

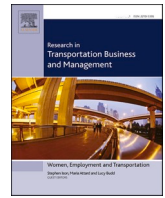


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U.S. network and low-cost carriers' performance in response to COVID-19: Strictness of government policies and passengers' panic

Sepideh Kaffash^{a,*}, Dariush Khezrimotlagh^b^a Department of Information Systems and Operations Management, Suffolk University, 8 Ashburton Pl, Boston, MA 02108, USA^b Department of Mathematics and Computer Science, Pennsylvania State University, 777 West Harrisburg Pike, Middletown, PA 17057, USA

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ABSTRACT

Coronavirus outbreak has been highly disruptive for aviation sector. There is strong correlation between COVID-19 related news, volatility in transportation, low confidence in travel safety, and uncertainty in this era. In this research, we study and distinguish the COVID-19's impact on U.S. airlines' performance. The network and low-cost carriers responded differently to it in terms of capacity reduction, market share reduction, scheduled flights reduction, flight cancellations, and service quality in the year 2020. We illustrate low-cost carrier had higher efficiency compared to network ones during pandemic by applying Network Data Envelopment Analysis. Furthermore, the effects of two key factors that emerge from COVID-19, the government's stringency actions and passengers' panic, on U.S. airlines efficiency are studied. Our analysis demonstrate that the negative effect is more significant for passengers' panic than it is for governments' stringency measures. In addition, we show that passengers' panic has more impact on the efficiency of network carriers compared to low-cost carrier.

1. Introduction

In response to the travel restrictions arising from the COVID-19's pandemic outbreak, domestic travel as well as the international travel were impacted from several measures that implemented by different countries (The New York Times, 2020). The correlation between the related COVID-19 news, low confidence in travel safety, volatility in transportation, and uncertainty in this era, has resulted in a stronger association between the travel and leisure industries in the time of COVID-19.

According to International Civil Aviation Organization (ICAO) reports (ICAO, 2021), from 2019 to 2020, there were 50% decrease in seat capacity and 60% drop in total number of passengers, globally. U.S. domestic travel was not affected until March 2020. Federal Aviation Administration (FAA) states that the overall corporate profitability for U.S.-travel sector was flat in 2020. U.S. airlines reported a pre-tax loss (% of operating revenues) of 58.8%. Weekly average domestic U.S. load factor¹ dropped from 83 in April 2019 to 10 in April 2020 (Airlines.org, 2021). The total number of U.S. passengers dropped by 51% in March 2020, 95.7% in April 2020 and 88.4% in May 2020 compared to 2019 (Hotle & Mumbower, 2021).

A recent survey from the International Air Transport Association (IATA) investigated the COVID-19's impact on passengers' perceptions of travel safety (IATA, 2020). The survey concludes that more than 30% of respondents were willing to "wait six months or more before considering travelling by air" and an additional 16% would prefer not to travel for one year at least. Apart from passengers' low confidence in taking flights, the preventive restrictive action by governments have also drastically dented the airline industry with huge losses.

All being said, the purpose of this study is to examine the COVID-19's impact on the performance of the U.S. airlines. Firstly, four different responses of U.S. network and low-cost carriers (capacity reduction, market share reduction, scheduled flights reduction, flight cancellations, and service quality) to the COVID-19 pandemic, in the year 2020, are studied. Secondly, the performance of U.S. airlines are estimated using Network Data Envelopment Analysis. Thirdly, the effects of two key factors that emerge from COVID-19 (the government's stringency action and passengers' panic) are studied. Stringency measurements show the process of lockdown for a country. The higher the Stringency Index, the higher the difficulty to conduct regular businesses. The lockdown stringency, strictions imposed on the people mobility, bans on "frequent inter-state" travels, and "entry of international flights" affect airlines'

* Corresponding author.

E-mail addresses: skaffash@suffolk.edu (S. Kaffash), dk@psu.edu (D. Khezrimotlagh).

¹ - "The load factor is measured by the ratio of revenue passenger miles to the available seat miles".

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performance. On the other hand, anxiety related to local news about health care limitation to treat COVID-19, increasing the number of cases, fear of diagnosing with the disease, and uncertainty about the future life (Dam et al., 2020) resulted in many passengers canceling or delaying their travels.

The contribution of this paper is different from that of previous ones (published on this subject). This is the first study that distinguish between factors of COVID-19 that impact airlines' performance. This paper explores how these two factors individually affect U.S. airlines' performance and how different are network carriers' responses compared to the ones of low-cost carriers. This study also discusses a detailed analysis of the relative status of U.S. airlines in the first year of pandemic in terms of capacity reduction, market share changes, scheduled flights reduction, flight cancellation, and service quality, and compares the airlines' efficiencies in the year prior to the pandemic to their efficiency in the first year of the pandemic.

In some studies, the used metrics to measure the performance of the U.S. carriers such as "the number of delayed flights", "the amount of delay per flight", "the number of cancelled flights", "the number of carried passengers", and return on asset. (Kalemba & Campa-Planas, 2018; Lange, 2019; Thiagarajan, Srinivasan, Sharma, Sreekantham, & Vijayaraghavan, 2017; Yimga, 2018). In some other studies, performance benchmarking (Zhang, Koutmos, Chen, & Zhu, 2021; Xu, Park, Park, & Cho, 2021; Choi, Lee and Olson, 2015; Tavassoli, Faramarzi, & Saen, 2014) is applied to represent the relative performance of airlines.

From a managerial perspective and a shareholder point of view, benchmarking and performance evaluation are vital, because the compensation schemes of upper management and "the chief executive office tenures are attached to operational productivity and financial performance" (Davila & Venkatachalam, 2004; Mellat-Parast, Golmohammadi, McFadden, & Miller, 2015). One of the most widely used models to assess performance benchmarking is Data Envelopment Analysis (DEA). We also use DEA in this study to measure the U.S. airlines' efficiencies for the period of 2019–2020.

The rest of this study is organized in six sections. Section 2 illustrates the theoretical framework. Section 3 describes the methodology and in Section 4 the used data is described. Section 5 provides the results and discussions. Finally, Section 6 offers concluding remarks and direction for future studies, as well as the limitations of this study.

2. Literature review

There are a very few research in academic literature to discuss the COVID-19's impacts on the aviation industry. Amankwah-Amoah (2020) examines "how airlines have responded to COVID-19 and the factors that facilitate, shape, or constrain their responses". The study illustrates that most of airlines aim to minimize declining on route networks, trust with customers, access to airports, market capabilities, and long-developed knowledge, in response to the pandemic and equipping then for improvement.

Budd, Ison, and Adrienne (2020) survey the variety of methods that European airlines has been used in response to COVID-19. They show that the most common responses are differences to flight operations, decreasing staff numbers, normalizing the fleet, and redesigning their capacity and network. Yimga (2021) examines "flight on-time performance responses to the COVID-19 pandemic and finds that flights are departing and arriving with less delay amid the pandemic". Li, Zhou, Kundu, and Sheu (2021) explore "the spatiotemporal variation of the worldwide air transportation network induced by COVID-19". They conclude "a remarkable decrease in the number of operating airports, connections, and flights during the recent pandemic".

Some scholars study the COVID-19's impact on aviation industry from a macro-level. Abate, Christidis, and Purwanto (2020) analyze "the implications of government support in response to the COVID-19 outbreak". They consider three factors: (1) liberalization and competition, (2) airline's control and ownership, and (3) sustainability of the

environment. They argue that "most governments give high priority to maintaining air transport connectivity in order to protect economic activity and jobs in the aviation sector itself and in related sectors such as tourism".

Andreana, Gualini, Martini, Porta, and Scotti (2021) provide "estimation of the destructive impact of the COVID-19 outbreak on air transport at the macro-regional level". They also argue "the impact of the pandemic crisis and of the subsequent lockdown has been dramatic, much higher than any previous crisis". Sobieralski (2020) also consider "past uncertainty shocks to forecast COVID-19 related decreases in U.S. airline employment".

A few studies also compare the effect of the pandemic on low-cost and full-service carriers. Santos, Oliveira, and Aldrighi (2021) investigate "the drivers of the plunge in air travel" and show that "business-oriented routes are more impacted than leisure ones and markets that have benefited from greater social inclusion in Brazil may be the most vulnerable to the current crisis". Andreana et al. (2021) show that the impact on intercontinental connections is greater for carriers with full-service, where carries with low-cost seem to be stronger slightly.

Airport operations during the pandemic is another topic which attracts scholars' attention. Hotle and Mumbower (2021) evaluates "the COVID-19's impact on domestic U.S. air travel operations and commercial airport service in light of the Coronavirus Aid, Relief, and Economic Security Act". The result of the study shows that "large-origin airports experienced a greater decline in domestic U.S. markets served as against non-primary markets. Also, the markets served by airports in multi-airport cities decreased in comparison with the markets served by airports in single-airport cities". Serrano and Kazda (2020) state that COVID-19 affected airport capacity, and the level of services provided, and airports turned to non-passenger revenues due to the decline in air traffic.

Monmousseau, Marzuoli, Feron, and Delahaye (2020) analyze "the effect of the travel restriction measures implemented during the COVID-19 pandemic, from a passenger perspective, on the US air transportation system". They proposed passenger-centric metrics (such as cancellations, refunds, empathy, and sentiment gaps) and "indicate that each airline has reacted differently to the COVID-19 travel restriction measures from a passenger perspective". Sokadjo and Atchadé (2020) argue that "when passenger air traffic increases by one unit, the number of cases increase by one new infection".

Amankwah-Amoah (2021) develop the concept of "CoviNovation" and provide perceptions on COVID-19 innovations from the airlines' industry around the world. Truong (2021) develops and applies "neural network models that calculate international air travel and domestic air travel in both medium-term and long-term according to the daily trips residents considering economic condition, distance condition, travel's restrictions, and the severity of COVID-19". The author's findings show that air travel is quicker to response to changes in the weekly economic index than COVID-19 variables. The author concludes that it might take a few years to see a normal situation for air travel. Finally, Gudmundsson, Cattaneo, and Redondi (2021a) assess "the relationship between economic shocks and recovery in air transport. They demonstrate that world recovery of passenger demand to pre-COVID-19 levels, with the most optimistic estimate, will be by mid-2022 and with the most pessimistic estimate will be by 2026".

To measure the efficiency of U.S airlines we use non-parametric Data Envelopment Analysis in this study. Many studies have adopted classic DEA model to estimate the efficiency of U.S. airlines Shirazi & Mohammadi, 2019; Suárez-Alemán & Jiménez, 2016; Costantino, Di Gravio, Nonino, & Patriarca, 2016; Ryley, Burchell, & Davison, 2013). More recent studies apply Network-DEA models. Table 1 summarized twenty studies which adopt Network-DEA models to measure the efficiency of airlines.

Table 1
Summary of Network-DEA studies for airlines.

Author	Airlines	Methodology
Zhu, 2011	2007–2008; 21 International airlines,	Network DEA
Lu, Wang, Hung, & Lu, 2012	2006, 30 US airlines	Network DEA, truncated regression (Production and Marketing process)
Yu, 2012	15 Taiwanese airlines	Enhanced-Russell measure (ERM) NDEA
Lee & Johnson, 2012	2006–2008; 4 US airlines	Three stage N_DEA MPP: Capacity design, Demand generation, Operation process; SPP: Capacity design, Operation, demand Consumption
Lozano & Gutiérrez, 2014	16 EU airlines	SBM_NDEA (Production and Sales process)
Tavassoli et al., 2014	2010, 11 Iranian airlines	SBM_NDEA with shared inputs (Technical efficiency and Service effectiveness process)
Chang & Yu, 2014	16 International low cost airlines	SBM-NDEA (Production and Consumption process)
Mallikarjun, 2015	2012, 27 US airlines	Three stage NDEA (Operations, Service and Sales process)
Li, Wang, & Cui, 2015	2008–2012, 22 international airlines	Virtual Frontier, three stage SBM_NDEA (Operation, Service and Sales process)
Li, Wang, & Cui, 2016	2000–2010, 87 Eu airlines	Network DEA
Yu, Chen, & Chiang, 2017	2008–2012, 22 International airlines	Three stage SBM-NDEA with weak and strong disposability (Operation, Service and Sales process)
Soltanzadeh & Omrani, 2018	2009–2012, 30 airlines	Dynamic Two-Stage Network DEA (2nd Stage: bootstrapped truncated regression model)
Li & Cui, 2018	2010–2012, 7 Iranian airlines	Dynamic network DEA with fuzzy data.
(Zhang, 2019)	2008 to 2015, 29 global airlines	Input-shared Network Range Adjusted Measure
Yu, Zhang, Zhang, Wang, & Cui, 2019	2006–2016 7 U.S. airlines and Air Canada	Two-Stage Network DEA
Tola Losa, Arjomandi, Dakpo, & Bloomfield, 2020	2008–2015, 13 Indian and Chinese airlines	Dynamic network DEA
Heydari, Omrani, & Taghizadeh, 2020	22 international airlines	Dynamic network DEA
Chen, Cheng, & Zhu, 2021	2014, 14 Iranian airlines	Fully fuzzy network DEA-Range Adjusted Measure
Zhang et al., 2021	2013–2018, 9 Chinese airlines	Two-stage undesirable SBM-NDEA
	2006–2016, 9 international airlines	Two-stage network DEA

3. Methodology

To investigate the COVID-19’s impact on the U.S. network and low-cost carriers, this study considers two-year period from January 2019 to December 2020 to investigate how differently these two types of carriers respond to the pandemic. We also use quarterly data to show how the operations of U.S. low-cost and network carriers in terms of capacity reduction, market share reduction, scheduled flights reduction, flight cancellation, and service quality, changed in 2020, when compared with 2019. In addition to analyzing the government stringency action and passengers’ panic effects on U.S. airline efficiency, this study applies DEA to estimate the airlines’ efficiencies.

DEA introduced by Charnes, Cooper, and Rhodes (1978) in constant returns-to-scale (CRS). The method is then developed in variable returns-to-scale by Banker, Charnes, and Cooper (1984). DEA evaluates a group of decision-making units (DMUs). In classic DEA, multiple-

inputs are consumed to produce single or multiple-outputs. Classic DEA models focus on the consumed inputs and the produced outputs without considering the inside of production process. In most real-world cases, the production process may be decomposed into sub-processes.

The Network-DEA approach provides an insight into the internal structure of DUMs by observing the final output that had consumed the intermediate outputs that were generated from the previous sub-process. Many recent DEA studies have used the Network-DEA to monitor the internal structure of units. In the past five decades, several DEA models have been adopted by scholars to assess efficiency across different disciplines (Cook, Tone, & Zhu, 2014; Cooper, Seiford, & Zhu, 2011; Emrouznejad & Yang, 2018) Network DEA was initially employed in evaluating the efficiency of an airline by Zhu (2011).

We use net income as one of the outputs of the model (Fig. 3). Net income has negative values for some of the airlines in the period of the study and we aim to measure the inputs’ excess. Several DEA models are proposed in the literature to deal with the presence of negative data (Toloo et al., 2015)Therefore, we use the input-oriented SORM-DEA model proposed by (Emrouznejad, Anouze and Thanassoulis, 2010) and adapt it as a network-DEA model.

Suppose there are n DMUs ($DMU_j, j \in J = \{1, 2, \dots, n\}$), where each DMU has m inputs, x_{ij} ($i \in I = \{1, 2, \dots, m\}$), p intermediates, z_{kj} ($k \in K = \{1, 2, \dots, p\}$), and s outputs, y_{rj} ($r \in O = \{1, 2, \dots, s\}$). Assume that I^+ is the set of inputs’ indexes such that x_{ij} is positive for all $j \in J$, that is, $I^+ = \{i \in I : x_{ij} \geq 0, \forall j \in J\}$. In this case, we replace x_{ij}^+ by x_{ij} .

Also assume that Γ is the set of inputs’ indexes such that x_{ij} is negative for some $j \in J$, that is, $\Gamma = \{i \in I : x_{ij} \leq 0, \text{ for some } j \in J\}$. In this case, we replace x_{ij}^- by x_{ij} . Since x_{ij}^- can be negative for some of $j \in J$, we assume that x_{ij}^- can be written as $x_{ij}^+ - x_{ij}^-$, where both x_{ij}^+ , and x_{ij}^- are nonnegative, for $i \in \Gamma$ and for $j \in J$. If $x_{ij}^- \geq 0$, we put $x_{ij}^- = 0$, and if $x_{ij}^- < 0$, we put $x_{ij}^- = 0$.

Similarly, assume that O^+ is the set of outputs’ indexes such that y_{rj} is positive for all $j \in J$, that is, $O^+ = \{r \in O : y_{rj} \geq 0, \forall j \in J\}$. In this case, we replace y_{rj}^+ by y_{rj} . Also assume that O^- is the set of outputs’ indexes such that y_{rj} is negative for some $j \in J$, that is, $O^- = \{r \in O : y_{rj} \leq 0, \text{ for some } j \in J\}$. In this instance, we replace y_{rj}^- by y_{rj} . Since y_{rj}^- can be negative for some of $j \in J$, we assume that y_{rj}^- can be written as $y_{rj}^+ - y_{rj}^-$, where both y_{rj}^+ , and y_{rj}^- are nonnegative, for $r \in O^-$ and for $j \in J$. If $y_{rj}^- \geq 0$, we put $y_{rj}^- = 0$, and if $y_{rj}^- < 0$, we put $y_{rj}^- = 0$.

Similarly, we denote the positive and negative intermediates by z_{kj}^+ , for $k \in K^+$, and z_{kj}^- , and z_{kj}^- , for $k \in K^-$, respectively.

In order to evaluate DMU_l ($l = 1, 2, \dots, n$), we solve the following input-oriented VRS DEA model including negative data.

$$\min \theta_l, \tag{1}$$

Subject to,

$$\sum_{j=1}^n \lambda_j x_{ij}^+ \leq \theta_l x_{il}^+, \text{ for } i \in I^+,$$

$$\sum_{j=1}^n \lambda_j x_{ij}^+ \leq \theta_l x_{il}^+, \text{ for } i \in \Gamma,$$

$$\sum_{j=1}^n \lambda_j x_{ij}^- \geq \theta_l x_{il}^-, \text{ for } i \in \Gamma,$$

$$\sum_{j=1}^n \lambda_j z_{kj}^+ \geq z_{kl}^+, \text{ for } k \in K^+,$$

$$\sum_{j=1}^n \lambda_j z_{kj}^+ \geq z_{kl}^+, \text{ for } k \in K^-,$$

$$\sum_{j=1}^n \lambda_j z_{kj}^- \leq z_{kl}^-, \text{ for } k \in K^-,$$

$$\sum_{j=1}^n \lambda_j = 1,$$

$$\sum_{j=1}^n \mu_j z_{kj}^+ \leq z_{kl}^+, \text{ for } k \in K^+,$$

$$\sum_{j=1}^n \mu_j z_{kj}^+ \leq z_{kl}^+, \text{ for } k \in K^-,$$

$$\sum_{j=1}^n \mu_j z_{kj}^- \geq z_{kl}^-, \text{ for } k \in K^-,$$

$$\sum_{j=1}^n \mu_j y_{rj}^+ \geq y_{rl}^+, \text{ for } r \in O^+,$$

$$\sum_{j=1}^n \mu_j y_{rj}^+ \geq y_{rl}^+, \text{ for } r \in O^-,$$

$$\sum_{j=1}^n \mu_j y_{rj}^- \leq y_{rl}^-, \text{ for } r \in O^-,$$

$$\sum_{j=1}^n \mu_j = 1,$$

$$\lambda_j \geq 0, \text{ for } j = 1, 2, \dots, n.$$

First, to study how the U.S. airlines’ efficiencies shift in the pandemic

year compared to the previous year, the DEA model is employed on each of the years 2019 and 2020, individually. In the second stage of analysis, the DEA approach is used with meta frontier on the period of 2019–2020 to obtain the relative efficiency score.

To study the Panic Index (PI) and Stringency Index (SI) influence on network and low-cost carriers' efficiencies, we adopt logistic regression. Several studies apply other regression modes (e.g., Ordinary Least Square, Fixed Effect, Random Effect, Tobit and Generalized Method of Moments) to evaluate the impacts of environmental variables on efficiency scores. However, [Simar and Wilson \(2007\)](#) argue that in the two-stage DEA firstly, the covariates in the second-stage regression are obviously correlated with the one-side error terms from the first stage. Secondly, the covariates in the second stage are likely to be (highly) correlated with the covariates in the first stage. Therefore, the covariates and the errors in the first stage cannot be independent [Kaffash, Aktas and Tajik, 2020](#). Therefore, we use logistic regression which is flexible regression model and can work well with different types of explanatory variables, and the assumptions undergirding logistic regression impose no requirements about the distribution of the predictor variables such as normally distributed, linearly related, equal variances ([Martínez-Núñez & Pérez-Aguilar, 2014](#)).

Two logistic regression models are used to determine. Regression models also account for size, service quality, and market concentrations of airlines. A dummy variable, D, is defined to show the carrier's type, 1 for network carrier and 0 for low-cost one. A two-way interaction term between PI and D in Model 1 and SI and D in Model 2 is generated to answer research questions.

Model 1: $Efficiency_{it} = a + \beta_1 S_{it} + \beta_2 MC_{it} + \beta_3 PI_t * D_i + \beta_4 AQR_{it}$

Model 2: $Efficiency_{it} = a + \beta_1 S_{it} + \beta_2 MC_{it} + \beta_3 SI_t * D_i + \beta_4 AQR_{it}$

4. Data

We collected data for nine U.S. airlines for the two years of 2019 and 2020, such as: "American Airlines", "United Airlines", "Delta Air Lines", and "Alaska Airlines" as the network carriers and "Southwest Airlines", "Spirit Lines", "JetBlue Airways", "Allegiant Air", and "Frontier Airlines" as the low-cost carriers ([Federal Aviation Report, 2020](#)). Data is collected from three different sources as explained in following sections. Since some of the data were available only quarterly, the daily data and monthly data were aggregated or averaged, based on the data's nature. To estimate the airlines' Airline Quality Rating, data reported in Air Travel Consumer Reports was collected manually.

4.1. Panic and stringency indices

The data for Panic Index and Stringency Index were collected from Ravenpack and [ourworldindata.org](#) respectively. Pandemic Index is a daily-reported index by Ravenpack (a leading data analytics provider for financial services).² The Coronavirus Panic Index determines "the news chatter's level that indicates to panic or hysteria and coronavirus; the higher the index value, the greater the number of references to panic found in the media. The index's values range between 0 and 100, (the index is computed as the daily count of distinct stories that co-mentions panic keywords and Coronavirus, divided by the total daily count of distinct stories)". Since some other variables in this research are quarterly, the average of daily values over each quarter is used to represent each quarter in the Panic Index. The first time the Panic Index was reported for U.S. was on January 9th, 2020. The reported index for that day is 0.01 and the highest reported value was 11.28 on March 30th, 2020.

Stringency Index measures "the severity of government actions undertaken to control the spread of the COVID-19 virus". "A higher score indicates a stricter response from the government. Stringency Index is a

composite measure nine distinct response metrics".³ The first appearance of Stringency Index in the U.S. was on February 2nd, 2020, with the value of 5.56. [Figs 1. and 2](#) show these two indices for the period of this study. Both Panic and Stringency indices are used in recent COVID-19 studies ([Cepoi, 2020](#); [Haroon & Rizvi, 2020](#); [Umar & Gubareva, 2020](#); [Zhu, Mishra, Han, & Santo, 2020](#)).

4.2. Inputs' and outputs' selection

As quoted by [Peyrache et al. \(2020\)](#) "The selection of inputs and outputs in DEA is an important step that is normally conducted before the DEA model is implemented". Following the literature ([Yu et al., 2017](#), [Duygun, Prior, Shaban and Tortosa-Ausina, 2016](#), [Mahmoudi, Emrouznejad, Shetab-Boushehri and Hejazi, 2020](#)), the production process in Network-DEA is decomposed into two sub-processes: i) profitability and ii) marketability. For the first sub-process we use energy, labor, and material costs as inputs, and average seat mile and average ton miles as outputs. The first sub-process' outputs are employed as the second sub-process' inputs. The second sub-process' output is the net income. The data is obtained from the Bureau of Transportation Statistics of the U.S. Department of Transportation (DOT) ([www.bts.gov](#)). The Network-DEA model is illustrated in [Fig. 3](#).

4.3. Control variables

To study the COVID-19's impacts on U.S. airlines' performance, we control the relevant flight and carrier and market characteristics that can most likely affect the airlines' performances. [Choi \(2017\)](#) studies the efficiency and productivity changes in U.S. domestic airlines, where "failure to consider airline service quality despite its importance in the airline industry" is stated as a limitation of the study. Therefore, we first account for the service quality of each airline. Some studies use single variable to estimate airlines' service quality. For instance, service customer complaints ([Golmohammadi, Parast and Sanders, 2020](#)), ticket over-sales ([Steven, Dong, & Dresner, 2012](#)); late arrival and lost luggage ([Tsikriktsis, 2007](#)) and on time performance ([Prince and Simon 2009](#)). In some other studies the combination of some attributes is used to assess the quality of airlines' service such as SERVQUAL ([Shah, Syed, Imam, & Raza, 2020](#)).

In this study we used the "Airline Quality Rating (AQR) index" which

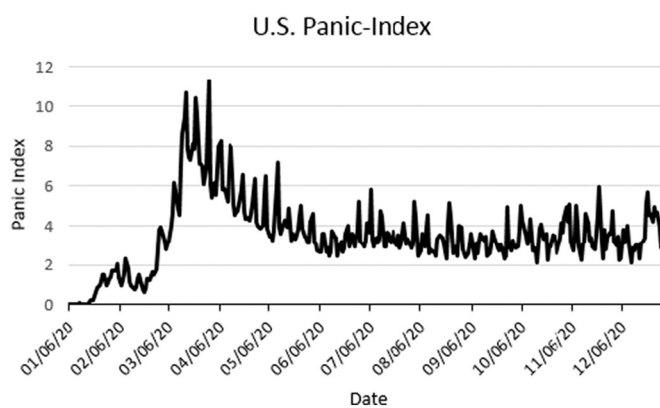


Fig. 1. U.S. monthly Panic Index 2020

³ - "The nine metrics used to calculate the Stringency Index are: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls ([https://ourworldindata.org/covid-stringency-index](#))"

² - <https://www.ravenpack.com/>

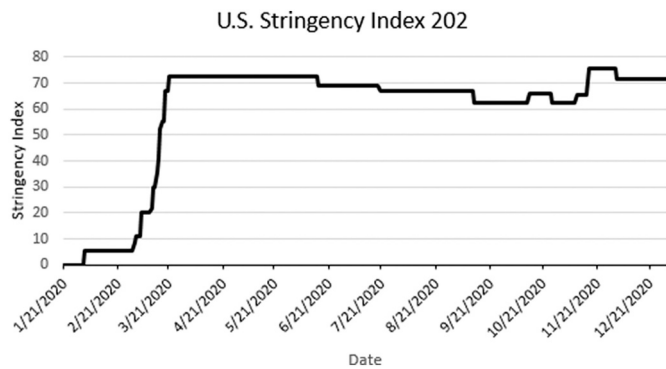


Fig. 2. U.S. monthly Stringency Index 2020.

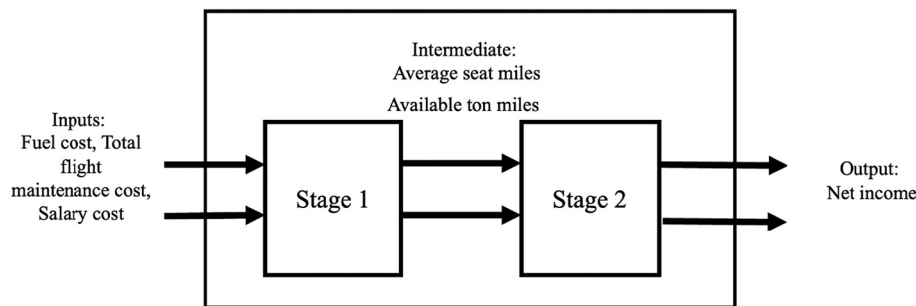


Fig. 3. Network-DEA model

was proposed and stated as “an objective method for assessing airline quality on combined multiple performance criteria” (Bowen, Headley, & Luedtke, 1992). The AQR index is “a multi-factor, weighted average approach using publicly available data that reports actual airline performance on critical quality criteria important to consumers”. Data for the critical quality criteria are gathered and maintained in the “U.S. Air Travel Consumer Report”. We use this index to estimate the airline service quality.

For the period of 1991–1998 the index was formed using “a weighted average of 19 quality related factors”. (Bowen, Headley, Kane and Lutte, 1999) “simplified the index and focused exclusively on only 4 quality related aspects: on-time arrivals (OT), involuntary denied boarding (DB), mishandled baggage (MB), and customer complaints (CC)”. As quoted by Airline Quality Rating (2021) “weights were originally established by surveying 65 airline industry experts regarding their opinion as to what consumers would rate as important (on a scale of 0 to 10) in judging airline quality. Each weight and element were assigned a plus or minus sign to reflect the nature of impact for that criterion on a consumer’s perception of quality”. The AQR index is calculated by the following formula:

$$AQR = \frac{(+8.63 \times OT) + (-8.03 \times DB) + (-7.92 \times MB) + (-7.17 \times CC)}{(8.63 + 8.03 + 7.92 + 7.17)}$$

The positive and negative sign of the weights is defined as the impact of the associated element on consumer perception. “On-time arrival” criterion is a desirable element in measuring the service quality and “involuntary denied boarding”, “mishandled baggage”, and “customer complaints” are undesirable elements on “consumer perception of service quality”. The weights also show the significant level for each criterion. As the formula illustrates, “on-time performance” is the most significant element. Since some of the data for the second stage of the study is reported quarterly, we obtain monthly data manually for

involuntary denied boarding, total consumer complaints and percentage of on time arrivals and aggregate them quarterly.⁴

Secondly, we control for the size of the airline by using the logarithm of available seat miles of each airline per quarter. Thirdly, we include market concentration for each airline in each quarter based on Revenue Passenger Miles (RPM). The data is obtained from the Bureau of Transportation Statistics of the U.S. Department of Transportation (DOT) (www.bts.gov). Table 2 illustrates the statistical summary of the dataset.

5. Results and discussions

5.1. U.S. network and low-cost carriers’ response to Covid

According to the Federal Aviation Administration (FAA) 2020 Re-

view Report (Federal Aviation Report, 2020), US network and low-cost carriers reported \$24.0 billion and \$6.6 billion combined operating losses in 2020. The business model of these two types of carriers is different. Network carriers follow a “Hub-and-Spoke network” where low-cost carriers have a “Point-to-Point business model”(See Fig.4). The “Hub-and-Spoke” model, heavily dependent on large airports, is designed to feed traffic to key airports while the Point-to-Point model allows low-cost carriers to use smaller airports.

Network carriers perform optimally by providing service to wide geographical areas. “Each route is highly dependent on other routes for connecting passengers” (Cook & Goodwin, 2008). In terms of pricing, hub connections significantly raise cost “per available seat mile per city-pair”. On the other hand, routes operate independently in “the Point-to-Point” model, and from other routes, traffic is not influenced by demand. Generally, these carriers are appealing for cost-conscious customers and have a lower cost per available seat miles (Cook & Goodwin, 2008).

In this section, the four different responses of U.S. network carriers and low-cost carriers to the COVID-19 pandemic, in the year 2020, are studied. These responses are capacity reduction, market share reduction, scheduled flights reduction, flight cancellations, and service quality.

5.1.1. U.S. airlines capacity reduction

In 2020, there was an overall reduction of 66% of seats offered by airlines across the globe (ICAO, 2021). “Severe capacity reductions, involving large scale fleet downsizing and reduction in flight frequency, and the number of destinations served were some of the immediate responses” (Budd et al., 2020).

Fig. 5 illustrates the percentage of change in the capacity of U.S. carriers in 2020 versus 2019 across four quarters. Available Seat Miles (ASM) is a measure used to represent capacity and is defined as one aircraft seat carried one mile. Fig. 5 shows that in the first quarter of 2020 the response of network carriers was different from that of low-cost

⁴ Mishandled baggage is reported quarterly.

Table 2
The statistical descriptive of the used dataset.

Variables	Mean	St. Dev	Min	Max
AQR	-31.56	107.3	-618.33	-0.14
On time flights (%)	81.49	8.42	44.7	94.39
Mishandled Baggage ^a	12.85	5.38	3.62	30.21
Customer complaints ^b	108.92	412.48	0.76	2730.75
Involuntary denied boarding ^c	0.14	0.24	-	1.47
Efficiency Score	0.83	0.16	0.39	1
Fuel expenses (000,000)	588,684,598.54	628,193,829.85	12,766,450.00	1,966,302,158.00
Salary expenses (000,000)	1,393,879.72	1,266,716.82	73,668.52	3,545,043.00
Maintenance expenses (000,000)	309,147.51	309,627.23	23,086.22	1,088,571.01
Available Seat Miles (000,000)	70,829.65	64,741.52	4642.61	208,731.07
Load factor	70.36	19.15	29.53	90.27
Net income (000)	-280,005.30	1,202,141.90	-5,691,876.01	1,493,988.00
Panic Index	1.77	1.81	-	4.31
Stringency Index	29.13	32.21	-	71.45
Size	10.65	0.44	9.67	11.32
Market concentration	10.45	6.27	1.22	19.16

^a -Number of bags mishandled per 1000 enplaned
^b -Complaints per 100,000 enplanements
^c -Involuntary Denied Boarding per 10,000 passengers

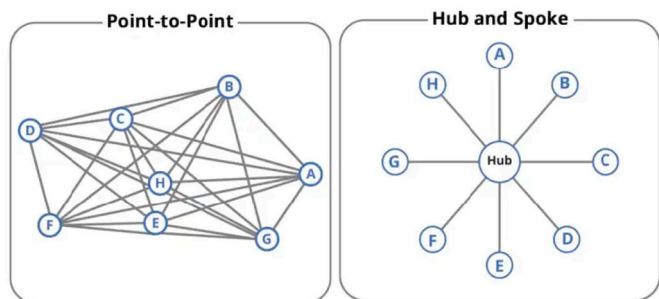


Fig. 4. Point-to-point model versus hub-and-spoke model. [“https://blog.locus.sh/hub-and-spoke-distribution-model-in-modern-supply-chains/”](https://blog.locus.sh/hub-and-spoke-distribution-model-in-modern-supply-chains/)

carriers. The capacities of all four network airlines declined in 2020 in comparison with that of 2019. However, the low-cost carriers, Allegiant Air, Frontier Airlines and Spirits Airlines increased their capacities.

In response to COVID-19, the capacity of all U.S. airlines declined dramatically in Q2, 2020. This decline was more significant for network carriers. Due to reduced domestic and international passengers, these airlines sent widebody aircrafts into storage. Also, several airlines followed a seat capacity policy and kept a number of seats free for the purpose of social distancing. Among low-cost carriers, Allegiant Air had the lowest reduction in capacity.

A gradual and phased return was observed in the second half of 2020. Delta Airlines was more aggressive in adding to its capacity (the reduction in ASM increased from 86% in Q2, 2020 to 43% in Q4, 2020) while American Airlines was more conservative in increasing its capacity (the reduction in ASM increased from 78% in Q2, 2020, to 56% in Q4, 2020).

5.1.2. U.S. airlines market share changes

“The primary revenue generator for most airlines is passengers and secondary revenue generators are freight and cargo” (Sinha, 2019; Wells, 2007). U.S. airlines reported “a net-loss of \$5.2 billion” (that includes a \$4.1 billion loss for domestic flights and a \$1.2 billion loss for international flights) in Q1, 2020, which was down from a \$3.4 gain in Q4, 2019 and a \$2 billion gain in Q1, 2019. The loss was \$11.0 billion in Q2, 2020 against the gain of \$4.8 billion in Q2, 2019.

In March 2020, the U.S. government introduced “the Coronavirus Aid, Relief, and Economic Security Act” and U.S. passenger carriers received \$50 billion in financial assistance. Airline operators initiated

measures to increase passengers’ confidence and provide a safer environment in planes. These actions didn’t result in a swift improvement though and the U.S. airline industry still experienced “a net loss of \$11.8 billion in the third quarter of 2020”. In Q4, 2020, nevertheless, the net loss of U.S. airlines decreased to \$7 billion (Bureau of Transportation Statistics, 2020a, 2020b).

Table 3 shows the percentage change in market share, based on RPM, for U.S. airlines, for the four quarters of 2020 versus the four quarters of 2019. Among network carriers, United and Alaska have the largest market share reduction in 2020. Among low-cost carriers, the market share of Allegiant Air has the highest reduction rate of 75% on an average.

Ultra-low-cost carriers (Frontier Airlines and Spirits Lines) have a larger market share in 2020. These airlines largely serve the leisure and domestic markets while network carriers serve business and international markets. With business travelers working from home, and with the restrictions imposed on international flights, demand for business and long-haul flights declined more than the demand for leisure, domestic destination, and short-haul flights.

Fig. 6 compares “the market share” for the nine U.S. airlines in years 2019 and 2020. It illustrates that U.S. low-cost carriers obtained 38% of market share in 2019, of which only 13% belonged to Ultra-low-cost carriers (Allegiant, Frontier and Spirit). This percentage increased in 2020 to 44% with Spirit Air Lines alone contributing 16%. The ultra-low-cost carrier business model allowed them to open new routes on a trial-and-error basis during Pandemic. During the pandemic, for example, they pivoted toward beach and mountain destinations. Although American, United and Delta also shifted flights to pick-up leisure demand, but geographical reach remained formidable (Rucinski, 2021).

5.1.3. US airlines scheduled flights reduction and flight cancellation

Following “the declaration of COVID-19 as an international public health emergency” by the WHO, leisure and business flight passengers cancelled their travel plans, many flights were cancelled, and airlines scheduled less flights. Figs. 7, 8, 9 and 10 shows the percentage reduction of scheduled flights in 2020 compared to 2019 (reduction rate) and the percentage of cancelled flights quarterly. These graphs also compare these rates for network and low-cost carriers. Reduction in scheduled flights Q1 2020 versus 2019 and Q1 2020 flight cancellations.

Overall, U.S. airlines experienced 6.68% flight cancellation in Q1, 2020. The corresponding rate was 2.57% in Q1, 2019 (Air Travel Consumer Report, May 2020). In Q1, 2020, no significant changes in scheduled flights are observed for network airlines. Among low-cost carriers, Frontier and Spirit had a 10% increase in scheduled flights.

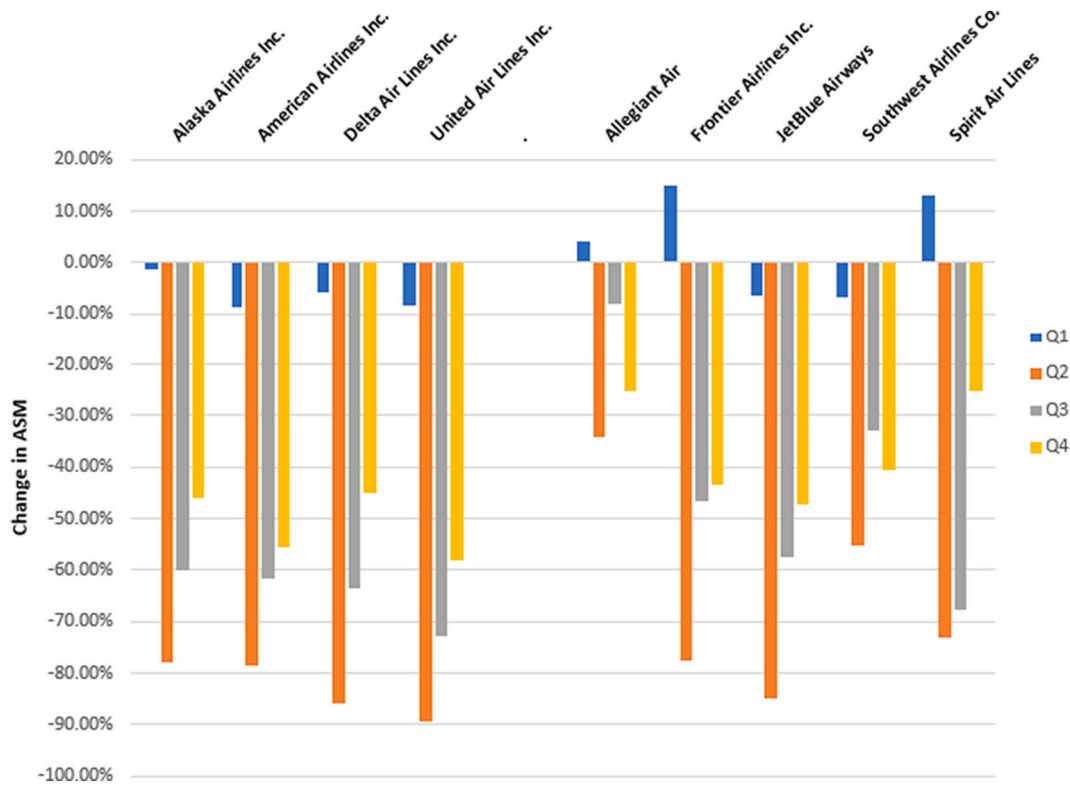


Fig. 5. U.S. carriers' capacity reduction 2020 versus 2019.

Table 3
U.S. carriers market shares (quarterly) change 2020 versus 2019.

U.S. Carriers	Q1	Q2	Q3	Q4
Alaska Airlines	0.63%	-0.78%	-5.18%	-13.05%
American Airlines	-1.35%	0.00%	4.20%	8.74%
Delta Air Lines	3.78%	2.52%	-3.53%	-9.23%
United Air Lines	-1.66%	-3.57%	-9.57%	-14.36%
Allegiant Air	-74.10%	-74.05%	-75.01%	-77.80%
Frontier Airlines	13.45%	16.55%	17.59%	18.60%
JetBlue Airways	-1.26%	-2.52%	-5.42%	-12.45%
Southwest Airlines	-5.87%	-5.14%	0.23%	2.66%
Spirit Lines	449.51%	443.59%	419.45%	394.58%

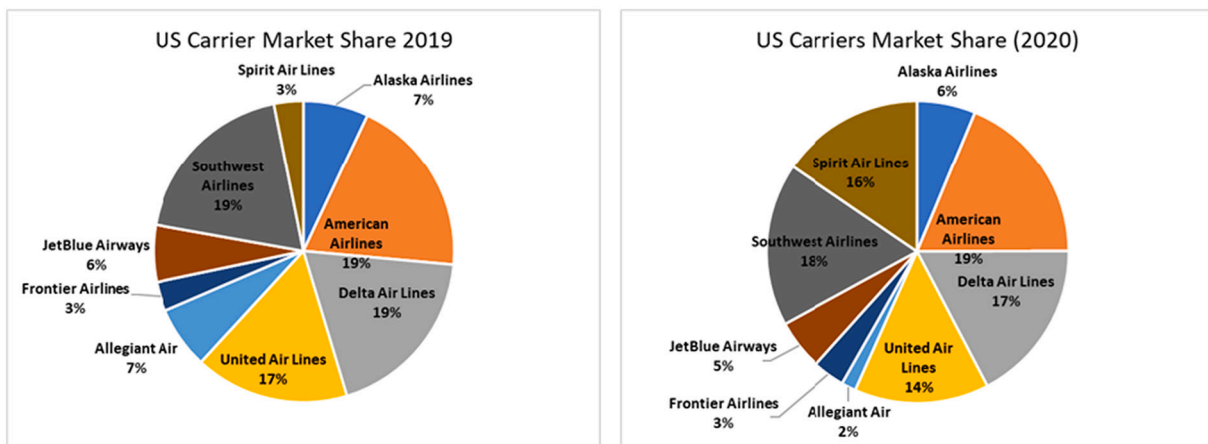


Fig. 6. U.S. carriers' market share changes 2020 versus 2019.

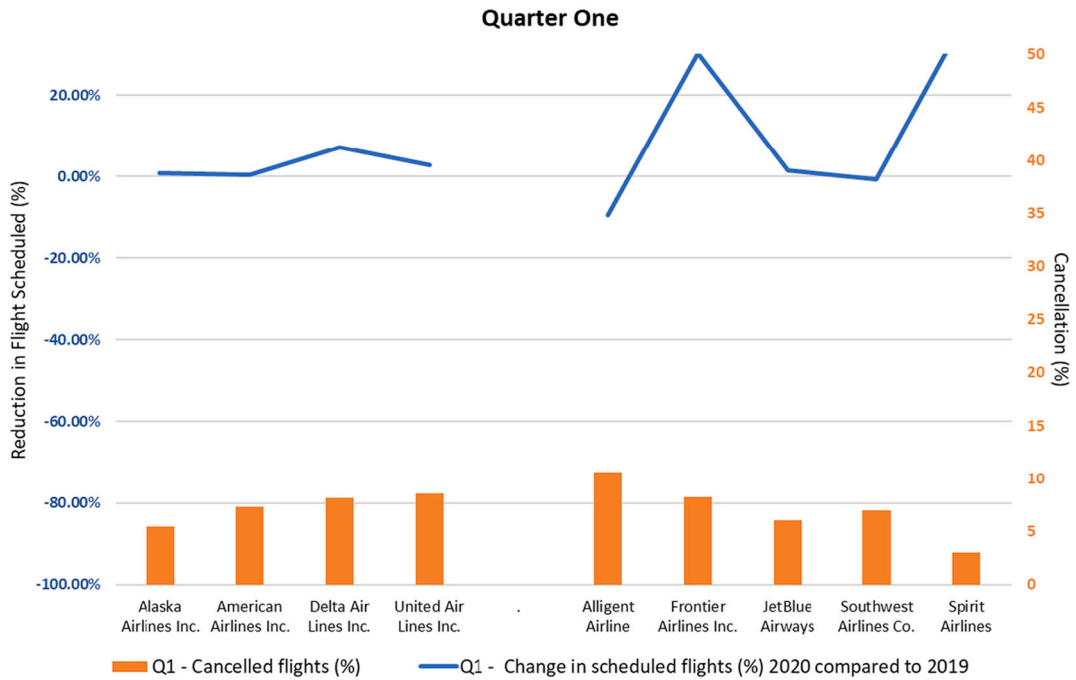


Fig. 7. Reduction in scheduled flights Q1 2020 versus 2019 and Q1 2020 flight cancellations.

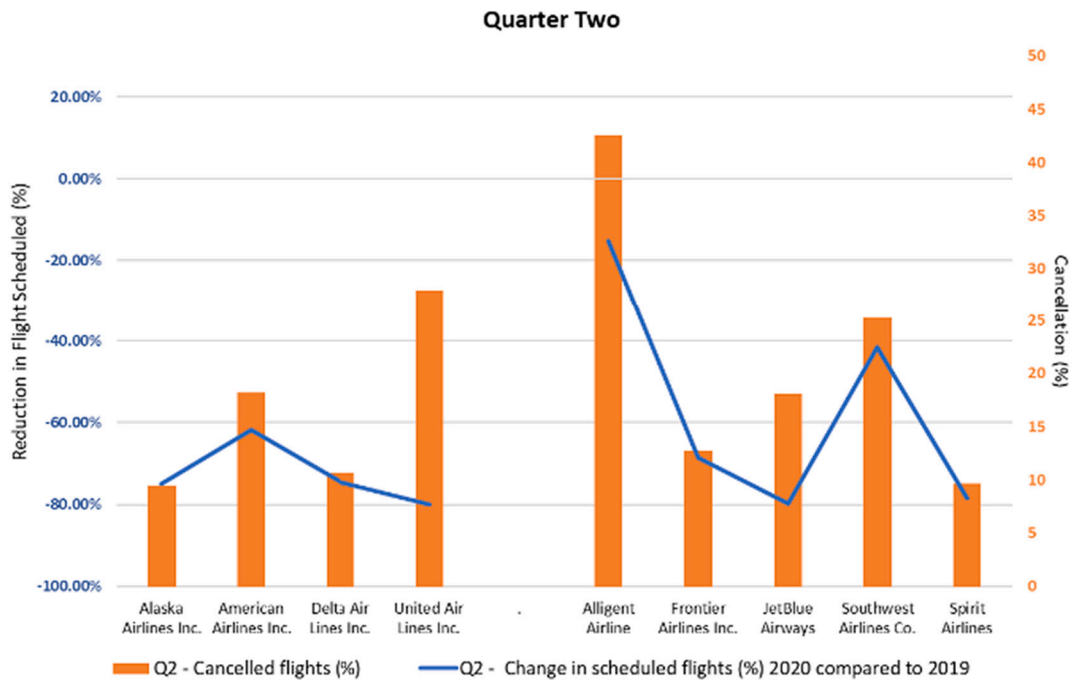


Fig. 8. Reduction in scheduled flights Q2 2020 versus 2019 and Q2 2020 flight cancellations.

Allegiant Air is the first airline that responded to COVID-19 strongly in Q1, 2020 compared to other U.S. airlines. The Allegiant scheduled flights dropped by 10% relative to Q1, 2019. This airline has the highest record (24%) of cancelled flights (relative to all U.S. airlines) in March 2020 (Air Travel Consumer Report, May 2020). Allegiant flies to several leisure-oriented destinations in the States. It also flies to more than 10 destinations only in Florida. Two of its largest airline hubs are Fort Lauderdale–Hollywood and Las Vegas McCarran. It is not surprising that with the emergence of the deadly virus, travel restrictions, and protective measures, many leisure passengers cancelled flights to these destinations. The relative ranking of this airline, in terms of the reduction in

scheduled flights and percentage of cancelled flights, didn't shift for the remaining quarters of 2020. When compared to other U.S. carriers, Allegiant is right on top of the cancellation rate list⁵ and on the bottom of the reduction rate list. In Q2, 2020 alone, more than 40% of Allegiant Air's flights got cancelled.

The comparison between the reduction rate and cancellation rate in Fig. 6 too, shows that Alaska and Delta cut more flights to have less cancelled flights. However, this strategy didn't work well for United.

⁵ -except for Q3 2020, which it ranked second place

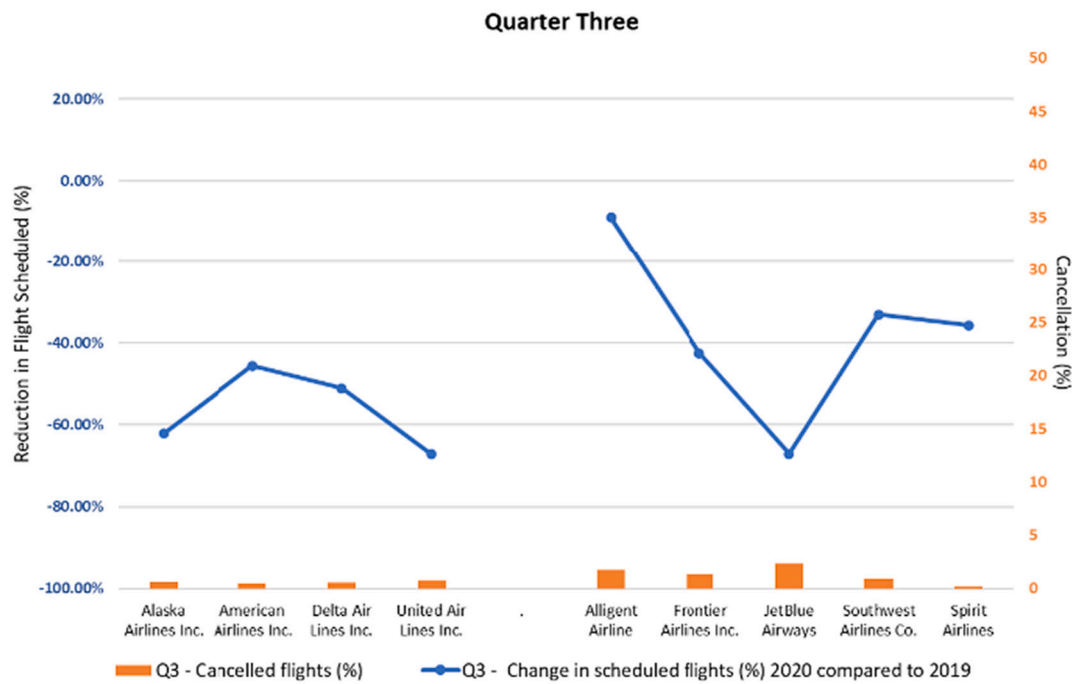


Fig. 9. Reduction in scheduled flights Q3 2020 versus 2019 and Q3 flight cancellation.

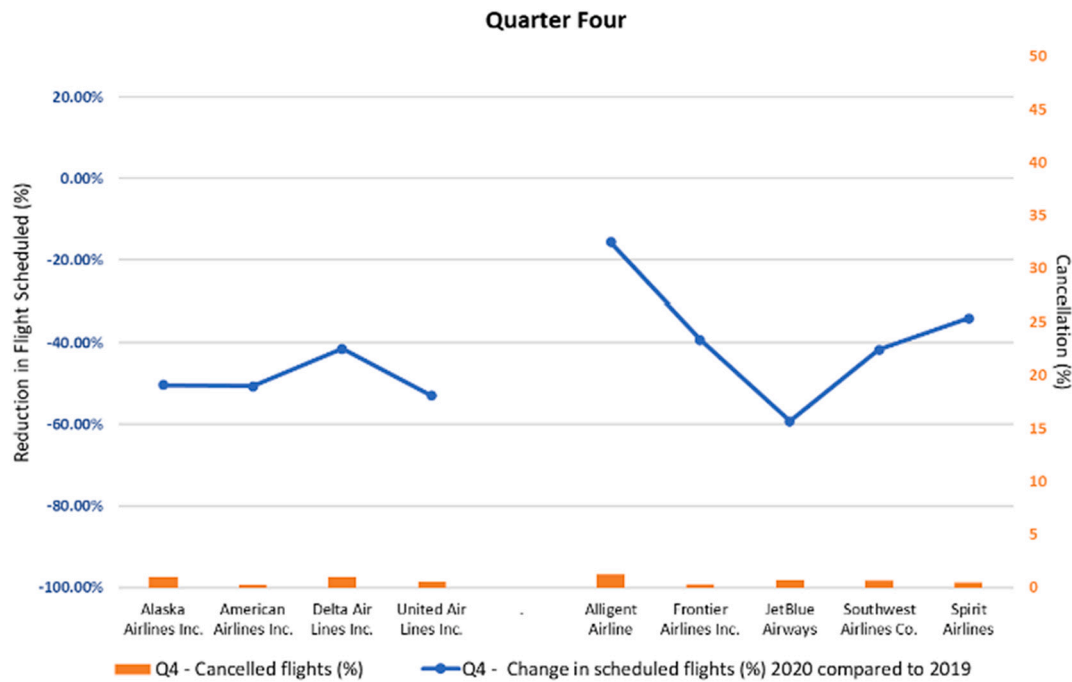


Fig. 10. Reduction in scheduled flights Q4 2020 versus 2019 and Q4 flight cancellation.

United Airlines’ reduction rate was lower than that of its competitors; however, its cancellation rate was more than double than that of its competition. Among network carriers, United Airlines had the highest cancellation rate in Q2, 2020.

As for other low-cost carriers, the number of scheduled flights decreased approximately 80% for JetBlue and Spirit Airlines. In Q4, 2020, the reduction rate improved very gently and the flight cancellation rate stayed below 2.5% for all U.S. airlines. In Q3 and Q4, 2020 Spirit boosted its number of scheduled flights by double relative to Q2, 2020. For Southwest Airways and Allegiant Air, no changes in the

reduction rate are observed in Q1, Q2, and Q3, 2020.

On the other hand, we observe a more consistent shift in reduction rate among network carriers in each quarter of 2020. Southwest Airways, one of the four largest carriers, “owning more than 80% of the market share combined” (Huang, Hsu, & Collar, 2021), has the lowest reduction rate compared to its biggest rivals (American, Delta and United). This carrier benefits from both leisure and business customers while its competitors mostly depend on business travel and long-haul international flying. The reduction rate stays steady around 60% for Southwest Airlines, whereas the reduction rate for its rivals shifts



Fig. 11. U.S. Airlines Service Quality Index 2019 versus 2020

between 40% and 80% across the four quarters of 2020.

In summary, more volatility in reduction rate is observed in the behavior of low-cost carriers when compared to network carriers. However, network carriers respond more aggressively than low-cost carriers in terms of flight cancellation. Monmousseau et al. (2020) study the evolution of tweets written by U.S. network and low-cost airline passengers containing the keyword ‘cancel’ and found that network carriers’ passengers had started to respond as early as the day Italy announced its lockdown.

5.1.4. U.S. Airlines Service Quality

Fig. 11 shows a comparison of the service quality index for U.S. airlines for years 2019–2020 on a quarterly basis. The top right graph shows the AQR index shrank dramatically in the second quarter of 2020 in comparison with that of 2019 for all U.S. airlines. This drop is more significant for Allegiant and Frontier. Examining the components of the AQR index shows that these two airlines have a much larger number of complaints in Q1, 2020 compared to Q1, 2019. Studying the 2020 AQR index shows that there is no recognizable pattern of correlation between service quality of network carriers and low-cost carriers. However, it can be noticed that Frontier Airlines and Southwest Airlines have the lowest and highest AQR index during the pandemic.

Monmousseau et al. (2020) ranked eight U.S. airlines based on the frequency of some keywords, such as the keyword ‘refund’, used in tweets by passengers in the Covid era. As per their findings, Southwest

Airways, that had the highest frequency of these keywords in their passengers’ tweets, took the first rank, and Frontier Airlines, with the lowest frequency of these keywords in their passengers’ tweets, took the bottom rank. Parast and Golmohammadi (2021) show that passengers flying full-service airlines are more likely to register complaints when their flights are cancelled.

5.2. U.S. airline efficiency during pandemic

To study the change in U.S. airlines’ efficiencies in the pandemic year and the year before, the DEA model is employed for each year individually. For comparison the results are represented in Fig. 8 and 9 and reported in Table (4)

Fig. 12) illustrates that the most efficient network carrier and low-cost carrier in the pre-pandemic year were United Airlines and Allegiant Air respectively. Alaska Airlines has the lowest efficiency level among other network carriers. Overall, the efficiency of every carrier was higher in Q2, 2019, compared to other quarters. Among network carriers it was only American Airlines that was not fully efficient in Q2, 2019. As shown by Choi (2017) “within the low-cost carriers, ultra-low-cost carriers (Frontier Airlines, Allegiant Air, and Spirit Lines) have higher efficiency than mega-low-cost carriers such as JetBlue. JetBlue Airways policy makers should make strategic approaches to enhance efficiency by diversifying into new markets and by adjusting the cost structure”.

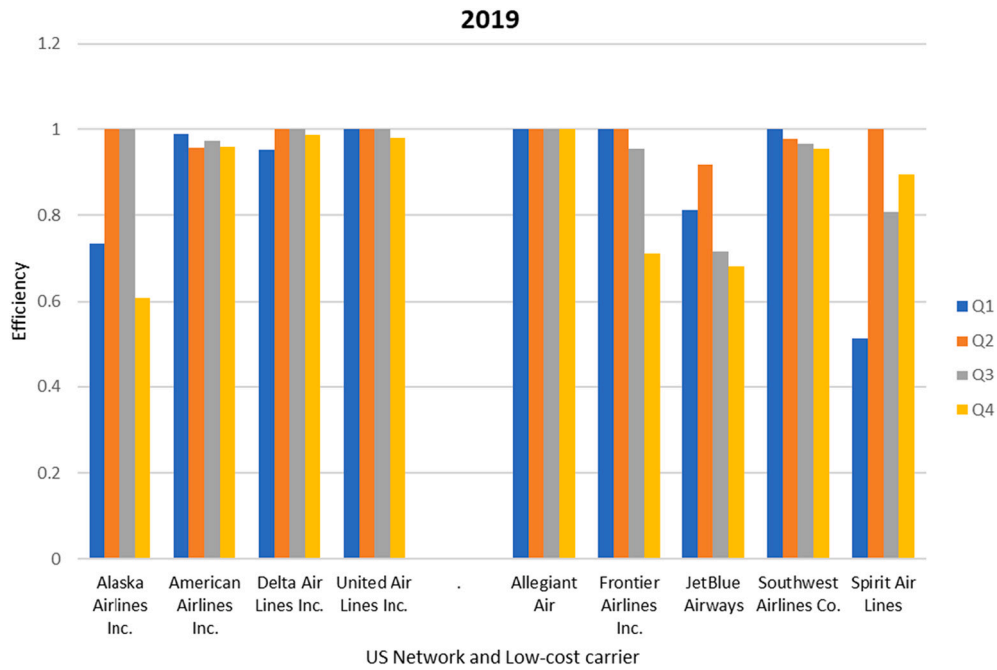


Fig. 12. U.S. carriers' efficiency 2019.

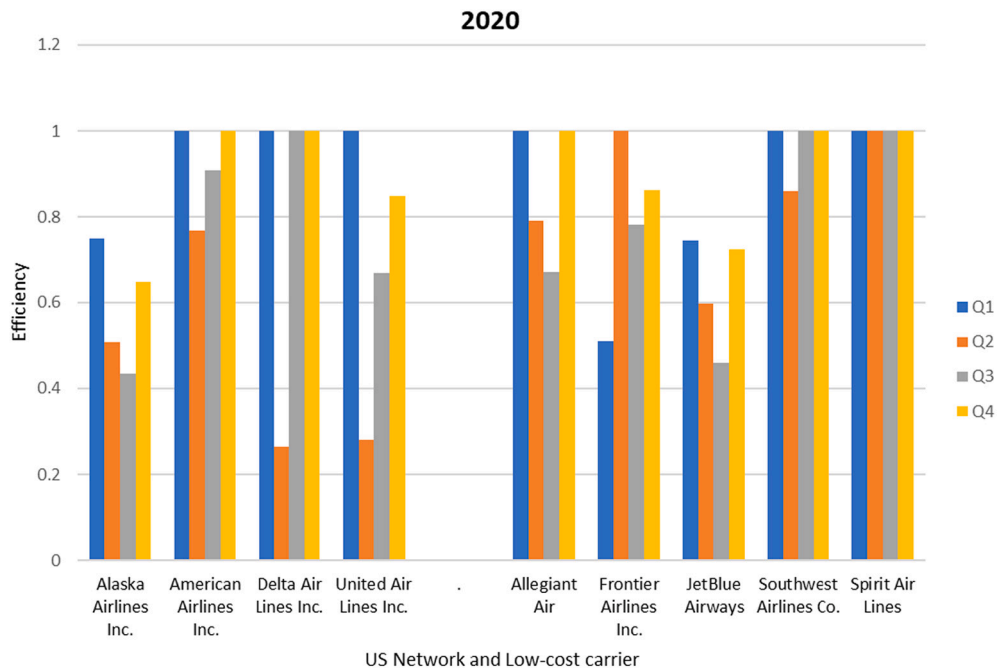


Fig. 13. U.S. carriers' efficiency 2020

Fig. 13 shows the efficiency of U.S. airlines in 2020. At the first glance, it can be noticed that, overall, low-cost carriers have higher efficiencies than network carriers. When comparing Q1, 2019 with Q1, 2020, no significant changes are observed for network carriers. Among low-cost carriers, Frontier Airlines went from being a fully-efficient airline to the least-efficient airline. Frontier also had \$60 million loss in the first quarter of 2020.

Among low-cost carriers, Spirit and Frontier are fully efficient in Q2, 2020 and Frontier Airlines has the lowest flight cancellation rate in Q2, 2020. The annual average market-share of Spirit boosts from 2.8% in 2019 to 15% in 2020. Spirit Line is the only airline which was fully efficient all four quarters of 2020.

Figs. 12 and 13 also shows that ultra-low-cost carriers have higher efficiencies compared to mega low-cost ones (JetBlue and Southwest) in the second quarter of 2020. At the same time, American Airlines has a higher efficiency than the other network carriers and been less effected by pandemic. It is the only network carrier that not only didn't lose any market share but also increased its market-share (by 8.7%) at the end of 2020. In the following quarters, all other network carriers' efficiencies improved. Delta achieved full efficiency in Q3, 2020 and Q4, 2020. In the second quarter of 2020, Delta Airlines had the greatest loss relative to all other U.S. carriers, to the extent of \$5.7 billion. Delta's loss reduced from \$5.7 billion to \$793 million in the third quarter of 2020.

Table 4 reports the efficiency of U.S. airlines for the period of

Table 4
U.S. Airline Efficiency Score for the period of 2019–2020.

	2019				2020			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Alaska Airlines Inc.	0.85	0.95	0.99	0.91	0.78	0.95	0.89	0.87
Allegiant Air	1.00	1.00	1.00	1.00	0.97	0.98	0.96	1.00
American Airlines Inc.	0.57	0.65	0.59	0.63	0.39	0.81	0.65	0.60
Delta Air Lines Inc.	0.73	0.93	0.98	0.88	0.48	0.64	0.66	0.62
Frontier Airlines Inc.	1.00	0.99	1.00	0.96	0.93	1.00	0.99	1.00
JetBlue Airways	0.83	0.88	0.89	0.89	0.74	0.97	0.89	0.88
Southwest Airlines Co.	0.78	0.90	0.88	0.80	0.66	0.77	0.71	0.71
Spirit Air Lines	0.90	0.94	0.91	0.91	1.00	1.00	0.96	1.00
United Air Lines Inc.	0.60	0.76	0.76	0.66	0.41	0.79	0.67	0.60

2019–2020. Table 4 shows that Allegiant Air’s efficiency for the entire year 2019 and Frontier Airlines’ efficiency for Q1 and Q3 are one. For year 2020, the only full efficient airlines are Allegiant Air in Q4, Frontier Airlines Q2 and Q4, Sprit Airlines Q1, Q2 and Q3. Barros et al., (2013) find that “airlines that engaged in international code sharing, and shared world-wide networks of routes and destinations, benefitted from greater efficiency”. Choi (2017) states that most network carriers have relatively higher efficiency when compared with low-cost carriers. On the other hand, our study does not show that “full-service carriers” have a higher efficiency score than “low-cost carriers”. Meanwhile, some of the other studies found that low-cost airlines have higher efficiency when compared with full-service carriers (Zhang et al., 2021; Greer, 2009). The main reasons for inconsistent findings across studies are that the number of airlines used and the period of experimentation differ across these studies. For example, Zhang et al. (2021) include Air Canada with 9 other U.S. airlines for the period of 2015–2016 in their empirical study and Greer (2009)’s study has 15 airlines for the period of 1999–2008.

5.3. Impact of strictness of government policies and passenger’s panic on U.S. airlines’ efficiency

As discussed earlier, we study the influence of passengers’ panic and the U.S. government’s stringency actions on the efficiency of U.S.

Table 5
Regression outcomes.

Variable	Model (1)	Model (2)
Size	-0.3008*** (0.03155)	-0.289*** (0.3577)
Market Concentration	-0.0017 (0.00190)	0.0014 (0.0021)
Network carrier Yes	0.02979 (0.03754)	0.0037 (0.04063)
AQR	-0.00002 (0.00001)	-0.0001 (0.00011)
Panic Index	-0.02495*** (0.00811)	
Stringency Index		-0.0013** (0.00051)
Network carrier Yes: Panic Index	-0.0355*** (0.01183)	
Network carrier Yes: Stringency Index		-0.0015* (0.00074)
Constant	4.25 (0.4842)	3.95 (0.556)
Observations	72	72
R ²	0.71	0.64

***P < 0.1 **P < 0.05 *P < 0.01

airlines. The efficiency score which serves as the response variable is estimated by our proposed model where the frontier is the same for both of 2019 and 2020.

Table 5 shows that both Panic and Stringency Indices affect the efficiency negatively; however, the impact of panic is more significant than the stringency effect.

The regression outcomes for Models (1) and (2) show that both Panic and Stringency Indices are significant. Panic Index is significant at 1% with estimated coefficient - 0.02495 and Stringency Index is significant at 5% with estimated coefficient - 0.0013.

The significance level of these two factors of COVID-19 implies that Panic Index impacts the efficiency of U.S. airlines more significantly than Stringency Index. The “government’s severe actions” (such as lockdowns for controlling the spread of the virus), “difficulties of conducting normal daily business”, “cancellation of public events”, and “international travel controls” have a negative influence on U.S. airlines’ efficiency. Nevertheless, the effect of passenger’s panic has a greater influence on efficiency than any of these factors.

The U.S. airline industry was severely affected by the cancellation of flights due to insufficient flight passengers too, and “frequent flyers had significant concerns about their health and wellbeing, with respect to the threat of infectious diseases” (Sotomayor-Castillo, Radford, Li, Nahidi, & Shaban, 2021). For both business and leisure flyers, “as a passengers’ perceived threat from COVID-19, agreeableness, and fear increases, their willingness to fly decreases” (Lamb, Winter, Rice, Ruskin, & Vaughn, 2020)

The interaction term between the network carrier dummy and Panic and Stringency indices shows that both Panic and Stringency indices negatively impact the efficiency of network carriers more significantly than they impact the efficiency of low-cost carriers. Furthermore, we found that the impact of passenger’s panic is more significant than that of the impact of stringency on the network carriers’ efficiencies. The interaction term between Panic Index and the network dummy is significant at 1% and the interaction term between stringency and dummy is significant at 10%.

Low-cost carriers follow a “Point-to-Point business” model which was more desirable during the pandemic. It allowed customers to avoid large hub airports and provided them with an uncongested environment that was less likely to spread Covid. Also, for years, low-cost carriers targeted cost-conscious customers and focused more on the leisure-oriented market while network carriers concentrated more on the business-oriented market. In the emergence of the pandemic, business and corporate customers learned how to do business remotely and that had an impact on the business-market which was the prime focus of network carriers. Additionally, an analysis of Oliver Wyman suggests that fares in business-oriented markets dropped 33% in the pandemic year of 2020 while leisure fare fell only 16% (Wyman, 2020). All these mentioned factors gave low-cost carriers not just the advantage of lower operating costs (because of their simplified fleet and less complex network), but also an advantage in revenue collection.

The analysis of this study does not provide any evidence of a significant relationship between market share and service quality and the efficiency of U.S. airlines. We also account for the size of the carrier in terms of ASM. A significant positive relationship between the efficiency of an airline and its size is found in the results. These findings support the findings of Pitfield, Caves, and Quddus (2010), (Cento, 2008), and Mallikarjun (2015) that generally state that “airline size has a positive impact on airline efficiency”.

While this study is novel and contributes to the understanding of the two drivers that impact the airlines’ efficiencies in the COVID-19 era, it does not come without limitations. Considering the data used, our results are only specific to U.S. operating carriers, and it excludes international carriers. Secondly, the market share used in this study is measured using the contribution of each airline to total revenue passenger miles and doesn’t include revenue cargo miles.

6. Conclusion, limitations, and future research

This study first examined how U.S. network and low-cost airlines responded differently to COVID-19. Next, it investigated the effect of two factors of COVID-19 on U.S. airlines' efficiency. These two factors are "passengers' panic" and "government-mandated actions in terms of travel restrictions, quarantines, and social-distancing schemes".

The pandemic caused in an unexpected and intense reduction in capacity, market concentration, operated flights, flight cancellation, and service quality as airlines pursued build up and deal with their operations. Examining the changes in the U.S. airlines' capacity and market concentrations in 2020 shows that network carriers had more capacity and market concentration reduction than low-cost carriers. A possible reason for the difference in response between network and low-cost carriers in the COVID-19 pandemic may be due to "the type of passengers", particular business model, or the route architecture.

Our results show that U.S. network carriers responded more aggressively to COVID-19 when it came to flight cancellations and reduction in scheduled flights, and network carriers recovered more moderately than low-cost ones. This can be attributed to the lower operating costs of low-cost carriers and their lower concentration on international routes. Low-cost carriers are attractive to both leisure and business passengers while a large segment of network carriers' market comprises business travelers and long-haul international flyers. Moreover, with business travelers working from home, demand for business and long-haul flights plunged. The route architecture of low-cost carriers follows the Point-to-Point structure which allows flights passengers to arrive at their destination with no connection stops and avoids large hub airports, which in turn provides passengers with a less congested Covid environment. The low-cost carriers' business model also allowed them to open new routes on a trial-and-error basis during the pandemic.

This study found that "the service quality of U.S. airlines" significantly declined in 2020. The AQR index was mostly affected by the massive increase in the number of complaints. There was no noticeable difference in pattern between network carriers and low-cost ones for this aspect.

Moreover, this paper investigates the U.S. airlines' efficiencies in 2020 versus 2019 by employing the DEA model for each year individually. Note that while there are individual differences, in general, network carriers had a higher efficiency than low-cost carriers in the pre-pandemic era. However, in 2020, on an average, low-cost carriers were more efficient. And among low-cost carriers, ultra-low-cost ones performed the best. This outcome supports the findings of Huang et al. (2021) that "low-cost carriers are better off when the demands are volatile". This also confirms that network carriers' economic sustainability is more at risk compared to low-cost carriers.

In the next stage of this paper's analysis, two regression models are used to investigate the impact of two specified factors of COVID-19 (passengers' panic and government-mandated actions) on the efficiency of airlines. Efficiency is obtained by using a single meta-frontier for all observations in 2019–2020. The empirical evidence of this study confirms the significant negative impact of both passengers' panic and government-mandated actions on the U.S. airlines' efficiencies. Also, the negative effect is more significant for passengers' panic than it is for governments' stringency measures. These finding state that spreading awareness and knowledge about public health, spreading of fake news and fake claims, and the frequency of news chatter that refer to COVID-19 influence the performance of U.S. airlines more than "government-mandated actions in terms of travel restrictions, quarantines, and social-distancing schemes". Both these factors influence network carriers more significantly than low-cost ones.

As part of recommended future research, these findings can be extended to international carriers and an attempt can also be made to research into the effect of passengers' panic and government stringency actions using regression models that are enriched with observations and data from a period post-lockdown, or from a time when new variants of

the COVID-19 virus emerge.

Since the pandemic is still ongoing, another interesting future study could analytically investigate the post-pandemic "recovery strategies" adopted by U.S. airlines. Moreover, it would yield interesting results if future research dedicates efforts on the studying the impact of vaccinations in improving passengers' confidence and therefore airlines' efficiency. We leave these extensions for future research.

Declaration of Competing Interest

none

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