linear combination effect on yield for each of those top five airlines at the LGA airports. The results are summarized in Table 7.

As shown in Table 7, the combined yield effect is found to be positive and significant for B6 at 0.0781, and for UA at 0.0950, and these two effects are not statistically different. Moreover, the combined yield effects are also found to be positive and significant for AA at 0.0491 and for DL at 0.0501, and their difference is not statistically significant. It is notable that the combined effect for B6 is not significantly different from that for AA, DL, and UA, whereas the combined effect for AA is significantly different from that for UA. Last, the combined yield effect for WN at LGA in the post-alliance period is found to be negative at −0.0185, but not significantly different from zero (*p-value* = 0.559).

Table 8 summarizes the yield effects for B6 and AA and their main rivals at the four NEA airports including JFK, BOS, EWR and LGA in the post-alliance period. The results show a greater, positive yield effect for B6 than for AA at both JFK and BOS airports, while the yield effects are not statistically different for these two airlines at LGA. Moreover, the results indicate that the main rivals of B6 and AA such as DL at JFK, DL and UA at BOS, and DL and UA at LGA are also associated with positive and significant yield effects in the post-alliance period. On the contrary, there is no such positive and significant yield effect for WN, an important low-cost rival at BOS and LGA. Finally, the yield effect is found to be negative and significant for NK, an important ultra-low-cost rival at the EWR airport.

## 6. Conclusion, implications and further research

The Department of Justice (DOJ)'s case against AA and B6 was heard in a Federal District Court in Boston during the fall of 2022. During their closing arguments, the DOJ argued that the NEA consists of two carriers "getting bigger through cooperating and collaborating rather than competing" and as a result, consumers would be paying more to fly into markets that are part of the alliance (Sider, 2022). The DOJ also argued that the alliance will cost consumers between $500 to $700 million a year in higher airfares (Moser, 2022).

The defendant airlines argued that the alliance has allowed them to better challenge Delta and United in New York and Boston, thereby increasing competition at those airports (Sider, 2022). The carriers' economic experts testified at the trial that the NEA will "save consumers up to $635 million a year" (Koenig, 2022). American Airlines argued that the NEA has allowed it to offer nonstop service to 47 of the top 50 destinations out of New York (Koenig, 2022), whereas it only operated nonstop services to 31 of those destinations before the NEA (Koenig, 2022).

**Table 7**
The linear combination effects for airlines at LGA in the Post-NEA period.

| | Combination Effects |
|---|---|
| B6 at LGA post-NEA | 0.0781** |
| AA at LGA post-NEA | 0.0491*** |
| DL at LGA post-NEA | 0.0501*** |
| UA at LGA post-NEA | 0.0950*** |
| WN at LGA post-NEA | −0.0185 |

Note: *p < 0.10, **p < 0.05, ***p < 0.001.

**Table 8**
The summary of yield effects for airlines at NEA airports.

| Airline/ Airport | JFK | BOS | EWR | LGA |
|---|---|---|---|---|
| B6 | 0.1651*** | 0.1847*** | Not significant | 0.0781** |
| AA | 0.0782** | 0.1119*** | Not significant | 0.0491*** |
| DL | 0.1046*** | 0.1608*** | Not significant | 0.0501*** |
| UA | NA | 0.1472*** | Not significant | 0.0950*** |
| WN | NA | Not significant | NA | Not significant |
| NK | NA | NA | −0.3015*** | NA |

Note: NA – not available, because the airline concerned is not in the top 5 airlines at the airport in terms of seat share; *p < 0.10, **p < 0.05, ***p < 0.001.

DOJ alleged in their case that through the formation of NEA, AA and B6 would increase their collective market power on the routes to and from the four airports – BOS, JFK, LGA, and EWR, and the competition on those routes will be unreasonably restrained, violating Section 1 of the Sherman Act. The allegation was supported by its market concentration analysis of 28 routes to and from BOS, JFK, and LGA where AA and B6 had direct competition prior to the NEA, and 98 routes where AA and B6 competed through the connection via BOS or JFK. Using the route-based passenger revenue data in 2019, DOJ calculated two sets of HHI – one is computed by using the combined market share of AA and B6, and the other using the market share of individual airlines. In our introduction section, we explicate the limitations of DOJ's method for investigating the anticompetition effect of the NEA, and note the insufficient relevancy of the criteria adopted for assessing the degree of market concentration at large hub airports.

The main contributions of this paper are twofold. First, we address the limitations of the DOJ's method. Through calculating the same two sets of HHI using data covering the periods not only before the NEA (2019), but also after the NEA (2021), our analysis takes into consideration the changes in the overall domestic air travel markets to and from the top 30 hub airports in the United States. By comparing the HHI values based on combined market share of AA and B6 in 2021 with those based on individual market share of AA and B6 in 2019, we find that market concentration on overlapped routes between AA & B6 out of BOS had the most increase in the post-NEA period from the pre-NEA period as compared to all the other routes. Moreover, the DID estimation results show a significant, positive effect of NEA on market concentration on the routes to and from BOS, while the effects are negative on routes to and from EWR, and not significant on routes to and from JFK and LGA. Our finding about the positive effects of NEA on market concentration at BOS is consistent with the conclusion from the DOJ's analysis, whereas the results for the other airports are contradictory to the DOJ's analysis. We believe that the comparison between the *ex post* market concentration based on combined market share of AA and B6 and the *ex ante* market concentration based on their individual market share is more meaningful than the comparison between the two sets of HHI both based on the pre-NEA data. The NEA's negative effect on market concentration at EWR is not surprising, as EWR is dominated by UA, and the NEA might help to weaken UA's market dominance. The insignificant effects on market concentration at JFK and LGA reflect the strong competition by Delta at these two airports.

Second, our estimation of the effects of NEA on airfare (as measured by yield) contributes to the literature considering the nature and timing of this alliance. While several previous studies on codesharing alliances find support for negative airfare effects, studies of joint ventures (JV) in the international airline markets show evidence for JV-induced airfare increases. NEA is beyond conventional codesharing, with characteristics of joint venture. Hence, in such a domestic setting, our results provide empirical evidence on the airfare effects of an alliance between a full-service airline and a low-cost carrier with characteristics of joint venture. Moreover, it is worthwhile investigating the airfare effects of alliances in the context of the pandemic, which has caused a dramatic decline of passenger demand. Under such an abnormally unfavorable environment, airlines are more likely to use alliance as a strategy to restrain competition, leading to higher airfare.

Although the NEA proposal was made before the pandemic, its implementation was effective at the beginning of the second year into the pandemic, making the empirical study of its airfare effects quite topical. Our results suggest that the airfare-increasing effects are higher at BOS than at JFK and LGA, while there is no evidence for the airfare-increasing effects at EWR. Furthermore, through estimating the airfare effects of NEA at the airline-route level, we find that the airfare increasing effects for B6 are greater than those for AA, particularly at JFK and BOS, whereas the airfare increasing effects are similar between B6 and AA at LGA. The higher airfare increase at BOS suggests that the NEA has switched some B6 flights to AA with higher airfares, and the results also reflect the Delta's increased market share at BOS. JFK and LGA are slot controlled, thus the ability of the NEA to "rationalize" operating carriers between AA and B6 would be somewhat limited, which in part explains the smaller airfare effects. The higher airfare effects for B6 than AA at BOS and JFK reflect the consideration that the NEA further strengthened its market power at these two airports where B6 already had significant market power prior to the NEA. B6 has very limited market share at LGA, consequently very limited ability to increase its airfares in spite of the NEA. Our results suggest that airline cooperation at slot-controlled airports may not lead to significant anti-trust consequence, highlighting the importance for regulators to consider airport differences in their review of future codesharing alliances.

The impacts of the Covid-19 pandemic on the U.S. domestic air travel remain strong in 2021. Despite the partial recovery of passenger enplanement on domestic routes, the domestic seat capacity and load factor remained at 19% and 9%, respectively, below the levels in 2019, the year before the pandemic. According to the U.S. Bureau of Transport Statistics report, the average yield on domestic routes dropped from 18.6 cents per passenger-mile in 2019 to 15.3 cents in 2020, and slightly recovered to 15.6 cents in 2021. The negative airfare (yield) impacts of the Covid-19 are the consequence of both its demand-suppression effects, and the changing mix of passenger traffic shifting away from business traveling during the pandemic. In their study of using traffic data relevant to Air France-KLM, Li et al. (2021) found that the segment of business passengers between age 41 and 60 experienced the most traffic reduction effects, while the segment of leisure passengers between age 20 and 40 experienced the least traffic reduction effects.

On the supply side, some airlines (Adrienne et al., 2020) have sped up their fleet replacement during the pandemic, grounding/retiring their older and/or smaller aircraft (e.g., DH, CRJ, and ERJ) and replacing them with newer aircraft that tend to have more first & business class seats. In addition, some mainline airlines also operated more routes with their own mainline aircraft instead of relying on regional connectors. Airlines may have also selected to keep the most important business routes while cutting those less important ones in terms of the potential business traffic demand. All these strategies may potentially help airlines to increase the percentage of first & business class seats,[11] thereby countering the yield-reduction effects. Due to the unprecedented impacts of the pandemic on the airline industry, and the strategies adopted by airlines in dealing with the pandemic, it is important for future research to study the competition and airfare effects of NEA using more recent data beyond the year of 2021 as the shadowing effects of the pandemic diminishes over time.

This paper only examines the effect of NEA on market concentration and airfare, which does not include ancillary fees. Given the importance of ancillary revenues for most airlines these days, and the different fee structures adopted by legacy airlines and LCCs (ULCCs), it is important to incorporate ancillary fees into the airfare impact study. Furthermore, our analysis of the overall airfare effect of the NEA does not differentiate the type of codeshare flights such as unilateral versus reciprocal, and non-stop vs. connecting codeshared flights. In the case of unilateral alliance, only one partner airline serves as the operating carrier on the route, and the other partner airline only serves as a marketing carrier, while in the reciprocal case, both partner airlines have flight operations on the route, and can cross-sell tickets on the partner's flights. Such unilateral codesharing arrangement is also known as fully virtual codesharing practices, as studied in Ito and Lee (2007). Since the airfare effects could be different between unilaterally and reciprocally codeshared flights, or between virtual and traditional codeshared flights, more granular data at the route level with the marketing and operating carrier identity will need to be investigated in future research for understanding how the NEA's effects at the route level are different for different types of codesharing arrangements.

As of December 2021, the majority of the NEA flights are unilaterally operated. Out of the 46 NEA non-stop destinations out of JFK, only 9 are operated by both AA and JetBlue. Similarly, only 6 out of the 46 NEA non-stop destinations out of BOS are operated by both AA and B6, 1 out of the 37 NEA non-stop destinations out of LGA is operated by both AA and B6, and there is no overlapped direct routes between AA and B6 out of EWR. Moreover, those overlapped routes have substantially different frequencies between the two operating airlines. It should be noted that the distinction between unilateral versus reciprocal codeshared flights and virtual versus traditional codeshared flights may not be clearly defined in this case as NEA allows the two carriers to "pool revenues and coordinate "which routes to fly, when to fly them, who will fly them, and what size planes to use" out of the four NEA airports. Considering that the case by the DOJ against the NEA is still ongoing, it is important to develop more empirical studies incorporating the effects on passenger traffic, flight frequency, market scope, and connectivity beyond airfare to fully examine its overall effect on passenger welfare. Future research needs to investigate these impacts in the international and domestic context beyond the U.S. air travel market.

## Author statement

Li Zou: Conceptualization; Methodology; Data Curation; Formal Analysis; Visualization; Writing-Original Draft, Review & Editing.

Chunyan Yu: Conceptualization; Methodology; Investigation; Writing-Original Draft, Review & Editing.

Daniel Friedenzohn: Conceptualization; Methodology; Resources; Writing-Original Draft, Review & Editing.

## Data availability

Data will be made available on request.

## References

ABC News (Ed.), 2001. United-US Airways Merger Dead. ABC News. Retrieved June 4, 2022, from. https://abcnews.go.com/Business/story?id=87893&page=1.

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

Airlines, Alaska, 2004. Alaska Airlines, Horizon Air and American Airlines Finalize Codeshare.

Alderighi, M., Cento, A., Nijkamp, P., Rietveld, P., 2012. Competition in the European aviation market: the entry of low-cost airlines. J. Transport Geogr. 24, 223–233. https://doi.org/10.1016/j.jtrangeo.2012.02.008.

American Airlines, 2020. JetBlue and American Airlines Announce Strategic Partnership to Create More Competitive Options and Choice for Customers in the Northeast. American Airlines Newsroom. July 16, 2020. https://news.aa.com/news/news-details/2020/JetBlue-and-American-Airlines-Announce-StrategicPartnership-to-Create-More-Competitive-Options-and-Choice-for-Customers-in-the-Northeast-NET-ALP-07/default.aspx.

[11] We find that the percentage of first & business class seats increased on average from 0.0723 in 2019 to 0.0768 to 2020, and to 0.0789 in 2021 in our data sample.

Armantier, O., Richard, O., 2008. Domestic airline alliances and consumer welfare. Rand J. Econ. 39 (3), 875–904.
Bachwich, A.R., Wittman, M.D., 2017. The emergence and effects of the ultra-low cost carrier (ULCC) business model in the U.S. airline industry. J. Air Transport. Manag. 62, 155–164. https://doi.org/10.1016/j.jairtraman.2017.03.012.
Bamberger, G.E., Carlton, D.W., Neumann, L.R., 2004. An empirical investigation of the competitive effects of domestic airline alliances. J. Law Econ. 47 (1), 195–222.
Bedford, J., Bilotkach, V., 2022. Competition on the UK-Australasia market: evidence from transaction data. Transport Pol. 122, 54–63. https://doi.org/10.1016/j.tranpol.2022.04.004.
Bilotkach, V., 2019. Airline partnerships, antitrust immunity, and joint ventures: what we know and what I think we would like to know. Rev. Ind. Organ. 54 (1), 37–60. https://doi.org/10.1007/s11151-018-9636-x.
Bilotkach, V., Hüschelrath, K., 2019. Balancing competition and cooperation: evidence from transatlantic airline markets. Transport. Res. Pol. Pract. 120, 1–16. https://doi.org/10.1016/j.tra.2018.12.008.
Brueckner, J.K., 2001. The economics of international code-sharing: an analysis of airline alliances. Int. J. Ind. Organ. 19, 1475–1498.
Brueckner, J.K., 2003. International airfares in the age of alliances: the effects to code-sharing and antitrust immunity. Rev. Econ. Stat. 85, 105–118.
Brueckner, J.K., Singer, E., 2019. Pricing by international airline alliances: a retrospective study. Economics of Transportation 20, 100139. https://doi.org/10.1016/j.ecotra.2019.100139.
BTS, 2019. Annual Airline Rankings 2019. Bureau of Transportation Statistics, United States Department of Transportation. https://www.bts.gov/topics/annual-airline-rankings.
Burton, T.M., 2002. DOT clears United-US Airways to form code-sharing pact. Wall St. J. 2002, Oct. 03 Retrieved November 18, 2022 https://www.wsj.com/articles/SB1033603101330020593.
Chua, C.L., Kew, H., Yong, J., 2005. Airline code-share alliances and costs: imposing concavity on translog cost function estimation. Rev. Ind. Organ. 26, 461–487 ezproxy.libproxy.db.erau.edu/10.1007/s11151-005-0223-6.
Complaint, U.S. and Plaintiff States v., 2021. American airlines Group, Inc. and JetBlue Airways corporation. https://www.justice.gov/atr/case-document/394633.
de Jong, G., Behrens, C., van Herk, H., Verhoef, E., 2022. Airfares with codeshares: (why) are consumers willing to pay more for products of foreign firms with a domestic partner? J. Econ. Behav. Organ. 193, 1–18. https://doi.org/10.1016/j.jebo.2021.10.027.
DOJ, 2021. Justice Department Sues to Block Unprecedented Domestic Alliance between American Airlines and JetBlue, Justice News, Office of Public Affairs. U.S. Department of Justice. September 21, 2021. Retrieved March 8, 2022, from. https://www.justice.gov/opa/pr/justice-department-sues-block-unprecedented-domestic-alliance-between-american-airlines-andw.justice.gov/opa/pr/justice-department-sues-block-unprecedented-domestic-alliance-between-american-airlines-and.
Du, Y., McMullen, B.S., Kerkvliet, J.R., 2008. The economic impact of the ATA/Southwest Airlines code-share agreement. Res. Transport. Econ. 24 (1), 51–60.
European Commission, 2007. Competition Impact of Airline Code-Share Agreements. Directorate General for Competition. January, 2007, Brussels, Belgium. https://ec.europa.eu/competition/sectors/transport/reports/airlinecodeshare.pdf.
Fageda, X., Flores-Fillol, R., Theilen, B., 2019. Hybrid cooperation agreements in networks: the case of the airline industry. Int. J. Ind. Organ. 62, 194–227. https://doi.org/10.1016/j.ijindorg.2017.10.008.
Gayle, Philip G., Thomas, T., 2015. Product quality effects of international airline alliances, antitrust immunity, and domestic merger. Rev. Netw. Econ. 14 (1), 45–74. https://doi.org/10.1515/rne-2015-0026, 2015.
Gellman Research Associates, 1994. A Study of International Airline Code Sharing. Office of Aviation and International Economics, US Department of Transportation, Washington, DC.
Gillen, D., Hasheminia, H., Jiang, C., 2015. Strategic considerations behind the network–regional airline tie ups – a theoretical and empirical study. Transp. Res. Part B Methodol. 72, 93–111. https://doi.org/10.1016/j.trb.2014.09.001.
Goetz, C.F., Shapiro, A.H., 2012. Strategic alliance as a response to the threat of entry: evidence from airline codesharing. Int. J. Ind. Organ. 30 (6), 735–747.
Goh, M., Yong, J., 2006. Impacts of code-share alliances on airline cost structure: a truncated third-order translog estimation. Int. J. Ind. Organ. 24 (4), 835–866.
Greenfield, D., 2014. Competition and service quality: new evidence from the airline industry. Economics of Transportation 3 (1), 80–89. https://doi.org/10.1016/j.ecotra.2013.12.005.
Grosche, T., Klophaus, R., Seredyński, A., 2020. Market concentration in German air transport before and after the Air Berlin bankruptcy. Transport Pol. 94, 78–88. https://doi.org/10.1016/j.tranpol.2020.05.006.
Gualini, A., Zou, L., Dresner, M., 2023. Airline strategies during the pandemic: what worked? Transport. Res. Pol. Pract. 170, 103625–103625.
Hassin, O., Shy, O., 2004. Code-sharing agreements and interconnections in markets for international flights. Rev. Int. Econ. 12, 337–352.
Ito, H., Lee, D., 2005. Domestic codesharing practices in the US airline industry. J. Air Transport. Manag. 11 (2), 89–97. https://doi.org/10.1016/j.jairtraman.2004.09.003.
Ito, H., Lee, D., 2007. Domestic code sharing, alliances, and airfares in the U.S. Airline Industry. J. Law Econ. 50 (2), 355–380. https://doi.org/10.1086/511318.
Ivaldi, M., Petrova, M., Urdanoz, M., 2022. Airline cooperation effects on airfare distribution: an auction-model-based approach. Transport Pol. 115, 239–250. https://doi.org/10.1016/j.tranpol.2021.11.006.
JetBlue, 2021. JetBlue Launches First Phase of Codeshare with American Airlines, Adding New Routes and Destinations. JetBlue Press Release. February 12, 2021. http://mediaroom.jetblue.com/investor-relations/press-releases/2021/02-18-2021-160050512.
Kenan, N., Diabat, A., Jebali, A., 2018. Codeshare agreements in the integrated aircraft routing problem. Transp. Res. Part B Methodol. 117, 272–295. https://doi.org/10.1016/j.trb.2018.08.008. Part A.
Klophaus, R., Yu, C., 2023. Short-haul airline services in Europe and North America - a cross-business model and cross-continental analysis. J. Air Transport. Manag. 109, 102400 https://doi.org/10.1016/j.jairtraman.2023.102400.
Koenig, D., 2022. US Bid to Kill American-JetBlue Partnership Goes to Judge. Daytona Beach. Retrieved November 26, 2022, from. http://ezproxy.libproxy.db.erau.edu/login?url=https://www.proquest.com/other-sources/us-bid-kill-american-jetblue-partnership-goes/docview/2737805655/se-2?accountid=27203.
Li, X., de Groot, M., Bäck, T., 2021. Using forecasting to evaluate the impact of COVID-19 on passenger air transport demand. Decis. Sci. J. https://doi.org/10.1111/deci.12549.
Lieshout, R., Malighetti, P., Redondi, R., Burghouwt, G., 2016. The competitive landscape of air transport in Europe. J. Transport Geogr. 50, 68–82. https://doi.org/10.1016/j.jtrangeo.2015.06.001.
Lu, J.L., Yang, C.-W., 2022. Good or bad? Passenger feelings regarding code-share alliances among airlines. J. Air Transport. Manag. 103, 102252 https://doi.org/10.1016/j.jairtraman.2022.102252.
Moser, D., 2022. Arguments conclude in federal antitrust lawsuit against airline alliance. Wash. Post, 2022-11-19. A.13.
Nasdaq, 2021. JetBlue and American airlines advance strategic alliance following regulatory review. January 12, 2021. https://www.nasdaq.com/press-release/jetblue-and-american-airlines-advance-strategic-alliance-following-regulatory-review.
Oliveira, M.V.R., Oliveira, A.V.M., 2018. What drives effective competition in the airline industry? An empirical model of city-pair market concentration. Transport Pol. 63, 165–175. https://doi.org/10.1016/j.tranpol.2017.12.021.
Oum, T.H., Park, J.-H., Zhang, A., 1996. The effects of airline codesharing agreements on firm conduct and international air fares. J. Transport Econ. Pol. 30 (2), 187–202. http://www.jstor.org/stable/20053109.
Pallini, T., 2020. The Past 2 Decades Saw the Number of Major Airlines in the US Cut in Half. See How Consolidation in the 2000s Left Customers with Fewer Options as Profits Soared. Insider. March 21, 2020. https://www.businessinsider.com/airline-mergers-and-acquisitions-in-the-us-since-2000-2020-3.
Park, J.-H., Zhang, A., 1998. Airline alliances and partner firms' outputs. Transport. Res. E Logist. Transport. Rev. 34 (Issue 4), 245–255, 1998.
RAA, 2021. *RAA 2021 Annual Report*. Regional Airline Association. Retrieved June 7, 2022, from. https://www.raa.org/content-hub/raa-annual-reports/raa-2021-annual-report/.
Sampaio, R.M.B., Urdanoz, M., 2022. Airlines' cooperation in the US domestic market: measuring the evolution of price gaps. Transport. Res. Pol. Pract. 166, 424–443. https://doi.org/10.1016/j.tra.2022.11.007.
Shen, C., 2017. The effects of major U.S. domestic airline code sharing and profit sharing rule. J. Econ. Manag. Strat. 26 (3), 590–609. https://doi.org/10.1111/jems.12202.
Sider, A., 2022. American, JetBlue Spar with DOJ. Wall Street Journal. B.3.
Tan, G., Zhang, Y., 2022. Competitive effects of joint ventures in the international airline industry. Transport. Res. Rec. 2676 (2), 59–68. https://doi-org.ezproxy.libproxy.db.erau.edu/10.1177/03611981211036342.
Tribune, Chicago, 2002. United, US Airways Agree to Sell Each Other's Tickets. Chicago Tribune. July 25, 2002. https://www.chicagotribune.com/news/ct-xpm-2002-07-25-0207250426-story.html.
Whalen, W.T., 2007. A panel data analysis of code-sharing, antitrust immunity, and open skies treaties in international aviation markets. Rev. Ind. Organ. 30 (1), 39–61.
Yimga, J., 2020. The impact of airline code-sharing on product quality. J. Transport Econ. Pol. 54 (1), 1–20.
Yimga, J., 2022. Code-sharing agreements and path quality in the U.S. airline industry. Transport Pol. 111, 369–385.
Yimga, J., Gorjidooz, J., 2019. Airline code-sharing and capacity utilization: evidence from the US airline industry. Transport. J. 58 (4), 280–308.
Zou, L., Chen, X., 2017. The effect of code-sharing alliances on airline profitability. J. Air Transport. Manag. 58, 50–57.