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Airline market exit after a shock event: Insights from the COVID-19 pandemic

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ABSTRACT

During the COVID-19 pandemic, passenger demand for air transportation declined drastically. In the United States (U.S.), the Coronavirus Aid, Relief, and Economic Security (CARES) Act provided financial assistance. In return, commercial passenger airlines were given minimum service obligations, which allowed airlines to remove markets (flights between origin and destination airport pairs) from their networks as long as they continued operating in all cities that they serviced pre-pandemic. A binary logit methodology is used to model airline-market level decisions to continue operating in a market or to exit it. Two time periods are modeled: during normal operating conditions (before the pandemic) and after a major shock event (after the beginning of the pandemic). Results show that after the pandemic, 8.4 times more airline markets are exited as compared to before. Interestingly, the probability of exit is found to vary widely across markets, airports, and airlines. Some market characteristics have a high probability of exit both before and after the pandemic, including low passenger revenue per available seat mile, low flight frequencies, and flights to/from multi-airport cities. In contrast, other market characteristics impact airlines’ market exit decisions in only one time period rather than both. For example, during normal operating conditions, airport size does not impact market exit. However, after the pandemic, the probability of exit is 1.8 to 2.2 times higher for the larger hub airports as compared to the smallest airports (non-hubs), a result that is explained within the context of the CARES Act minimum service obligations.

Introduction

In an industry where large shock events are not uncommon, airlines must continue to adapt. Shock events such as the September 11th, 2001 terrorist attacks in the United States (U.S.) and the global economic downturn during the Great Recession of 2008 caused sharp declines in air travel demand that were felt across the world for many years after they occurred (Ito & Lee, 2005; Harvey & Turnbull, 2009). At the same time, airlines face other financial pressures, such as high fixed costs, volatile jet fuel prices, and intense competition with other airlines (U.S. Government Accountability Office (U.S. GAO), 2005). During the Great Recession, airlines responded to financial pressures by altering their networks (Atallah et al., 2018), decreasing flight frequencies (Spitz et al., 2015), retiring fuel inefficient aircraft types (Spitz et al., 2015), and introducing new ancillary revenue streams (Garrow et al., 2012). Air travel demand eventually returned to pre-Recession levels, but not all airlines survived. Worldwide, the impacts of the Great Recession led to airline consolidation, bankruptcies, and closures (Harvey & Turnbull, 2009).

Currently, the industry is going through another shock to the system due to Coronavirus Disease 2019 (COVID-19). In early 2020, COVID-19 began to spread internationally, and travel restrictions were implemented across the world. Subsequently, all modes of transportation were impacted, including public transit, driving, walking (Abdulllah et al., 2020; Bucsky, 2020; De Vos, 2020; Hadjidemetriou et al., 2020), travel by cruise ship (Ito et al., 2020), and air travel (Monmousseau et al., 2020; Arora et al., 2021; Holte & Mumbower, 2021). Global air passenger demand dropped drastically starting in mid-March 2020 (Iacus et al., 2020; Suau-Sanchez et al., 2020). Year-over-year available seat kilometers for international air travel decreased by approximately 90% in April 2020 (Suau-Sanchez et al., 2020). Within the U.S., April 2020 was the largest decline in passenger traffic ever recorded, with year-over-year domestic air passenger traffic declining by 96% (Bureau of Transportation Statistics (BTS), 2020a). With reduced demand for travel, airlines across the world faced large revenue loss. Scheduled passenger airlines in the U.S. reported an after-tax net loss of $35 billion for 2020 (Bureau of Transportation Statistics (BTS), 2021a).

In reaction to industry conditions, many governments offered...
financial support to their nations’ airlines to maintain essential connectivity and protect industry jobs (Abate et al., 2020). Within the U.S., the Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27, 2020; it provided $58 billion in financial assistance to passenger and cargo carriers (U.S. Congress, 2020). Airlines who received financial assistance were prohibited from involuntarily furloughing workers. Also, airlines with scheduled passenger service were given minimum service obligations which required that they continue operating at least 1 to 5 flights per week, depending on their flight frequencies pre-pandemic, in all domestic cities that they served before the pandemic started (U.S. Department of Transportation (U.S. DOT, 2020a). Airlines serving airports within cities with multiple commercial airports (e.g., Washington, DC is served by Baltimore/ Washington International, Regan National, and LaGuardia airports) were required to maintain service at each airport if they served within each multi-airport city that they served before the pandemic started.

The CARES Act minimum service obligations effectively shielded any airport from losing all service, which is especially important for the smallest airports since they are often the first to be impacted by service reductions in response to shock events (Spitz et al., 2015). Even with these policies in place, over a third of the commercial domestic U.S. air transportation network was dropped from airline schedules as airlines altered operations in response to weak demand (Hotle & Mumbower, 2021). This large reduction was possible because the minimum service obligations were based on “points” (i.e., cities) and not markets (i.e., flights between an origin airport and destination airport pair). Airlines were allowed to drop markets from their networks (referred to as “market exit” in this paper), as long as they met their minimum service obligations by operating flights out of each city served pre-pandemic. Early research on the impacts of the pandemic found that service reductions were not uniform across airports, with greater service reductions realized at larger airports (Fuellhart et al., 2021; Hotle & Mumbower, 2021) and airports located within multi-airport cities (Hotle & Mumbower, 2021).

Using airline schedules immediately after the CARES Act minimum service obligations were implemented, this research aims to better understand the factors that impacted U.S. airlines’ decisions to exit markets in response to the COVID-19 pandemic. A baseline measurement of market exit during a pre-pandemic period is also analyzed in order to assess U.S. airlines’ decisions to exit markets during a period of normal operating conditions (i.e., a time when no systemwide shock is observed, such as a pandemic or recession period). This objective will be guided by the following research questions.

**Research Question 1:** During normal operating conditions, what are the factors that impact airlines’ decisions to exit markets?

**Research Question 2:** During the peak of the COVID-19 pandemic (when the CARES Act minimum service obligations are in place), what are the factors that impact airlines’ decisions to exit markets?

**Research Question 3:** How do airlines’ decisions to exit markets differ during normal operating conditions as compared to during the peak of the COVID-19 pandemic?

An analysis of airlines’ decisions to exit markets is quite relevant to the industry. Airport service is viewed by many communities as vital to their local economies and has been linked to local and regional economic activity and employment (Bel & Fageda, 2008; Brueckner, 2003). Many airports have air service development teams on staff who are tasked with maintaining current airport service and acquiring new service through stakeholder engagement (Halpern & Graham, 2015; Lohmann & Vianna, 2016; Stephenson et al., 2018). When airlines exit markets, it can have negative impacts on airport connectivity and consumer welfare, such as leaving small airports with no commercial service or increasing airfares due to decreased competition on certain routes (for discussions, see Morrison & Winston, 2010; Spitz et al., 2015). Airport tenants that offer services such as food, car rentals and parking are also negatively impacted (Rust et al., 2021). The model methodology and results presented in this paper provide airport managers a way to better understand how at-risk their airports are of losing markets due to a large shock event. Also, insights are provided to help policymakers better understand how federal policies surrounding the minimum service obligations of the CARES Act impacted the connectivity of the U.S. air transportation network during the shock event, a subject that has received little attention in the literature to date.

This paper is organized as follows. First, Section 2 reviews the literature. Then, Section 3 describes the data and modeling methodology. Section 4 presents the results of the analysis and discusses policy implications. Section 5 addresses model fit, sensitivity checks that were performed to test for robustness, and limitations. Lastly, Section 6 provides a conclusion and ideas for future research.

**Literature**

Dixit & Chintagunta (2007) point out that literature on airline market entry is abundant (e.g., see Reiss & Spiller, 1989; Berry, 1992; Lin et al., 2001; Oliveira, 2008; Murakami, 2011; Zou & Yu, 2020), but literature that empirically investigates market exit is “relatively rare.” This gap in the literature is significant because better understanding characteristics associated with market exits can lead to useful insights that managers might use to help prevent future exits (Schnell, 2006; Dixit & Chintagunta, 2007). Readers are referred to Karakaya (2000) and Cefis et al. (2021) for systematic literature reviews of market exit in general which includes literature across industries such as manufacturing and healthcare. Although there are studies that have empirically investigated market exit within the airline industry, there is a “nonexistence of an overall framework in the academic literature” that presents key factors that drive exit (Lohmann and Vianna, 2016). Across the literature, authors use different phrases to refer to airlines’ market exit decisions, including terms such as: “suspension” (Lohmann & Vianna, 2016), “discontinued service” (Atallah and Hotle, 2019), and “churn” (de Wit and Zuidberg, 2016).

Hüschelrath and Müller (2013) define two reasons for airline market exit: operational exit and firm exit, which are presented separately in the next two sections. Afterwards, the literature on shock events and COVID-19 are presented.

**Operational exit**

Airline networks are constantly changing and evolving. In countries where the airline industry is deregulated, such as the United States, airlines control their own prices and networks (U.S. Government Accountability Office (U.S. GAO), 2006). Airlines reorganize their networks to maintain or increase profitability, and this process is a part of their normal network optimization efforts. As a consequence, airlines may make an “operational exit” from a market in their network by discontinuing service (Hüschelrath & Müller, 2013). Similarly, airlines may reallocate capacity to other airports or markets, often called capacity switching, by decreasing flight frequencies (or seat capacity) at one airport while increasing frequencies at another (Wiltshire, 2013, 2018). Airlines make decisions to exit and/or reduce capacity in their markets for a variety of reasons, such as insufficient growth potential, increases in passenger facility and/or airport charges, economic conditions, and route profitability (Hüschelrath & Müller, 2013; Wiltshire, 2018). Through semi-structured interviews with stakeholders in aviation and tourism, Lohmann and Vianna (2016) find that interviewees cited lack of demand as an important reason for exit. When airlines exit markets, the reduced route-level competition may result in increased airfares, but the impact on airfares will depend on competitive effects such as presence of low-cost carriers (LCCs) and whether the exiting airline is replaced by other entrant carriers (Joskow et al., 1994; Morrison & Winston, 1999, 2010).

Button (2012) points out that LCCs are not stable in the services that

2
they offer and notes that LCCs frequently enter and exit markets. Dixit & Chintagunta (2007) model the exit decisions of discount airlines in the U.S who have recently entered new markets. The authors incorporate the concept of firm learning into a binary logit model using Bayesian belief-updating and show that airlines have prior beliefs about the attractiveness of a market, which may or may not be similar to what will be observed when they actually enter the market. The results indicate that airlines learn about market attractiveness over time, which influences their decisions to exit. Atallah and Hotle (2019) also investigate market exit within the U.S and focus on airline service to airports in small communities during and after the Great Recession (2007–2013). The authors find that small communities are more likely to lose markets that are operated using fuel inefficient small aircraft. A study by Baum & Korn (1996) models market entry and exit of U.S. commuter airlines operating markets in California in the years following deregulation (1979–1984) and find that more competitive markets (measured as market domain overlap) have an increased number of both market entries and market exits. Sinclair (1995) shows that U.S. airlines’ entry and exit behavior is affected by their network characteristics, such as the size of their hub-and-spoke systems.

To investigate four European LCC’s market exit decisions during 2001–2013, de Wit and Zuidberg (2016) use binary logit models and find several airport and market characteristics associated with exit, including airport size, geographic market, distance, number of seats, market share, seasonality, and route age (how long the route has been operated). Interestingly, the authors identify quadratic relationships between continuous explanatory variables and the binary exit decision, highlighting that complex nonlinear relationships exist. Another particularly interesting finding is that European LCCs were more than four times more likely to exit markets during the peak of the Great Recession in 2008 as compared to other years (de Wit & Zuidberg, 2016), demonstrating the Recession’s large impact on airlines’ decisions to exit markets.

Firm exit

In addition to operational exit, a second reason that airlines exit markets is due to “firm exit”, which occurs due to airline consolidation such as mergers, acquisitions, and liquidation (Hüschelrath & Müller, 2013). In the case of firm exit due to mergers and acquisitions, a portion of the acquired airline’s markets will generally be exited, rather than elimination of the entire network. However, in the case of airline liquidation, the airline ceases operations and exits all markets it once served. Using U.S. domestic markets serviced during 1995–2010, Hüschelrath and Müller (2013) find that firm exit due to liquidation leads to long-term increases in airfares (12% on average) on the affected routes. However, the authors did not find the same effect for routes impacted by mergers; an increase in airfares was found in the short-term but it dissipated over time. Fageda et al. (2017) find that after Spanish network carrier Spanair ceased operations in 2011, flight frequencies on routes impacted by the airline’s exit where not reduced because other airlines replaced its operations. Prices decreased on routes where Spanair’s operations were replaced by LCCs and increased on routes where its operations were replaced by network carriers (Fageda et al., 2017). When Malev Hungarian Airlines ceased operations in 2012, it impacted over half of the air traffic at hub airport Budapest Liszt Ferenc International (BUD) and resulted in increased LCC market share (Torok & Heinitz, 2013). In a study on the consumer welfare effects of Malev’s exit, Biloktach et al. (2014) demonstrate a “price-frequency trade-off” where airlines operating point-to-point networks replaced Malev’s hub-and-spoke network with less frequent service but at lower airfares for customers (Biloktach et al., 2014).

While these papers assess the effects of airline exit on airfares and operations, Budd et al. (2014) take a different approach and attempt to better understand reasons why airlines fail. The authors study 43 new European LCCs that began operations between 1992 and 2012, of which the majority (77%) eventually ceased operations. The authors identify several factors that contribute to success or failure, including aircraft fleet mix, size of operations, and start-up date. One of the most interesting aspects is that the authors find a significant spatial dimension and note that many LCCs failed due to their route network and aircraft decisions. Button (2012) also reiterates this point in a paper about the low-cost airline business model when the author suggests that the financial success of LCCs may ultimately be due to the markets that they have entered rather than the LCC business model itself. This highlights just how important it is for airlines to make good decisions when it comes to their network planning strategies. At the same time, making good decisions is more difficult during shock events, as system shocks add uncertainty to route scheduling and air traffic forecasting efforts (Kincaid et al., 2012).

Shock events and COVID-19

Shock events within the airline industry are not uncommon and often cause declines in passenger traffic that last for multiple years (Itô & Lee, 2005; Harvey & Turnbull, 2009; Kincaid et al., 2012). Literature has addressed the impact of past shock events on air transportation, including events such as the September 11th, 2001 terrorist attacks in the U.S. (Itô & Lee, 2005; Siozos-Rousoulis et al., 2021), the spread of severe acute respiratory syndrome in 2003 (Joharis, 2007), the Great Recession of 2008 (Harvey & Turnbull, 2009; Atallah et al., 2018), and the outbreak of Ebola in West Africa that started in 2014 (Amankwah-Amaoh, 2016) to name a few. Large shock events are often studied for many years after they happen, revealing insights into long-term impacts as new data is collected and the industry evolves. Siozos-Rousoulis et al. (2021) use a complex network analysis approach to study the long-term impact of the 9/11 terrorist attacks over two decades using 1996–2016 data and find that the attacks triggered a “vast restructuring” of the U.S. domestic air travel network, as many new routes were added in an effort to increase the network’s resilience to disruptive events and targeted attacks. Other authors point out that airline and airport managers, as well as policymakers, must learn from past shock events and incorporate this uncertainty into their short- and long-term planning efforts (Kincaid et al., 2012; Linden, 2021).

Currently, there is a growing body of diverse literature studying the impacts of the COVID-19 pandemic on the world economy and global transportation. For example, Sobieralski (2020) uses past uncertainty shocks to forecast the impacts of the COVID-19 pandemic on the U.S. airline workforce. For reviews of literature addressing the impacts of COVID-19, readers are referred to Brodeur et al. (2021) and Kim (2021). For findings from a worldwide expert survey on COVID-19 and transportation, see Zhang et al. (2021). The COVID-19 literature most relevant to this paper is the research that addresses the pandemic’s impacts on air transportation operations and connectivity. In early research on the subject, Hotle & Mumbower (2021) demonstrate the non-uniform impacts of the pandemic across U.S. commercial passenger airports, showing that some airports experienced larger reductions in flight operations and service than others. The authors find that 32.1% of nonstop markets in the domestic U.S. were removed from airline schedules during the peak of the pandemic. Schedule changes such as this reduce connectivity of the air transportation network. Sun et al. (2021) point out that on the one hand, countries have incentives to maintain the connectivity of their air transportation networks because connectivity impacts mobility and economic activity. On the other hand, the spread of COVID-19 might have been minimized if flight lock-down measures had been implemented earlier (Sun et al., 2021) because there is a positive correlation between air traffic and COVID-19 infections (Sokolj & Atchadé, 2020; Arora et al., 2021). Sun et al. (2021) recommend that future policy and regulatory restrictions address this challenging tradeoff.

Also motivated by the ongoing pandemic, Zhou et al. (2021) propose a method to assess the vulnerability of air transportation networks to
airport-level disruptions that are caused by global catastrophes. Outside of the literature specific to COVID-19, there is a related stream of research that assesses the evolution of air transportation networks over time (e.g., Cheung et al., 2020; Chung et al., 2020; Roucolle et al., 2020). This stream of research shows that route changes have an impact on many different network metrics, such as robustness to disruptions (i.e., airlines’ ability to mitigate disturbances by using alternative flights) and centrality of airports (e.g., the number of direct flights from a departure airport). A related stream of literature studies airlines’ differing strategies for building their networks, such as hub-and-spoke versus point-to-point networks, and the impacts that these strategies have on congestion, customers, and the environment (e.g., Klophaus et al., 2021; Pels, 2021).

Data and methodology

To examine the characteristics that impact airlines’ decisions to exit markets during normal operations and during the peak of the COVID-19 pandemic, a dataset is compiled at the airline-market level for two time periods: before and after the shock event. Explanatory variables are compiled for time t-1 to identify variables that impact an airline’s decision to exit a market in time t. The dependent variable is binary and indicates whether an airline decided to exit a market or continued to serve the market. An exit before the shock event is defined as an airline market that is present in May 2018 data but not in May 2019, whereas an exit after the shock event is an airline market that is present in May 2019 data but not in May 2020. In this section, details about the data and variable definitions are provided first and then the binary logit model is presented.

Data

Although the COVID-19 pandemic impacted the airline industry on a global scale, this paper takes the approach of others who focus on the airlines of one country (e.g., Fageda et al., 2017; Atallah et al., 2018; Atallah & Hotle, 2019), and limit analysis to the U.S. airline industry. The environments that airlines operate in vary widely across different countries, especially due to underlying factors such as government regulations, subsidies, and taxation, as well as financial support during the pandemic (Abate et al., 2020). This approach ensures the data represent a subset of airlines operating in a similar environment before and after the beginning of the COVID-19 pandemic. This approach also allows a closer investigation of how market exit strategies may have been impacted by federal government policies introduced immediately after the beginning of the pandemic.

The primary dataset used in this analysis was purchased from Official Airline Guide (OAG), a company that maintains comprehensive flight schedules data (Official Airline Guide (OAG), 2021). Although the data is not freely available to researchers, it has been used by other authors (e.g., de Wit & Zuidberg, 2016; Atallah & Hotle, 2019; Roucolle et al., 2020). Airlines supply similar data to the U.S. DOT as part of their reporting requirements for the publicly available datasets called T-100, which are available through the Bureau of Transportation Statistics (Bureau of Transportation Statistics (BTS), 2021b). However, the free public data has a major limitation in that it does not report identifying information for both the marketing and operating carrier. The marketing carrier is the airline who sells seats on a flight (sometimes called the ticketing carrier), and the operating carrier is the airline who operates, or flies, the aircraft. In many U.S. markets, a major network carrier will sell flights that are flown by smaller regional carriers (Reynolds-Feighan, 2019). The CARES Act minimum service obligations were given to marketing carriers rather than operating carriers (U.S. Department of Transportation (U.S. DOT), 2020a). In other words, a regional carrier was not obligated to continue service in cities where they were not the marketing carrier. Instead, it was the marketing carrier who was obligated to continue service, and, therefore, it was the marketing carrier who was the decision-maker in any market exit decisions. In fact, the CARES Act minimum service obligations were created by the U.S. DOT using schedules data acquired from OAG for the marketing carriers (U.S. Department of Transportation (U.S. DOT), 2020a).

Markets are defined as directional departure (origin) airport to arrival (destination) airport pairs. For example, departure airport ATL (Atlanta, GA) to arrival airport LAS (Las Vegas, NV) is one market, whereas the reverse direction from LAS to ATL is defined as a different market. Markets between U.S. airports designated as commercial primary by the FAA are included in the analysis, which includes airports with more than 10 thousand annual commercial enplanements (Federal Aviation Administration (FAA), 2021). Nonstop domestic passenger service within the continental U.S. is the focus of the analysis. Markets to international destinations, Alaska, Hawaii, and U.S. territories are excluded, which was necessary as travel to many of these destinations were subject to government-imposed flight suspensions, inbound quarantine, and border closings aimed at reducing the spread of COVID-19 (e.g., see U.S. DOT, 2020b, 2020d; Li et al., 2021a; Li et al., 2021b).

Essential Air Service (EAS) markets are also eliminated from the analysis. The EAS program is a government-subsidized program that contracts with airlines in order to maintain service to small and remote communities in the U.S. which may not otherwise receive similar service without aid (Fuellhart et al., 2021; U.S. Department of Transportation (U.S. DOT), 2021). EAS markets were protected from service loss during the pandemic and could not be exited, as airlines were required to abide by their preexisting contracts (U.S. Department of Transportation (U.S. DOT), 2020a; U.S. Department of Transportation (U.S. DOT), 2021).

For model estimation, the OAG flight schedules data are aggregated to the airline-market level for each of three months of interest: May 2018, May 2019, and May 2020. Any airlines with infrequent service in a market are excluded, which is defined as having less than four flights performed during a month. This is consistent with the CARES Act minimum service obligations which required that airlines continue operating at least 1 to 5 flights per week, depending on their flight frequencies pre-pandemic (U.S. Department of Transportation (U.S. DOT), 2020a). It was also necessary to exclude some of the smallest carriers from the analysis, as some were observed to exit all or none of their markets. The analysis includes all U.S. marketing carriers that sell flights in at least 70 nonstop domestic markets in the continental U.S, which includes: Alaska Airlines, Allegiant Air, American Airlines, Delta Air Lines, Frontier Airlines, JetBlue Airways, Southwest Airlines, Spirit Airlines, and United Airlines. None of the nine airlines included in this study merged or ceased operations during this timeframe. Any flights marketed by these airlines, even if operated by their regional carrier affiliates, are included in the analysis.

It should be noted that the month of May is chosen for analysis because it represents a month during the height of the pandemic; in May 2020 passenger demand was down 88.4% and load factors were down 56.4% as compared to May 2019 (Hotle & Mumbower, 2021). May 2020 is also ideal for analysis because of the timing of the CARES Act. The CARES Act was signed into law on March 27, 2020 (U.S. Congress, 2020) and airlines spent April 2020 adapting their flight schedules to the minimum service obligations that were put in place. According to Hotle & Mumbower (2021), in April 2020 airlines operated only 63% of their scheduled flights, as many flights were cancelled. However, in May 2020 airlines operated over 97% of their scheduled flights, as by this time they had adjusted their schedules operatively to the pandemic and the new government regulations (Hotle & Mumbower, 2021).

Secondary sources of data are also utilized for this analysis. Although the OAG dataset includes number of seats per flight, it does not include the actual number of passengers transported or load factors. The BTS’s T-100 Domestic Segment datasets are used to determine the number of passengers transported per market (Bureau of Transportation Statistics (BTS), 2021b). Load factors are then calculated as the number of passengers transported divided by number of seats. Due to the limitation of...
the T-100 data already discussed, only the operating carrier is identified; it was necessary to calculate the number of passengers at the market level rather than the airline-market level. Using this methodology, the T-100 data are able to be matched to OAG data for 100% of the markets. In addition, BTS’s Origin Destination Survey (DB1B) data, which is a 10% sample of reported tickets, are used to calculate median airfare per seat mile for each airline market (Bureau of Transportation Statistics (BTS), 2021c). Median airfares are calculated using nonstop routes, and extreme airfares (less than $30 or greater than $5,000) are excluded. The DB1B data includes identifying information about the marketing airline, and the data are able to be matched to the OAG data for 99.6% of airline markets. Where a match is not possible airline median airfares are used. This high rate of matches to the DB1B data is achieved because the smallest airlines (with<.70 nonstop markets) and airports (commercial non-primary airports) are excluded from this analysis; otherwise, the data would be much more incomplete, as DB1B data has been shown to be incomplete for the smallest markets (Teixeira & Derudder, 2020).

Lastly, three sources of information are used to determine airport characteristics. The FAA commercial airport size categories are used to determine airports sizes; the FAA categorizes primary airports into large hub, medium hub, small hub, and non-hub (Federal Aviation Administration (FAA), 2021). The BTS’s Master Coordinate table is used to identify airports that the BTS considers to be within the same city-market (BTS, 2021d), referred to in this study as multi-airport cities. This definition of multi-airport cities is consistent with the definition used in the CARES Act minimum service obligations (U.S. Department of Transportation (U.S. DOT), 2020a).

To summarize, the data for this study include nine U.S. marketing airlines and their nonstop continental U.S. domestic markets between primary commercial airports, excluding EAS airports. The analysis dataset represents 93.9% of all commercial air traffic in the domestic U.S. (defined as number of scheduled seats).

Variables

Two time periods are of interest in this analysis: 1.) before the shock event, and 2.) after the shock event. For the former (before the shock event), the explanatory variables use May 2018 data. Then, the binary dependent variable is captured by identifying whether each market present in the May 2018 data continued to be serviced or not in May 2019. For the latter (after the shock event), the explanatory variables use May 2019 data, and the dependent variable is captured by identifying whether each market present in the May 2019 data continued to be serviced or not in May 2020. The use of time-lagged explanatory variables is also used in other related research in this area (Dixit & Chintagunta, 2007; de Wit and Zuidberg, 2016; Atallah & Hotle, 2019). As de Wit and Zuidberg (2016) point out, the time period prior to the actual market exit represents the best measure of normal operations on which market exit decisions are generally made. Because an exited market is dropped from the schedule, the values of the explanatory variables are impacted considerably during the time period of market exit. For example, the market share of an airline who drops a given market would be zero during the time period the market is dropped from the schedule. Also, as others have noted, airline schedules are highly seasonal (Teixeira & Derudder, 2020; Fuellhart et al., 2021) and can be either explicitly incorporated into the model with seasonality variables (e.g., de Wit & Zuidberg, 2016) or avoided altogether by comparing the same month (or week) when using multiple years of data (e.g., Atallah & Hotle, 2019). This paper takes the latter approach in order to focus on the variability that occurs due to the shock event rather than the regular seasonal variability that is commonly observed in airline schedules.

To identify relevant explanatory variables to use in this study, the empirical literature on airline market exit was utilized. Detailed variable definitions are included in Table 1, along with the data source for each variable. Some of the continuous variables are log transformed due to

Table 1
Variable definitions.

| Name                                      | Definition                                                                 | Source       |
|-------------------------------------------|---------------------------------------------------------------------------|--------------|
| **Dependent Variable (calculated at time t)** |                                                                           |              |
| Exit                                      | An airport-pair market scheduled by a marketing airline at time t-1 either continued to be serviced by the airline (0) or did not (1) during time t. | OAG          |
| **Market Specific Variables**             |                                                                           |              |
| Distance                                  | Categorical variable that represents distance in miles between arrival and departure airports. Categories are: Short Haul (<500 miles), Medium Haul (>500 & <1200), Long Haul (>1200). | OAG          |
| Multi_Airport                             | Categorical variable that represents whether an airport-pair market is between multi-airport and/or single-airport cities. Categories are: Single-Single, Multi-Single, Multi-Multi. As defined by the BTS’s Master Coordinate Table, multi-airport cities in this study include: Boston, MA; Chicago, IL; Cleveland, OH; Columbus, OH; Dallas/Fort Worth, TX; Houston, TX; Los Angeles, CA; Miami, FL; New York City, NY; Norfolk, VA; Phoenix, AZ; San Francisco, CA; Seattle, WA; Tampa, FL; Washington, DC. | Bureau of Transportation Statistics (BTS), 2021d |
| **Airline-Market-Time Specific Variables (calculated at time t-1)** |                                                                           |              |
| Busi_Seats                                | A binary variable that represents whether the airline used aircraft with business and/or first-class seats in the market at time t-1. | OAG          |
| ln(FLt,Freq)                              | Log transformed number of flights the airline scheduled in the market at time t-1. | OAG          |
| ln(PRASM)                                 | Log transformed passenger revenue per available seat mile. Calculated as the product of an airline’s airfare per seat mile and market load factor at time t-1. Load factor is calculated from T-100 data as the number of passengers divided by the number of available seats for all flight departures performed in a market. Airfare per seat mile is calculated from DB1B as an airline’s median airfares in a market divided by the (continued on next page)
skewed data, and these are denoted in the definitions. Table 1 breaks the explanatory variables into market, airline-market, and airline specific variables. The market-specific explanatory variables do not vary over time and include characteristics of the air travel network, including market distance and multi-airport city status. The airline-market specific variables vary over time. These are compiled for time period for the continuous variables. All correlations are well below the commonly used rule of thumb of ±0.90 for indicating very high correlations (Midt et al., 2010).

Model

The binary dependent variable equals 1 if the airline decided to exit the market and 0 if the airline continued to serve the market. A binary

Table 2 provides descriptive statistics per variable for the two time periods, before and after the shock event. All of the descriptive statistics are similar across the two time periods with the exception of the dependent variable called Exit. Table 2 shows that 5.4% of markets present in May 2018 were exited by May 2019, whereas 42.3% of markets present in May 2019 were exited by May 2020. This large increase is due to the pandemic and will be explored in more detail when the model results are presented. Table 3 provides a correlation matrix by time period for the continuous variables. All correlations are well below

| Name | Definition | Source |
|------|------------|--------|
| In(NumMkts_ArrAirport), In(NumMkts_DepAirport) | distance in miles between arrival and departure airports. | OAG |
| ULCC, LCC, Network | Three binary variables that represent whether competitor airlines serve the market for each airline type at time t-1. Categories are: ultra-low cost carriers (ULCCs), Allegiant, Frontier, and Spirit; low cost carriers (LCCs) JetBlue and Southwest; network carriers American, Alaska, Delta, and United. | OAG |
| Codeshare | A binary variable that represents whether the airline codeshares with international (non-U.S.) airlines on the route at time t-1. | OAG |
| MktShare_Airline | Categorical variable for an airline’s share of total scheduled flights in a market at time t-1, represented as a proportion. Categories are: <0.3, >0.3 & <0.5, >0.5 & <1.0, and 1.0 (monopoly). | OAG |
| MktShare_ArrAirport, MktShare_DepAirport | An airline’s share of total scheduled flights for an arrival (departure) airport at time t-1, represented as a proportion. A value of 1 indicates they operate a monopoly at the airport. | OAG |
| Airline Specific Variables | Airline fixed effects are included for the airlines in this study: Alaska, Allegiant, American, Delta, Frontier, JetBlue, Southwest, Spirit, and United. | OAG |

Table 2 provides descriptive statistics per variable for the two time periods, before and after the shock event. All of the descriptive statistics are similar across the two time periods with the exception of the dependent variable called Exit. Table 2 shows that 5.4% of markets present in May 2018 were exited by May 2019, whereas 42.3% of markets present in May 2019 were exited by May 2020. This large increase is due to the pandemic and will be explored in more detail when the model results are presented. Table 3 provides a correlation matrix by time period for the continuous variables. All correlations are well below the commonly used rule of thumb of ±0.90 for indicating very high correlations (Midt et al., 2010).
The logit model is used to estimate the likelihood of an airline exiting a market for each observation \( t \), where an observation is at the airline-market-time level. The estimation dataset includes two time periods and a binary indicator of time period, \( T_t \), which is 0 before the shock event and 1 after the shock event. \( T_t \) is interacted with all explanatory variables, which is sometimes referred to in the literature as a fully interacted model. The model takes the form of:

\[
\text{Exit}_t = \left(1 - T_t\right) \left(\alpha_0 + \alpha_1 X_{t1i} + \ldots + \alpha_k X_{tki} + T_t (\beta_0 + \beta_1 X_{t1i} + \ldots + \beta_k X_{tki}) + \epsilon_i\right)
\]

where there are \( k \) explanatory variables. For each explanatory variable, the model estimates a separate parameter for each of the two time periods, \( \beta_k \) for the time before the shock event and \( \beta_k \) after the shock event. Separate constants are also estimated for each of the two time periods, \( \alpha_0 \) and \( \alpha_1 \). The error term is denoted as \( \epsilon_i \). Robust standard errors are clustered at the market level, which relaxes the assumption of independent observations. It should be noted that quadratic relationships among continuous variables and exit have been identified in similar research (e.g., Baum & Korn 1996; de Wit & Zuidberg, 2016). Also, exploratory analysis of the data identified similar non-linear relationships that exist in this dataset. Therefore, some of the continuous variables in the model include a squared term to account for the quadratic relationships (which will be denoted in the model results). Log likelihood tests are used to determine whether squared terms increase model fit or not.

A fully interacted model is equivalent to running separate regressions (Allison, 1999), but has the advantage of making postestimation computations simpler (Long and Mustillo, 2018). Other authors use a similar modeling approach to study changes in likelihood over time. For example, Hipp and Bünning (2021) model the probability of working from home before and after the beginning of the COVID-19 pandemic. The authors use a fully interacted model (where all covariates are interacted with time) to compare the time periods before the pandemic, shortly after lockdowns, and after loosening of lockdowns in Germany. Combs and Rodriguez (2014) model the probability that a household owns a vehicle before and after implementation of a Bus Rapid Transit system in Bogotá, Colombia.

After estimating the model, calculations for marginal effects and predicted probabilities are made using the postestimation command margins in Stata 16.1. Long and Mustillo (2018) advocate for using marginal effects and predicted probabilities to interpret model results since they are not impacted by change of scale, a well-known issue with binary logit models whose underlying model assumptions fix the residual variance. As variables are removed from or added to models, both the explained variance and total variance change, meaning that coefficient estimates are only identified up to a scale factor (e.g., see Allison, 1999; Guevara and Ben-Akiva, 2012; Bestard and Font, 2021).

### Results and discussion

The results of the binary logit model are displayed in Table 4, with separate columns for coefficient estimates before and after the shock event. In this section, model results for variables significant only in one time period are discussed first. Next, variables significant in both time periods are discussed. Lastly, predicted probabilities will be presented that demonstrate how the pandemic’s impact on market exit differs across airports and airlines.

#### Explanatory variables significant during only one time period

The model results in Table 4 show that some variables are significant before the pandemic but are not significant afterwards. These results show how relationships between explanatory variables and the exit decision shift in response to the pandemic and demonstrate the pandemic’s impact on airlines’ market exit decisions. For example, the results for Distance show that longer distance flights are significantly less likely to be exited during the period of normal operations before the pandemic. However, the model results also show that Distance is insignificant after the pandemic, indicating it has no impact on exit decisions after the pandemic. The importance of distance on the exit decision was diminished after the pandemic as factors that impact exit decisions shifted in response to the different operating environment.

Also, the variable Busi Seats, an indicator of airline markets with first class and/or business class seats, is significant before the shock event but not after. Odds ratios are not displayed in the table, as they are difficult to interpret for the log transformed variables and squared terms. However, they can be quickly calculated and interpreted for the categorical variables. The odds ratio for airline markets with business seats is exp \((-1.499) = 0.223\) in the first time period, or \(1/0.223 = 4.5\). These results indicate that before the shock event, airline markets with business class seats are 4.5 times less likely to exited than markets without business seats. Business class travel is an important revenue stream for airlines, and it is intuitive that markets with business class would be less likely to be exited during normal periods of operations. However, it is interesting to see that after the shock event, markets with business class seats are more or less likely to be exited than other markets. This is because the pandemic significantly reduced demand for all types of travel as conferences moved online, workplaces closed in favor of remote work, and travelers put leisure trips on hold.

The Codeshare indicator for markets where airlines codeshare with international carriers is insignificant before the shock event. However, these codeshare markets are found to be \(1/exp(-0.383) = 1.5\) times less
likely to be exited after the pandemic, highlighting the importance of these markets to airlines. Other variables that are only significant in one time period include the competitor dummy variables ULCC and LCC. Model results for before the shock event show that markets with ULCC competitors are more likely to be exited, but this effect is not present after the shock event. Also, before the shock event LCC competitors have no impact on the exit decision, but afterwards markets with LCC competitors are more likely to be exited. On the other hand, Network indicates that markets where airlines compete with network carriers are more likely to be exited both before and after the shock event. This shows that the effect of airline competition on exit decisions shifted in response to the pandemic for some, but not all, types of competitors.

**Table 4**

| Explanatory Variables | Before Shock Event | After Shock Event |
|-----------------------|--------------------|-------------------|
|                       | Est. | SE  | z    | P     | Est. | SE  | z    | P     |
| Constant              | 5.233 | 0.737 | 7.10 | 0.000 *** | 7.231 | 0.494 | 14.64 | 0.000 *** |
| Distance (Reference is Short Haul) | | | | | | | | |
| Medium Haul           | –1.392 | 0.227 | –6.14 | 0.000 *** | –0.184 | 0.124 | –1.48 | 0.139 |
| Long Haul             | –2.628 | 0.324 | –8.12 | 0.000 *** | 0.029 | 0.194 | 0.15 | 0.882 |
| Multi_Airport (Reference is Single-Single) | | | | | | | | |
| Multi-Single          | 0.377 | 0.150 | 2.51 | 0.012 ** | 0.157 | 0.085 | 1.84 | 0.065 * |
| Multi-Multi           | 0.952 | 0.234 | 4.08 | 0.000 *** | 0.524 | 0.133 | 3.95 | 0.000 *** |
| Bus_Sea               | –1.499 | 0.288 | –5.19 | 0.000 *** | –0.209 | 0.135 | –1.54 | 0.123 |
| ln(Pt_Freq)           | –1.389 | 0.109 | –12.72 | 0.000 *** | –2.056 | 0.093 | –22.21 | 0.000 *** |
| ln(PRASM)             | 1.381 | 0.307 | 4.49 | 0.000 *** | –0.201 | 0.215 | –0.93 | 0.350 |
| ln(PRASM)²            | 1.089 | 0.092 | 11.87 | 0.000 *** | 0.191 | 0.071 | 2.68 | 0.007 *** |
| ln(NumMkt_ArrAirport) ¹ | –0.280 | 0.270 | –1.04 | 0.300 | 1.264 | 0.143 | 8.85 | 0.000 *** |
| ln(NumMkt_ArrAirport) ² | –0.040 | 0.049 | –0.81 | 0.417 | –0.386 | 0.026 | –15.04 | 0.000 *** |
| ln(NumMkt_DepAirport) ¹ | –0.160 | 0.280 | –0.57 | 0.567 | 1.319 | 0.140 | 9.41 | 0.000 *** |
| ln(NumMkt_DepAirport) ² | –0.064 | 0.051 | –1.26 | 0.208 | –0.392 | 0.026 | –15.36 | 0.000 *** |
| LCC                   | 0.542 | 0.215 | 2.52 | 0.012 ** | –0.101 | 0.112 | –0.90 | 0.368 |
| Network               | 0.857 | 0.260 | 3.30 | 0.001 *** | 0.411 | 0.141 | 2.91 | 0.004 *** |
| Codeshare             | –0.084 | 0.181 | –0.46 | 0.642 | –0.383 | 0.115 | –3.34 | 0.001 *** |
| MktShare_Airline (Reference is < 0.3) | | | | | | | | |
| >0.3 and < 0.5        | 0.743 | 0.208 | 3.58 | 0.000 *** | 0.110 | 0.129 | 0.85 | 0.395 |
| >–0.5 and < 1.0       | –0.068 | 0.320 | –0.21 | 0.831 | 0.171 | 0.146 | 1.17 | 0.243 |
| –1.0 (monopoly)       | 1.342 | 0.349 | 3.84 | 0.000 *** | 0.478 | 0.212 | 2.25 | 0.024 ** |
| MktShare_ArrAirport   | –3.245 | 1.345 | –2.41 | 0.016 ** | 3.617 | 0.647 | 5.59 | 0.000 *** |
| MktShare_ArrAirport²  | 2.661 | 1.228 | 2.17 | 0.030 ** | –3.855 | 0.597 | –6.46 | 0.000 *** |
| MktShare_DepAirport   | –3.295 | 1.315 | –2.51 | 0.012 ** | 3.410 | 0.648 | 5.26 | 0.000 *** |
| MktShare_DepAirport²  | 2.742 | 1.207 | 2.27 | 0.023 ** | –3.679 | 0.597 | –6.17 | 0.000 *** |
| Airline (Reference is American) | | | | | | | | |
| Alaska                | –0.141 | 0.384 | –0.37 | 0.713 | –1.501 | 0.199 | –7.55 | 0.000 *** |
| Allegiant             | –6.035 | 0.511 | –11.80 | 0.000 *** | –7.687 | 0.340 | –22.63 | 0.000 *** |
| Delta                 | 0.518 | 0.308 | 1.68 | 0.093 * | 1.606 | 0.140 | 11.50 | 0.000 *** |
| Frontier              | –5.323 | 0.562 | –9.47 | 0.000 *** | –3.504 | 0.341 | –10.28 | 0.000 *** |
| JetBlue               | –1.906 | 0.407 | –4.05 | 0.000 *** | –1.558 | 0.242 | –6.44 | 0.000 *** |
| Southwest             | –1.709 | 0.406 | –4.21 | 0.000 *** | –1.628 | 0.178 | –9.16 | 0.000 *** |
| Spirit                | –4.929 | 0.545 | –9.04 | 0.000 *** | –1.476 | 0.299 | –4.93 | 0.000 *** |
| United                | 0.844 | 0.282 | 2.99 | 0.003 *** | 1.279 | 0.125 | 10.24 | 0.000 *** |

Number of Observations 14,924
Log Likelihood –3,847.9
Pseudo R² 0.534

SE = Cluster robust standard errors.
* Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

![Fig. 1. Predicted Probabilities and Marginal Effects for Airport Number of Markets.](image-url)
The variables NumMkts_ArrAirport and NumMkts_DepAirport measure arrival and departure airport size in terms of the total number of markets that an airline operates at the airport. Table 4 shows that before the shock event, these variables are insignificant and have no impact on the probability of exit. However, after the shock event, the variables are significant for their main effects, as well as for their squared terms. To interpret the trend, Fig. 1 provides plots of the predicted probability of exit per time period (left chart) and marginal effects (right chart) for NumMkts_DepAirport as calculated from the model (results for NumMkts_ArrAirport are similar). First, looking at the left chart in Fig. 1, the relationship between NumMkts_DepAirport (x-axis) and predicted probability of exit (y-axis) is shown. Since the variable is included as a log transformed explanatory variable in the model, the x-axis also includes in parentheses values of the variable in original scale for ease of interpretation. Separate lines are displayed per time period, and shaded areas represent 95% confidence intervals. The two lines will be parallel if there is not a significant interaction between time period and the explanatory variable (Stata, 2021). Since the shape of the two trendlines differ, the effect of the explanatory variable on the probability of exit is different in each time period, demonstrating how airlines changed their decision-making process after the pandemic.

The solid line in the left chart in Fig. 1 shows that before the shock event, airline markets with departure airports that have the smallest number of markets (1 market) have an average predicted exit probability of 0.11 whereas those with the largest number of markets (148 markets) have a predicted probability of 0.02. The trendline decreases linearly as the number of markets out of a departure airport increases, but these differences are not significant since the coefficient estimates in the model are insignificant. Looking at the time period after the shock event tells a different story. The dashed line shows that airline markets with departure airports that have the smallest number of markets have an average predicted exit probability of 0.47. The trendline is non-linear with a probability of exit that increases as number of markets increases, but then begins to decrease, where those airline markets with departure airports that have the largest number of markets have a 0.13 probability of exit. These differences are significant based on the coefficient estimates in the model. It is noteworthy that as the number of markets increases, the two trendlines are closer together. This can be better seen in the right chart in Fig. 1 that displays marginal effects, which are the differences in average predicted probability after the shock event as compared to before the shock event for each value on the x-axis. Marginal effects that differ from zero, indicated by confidence intervals that do not touch the red reference line at zero, represent significant differences between the two time periods (Stata, 2021). The probability of exit after the shock event is significantly higher than before the shock event across all values of the explanatory variable. However, the curved trendline shows that some marginal effects are larger than others. The marginal effect of airline markets with departure airports that have the smallest number of markets is 0.36, whereas the marginal effect for departure airports with the largest number of markets is 0.11. The highest marginal effect of 0.53 is for those departure airports towards the middle of the chart with 7 markets. This demonstrates how the shock event impacted some airline markets more than others.

Explanatory variables significant during both time periods

Several variables remain significant in both time periods. Flt_Freq is the number of monthly flights the airline schedules in a market. It is significant and negative in both time periods indicating that it remained an important factor in airline’s decisions to exit markets both before and after the shock event. Airlines are less likely to exit markets where they offer higher flight frequencies. To interpret the trend, plots of predicted probabilities of exit and marginal effects are shown in Fig. 2. Before the shock event, markets with the lowest monthly flight frequency (4 flights) have an average predicted exit probability of 0.34 and the trendline shows that the probability of exit quickly drops as flight frequency increases. Looking at the trendline for the time period after the shock event shows that markets with the lowest monthly flight frequency (4 flights) have a very high probability of exit, with an average predicted exit probability of 0.93. The probability of exit for markets with the highest flight frequency (493 flights) is 0.002 before the shock event as compared to 0.03 after the shock event. The right chart in Fig. 2 displays the marginal effects. The probability of exit after the shock event is significantly higher than before the shock event across all flight frequencies. However, as the flight frequency increases, there is a smaller difference between the two time periods; the shock event impacted those markets with the lowest flight frequencies less than other markets.

PRASM, the passenger revenue per available seat mile, is another variable that remains significant in both time periods. However, the signs of the estimated coefficients change. Fig. 3 provides plots of predicted probabilities of exit and marginal effects. Perhaps one of the most interesting aspects uncovered is that markets with the lowest PRASM ($0.044 or less) are not significantly different before and after the pandemic. This can be seen in the right chart where confidence intervals touch the red reference line at zero. Airport managers should be aware that any of their markets with very low PRASM have a high probability of being exited, regardless of whether there is a shock event or not. On the other hand, the trendlines show that before the shock event, markets with high PRASM have an extremely low probability of being exited. Any markets with PRASM greater than $0.29 have an exit probability<0.02, which is intuitive as these are the most profitable markets.
for airlines to operate. However, after the shock event the probability is much higher. Even the most profitable markets with PRASM of $1.28 have a 0.30 predicted probability of exit after the shock event. During a large shock event such as the COVID-19 pandemic, even the most profitable markets are at risk of being exited.

The model results in Table 4 for Multi_Airport indicate that markets with one or both airports located within multi-airport cities are more likely to be exited than markets between two airports that are not located within multi-airport cities; this trend is also the same for both time periods. The post-pandemic finding agrees with results previously found by Hotle and Mumbower (2021) in a study on the early impacts of the COVID-19 pandemic. However, this study extends the findings of Hotle and Mumbower (2021) by showing that this relationship was also present during the time period before the pandemic, when airlines were operating under normal conditions. The minimum service obligations of the CARES Act allowed airlines to consolidate their operations to one airport within a multi-airport city, rather than requiring that they continue serving all airports within a multi-airport city that they served pre-pandemic. It is interesting to see that although markets out of multi-city airports were more likely to be exited after the shock event, these markets were also more likely to be exited before the shock event.

Lastly, the results of the market share variables are discussed. The variable MktShare_Airline indicates an airline’s market-level share of total scheduled flights in a market. The results show that airlines are more likely to exit markets where they have a monopoly, as compared to their more competitive markets where other airlines also offer flights. This is true both before and after the shock event. Airport managers should be aware that monopoly markets with service from only one airline are more at-risk of losing service. Although it may initially seem counterintuitive that airlines would exit their markets where they face no competition, this trend for monopoly markets was also found in de Wit and Zuidberg (2016) and Atallah and Hotle (2019). When compared to other more competitive markets, monopoly markets are lower-density markets with a smaller number of flights and passengers. These markets are more vulnerable to market conditions and demand fluctuations, so they are exited more often (de Wit and Zuidberg, 2016).

The other market share variables MktShare_ArrAirport and MktShare_DepAirport indicate an airline’s airport-level market share, which is their portion of all arrival and departure flights at an airport. The variables remain significant in both time periods, but the signs of the estimated coefficients change. Fig. 4 provides plots of predicted probabilities of exit and marginal effects. Results for before the pandemic show that markets where an airline has the lowest and highest airport market shares are the most likely to be exited. Again, this trend is in line with what de Wit and Zuidberg (2016) previously found. However, after the pandemic, it is surprising to see that these same markets are the least likely to be exited, especially for markets operated out of monopoly airports (airports where all flights are marketed by only one airline) which have the lowest probability of exit. All monopoly airports in the dataset used for this study are small hub or non-hub airports, whereas all medium and large hub airports in the dataset have two or more airlines that operate out of the airport. Understanding why market exit after the shock event is lower out of these smaller airports is not immediately intuitive. However, it can be explained within the context of the minimum service obligations of the CARES Act, which led to the smallest airports being impacted by the pandemic less than other...
airports. The next section investigates this further and discusses market exit as a function of airport size.

**Predicted probability of exit by airport size**

The model is also used to look at the average predicted probability of exit across airports of different sizes, using the FAA commercial airport size categories (Federal Aviation Administration (FAA), 2021). The predicted probability of exit during each time period is calculated per airline market using the estimated model in Table 4, and then an average airport-level probability of exit is calculated by averaging across airline markets for each airport. Afterwards, an average predicted probability is calculated across airports within each size category, along with standard deviation and coefficient of variation. The results are displayed in Table 5 for the 276 commercial airports within the dataset.

The overall probability of exit is found to increase from 0.05 before the pandemic to 0.42 after. Before the shock event, the average probability of exit for airports of different sizes ranges from 0.05 to 0.07, a difference that is not significant. However, after the shock event, the smallest airports (non-hubs) have the lowest predicted probability of exit (0.24) and are significantly less likely to be exited than the larger hub airports, including large, medium, and small hub airports (which have average exit probabilities of 0.44, 0.49, and 0.41 respectively). It is also interesting to see that the coefficient of variation is largest for non-hub airports, and that is true both before and after the pandemic. This highlights the large variation in market exits across non-hub airports, where some airports are impacted by exits much more than others. These general trends agree with what was found in studies that measured the early impacts of the pandemic on U.S. air travel (Fuellhart et al., 2021; Hote & Mumbower, 2021).

It is particularly interesting to see that the smallest airports are found to be impacted by the pandemic less than other airports. Past research has shown that the smallest airports are often the first to be impacted by service reductions in response to shock events (Spitz et al., 2015). However, Table 5 shows that after the pandemic, the average predicted probability of exit is 1.8 to 2.2 times higher for the larger hub airports as compared to the small non-hub airports. This trend can be explained by the CARES Act minimum service obligations, which required that airlines continue servicing all cities that they served pre-pandemic, but allowed them to reduce flight frequencies out of larger airports more than smaller airports. As an example, the U.S. Department of Transportation (U.S. DOT) (2020a) shows that before the pandemic Delta Air Lines scheduled 362 flights per week out of Orlando, Florida, which is served by the non-hub Orlando International Airport (MLB). At the same time, Delta scheduled 1,248 flights per week out of Orlando, Florida, which is served by the large-hub Orlando International Airport (MCO). The minimum service obligations of the CARES Act required that Delta continue operating at least 5 flights per week for each of these cities. Stated another way, Delta had to maintain at least $5/28 = 17.9\%$ of their flight operations out of the non-hub airport and $5/362 = 1.4\%$ of the large-hub airport. It was up to Delta to decide how to distribute the required number of flights across the markets it served out of each city. Before the pandemic, Delta operated 2 nonstop markets out of MLB and 24 out of MCO. After the pandemic, Delta exited none of the MLB markets and 75% of the MCO markets. Although flight frequency is not exactly the same as number of markets, these differences do demonstrate that non-hub airports had significantly fewer markets pre-pandemic, and airlines needed to keep operating in most of those markets to meet their minimum service obligations.

**Predicted probability of exit by airline**

The model is also used to investigate exit behavior across airlines in this study. For each time period, the predicted probability of exit is calculated per airline market using the model in Table 4. Afterwards, the average predicted probability is calculated per airline. The results are displayed in Table 6 for the nine airlines in this study. Results are sorted by largest difference between predictions in the two time periods. It is noteworthy that ULCC Spirit Airline’s average exit probability is 0.06 before the shock and event and 0.82 afterwards, an absolute difference of 0.76, which is much larger than any of the other airlines in this study. Airport managers should be aware that during a shock event, markets served by Spirit are at high risk of being exited.

On the other hand, ULCC Allegiant Air’s average exit probability before the shock event is 0.09 and only increases to 0.15 after the shock event, a difference of 0.06 which is the lowest out of all airlines in this study. Initially, this is a surprising finding. ULCCs are generally

| Airport Size       | Number Airports | Before Shock Event | After Shock Event | PredExit Difference |
|--------------------|-----------------|-------------------|------------------|---------------------|
|                    | PredExit StdDev CV | N                | PredExit StdDev CV | N                |
| Large Hub          | 29              | 0.05 0.02 0.47    | 4,062            | 0.44 0.14 0.31    | 4,167 0.40 |
| Med Hub            | 28              | 0.06 0.04 0.57    | 1,474            | 0.49 0.10 0.20    | 1,512 0.43 |
| Small Hub          | 63              | 0.06 0.05 0.83    | 1,217            | 0.41 0.15 0.37    | 1,301 0.35 |
| Non-Hub            | 156             | 0.07 0.09 1.33    | 579              | 0.24 0.22 0.92    | 612 0.17 |
| All Airports       | 276             | 0.06 0.07 1.16    | 7,332            | 0.32 0.21 0.66    | 7,592 0.26 |

**Predicted Exit Probabilities, by Airline and Time Period.**

| Airline    | Before Shock Event | After Shock Event | PredExit Difference |
|------------|--------------------|-------------------|---------------------|
|            | PredExit N         | PredExit N        |                     |
| Spirit     | 0.06 372           | 0.82 426          | 0.76                |
| JetBlue    | 0.07 320           | 0.55 310          | 0.48                |
| Delta      | 0.02 1,248         | 0.49 1,262        | 0.47                |
| Frontier   | 0.21 486           | 0.64 562          | 0.43                |
| Southwest  | 0.03 1,310         | 0.42 1,342        | 0.38                |
| United     | 0.05 1,118         | 0.40 1,136        | 0.35                |
| Alaska     | 0.10 386           | 0.44 358          | 0.34                |
| American   | 0.02 1,428         | 0.29 1,516        | 0.27                |
| Allegiant  | 0.09 664           | 0.15 680          | 0.06                |
| All Airlines | 0.05 7,332     | 0.42 7,592        | 0.37                |

**PredExit** = Average predicted probability of exit per airline. Probability of exit is calculated for each airline market using observed values of explanatory variables and then averaged for each airline. 
**PredExit Difference** = PredExit after shock event – PredExit before shock event. 
**N** = Number of airline markets.

Airlines are sorted by PredExit Difference, descending.

<sup>Table 5 Predicted exit probabilities across airports, by airport size and time period.</sup>
considered to be unstable in the services that they offer with frequent market entry and exit (Button, 2012). After the Great Recession of 2008, those markets served by Allegiant are found to be more at risk of losing service than other markets (Atallah and Hotle, 2019). Investigating this issue further uncovered a letter written to the U.S. Department of Transportation (DOT) by Allegiant. The airline stated that the minimum service obligations of the CARES Act required them “to operate a much higher proportion of its normal schedule” as compared to other carriers; according to the airline, they were required to maintain a schedule that was 6.9 times higher than the schedule of Southwest Airlines, 4.6 times higher than American, and 4.1 times higher than Delta (U.S. Department of Transportation (U.S. DOT), 2020c). The airline noted that this large difference was due to their point-to-point network structure, low weekly flight frequencies, and focus on small to medium sized markets. Looking at the pre-pandemic data used in this study, the majority (72.4%) of Allegiant’s markets are to non-hub and small hub destination airports, whereas only 12.9% are to large hubs. Spirit’s markets are quite opposite, with a majority (71.4%) of markets to large hub destination airports and only 10.1% to non-hub and small hub airports. With the CARES Act minimum service obligations in place, Allegiant’s network of smaller airports appears to have limited its ability to reduce its flight operations and exit markets in response to the pandemic. A lesson learned for policymakers is that the regulations attached to the government financial aid had non-uniform impacts on airlines. For any future shock events that require minimum service obligations in exchange for financial aid, a formula that considers an airline’s entire network may be more appropriate than one that only considers individual cities served.

Model specification, robustness, and limitations

A likelihood ratio test was used to determine whether the model in Table 4 has a better fit than a pooled model without time-specific parameters. The value of the likelihood ratio test (LRT) is \(-2 \times (\text{LL}_{\text{pooled}} - \text{LL}_{\text{time-specific}}) \approx 802.6\). Using a chi-squared distribution with 31 degrees of freedom (df), the difference in the number of parameters between the models, gives a p-value<0.001. This indicates that the model with time-specific parameters has the better fit. Likelihood ratio tests were also used to test whether variables could be left out of the model. All variables in Table 4 are significant in at least one of the time periods and should be included in the model. It is worth noting that the codeshare variable in the model indicates markets where U.S. airlines codeshare with international airlines. A similar variable that indicates markets where U.S. airlines codeshare with other U.S. airlines was left out of the model, as this additional codeshare variable was insignificant in both time periods and did not improve model fit (LRT = 0.14 df = 1, p-value = 0.708).

Several checks for robustness of model results were also conducted. Markets in this paper are defined as directional airport pairs. To check for robustness of this assumption, models were also estimated for a non-directional definition of market (for example, by defining ATL to LAS and reverse direction LAS to ATL as the same market rather than two markets). The directional market definition has the advantage of allowing the explanatory variables to vary in each direction, which could be important for variables such as market share and PRASM, and also allows the model to estimate exits in each direction separately. Interestingly, before the pandemic, all of the market exits are observed to be symmetric, where an airline always exits both directions. After the pandemic, some airlines exited only one direction of a two-way directional market, and this type of exit made up 3.3% of total exits observed during the time period. After running the model with a non-directional market definition, coefficient estimates and significance for nearly all results were found to be robust and interpretation of main results did not change. The single result not robust to the market definition is one category of the multi-airport indicator variable (the category representing airline markets between a multi-airport city and a single-airport city), which had similar coefficient estimates but was no longer significant in either time period. The other category of this variable representing airline markets between two multi-airport cities had similar coefficient estimates and remained significant.

Additionally, the estimated model was compared to alternative models that estimated the continuous variables differently, such as excluding squared terms and transforming the continuous variables into categorical variables. The continuous variables in the estimated model that have a squared term included were found to result in significantly better model fit over alternative models. This is not surprising as nonlinear relationships have been found in past literature on market exit and were also noted as part of exploratory analysis. The tradeoff is that the more complex models are also harder to interpret. However, the charts of predicted probabilities and marginal effects used in this paper are useful in better understanding the complex relationships.

There are a few limitations of this study that provide opportunities for future improvements and analysis. As was discussed previously, the comprehensive OAG flight schedules data used in this study is not freely available. Because the data must be purchased, limited time periods were available for analysis. If available, OAG data for May 2021 could be used in a follow-up analysis to determine which of the markets exited during the peak of the pandemic were eventually reentered and which ones were not. On the other hand, utilizing the paid OAG flight schedules data is also a strength of this study since the data include identifying information for both marketing and operating airlines. As described in more detail previously, the publicly available government datasets known as T-100 have a major limitation in that they are missing identifying information for the marketing airlines. The CARES Act minimum service obligations were given to marketing carriers rather than operating carriers (U.S. Department of Transportation (U.S. DOT), 2020a). Therefore, it was the marketing carrier who was the decision-maker in any market exit decisions. In fact, the CARES Act minimum service obligations were created by the U.S. DOT using schedules data acquired from OAG for marketing carriers (U.S. Department of Transportation (U.S. DOT, 2020a). An additional strength is that the specific months of data used in this study are ideal for analyzing the time period immediately after the CARES Act minimum service obligations were implemented, which allows a better understanding of how federal policies associated with the CARES Act impacted airline market exit decisions. Although load factors and prices are missing from the OAG data, this information was merged into the OAG data using government datasets. A high percentage of matches (99.6%) were achieved between OAG data and DB1B data because this study excluded the smallest airlines (with<70 nonstop markets) and smallest airports (commercial non-primary airports). DB1B data is known to be incomplete for the smallest markets (Teixeira & Derudder, 2020). A future analysis could further investigate the small markets left out of this study but would need to develop a methodology to account for the missing data. Even with this limitation, the analysis dataset in this study represents a large majority (93.9%) of all commercial air traffic in the domestic U.S. Another limitation is that it is possible some of the exits observed during the shock event could have been planned exits that would have been implemented even if the shock had not happened. However, it is impossible to observe this type of decision with the data available. An airline that is privy to their own advanced schedules could incorporate this into the model methodology. Lastly, although the model includes many explanatory variables, there could be additional variables (or alternative forms of variables) that could be investigated in the future. For example, de Wit and van der Ploeg (2016) found that smaller markets that have been operated longer are less likely to be exited. However, due to the limited data available, this was not able to be incorporated into the model but could be an interesting avenue of future research.

Conclusions and future research

To summarize, this research found several key ways that airlines’ market exit decisions differ during normal operating conditions (before
the pandemic) as compared to a major shock event (after the beginning of the pandemic). While the overall probability of exit increased from 0.05 before the pandemic to 0.42 after, the results vary widely across markets, airports, and airlines. Low passenger revenue per available seat mile, low flight frequencies, multi-airport cities, competition from network carriers, and monopoly markets were found to be associated with a high probability of market exit both before and after the pandemic. Other factors were found to impact airlines’ market exit decisions in only one time period. During normal operating conditions, longer distance flights and markets with first class and/or business seats were less likely to exit than other markets. However, no impact on exit was found for these variables after the pandemic. During normal operating conditions, airport size and presence of codeshares with international airlines did not impact market exit. However, after the pandemic, non-hub airports and codeshare markets were significantly less likely to be exited than other markets. These results demonstrate how airline decision-making shifted in response to the pandemic and can be used by airport managers and policymakers to better understand how at-risk airports are of losing service during a large shock event.

Interestingly, some airlines were shown to exit a larger portion of markets in response to the pandemic than other airlines. Markets serviced by Spirit were most at-risk of exit after the pandemic, whereas markets serviced by Allegiant were least at-risk of exit. With the CARES Act minimum service obligations in place, Allegiant’s network of smaller airports appears to have limited its ability to reduce its flight operations and exit markets in response to the pandemic. A lesson learned for policymakers is that the regulations attached to the government financial aid had non-uniform impacts on airlines and the airports that they service.

Although this study focused on domestic U.S. markets, the same modeling methodology can be used to study the impact of the COVID-19 pandemic on airlines’ market exit decisions for domestic markets of other countries. Also, it would be informative to study international markets in the future as international travel restrictions are lifted and international travel recovers. Governments’ support to their national airlines in response to the pandemic have varied widely and could lead to imbalances in air transport connectivity at an international level. Quantifying this change could lead to insights for international policies on financial support during large shock events, a topic that would be of interest to policymakers worldwide.

It will likely be many years until the full impacts of the pandemic on air travel networks are understood. The results presented in this study serve as a first step in documenting airline market exit decisions in response to the COVID-19 pandemic. As more data is collected, there is an opportunity to analyze the impacts of federal polices associated with the CARES Act over a longer period, which could lead to insights that help policymakers better design policies for future shock events. The minimum service obligations expired on September 31, 2021. This provides an opportunity to study market exit during a recovery period when the minimum service obligations are no longer in place. The 9/11 terrorist attacks triggered a vast restructuring of the U.S. domestic air travel network (Sziosz-Rousoulis et al., 2021) and it is likely that the pandemic will do the same. As airlines alter their networks, it will be important to assess how airports are impacted. Some of the smallest airports may lose all commercial air service, as happened after the Great Recession. Wittman and Swelbar (2013b) previously developed a taxonomy for identifying small airports at risk of future service loss, and it would be helpful to upsample that research to account for industry conditions that have changed due to the pandemic. A metric called the Airport Connectivity Quality Index (ACQ) was also created to assess an airport’s connection to the global air transportation system (Wittman and Swelbar, 2013a). Updating that research could lead to insights about how connectivity scores have changed over time for airports of different sizes, such as the small non-hub airports as compared to the larger hub airports. Additionally, although none of the U.S. airlines included in this study merged or ceased operations during the analysis timeframe, it is possible that airline consolidation could impact airports in the future as the industry continues to recover from the pandemic.

Future research on airline consolidation and its impacts would add to the literature on firm exit after a shock event. Similarly, assessing how the air travel network may be impacted by airline competition and cooperation (such as alliances and revenue-sharing joint ventures) would also be a fruitful area of future research (Biloktach & Hüsselrath, 2019).

Future research could also study airline entry into new markets post-pandemic, which could help airport managers and policymakers better understand market characteristics that attract the interest of airlines (Calzada & Fageda, 2019). In order to retain and build new service, many airport sponsors provide incentive packages to airlines, such as airport facility fee waivers and marketing assistance (Ryerson, 2016; Rex et al., 2022). Route development activity and incentives are known to vary widely across airports, with some airports participating more than others (Halpern & Graham, 2015; Rex et al., 2022). However, data on air service incentives are not systematically collected and made available, which has limited research in this area. Recently, Rex et al. (2022) compiled a database of air service incentive agreements using 2017 data and made it available publicly. It would be informative to update this database and determine how the pandemic has impacted air service incentives.

Lastly, as the air transportation network evolves during the recovery period post-pandemic, it will be important to quantify how alternative forms of transportation are impacted by these changes. For example, if small airports lose much of their commercial service, passengers may increase their preference to drive to larger airports that are further away (known as “leakage”) which results in increased automobile traffic on roads (National Academies of Sciences, Engineering, and Medicine (NASEM), 2019). Similarly, it is unclear how travel behavior will change long-term after the pandemic is over. Transportation research has already documented a shift in travel behavior due to the infectious nature of COVID-19, where people viewed shared modes of travel as riskier than individual modes of travel, such as driving alone (Shamshiripour et al., 2020; Ozbilen et al. 2021). It would be interesting to study whether this shift in travel behavior persists after the pandemic is over, as well as quantifying its impact on demand for various travel modes, such as air travel demand and automobile traffic.

CRediT authorship contribution statement

Stacey Mumbower: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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13
