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DOCTORAL THESIS

Competition and Cooperation in the Airline Industry

Author:
Andrea GUALINI
ID: 1029892

Supervisor:
Prof. Gianmaria MARTINI

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Chapter 1

Introduction

1.1 Preamble

Following the profound impact of airline industry deregulation occurred since the 1970's, the strategic behavior of airlines operating in the whole industry were subject to a great and unprecedented transformation. The liberalization process took several years and packages to become effective, and its adoption was triggered in different times and ways depending on the geographical area. The United States led the change while Europe followed from the 1980's, but it is from the late 90's that the actual changes took place with a series of liberalization packages.[1] While a strictly regulated environment was providing a certain degree of stability for both sides of the market, deregulation changed everything. Incumbent carriers had to manage the new economic freedom and flexibility and soon faced the entry of new (and sometimes low-cost) competitors. Inefficient players were forced to leave the market or to became more efficient. Moreover, according to new business models, networks changed towards hub-and-spoke network service structures. Consolidation of airlines have also been a huge phenomenon that happened through several means, from sporadic cooperation to actual waves of merges, especially in the most recent years. Indeed, the liberalization package opened the door to increased competition, but also to anti-competitive practices potentially leading to increased market concentration. Questions about the effectiveness of a deregulated industry and its profitability have always been at the heart of the debate about the airline industry as airline deregulation policies have been designed to ensure a fair and competitive marketplace. Many have been the papers studying the relationship between

[1] The liberalization process in Europe began in 1987 with the First Package, continued with the Second Package in 1990, and was completed by the Third Package in 1993 (Authority, 1998). It is only in April 1997 that airlines could freely serve and setting their own fares on domestic and international routes in Europe.

prices and competition, and much has been written on the evolution of the airline industry, on the benefits of deregulation for travelers and carriers, and on the evaluation of the deregulation process. Fares have often been the focus of any discussion on the airline industry, and certainly the most popular metric being analyzed while assessing the consequences of any change to the market, in general. Other studies focused on different relevant consequences of a liberalized market by posing questions of how deregulation affected service quality or airlines' performance. In a fast-changing environment as the airline industry it is important to rely on updated information and to constantly monitor the markets. This is the hard task that government departments of transport and regulating authorities must bear. With this thesis I hope I can also contribute to enrich the set of information at disposal of regulatory bodies in their decision-making process, and to shed light on some still unclear findings from the existing literature.

1.2 Research Content and Outline

This thesis applies empirical methods in industrial organization and applied economics to investigate about cooperation and competition strategies and mechanisms, and their effect on the main microeconomic dimensions. This manuscript collects three empirical independent works, each of them applied to the airline industry. Chapter 2 consists of a paper, published in the Journal of Transport Economics and Policy (Dresner et al., 2021) and focused on the North Atlantic air transportation market to investigate about the price effect of two different peculiarities of such a market: the entry (for the first time) of a Low-Cost Competitor (LCC), and cooperative agreements (namely, alliances) active on the market. Chapter 3 focuses on a paper coauthored with Martin Dresner and Li Zou and that is currently under review for publication on the Transportation Research Part A journal. This third chapter scrutinizes the effect of a strategic policy introduced by some US domestic airlines during the first wave of Covid-19 pandemic on a set of performance indicators in order to assess whether the policy benefitted the adopters or not. Finally, Chapter 4 extends the understanding of the outcome of airlines cooperation where deregulation is still to happen, and in a context where efficiency is hindered by socioeconomic and geopolitical factors, and it is therefore difficult to achieve. The international African market is considered to evaluate whether the most widespread cooperative agreement (i.e., code sharing) results in an effective economic advantage for the final users. In order to detail more on the content of the three core chapters of this manuscript, below I provide a summary of their contribution.

1.2.1 Chapter 2: Airline Competition and LCCs in the North Atlantic Market

An analysis of the impact of low-cost carrier competition and alliance cooperation on the open skies North Atlantic gateway-to-gateway airfares is conducted. Our results indicate that the presence of the largest low-cost carrier, Norwegian, on a gateway-to-gateway route is associated with lower airfares after controlling for the other factors that may influence fares. The estimated reduction is about 5%. The alliance results indicate that when two or more carriers from the same alliance operate on a route, fares are higher than they would be otherwise. The estimated fare effect is about +5%. Then, we show that the entry of a non-alliance competitor generates an 8% decrease in North Atlantic airfares; furthermore, if the entrant is Norwegian the effect is greater, equal to -12.1%, while if the entrant is an allied airline there is no significant price impact. Finally, the combined entry of Norwegian and an allied airline leads to a fare effect equal to -14.9%.

1.2.2 Chapter 3: Airlines Strategies During Pandemic: What Worked?

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

1.2.3 Chapter 4: Pricing Effects of Code Sharing in Africa

There has been considerable research on cooperation form of agreements in the airline industry, but little effort has been spent on underdeveloped countries like Africa. In our empirical work we exploit a rich set of fixed effects to estimate the direct and indirect impact of code sharing on airfares in the African international connecting routes between 2017 and 2019. The main objective of this paper is to investigate whether cooperation helps to internalize double marginalization, and results in lower fares. Moreover, we check whether the pro-competitive effect of the introduction of code sharing percolates to interline, online, and direct airfares on the same route. Our main results show that the activation of a CS agreement generates a strong reduction of airfares equal to about -18%. Evidence regarding the codeshare spillover effect is mixed: in connecting flights with interline service we find that, all else equal, when code sharing is introduced on a route, other airlines react by reducing their price of about 10%. In flights with online or direct service airlines do not react to the CS introduction as they do not perceive CS products as a threat. Our findings confirm that the African aviation market has a high potential growth coming from airlines' cooperation.

This thesis collects three empirical papers which are organized in three chapters that compose this manuscript. The first contribution is presented in Chapter 2, the second paper is illustrated in Chapter 3, while the last one is presented in Chapter 4. Finally, Chapter 5, that concludes my thesis, presents and discusses the conclusion, and proposes some possible directions for future research.

Chapter 2

Airline Competition and LCCs in the North Atlantic Market

2.1 Introduction [1]

In 2007, the United States (US) and the European Union (EU) concluded an "open skies" agreement (OSA) covering air traffic across the North Atlantic. The agreement allowed airlines from both sides of the Atlantic, including new entrants, to freely determine North Atlantic airfares and routes (subject to airport slot availability). Canada and the EU signed a similar agreement in 2009, while two non-EU states, Iceland and Norway, were effectively added to the US-EU agreement in 2011. A "fact sheet" published by the EU in 2017 claimed that the US-EU open skies agreement contributed to 6 million additional North Atlantic passengers, 52 new North Atlantic connections and a savings of 230 euros per passenger, compared to pre-agreement fares (European Union, 2017).

A beneficiary of OSAs has been Norwegian Air Shuttle ("Norwegian"). Norwegian was founded in 1993 and grew rapidly to become the third largest European low-cost carrier (LCC) (Chen and Pawlikowski, 2015). However, unlike most LCCs, Norwegian entered long-haul markets, including routes between Europe and the US. Long-haul entry was facilitated by Norwegian's purchase of wide-bodied Boeing 787 Dreamliners. By summer 2019, Norwegian was flying between 17 North American destinations and 14 cities in Europe[2] using a fleet of 36 Dreamliners.[3] Hence, our first goal is to estimate

[1]This Chapter has been coauthored with Martin Dresner, Gianmaria Martini, and Michela Valli and it has been published on the Journal of Transport Economics and Policy in 2021 (Dresner et al., 2021)

[2]World Airline News, https://worldairlinenews.com/category/norwegian-long-haul/, accessed Sept. 24, 2019.

[3]Norwegian.com, https://www.norwegian.com/en/about/our-story/our-aircraft/, accessed Sept. 24, 2019.

the impact of Norwegian; notably, how its operations have affected North Atlantic airfares.

Although OSAs may have had positive consumer impacts, opening North Atlantic markets to increased competition, the agreements may also have had a negative side for consumers. OSAs allowed airlines to enter cooperative arrangements that would otherwise have been prohibited by US competition laws.[4] Consequently, several US, Canadian and European allied airlines were granted antitrust immunity (ATI) by the US Government and its European and Canadian counterparts to engage in cooperative behaviors. A more limited number of carriers were granted the additional authority to conduct joint ventures (JV) with their alliance partners. According to Brueckner and Singer, 2019, ATI allows allied carriers to coordinate pricing and scheduling, while JVs additionally permit revenue pooling by allied airlines on routes. Although these arrangements may have been authorized to promote "synergies" and "seamless connections" among partner airlines, they may also have acted to reduce competition. Notably, Brueckner and Singer, 2019 find that airline cooperative agreements with ATI or JV contributed to small, but significantly higher North Atlantic airfares. Thus, as a second research objective, we expand on Brueckner and Singer's (2019) research using a recent dataset covering both European and North American carriers to examine the impact of airline cooperation on North Atlantic airfares. The data source is Traffic Analyser from the Official Aviation Guide (OAG).

To address our research questions, we estimate a panel data set with observations from January 2017 to December 2018 on gateway-to-gateway air routes between Europe and North America.[5] We find a significant impact of Norwegian on airfares, after controlling for other relevant factors. On routes where Norwegian is present, fares are significantly lower, by about 5%. On the other hand, operations by two or more carriers of the same alliance on a route are associated with 5% higher fares. Given the opposing impacts of alliances and LCC operations on airfares, it is not clear if North Atlantic OSAs have resulted in lower overall airfares, although our results also show that, in general, more competitors are associated with lower fares on a route. The latter effect is estimated to be equal to -8% per additional competitor.

[4]The US also has an open skies agreement with Canada, so that Canadian-based carriers can participate in these North Atlantic agreements as well.

[5]As more fully described below, these are nonstop routes operated by carriers between Europe and North America. Our sample does not include "behind-the-gateway" routes involving hubbing at a gateway airport. For example, the route Washington-Paris, operated by United Airlines on a non-stop basis is included. However, the Pittsburgh-Washington-Paris connecting route, also operated by United Airlines, is not included.

Hence, the entrance of Norwegian on a route is estimated to produce a 12.1% reduction in airfares. The entrance of a carrier belonging to an alliance generates no significant effect on airfares. Finally, the joint entrance of Norwegian and a carrier belonging to an alliance already operating on the route generates a 14.9% decrease of airfares. Other results indicate that the probability of Norwegian operating on a route increases with route distance, there was greater probability of Norwegian operating in 2018 than in 2017, and Norwegian tends not to operate routes where both endpoints are hub airports, but it does operate on routes where alliance-affiliated carriers are present.

In the next section, we provide a brief literature review of research connected to our paper, while in Section 3 we discuss our data and the estimation methods. In Section 4 we show the econometric results and in Section 5, discuss these results and conclude our paper. In the Appendix, we report some additional econometric results and further information about the dataset.

2.2 Literature Review

2.2.1 Long-Haul Low-Cost Carriers

Starting shortly after US deregulation in 1978, pioneering LCC, Southwest Airlines, developed an aviation model that reduced costs and increased efficiencies, relying on a standardized aircraft fleet, simple point-to-point scheduling, fast turnaround times at gates, high aircraft utilization, and the use of lower-cost secondary airports. Operations emphasized short-medium haul routes, where the low-cost model could readily be implemented. Other LCCs in North America, Europe, Asia and elsewhere followed suit. Research findings show that LCCs have operating costs 20-30% below network carrier competitors (Zou, Yu, and Dresner, 2015; Wilken, Berster, and Gelhausen, 2016), with fares 20% or more below competitors (Kwoka, Hearle, and Alepin, 2016).

As the LCCs grew and saturated their markets, they searched for new operating strategies to gain market share. Some LCCs moved operations from secondary airports to more costly, primary airports to gain business travelers.[6] Other LCCs diversified their fleets or established hubs to connect passengers. Finally, some LCCs began operating long-haul routes in addition to (or instead of) short-medium haul routes.

[6]Southwest Airlines, in fact, moved a significant percent of its operations to primary airports

Wensveen and Leick, 2009 indicate that long-haul LCCs are "inherently different" from short-haul LCCs in operating procedures, training procedures, route densities and turnaround times, among other factors. These operational differences reduce the cost advantages that LCCs enjoy over network carriers (Wilken, Berster, and Gelhausen, 2016). Whyte and Lohmann, 2015 calculate cost differentials between low-cost carriers operating on Australian long-haul routes and their network competitors in the range of 13-20%, lower than the 20-30% advantage LCCs enjoy on short-medium haul services (Zou, Yu, and Dresner, 2015; Wilken, Berster, and Gelhausen, 2016). Moreover, LCCs face difficulties competing against network carriers in long-haul markets, such as the North Atlantic, since network carriers generate significant revenues from high-yield business-class seats and, therefore, can price economy seats close to marginal cost.

Wilken, Berster, and Gelhausen, 2016 note that demand elasticity on many long-haul routes may be lower than on short-haul routes, thus limiting the opportunity for traffic generation through low fares by LCCs. Moreover, the authors find limited long-haul European markets with sufficient traffic to accommodate LCC services, thus requiring LCCs to establish hubs and veer from cost-efficient point-to-point models. Finally, De Poret, O'Connell, and Warnock-Smith, 2015 see difficulties for LCCs in generating sufficient traffic to operate on long-haul routes, suggesting that cargo revenues may be vital for profitable operations.

In summary, the traditional LCC model may not transfer well to long-haul routes since the cost advantages enjoyed by LCCs may be lower on long-haul routes than on shorter routes. Moreover, there may be limited opportunities for LCCs on long-haul routes due to required traffic densities and to the inability to generate business class revenues. These arguments make it interesting to investigate whether Norwegian has the ability to set lower airfares on long-haul North Atlantic routes.

2.2.2 Alliance Operations

Much of the alliance research has been conducted by Jan Brueckner and his colleagues (Brueckner and Whalen, 2000; Brueckner, 2001; Brueckner, 2003; Brueckner and Proost, 2010; Brueckner, Lee, and Singer, 2011; and Brueckner and Singer, 2019), with other efforts by Oum, Park, and Zhang, 1996, Park, 1997, Bilotkach, 2005, Bilotkach and Hüschelrath, 2013, and Calzaretta Jr, Eilat, and Israel, 2017. Brueckner and Singer, 2019 provide an excellent summary of the literature, with research divided between studies on gateway-to-gateway routes and research on routes from behind international gateways (i.e., one- or multi-stop connecting itineraries). The results from research on connecting itineraries is overwhelmingly positive, indicating that alliances provide lower fares than non-alliance itineraries, notably, through the elimination of double marginalization. For example, Brueckner, Lee, and Singer, 2011 find that airline cooperative arrangements, including code-sharing, alliance membership and ATI, reduce fares on connecting itineraries by 11% relative to fares from "non-cooperating" carrier connections, with an even higher reduction (16%) for transatlantic itineraries.

The evidence on the impact of alliances on gateway-to-gateway fares is less certain. While most of the studies show little-to-no impact (e.g., Brueckner and Whalen, 2000; Wan, Zou, and Dresner, 2009; and Calzaretta Jr, Eilat, and Israel, 2017), Brueckner and Singer, 2019 find that since 2010, alliance arrangements on US international routes, including ATI and JV, increase fares in the order of 4-7%.[7]

For this paper, we extend the work on LCCs and alliances by analyzing the fare effects from Norwegian's presence in North Atlantic markets and from alliance cooperation in the same markets. For our analysis, we use a recent dataset covering the period January 2017-December 2018 with a sample that includes US, European and Canadian carriers.[8]

2.3 Model and Data

The setting for our analysis is the North Atlantic market; specifically, gateway-to-gateway routes over the period January 2017 to December 2018. In 2017, 79 million passengers traveled between Europe and the US. This number increased to 85 million in 2018.[9] Traffic flows between Canada and Europe increased from 9.9 million to 10.3 million between 2017 and 2018.[10] The majority of North Atlantic seats are provided by carriers affiliated with the three

[7]Brueckner and Singer (2019) also include an LCC variable in their dataset showing that when an LCC is in a market, fares are reduced by 14%.

[8]Brueckner and Singer, 2019 use the US Department of Transportation's DB1B database, that only includes US carrier data and data from foreign carriers on codeshare routes with US carriers.

[9]https://www.statista.com/statistics/193551/atlantic-air-traffic-passengers-travelling-to-or-from-the-us/, accessed September 27, 2019.

[10]https://www.statista.com/statistics/483702/number-of-air-passengers-between-canada-and-europe/, accessed September 27, 2019.

major alliances, Star, oneworld and Skyteam. In the summer of 2016, alliance carriers that also participated in joint ventures operated 72% of available seat-kilometers (ASKs) on the North Atlantic.[11] Norwegian, the largest LCC operator on the North Atlantic, carried almost 5 million passengers in 2018.[12]

In this Section, we first present the econometric model adopted to study the impact of Norwegian and alliances on airfares on North Atlantic routes, the related econometric challenges that we face, and how our models accommodate these challenges. Second, we describe the data used to estimate the econometric model. Finally, we specify the explanatory variables and the instruments introduced due to endogenous variables in the models.

2.3.1 The Econometric Model

Our aim is to investigate the impact of long-haul LCC (namely Norwegian) competition and carrier cooperation (i.e., alliances) on the North Atlantic airfares. Our baseline model is stated below:

$$\log(FARE) = \boldsymbol{X_1} \cdot \boldsymbol{\beta_1'} + \alpha_1 \cdot COMP + \alpha_2 \cdot NOR + v \tag{2.1}$$

$$NOR = 1\{\boldsymbol{X_2} \cdot \boldsymbol{\beta_2'} + \alpha_3 \cdot COMP + u \geq 0\} \tag{2.2}$$

$$COMP = \boldsymbol{X_3} \cdot \boldsymbol{\beta_3'} + e \tag{2.3}$$

In Eq. 2.1, the logarithm of monthly fares on a North Atlantic city-pair is function of a vector $\boldsymbol{X_1}$ of exogenous explanatory variables, and of two possible endogenous variables: one capturing the degree of competition ($COMP$), and the other a dummy variable for the presence of Norwegian (NOR).[13] $\boldsymbol{\beta_1'}$ is a column vector of coefficients for the exogenous explanatory variables,

[11] https://centreforaviation.com/analysis/reports/north-atlantic-airline-market-closed-jvs-to-have-78-of-asks-in-2016-weighing-the-benefits-272815, accessed September 27, 2019.

[12] A second much smaller LCC operating in the North Atlantic market, Iceland-based WOW airline, is also included in our analysis. WOW operated a fleet of 10 Airbus A321 neos during our study period but ceased operations in 2019.

[13] A third possible source of endogeneity in Eq. 2.1 is that the presence of alliance operations on a route may depend on the level of fares on that route. However, we disregard this issue for two reasons: First, airlines join alliances as a complete entity. Alliance membership is not route specific. Second, the main impact of alliances may be on the number of carriers operating on a route. For example, if two carriers are alliance members, they may choose to have one of the carriers operate the route, with the other carrier code sharing. Since we already consider the number of carriers (i.e., $COMP$) as endogenous, we can include the alliance dummy as a predictor for the number of carriers. In this way, we believe that we account for alliance endogeneity concerns.

α_1 is the coefficient for the effect of competition on airfares, and α_2 identifies the impact of Norwegian, while v is the error term, with 0 mean and variance σ_v^2. Eq. 2.2 highlights that the presence of Norwegian is a function of a vector of exogenous variables $\boldsymbol{X_2}$ ($\boldsymbol{\beta_2'}$ is a vector of coefficients), and of the degree of competition ($COMP$) that might be endogenous; u is the error term with 0 mean and for identification reasons, variance set equal to unity ($\mathbf{1}[\cdot]$ is a binary indicator function). Eq. 2.3 is related to the degree of competition ($COMP$), which is function of a vector of exogenous variables $\boldsymbol{X_3}$ ($\boldsymbol{\beta_3'}$ is a vector of coefficients), and of the error term e, with 0 mean and variance σ_e^2.

To estimate the parameters in Eq. 2.1 and to control for endogeneity, we adopt a control function approach (CFA, Heckman and Robb Jr, 1985; Wooldridge, 2010; Wooldridge, 2015) twice: first, we control for the endogeneity of $COMP$ on NOR. Next, we control for the possible endogeneity of NOR and $COMP$ on $FARE$.

To treat the possible endogeneity of COMP in Eq. 2.2, it is necessary that $\boldsymbol{X_3}$ contains at least one exogenous variable that is not in $\boldsymbol{X_2}$. We define $\boldsymbol{X_3}$=($\boldsymbol{X_2}$, Z_2, Z_3), where Z_2 and Z_3 are instruments as defined below. As shown by Wooldridge, 2010,[14] to implement a CFA we first estimate the residuals $\hat{e}$ from an OLS regression of $COMP$ on $\boldsymbol{X_3}$, and then coefficients ($\boldsymbol{\beta_2'}$, α_3) are estimated from a probit of NOR on $\boldsymbol{X_2}$, $COMP$, and $\hat{e}$. A test for the endogeneity of $COMP$ in Eq. 2.2 is given by the t-ratio of the estimated coefficient of $\hat{e}$.[15] The null hypothesis is that there is no endogeneity. If the coefficient is statistically significant, we can reject the null and obtain valid estimates of the coefficients with the CFA. On the contrary, probit estimates from Eq. 2.2 without $\hat{e}$ are valid.

Wooldridge, 2010 shows that the estimated coefficients ($\hat{\beta}_2$, $\hat{\alpha}_3$) from the probit model including $\hat{e}$ need to be scaled by a factor $\psi = \frac{1}{\sqrt{1-\rho^2}}$), where ρ represents the correlation between u and e. However, $\frac{1}{1-\rho^2} = 1 + \hat{\alpha}_4 \cdot \tau^2$, where $\hat{\alpha}_4$ is the estimated coefficient of $\hat{e}$ in the probit model and τ^2 is the variance of $\hat{e}$.[16]

In order to control for the possible endogeneity of $COMP$ and NOR in Eq. 2.1 we implement a second CFA, where $\hat{e}$ is included in Eq. 2.1 to control for the endogeneity of $COMP$. Regarding the endogeneity of NOR, we adopt the control function approach as explained by Wooldridge, 2015.[17] It

[14]The complete procedure is shown in Wooldridge, 2010, section 15.7.2.
[15]See Wooldridge, 2010, p. 587.
[16]See Wooldridge, 2010, pp. 586-588.
[17]The complete procedure is shown at pages 427-428.

involves a first stage where we estimate the probit model in Eq. 2.2, including $\hat{e}$, where $\boldsymbol{X_2} = (\boldsymbol{X_1}, Z_1)$. Z_1 is another instrument defined below. We obtain the generalized residuals $\hat{r} = [NOR \cdot \lambda \cdot (\boldsymbol{X_2} \cdot \hat{\boldsymbol{\beta}}_2' + \alpha_3 \cdot COMP + \hat{\alpha_4} \cdot \hat{e}) - (1 - NOR) \cdot \lambda \cdot [-(\boldsymbol{X_2} \cdot \hat{\boldsymbol{\beta}}_2' + \alpha_3 \cdot COMP + \hat{\alpha_4} \cdot \hat{e})]]$, where λ is the well-known inverse Mills ratio (Heckman (1979); that is, $\lambda = \frac{\phi \cdot (\boldsymbol{X_2} \cdot \hat{\boldsymbol{\beta}}_2' + \alpha_3 \cdot COMP + \hat{\alpha_4} \cdot \hat{e})}{\Phi \cdot (\boldsymbol{X_2} \cdot \hat{\boldsymbol{\beta}}_2' + \alpha_3 \cdot COMP + \hat{\alpha_4} \cdot \hat{e})}$. Then we run the OLS regression in Eq. 2.1, including $\hat{r}$ and $\hat{e}$. As with the first CFA, a simple test of the null hypothesis that NOR ($COMP$) is exogenous is obtained as the t-ratio on $\hat{r}$ ($\hat{e}$). If the null cannot be rejected, the OLS estimates of Eq. 2.1 without either $\hat{r}$ or $\hat{e}$ are valid (the exclusion of one component is subject to the result of the endogeneity test).

2.3.2 The Data

Our dataset is a panel with 2 years and 512 city-pairs and is built as follows: we consider all round-trip gateway-to-gateway routes between North America and Europe from January 2017 to December 2018 on a monthly base. Data on all flights are aggregated to the city-pair level by grouping airports in the same metropolitan area following multi-airport designations in the Official Aviation Guide (OAG). Passengers traveling on connecting flights (e.g., from Milan to Washington, DC with a stop in London) are not included. The data are related to operating carriers only.

Fares are obtained from the OAG Traffic Analyser. The OAG provides fares charged by airlines on flights on routes worldwide. The OAG Traffic Analyser data consist primarily of Marketing Information Data Transfer (MIDT) data obtained through MIDT's arrangement with the Travelport Global Distribution System (GDS) and adjusted with additional data from other GDS's.[18] Bookings are divided into first class, business class, premium economy, full economy, and discount economy tickets. Since one of our main purposes is to determine the impact of LCC operations on route fares and since LCCs sell predominantly discount economy tickets, we only include

[18] Data include both fares and bookings and are adjusted to estimate the "true" market figure. Average monthly fares below $100 are omitted to exclude employee and frequent flier ticket fares, as well as data errors. In addition, air services on routes with fewer than 3 flights per week are also excluded to increase the reliability of route-specific data. Fares are expressed per kilometers flown (i.e., as yields) so that they are comparable across routes. For information on the MIDT dataset, see Devriendt, Derudder, and Witlox, 2006 Devriendt et al. (2005). Information on the OAG Traffic Analyser can be found at the following website: https://www.oag.com/hubfs/User%20Guides/Traffic%20Analyser/TA-Main-Guide-July2017.pdf (accessed October 25, 2019). Research papers that have used MIDT and/or OAG Traffic Analszer data include the following: Delhaye et al. (2017), Scotti and Volta, 2018 and Zou, Oum, and Yu, 2011

discount economy bookings. Fares are directional (i.e., A-B and B-A are counted as separate routes) calculated in US dollars and do not include fees paid for allocating seats, baggage, or priority boarding. Nor do they include payments for onboard food and drinks, taxes, airports fees and surcharges. OAG Traffic Analyser uses round-trip data (as well as one-way data) and divides the round-trip information into directional monthly bookings and fares, after considering revenue allocation procedures implemented by carriers.

Our dataset includes booking information from US, Canadian and European airlines serving the North Atlantic market. The dataset differentiates our contribution from the existing literature. Data from existing studies are generally derived from US DOT DB1B data. This dataset excludes operations by non-US carriers, except for codeshare tickets. Therefore, key airlines operating on North Atlantic routes, such as Norwegian and Emirates, are excluded from previous studies. Our dataset consists of 6,288 month-city-pair observations over the period 2017-18.

2.3.3 Variables and Descriptive Statistics

All the variables included in Eq. 2.1 are shown below:

$$\begin{aligned} \log FARE_{jt} = \beta_0 + \beta_1 \cdot DIST_{jt} + \beta_2 \cdot ALL_{jt} + \beta_3 \cdot 2018_t + \\ + \alpha_1 \cdot COMP_{jt} + \alpha_2 \cdot NOR_{jt} + \alpha_4 \cdot \hat{e_{jt}} + \eta \cdot \hat{r_{jt}} + m_t + \mu_j + v_{jt} \end{aligned} \tag{2.4}$$

In the above equation, $\hat{r_{jt}}$ is the control function variable for the possible endogeneity of NOR and $\hat{e_j}t$ is the control function variable for the endogeneity of $COMP$. $\boldsymbol{X_1}$ in Eq. 2.1 includes the route length ($DIST$, the distance between the two endpoints of the city-pair measured by flown kilometers and transformed to logarithms)[19] , a dummy variable equal to 1 if in period t there are at least two carriers from the same alliance in a city-pair market, capturing carrier cooperation through alliances (ALL), a year fixed effect (2018), and monthly fixed effects (m_t), where t indicates the month. We also include city-pair fixed effects (μ_j), where j is the city-pair. The city-pair fixed effects capture time-invariant factors that may affect fares on a route, and other unobserved variables including airport congestion measures and the

[19] We adopt the city-pair definition as defined by OAG. Therefore, for routes that involve cities with multiple airports, this variable varies according to the number of flights operated at the different airports.

intensity of business activities. We consider two specifications for the degree of competition $COMP$: $TOTCOMP$, the number of operating carriers in the city-pair (as in Brueckner and Singer, 2019, and Calzaretta Jr, Eilat, and Israel, 2017), and HHI (not shown in Eq. 2.4, the Hirschman-Herfindahl concentration index. HHI is based on market shares for gateway-to-gateway routes using seats as market outputs. Since the city-pairs identify our markets, we exploit heterogeneity across North Atlantic markets to estimate, through Eq. 2.4, the impact of our two main variables of interest; that is, variables for Norwegian and alliance operations. We focus on route-level market prices and not on the fares charged by individual airlines. As a result, we collapse fares charged by operating carriers on a city-pair and calculate the monthly mean fare for all airlines on a route.

Eq. 2.2 is a probit regression, where $\boldsymbol{X_2}$ includes $\boldsymbol{X_1}$ and Z_1, the instrument for NOR in Eq. 2.1. The latter is $HUBOD$, a dummy variable equal to 1 if at both endpoints there are hub airports. In order to be a good instrument for NOR, $HUBOD$ must satisfy two requirements: (1) it must be correlated with NOR; (2) must not be correlated with error v in Eq. 2.1. Regarding the first condition, the number of operating carriers at a hub airport is very likely to be lower than at a non-hub airport. The operating carrier that uses the airport as a hub tends to occupy the majority of available slots. Furthermore, at a hub airport, slots are often scarce and are allocated according to the "grandfather" rule;[20] therefore, it is very difficult for new entrants, such as Norwegian, to obtain slots.[21] Hence, $HUBOD$ should be an important determinant of NOR (with negative impact), satisfying the first condition.

Regarding the second condition, it is necessary to consider whether an increase in unobserved determinants of $FARE$ (which are included in the error term v) might affect $HUBOD$. Main factors affecting fares are market size, the composition of business activities at the origin and destination, tourist flows, the fuel price, the location of the airport, and the degree of competition. With $\boldsymbol{X_1}$, we control for most of these factors. Remaining factors may be captured by the fixed effects and month effects variables. The remaining time-varying unobserved factors that may affect $FARE$ are not likely to influence Norwegian's participation decision in a market, so that the second condition is also fulfilled. Hence, the estimated probit equation is as follows:

[20] Slot holders are permitted to maintain slots as long as they are used.

[21] Bilotkach and Hüschelrath, 2013 show that routes between hubs are a deterrent for new entrants, including low-cost carriers, such as Norwegian.

$$NOR_{jt} = \rho_0 + \rho_1 \cdot DIST + \rho_2 \cdot ALL_{jt} + \rho_3 \cdot COMP_{jt} + \omega_1 \cdot HUBOD_j + \\ + \hat{e_{jt}} + m_t + u_{jt} \tag{2.5}$$

Moving to Eq. 2.3, $\boldsymbol{X_3}$ includes $\boldsymbol{X_2}$ and Z_2, Z_3, the two instruments employed to treat the possible endogeneity of $COMP$ on NOR. They are given by the estimated number of seats on a city-pair, considering the 25th and the 75th quantiles of the seats' distribution. Available seats on a flight are the output of a long-run decision, planned by an airline prior to the observed month (i.e., flight schedules are usually fixed for a season and disclosed at least one season in advance). Inspired by Berry and Jia, 2010, those instruments are used because the 25th and the 75th quantiles are nonlinear function of exogenous city-pair characteristics (i.e., they are not correlated with the error component u). Moreover, they are clearly related to the number of competitors on a city-pair, since the larger the volume of available seats (i.e., the greater is the market size), the greater the number of operating carriers, holding the exogenous variables fixed. Therefore, the first requirement (correlation between $COMP$ and the fitted quantiles of seats distribution) is satisfied. Hence, all the variables included in the estimation of Eq. 2.3 are shown below:

$$COMP_{jt} = \pi_0 + \pi_1 \cdot DIST + \pi_2 \cdot ALL_{jt} + \pi_3 \cdot 2018_t + \omega_1 \cdot HUBOD_j + \\ + \omega_2 \cdot QUA\hat{N}T25_{jt} + \omega_3 \cdot QUA\hat{N}T75_{jt} + m_t + \mu_j + e_{jt} \tag{2.6}$$

where the two instruments $QUA\hat{N}T25_{jt}$, $QUA\hat{N}T75_{jt}$ are the fitted values obtained by estimating the following quantile regression:

$$QUANT_{jt} = \theta_0 + \theta_1 \cdot DIST + \theta_2 \cdot ALLPRES_{jt} + \theta_3 \cdot OLINKS_{jt} + \theta_4 \cdot DLINKS_{jt} + \\ + \theta_5 \cdot POP_{jt} + \theta_6 \cdot GDP_{jt} + \theta_7 \cdot TOURISM_{jt} + \theta_8 \cdot 2018_t + \\ + \theta_9 \cdot ONESTOP_{jt} + m_t + \phi_{jt} \tag{2.7}$$

where $ALLPRES$ is a dummy variable equal to 1 if at least one operating carrier in city-pair i belongs to an alliance, $OLINKS$ is the number of direct connections at the origin, $DLINKS$ is the number of direct connections at the destination, POP is the product of the two endpoints' population, GDP is the product of the two endpoints' income per capita, and $TOURISM$ is the tourist flow in the city-pair and is the product of the tourist flows at the endpoints.[22] POP, GDP and $TOURISM$ are logged. Finally, $ONESTOP$ is a dummy variable indicating whether the city-pair is also connected through a one-stop flight, and the variable ϕ_{jt} is the error term.

Using CFA, standard errors may be underestimated, leading to inflated t-statistics. In this case, the standard errors can be adjusted by implementing a bootstrap procedure. As a result, we implement a bootstrap method with 10,000 replications.[23] Given the nature of our data, we implement a bootstrap procedure by time blocks, resampling routes without resampling months or pairs of route-months to keep the time series properties of the observations.[24] Equation 2.4 is estimated using a panel data approach. We implement a Hausman test to determine whether fixed or random effects should be applied. Moreover, standard errors are always clustered at the route level. We test the validity of our model using the Hansen J-test.

Table 2.1 presents descriptive statistics for the variables.

[22]Tourist flows at the local level are extracted from Statistics Canada, Tourism Industry Association of Canada, Visa Canada, the U.S. Department of Commerce's Office of Travel and Tourism Industry, and the Tourism Statistics of the European Commission. When not directly available from these sources, additional data from web searches are used to complete the picture.

[23]See a formal treatment of the procedure in Wooldridge, 2010, section 19.6.2.

[24]The Stata command "vce(bootstrap)" as well as the option "cluster(*route*)" can account for the specific characteristics of the panel data and bootstrap by time blocks.

TABLE 2.1: Summary Statistics for the Data Set

Variable	Mean	Std. Dev.	Min	Max	Description
FARE	0.04	0.01	0.01	0.16	Average fare per kilometer in discount economy class ($)
TOTCOMP	1.83	1.22	1	8	Number of operating carriers on a city-pair
HHI	7,545	2,884	1,213	10,000	Herfindahl-Hirschman Index on a city-pair
ALL	0.19	0.39	0	1	At least two airlines of the same alliance on the city-pair
ALLPRES	0.88	0.33	0	1	At least one carrier belonging to an alliance on the city-pair
NOR	0.17	0.37	0	1	Norwegian presence on the city-pair
DIST	6,874	1,372	3,714	11,029	Average route distance
TOURISM	40,151	47,128	141	274,108	Product of the two endpoints' tourist arrivals (bln.)
POP	11,458	23,338	1.75	193,493	Product of the two endpoints' population (bln.)
GDP	2,382	1,301	139	12,730	Product of the two endpoints' income per capita (mln. $)
OLINKS	12.41	11.38	1	42	Number of direct connections at the origin
DLINKS	12.07	11.26	1	38	Number of nonstop connections at destination
ONESTOP	0.97	0.17	0	1	If the city pair is also connected through a one-stop flight
HUBOD	0.27	0.45	0	1	If at both endpoints there are hub airports

The average fare per kilometer flown in the discount economy class is $0.04, with a maximum of $0.16. The standard deviation is about one fourth of the mean. The mean number of operating carriers on a route is 1.83, with a maximum of 8 competitors on a city-pair. The average city-pair HHI is quite high at 7,545 since many of the city-pair routes are monopolies (with an HHI of 10,000). On average, 19% of the city-pairs have at least two airlines of the same alliance (ALL), while on 88% of the city-pairs there is at least one carrier belonging to an alliance ($ALLPRES$). Norwegian operates on about 17% of city-pairs in the North Atlantic market, including city-pairs where it is a monopolist. The average route distance is 6,874 kilometers with the longest route equal to 11,029 km. The average product of tourist arrivals in the city-pair ($TOURISM$) is about 40 million, the average product of the two endpoints' population (POP) is about 11 billion, the average product of per capita income (GDP) is $2.4 billion. At the city of origin there are on average 12.4 nonstop connections ($OLINKS$), while at the destination city there are 12.07 ($DLINKS$). On about 97% of city-pairs, there are possible one-stop connections ($ONESTOP$). About 27% of the city-pairs have hub airports at both endpoints ($HUBOD$). (Table 2.7 in the Appendix reports the list of hub airports.)

North Atlantic routes exhibit high monthly variability in market structure, as shown in Figure 2.1. The plurality of routes are monopolies, with about 80 monopoly routes operating during the winter period and more than 200 monopoly routes during the peak demand period in the summer. The remaining routes are split about evenly between duopolies and routes with 3 or more operating carriers (there are additional airlines that market tickets on the routes and code share with operating carriers). There are about 50 routes in each of these categories during the winter period and 90 during the summer. Our primary analysis uses monthly observations, but we replicate our study with quarterly data to provide results comparable to previous studies.[25]

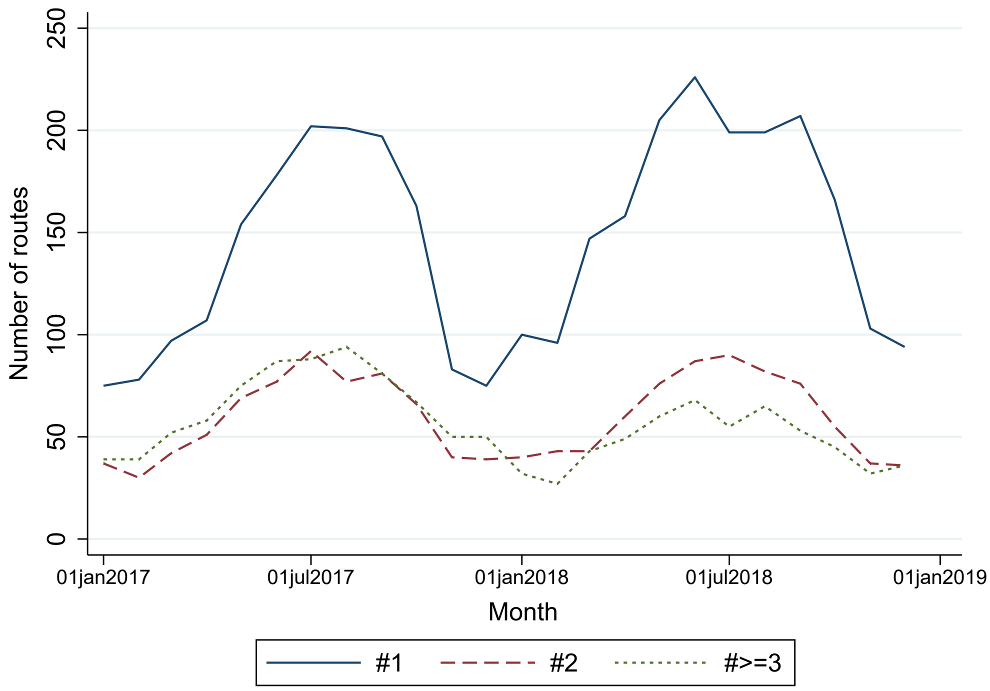

FIGURE 2.1: Number of Nonstop City-pairs by Competitors and Month on the North Atlantic

[25]Previous studies are based on quarterly data since they use the US DOT DB1B database.

2.4 Results

In this section we present the empirical results of our econometric model to estimate the impact of alliances and Norwegian's presence on airfares in North Atlantic markets. As a first step we show the results of the regression to estimate Eq. 2.7 to obtain the fitted value of the seats quantile regressions, i.e., $QUA\hat{N}T25_{jt}$, $QUA\hat{N}T75_{jt}$, which are used as instruments for $COMP$ in Eq. 2.6. Table 2.2 shows the estimated coefficients.

TABLE 2.2: Seat Quantiles Estimates

Dependent variable: *SEATS*		
	(2) *QUANT25*	(3) *QUANT75*
ALLPRES	2786.4***	2820.0***
	(38.05)	(6.54)
OLINKS	112.8***	720.8***
	(12.74)	(24.32)
DLINKS	124.9***	900.2***
	(12.92)	(25.84)
POP	145.2***	-491.9***
	(3.66)	(-5.54)
GDP	1339.6***	3078.5***
	(15.74)	(14.79)
TOURISM	1060.0***	2541.7***
	(20.04)	(20.96)
ONESTOP	-1271.8***	-5100.9***
	(-3.97)	(-11.92)
DIST	107.9***	869.6***
	(4.32)	(13.90)
2018	186.7+	757.0***
	(1.95)	(3.38)
Constant	-45198.7***	-86673.2***
	(-25.30)	(-18.13)
Monthly dummies	✓	✓
Observations	6,288	6,288
R-squared	0.09	0.24

Robust t statistics in parentheses
Legend: + = p <0.1; * = p <0.05; ** = p <0.01; *** = p <0.001

Both the 25th and 75th seat quantiles on a route are increasing in income per capita (GDP), tourist flows ($TOURISM$), route distance ($DIST$), nonstop connections at the origin ($OLINKS$), nonstop connections at the destination ($DLINKS$), and the presence of at least one carrier belonging to an alliance. Both seat quantile values are negatively related to the presence of one-stop connections ($ONESTOP$) and are higher in 2018 compared to 2017. The 25th quantile is increasing in population (POP) while the 75th quantile is decreasing in the same variable.

The first stage OLS results from Eq. 2.6 are shown in Table 2.3. Column (2) has the number of competitor ($TOTCOMP$) as dependent variable while Column (3) has the HHI.

TABLE 2.3: First-Step CFA Estimates for Treating *COMP* Endogeneity

Dependent variable: *COMP*		
	(2) *TOTCOMP*	(3) *HHI*
ALL	0.523***	-1735.2***
	(19.38)	(-22.27)
DIST	0.0546***	-106.8***
	(11.88)	(-7.46)
2018	-0.0822***	281.5***
	(-5.20)	(6.32)
HUBOD	0.530***	-2045.7***
	(5.26)	(-4.99)
$QU\hat{AN}T25$	0.000103***	-0.655***
	(5.77)	(-9.58)
$QU\hat{AN}T75$	0.0000214***	0.0241*
	(5.22)	(2.11)
Constant	-0.359***	14021.2***
	(-4.15)	(51.64)
Monthly dummies	✓	✓
Observations	6,288	6,288
R-squared	0.89	0.92

Robust t statistics in parentheses

Legend: + = $p < 0.1$; * = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$

All coefficients are statistically significant, with an R^2 of 0.89 (0.91 when HHI is dependent variable), inferring that the regression well describes the level of competition on a route. In general, a positive coefficient for a variable in the regression on $TOTCOMP$ and a negative coefficient for a variable in the regression on HHI implies that the variable is associated with greater competition. The coefficients for ALL indicate that markets where two or more airlines belong to the same alliance are markets with greater overall competition. We also find that there is greater competition on longer routes, while in 2018 the level of competition seems to be lower compared to 2017. $HUBOD$ is associated with greater competition positive. $QU\hat{A}NT25$ is also associated with greater competition, while we get mixed results for $QU\hat{A}NT75$. Next, we present the results of the first CFA, implemented to estimate Norwegian's participation on a city-pair: we compute $\hat{e_{jt}}$ from the OLS results shown in Table 2.3, include it in Eq. 2.5, and then present the probit estimates of the second stage Norwegian participation decision; that is, Eq. 2.5, shown in Table 2.4.

TABLE 2.4: Probit Estimates for Norwegian Route Participation

	Dependent variable: *NOR*	
	(2)	*(3)*
TOTCOMP	0.0814*	
	(2.20)	
HHI		-0.0000092
		(-0.52)
ALL	0.559***	0.602***
	(8.23)	(7.66)
DIST	0.0891***	0.0953***
	(5.92)	(6.45)
2018	0.713***	0.686***
	(11.94)	(11.72)
HUBOD	-0.856***	-0.625***
	(-11.87)	(-9.59)
	0.429***	-0.000145***
	(9.17)	(-6.80)
Constant	-1.912***	-1.740***
	(-13.35)	(-7.92)
Monthly dummies	✓	✓
Observations	6,288	6,288
Log likelihood	-2,384.88	-2,507.32

Robust t statistics in parentheses
Legend: + = $p < 0.1$; * = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$

Column (2) in Table 2.4 reports the results when *TOTCOMP* is included in the estimation, and Column (3) uses *HHI* as the competition variable. We find mixed results regarding the impact of route competition on Norwegian's route operating decision. The estimated coefficient for *TOTCOMP* is +0.08 (and significant), suggesting that Norwegian operates on routes with greater competition; however, the coefficient for *HHI* not statistically significant. Other results indicate that the probability of Norwegian operating on a route increases with route distance, there was greater probability of Norwegian operating in 2018 than in 2017, and Norwegian tends not to operate routes where both endpoints are hub airports, but it does operate on routes where alliance-affiliated carriers are present. The estimated coefficient for the control function variable $\hat{e}$ is positive and statistically significant in both models in the table. This implies that route competition is endogenous to the Norwegian participation decision. Having two more variables ($Z2$, $Z3$) in the equation which generates $\hat{e}$ ensures that it has separate variation from ($\boldsymbol{X_2}$, $COMP$).[26]

Moving to the air fares analysis, Figure 2.2 presents descriptive evidence on the impact of number of competitors on North Atlantic fares. It shows monthly fare per kilometer flown on monopoly routes (#1), duopoly routes (#2) and on routes where 3 or more airlines operate (#>=3). It is evident that average monthly fares are higher on monopoly routes than on routes with at least two competitors. However, a regression must be estimated to account for other factors that may be influencing fares.

[26] Monthly dummies were also included in the model, but not reported due to space considerations.

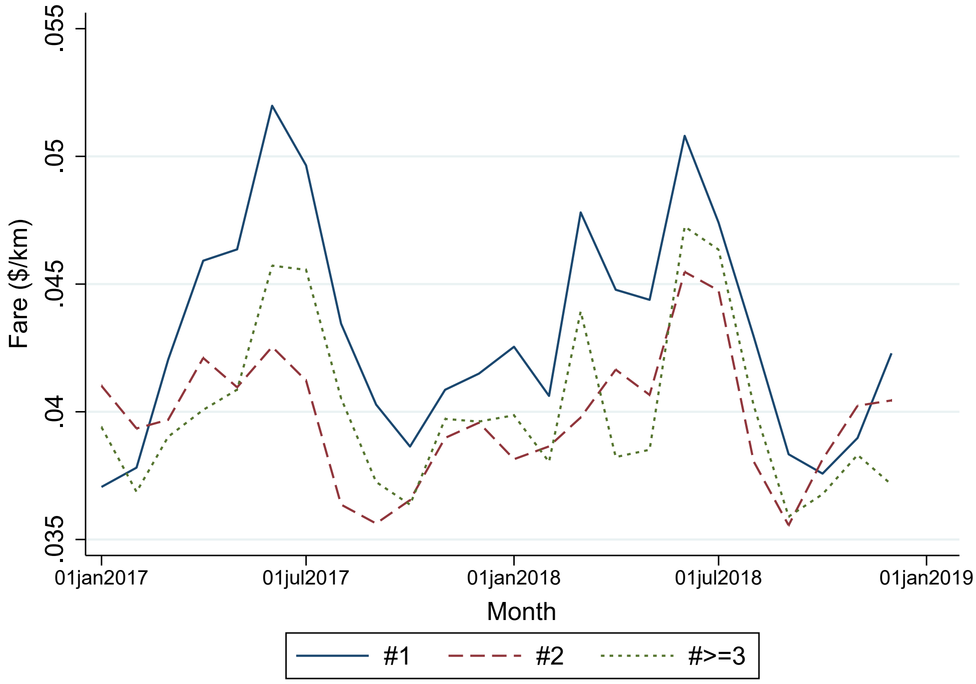

FIGURE 2.2: Fares on North Atlantic City-pairs as Function of Number of Competitors

The results from our North Atlantic fare regression (Eq. 2.4) on gateway-to-gateway routes are shown in Table 2.5.[27] Columns (2)-(4) in Table 2.5 include *TOTCOMP* as the variable measuring degree of competition, while Columns (5)-(7) use *HHI*. Column (2) presents the OLS results without considering *TOTCOMP* as endogenous. Column (3) presents the CFA results considering only *TOTCOMP* as endogenous, while Column (4) provides the CFA results considering both *TOTCOMP* and *NOR* as endogenous. In Columns (5)-(7) we replicate the sequence of estimations using *HHI*.

[27] Using the Wooldridge (2002) test in Stata, we test whether to adopt a fixed or random effects panel data model, with the results suggesting we use a fixed effects model.

TABLE 2.5: Fare Estimates from Different Specifications – Monthly Data

	Dependent variable: *LFARE*					
	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	CFA	2-CFA	OLS	CFA	2-CFA
TOTCOMP	-0.0152*	-0.0805*	-0.0592*			
	(-2.03)	(-2.37)	(-2.52)			
HHI				0.00000683	0.0000303+	0.0000344*
				(1.61)	(1.90)	(2.42)
ALL	0.0125	0.0484*	0.0458*	-0.0119	0.0595+	0.0893*
	(0.89)	(2.11)	(2.06)	(-0.48)	(1.84)	(2.39)
NOR	-0.0443*	-0.0485*	-0.0772	-0.0727**	-0.0519*	-0.0893
	(-2.16)	(-2.26)	(-1.26)	(-2.91)	(-2.51)	(-1.21)
DIST	0.00179	0.00467	0.00478	0.00151	0.00343	0.00704+
	(0.62)	(1.40)	(1.38)	(0.26)	(1.05)	(1.77)
2018	0.0136	0.00820	0.0149	0.0110	0.00909	0.0183
	(1.54)	(0.90)	(1.22)	(0.66)	(0.96)	(1.40)
		0.0698*	0.0512*		-0.0000289+	-0.0000341*
		(2.02)	(2.03)		(-1.82)	(-2.34)
			0.0173			0.0223
			(0.50)			(0.55)
Constant	-3.271***	-3.187***	-3.214***	-3.326***	-3.554***	-3.598***
	(-148.90)	(-67.94)	(-91.03)	(-61.85)	(-24.90)	(-27.42)
Monthly dummies	✓	✓	✓	✓	✓	✓
Observations	6,288	6,288	6,288	6,288	6,288	6,288
R-squared (within)	0.21	0.21	0.21	0.08	0.21	0.21

TEST	
TOTCOMP + *ALL* = 0	$p = 0.1280$
TOTCOMP + *NOR* = 0	$p = 0.0009$
TOTCOMP + *NOR* + *ALL* = 0	$p = 0.0044$

Robust t statistics in parentheses
Legend: + = $p < 0.1$; * = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$

Table 2.5 shows that the estimated coefficients of *COMP* become significant when endogeneity is properly considered. As shown in Column (3), with *TOTCOMP* measuring the degree of competition, an increase in the number of competitors has a -8.1% effect on airfares on a North Atlantic route, while the presence of alliances has a 4.8% upward effect. Norwegian generates 4.9% lower air fares. The control function variable $\hat{e}$ has a significant coefficient, confirming that *TOTCOMP* can be considered to be endogenous in Eq. 2.4, and that $\hat{e}$ has separate variation from ($\mathbf{X_1}$, *TOTCOMP*,*NOR*). On the contrary, Column (4) shows that the estimated coefficient of the control function variable $\hat{r}$ is not statistically significant. Hence, we cannot reject the null hypothesis that NOR is exogenous in Eq. 2.4, and this implies that the results obtained without including $\hat{r}$ are not biased (i.e., the results shown in Column (3). Therefore, the results in Column (3) may be used to assess our research questions.[28]

With respect to the other variables in the fare equation, there is no significant effect from route distance since this impact is likely already captured by the city-pair effects. Airfares are not significantly different in year 2018 compared to 2017.

Column (6) presents the results using HHI as a proxy for the degree of competition. The estimated coefficient is positive and significant and implies that a 100-point increase in HHI, (i.e., a reduction in the degree of competition) generates a 0.3% increase in airfares. The presence of two carriers in an alliance on a route (ALL) increases fares by 6%, while Norwegian's presence on a route is associate with 5.2% lower ticket prices. Again, there is no effect of distance on airfares, nor of 2018 compared to 2017. As before, $\hat{e}$ has an estimated coefficient significantly different from 0, implying that HHI is endogenous in Eq. 2.4; on the contrary, $\hat{r}$ in Column (7) is not statistically significant and so, as before, estimates shown in Column (6), obtained without considering the control variable $\hat{r}$ are not biased.[29] The combined coefficients for the variables $TOTCOMP$, ALL, and NOR (i.e., $\hat{\alpha_1}$, $\hat{\beta_2}$, and $\hat{\alpha_2}$) allow us to analyze the effects of entry on a North Atlantic route.[30] If an alliance carrier enters a route, the additional competitor generates the following effect on air fares: since we have a log-linear equation, the estimated percentage impact is computed as $(e^{(\hat{\alpha_1}+\hat{\beta_2})} - 1) \cdot 100$. Hence, an additional alliance competitor (bringing the number of alliance competitors on a route to 2) would reduce fares by 3.2%. The entry effect (from an additional competitor) is partially offset if the entrant belongs to an alliance already operating on the route. However, as shown at the bottom of Table 2.5, the null hypothesis, $H_0 : \hat{\alpha_1} + \hat{\beta_2} = 0$, cannot be rejected, implying that the combined effect of the two relevant coefficients is not significantly different from zero. On the

[28] The J index to apply the Hansen J-test to check if our model is overidentified is equal to 0.26, with p-value equal to 0.61. Hence, our model is not overidentified. We compute the J index as follows: the residuals $\hat{v}$ are obtained from Column (3), and regressed with ALL, NOR, $DIST$, 2018, $\hat{e}$, m, μ, $QUA\hat{N}T25$ and $QUA\hat{N}T75$ as explanatory variables. Second, we calculate the F-test of whether the coefficients of $QUA\hat{N}T25$ and $QUA\hat{N}T75$ are 0; last $J = 2{\times}F$. The first-stage F-statistic to test the relevance of instruments is equal to 157.2.

[29] The J index to apply the Hansen J-test to check if our model is overidentified is equal to 0.13, with p-value equal to 0.73. The first-stage F-statistics to test the relevance of instruments is equal to 123.6.

[30] We are grateful to an anonymous referee for suggesting this point.

other hand, if the entrant is Norwegian, the estimated effect on air fares is -12.1%. The results at the bottom of Table 2.5 shows that the null hypothesis, $H_0 : \hat{\alpha_1} + \hat{\alpha_2} = 0$, can be rejected ($p$-value 0.005), implying that Norwegian's entry leads to reduced fares on a route. Finally, we test the effect of the simultaneous entries of an alliance airline and Norwegian on a route. In this case, we have two new competitors, and the estimated total effect is -14.9%. Since we can reject the null $H_0 : \hat{\alpha_1} + \hat{\alpha_2} + \hat{\beta_2} = 0$, this combined entry has significant impact on airfares. This implies that if Norwegian and an alliance competitor both enter a city-pair, the airlines behave competitively, generating a robust decrease in air fares.

To better compare our results with previous studies, we also estimate our model using quarterly data. The results are shown in Table 2.6. Column (2) reports the OLS estimates, while Columns (3)-(4) show the CFA results, when $TOTCOMP$ is adopted as proxy for total competition. Columns (5)-(7) present the results when HHI is included in the analysis. An increase in HHI leads to an increase in airfares. If market concentration on a city-pair increases by 100 points, airfares increase by 0.4%. while the presence of two alliance carriers has no significant impact on airfares. Norwegian's presence is associated with 5% lower airfares. $DIST$ and 2018 have no significant effect on fares. In sum, the results are similar to our estimates using monthly data, but from quarterly data we cannot identify a positive effect of alliances on North Atlantic nonstop airfares.

TABLE 2.6: Fare Estimates from Different Specifications – Quarterly Data

Dependent variable: *LFARE*						
	(2) OLS	(3) CFA	(4) 2-CFA	(5) OLS	(6) CFA	(7) 2-CFA
TOTCOMP	-0.00769	-0.0673+	-0.0286			
	(-0.78)	(-1.66)	(-1.00)			
HHI				0.00000647	0.0000413+	0.0000248
				(1.48)	(1.90)	(1.41)
ALL	-0.0344	0.0182	0.00554	-0.0232	0.0389	0.0409
	(-1.44)	(0.88)	(0.25)	(-0.96)	(1.37)	(1.05)
NOR	-0.0920***	-0.0462*	-0.0345	-0.0903***	-0.0496*	-0.0390
	(-3.86)	(-2.17)	(-1.11)	(-3.73)	(-2.21)	(-1.17)
DIST	-0.000143	0.00571	0.00373	0.000781	0.00738	0.00690
	(-0.02)	(1.46)	(1.04)	(0.14)	(1.61)	(1.45)
2018	0.0105	0.0129	0.0146	0.0105	0.0101	0.0155
	(0.64)	(1.31)	(1.41)	(0.64)	(0.95)	(1.50)
		0.0533	0.0104		-0.0000395+	-0.0000215
		(1.21)	(0.36)		(-1.82)	(-1.23)
			-0.0105			-0.00819
			(-0.42)			(-0.32)
Constant	-3.206***	-3.201***	-3.248***	-3.277***	-3.658***	-3.516***
	(-73.49)	(-55.50)	(-86.56)	(-61.12)	(-18.09)	(-20.82)
Quarterly dummies	✓	✓	✓	✓	✓	✓
Observations	2,670	2,670	2,670	2,670	2,670	2,670
R-squared (within)	0.05	0.12	0.12	0.05	0.12	0.12

TEST	
TOTCOMP + *ALL* = 0	$p = 0.0962$
TOTCOMP + *NOR* = 0	$p = 0.0137$
TOTCOMP + *NOR* + *ALL* = 0	$p = 0.0086$

Robust t statistics in parentheses
Legend: + = $p < 0.1$; * = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$

Our findings on the impact of Norwegian on airfares can be compared to the results in Brueckner and Singer, 2019 and Calzaretta Jr, Eilat, and Israel, 2017. These contributions use quarterly data and do not focus on the North Atlantic market. They show that an LCC presence on a route decreases air fares by 10-14%. Our estimate using North Atlantic routes and Norwegian as the LCC shows that its presence leads to fares 5% lower, compared to routes without Norwegian's presence. However, our estimations are at the route level and are related to North Atlantic markets only, while Brueckner and Singer, 2019 results are at the carrier level (the individual airline price elasticity is always at least as great as the market elasticity) and for all routes outside the US, including shorter routes to Central America, where the LCC competition is much stronger than between North America and Europe. The estimated fare effect of Norwegian's entry onto a North Atlantic route (i.e., the impact of an additional LCC competitor, Norwegian) is significant (see bottom of Table 2.6) and equal to -10.7%.

Our estimates can also be compared to findings from studies investigating the effect of LCCs on ticket price. The literature on this topic has focused on domestic markets (US) or intra-continental routes (mainly Eastern-Southern Asia). As shown by Kwoka, Hearle, and Alepin, 2016, there is evidence that LCCs generate fares 20% or more below the network carriers in the US. Wang, Zhang, and Zhang, 2018 find that in China and India, fares on routes with an LCC presence are 2% and 12% (respectively) lower than on comparable routes. With our long-haul route database, we find a fare impact lower in magnitude to the reductions found in shorter-haul markets. This result is to be expected since the relative cost advantage for LCCs on long-haul routes is likely to be lower than on shorter-haul routes.

2.5 Discussion and Conclusions

The OSAs between the EU and the US and between the EU and Canada opened the North Atlantic to greater competition, including from long-haul low-cost carriers. However, the agreements also allowed alliance carriers more latitude to jointly set fares and schedules. Our results indicate that the presence of the largest transatlantic LCC, Norwegian Airlines, on a route is associated with lower airfares (about 5%) after controlling for the other factors that may influence fares. After controlling for route characteristics and for the level of competition on a route, Norwegian's presence is associated with fares significantly lower from those found on other routes. However, we find a lower fare reduction effect for the long-haul routes in our dataset compared to the impacts found in most prior research that used datasets with shorter-haul routes.

The alliance results indicate that when two or more carriers from the same alliance operate on a route, fares are higher (about 5% for monthly estimates) than they would be otherwise. Our monthly-based alliance results are similar to those found by Brueckner and Singer, 2019 and may indicate that alliance partners refrain from actively competing on price. We also find that adding a carrier to a nonstop route in the North Atlantic market generates a reduction of about 8% in airfares, similar in sign but with higher magnitude (almost double) to the impact estimated by Brueckner and Singer, 2019, Calzaretta Jr, Eilat, and Israel, 2017, Gillespie and Richard, 2012, and Brueckner, 2003. This prior research, however, did not focus on North Atlantic markets. Finally, we show that carrier entry on a North Atlantic route does not necessarily lead to lower airfares. If the entry is from an alliance airline on a route already served by a carrier from the same alliance, then the downward impact of fares due to entry will be at least partially offset by the upward impact from having two carriers from the same alliance operating on a route.

Our results provide information to policymakers and regulators as they assess the value of the North Atlantic OSAs. Clearly, opening a market to increased competition can have potential benefits to consumers. Competitive markets, on average, have lower fares than monopoly markets. These insights are confirmed by our results and highlight the importance of competition and entry on long-haul nonstop routes. A higher number of competitors leads to fare reductions. On North Atlantic routes, competition may be enhanced (for example) through slot allocation at congested airports. Moreover, based on our results, it may be appropriate for policymakers to monitor the activities of alliances, as they are associated with higher fares in gateway-to-gateway markets; on top of this, entry from an alliance carrier may have limited downward impact on fares. Finally, despite the inherent difficulties of LCCs to successfully operate in long-haul markets, their presence may lead to lower fares. As we find, routes operated by the main long-haul LCC, Norwegian, have fares significantly lower than comparable routes without LCC competition. However, Norwegian's fare impact is lower than the impacts of LCCs observed on medium/short-haul routes (mainly domestic or intra-continental), probably due to narrower cost advantages for LCCs on long-haul routes (compared to network carrier costs).

This paper analyzes GTG flights and does not consider the effects of LCCs operating in the North Atlantic long-haul markets on connecting flights. Moreover, our analysis is restricted to the North Atlantic market. Finally, we do not specifically control for joint ventures or other features of alliances. On the other hand, previous work is restricted to US carrier data or to airlines operating code-share flights with US carriers. We use a dataset that also includes fares from European and Canadian carriers, so may provide a broader analysis of fare impacts than in previous studies. The dataset used for this paper allows for the extension of the analysis to connecting flights. We leave this analysis for future research.

2.6 Appendix A

TABLE 2.7: List of Hub Airports

Region Code	Airport Code	City Name
US	ATL	Atlanta
US	CLT	Charlotte
US	DEN	Denver
US	DFW	Dallas
US	DTW	Detroit
US	EWR	Newark
US	IAD	Washington DC
US	IAH	Houston
US	JFK	New York
US	LAX	Los Angeles
US	MIA	Miami
US	MSP	Minneapolis/St Paul
US	ORD	Chicago
US	PHL	Philadelphia
US	PHX	Phoenix
US	SEA	Seattle
US	SFO	San Francisco
CA	YUL	Montreal
CA	YVR	Vancouver
CA	YYC	Calgary
CA	YYZ	Toronto
EU	AMS	Amsterdam
EU	CDG	Paris
EU	FCO	Rome
EU	FRA	Frankfurt
EU	IST	Istanbul
EU	LHR	London
EU	MAD	Madrid
EU	MUC	Munich

Chapter 3

Airline Strategies During the Pandemic: What Worked?

3.1 Introduction [1]

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,[2] while worldwide airlines were expected to lose $157 Billion.[3] According to estimates from the U.S. Federal Aviation Administration (FAA),[4] 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.[5]

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

[1] This Chapter is based on a joint work with Martin Dresner, and Li Zou. The paper has been submitted to the Transportation Research Part A, and it is currently at the second round of review.

[2] 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.

[3] https://www.cnn.com/2020/11/24/business/iata-airlines-coronavirus/index.html, accessed June 7, 2021.

[4] https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/, accessed October 4, 2021.

[5] https://www.bts.gov/newsroom/average-air-fares-dropped-all-time-low-2020, accessed October 4, 2021.

(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, Budd, and Ison, 2020; Albers and Rundshagen, 2020; Bombelli, 2020; Czerny et al., 2021; Wenzel, Stanske, and Lieberman, 2020; Tay et al., 2020). In addition, airlines sought to generate demand by reassuring passengers of increased safety-related procedures; for example, by changing boarding processes (e.g., boarding from back to front of aircraft), improving the cleaning regimen between flights, mandating facemasks, and leaving the middle seats open to increase social distances (Barnett and Fleming, 2020; Dube, Nhamo, and Chikodzi, 2021; Li, 2020; Milne, Delcea, and Cotfas, 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.[6]

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

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

Our major results show that the middle seat blocking strategy did lead to lower load factors, with a decrease of about 4.75 percentage points when

[6]See Bielecki et al., 2020 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.

middle seats were blocked (although, if the blocked middle seats are excluded from the seat total, the "effective load factor" actually increased by 12.28 percentage points). The middle seat blocking strategy also did not contribute to higher yields suggesting that the strategy may not have been effective at getting passengers to pay extra for the safety associated with the blocked middle seat. Yields were lower by $0.026 per revenue-passenger mile when the middle seats were blocked. Finally, airlines blocking middle seats operated routes with higher seat shares of about 2.1% and higher passenger shares of 7.93%. Based on a mean plane size of 168 seats, a mean load factor of 53%, a mean yield of $0.12/revenue-passenger mile, and a mean route distance of 1,119 miles, the blocking of the middle seat on average resulted in decreased revenues of about $3,300 per flight.[7]
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.[8]

This paper contributes to the growing literature on how the Covid-19 pandemic impacted airline operations. Prior research describes how the pandemic has negatively affected the airline industry through decreased demand and lower revenues (e.g., Czerny et al., 2021; Iacus et al., 2020; Suau-Sanchez, Voltes-Dorta, and Cugueró-Escofet, 2020; Tay et al., 2020), led to

[7]These means are based on operations without middle seats blocked. As noted, load factors fell, and yields increased when middle seats were blocked.
Calculations are as follows:

WITHOUT MIDDLE SEAT BLOCKING:
168 seats X 0.53 pax/seat = 89 pax/flight
$0.115/m X 1,119 m = $129/pax
Revenue = 89 pax/flight X $129/pax = $11,481/flight

WITH MIDDLE SEAT BLOCKING:
168 seats X 0.48 pax/seat = 81 pax/flight
$0.09/m X 1,119 m = $101/pax
Revenue = 81pax X $101/pax = $8,181/flight

NET REVENUE FROM MIDDLE SEAT BLOCKING = $8,181– $11,481 = -$3,300/flight

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

various "pivot" strategies undertaken by the airlines to respond to the pandemic (Adrienne, Budd, and Ison, 2020; Amankwah-Amoah, 2020; Bauer, Bloch, and Merkert, 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, Nhamo, and Chikodzi, 2021; Milne, Delcea, and Cotfas, 2021; Bielecki et al., 2020). Moreover, Hyman and Savage (2021 & 2022) have examined the impact of the middle seat blocking strategy used by Delta Air Lines and Li, 2020 has undertaken a SWOT (strengths, weaknesses, opportunities, and threats) analysis of the middle seat blocking strategy. We add to this literature by demonstrating the variations in strategies undertaken by U.S. carriers in response to the Covid-19 pandemic, and then use a wide sample of routes and carriers to analyze the impact on carrier operations of the blocking of middle seats.

The rest of the paper is organized as follows. Section 3.2 reviews the aviation-related pandemic literature. Section 3.2.3 presents an industry-level descriptive analysis of U.S. airline operations during the pandemic period. Section 3.4 describes our econometric model and the data used to assess the performance impact of the middle-seat blocking strategy. Section 3.5 presents our results. We conclude with a discussion of our results, the limitations of this research and suggestions for future research projects.

3.2 Literature Review

3.2.1 Covid-19 Impact on Airlines[9]

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, Budd, and Ison, 2020). Between March 2020 and July 2020, 19 airlines had declared bankruptcy, including larger, well-established airlines, such as the South American-based carrier, LATAM, with a fleet of 315 aircraft (Czerny et al., 2021).

Tay et al., 2020 note that airlines have been differentially impacted by the pandemic. Airlines that have done better (than average) tended to have had

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

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),[10]

Iacus et al., 2020 and Suau-Sanchez, Voltes-Dorta, and Cugueró-Escofet, 2020 compare the impact of Covid-19 on air transport to the impacts from previous pandemics, including SARS in 2003, the Avian Flu in 2005 and 2013 and MERS in 2015. The authors find that the 2003 SARS pandemic previously had the most serious effect on aviation. Its impact was mainly in the Asia-Pacific region, with traffic volumes in that region down about 35% at the peak of the pandemic. Recovery from the pandemic to pre-outbreak levels took about 6 months. Gudmundsson, Cattaneo, and Redondi, 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.

3.2.2 Impact of Air Mobility on Viral Spread

The main rationale for direct governmental restrictions on aviation, such as bans on international flights, is that air travel is believed to contribute to viral transmission. Gössling, 2020 and Christidis and Christodoulou, 2020, for example, state that air travel is a vector for the spread of pathogens and diseases, including Covid-19. The risks of viral spread facilitated by air transport have been identified and quantified for previous epidemics; for example, with respect to the MERS epidemic in 2015 (Poletto, Boëlle, and Colizza, 2016), the Ebola epidemic in 2014 (Bogoch et al., 2015), and the SARS epidemic in 2003 (Bowen Jr and Laroe, 2006; Gardner, Chughtai, and MacIntyre, 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

[10]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.

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 arrival times of a contagion, even without considering epidemiological parameters such as viral reproduction rate and recovery rate. The authors use their effective distance measure to simulate the diffusion of the 2009 H1N1 influenza virus and 2003 SARS infections and find that this measure can successfully predict viral spread and arrival times in the context of a global, air transport mobility network.

Air travel may be restricted by governments during a pandemic because the travel mode, itself, may be unsafe due to the transmission of viruses within the closed quarters of aircraft cabins and airport facilities. Aircrafts have been described as incubators of respiratory pathogens due to the density of passengers in cabins (Gössling, 2020). Barnett and Fleming, 2020 seek to determine the increased risks for infections and mortality due to viral transmissions among passengers while flying. The authors use stated infection and mortality data from Covid-19 and a probabilistic model to estimate the viral risks to a passenger traveling on a two-hour flight. The authors calculate the chance of catching the coronavirus at about 1 in 3,900 if the flight is full and 1 in 6,400 if the middle seats are left empty.[11] Given mortality rates from the virus, 1 in 710,000 air passengers could expect to encounter a fatal exposure to the coronavirus on a full flight. If the middle seat is left empty, the fatality rate from the coronavirus is predicted to fall to 1 in 920,000 passengers.

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

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

3.2.3 Airlines Strategies to Combat Covid-19

Airlines have engaged in a diverse array of strategies to respond to the decline in passenger demand due to the pandemic. These strategies can be divided into three categories: (1) cost reduction; (2) cash flow enhancement; and (3) safety improvement. The cost reduction strategies include, the grounding of aircraft, the retirement of entire fleets (of mainly older, less efficient aircraft) (Adrienne, Budd, and Ison, 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, and 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, Bloch, and Merkert, 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, Nhamo, and Chikodzi, 2021), the enhancement of passenger screening measures, including temperature checks and covid testing, the mandating of facemasks on aircraft (Dube, Nhamo, and Chikodzi, 2021), improved protective equipment for cabin crews (Dube, Nhamo, and Chikodzi, 2021), and safer boarding procedures (Milne, Delcea, and Cotfas, 2021).

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

3.3 Airline Pandemic Strategies

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

As shown in Table 3.1, Southwest was the largest airline in the U.S. by passenger enplanements in 2019. However, as opposed to the other three airlines, it had a greater focus on domestic routes, with international traffic accounting for only 3% of its total passenger traffic. In comparison, the share of international traffic ranged from 16% to 25% for the other three airlines. The focus on domestic markets, with fewer international destinations, made Southwest less vulnerable to the closing of international markets during the pandemic, since it was less reliant on international traffic to feed its domestic routes. As a result, Southwest was in a better position to maintain its domestic route structure following the onset of the pandemic, compared to American, United and Delta.

TABLE 3.1: Passenger Enplanements of the Four Largest U.S. Airlines in 2019

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

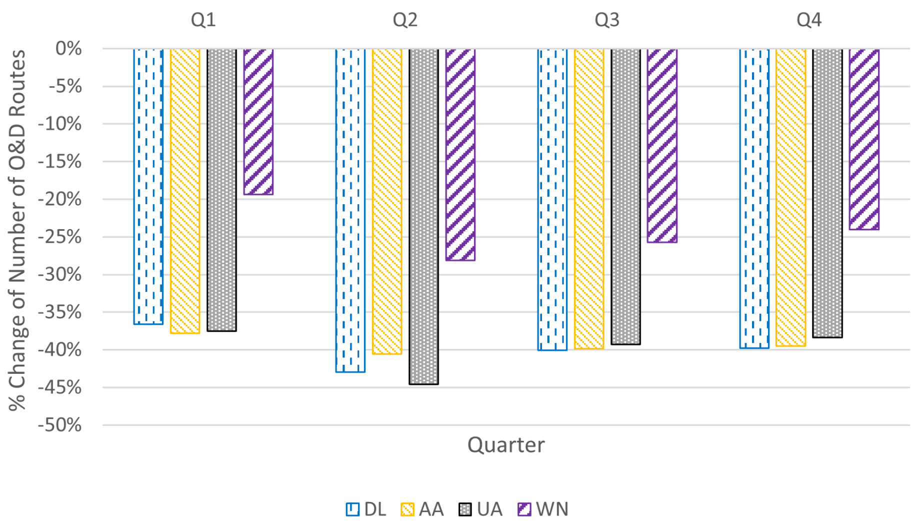

FIGURE 3.1: The % Change of Number of O&D Routes in 2020 vs 2019

Figure 3.1 compares the number of origin-and-destination (O&D) routes offered by the four airlines in 2020 to the corresponding quarter in 2019. The figure shows that Southwest was the least aggressive of the four airlines in cutting routes during the pandemic, maintaining over 70% of its route total during the lowest point for airlines during the pandemic – the second quarter of 2020. The other three airlines reduced their route offerings by 60-65%, thus retaining only about half the routes (in percentage terms) as Southwest. Although the three network carriers all brought back routes during the third and fourth quarters of 2020, a gap in routes offered (compared to 2019) between Southwest and the three network carriers remained throughout the year.

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

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

a hub-and-spoke route structure, a point-to-point route structure could give an airline more flexibility to withdraw from routes or add new destinations with less disruption to the rest of the route network.[13]

As noted by Gary Kelly, the CEO of Southwest, the ability of Southwest to rapidly add vacation destinations to target leisure travelers during the pandemic enabled the airline to turn the pandemic crisis into an opportunity to outcompete its rivals.[14] After cutting its domestic routes from 1,404 in the second quarter of 2020 to 1,094 in the third quarter of 2020, Southwest quickly reversed this trend, adding 204 new routes into its network in the fourth quarter of the year, flying to several new destinations in Florida, Colorado, California, and Georgia that appealed primarily to vacation travelers.

Another factor that could impact the ability of an airline to maintain its network is its relationship with regional carriers since regional carriers provide traffic feed for network carriers, such as American, Delta and United. Of the three network airlines, Delta reported about 15% of its passenger revenue was derived from traffic feed provided by its regional carriers under capacity purchasing agreements in 2019.[15] In comparison, United Airlines reported about 11% of its capacity was operated by regional carriers that year, while American Airline reported that about 27% of its passenger enplanements were provided by its regional affiliates (owned or contracted) in 2019.

The relatively high use by American Airlines of regional carriers may have helped it maintain its network during the pandemic, since the regional services can be operated with fewer passengers. Network carriers, such as American, Delta and United, may act to maintain the centralized structure of their hub-and-spoke networks to run feed through their hubs. As shown in Figure 3.2, the average degree of centrality[16] across all the airports in American's domestic route network dropped by only 0.43% (from 0.257 to 0.256), while it dropped by 11.29% for United (from 0.261 to 0.232), by 8.77% for Delta (from 0.232 to 0.211), and by 6% for Southwest (from 0.378 to 0.356) in the 2nd quarter of 2020, as compared to the same quarter of 2019. Similarly,

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

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

[15] Data are based on the airlines' 2019 10-K filings to the U.S. Securities and Exchange Commission.

[16] See Cheung, Wong, and Zhang, 2020 for definitions of these centrality measures.

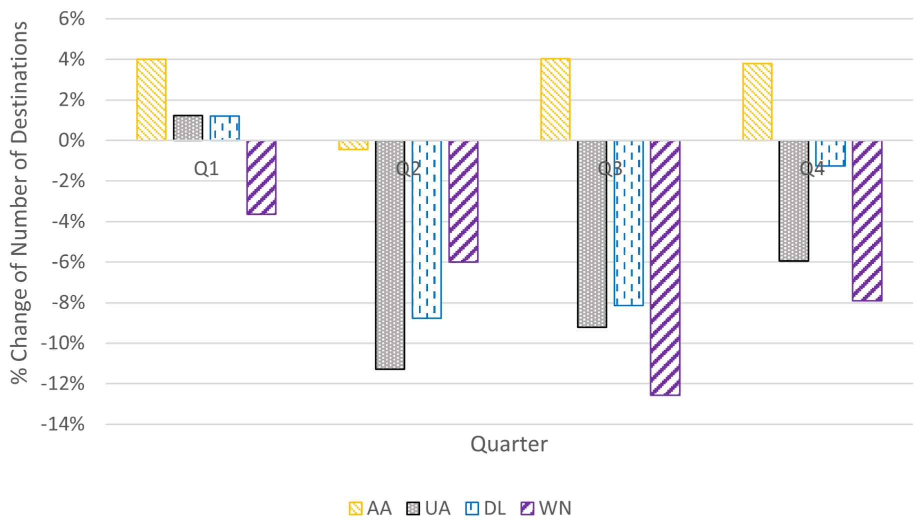

FIGURE 3.2: The % Change of the Average Degree of Centrality in 2020 vs 2019

Figure 3.3 shows that the average degree of closeness centrality for American Airlines across all the airports in its domestic route network remained almost unchanged (i.e., 0.57735 vs. 0.57744) in the 2nd quarter of 2020, as compared to the same quarter of 2019, while the average degree of closeness centrality decreased by 3.62% for United (from 0.575 to 0.554), by 2.48% for Delta (from 0.561 to 0.547), and by 2.34% for Southwest (from 0.617 to 0.603).

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

As shown in Figures 3.4 and 3.5, all the four major carriers started trimming their domestic flight operations in March 2020, with the greatest reductions in May 2020. Compared to United and Delta, American made a smaller reduction in flight and seat capacity, especially during the worst months of the pandemic. As shown in Figure 4, in May 2020, American Airlines kept 49% of its flights compared to the same month in 2019 compared to 41% for Delta Air Lines and only 22% for United Airlines. Similar findings based on seat capacity are illustrated in Figure 5.

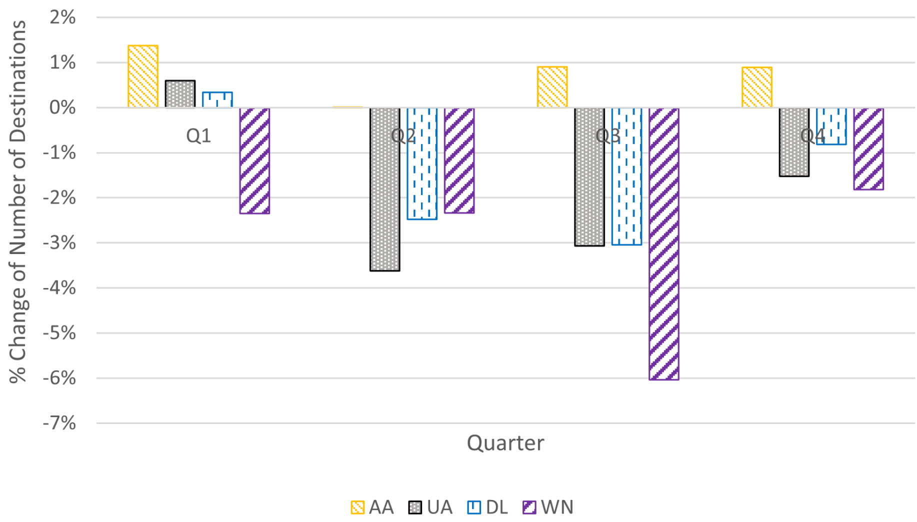

FIGURE 3.3: The % Change of the Average Degree of Closeness Centrality in 2020 vs 2019

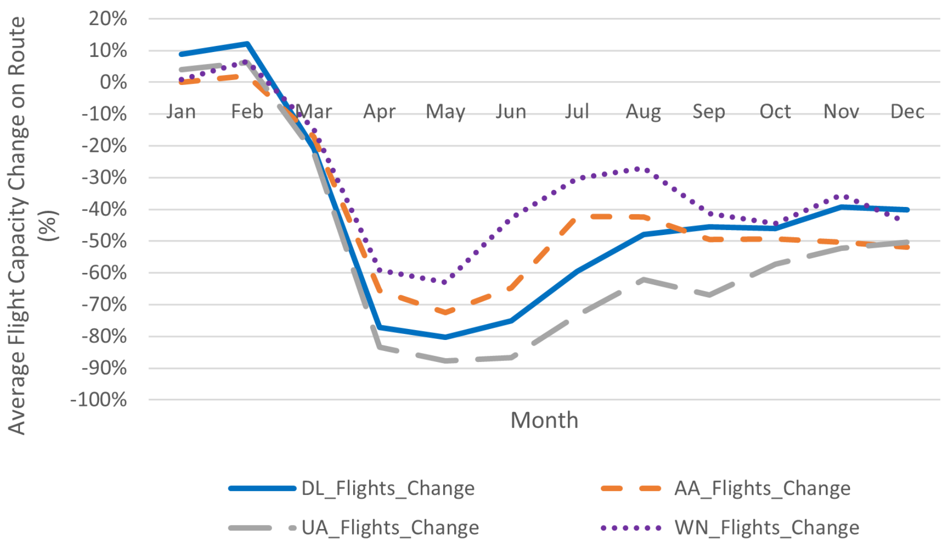

FIGURE 3.4: The Comparison of Flights Capacity Change (%) in 2020 vs 2019

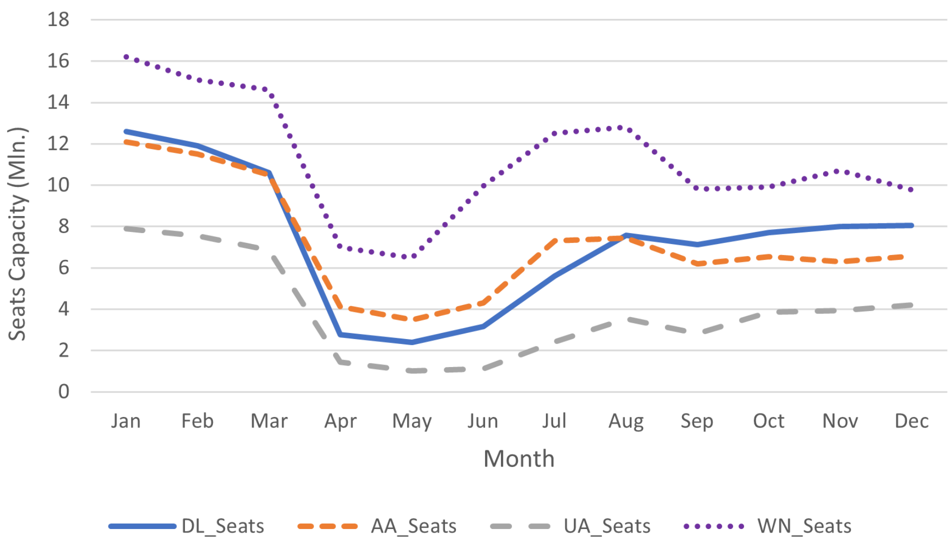

FIGURE 3.5: The Comparison of Monthly Seat Capacity in 2020

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

Summarizing its commitment to both safety and financial measures during the pandemic, Edward Bastian, the CEO of Delta Air Lines, stated the following: "Our response has been focused on three priorities. First, protecting the health and the safety of our employees and our customers. Second, preserving our financial liquidity to work through this crisis. And third, ensuring we are well-positioned to recover once the virus is contained and building a plan to accelerate our progress through this period of recovery."[17]

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

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

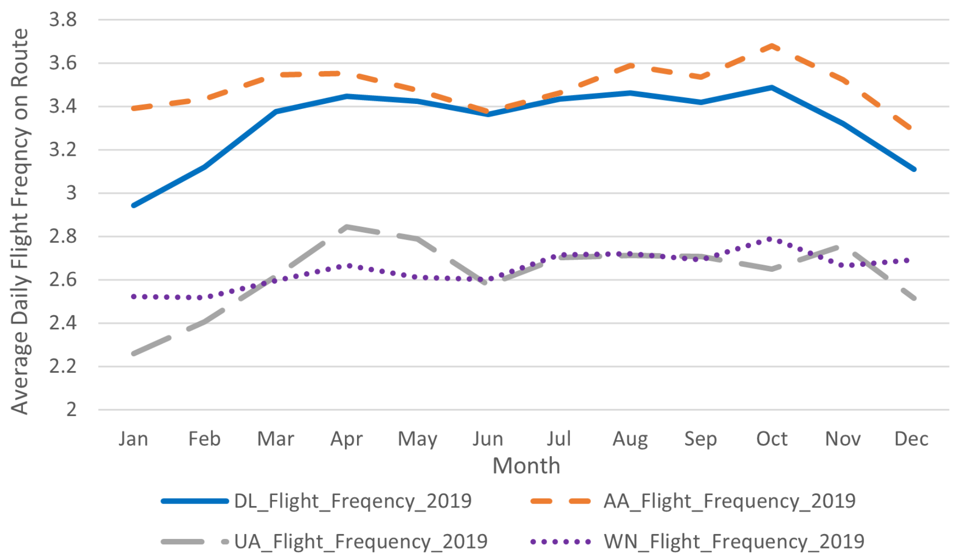

FIGURE 3.6: The Average Daily Flight Frequency on Route in 2019

Southwest consists of B737-700, B737-800, and B737-Max 800 aircraft,[18] and middle seats account for more than 32% of the aircraft seat capacity across all three aircraft types. In contrast, the fleet of Delta Air Lines consists of 22 aircraft types with only 5 operating in domestic markets having middle seats.[19] As a result, middle seats account for only 30% of Delta's aircraft seat capacity. Therefore, middle seat blocking may have a lower impact on Delta compared to Southwest.

Figures 3.6-3.8 show how daily flight frequencies on domestic routes evolved for the four major airlines between 2019 and 2020. As shown in Figure 6.1, average daily flight frequencies per route were higher for American and Delta than for Southwest and United in 2019, prior to the pandemic. Figure 6.2 shows that all four airlines cut their frequencies significantly beginning March 2020. By April 2020, frequencies had been reduced by their maximum compared to the corresponding month in 2019 – 73.1% by United; 62.9% by American; 61.4% by Delta and 56.9% by Southwest. Figure 6.3 indicates that the frequency reduction pattern varied by airline. In general, Delta and Southwest cut frequencies by the least amount, while United cut frequencies by the greatest amount.

Figure 3.9 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

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

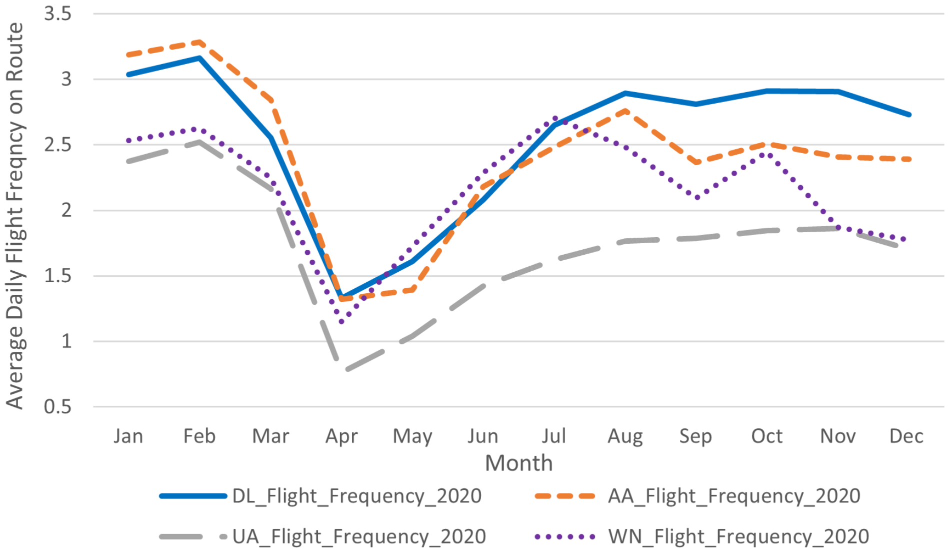

FIGURE 3.7: The Average Daily Flight Frequency on Route in 2020

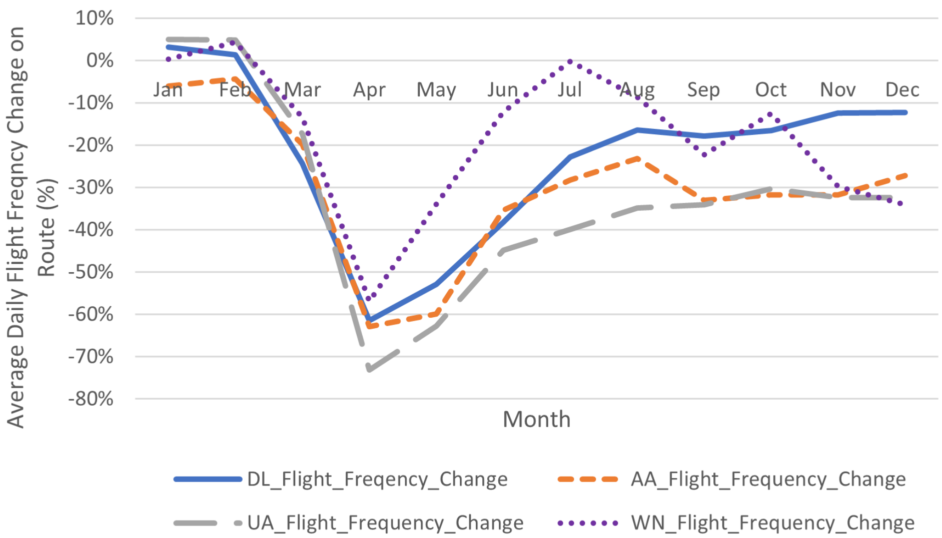

FIGURE 3.8: The % Change of Average Daily Flight Frequency on Route in 2020 vs 2019

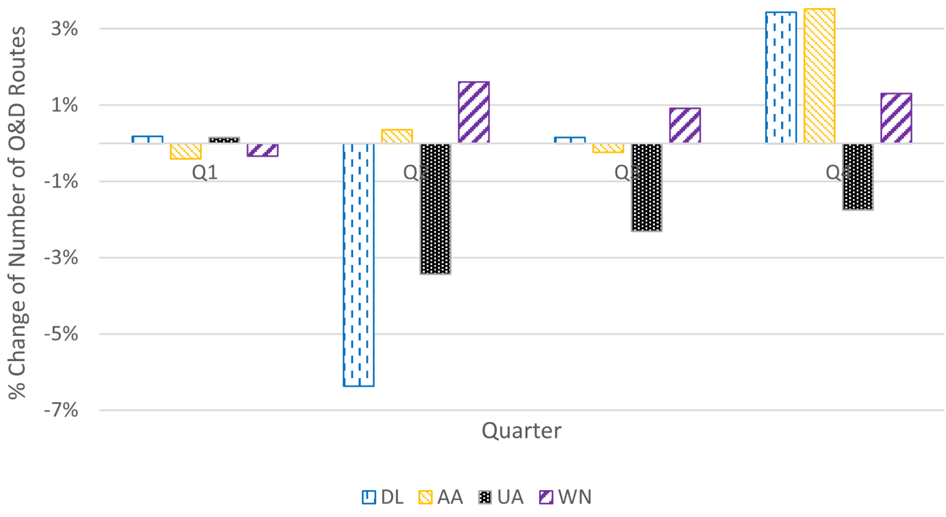

FIGURE 3.9: The % Change of Average Aircraft Size on Route in 2020 vs 2019

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.

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

Figure 3.10 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

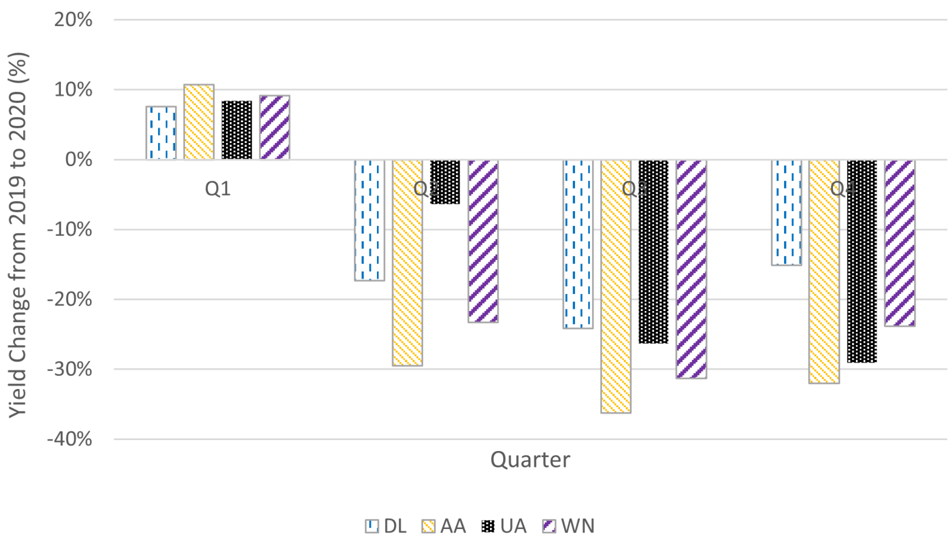

FIGURE 3.10: The Comparison of Average Yield Change in 2020 vs 2019 among DL, AA, UA and WN

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.

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

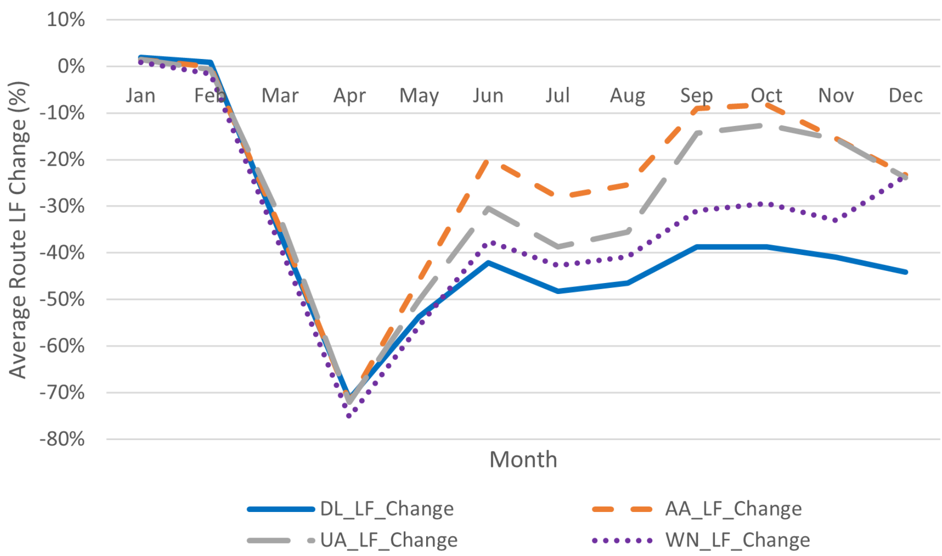

FIGURE 3.11: The Average Route LF Change in 2020 vs 2019

3.4 Models and Data

3.4.1 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 3.2 shows the airlines included in our dataset and the periods of time in which they pursued middle seat blocking strategies. According to the Bureau of Transportation Statistics, by including the top ten airlines by revenue-passenger miles (RPMs), our dataset describes over 90 percent of the available seat miles (ASMs) in the US domestic market.[20] In examining the three major network carriers in the U.S. domestic market (American, Delta and United), strong variations in the use of middle seat blocking are evident, as shown in Table 3.2. United never blocked middle seats, American only blocked middle seats during the first wave of the pandemic (April 2020 to June 2020), while Delta initially blocked middle seats during the first pandemic wave and then continued with this strategy throughout the year. Variations in middle seat blocking strategies also appear among the other seven carriers in the dataset. Notably, three airlines – JetBlue, Hawaiian and Southwest, blocked middle seats from May to November 2020, while Alaska continued middle seat blocking to December 2020. At the other end of the spectrum, Spirit and Allegiant joined United in

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

never blocking middle seats, while Frontier blocked middle seats in only one month, May 2020.

TABLE 3.2: Airlines in Dataset and Middle Seat Blocking Time Periods[21]

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

3.4.2 Data Source

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.[22] 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

[22] 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.

passenger facility charges.[23] To convert fares into yields, fares are divided by route distance. The distance used for these calculations is the great circle distance between the O&D airports. We include in our model a social distancing index to control for decreases in mobility due to the spread of Covid-19. The index is compiled by the University of Maryland Transportation Institute at the state level, based on several factors, such as percent of people staying at home and traveling to work, as well as the number of reported covid cases.[24] For each of our sample airlines, we also collect aircraft seat layout data primarily from seatguru.com, supplemented by the airlines' own fleet information webpages. For those aircraft models that have multiple layout designs, we use the number of seats per flight departure of an airline on a given route as a reference and select the layout design that provides the seat capacity closest to the reference.

3.4.3 Variables

Table 3.3 provides a description of variables in our models. We estimate our models with five dependent variables: passenger share, load factor, effective load factor, seat share, and yield. Passenger shares are computed using T-100 flight segment data for each carrier-specific route. Shares are based on the percentage of passengers carried during a period on a route by a specific carrier to the total number of passengers on the route during the time period. Load factors are computed for each carrier-specific route as passengers divided by seats on the route during the period. Seat shares are computed using the same data, based on seats offered by a carrier during a period on a route. In addition to computing the load factor for airline i on route j a given month, we also calculate the "effective load factor" after excluding the number of middle seats that are blocked by an airline in a period. Similarly, we develop the "effective seat share" as the modified seat share measure. Given that passengers can use several itineraries to fly an O&D route, we calculate O&D yield based on the shares of the various itineraries for a route. Specifically, for airline i on route j in quarter t, we develop the variable $YIELD_{ijt}$

[23]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, Lee, and Singer, 2013, set the threshold at $25. Given the nature of our research objective, we cautiously chose a less stringent level, but we also impose a percentile restriction by excluding those observations belonging to the first or the last percentile of the yield distribution. By doing so we exclude a total of about 0.4% of the records.

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

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:

$$YIELD_{ijt} = \sum_{m=0}^{n} (\text{Share of Passengers per day by Itinerary } m)_{ijt} \times YIELD_{ijmt} \tag{3.1}$$

TABLE 3.3: Variable Descriptions

Variable	Description
$PAXSHR$	Passenger share of each airline i on route j at time t
$LOADFACTOR$	Average (absolute) load factor of each airline i on route j at time t
$EFFLOADFACTOR$	Average (effective) load factor of each airline i on route j at time t
$SEATSHR$	Seat share of each airline i on route j at time t
$YIELD$	Average fare per mile flown by each airline i on route j at time t (US$/mile)
MSB	Dummy variable equal to 1 if airline i blocks the middle seat at time t
$RESROUTE$	Dummy variable equal to 1 if airline i operates route j at time t of both years
SDI	Product of the endpoints state-based social distancing index
$TOTCOMP$	Number of competitors at the city pair level
LCC	Dummy variable equal to 1 if the airline i is a Low-Cost Carrier
$DIST$	Average route distance (miles)
$SUNBELT$	Dummy variable equal to 1 if one or both the endpoints are US southern belt states
POP	Product of the two endpoints' population
INC	Product of the two endpoints' income per capita (US$)
$FREQ$	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
$ONESTOP$	Percentage of passengers flying one-stop on route j at time t
$TWOSTOP$	Percentage of passengers flying two-stop on route j at time t
$EFFSEATSHR$	Effective seat share of each airline i on route j at time t
$CENTRALITY19$	Maximum closeness centrality index of the endpoint airports by i-j-t in 2019
$MIDDLESEATSHR19$	Percentage of middle seats in the total number of seats provided by i-j-t in 2019

We also compute two measures that will be used in first-stage equations in our model, estimated to address potential econometric concerns (see Section 3.4.5). First, to measure the importance of origin and destination airports for an airline in terms of the connectivity in the airline's route network, we calculate an airport-specific network metric in period t, and then take the maximum of the network metric between the two endpoint airports on a given route j. The closeness centrality index is calculated as follows:

$$Closeness\ Centrality_{ivt} = \frac{N_{it} - 1}{\sum_{w=1}^{N_{it}-1} S_{vwt}} \tag{3.2}$$

where S_{vwt} represents the length of the shortest paths from airport v to w in airline i's domestic route network in period t. The length of the shortest paths indicates the minimum number of connections needed for traveling from airport v to w, based on airline i's domestic route network in period t. The shorter the length, the greater the value of closeness centrality. This network metric has been applied in recent aviation research (e.g., Malighetti et al., 2019, Cheung, Wong, and Zhang, 2020, Sun, Wandelt, and Zhang, 2021 and Reynolds-Feighan, Zou, and Yu, 2022). We select this variable and incorporate its 2019 values into the estimation of an airline's resilient route selection (i.e., routes maintained in both 2019 and 2020) during the pandemic.

Second, we compute the percentage of middle seats to the total number of seats provided by airline i on route j in period t. We incorporate values for 2019 to estimate the likelihood of an airline blocking a middle seat in a given period. The variable is computed as follows:

$$\text{Middle Seat Share}_{ijt} = \frac{\text{Number of Middle Seats}_{ijt}}{\text{Total Number of Seats}_{ijt}} \tag{3.3}$$

3.4.4 Models

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

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

We present the results of the five models in Table 3.5 in Section 3.5. As robustness checks, we estimate all our models on different samples, and with several econometric specifications. We perform four robustness checks. First, we run the five models without including airline fixed effects. These estimations allow us to compare our results with references in the existing literature (Hyman and Savage 2021 & 2022). Second, we add route-time fixed effects to our main specification, hence adding an extra level of fixed effects and capturing all the time variant characteristics of a given route. Results from these estimations are reported in Table 3.7 and Table 3.8 in the Appendix. Third, we run our models based on year-over-year changes to the dependent variables (from 2019 to 2020).[25] Finally, we restrict our analysis to Delta Air Lines' middle seat blocking strategy and estimate our yield equation using the subset of data focusing on those routes where Delta Air Lines competed with the other two legacy airlines, i.e., American Airlines and United Airlines. As with Hyman and Savage (2021, 2022) we find that blocking middle seats has a positive effect on yields, when examining this restricted database. This last result is reported in Table 3.9 in the Appendix.

The baseline models for the *PAXSHR* equation (Eq. 3.5), *LOADFACTOR* equation (Eq. 3.6), and *SEATSHR* equation (Eq. 3.7), is generalized in Eq. 3.4 as follows:

$$Y_{ijt} = \alpha_0 + \boldsymbol{X_1}_{ijt} \cdot \hat{\boldsymbol{\alpha}}_{\boldsymbol{1}}' + \alpha_2 \cdot MSB + \eta_i + \theta_j + \kappa_t + e \tag{3.4}$$

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

[25] We use the subset of routes that were operated both in 2019 and 2020 to estimate the change models at the month or quarter level. Results are very similar to the ones in Table 3.5 and are available upon request.

over time and not across entities. In this way it is possible to exploit the variations within each carrier, route, and month.

Among the exogenous explanatory variables, we include regressors for market and airline characteristics such as pandemic intensity measures, sociodemographic data, a city pair-specific measure of competition (*TOTCOMP*), a dummy variable capturing the business model type of each airline (*LCC*) and other supply and demand shifters. As an additional regressor in the *PAXSHR* model, we include the effective share of seats each carrier offers during a period on a given route.[26]

The extended formulations of Eq. 3.4 are reported in Eq. 3.5, 3.6, and 3.7 as follows:

$$\begin{aligned} PAXSHR_{ijt} = \gamma_0 + \gamma_1 \cdot MSB_{it} + \gamma_2 \cdot IMR1_{it} + \gamma_3 \cdot RESROUTE_{ijt} + \gamma_4 \cdot IMR2_{it} + \\ + \gamma_5 \cdot log(SDI)_{jt} + \gamma_6 \cdot TOTCOMP_{jt} + \gamma_7 \cdot LCC_{ijt} + \\ + \gamma_8 \cdot log(DIST)_{ijt} + \gamma_9 \cdot SUNBELT_j + \gamma_{10} \cdot log(POP)_{jt} + \\ + \gamma_{11} \cdot log(INC)_{jt} + \gamma_{12} \cdot FLEETMIX_{it} + \gamma_{13} \cdot TOTROUTE_{it} + \\ + \gamma_{14} \cdot FREQUENCY_{itj} + \gamma_{15} \cdot AIRCRAFTSIZE_{it} + \\ + \gamma_{16} \cdot EFFSEATSHR_{ijt} + \eta_i + \theta_j + \kappa_t + h \end{aligned} \tag{3.5}$$

$$\begin{aligned} LOADFACTOR_{ijt} = \delta_0 + \delta_1 \cdot MSB_{it} + \delta_2 \cdot IMR1_{it} + \delta_3 \cdot RESROUTE_{ijt} + \delta_4 \cdot IMR2_{it} + \\ + \delta_5 \cdot log(SDI)_{jt} + \delta_6 \cdot TOTCOMP_{jt} + \delta_7 \cdot LCC_{ijt} + \\ + \delta_8 \cdot log(DIST)_{ijt} + \delta_9 \cdot SUNBELT_j + \delta_{10} \cdot log(POP)_{jt} + \\ + \delta_{11} \cdot log(INC)_{jt} + \delta_{12} \cdot FLEETMIX_{it} + \delta_{13} \cdot TOTROUTE_{it} + \\ + \delta_{14} \cdot FREQUENCY_{itj} + \delta_{15} \cdot AIRCRAFTSIZE_{it} + \\ + \delta_{16} \cdot EFFSEATSHR_{ijt} + \eta_i + \theta_j + \kappa_t + k \end{aligned} \tag{3.6}$$

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

$$
\begin{aligned}
SEATSHR_{ijt} = {} & \epsilon_0 + \epsilon_1 \cdot MSB_{it} + \epsilon_2 \cdot IMR1_{it} + \epsilon_3 \cdot RESROUTE_{ijt} + \epsilon_4 \cdot IMR2_{it} + \\
& + \epsilon_5 \cdot log(SDI)_{jt} + \epsilon_6 \cdot TOTCOMP_{jt} + \epsilon_7 \cdot LCC_{ijt} + \\
& + \epsilon_8 \cdot log(DIST)_{ijt} + \epsilon_9 \cdot SUNBELT_j + \epsilon_{10} \cdot log(POP)_{jt} + \\
& + \epsilon_{11} \cdot log(INC)_{jt} + \epsilon_{12} \cdot FLEETMIX_{it} + \epsilon_{13} \cdot TOTROUTE_{it} + \\
& + \epsilon_{14} \cdot FREQUENCY_{itj} + \epsilon_{15} \cdot AIRCRAFTSIZE_{it} + \\
& + \epsilon_{16} \cdot EFFSEATSHR_{ijt} + \eta_i + \theta_j + \kappa_t + r
\end{aligned} \tag{3.7}
$$

As shown in Eq. 3.8, 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):

$$YIELD_{ijt} = \beta_0 + \mathbf{X_2}_{ijt} \cdot \boldsymbol{\beta_1'} + \beta_2 \cdot MSB_{it} + \epsilon_i + \mu_j + \epsilon_t + u \tag{3.8}$$

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 X_2 of exogenous explanatory variables and of a variable capturing the middle seat blocking strategy for each airline i. $\hat{\beta_1}$ is a column vector of coefficients for the exogenous explanatory variables and α_2 the coefficient for the MSB dummy variable. The airline fixed effects are identified by γ_i, while μ_j captures airport pair fixed effects and ϵ_t refers to quarter fixed effects. Finally, u is the error term which is assumed to be normally distributed with zero mean and constant variance $\hat{\sigma_u^2}$.

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. 3.7 is reported in Eq. 3.8 as follows:

$$
\begin{aligned}
YIELD_{ijt} = {} & \pi_0 + \pi_1 \cdot MSB_{it} + \pi_2 \cdot IMR1_{ijt} + \pi_3 \cdot RESROUTE_{ijt} + \\
& + \pi_4 \cdot IMR2_{ijt} + \pi_5 \cdot log(SDI)_{jt} + \pi_6 \cdot TOTCOMP_{jt} + \pi_7 \cdot LCC_{ijt} + \\
& + \pi_8 \cdot log(DIST)_{ijt} + \pi_9 \cdot SUNBELT_j + \pi_{10} \cdot log(POP)_{jt} + \\
& + \pi_{11} \cdot log(INC)_{jt} + \pi_{12} \cdot FLEETMIX_{it} + \pi_{13} \cdot TOTROUTE_{it} + \\
& + \pi_{14} \cdot ONESTOP_{itj} + \pi_{15} \cdot TWOSTOP_{it} + \gamma_i + \mu_j + \epsilon_t + w
\end{aligned} \tag{3.9}
$$

3.4.5 Econometric Concerns

Eq. 3.9 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 do not specifically control for endogeneity for several reasons: First, by explicitly including fixed effects and market characteristics in our model, we already capture much of the unobserved heterogeneity among observations, hence limiting potential bias; second, there is evidence in the literature (i.e., Gayle and Wu, 2013) showing that directly addressing endogeneity of carrier competition via a structural model has little impact on the final estimates; third, the potential endogeneity between $TOTCOMP$ and $YIELD$ is 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 use its coefficient to interpret the causal impact on the dependent variable. $TOTCOMP$ only serves as a control variable. Therefore, potential endogeneity between $TOTCOMP$ and our dependent variables will not influence the main results measuring the influence of MSB on the dependent variables. For these reasons, we do not specifically control for the potential endogeneity of $TOTCOMP$.[27]

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. 3.10 through a probit regression to generate the Inverse Mills Ratio ($IMR1$) to correct for route selection bias in Eqs. 3.5, 3.6, 3.7 and 3.9.

$$\begin{aligned} RESROUTE_{ijt} = {} & \phi_0 + \phi_1 \cdot CENTRALITY_{ijt} + \phi_2 \cdot log(SDI)jt + \\ & + \phi_3 \cdot log(DIST)_{ijt} + \phi_4 \cdot TOTCOMP_{jt} + \phi_5 \cdot SUNBELT_j + \\ & + +\phi_6 \cdot log(POP)_{jt} + \phi_7 \cdot log(INC)_{jt} + \phi_8 \cdot TOTROUTE_{it} + \\ & + v_t + z \end{aligned} \tag{3.10}$$

[27] To check for the robustness of the estimates presented in Table 3.5 we also run the models including fixed effects at the $ROUTE \times TIME$ level. In this way we capture all the time-varying characteristics of each route across time, implicitly excluding some of the variables from the models (i.e., $TOTCOMP$).

In Eq. 3.10, $RESROUTE_{ijt}$ is a binary outcome variable indicating whether a route is operated by a carrier in both 2019 and 2020. It is estimated as a function of the intensity of the pandemic at the state level, route cost and demand shifters and route market and origin and destination characteristics. Seasonal trends are captured by v_t while z is the error term with 0 mean and, for identification purposes, variance σ_z^2 set equal to unity. In Eq. 3.10 we also include the network variable $CENTRALITY19$ that serves as an instrumental variable to tackle the route selection bias in the main equations. This variable is included in the selection equation, but not in the equations of interest. We believe that an airline is more likely to keep a route if it is important in terms of connectivity for its entire network. To save operating expenses while minimizing the disruption to the overall route network connectivity, an airline is more likely to cut those routes involving endpoint airports that have lower centrality values. This intuition is indeed supported by the probit results in Table 3.6 in the Appendix. Since the connectivity of a route network is important for passengers (as well as for airlines), the centrality index may also impact passenger share, load factor, seat share, and yield. Given the exclusion restriction (i.e., the instrumental variable should not directly impact the dependent variables), we base our centrality measure on (pre-pandemic) 2019 data. A third econometric concern rises because the adoption of a middle-seat blocking strategy is highly possibly a result of self-selection by an airline. Systematic differences between airlines that did or did not adopt the strategy might yield biased measures of the effects of the middle-seat blocking strategy even after correcting for route selection bias (i.e., due to carrier bias). Therefore, we estimate Eq. 3.11 through a probit regression to generate the Inverse Mills Ratio ($IMR2$) to correct for airlines' self-selection bias in Eqs. 3.5, 3.6, 3.7 and 3.9. We included the variable $MIDDLESEATSHR19$ in Eq. 3.11.It measures the percentage of middle seats to total seats operated by airlines in 2019 (lagged to limit endogeneity concerns), and serves as an instrumental variable to address self-selection bias in the main equations. The percentage of middle seats on an airline's network may be linked to the likelihood that the airline will adopt a middle-seat blocking strategy. For example, the percentage of middle seats is higher for wide-body aircraft than for narrow-body aircraft; therefore, airlines that operate a high percentage of wide-bodied aircraft may be less likely to block middle seats.[28] The lagging of the variable allows us to exclude $MIDDLESEATSHR19$ from the

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

estimation of the performance variables, passenger share, load factor, seat share, and yield, since passenger choices are based on current, rather than on lagged, seat configurations.

$$\begin{aligned} MSB_{it} = {} & \xi_0 + \xi_1 \cdot MIDDLESEATSHR_{ijt} + \xi_2 \cdot log(SDI)_{jt} + \\ & + \xi_3 \cdot log(DIST)_{ijt} + \xi_4 \cdot TOTCOMP_{jt} + \xi_5 \cdot SUNBELT_j + \\ & + \xi_6 \cdot log(POP)_{jt} + \xi_7 \cdot log(INC)_{jt} + \xi_8 \cdot TOTROUTE_{it} + \\ & + \tau_t + \omega \end{aligned} \tag{3.11}$$

Given the multi-step estimation procedure leading to our final estimates, standard errors may be underestimated, leading to inflated t-statistics. To adjust for potentially inflated standard errors, we employ a bootstrap procedure with 1,000 replications. Given the nature of our data, we implement the procedure by time blocks, resampling on the airline-route dimension (without resampling months or airline-route-months) to keep the time series properties of the observations (Dresner et al., 2021).[29] Moreover, Eqs. 3.5, 3.6, 3.7 and 3.9 are estimated using high dimensional fixed effects regressions. For identification reasons we include route, airline, and time dummies. Finally, standard errors are always clustered at the airline-route level.[30]

3.4.6 Descriptive Statistics

Table 3.4 presents descriptive statistics for the variables in our models. The statistics for our five dependent variables show that, on average, a US carrier averaged about 23% of the market in terms of both seat share and passenger share. Airlines filled about 53% of seats on a route during the time of our dataset. Average load factors were, thus, quite low, during the first year of the Covid-19 pandemic.[31] Yields averaged \$0.12 per revenue-passenger mile. Data from the table indicate that the middle seat was blocked in 48% of our observations, about 91% of our observations are for routes operated both in 2019 and 2020 (the remaining 9% are new routes, introduced in 2020). There was an average of just over three carriers operating a route segment. Airlines

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

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

[31] Average load factors per route fell to 11.4% in April 2020.

employed about two different aircraft types on a route on average and the average aircraft size was 168 seats and the average route distance 1,119 miles.

TABLE 3.4: Descriptive Statistics[32]

Variable	Obs.	Mean	Std. dev.	Min	Max
PAXSHR	7,135	22.54	15.31	0.99	93.35
LOADFACTOR	7,135	52.95	19.34	2.63	94.76
EFFLOADFACTOR	7,135	62.35	20.23	2.91	99.97
SEATSHR	7,135	22.56	15.22	2.07	90.86
YIELD	4,554	0.12	0.09	0.02	0.71
MSB	7,135	0.48	0.50	0.00	1.00
RESROUTE	7,135	0.91	0.28	0.00	1.00
SDI	7,135	1240.10	627.80	0.00	4683.50
TOTCOMP	7,135	3.00	0.92	2.00	6.00
LCC	7,135	0.54	0.50	0.00	1.00
DIST	7,135	1118.90	608.66	153.00	2918.00
SUNBELT	7,135	0.46	0.50	0.00	1.00
POP	7,135	186.00	241.00	4.00	1,560.00
INC	7,135	4,040.00	946.00	1,090.00	6,660.00
FLEETMIX	7,135	1.96	0.97	1.00	11.00
TOTROUTE	7,135	461.72	282.06	13.00	1,004.00
FREQ	7,135	66.61	55.39	16.00	1,080.00
AIRCRAFTSIZE	7,135	167.76	25.40	100.00	364.00
EFFSEATSHR	7,135	22.39	14.45	2.03	93.58
ONESTOP	4,554	0.11	0.20	0.00	1.00
TWOSTOP	4,554	0.00	0.01	0.00	0.15
CENTRALITY19	7,135	65.54	11.26	28.67	100.00
MIDDLESEATSHR19	7,209	30.07	4.91	0.00	45.10

3.5 Results

Results from our main estimations are presented in Table 3.5, while the probit route selection results are shown in Table 3.6 in the Appendix. The main results show that blocking the middle seat contributes to higher passenger shares on a route, to lower absolute load factors, but to higher "effective" load factors (assuming that the seat capacity of an aircraft with middle seats blocked is lower by the number of blocked middle seats), to higher seat shares on a route, but, surprisingly to lower yields (after controlling for airline fixed effects). Based on a mean plane size of 168 seats, a mean load factor of 53%, a mean yield of $0.12/revenue-passenger mile, and a mean route distance of 1,119 miles, the blocking of the middle seat on average results in decreased revenues of more than $3,000 per flight.

Note that when fixed effects are not included in the model, the middle seat blocking strategy is associated with higher yields (see Appendix table, 3.7). This result indicates that there may be systematic decisions related to the blocking of middle seats, likely associated with the yields airlines, on average, are able to achieve. Importantly, Delta Airlines, a carrier that blocked middle seats from April-December 2020, is associated with higher yields than most of its competitors. On the other hands, ultra-low-cost carriers Allegiant and Spirit never blocked middle seats. Therefore, accounting for systematic difference among airlines using fixed effects may be necessary to isolate the impact of the middle seat blocking strategy.[33]

Other results in Table 3.5 from our estimations seem reasonable: increased social distancing at the endpoints of a route (SDI) reduces load factors. Resilient routes have higher load factors and seat shares. The significant coefficients for the Inverse Mills Ratios show that there is selection bias in both choosing whether to block middle seats and which routes to operate. As expected, connecting flights have lower yields.

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

TABLE 3.5: Estimates of the Five Models

Variables	(1) *PAXSHR*	(2) *LOADFACTOR*	(3) *EFFLOADFACTOR*	(4) *SEATSHR*	(5) *YIELD*
MSB	7.925***	-4.751***	12.279***	2.098***	-0.026***
	(21.823)	(-9.784)	(20.141)	(4.328)	(-6.155)
IMR1	2.668***	-3.432*	6.965***	7.756***	-0.170***
	(2.884)	(-1.809)	(3.100)	(4.402)	(-6.162)
RESROUTE	-1.498***	-0.955	-2.590***	0.419	0.113***
	(-5.755)	(-1.499)	(-3.689)	(0.785)	(20.596)
IMR2	-2.829***	-10.638***	-13.506***	-4.376***	-0.082**
	(-4.235)	(-8.208)	(-8.912)	(-3.264)	(-2.575)
SDI	0.718**	-14.856***	-17.122***	6.773***	0.029***
	(2.415)	(-8.682)	(-8.803)	(6.033)	(4.337)
TOTCOMP	0.445***	-0.417	-0.218	-3.760***	-0.003**
	(5.530)	(-0.989)	(-0.431)	(-11.295)	(-2.491)
FLEETMIX	0.146	0.086	-0.150	-8.712***	-0.000
	(1.456)	(0.448)	(-0.720)	(-21.488)	(-1.438)
TOTROUTE	-0.009***	-0.017***	-0.007	-0.001	-0.000***
	(-4.521)	(-4.320)	(-1.602)	(-0.276)	(-7.242)
FREQ	-0.004	-0.017***	-0.007	0.177***	
	(-1.437)	(-3.963)	(-1.413)	(20.929)	
AIRCRAFTSIZE	-0.000	-0.003	0.018*	0.130***	
	(-0.010)	(-0.318)	(1.846)	(13.121)	
EFFSEATSHR	1.040***				
	(101.207)				
ONESTOP					-0.018***
					(-4.616)
TWOSTOP					-0.143*
					(-1.950)
AA	7.609***	16.820***	17.117***	-1.175	-0.011*
	(16.337)	(19.284)	(16.167)	(-1.212)	(-1.749)
AS	-1.387**	2.136	3.856**	-12.584***	-0.047***
	(-2.002)	(1.616)	(2.362)	(-8.208)	(-10.078)
B6	1.499**	7.407***	11.880***	-7.920***	-0.084***
	(2.005)	(5.534)	(7.238)	(-5.555)	(-6.572)
F9	3.426***	13.924***	9.070***	-14.042***	-0.179***
	(4.480)	(8.286)	(4.319)	(-9.815)	(-14.833)
G4	1.998	9.081**	4.681	-12.884***	-0.167***
	(1.123)	(2.291)	(1.135)	(-3.913)	(-11.463)
HA	-6.505***	-1.700	-2.365	-9.604***	-0.044***
	(-3.206)	(-0.758)	(-0.726)	(-4.134)	(-7.714)
NK	6.820***	22.791***	19.447***	-10.345***	-0.169***
	(10.448)	(16.666)	(11.302)	(-7.824)	(-12.542)
UA	4.701***	8.791***	9.641***	-3.681***	-0.037***
	(8.710)	(7.428)	(7.136)	(-3.969)	(-7.255)
WN	7.436***	10.698***	17.728***	1.206	-0.032***
	(10.940)	(7.171)	(10.549)	(0.779)	(-6.610)
Constant	-11.767***	162.964***	162.255***	-32.177***	0.197***
	(-4.668)	(13.446)	(11.682)	(-3.872)	(2.841)
Observations	7,135	7,135	7,135	7,135	4,554
Adj. R-squared	0.94	0.83	0.79	0.74	0.87
MONTH FEs	✓	✓	✓	✓	✓
ROUTE FEs	✓	✓	✓	✓	✓
AIRLINE FEs	✓	✓	✓	✓	✓
ROUTETIME FEs	×	×	×	×	×

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

The results from our estimations to demonstrate the robustness of our results are presented in the Appendix (Tables 3.7, 3.8 and 3.9). As noted above, when airline fixed effects are not included in the model, the impact of the middle seat blocking strategy on yields changes from negative to positive (Table 3.7, Column 4). Results for the other performance variables (load factor, effective load factor, seat share and passenger share) are reasonably consistent with our base results. When we include a different set of fixed effects (route-time fixed effects) in our estimations, we also get results consistent with our base results (Table 3.8). Finally, when we use a database similar to Hyman and Savage (2021 & 2022), confining our analysis to Delta and its network carrier competitors (American and United) and using a model without fixed airline effects, we obtain results similar to Hyman and Savage (2021 & 2022); that is with this limited dataset, the middle seat blocking strategy is associated with about 12% higher yields. It should be noted, that even if yields are marginally higher with the middle seats blocked as per our results in Tables 3.7 and 3.9, the revenue losses from the decrease in load factors associated with the strategy will outweigh the revenue gains from the higher yields. Thus, using any of our models presented (base model and robustness check models), there will be net revenue losses for airlines undertaking the middle seat blocking strategy. This result likely indicates why airlines either did not implement the strategy or ceased implementing the strategy, despite continued safety concerns.

3.6 Conclusion

3.6.1 Implications

For this paper, we first provide a general analysis of strategies undertaken by the four largest U.S. airlines and then provide a more detailed analysis on a route-level basis of one of the key safety-related strategies, the blocking of middle seats. Our airline-level analysis shows distinct difference among the largest airlines in terms of the strategies undertaken during the pandemic. In particular, strategic decisions may be closely tied to pre-pandemic operations. Southwest Airlines, notably, without an extensive international route network, was best able to maintain domestic routes during the pandemic. Moreover, American Airlines, with its greater reliance on regional carriers, was able to keep a higher percent of flights and seats in operation during the pandemic compared to its network carrier rivals. The regional carriers were especially suited to operating routes when passenger demand declined early in the pandemic. The strategies undertaken by the carriers likely resulted in variations in performance outcomes. Although American Airlines maintained a higher percentage of flights and seats than its rivals, it also had a higher decline in yields during the pandemic, compared to the previous year. Therefore, American's decision to maintain its capacity may have had a cost, with the higher capacity resulting in lower yields.

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

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

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

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

3.6.2 Limitations and Future Research

A limitation of this paper is in its scope. We examine only the short run implications of blocking middle seats. Clearly some of the airlines that maintained this strategy for several months (e.g., Delta) must have seen some benefits to continuing to block middle seats. We do not assess these spillover effects from the middle seat blocking strategy. Furthermore, we only estimate a dataset for U.S. airlines. Since the viral levels 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.

3.7 Appendix B

TABLE 3.6: Estimates of the Selection Probit Models

Variables	(1) *RESROUTE*	(2) *MSB*
CENTRALITY19	0.037***	
	(10.290)	
MIDDLESEATSHARE19		-0.041***
		(-5.711)
DIST	-0.013	0.358***
	(-0.223)	(9.903)
TOTCOMP	-0.022	0.045**
	(-0.718)	(2.123)
TOTROUTE	0.002***	0.003***
	(13.043)	(24.046)
SUNBELT	0.108*	0.014
	(1.700)	(0.336)
LCC	-1.122***	-0.239***
	(-10.220)	(-3.083)
POP	0.035	0.049**
	(1.132)	(2.489)
INC	0.073	-0.083
	(0.613)	(-0.954)
Constant	-3.104	-2.531
	(-1.164)	(-1.240)
Observations	7,441	7,209
MONTH FEs	✓	✓
ROUTE FEs	×	×
AIRLINE FEs	×	×
ROUTETIME FEs	×	×

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

TABLE 3.7: Estimates from the Main Model – Without Airline Fixed Effects

Variables	(1) *PAXSHR*	(2) *LOADFACTOR*	(3) *EFFLOADFACTOR*	(4) *SEATSHR*	(5) *YIELD*
MSB	3.866***	-12.905***	5.571***	2.298***	0.029***
	(13.688)	(-25.644)	(10.403)	(4.556)	(16.555)
IMR1	3.044***	-2.500	6.967***	3.544**	-0.117***
	(2.940)	(-1.145)	(2.746)	(2.207)	(-6.275)
RESROUTE	-1.712***	-3.812***	-3.627***	2.210***	0.120***
	(-6.299)	(-5.559)	(-4.836)	(4.395)	(38.184)
IMR2	-2.961***	-11.563***	-14.396***	-2.983**	-0.114***
	(-4.234)	(-7.487)	(-8.213)	(-2.208)	(-4.185)
SDI	0.719***	-15.904***	-18.196***	6.820***	0.022***
	(2.753)	(-9.258)	(-9.237)	(6.073)	(3.047)
TOTCOMP	0.488***	0.075	0.474	-3.948***	-0.003**
	(6.228)	(0.176)	(0.902)	(-12.133)	(-2.212)
LCC	1.263***	5.909***	7.614***	-4.131***	-0.085***
	(2.662)	(6.097)	(6.672)	(-5.302)	(-18.862)
FLEETMIX	0.336***	1.223***	1.375***	-8.720***	-0.000
	(3.106)	(4.154)	(4.387)	(-19.277)	(-1.420)
TOTROUTE	-0.000	-0.013***	0.004	0.009***	-0.000***
	(-0.096)	(-3.531)	(0.970)	(3.518)	(-5.220)
FREQ	-0.009***	-0.051***	-0.039***	0.182***	
	(-2.948)	(-8.096)	(-5.707)	(20.876)	
AIRCRAFTSIZE	-0.003	0.004	-0.017	0.111***	
	(-0.510)	(0.520)	(-1.598)	(11.571)	
EFFSEATSHR	1.049***	0.135***	0.148***		
	(88.724)	(7.137)	(6.947)		
ONESTOP					-0.005
					(-1.163)
TWOSTOP					0.039
					(0.529)
Constant	-10.084***	176.377***	176.388***	-34.219***	0.049
	(-4.262)	(14.499)	(12.460)	(-4.237)	(0.822)
Observations	7,135	7,135	7,135	7,135	4,554
Adj. R-squared	0.93	0.79	0.77	0.73	0.84
MONTH FEs	✓	✓	✓	✓	✓
ROUTE FEs	✓	✓	✓	✓	✓
AIRLINE FEs	×	×	×	×	×
ROUTETIME FEs	×	×	×	×	×

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

TABLE 3.8: Estimates from the Main Model – With Route-Time Fixed Effects

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

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

TABLE 3.9: Results Based on a Subsample Where DL is Always Competing With AA, UA, or Both

Variable	(1) *YIELD*
MSB	0.017***
	(5.646)
IMR1	-0.008
	(-0.905)
IMR2	0.040***
	(3.648)
SDI	-0.029***
	(-3.272)
TOTCOMP	-0.000
	(-0.106)
FLEETMIX	0.000
	(0.087)
TOTROUTE	-0.000
	(-0.573)
ONESTOP	-0.020**
	(-2.420)
TWOSTOP	0.096
	(0.956)
Constant	0.353***
	(5.564)
Observations	544
Adj. R-squared	0.96
MONTH FEs	✓
ROUTE FEs	✓
AIRLINE FEs	×
ROUTETIME FEs	×

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

Chapter 4

Pricing effects of code sharing in Africa

4.1 Introduction [1]

Air transport is a critical factor for Africa's economic development (Button, Martini, and Scotti, 2017). The continent has one of the largest territories in the world: this implies long distances between the main urban centers of the various African countries, but also for domestic connections. Furthermore, several countries are landlocked, making the aviation sector even more crucial for mobility of people and freight. Nevertheless, the sector is lagging behind: it accounts for around 2% of world passenger transport, and for about 1.5% of freight transport (Button, Martini, and Scotti, 2017). In addition, efforts to improve the sector through liberalization are slowed down by antagonisms between nations, poor negotiation effectiveness, political instability (Njoya, 2016).[2]

The industry's delay is also due to the lack of cooperation between African airlines, both with each other and with major worldwide carriers and alliances (Button, Porta, and Scotti, 2022), even if other continents we are observing a trend for airlines' consolidation, also to tackle the strong crises triggered by COVID-19 (Andreana et al., 2021). For instance, AFRAA, 2022 claims that the enhancement of cooperation among African airlines is a crucial factor in the process of recovery and long-run sustainability of air transportation in Africa. Airlines' cooperation may foster the industry and improve the contribution of air transportation for economic growth in Africa

[1] This Chapter is coauthored with Gianmaria Martini, Laura Ogliari, and Davide Scotti

[2] In 1999 the African countries signed the Yamoussoukro Decision, with the aim of liberalizing intra-African flights, and implementing uniform safety and security standards. Today, African states mutually grant themselves the right to exercise traffic rights, but retain the power to designate the airlines, and tariff freedom is limited to eligible airlines. Cabotage is not in place, as it is, for instance in the European Union.

through network expansion, internalization of external effects such as double marginalization, and cost savings due to synergies. At the same time, cooperation can reduce competition and lead to higher prices. Hence, looking at the relation airlines' cooperation-airfares is essential to evaluate whether in Africa the benefits of cooperation translate to passengers through lower prices, that can act as a stimulus for an increase in the passengers' volume, as it happened in the United States, and in Europe. The aim of this paper is to estimate the effect of airlines' cooperation on airfares in Africa.

Among the different forms of airline cooperation this paper focuses on code sharing (CS), the most widespread cooperation strategy at a global level.[3] Code sharing is a marketing arrangement between two airlines whereby one airline's designator code is shown on flights operated by its partner airline (Oum, Park, and Zhang, 1996). CS extends the network of routes and increases the load factor of the aircraft. CS has long been a practice in air transport: the first international codeshare agreement took place in 1985 between American Airlines and Qantas (Dresner and Windle, 1996). It has progressively developed to cover a large percentage of flights (Jong et al., 2022 states that in 2018 about 75% of all direct and indirect flights between the US and Australian were in code sharing, and that a similar percentage applies to flights between Europe and the US) in parallel with the liberalization of air transport.

Previous contributions on the effects of CS are mainly empirical, but there are also some theoretical papers (e.g., Hassin and Shy, 2004, Heimer and Shy, 2006, Chen and Gayle, 2007; Adler and Hanany, 2016) that have highlighted the possible existence of a trade-off between positive and negative effects of CS agreements .[4] The vast majority of studies is related to the US, since they exploit information available in the Department of Transportation origin and destination data bank 1B, which provides data on a 10% sample of passengers traveling both domestic and international flights extracted from

[3] In the air transportation sector there is a variety of cooperation strategies, i.e., global alliances, antitrust immunity, and joint ventures. While CS is usually an agreement between two airlines, a global alliance is a coordination among several alliances, granting benefits like a high network expansion to the allied carriers, and the possibility to collect advantages from frequent flyer programs to passengers.

[4] Chen and Gayle, 2007 study the effect of CS with a vertical product differentiation model in itineraries involving one stop, and show that it decreases prices by eliminating the double markup only if there is no CS partner offering online flights (i.e., the same airline operates both legs) in the same itinerary. Adler and Hanany, 2016 present a game-theoretic model to study the impacts of CS in parallel networks, i.e., routes where airlines overlaps. They show that consumers are better off only if CS covers a small share of the flights offered in the parallel networks.

reporting carriers.[5] A large number of these papers finds that CS decreases prices in connecting prices, while there is no effect on direct flights. The intuition is that through cooperation airlines realize that in a one stop itinerary if both charge prices independently on the leg they operate, they do not take into account the external effect on the demand for the other leg, i.e., a typical double markup effect, and this leads to higher prices.

The magnitude of the price reduction due to CS in connecting flights has decreased from the early cross section studies of Brueckner, 2003 and Bilotkach, 2007, that find about a 20% price decrease, to later contributions using panel data (Whalen, 2007; Armantier and Richard, 2008; Brueckner, Lee, and Singer, 2011; Calzaretta Jr, Eilat, and Israel, 2017; Brueckner and Singer, 2019), with estimates varying between -4% and -6%.[6]

Some papers do not find any effect, or that CS increases prices. Gayle, 2008 examines US data for the 4*th* quarter of 2002 and of 2003, to test the effect of the announcement made in August 2002 of Delta Airlines, Continental Airlines, and Northwest Airlines to implement CS, and he does not find any effect. Gayle, 2013 presents a structural model using US data for domestic flights covering the four quarters of 2006, and explores a counterfactual analysis where a CS between carriers is transformed as a complete integration, and finds that in this case prices would decrease by 20%, highlighting that CS does not reduce double marginalization. Other papers present a structural model, and find that CS is not facilitating collusion. Gayle and Brown, 2014 using US data for the 4th quarter of 2002 and 2003 to study the effects of the alliance (involving also CS agreement) between Delta Airlines, Continental Airlines, and Northwest Airlines, show that data are better fitted by a model that assume Bertrand competition among the carriers, even if they

[5]Carriers are US-based (domestic) carriers, and reflect US airline and codeshare partner (foreign) airline routes.

[6]Brueckner, 2003 investigates cross-section data on the 3*rd* quarter of 1999 and find that in one stop flights CS reduces the prices by 17%. Bilotkach, 2007 use the same data set but focuses only on EU-US routes and finds that CS reduces prices by 22%. Whalen, 2007 investigates a data set composed by international EU-US flights related to the 3*rd* quarter of each year from 1990 to 2000 and finds a 4% price reduction. Armantier and Richard, 2008 study a data set composed by US domestic flight in the period 1998-2000 to identify the effect of the CS agreement between Continental Airlines and Northwest Airlines, and find that it reduces prices by 6% in connecting flights, but it increases them by 10% in direct ones. A reduction in prices (-4%) is found also by Brueckner, Lee, and Singer, 2011 using US data for a longer period (1998-2009). Calzaretta Jr, Eilat, and Israel, 2017 analyze international flights departing/arriving in the US between 1998 and 2015, and find alliances involving also CS agreements lead to a 4% price decrease on connecting fares (even after controlling for antitrust immunity and joint-ventures). Brueckner and Singer, 2019, using a more detailed data set, find a much smaller price reduction due to CS (-1%) for the period (1997-2016) for connecting flights.

cooperate, rather than collusion. On the contrary, Ciliberto, Watkins, and Williams, 2019 with US data for a long period, i.e., 1993-2016, finds that CS might be a factor facilitating price fixing, since airfare are more rigid in presence of CS. Ito and Lee, 2007 makes an important contribution on the effect of CS, using the US data for domestic flights in the $3rd$ quarter of 2003. They provide a classification of CS agreements, introducing the difference between traditional and virtual CS, that will be specified later, and show that CS may be implemented not only for expanding the network, increasing the flight frequency, and eliminating double marginalization, but also for market segmentation. The idea is that the CS flight is perceived a lower quality product by passengers, since when the itinerary is operated by a different carrier than the passenger's preferred one, luggage, check-in and boarding operations may be treated differently. They find that virtual CS reduces prices by 5%, while, as expected, traditional CS increases prices by 6%, in comparison to online flights.

Few studies have investigated the effects of CS outside the US, due to lack of data.[7] Alderighi, Gaggero, and Piga, 2015 analyze 49 European routes from April 2003 to February 2004 by web-scrapping data from Opodo website with a focus on the dynamic pricing, i.e., the possible price differences among early and later buyers.[8] They show that CS increases prices by 10% on early bookers, due to the higher airfares charged by the marketing carrier, i.e., the airline that does not operate the flight. Jong et al., 2022 use data from a survey involving Australian passengers flying on two routes: Australia-Chile, and Australia-North America. They show that CS increases passengers' willingness to pay for flights provided by non-Australian carrier, i.e., there is an evidence that passengers have a bias towards home airlines, and CS is a factor increasing the reputation of foreign carriers.

Last, Adler and Mantin, 2015 is the closer contribution to this paper regarding the empirical method. They study data on El Al Israel Airlines flights from/to Israel for March 2008 and March 2010, to observe the effect of the Israeli antitrust authority taken in 2009 that limited several cooperative agreements between El Al and other international airlines. They adopt a difference-in-difference econometric model to observe the impact of a variation in the CS settings on airfares, and find that in the connection flights

[7] A similar data set to the US Databank B1 is not available in other countries, where it is instead necessary to buy proprietary data from specialized companies, e.g., OAG–Official Aviation Guide, of from web scrapping, limited to some routes/airlines.

[8] Opodo is a online travel agency operating in Europe, developed by some European airlines, e.g., British Airways, Lufthansa, Air France, KLM, Iberia, etc.

where the Israeli antitrust authority decision removed CS, prices increase by 4% in case of free sale CS.[9]

This paper fills some gaps existing in the literature. First, it provides some empirical evidence of the changes in price when a CS agreement is implemented in a connecting flight where the two operating airlines were not cooperating before. Similarly to Adler and Mantin, 2015 this paper adopts a sort of difference in differences method, but the implementation of CS is not due to an imposition of a antitrust authority (with the usual monitoring of behavior after the decision) but rather is the independent decision of some airlines. Hence, it is possible to observe whether the potential benefits coming from the elimination of double marginalization outweigh the possible losses due to collusion. Second, the paper analyzes data related to Africa, providing, to the best of our knowledge, insights on the effect of CS not yet available in the literature. Third, differently from Alderighi, Gaggero, and Piga, 2015; Adler and Mantin, 2015 the paper investigates official data (i.e., not obtained through web scraping) and for all airlines and flights (not limited to a sample, as in Alderighi, Gaggero, and Piga, 2015 and Adler and Mantin, 2015). Last, it presents new empirical evidence on possible spillover effects of CS, i.e., what is the impact of a CS agreement on the airfares of carriers not involved in CS but with some strategic interactions (e.g., they operate the same route but with different products) with the airlines involved in CS. The idea is to analyze whether there is a price effect in three different types of flights: (1) in connecting flights, the prices charged by the two carriers that remain independent, i.e., a interline itinerary, and (2) by the carrier that operate both legs (i.e., a online itinerary); (3) the prices charged by airlines operating a direct flight in the same itinerary where there is a connecting flight with CS. The spillover analysis may shed light on possible market segmentation involved by CS, as in Ito and Lee, 2007: for instance, it may be possible to find no effect on direct flight because passengers consider this product completely different from a CS connecting flight even if the ticket is sold by the same company also operating the direct flight in that itinerary.

In order to fill these gaps the paper develops a fixed effects econometric model applied to a panel data set covering the period 2017-2019, with fares monthly observation at the airline level for each commercial route in Africa. The identified empirical evidence is that CS acts as a potential stimulus for air transportation demand in Africa, since, when it is introduced in a connecting

[9] A free sale CS agreement means that seats are not allocated to the marketing carrier, and the latter can operate directly on the operating carrier's computer reservation system.

route previously served by interline service, it generate a strong reduction in airfares, i.e., about -18%. The magnitude of the price reduction effect of CS is larger than any previous results, implying that the impact of double markup is strong in Africa where the lack of cooperation among the airlines generates too high prices. The diffusion of protectionism and monopoly in Africa aviation generates high prices, and only when, through a initial stage of cooperation, airlines start to consider the possible negative effect on demand of single leg high markups, they realize how many improvements can be obtained by limiting the monopoly power. This large impact of CS is a confirmation that the African aviation market has a high potential growth coming from airlines' cooperation, as suggested by AFRAA, 2022).

Furthermore, the evidence regarding the CS spillover effects is mixed: in connecting flights with interline service we find that the airlines react to the introduction of CS by reducing the price of about 10%. In flights with online service the airlines does not react to the CS introduction. These insights imply when providing online or direct services the airline do not perceived CS as a threat for their market share. Definitions of these types of itineraries are provided in the next subsection.

The plan of the paper is as follows. Section 4.2 introduces some definitions regarding the different types of air transportation services we analyze. Section 4.3 presents the African context, while Section 4.4 describes the empirical strategy. Section 4.5 provides information regarding data sources and variable definitions, while Section 4.6 show the econometric results. Section 4.7 offers some conclusions.

4.2 Definition of Air Transportation Services

In order to understand the impact of CS agreements once that they have been implemented in Africa it is essential to clarify some important definitions that apply to both itineraries and CS types. Regarding itineraries, it is necessary to distinguish first between direct and connecting flights. A direct flight links two airports without any intermediate stop. A connecting flight provides instead service between two airports, one defined as origin airport and the other as destination airport, but with at least one stop in another airport, defined as gateway. Many international itineraries involve connecting flights, also because, typically, the business model of full service carriers

(FSCs) is based on the hub-and-spoke system.[10]

A further important distinction is related to connecting flights. In this case it is necessary to distinguish itineraries between self-connecting, interline, and online. Figure 4.1 shows the differences between self-connecting (*a*), interline (*b*), and online (*c*). In case of self-connecting, the passenger buys two tickets, one from the origin airport O to the gateway airport G, operated buy airline A_1, and one from G to the destination airport D, operated by airline A_2 (or airline A_1, it does not matter). The passenger has to check-in, drop baggage, pass through security controls at O and G, and to claim baggage both at G and D. If there is a delay in the flight between O and G, and the passenger misses the flight between G and D, there is not protection on another flight. If the passenger participates in a frequent flight program, e.g., related to carrier A_1, can only collect the points related to this flight.

If the itinerary is interline (Figure 4.1(*b*)), the passenger buys a single ticket, usually from a travel agency, the flight from O to G is operated by airline A_1, while the flight from G to D is operated by the other airline A_2. The check-in, baggage drop, and security controls are performed only in O, and baggage claim is only in D. If there is a delay in the flight between O and G, and the passenger misses the following flight, there is protection. However points are treated as in the self-connecting case.

The characteristics of the online itinerary are described in Figure 4.1(*c*). The two legs O-G and G-D are operated by a single airline, e.g., A_1, the passengers buys a single ticket both from a travel agency or on the airline's website, check-in, drops baggage and make security checks only at O, claims baggage only at D, there is protection in case of delay, and can collect points for both legs. Clearly, in terms of service quality, online is the best, then interline, and last, self-connecting. In interline and self-connecting itineraries the two airlines A_1 and A_2 choose the ticket price to maximize each individual profit. In this way, airline A_1 adds a markup on the leg O-G, and airline A_2 a markup on leg $G - D$, i.e., we have a double marginalization effect. The

[10]In aviation there is a traditional distinction between FSCs and low cost carriers (LCCs). A LCC has a business model based on low prices, essential cabin and ground services, use of secondary airports, direct sale of tickets through its website, concentration on medium-short haul flights. A FSC provides higher quality services (fidelity premiums for frequent flyers, protection in case of delays, lounges, differentiation of in-flight service between business and leisure travelers, use of primary airports, a network with many long-haul flights. FSCs typically adopt a hub-and-spoke system, where many medium-short haul flights are connected to a large airport that operates as a operational base for the airline, and from where many long haul flights departs. In this way FSCs increase the load factor in long haul flights, by gathering in the hub airport people sharing the same destination but staring from different origins.

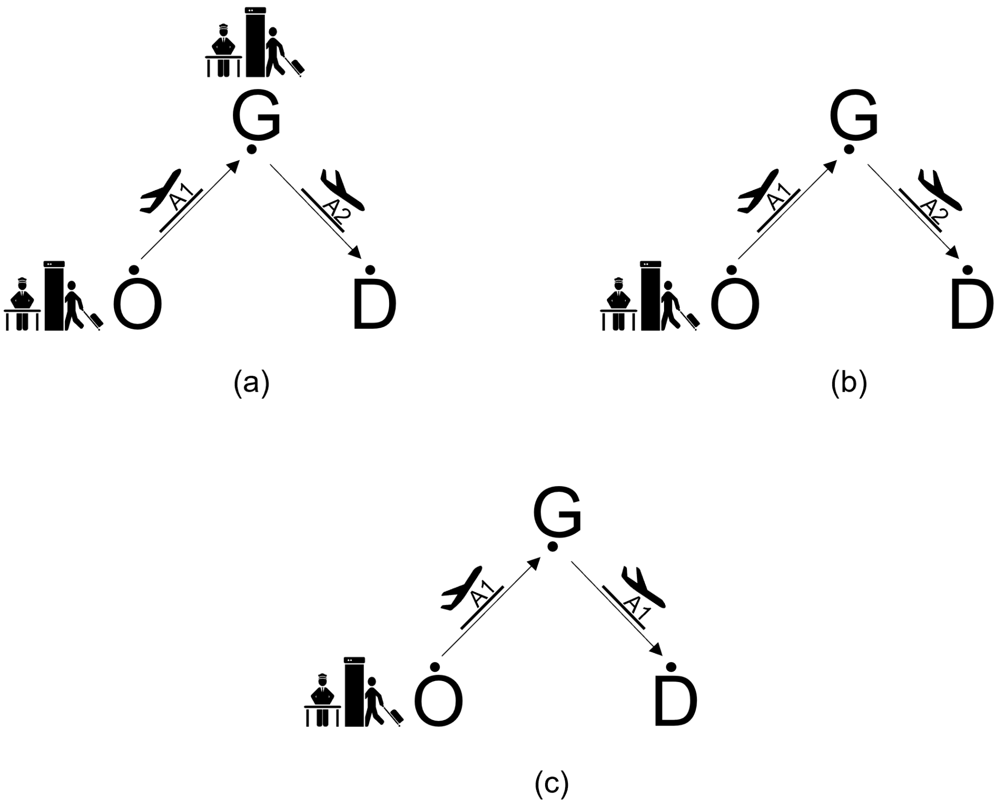

FIGURE 4.1: Different Types of Connecting Flights

CS agreement introduces an important change and generates a new itinerary type. In connecting flights if airlines A_1 and A_2 are code sharing, this implies a difference between the carrier that operates and sells the ticket–defined as operating carrier–and the carrier that only sells the ticket–classified as marketing carrier. A CS agreement implies the possibility for the marketing carrier to sell tickets on the leg that it does not operate.[11] In a CS itinerary the passenger buys a single ticket from the marketing carrier, that can be either the airline that operates the flight or the one in codeshare, check-in, drops baggage and pass through security at the origin airport *O*, claims baggage only at *D*, there is protection, and can collect points for both legs. Hence, a CS itinerary is close to the only even if there are some important differences, as shown by Ito and Lee, 2007: since the passenger buys the ticket from the marketing carrier, and then travels with a different airline, the check-in, onboard, etc. treatments might be different, the points that may be collected may be lower, baggage may not be completely seamless. These characteristics make the quality of a CS itinerary between interline and online.

A further distinction regarding CS is between traditional and virtual: the former is implemented when, for instance, airline A_1 operates the leg *O-G* in Figure 4.1 and airline A_2 is the marketing carrier, while airline A_2 operates leg *G-D* and A_1 is the marketing carrier.[12] A virtual CS is when in the itinerary one airline does not operate in any leg of the itinerary *O-(G)-D*, but only markets some tickets. Clearly, in case of direct flight the only type of CS is virtual.

This paper focuses on connecting flights, therefore it is focused on the traditional type of codeshare. As shown by Adler and Mantin, 2015; Adler and Hanany, 2016, there are several factors that may induce airlines to sign a CS agreement, ranging from network expansion, increasing flight frequency, the stimulus to demand through the elimination of double marginalization, price discrimination through market segmentation (Ito and Lee, 2007), cost reductions through economies of density and scope (the airline can open new connections without operating an aircraft and grasp benefits from higher passengers in the hub airport), higher load factor through better listing in the reservation systems. A further incentive may be increasing prices through

[11] This right to sell ticket on the flight operated by the other CS member under different specifications. In a free-sale CS seats in the aircraft that operates the leg are not allocated to the marketing carrier, that can access directly to the operating carrier reservation system and sell. In a hard-block CS agreement the marketing carriers buys some seats from the operating carrier, and sell them independently.

[12] In a traditional CS it is enough that at least in one leg there is a operating and different marketing carrier.

cooperation. The paper aims to identify if CS is a factor decreasing prices in African aviation, that implies that it limits double marginalization and/or generates cost reductions. Furthermore, by analyzing the CS spillover effects on interline, online, and direct itineraries, the paper provides some evidence on whether CS may be implemented for market segmentation: for instance, if airlines involved in online itineraries react to the introduction of CS by reducing the price it means that the CS itinerary is a strong substitute of the online one.

4.3 Air Transportation in Africa

The great potential of Africa for the development of air services is not in question. Africa's demography (about 15% of the world's population, spread in more than 50 countries) combined to its geography (huge distances and larger and larger urban concentrations) and to the underdevelopment of alternative transport modes are ideal conditions for successfully developing aviation (Button et al., 2015; Abate, 2016; Lubbe and Shornikova, 2017). Despite that, African continental airline markets are underdeveloped (only about 2% of global traffic) and concentrated in a few countries, with most of the airlines characterized by local orientation and inefficiency (Button, Porta, and Scotti, 2022). In other words, African airlines (and this is especially true for the Sub-Saharan ones) benefit little from economies of scope and density, and, on top of that, are often subjected to significant political interference. A contribution to make airlines' business particularly costly is also given by high finance costs of aircraft acquisitions, lack of connectivity and liberalization, high costs of jet fuel, and high aviation fees and charges. As a result, air tickets in Africa cost much more compared to more developed industries like in Europe or US. When also the GDP per capita is considered, the "real cost" increases to the point that an African middle-class citizen cannot bear more than 1 air trip per year, compared to the about 26 in Europe and 33 in North America (Logistic, 2022). The fact that airlines are unprofitable and unable to offer competitive fares to passengers is a dramatic obstacle to the development of the industry in many African countries. The main direction along which to proceed in order to get out from this quicksand is represented by the enhancement of the liberalization process of the African Skies. Several efforts have been made over the last 30 years to improve connectivity and remove many of the rigid bilateral constraints. The Yamoussoukro Decision (YD) of

1999 is the most important agreement in this direction (Scotti et al., 2017). Although the efforts have not been sufficient to date (Button, Porta, and Scotti, 2022), the launch of the Single African Air Transport Market (SAATM) in 2018 represents a further clear attempt toward the full implementation of the YD. As pointed out by the African Airlines Association (AFRAA), the implementation of the liberalization is important also to guarantee a favorable environment for airlines cooperation allowing them to enter into agreements providing the required commercial and operational flexibility. Globally, the benefits from commercial cooperation (especially strategic alliance memberships and code sharing agreements) have been remarkable. On the contrary, there is currently lack of cooperation across African airlines (Button, Porta, and Scotti, 2022). Njoya, 2016 attributes part of the failure to the past effort toward liberalization to this lack of cooperation between African carriers and airlines from elsewhere. Commercial cooperation is therefore seen as one of the keys to make intra-Africa travel convenient and affordable thanks to fare reductions and revenue increase for African carriers.

4.4 The Empirical Strategy

This section describes the econometric model to identify the impact of CS on airfares in Africa. Since the aims are to obtain evidence (1) on the change in prices once that CS has been adopted on particular routes, and (2) on the spillover effects of the CS adoption on the same set of routes when offered under alternative circumstances (i.e., nonstop, connecting but with only one single player for both legs, etc.), two different empirical settings are designed. For the first goal, we exploit the panel dimension of the dataset and implement a fixed effect econometric model as follows:

$$\log FARE_{ijt} = \gamma CS_{ijt} + \alpha_{ij} + \alpha_{jt} + \epsilon_{ijt} \tag{4.1}$$

where $FARE_{ijt}$ is the average fare charged by the operating carriers pair i (i.e., the pair A_1-A_2 or A_1-A_1 in Figure 4.1), on the O&D market j (the connecting itinerary *O-(G)-D* in Figure 4.1) during period t (month-year), expressed in logarithm. CS_{ijt} is a dummy variable equal to 1 if the two operating carriers are in a CS agreement on market j, and 0 otherwise. α_{ij} is the carrier pair×market fixed effect, α_{jt} is the market×period fixed effect, and ϵ_{ijt} is the error term, which is assumed to be normally distributed.

The model is applied to connecting itineraries where there are at least two pairs of operating carriers covering the two different legs, with at least six observations, of which at least in the first three periods the itinerary is interline, and then one carrier pair adopts the CS agreement and keeps it until the end of the observed time interval. Table 4.1 offers a clear view of our definition of a CS agreement.

TABLE 4.1: Example of the Activation of Code Sharing

t	OC1	MC1	OC2	MC2	CS
1	A1	A1	A2	A2	0
2	A1	A1	A2	A2	0
...	...	...	...	...	...
23	A1	A1	A2	A2	0
24	A1	A1	A2	A1	1
...	...	...	...	...	...
T	A1	A1	A2	A1	1

The rich set of fixed effects allows us to parsimoniously control for many sources of unobserved heterogeneity. In particular, the carrier pair$\times$market fixed effect controls for all time-invariant factors involving two airlines on a given market. The market$\times$period fixed effect absorbs all unobserved time-varying factors that may affect the ticket price charged in a specific market, such as demand shocks due to seasonality, country pair characteristics, and the competition on the route. The dummy variable *CS* captures the switch from interline to codeshare. The coefficient, γ, is identified only using fare variation in the same market and period between pairs that are in CS and those who are not, as well as variation within pairs and market before and after the switch to CS. It is therefore possible to interpret γ as a difference in difference effect: the difference in fares charged in market j between airline pairs operating in CS and those operating interline, before and after code sharing is introduced.[13]

Even with the rich set of fixed effects, in the model shown in (4.1), the *CS* dummy may still be endogenous (Brueckner, 2003). Airlines may select the route where to adopt CS due to unobserved factors, implying that the

[13]The inclusion of market $\times$ period and market pair fixed effects implies that to identify gamma we are using only those itineraries where that are at least two pairs of operating carriers covering different legs in which at least one of the two switches.

dummy CS may be correlated with the error term ϵ, generating a challenge in the identification of the effect of the adoption of codeshare on ticket prices. We tackle this issue with an instrumental variable approach. As an instrument we exploit the "gateway characteristics", and in particular the number of direct connections that the two airlines operate in codeshare with any airline from the gateway to other destinations rather than the origin and the destination of the considered market. We call this variable $CS_{PROPENSITY}$ as we believe it captures the attitude of an airline pair to cooperate through a code sharing agreement on the observed O&D market at a given period t. This measure allows us to exploit some variation at the airline pair (i) - market (j) level. Moreover, supported by the theory on multimarket contact, we believe that if the codeshare agreements are signed for a group of routes, then the decision to codeshare on another route is driven by the same reasons. If at time t the interline connection A1/A1 $\rightarrow$ A2/A2 on the itinerary Origin-Gateway-Destination $O_0 - (G_0) - D_0$ is observed, it is reasonable to assume that the probability that at period t a CS agreement is observed (i.e., A1/A1 $\rightarrow$ A2/A1*) is positively linked to the number of segments in CS that the two operating carriers (A1 and A2) have with any partner connecting that specific gateway G_0 to airports different from the origin and destination of the route. This number explains the propensity of CS in G_0, but does not affect the fare of the itinerary $O_0 - (G_0) - D_0$ given that regards other O&Ds.[14] Figure 4.2 and Figure 4.3 illustrate this concept.

[14]When an airline pair A1/A2 flies the same interline itinerary passing through different gateways this number is computed as the mean across the gateways.

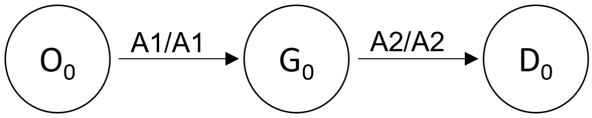

FIGURE 4.2: An Interline Itinerary operated by A_1 and A_2

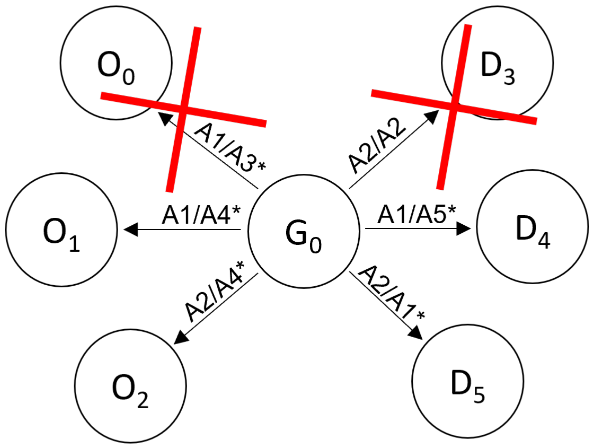

FIGURE 4.3: A Gateway and All Its Outbound Direct Codeshare Flights That We Count to Build Our IV

Our second goal is to investigate whether CS adoption by a carrier pair in a particular market has spillover effects on the same route when served under different circumstances: by airline pairs that never switch to codeshare (the interline case), by airlines offering the two legs on their own (the online scenario), and when the O&D market is served without any intermediate stop (the direct case). To this purpose we use three different subsamples and estimate the following econometric model:

$$\log FARE_{ijt} = \theta CS_{jt} + \alpha_{it} + \alpha_{js} + \alpha_{ct} + \psi_{ijt} \tag{4.2}$$

where $FARE_{ijt}$ is, in the interline subsample, the fares charged by the airline pair i that never adopt CS in market j (t identifies the period, as before); in the online subsample, the price charged in the connecting route j by the single carrier i that operates both legs; on the direct itinerary subsample, the price charged by airline i that serves market j without stops (i.e., a direct flight from origin O to destination D). CS_ROUTE_{jt} is specified as a dummy variable equal to one if on route j a carrier pair operating a connecting flight switches from interline to codeshare; hence, the coefficient θ identifies the spillover effect, i.e., how the other airlines, offering a different product, react to the introduction of CS by some competitors on the same route. The set of fixed effects is now different than the one we exploited to estimate the double difference in the main model (4.1). α_{it} is the airline pair$\times$period (or the single airline$\times$period in the online and direct subsamples) fixed effect, α_{js} the market$\times$semester fixed effect, α_{ct} the country pair$\times$period fixed effect capturing all the time varying characteristics of the route at the country pair level (all the sociodemographic attributes that we could have included at the country level are taken into account).[15]

4.5 Data and Variables

This Section presents the data sets used in the empirical application to identify the impact of code sharing on airfares in Africa. The main dataset covers 36 months within the 2017-2019 period and focuses on connecting flights in the intra-African international market.[16] Data used for investigating the spillover effects extend also to non-stop (direct) flights. Data are available from the OAG (Official Aviation Guide) Traffic Analyzer, which provides aggregated traffic information on tickets sold (prices, passengers, etc.). Sociodemographic data as political stability, population, and gdp per capita in PPS[17] at the country-year level are collected from the World Bank dataset.[18] The basic unit of observation is an airline pair in a market, where the airline pair is the combination of the airlines operating the first and the second leg of the itinerary, which differ in the case of code sharing. We define a market as a directional flight between two airports, irrespective of intermediate connecting points (gateways). Considering directionality (that is, A–B and B–A are counted as separate routes) is common in the literature that relies on the same data source (e.g., Dresner et al., 2021).

Data cleansing actions have been applied to keep the most credible and relevant observations only. First, observations reporting airfares below 10$ are excluded as they are unlikely credible. This threshold has been set in a cautionary way not to risk losing too much information. Yet, with this cutoff we exclude about 50% of the total number of observations. Those are

[15]Market and period fixed effects cannot be included since they are collinear with CS_{jt}. To alleviate this concern we included the α_{js} which we believe it captures most of the airline competition at the $j-t$ as the entry/exit decision is rarely something changing within the season, but rather decided months in advance and stable along the semester. Birolini et al., 2021

[16]Itineraries with gateways outside Africa have not been included.

[17]A common currency that eliminates the differences in price levels between countries allowing meaningful volume comparisons of GDP between countries.

[18]Available at https://databank.worldbank.org/source/worldwide-governance-indicators, https://data.worldbank.org/indicator/SP.POP.TOTL and https://data.worldbank.org/indicator/NY.GDP.MKTP.PP.CD, accessed, March 13, 2022

likely the results of misreporting or missing data; other cases might be related to frequent flier programs and discounted fares for cabin crews. We are not surprised by such a huge drop in the number of records as this is often observed with OAG-based data, especially for secondary and poorly researched markets, as Africa.[19] Second, observations that appear less than six times (consecutives or not) in our sample are excluded as actual changes in the code sharing agreements are difficult to appraise. Similarly, to have a clearer pattern to apply our models on, we exclude from the sample the pairs switching on and off. As consequence of this second cutoff we restrict the sample by an additional 20%.[20]

Although we do not exploit a classical Difference in Differences framework, we borrow its taxonomy and identify the Treatment Group (TG) as those observations that are interline for the first three periods, and then are in code sharing for the rest of the periods in the sample. The Control Group (CG) is composed of those observations that are always interline. Our dataset shows some cases of virtual codeshare that we consider as interline, but those account for less than 0.8% of the total number of records and do not change the estimates if treated differently.

After the data cleansing actions are applied, there are 1,008 unidirectional markets with 83 carriers, including 6 Low-Cost carriers (e.g., FA (Safair), JE (Mango)), some European and Gulf carriers (e.g., AF (Air France), BA (British Airways), EK (Emirates)).[21] The Top 10 airlines and airline pairs in our main sample are reported in tables 4.2 and 4.3.

[19] Airfares are calculated in US dollars, and do not include fees paid for allocating seats, baggage, or priority boarding. Nor do they include payments for on-board food and drinks, taxes, airports fees, and surcharges (Dresner et al., 2021).

[20] As robustness checks, different thresholds have been tested without any relevant change. The same applies to the threshold on the level of airfares.

[21] Before the cutoffs were applied we had 6,580 markets, 128 carriers. Proportions were similar with respect to the carriers' identity

TABLE 4.2: Top 10 Operating Carriers in *Panel A*

Airline Code	Airline Name	Business Model
SA	South African Airways	Mainline
KQ	Kenya Airways	Mainline
ET	Ethiopian Airlines	Mainline
BA	British Airways	Mainline
FA	Safair	Low Cost
MN	Comair	Mainline
BP	Air Botswana	Mainline
WB	Rwandair Express	Mainline
KP	ASKY Airlines	Mainline
HF	Air Cote d'Ivoire	Mainline

TABLE 4.3: Top 10 Operating Pairs in *Panel A*

Airline Pair Code	Airline Pair Name
BA-SA	British Airways-South African Airways
FA-SA	Safair-South African Airways
MN-SA	Comair-South African Airways
BP-SA	Air Botswana-South African Airways
KQ-SA	Kenya Airways-South African Airways
WB-KQ	Rwandair Express-Kenya Airways
ET-SA	Ethiopian Airlines-South African Airways
5H-KQ	Five Forty Aviation-Kenya Airways
KQ-ET	Kenya Airways-Ethiopian Airlines
MS-ET	Egyptair-Ethiopian Airlines

Our final data set contains 2,061 products (airline pair-market) for which we observe ticket prices across time. Summary statistics for the variables used in our empirical models are reported in Table 4.4, *Panel A* describes the characteristics of the main sample, while panels B, C, and D, report the summary statistics for the subsets exploited in the spillover analyses. *Panel B* is composed of interline observations that never experience a switch to codeshare. In this case, we suspect there might be an indirect effect from the activation of code sharing by some airline pairs on airfares proposed by those never cooperating on this level in the same market. Panels C, and D are, respectively, the online type of observations (where the operating carrier of both legs is the same) and the direct (nonstop) observations that is expected to be representing the highest quality product, or at least the highest level of integration by definition.

TABLE 4.4: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
		Panel A: main sample			
FARE	31,085	215.26	127.11	10	1,892
CS	31,085	0.04	0.20	0	1
CS_PROPENSITY	31,085	1.520	5.311	0	56
DOM_LEG	31,085	0.50	0.50	0	1
KEY_GTW	31,085	0.66	0.36	0	1
		Panel B: interline sample			
FARE	27,959	210.15	122.55	10	1,892
CS_ROUTE	27,959	0.03	0.48	0	1
DOM_LEG	27,959	0.52	0.50	0	1
KEY_GTW	27,959	0.636	0.362	0	1
DIST	27,959	2,863	1,503	283	9,149
POP	27,959	1,660	2,810	0.12	22,500
GDP	27,959	65.60	94	47	585
POL_STAB	27,959	-0.44	0.55	-2.15	1.00
		Panel C: online sample			
FARE	19,729	194.25	118.18	10	1,523
CS_ROUTE	19,729	0.07	0.26	0	1
DOM_LEG	19,729	0.27	0.44	0	1
KEY_GTW	19,729	0.88	0.17	0	0.99
DIST	19,729	3,415	2,002	294	11,374
POP	19,729	1,630	2,480	0.32	20,300
GDP	19,729	42.25	65.40	0.47	560.00
POL_STAB	19,729	-0.559	0.536	-2.11	1.00
		Panel D: direct sample			
FARE	9,299	176.48	104.85	14	1,319
CS_ROUTE	9,299	0.05	0.22	0	1
DIST	9,299	2,156	1,360	278	6,711
POP	9,299	1,700	3,100	0.12	22,500
GDP	9,299	51.60	76.60	0.85	585.00
POL_STAB	9,299	-0.58	0.54	-2.15	0.88

Panel A includes all the observations that either belong to the control or to the treatment group. In this case, the effect of the adoption of code sharing has a direct impact, which is assessed on the *i-j-t* level. Differently, for the spillover analyses the level of detail is the *j-t* level. After excluding the observations according to the criteria described above we are left with 31,085 interline observations where a change in CS takes place (*Panel A*), and 27,959 records with airline pairs never activating CS (*Panel B*). Within the online itineraries (*Panel C*), 19,729 observations are identified, while direct flights (*Panel D*) represent the smallest group, and account for 9,299 observations. In *Panel A* are included 1,008 markets and 2,061 products, *Panel B* has 886 markets and 1,862 products, *Panel C* has 878 routes and 1,686 products, while *Panel D* includes 455 markets and 616 products.

Our key variable of interest is CS, which is a dummy variable describing whether the two airlines operating the interline itinerary are cooperating through a code sharing agreement.

From *Panel A* it is evident that the average level of fare is the highest among the four panels, maybe reflecting that airlines codeshare in the most profitable markets. Code sharing is typical of about 4% of the sample. On average, about 20% of the routes (i.e., 198) are characterized by the adoption of code sharing during the observed time window. $CS\_PROPENSITY$ is the instrumental variable used to tackle the CS endogeneity problem. As described in Section 4, it represents the airline pair's propensity to codeshare from each specific gateway as it counts the number of segments in CS that the two carriers (A1 and A2) have with any partner connecting that specific gateway to airports different from the origin and destination of the itinerary. On average, about 25% of the direct flights from the gateway are operated under a codeshare agreement (i.e., about 2 routes per carrier pair). Among the interline routes, more that 70% of them are connected through a gateway from which airlines codeshare to other destinations. DOM_LEG is a binary variable taking one if at least one of the two segments is domestic (links two points within the same country). In *Panel A*, half of the observations involve a connection of this kind. Lastly, KEY_GTW is a continuous variable ranging between 0 and 1, and describing the importance of the gateway for the airline pair by the percentage of flights of the two airlines having the gateway as origin for other destinations with respect to the total number of destinations operated by the two players. This is a proxy measure of the hub nature of a gateway, which we believe to be important to control for.[22] In the main sample, on average, the gateway is often key for the airline pair.

Moving to Panels B, C, and D, consistently with the theory of double

[22]We considered the maximum percentage of direct flights from the gateway between A1 and A2. A value equal to one would mean that the airline pair (or at least one of the two airlines) serves all its direct routes from that particular gateway.

marginalization, the average fare progressively decreases as it does the number of observations in the samples. When studying the spillovers we define CS_ROUTE to take one if at least an airline pair activates codeshare on that particular market. On average, in our samples, this is typical of 3-7% of the observations, with the online sample the one with the highest percentage of observations on routes where codeshare is activated by some other airline pairs.

In addition to the variables already described for *Panel A*, to capture the disutility of the travel, and a cost term for the airlines, the average distance connecting origin and destination ($DIST$) has been included in the spillover models. As expected, the average distance is higher for connecting itineraries than for non-stop flights. Finally, population, gdp, and political stability are computed at the country pair-year level: POP and GDP are computed as the product of the endpoints' population and gdp per capita (PPS). Direct routes seem to connect bigger areas, while online routes richer markets. POL_STAB reflects the average political stability index of the two countries involved in the international O&D route: the lowest value (-2.15) belongs to the Congo-Nigeria country pair, while the highest refers to Botswana-Mauritius. $FARE$, $DIST$, POP, and GDP variables have all been logged when included in the regression models.

4.6 Results

4.6.1 The Effect of Code Sharing Agreements on Fares

This section estimates model 4.1 to determine a direct causal relationship between code sharing and fare levels. Table 4.5 collects the results. Column (1) reports the correlation between the activation of a codeshare agreement and the logarithm of fare, conditional on carriers pair×market and market×period fixed effects. The coefficient on CS indicates the change in fares charged by a pair of carriers on a specific market j after they start operating in code sharing, compared to the fares of pairs that remain interline on the same route. The conditional correlation is small, positive and statistically insignificant, suggesting that, on average, in a market, prices charged by carriers operating interline and in code sharing are comparable.

As discussed in Section 4.4, we expect carriers to choose which markets to operate in code sharing and who to stipulate the agreement with in order to maximize their expected profits. This makes the CS variable endogenous and the effect we estimate with a simple OLS regression biased. Therefore, to estimate the causal effect of the introduction of CS on fares, we employ an instrumental variable approach. Column (3) reports the results of the 2SLS estimate of model 4.1, where *CS_PROPENSITY* is used as an instrument for CS. The first stage coefficient in Column (2) suggests that the instrument is strong (*0.011 (0.003)*), and positively correlated with CS, implying that the higher the number of segments that the two carriers operate in (virtual) code sharing from the gateway (other than those connecting the gateway to the origin and the destination of the specific route) the higher the likelihood that they will have a code sharing agreement also on that route. In accordance with the exclusion restriction, the reduced form in Column (4) shows no correlation between the instrument and the dependent variable. The 2SLS estimates of γ is now negative and statistically significant, and implies that airline pairs that switch to CS lower their fares by approximately 18% on a route, compared to fares charged by carriers that continue to operate interline. The comparison of the OLS and the 2SLS estimate suggests that carriers typically enter in code sharing agreements in markets where fares are higher (either because they have higher margins or because they have higher costs to serve that market). The magnitude of the effect is sizable and slightly larger than what the literature finds when analyzing code sharing on intercontinental or US domestic routes.[23] This could be due to the underdevelopment of the African air service sector. As a final step, Column (4) presents the result of the reduced form model which show a negative and non significant coefficient of $CS\_PROPENSITY$ which supports the exclusion restriction assumption.

In order to check the robustness of our results we propose a sensitivity analysis which results are summarized in Table 4.8. First, we include additional control variables including DOM_LEG and KEY_GTW. We do not find any significant difference. Second, we propose a set of robustness regarding the sample composition and arbitrary decisions that were taken in the dataset construction. In the context of air transportation in Africa, the North-African market tends to be more developed, integrated and dominated by European players. The effect of code sharing on fares is likely to differ between North Africa and the rest of the continent; therefore, to test the robustness of our results, we exclude from the sample all routes with origin and destination in North-African Mediterranean countries and we propose a focus on the Sub-Saharan Africa as robustness check. Similarly, moved by the same suspect, we also repeat the analysis focusing on African airline pairs only. Indeed, in both cases, the magnitude of the 2SLS coefficient increases, and it now suggests that, when compared with their interline counterparts, pairs who start operating in code sharing reduce their fare on the route by approximately 30%. When we exclude LCCs from the sample results do not change, while when setting different cutoffs for the acceptable level of fares we find a slightly stronger effect (-20.5 to -23.2%). On the contrary, when we allow for our products to be in the sample if observed for less or more periods, we end up with slightly lower coefficients (both around -15%). Finally, three different ways of clustering the standard errors are proposed. In this latter case, and no change in the significance of our results is detected.

Overall, the results in this section show that the switch to code sharing lowers the fares charged by the airline pairs. This squares with the results of the literature on cooperative pricing (see Brueckner, 2003, Ito and Lee, 2007, among others) which find code sharing to lead to reduced fares compared

[23] Among others, Brueckner, 2003 finds a reduction of fares of 8%-17%, Ito and Lee, 2007 compares the codeshare case to the online case but the direction and the magnitude of the coefficient is comparable. In Brueckner, Lee, and Singer, 2011 the effect is estimated in about a 4% reduction of fares with respect to the interline case.

to the interline case. As already mentioned before, we are not surprised to find the effect of code sharing to be stronger than that found in other, more developed and efficient, air transport markets.

TABLE 4.5: Fare Estimates from the Main Model

Dependent Variable	(1) *LFARE*	(2) *CS*	(3) *LFARE*	(4) *LFARE*
CS	0.038		-0.202***	
	(0.041)		(0.074)	
CS_PROPENSITY		0.011***		-0.002
		(0.003)		(0.002)
Observations	19,800	19,800	19,800	19,800
Model	OLS	FS	2SLS	RF
Adj. R-Squared	0.84	0.50	-	0.84
OPERATING PAIR×ROUTE FEs	✓	✓	✓	✓
ROUTE×TIME FEs	✓	✓	✓	✓

Standard errors, clustered at the route level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4.6: Robustness of the Fare Estimates from the Main Model

Dependent Variable: *LFARE*		
	CS (2SLS)	Observations
Specification		
Add. Controls	-0.192***	19,800
	(0.074)	
Sample		
Sub-Saharan Africa	-0.333***	18,656
	(0.089)	
African pairs	-0.328***	19,772
	(0.074)	
w/o LCC	-0.201***	13,298
	(0.074)	
FARE>=25	-0.229***	19,730
	(0.072)	
FARE>=50	-0.264***	19,204
	(0.068)	
T >=3	-0.157**	22,903
	(0.070)	
T >=12	-0.160**	14,551
	(0.074)	
Clustering		
Operating pair and Route	-0.202***	19,800
	(0.074)	
Operating pair × Time and Route	-0.202***	19,800
	(0.074)	
Operating pair and Route × Time	-0.202***	19,800
	(0.077)	
OPERATING PAIR×ROUTE FEs	✓	✓
ROUTE×TIME FEs	✓	✓

Standard errors, clustered at the route level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.6.2 Spillover Effects

We now turn to the analysis of spillover effects. Since interline flight operated in code sharing have lower prices than interline flights on a particular route, we investigate whether code sharing generates pro-competitive spillover effects on fares charged by airlines which do not operate in code sharing. To do so we concentrate on different categories of flights that may respond to the introduction of code sharing on a given route.

We start by analyzing the impact of the introduction of code sharing on interline flights; to do so, we restrict the sample to those carrier pairs that operate as interline on the connecting routes *O-(G)-D* and we compare their fares on routes where code sharing is introduced (by other carrier pairs) to those where there is no code sharing at all. In this exercise the CS variable varies at the route-time level. The inclusion of carrier pair interacted with time fixed effects ensures us that we are accounting for time-varying factors that may influence each airline pair, such as changes in the governance, political pressure or restructuring of the company, etc. The market $\times$ semester fixed effects ensure us that we absorb all route-specific confounding factors varying each six months (i.e., the competition on the route is likely to be absorbed by those fixed effects), while the country pair $\times$ period fixed effects accounts for origin and destination non observable characteristics (e.g., population characteristics, trade, occupation) and basically allows to capture changes in demand of the itinerary without explicitly including market-level time-varying controls. As before, the interpretation of the codeshare coefficient is akin to a difference in differences estimator as we are comparing fares within routes before and after the introduction of code sharing, and within company pairs between routes that have some form of code sharing and markets which do not. Table 4.7 collects the results of this exercise. The main explanatory variable is CS_ROUTE: an indicator that takes value 1 if some carrier pairs (other than those included in the sample) operate in code sharing on that route in that period. Columns (1), (2), and (3) report the coefficients estimated via OLS. The results of Table 4.7 suggest that, all else equal, when code sharing is introduced on a route, interline prices drop on average by approximately 10% (Column 1). We are also interested in understanding whether the pro-competitive effect of the introduction of code sharing percolates to online and direct itineraries serving the same route. On the one hand, online and direct flights tend to be considered as different products from interline flights, thus might not feel the effect of increased competition on the interline market. Besides, as shown in Table 4.4 online and direct fares are already on average lower than interline fares. On the other hand, even if they are differentiated products, a higher competitive pressure on the route may still have some effect if, for example, it increases service frequencies of the interline carriers on the route. However, Columns (2) and (3), do not show any pro-competitive spillover effect on both online and direct itineraries: the presence of at least one pair operating in code sharing on the same market-period it is not enough to drive down the prices of online and direct competitors.

TABLE 4.7: Spillover Fare Estimates on the Interline, Online, and Direct Samples

Dependent Variable: *LFARE*			
	(1) INTERLINE	(2) ONLINE	(3) DIRECT
CS_ROUTE	-0.107**	-0.028	0.024
	(0.051)	(0.069)	(0.051)
Observations	15,617	14,899	4,730
Model	OLS	OLS	OLS
Adj. R-squared	0.74	0.60	0.86
OPERATING PAIR×TIME FEs	✓	✓	✓
ROUTE×SEMESTER FEs	✓	✓	✓
COUNTRY PAIR×TIME FEs	✓	✓	✓

Standard errors, clustered at the route level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

As for the main results, we propose some robustness checks on the spillover results as well. With a similar setting, Table 4.8 below collects these results.

TABLE 4.8: Robustness of the Spillover Fare Estimates on the Interline Sample

Dependent Variable: *LFARE*			
	CS_ROUTE	Obs.	Adj. R-Squared
Specification			
Add. Controls	-0.105**	15,617	0.745
	(0.050)		
Sample			
Sub-Saharan Africa	-0.107**	15,364	0.745
	(0.051)		
African pairs	-0.161**	10,587	0.749
	(0.068)		
w/o LCC	-0.107**	15,617	0.744
	(0.051)		
FARE>=25	-0.131***	15,514	0.745
	(0.037)		
FARE>=50	-0.124***	14,898	0.726
	(0.036)		
T >=3	-0.107**	15,617	0.744
	(0.051)		
T >=12	-0.124***	11,804	0.760
	(0.044)		
Clustering			
Route and Time	-0.107**	15,617	0.734
	(0.041)		
Operating pair × Route and Time	-0.107**	15,617	0.734
	(0.040)		
Operating pair and Route × Time	-0.107*	15,617	0.758
	(0.060)		
OPERATING PAIR×TIME FEs	✓	✓	✓
ROUTE×SEMESTER FEs	✓	✓	✓
COUNTRY PAIR×TIME FEs	✓	✓	✓

Standard errors, clustered at the route level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Again, the sensitivity analysis shows our results are robust to alternative specifications, but African pairs seem to feel more the effect of higher competition from the interline new products as the spillover effect is estimated to reduce their interline airfares by about 15%.

4.7 Conclusions

There has been considerable research on cooperation form of agreements in the airline industry, but most of the studies were applied to highly developed markets such as the US, and little work has been done on underdeveloped countries like Africa. The main objective of this paper revolves around understanding whether the key findings from the literature apply also to those markets that are still developing and trying to fill the gap. Moreover, we were interested in understanding whether the pro-competitive effect of the introduction of code sharing percolates to interline, online, and direct airfares on the same route. We rely on two simple models exploiting a rich set of fixed effects to estimate the impact of codeshare on airfares in the African aviation market. We focus our attention on international connecting flights to investigate whether cooperation actually helps to internalize double marginalization and results in lower fares. Our main results show that CS acts as a potential stimulus for air transportation demand in Africa, since, when it is introduced by a pair previously serving the connecting route by interline service, it generate a strong reduction in airfares equal to about -18%. The magnitude of the price reduction effect of CS is larger than any previous results, implying that the impact of double markup is strong in Africa where the lack of cooperation among the airlines generates too high prices. The direct effect is not the only one, since our second set of results highlight the presence of significant spillover effects on airfares of interline products. Indeed, all else equals, when code sharing is introduced on a route by at least a pair of operating carriers, interline prices drop on average by approximately 10%. With this respect, the fact that no pro-competitive significant spillover effect is found on neither the online nor the direct sample means that the CS itinerary is not a strong substitute of online or direct itineraries connecting the same O&D market and do not feel the effect of increased competition on the interline market. Our estimates are robust to all the alternative specifications; yet we are able to distinguish the effect of cooperation in the most developed regions of Africa from the one we find for the Sub-Saharan countries, and to distinguish the effect of increased cooperation and efficiency when this happens between African airline pairs and partners from elsewhere. In light of our findings we can confirm that the African aviation market has a high potential growth coming from airlines' cooperation, as suggested by

AFRAA, 2022). Among the possible future developments of our work, perhaps, one important point would be to incorporate a realistic treatment of the dynamism of the activation of code sharing agreements as well as the identification of delayed effect and its persistence across time. We leave the modeling of this for future research.

Chapter 5

Conclusion

5.1 Discussion and Conclusion

This thesis presents a collection of three empirical works applied to the airline industry and investigates the effect of airline cooperation and competition strategies on different metrics, focusing particularly on the price dimension. The three papers apply econometric techniques to the North-Atlantic, US domestic and African markets, and share similar identification strategies. Chapter 2 and Chapter 4 also rely on the same main data source (i.e., OAG Traffic and Schedule Analyser) that is exploited at the aggregated (airline)-route-month level, distinguishing - where appropriate - by operating and marketing airlines in the markets. Similarly, Chapter 3 relies on the US data counterpart which provides, at least, the same level of information.

The air liberalization process opened the aviation market to greater competition. However, the agreements also allowed alliance carriers more latitude to jointly set fares and schedules. In the first paper, presented in Chapter 2, after controlling for other factors that may influence fares and after tackling severe econometric issues, our results show that despite the inherent difficulties of LCCs to successfully operate in long-haul markets, their presence may lead to lower fares. However, this 5% reduction looks lower than most of the findings from prior research which refers to shorter-haul routes. In these terms, distance seems to have a significant moderating effect as this lower impact is probably due to narrower cost advantages for LCCs on long-haul routes (compared to network carrier costs). Our second set of results from the first paper indicates that when two or more carriers from the same alliance operate on a route, fares are higher (about 5% for monthly estimates) than they would be otherwise. Finally, we show that carrier entry on a North Atlantic route does not necessarily lead to lower airfares. If the entry is from an alliance airline on a route already served by a carrier from the same alliance, then the downward impact of fares due to entry will be at least partially offset by the upward impact from having two carriers from the same alliance operating on a route.

Chapter 3 presents the results of Covid-19 pandemic safety-related strategies introduced by some airlines in the US domestic market in the attempt to combat and mitigate the sharp decline in air transportation demand. We first provide a general analysis of strategies undertaken by the largest U.S. airlines and then provide a more detailed analysis on a route-level basis of one of the key safety-related strategies: the blocking of middle seats. This chapter analyzes the consequences of such a policy adoption on several airlines' performance measures and concludes that this choice was indeed effective in generating more demand, though it was not supported by economic profit maximization in the short run. The major implication of this third chapter is that strategy matters. Although some passengers may view airline travel as a commodity and the services offered by airlines to be largely undifferentiated, airlines do attempt to differentiate their services. This was evident with the various strategies undertaken by U.S. carriers during the pandemic, especially with respect to 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 took to increase the safety levels in their aircraft.

Finally, Chapter 4 studies the effect of cooperation in a market that is only poorly researched and, particularly in recent times, has been extensively debated by airlines associations, regulatory bodies, and governments. The main objective of this paper revolves around understanding whether the key findings from the literature apply also to those markets that are still developing and characterized by ad-hoc bilateral agreements between countries. Moreover, we were interested in understanding whether the pro-competitive effect of the introduction of code sharing percolates to interline, online, and direct airfares on the same route. We rely on two simple models exploiting a rich set of fixed effects to estimate the impact of codeshare on airfares on African international routes. Our main results show that CS generates a strong reduction in airfares equal to about -18%. The larger magnitude of the price reduction effect of CS implies that the impact of double markup is stronger in Africa where the lack of cooperation among the airlines generates too high prices. The direct effect is also accompanied by significant spillover effects on airfares of interline products. Indeed, all else equal, when code sharing is introduced on a route by at least a pair of operating carriers, interline prices drop on average by approximately 10%. CS itinerary is not a strong substitute of online or direct itineraries connecting the same O&D market and do not feel the effect of increased competition on the interline market. Considering our findings, we can confirm that the African aviation market has a high potential growth coming from airlines' cooperation.

This manuscript scrutinizes the effect of economic phenomena in the airline industry on airfares and few other dimensions. Conclusions are always supported by empirical findings. As already stated in the three chapters, even if standing on robust grounds, there are limitations to the conclusions derived out of these empirical works. Chapter 2 ignores the effects of LCCs operating in the North Atlantic long-haul markets on connecting flights. Moreover, it does not include specific controls for joint ventures or other features of alliances. The main limitation of 3 is in its scope as only the short run implications of blocking middle seats are assessed. Clearly some of the airlines that maintained this strategy for several months must have seen some benefits (e.g., safety-image) to continuing to block middle seats. 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. 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. In Chapter 4, among the possible future developments, perhaps, one important point would be to incorporate a realistic treatment of the dynamism of the activation of code sharing agreements as well as the identification of delayed effect and its persistence across time. We leave the empirical modelling of these features for future research. Collectively, these three empirical works contribute to the literature on competition and cooperation, and offer several policy implications that can inform policy-making in the aviation industry. The information presented in the manuscript could be valuable for researchers, practitioners, regulators, and competition policy authorities who are interested in understanding the effects of air liberalization and cooperative agreements on the airline industry, as well as the strategies that airlines have used to navigate difficult times. Additionally, the manuscript provides insights into how cooperative agreements have affected competition in less developed markets, particularly in Africa. By contributing to the literature on this topic, these works provide precious insights that could inform policy-making in this area. Specifically, the policy implications identified in this thesis could be useful for regulators and other stakeholders who are responsible for promoting competition and cooperation within the aviation industry. By considering the findings and recommendations of these works, policymakers may be better equipped to develop policies and enforce rules that are effective at achieving their goals while minimizing unintended negative consequences. Ultimately, this manuscript can be a valuable contribution to the ongoing debate on competition and cooperation in the airline industry.

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