Capacity Disruptions and Pricing: Evidence from US Airlines

Anantha Divakaruni* Paula Navarro†

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Abstract

We study how capacity shocks to firms' technology adoption impact input costs and consumer prices, focusing on the sudden grounding of the fuel-efficient Boeing 737 MAX. Using novel data on US carrier fleets and flights, we apply a difference-in-differences design to reveal that the largest MAX operator, Southwest, increased average economy fares by 1.7% ($4.12) following the grounding. These fare hikes were mainly in the short-term and with the greatest impact in the middle to top fare brackets. Capacity disruptions led to the use of less fuel-efficienct aircraft to sustain operations, raising per-passenger fuel costs that were fully passed through to fares with substantial heterogeneity. These operational changes led to a rise in the carbon footprint of the impacted carriers. Our findings illustrate the transformative impact of technology on consumer prices, emphasizing its vital role in shaping a more sustainable future for air travel.

JEL classification: L11, L13, L93

Keywords: Pricing, Airlines, Fuel Costs, Pass-Through, Competition, Emissions

*Dept of Economics, University of Bergen, Bergen, Norway. e-mail: anantha.divakaruni@uib.no

†Dept of Economics, Norwegian School of Economics, Bergen, Norway. e-mail: paula.navarro@nhh.no

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I Introduction

There are several high-stakes settings in which firms actively adopt innovative technologies to reduce costs, boost productivity, tap new business opportunities, gain competitive edge, and meet the rising demand for environmentally sustainable products. One such important setting is the airline industry, where carriers consistently invest in state-of-the-art aircraft to address two important challenges: (i) reduce operating costs, and, (ii) minimize emissions from jet fuel combustion to address the growing call for environmental sustainability.[1]

Central to navigating these two complex challenges is the concept of aircraft fuel efficiency, which has been the longstanding focus of technological innovation in aviation. Aircraft fuel efficiency comprises a wide spectrum of innovations in engine efficiency, aircraft design, and operational practices. These innovations have the potential to exert substantive influence on ticket pricing decisions by virtue of their impact on carrier marginal costs and consequently impact consumer welfare. Since fuel constitutes up to a third of a carrier's operating expenses (Csereklyei and Stern, 2020; Kahn and Nickelsburg, 2016), even small improvements in fuel efficiency can yield substantial cost savings for carriers. However, little is known about whether these cost savings are passed on to passengers in the form of reduced ticket fares or reinvested to boost carrier profitability and competitiveness. Correspondingly, there is very limited evidence on how improvements in fuel efficiency have impacted the carbon footprint of carriers. Understanding the implications of aircraft fuel efficiency thus holds significance both from economic and environmental standpoints.

Our study investigates these questions by capitalizing on a unique and asymmetric capacity disruption to carriers operating in domestic airline markets in the United States (US). Specifically, we exploit the unexpected grounding of Boeing 737 MAX aircraft (henceforth MAX) by the US Federal Aviation Administration (FAA) in March 2019 as a natural experiment.[2]

[1] The airline industry plays a crucial role in global transportation, having carried more than 4.5 billion passengers in 2019 alone (IATA, 2020). Carriers collectively consumed 86 billion gallons of fuel annually on average between 2010 and 2019, constituting 11% of global CO_2 emissions from transportation during this period (BTS, 2020; Jaramillo et al., 2022; Kwan and Rutherford, 2015). Although the airline industry contributes only 2.5% of global CO_2 emissions, emissions from jet fuel combustion during flight at high altitudes tend to have double the impact on global warming compared to jet fuel emissions of similar magnitude at the ground level (Lee, Lukachko, and Waitz, 2004). Cost reduction strategies are important to be able to serve price-sensitive travellers, who typically fall under the *economy* class, featuring standard seating and service offerings during flight. Additionally, many carriers also offer premium quality seats with enhanced comfort and service at higher fares, targeting travelers with a greater willingness to pay.

[2] Other noteworthy examples of unforeseen disruptions to supply-side capacity that had significant economic repercussions are the Suez Canal blockage in 2021 and the Ukraine-Russia war that began in early 2022. The Suez Canal is a vital trade route linking Europe and Asia, handling about 12% of global trade. The canal was obstructed briefly in March 2021 by the Ever Given container ship, which caused an estimated \$54 billion in trade losses and raised the prices of essential commodities such as crude oil and gas due to concerns over prolonged blockage (Fitch, 2021). Similarly, the military conflict between Ukraine and Russia has severely impacted global energy and commodities markets. Crude oil prices have surged by over 52%,

This unprecedented grounding marked the first-ever nationwide ban on the operation of an aircraft model, profoundly impacting the US airline industry for three key reasons. First, the MAX, which made its commercial debut in 2017, stands out among peer aircraft models with its groundbreaking innovations in engine efficiency, aerodynamics, and the use of lighter materials in aircraft construction. Boeing claimed that these innovations enable the MAX to achieve between 14%-32% reduction in fuel consumption compared to legacy aircraft models of similar size such as the Boeing 737 and Airbus 320 (Boeing, 2024). Consequently, the MAX emerged as a prime contender to replace these legacy aircraft, gaining significant popularity among carriers with nearly 4,400 orders placed for it by end-2017 (Boeing, 2023). Second, the grounding was completely unexpected, stemming from two tragic accidents involving MAX aircraft within a relatively short timeframe.[3] Experiencing two deadly crashes so close together in time was highly unprecedented for a new aircraft model, developed by a leading manufacturer such as Boeing and certified to fly after extensive testing. Third, the grounding had an asymmetric impact on US carriers, mainly affecting those that had already begun integrating the MAX into their fleets (Southwest, American, and United).

Past research examining pricing trends in the airline industry has considered factors like market-level traffic and passenger statistics available publicly via the US Department of Transportation (DoT) (Borenstein and Rose, 1994; Brueckner, Dyer, and Spiller, 1992; Dai, Liu, and Serfes, 2014; Gerardi and Shapiro, 2009; Gualdani, Bontemps, and Remmy, 2023). However, information contained in the DoT databases, such as the T-100 Domestic Segment, are self-reported by carriers to the DoT's Office of Airline Information, possibly resulting in incomplete or missing data due to inconsistent reporting practices by carriers.[4] Furthermore, without access to real-time flight information, measuring aircraft utilization along the intensive and extensive margins, which collectively influence aggregate jet fuel consumption and carbon dioxide (CO_2) emissions, becomes exceedingly challenging.[5]

wheat prices by 68%, and fertilizer prices more than doubled since the conflict began (Arndt et al., 2023; Zhang et al., 2024).

[3]The FAA refrained from grounding the MAX following the first crash involving Lion Air Flight JT610 on October 29, 2018. However, following the second crash involving Ethiopian Airlines flight ET302, The MAX aircraft model was banned from flying in all countries where it operated. The US, through the FAA, was among the last to enact the ban on the MAX on March 13, 2019 (Herkert, Borenstein, and Miller, 2020).

[4]Surprisingly, the T-100 not does not document any flight activity involving MAX aircraft, despite their integration into US carrier services since mid-2017 — a critical requirement for our study.

[5]A flight comprises two distinct phases: Landing/Take-Off (LTO) and Climb/Cruise/Descent (CCD). Jet fuel emissions during the LTO phase primarily impact local air quality around airports, whereas fuel emissions during CCD have broader regional and even global effects, contributing to climate change (Liao et al., 2021). A contemporaneous study by Forbes and Park (2024) leverages the DoT's Airline On-Time Performance (OTP) data to quantify the emissions impact of the MAX grounding on US carriers during the LTO phase (when the aircraft is idle, taxiing, taking-off, or landing). Alternatively, our CO_2 emission estimates related to the MAX grounding are based on fuel consumption rates during the CCD phase, which is known to contribute up to 85% of an aircraft's CO_2 emissions during flight (Liao et al., 2021, p.7).

We overcome these challenges by constructing a novel, comprehensive dataset on the domestic flight activity of every aircraft operated by US carriers between 2017 and 2019. These flights are tracked from mandatory real-time communications between the aircraft and ground control, and are thus largely free of measurement errors and self-reporting bias. We also know each aircraft's model, seating capacity, and fuel consumption rate among other details. For simplicity, each aircraft is classified into one of six primary aircraft types.[6]

For estimation, it is important to note that the panel data on ticket fares required for our analysis is available publicly only on a quarterly basis. We therefore aggregate information on individual flights in our sample by carrier, market (unidirectional origin-destination airport pairs), and aircraft type at a quarterly level. This approach enables us to compute the total number of flights and flight hours for each individual aircraft type operated by carriers within their respective markets for every quarter in our sample period. Subsequently, we merge these aggregated flight metrics with quarterly ticket fares per carrier-market and other market-level attributes sourced from the publicly accessible DB1B and T-100 Domestic Segment databases, respectively. Given that a carrier may charge and report multiple fares for the same flight within a quarter, we use both the average fare and various percentiles from these fare distributions as our primary outcome measures of prices.

Since the MAX grounding was completely unexpected and the reasons for enforcing it are plausibly exogenous to ticket fares or aircraft emissions, we employ a difference-in-differences (DiD) design to investigate whether the grounding had an impact on both ticket fares and aircraft CO_2 emissions. Specifically, we compare quarterly fare outcomes in carrier-markets where the MAX was operational before the grounding (our *treatment* group) with similar carrier-markets where this aircraft type had never been used (our *control* group). Our analysis focuses exclusively on economy class fares, as the carrier that was most affected by the grounding (Southwest) offers only economy class seats.

Our analysis reveals that, on average, 11% of all pre-grounding flights in treated carrier-markets were operated using the MAX. Following the grounding, average fares in treated carrier-markets increased by approximately $1.85 compared to average fares in control carrier-markets, representing a 0.9% increase relative to average fares in the control group before the grounding.[7] However, among the three carriers flying the MAX before its grounding,

[6]We classify each aircraft in our sample into one of three broad categories: $Large$, $Narrow-body$, and $Small$ based on commonalities in costs, flying range, and seating capacity. Within the $Narrow-body$ category, we further subdivide aircraft into four types: $Boeing$ 737, $Boeing$ 737 MAX, $Airbus$ 320, and $Airbus$ 320 NEO. Overall, this classification results in a total of six major aircraft types in our sample.

[7]This result suggests that, *ceteris paribus*, in a scenario where all pre-grounding flights in the treated group were operated using the MAX (i.e., at *full* treatment intensity), the increase in average fares in treated carrier-markets post-grounding would have been at least $16 with respect to the control group (an 8% increase in relative terms).

only Southwest – which operated this aircraft type the most for 4.8% of all its flights pre-grounding – raised its fares significantly on average by \$4.12 (1.7%) in treated markets post-grounding relative to the control group. The post-grounding increase in average fares is more pronounced in longer-distance markets possibly due to higher fuel consumption in these routes, and is stronger in the quarter following the ban than in the following two quarters.

Our DiD estimates yield consistent results when we replace the outcome variable with the logarithm of average fares. Price differences may however exist because of carriers' practice to offer different fares to passengers travelling within the same market, which are reported in the DB1B database at quarterly frequency.[8] The disparity in ticket fares between the treated and control groups post-grounding may therefore vary across different segments of the fare distribution. To confirm whether this is true, we follow the approach employed by Chetverikov, Larsen, and Palmer (2016) and Chandra and Lederman (2018), constructing five distinct percentiles for each available fare distribution at the carrier-market-quarter level in our sample. We then run separate DiD regressions with the logarithm of each fare percentile as the outcome variable. Our estimates show that the grounding had the most significant impact on fares in the upper percentiles, likely comprised predominantly of price-inelastic passengers. The relative fare increases in the grounding's aftermath, at the average treatment intensity level, ranged from 0.77% to 1.21% between the 25$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the fare distribution. Conversely, no statistically significant impact is observed at the lowest end of the fare distributions, denoted by the 10$^{\text{th}}$ percentile. The upper-end fare increases are most prominent for Southwest and comparatively less so for the other two carriers, American and United, that also operated the MAX prior to the grounding.

We next focus on understanding the extent to which the grounding impacted the fuel expenses borne by carriers.Our DiD analysis reveals that fuel consumption rates were expectedly lower for flights operated using the highly fuel-efficient MAX in treated markets by 18%–30% relative to comparable flights in the control group. In order to counter the operational disruptions caused by the grounding, the three impacted carriers were forced to rely on other legacy aircraft models present in their fleet that are less fuel-efficient and consequently have higher operating costs than the MAX.[9] These operational adjustments resulted in a significant rise in fuel consumption rates after the grounding.More in detail,

[8]This practice stems from a variety of reasons including carrier-specific pricing variations within the same fare class across specific markets and timeframes, disparities in market and carrier attributes, type of aircraft used, and dynamic fare adjustments made as flight departure dates approach.

[9]Analysis of our rich flight-level dataset in Section IV.D reveals that carriers, especially those affected by the grounding, did not make substantial changes to their fleets or operations in response to the incident. Challenges in swiftly acquiring spare aircraft likely led impacted carriers to prioritize maximizing the utilization of existing legacy aircraft in their fleets. This strategic decision may have proved instrumental in maintaining smooth flight operations, possibly circumventing the need for major fleet or market adjustments.

we find that for Southwest the grounding led to an increase of around 4.7% in average per market fuel consumption in MAX operated routes. However, the average per flight increase in fuel consumption from substituting a MAX operated flight to the replacement aircraft for Southwest is much higher, 60% but only 10% of the flights in the affected routes were MAX. In contrast, the average per market and per flight increases in fuel consumption for American and United was not as high: the average fuel consumption increased by 1.6% and 3.2% in markets were the MAX was operated for some of the flights, which represents a 19% and 21% increase in the fuel consumption relative to pre-grounding levels of those markets-carrier combinations.

We then systematically assess the environmental impact of the observed increase in jet fuel consumption among the affected carriers. Using the estimates on marginal jet fuel consumption rates within the treated group, we compute the corresponding changes in CO_2 emissions per quarter. Use of legacy aircraft by the affected carriers resulted in a cumulative, incremental rise in CO2 emissions, averaging approximately 121,082 tonnes per quarter during the first three quarters following the grounding. To put it into perspective, this increase is equivalent to the collective CO_2 emissions of approximately 104,720 cars.[10] The long-term environmental damage caused by these incremental CO_2 emissions is projected to incur a social cost of approximately $108 million per annum.[11]

Finally, we analyse the extent to which carriers passed on the increase in fuel costs attributable to the grounding to ticket fares, using an approach similar to Fabra and Reguant (2014). Our estimates suggest a high jet fuel pass-through rate of up to 4 on average ticket fares, depending on the relative weight of fuel costs in carriers' marginal costs for issuing an additional ticket. We attribute this high pass-through rate to an increase in the shadow price of existing capacity. Importantly, the pass-through rate significantly rises at higher percentiles of the fare distribution. This is likely because carriers find it easier to pass on marginal cost increases to price-inelastic passengers who have higher willingness to pay and tend to buy closer to the departure date.

II Related Literature

Our paper relates to the extensive literature in industrial organization and transportation on pricing dynamics in the airline industry.[12] In this literature several studies focusing

[10] Each car is assumed to travel 18,500 kilometres per quarter and emit 250 grams of CO_2 per kilometre.

[11] This estimate is derived from the *social cost of carbon*, as proposed by the US Environmental Protection Agency (EPA) in 2022, which estimates the long-term cost per additional ton of CO_2 released into the atmosphere to be $190 (EPA, 2022).

[12] Academic interest in studying the effect of competition on air fares was sparked by the deregulation of the US airline industry in 1978, which allowed market forces to set airfares and lowered entry restrictions. Researchers began to investigate the effects of competition on airfares during this time, resulting in numer-

on the US airline industry and one of the main questions studied have been assessing the implications of market power within the industry (Borenstein, 1989; Ciliberto and Tamer, 2009), the effects of market structure and competition on price dispersion within ticket fares (Borenstein and Rose, 1994; Dai, Liu, and Serfes, 2014; Gerardi and Shapiro, 2009), and understanding second- and third-degree price discrimination strategies that are practiced by carriers, as well as inter-temporal price discrimination (Alderighi, Nicolini, and Piga, 2015; Aryal, Murry, and Williams, 2021; Chandra and Lederman, 2018; Chen, 2018; Escobari, 2012; Gaggero and Piga, 2011; Lazarev, 2013; Williams, 2022).[13] A related strand of the literature has focused on structurally estimating the preferences of consumer and suppliers and evaluating the welfare implications of mergers and other policies (Berry and Jia, 2010; Bontemps, Remmy, and Wei, 2022; Doi and Ohashi, 2019; Gualdani, Bontemps, and Remmy, 2023). We complement these literatures by providing insights on the extent to which supply-side cost shocks that affect the fleet availability, increasing the average operating costs, are passed through to ticket fares along their entire distribution. Supply side disruptions have been studied in the context of product harm crisis where supply shortages may arise and raise firms' costs or situations in which consumers can not avoid the affected product (Ferrer and Perrone, 2023; Jin and Leslie, 2003).

Since the pass-through of the shock to prices is one of the main outcomes that we estimate, our study will is related to the broad literature on the passthrough of costs shocks, which have been studied in a wide range of industries outside aviation. Amiti, Itskhoki, and Konings (2014) explore variation in exchange rate pass-through rates across exporters, finding that small non-importing firms have a nearly complete pass-through, whereas larger import-intensive exporters have pass-through rates of around 50%. Studies measuring exchange rate pass-through to imported goods such as beer and coffee report estimates below 50% (Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010). Genakos and Pagliero (2022) study isolated oligopolistic island markets in Greece with captive consumers and find full pass-through in competitive markets and a 40% pass-through in corresponding monopoly

ous studies including Bailey, Graham, and Kaplan (1985), Berry (1992), Berry (1990), Borenstein (1989), Borenstein (1990), Borenstein (1991), Borenstein (1992), Brueckner, Dyer, and Spiller (1992), Brueckner and Spiller (1994), Call and Keeler (1985), Evans and Kessides (1993), Evans and Kessides (1994), Graham, Kaplan, and Sibley (1983), Hurdle et al. (1989), Morrison and Winston (2010a), Morrison and Winston (2010b), and Morrison et al. (1989). These studies generally show that ticket fares respond significantly to competition in carrier markets.

[13] Carriers employ a variety of pricing strategies, including simple pricing, two-part tariffs, bundling, peak-load pricing, and dynamic pricing. Simple pricing involves charging a fixed price for a ticket regardless of demand, while two-part tariffs involve charging a fixed fee plus a variable fee based on usage. Bundling involves selling multiple products or services as a single package, while peak-load pricing involves charging different prices for the same product or service depending on the level of demand. Dynamic pricing involves setting prices based on real-time market conditions, such as supply and demand (Belobaba, Odoni, and Barnhart, 2015, Chap. 4).

markets. While most studies have found incomplete cost pass-through (Amiti, Itskhoki, and Konings, 2014; Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010), few studies also report higher pass-through rates. Among them, Fabra and Reguant (2014) find that emissions costs are nearly fully passed through to electricity prices. Similarly, Miller, Osborne, and Sheu (2017) find high pass-through rates above one in the Portland cement industry. They rationalize their findings using the framework of Weyl and Fabinger (2013), which establishes that the pass-through rate can exceed unity in a symmetric oligopoly setting characterised by constant marginal costs, market power, and log-convex demand. We contribute to this literature by showing the grounding led to a fuel cost pass-through rate well above one on economy class fares. This high pass-through rate is attributed to an increase in the shadow price of capacity due to the fact that the reduction of capacity is coming from the removal of the aircraft model with lower operating costs.

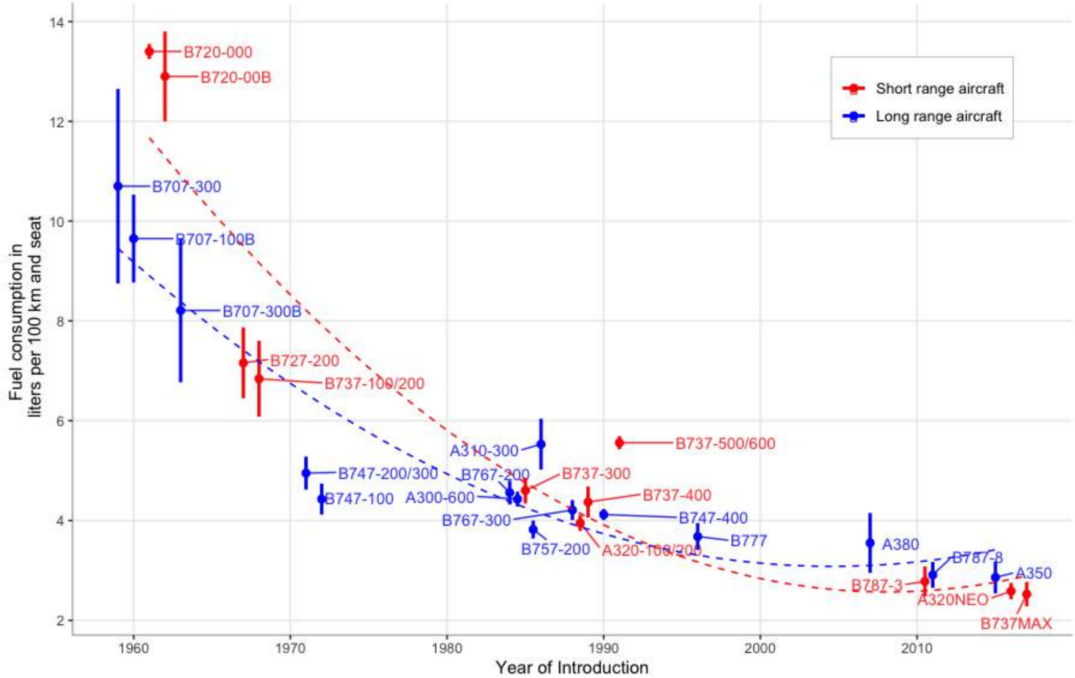
III Background

Efforts to improve fuel efficiency have long been a key focus of the aviation industry, driving significant innovation in areas such as engine technology, aerodynamic design, and weight reduction through the development of lighter airframes made from carbon composites. According to the International Energy Agency (2009), these innovations have led to a reduction in aviation fuel consumption of more than 60% between 1971 and 1998. However, as shown in Figure 1, much of this progress occurred prior to 1990, with the rate of improvement slowing in recent decades. While there is still room for further innovation, it is possible that some of the most significant advances in fuel efficiency have already been achieved, and that future improvements may be rather incremental in nature.

Figure 1 illustrates the constant improvements by Boeing and Airbus to create more fuel-efficient aircraft. The introduction of the 737 model by Boeing in 1967 was a direct response to intense competition in the narrow-body aircraft segment, particularly from rival Airbus. The 737 represented a major breakthrough in fuel efficiency with the use of only two engines, compared to four and three engines required by its predecessors, the 707 and 727, respectively. In the 1990s, Boeing further improved the 737's fuel efficiency with the development of the Next Generation (NG) engine and a fly-by-wire control system that replaced conventional manual flight controls with a fully electronic cockpit. These advancements allowed the 737 model to remain competitive and maintain its position as a popular narrow-body aircraft for decades.

In 2011, Boeing responded to Airbus' announcement of its most fuel-efficient narrow-body aircraft, the Airbus 320 Neo, by developing the 737 MAX series. The MAX featured significant improvements in engine performance and fuel efficiency, as well as new aerodynamic

Figure 1: Fuel efficiency of commercial aircraft.



NOTE. – Figure shows the fuel consumption rates of aircraft models developed by Boeing and Airbus against their year of entry into scheduled commercial passenger service. Models beginning with the letter A(B) are from Airbus (Boeing). The X-axis represents year of service entry while the Y-axis denotes aircraft fuel consumption rates expressed in litres per passenger seat per 100 kilometres. The aircraft fuel consumption rates were estimated based on data obtained from the International Energy Agency (2009), from Form 41 data reported by carriers to the US Department of Transportation (DoT), and from individual aircraft specifications published by manufacturers on their respective websites. Based on the definitions provided by Wragg (1974), we designate an aircraft as *short range* if it can fly a maximum distance of up to 4,100 kilometres on a single flight, and is designated as *long range* otherwise. Dots represent average fuel consumption rates and the bars denote 90% confidence intervals. Dotted lines represent the predicted trend lines for short- and long-range aircraft, respectively.

improvements, such as unique split winglets that further enhanced fuel efficiency. The aircraft was well received by carriers and aircraft leasing companies, with over 4,387 orders placed between 2011 and 2017, particularly in the United States where American, Alaska Airlines, Southwest, and United placed a total of 1,078 orders.[14]

Figure 2 depicts the trends in air passenger traffic and ticket fares in the US, beginning from 1970. Panel 2(a) shows a steady increase in the number of flights operated by carriers, as well as the number of air passengers, which coincides with the repeated introduction of newer fuel-efficient aircraft. Although both air traffic and passenger volumes declined during the COVID-19 pandemic, they seem to have bounced back by the end of 2022. Panel 2(b)

[14]Among these early adopters of the MAX, Alaskan airlines did not operate this aircraft type during our sample period. Table A1 in the appendix provides an overview of the fleet compositions of all major US carriers in our sample.

displays the average annual airfares reported by carriers in their Form 41 filings to the DoT since 1990, both in nominal and real terms adjusted for inflation. The gradual decline in fares over time suggests that passengers have generally benefited from the cost savings resulting from constant improvements in aircraft fuel efficiency.

The widespread adoption of the 737 MAX by carriers was interrupted by two fatal crashes. The first incident occurred on October 29, 2018, when a Lion Air-operated 737 MAX crashed shortly after takeoff from Jakarta's Soekarno–Hatta International Airport, killing all 189 passengers onboard. Despite the tragedy, aviation regulators initially allowed carriers to continue operating the aircraft type. However, approximately six months later, on March 10, 2019, another 737 MAX operated by Ethiopian Airlines crashed shortly after takeoff from Addis Ababa, resulting in the deaths of all 157 people onboard. This second crash prompted aviation regulators worldwide, including the US Federal Aviation Administration (FAA), to ground the 737 MAX just three days later on March 13, 2019, pending further investigation. The crashes were attributed to erroneous readings from onboard aircraft sensors and malfunctioning of the Manoeuvering Characteristics Augmentation System (MCAS) system, which was another notable innovation developed by Boeing for the MAX series. Appendix C provides detailed description of these issues that led to the two fatal MAX crashes. Boeing suffered significant financial losses as a result of the MAX accidents and subsequent grounding. It is estimated that the company incurred \$21 billion in fines, compensation, and legal fees, as well as indirect losses of up to \$60 billion due to the cancellation of 1,200 orders of the MAX model (Isidore, 2020). The grounding, which lasted for a record-breaking 20 months, was finally lifted by the FAA in November 2020 (CBS News, 2020; Gates, 2020). The MAX resumed commercial flights in the US by December 2020, and was recertified for use in Europe and Canada by January 2021 (American Machinist, 2020).

Although Figure 2 indicates a decline in flights, passenger volumes, and fares in 2020, it is challenging to attribute this decrease entirely to the grounding of the MAX, as this period also coincides with the outbreak of the global COVID-19 pandemic. Therefore, to avoid these complications, we limit our sample to the end of 2019.

IV Data

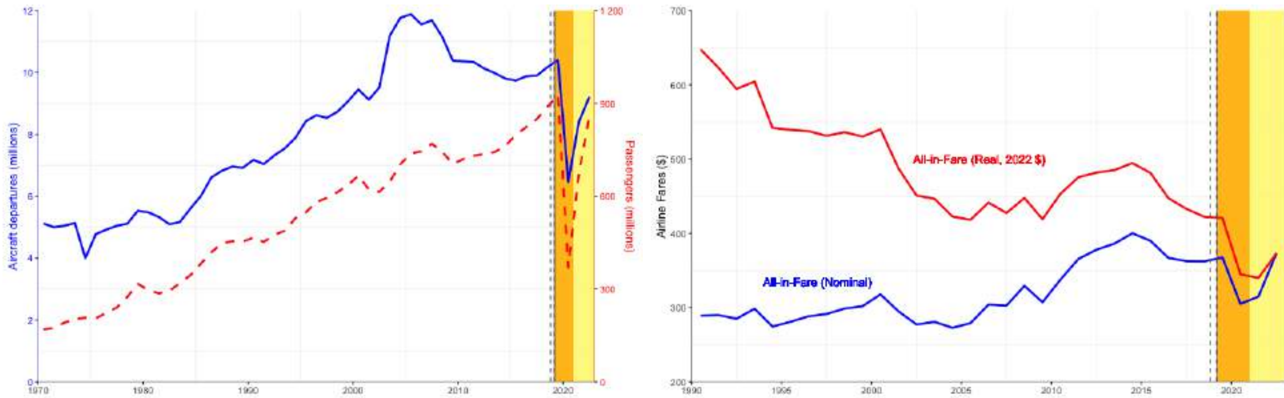
IV.A Data Sources

We combine data from several sources for our empirical analysis. Below is a brief description of these data sources.

Bureau of Transportation Statistics. Data on airline ticket prices was obtained from the Airline Origin and Destination Survey (DB1B) database made publicly available by

Figure 2: Air passenger traffic and ticket fares in the US.

(a) Flight departures and passenger traffic (b) Ticket fares



NOTE. – Panel (a) depicts the evolution of US airline traffic and passenger volumes since 1970, based on data from the trade association Airlines for America. The number of departures made by commercial aircraft operating scheduled passenger services between US airports is used to measure air traffic. Panel (b) shows average all-in-fares reported by US carriers in their periodic Form 41 filings to the DoT since 1990. We report both nominal and real fares in 2022 dollars. In each plot, the orange area represents the period from March 2019 to December 2020 during which the FAA grounded the Boeing 737 MAX, while the yellow area spans from January 2020 to December 2022 and represents the COVID-19 pandemic period.

the Bureau of Transportation Statistics (BTS).[15] DB1B is a 10 percent random sample of domestic flight itineraries of all reporting US carriers in each quarter, and provides details of ticket prices and *coupon*-specific information for each itinerary (origin, destination, and all connecting airports).[16] In addition to these, DB1B provides details of the ticketing and operating carriers, origin and destination airports, fare class, as well as number of passengers and coupons for each itinerary per quarter.

The OpenSky Network. Data on individual domestic flights by US carriers were obtained from the OpenSky Network, which has been providing real time access to air traffic control (ATC) communications since early 2017. OpenSky collects this data using a global network of low-cost surveillance receivers that track the position transmitted by aircraft to ATC ground stations during flight. This positional information is made available via two types of surveillance systems, namely *Mode S* and *Automatic Dependent Surveillance–Broadcast* (ADS-B). Under Mode S, receivers maintaned by the OpenSky network continuously interrogate aircraft within their coverage area spanning up to a radius of 600 km, and collect data

[15] The data is publicly available at `https://transtats.bts.gov/prezip/`.

[16] A coupon represents a passenger's itinerary and contains details of each flight segment of the passenger. For example, a flight from New York (JFK) to Los Angeles (LAX) with a stopover in Chicago (ORD) will consist of two coupons, JFK–ORD and ORD–LAX.

transmitted back by the queried aircraft. On the other hand, ADS-B is a satellite-based surveillance system under which the positional information of an aircraft is broadcast autonomously every second by an onboard transmitter over a publicly accessible radio frequency channel, which is captured by OpenSky through its receiver network.[17] Under either system, the positional information relayed back to OpenSky contains details such as aircraft's identification (permanent transponder ID known as *hexcode*), current location (latitude/longitude), altitude, and velocity.

Flight tracking via Mode S and ADS-B is extremely accurate compared to conventional radar technology, which is able to provide such information only once every 5 to 12 seconds and is also much more expensive, erroneous, and cumbersome to operate. Under FAA regulations, aircraft operating above 18,000 feet above mean sea level were required to have a Mode S transponder. In recent times, these requirements have grown considerably stricter. Currently, any aircraft operating within US airspace must be fitted with an ADS-B transponder, unless exempted by the FAA.[18] While Mode S transmissions depend on selective interrogation of aircraft by ground radars, ADS-B transmissions occur automatically without pilot involvement. However, both these types of transmissions cannot be self-reported by carriers, unlike the case with DB1B. Internet appendix B provides additional details on the real-time flight tracking capabilities of the OpenSky network.

Aircraft Registries. We use aircraft identification details (*hexcode*) from the OpenSky data to determine aircraft type and the historical fleet composition of individual carriers. This exercise is a bit complicated as US carriers often use a combination of directly-owned aircraft, typically registered with the FAA, and also lease aircraft registered in other countries for their flight operations.[19] It is therefore difficult to identify the entire historical fleet composition of a carrier by simply querying the FAA's aircraft registry. We overcome this challenge by obtaining aircraft lookup tables from the aviation portals `www.airframes.org` and `www.planespotters.net`. These lookup tables contain the most comprehensive information on global aircraft registries, and are continuously updated using crowdsourced information from a global network of aviation enthusiasts. We query the hexcode of each aircraft

[17]Access to OpenSky data is subject to approval by the platform's administrators. Although commerical ADS-B data providers such as `www.flightradar24.com` and ADS-B Exchange exist, most of them provide historical flight tracking data with several restrictions and up to the past year only.

[18]See `www.faa.gov/air_traffic/technology/equipadsb/` for more information on possible exemptions from ADS-B broadcasting. According to Flightradar24, just 3% of aircraft are currently exempt from mandatory ADS-B transmission requirements of the FAA.

[19]While an aircraft's hexcode is unique and does not change after issuance, the aircraft must then be registered with the aviation regulator of a country before it can commence flight operations. Aircraft registered with US FAA receive a six-digit registration code known as *N-Number*. Other countries follow their own registration schemes. For example, N8767M is the FAA-assigned registration number of a Boeing 737 MAX aircraft operated by Southwest Airlines that has a permanent assigned hexcode AC0FF9.

against these lookup tables to obtain its national registration ID and aircraft type. These are cross-checked with the aircraft registeries of different countries including the FAA wherever possible to remove any outstanding errors. We then manually collect specifications of each aircraft type from manufactuer websites and marketing brochures. These specifications include details such as the fuel consumed (*Fuel Burn*, expressed in gallons per seat-km) and cruising speed (*Cruise Speed*, expressed in km per hour) of the aircraft type.

T-100 Domestic Segment Database. We complement the data on ticket prices from the DB1B with additional market characteristics from the T-100 Domestic Segment database maintained by the BTS and which is available monthly, disaggregated by aircraft type, and for every domestic market where a carrier operates. The T-100 contains information reported by carriers on aggregate statistics such as number of enplaned passengers, available seat capacity, as well as scheduled and actual departures performed. We use this data to estimate the *Load Factor* per carrier-market as the ratio of enplaned passengers to the total available seat capacity for all flights operated by the carrier in a given quarter in that market. $LoadFactor$ captures the typical rate at which flight seats sell out on a particular carrier/market combination prior to the departure date Dana Jr and Orlov (2014) and Sengupta and Wiggins (2014).

The T-100 does a better job of counting passengers than the DB1B since it includes passengers who connect to and from other flights at either airport, in addition to those who begin and end their trips at the origin and destination airports. To ensure consistency, we rely on passenger counts reported by the T-100 and aggregate the data at the carrier–market–year quarter–fare class level.

Energy Information Agency. Data on jet fuel prices were sourced from the Energy Information Agency (EIA). These are available daily on a spot price basis from the EIA website.[20] We use this data to compute the unit fuel cost borne by carriers to operate a given aircraft type per seat-km, see the variable construction section for more details.

IV.B Sample Construction

Legacy full-service carriers such as American, Delta, and United employ a wide range of aircraft made by different manufacturers, such as Boeing, Airbus, and Embraer, and variants of the same aircraft type, such as the Boeing 737 600/700/800/900 series, depending on distance, fuel, seating capacity, and other requirements. In contrast, LCCs typically use aircraft from a single manufacturer to minimize operating costs related to maintenance and pilot training. For example, Southwest exclusively uses the Boeing 737 while Allegiant

[20]Data on jet fuel spot prices is from `www.eia.gov/dnav/pet/hist/eer_epjk_pf4_rgc_dpgD.htm`

operates only the Airbus 320.[21] We include LCCs in our study because of the important role they played in the expansion of the US airline industry in recent decades (Chandra and Lederman, 2018). LCCs have also been actively incorporating the latest narrow-body aircraft, such as the Boeing 737 MAX and Airbus A320 NEO, into their fleets given that they are the most fuel-efficient aircraft models available and are also cheaper to operate in terms of pilot training, maintenance, and crew service costs per passenger (Camilleri, 2018).

For simplicity, we group the aircraft listed in our sample into six broad types based on similarities in their costs, overall size, flying range, and seating capacity:

1. *Large aircraft*: wide body, twin aisle, long-range aircraft that can seat between 200 to 440 passengers and have a flying range of up to 16,000 kilometers. Examples include the Boeing 757/767/777/787 Dreamliner, and Airbus 330/340/350 series of aircraft.[22]
2. *Narrow-body aircraft*: single aisle, medium- to long-range aircraft that can seat between 130 to 200 passengers and have a flying range of up to 7,130 kilometres. These are further split into four major categories based on manufacturer and fuel efficiency: *Boeing 737*, *Boeing 737 MAX* , *Airbus 320*, and *Airbus 320 NEO*.
3. *Small aircraft*: single aisle, short-range aircraft that can seat up to 120 passengers and have a flying range of up to 4,300 kilometres. Examples include the Embraer 170/195 and Bombarder CRJ series of aircraft.

We aggregate the OpenSky flights data at the carrier–market–year quarter level and calculate the number of flights and flight hours operated by each carrier in each market per quarter across the six aircraft types. This data is then merged with our primary sample, which includes quarterly ticket fares and market characteristics derived from DB1B and the T-100 Domestic Segment databases. Given that the DB1B database constitutes a 10 percent random sample of domestic tickets issued by carriers, merging the OpenSky sample with it leads to a notable reduction in the markets covered in our empirical analysis.

Figure 3 presents the total number of flights and flight hours by carriers over time, categorized by the six distinct aircraft categories. There were no significant changes in aggregate flight volume or hours following the MAX grounding among five of the six aircraft types. In the case of the MAX, few flights were operated using this type in end-2017, likely involving carriers receiving and incorporating these aircraft into their fleets during this period.[23] To

[21] See Table A1 in the online appendix for a detailed overview of the various types of aircraft operated by US carriers.

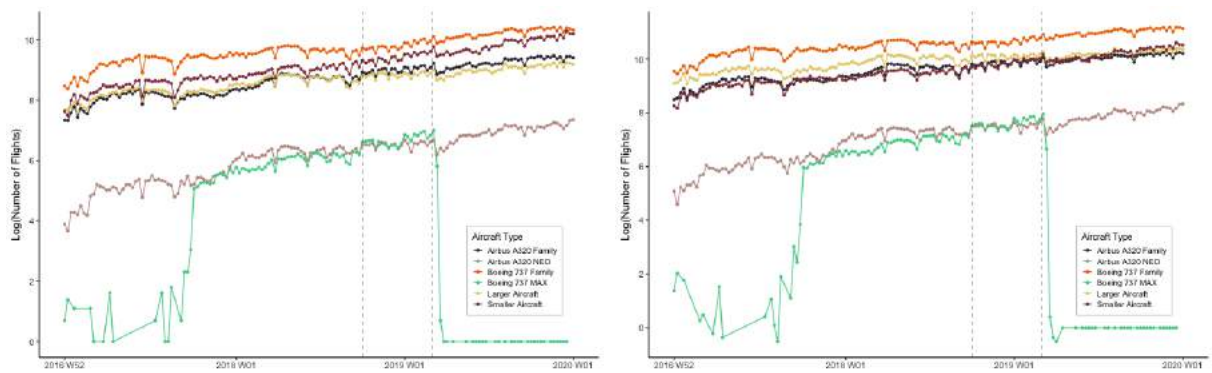
[22] We do not consider the Airbus A380 in our analysis since US carriers did not operate this aircraft for domestic flights during the sample period.

[23] Boeing commenced deliveries of the 737 MAX to flight operators in May 2017. Thus many of the MAX flights made in 2017 were likely related to aircraft deliveries and preparations for scheduled commercial flights by carriers. Taking this into consideration, we excluded flights to and from the King County Airport (ICAO code: KBFI) in Seattle, which is the primary airport used by Boeing for final aircraft deliveries to

avoid including such non-scheduled flights involving the MAX, we excluded all observations involving flights made during 2017 or before. Additionally, to ensure that the results are not affected by the fallout from the COVID-19 pandemic, which severely curtailed air travel, we excluded the period from January 2020 onwards from our analysis. As a result, our primary sample comprises eight quarters ranging from 2018'Q1 to 2019'Q4.

Figure 3: US domestic flight activity by aircraft type.

(a) Number of flights (b) Total flight hours



NOTE. – Figure shows the total count of domestic flights and corresponding flight hours operated by all US carriers from 2017 to 2019, categorized by aircraft type. The flight data utilized for this analysis is from OpenSky. Dotted lines on the chart indicate the timelines of the two crashes involving the Boeing 737 MAX aircraft. Following the second crash, the FAA ordered an immediate grounding of all Boeing 737 MAX aircraft.

Table 1 compares flight hours grouped by aircraft type based on the data from OpenSky's direct tracking ADS-B system and the T-100 Domestic Segment database. Opensky provides better coverage of commercial flight activity by at least 20% relative to the T-100. Notably, the T-100 does not report any flight activity by MAX aircraft, despite their entry into service with US carriers from mid-2017, which is a crucial requirement for our study. However, this limitation is addressed by our OpenSky sample, which shows that US carriers flew a total of 37,700 hours using the MAX before its grounding in March 2019. OpenSky thus provides a more robust and detailed view of commercial flight activity in the US, which consequently enhances the accuracy and reliability of our findings.

carriers. However, we do acknowledge that we are still unable to identify all such unscheduled flights in our sample.

Table 1: Differences in flight coverage between OpenSky and T-100 domestic segment.

Aircraft Type	Flight hours (1000s)		Difference (%)
	OpenSky	T-100 Domestic Segment	
Boeing 737 Family	2738.10	1121.00	59.06
Boeing 737 MAX	37.70	0.00	100.00
Airbus A320 Family	1031.60	805.30	21.94
Airbus A320 NEO	90.90	72.50	20.24
Larger Aircraft	933.10	616.90	33.89
Smaller Aircraft	1688.60	486.70	71.18

NOTE. – Table provides a breakdown of the total flight hours operated by all US carriers from 2017 to 2019, categorized by aircraft type. Separate analyses are conducted using data from OpenSky and the T-100 domestic segment database.

IV.C Key Variable Definitions

In this section, we provide an overview of key definitions, describe the main variables utilized in our analysis, and compare our approach to prior studies in the literature.

Time (t): Our primary sample covers the period from 2018'Q1 to 2019'Q4, as including flights from 2020'Q1 onwards could confound our analysis with the unprecedented effects of the COVID-19 pandemic on air travel. Therefore, we limit our analysis to flights recorded before the pandemic. We further exclude flights prior to 2018 due to the likelihood that many of the flights operated using the MAX in 2017 may have involved delivering aircraft to individual carriers and preliminary flights made in preparation for scheduled commercial operations, as shown in Figure 3. Due to the quarterly frequency of our sample, t refers to a year quarter.

Carrier (c): The OpenSky sample covers 11 major US carriers, including both legacy and low-cost carriers (LCCs). Legacy carriers include Alaska, American, Delta, Hawaiian, and United airlines. The LCCs comprise Allegiant, Frontier, JetBlue, Southwest, Spirit, and Sun Country airlines.

Market (m): We define a market as a unique unidirectional route serviced by a carrier between an origin and destination airport within the US.[24] For instance, the Chicago–Houston and Houston–Chicago routes operated by Delta Airlines are treated as distinct markets. We consider co-located airports as a single airport if they are situated within the same metropolitan statistical area (MSA) or within a distance of 25 miles of each other, since such co-located airports are expected to serve a common local population.[25] In every such

[24] It is worth noting that the definition of a carrier *market* varies substantially across prior literature. Our definition aligns closely with Berry and Jia (2010) and Bontemps, Remmy, and Wei (2022) as we use unidirectional origin-destination airport pairs.

[25] For instance, flights departing from or arriving into Chicago O'Hare (ORD) and Chicago Midway (MDW)

case, we substitute the name of the smaller airport with that of the larger one, determined by the number of passengers handled by these airports between 2010 and 2016. We only focus on direct flights comprising both non-stop flights and flights involving a stop but no change of aircraft. The rationale behind this decision stems from the fact that the T-100 Domestic Segment Database reports aggregate details on enplaned passengers, seat capacity, and flight departures at the non-stop segment level, which are most compatible with the DB1B data on ticket fares for direct flights only Gerardi and Shapiro (2009). We exclude markets with fewer than 10,000 inhabitants as smaller markets have demand patterns and operational costs that differ significantly from larger markets, which can make it difficult to obtain consistent estimates.[26] The exclusion of smaller markets leaves us with a sample covering 3,137 markets.

Ticket fare: Fares refer to the ticket prices reported by DB1B, which encompass a wide range of itineraries and fares charged by a carrier within a particular fare class and are reported at a quarterly frequency. Thus, our sample comprises distributions of ticket fares for individual carrier–market itineraries. Following Gerardi and Shapiro (2009) and our definition of a *market*, we define a ticket fare as the price charged for a one-way trip, whereas prices reported for round-trip itineraries are divided by two. We exclude tickets priced below $20 as these are typically issued to frequent flyers. Furthermore, we only conduct our analysis on economy class fares.

We exclude business class fares from our analysis due to significant fluctuations in the market-level composition of seat offerings within this fare class among carriers. As depicted in Figure A3, legacy carriers such as American, United, and Delta (which never operated a MAX) have been consistently reducing their business class offerings across various markets prior to the grounding. In contrast, low-cost carriers like Southwest, Spirit, and Frontier do not provide business class seats. Additionally, there may be considerable variations in the product characteristics and service quality of business class seats across carriers, which are not observable to the researcher. These factors collectively pose challenges in estimating the impact of the MAX grounding on business class fares.

We estimate the average fare and various percentiles of the fare distribution at the carrier–market–year quarter level, exploiting the fact that the DB1B data contains multiple itineraries and fares for the same flight by the same carrier at a quarterly frequency. The average fare is the mean price that passengers in a given fare class pay for a scheduled flight operated by a specific carrier between an origin and destination airports in a particular quarter within

airports are considered to both serve the greater Chicago metropolitan area, and both are hence treated as a single airport.

[26] Berry and Jia (2010) notes that smaller airports account for less than 20% of total passengers and 33% of all flights, supporting our decision to exclude smaller markets.

the US. The variation in fares across itineraries occurs because passengers travelling on the same flight may pay different fares if the airline changes the price in the days leading up to the departure, and further because the carrier may set different prices within the same quarter for passengers flying on different flights in the same fare class. We assume that every passenger in a fare class pays the average fare for that class and compute the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles at the carrier–market–year quarter level.

Jet fuel consumption and costs: Unlike service-related costs that are unobservable, fuel costs represent a tangible component of carriers' marginal costs that we can accurately observe and estimate. This is achievable through our unique dataset on individual flights, which includes comprehensive details of aircraft type and flight distances/durations. The first key variable in this context is the $Fuel\ Burn$ rate, representing the fuel consumed during flight by an aircraft per passenger and unit distance travelled. It is expressed in units of gallons per seat per 100 kilometers (gps). To compute $Fuel\ Burn$, we first obtain details of jet fuel consumption per 100 kilometres at cruising altitude from the official websites of aircraft manufacturers for each aircraft type in our study.[27] To convert this metric on a per-passenger basis, we scale it by the expected number of passengers on the flight (given as the number of seats available for the specific aircraft model times the average load factor of the corresponding carrier in that market and quarter available from the T-100 Domestic Segment Database).

Next, we calculate $Fuel\ Cost$, representing the unit fuel expense incurred per flight based on the aircraft type used. This metric is expressed in US dollars per seat per 100 kilometers and is derived by multiplying $Fuel\ Burn$ and the prevailing spot price of jet fuel.[28] We operate on the assumption that carriers face similar marginal costs for operating aircraft type k, such that both $Fuel\ Burn$ and $Fuel\ Cost$ remain constant for each such type at any given time.[29]

IV.D Operational Responses of Carriers to the Grounding

Carriers impacted by the MAX grounding could have adopted various strategies to manage the situation and avoid major disruptions to their flight operations. These strategies include: (i) Maximizing utilization of other legacy aircraft present within the fleet, that are less fuel-efficient compared to the MAX, and deploying them in markets disrupted by the grounding

[27] It is important to note that the estimation of $Fuel\ Burn$ excludes fuel consumption during takeoff and landing.

[28] $Fuel\ Burn$ values are expressed in gallons, consistent with the units in which the EIA reports jet fuel prices.

[29] Note that "seat" refers to each available seat within an aircraft as reported by the manufacturers. Since passenger load factors among US carriers are very high at around 81±11% (See Table 2), using actual number of enplaned passengers in place of total available seat capacity is expected to yield similar results.

to compensate for the absence of MAX aircraft, (ii) Leasing new aircraft from third-party lessors, (iii) Placing new aircraft orders with a manufacturer, (iv) Reconfiguring the flight network by either exiting less profitable markets or delaying entry into new ones, (v) Diverting flights and extending flight legs from unaffected markets to compensate flight disruptions in treated markets, and, (vi) Adopting a passive approach by making no changes to flight schedules or fleet composition, causing temporary flight disruptions in treated markets.

Among these strategies, carriers impacted by the grounding would be expected to adopt those that effectively minimize both capital and labor adjustment costs. During this process, carriers would be expected to focus specifically on reducing expenses related to pilot retraining for non-MAX models, aircraft maintenance, and administrative changes during the transition to operate a non-MAX model. Additionally, consideration must be given to the additional storage costs incurred due to the grounding of MAX aircraft. It is however worth noting that the switching to non-MAX models, which have lower fuel efficiency, as a result of the grounding would lead to carriers encountering higher average marginal costs.[30]

We examine carrier response strategies to the grounding by analyzing various aspects such as shifts in the composition of aircraft types within carrier fleets, induction of new aircraft, adjustments in the range and types of markets served, and the overall number of flights operated. Our findings are described in detail below.

Changes in carrier fleets: Figure A1(a) in the appendix exhibits the number of individual narrow-body aircraft in service with carriers during the period of the MAX grounding, with each aircraft counted only once based on its unique hexcode. As shown, there was a sharp decline in the number of MAX aircraft with carrier fleets following the grounding, while the other three narrow-body types (Boeing 737, Airbus 320, and Airbus 320 NEO) saw no corresponding changes. Furthermore, Figures A1(b)–A1(d) show similar compositions of narrow-body aircraft for the three carriers operating the MAX. United and Southwest show no significant alterations in their narrow-body fleets, whereas American Airlines appeared to have quickly replaced its grounded MAX aircraft with Airbus 320 NEOs.[31] Collectively, these findings suggest that carriers, particularly the ones affected by the grounding, did not make substantial changes to their narrow-body fleets in response to the incident, possibly due to short-term logistical difficulties in modifying flight schedules, market- and network-level rigidities, and limited availability of spare aircraft both within the carrier's own fleet

[30] As illustrated in Figure 1, the MAX stands out as the narrow-body aircraft with the highest fuel efficiency, consuming merely 0.60 gallons per seat–100km (gps). In contrast, the older Airbus 320 and Boeing 737 models consume 0.69 (14% more) and 0.79 (32% more) gps than the MAX, respectively. Although the Airbus 320 NEO has a similar fuel efficiency to the MAX, we excluded this model from our analysis due to its limited presence in the sample period, with only one affected carrier, American, operating a single aircraft of this type.

[31] See Figure A4 for an overview of changes in the fleet composition among all carriers over time.

and from third-party leasing companies.

Induction of new aircraft: Figure A2(a) illustrates the percentage of newer narrow-body aircraft in carrier fleets that are less than three years old since the date of manufacture. There have been no discernible changes in the share of new Boeing 737, Airbus 320, or Airbus 320 NEO aircraft in the aftermath of the MAX grounding. Moreover, Figures A2(b)–A2(d) demonstrate that there has been no significant shift in the proportion of new narrow-body aircraft among the three carriers affected by the grounding. This evidence indicates that carriers were unable to mitigate the effects of supply disruptions due to the grounding by inducting newer, potentially more fuel-efficient, aircraft into their fleets.

Changes in markets served: The number of markets in which individual carriers operated during the sample period are shown in Figure A3. Markets where carriers exclusively offered economy class seats and those where both economy and business class seats were sold for the same flight are counted separately. While full-service carriers, such as American, Delta, and United, offer both types of fares, LCCs such as Southwest, Allegiant, and Spirit offer only economy class seats in all the markets they operate. Overall, the figure suggests that the grounding did not lead to any significant substitution between the fare class offerings of individual carriers.

Changes in flight activity: Figure A6 shows the number of flights operated by carriers impacted by the grounding during the sample period. Panel A5(a) demonstrates that the total number of flights by these carriers remained stable after the grounding. Moreover, panel A5(b) reveals that affected carriers increased the use of non-MAX aircraft to compensate for the grounding. This finding, coupled with the fact that affected carriers did not add new aircraft, suggests that they operated more flights using existing aircrafts in their fleets to minimize disruptions in the markets they served.

Overall, our findings suggest that carriers, especially those impacted by the grounding, did not make significant alterations to their fleets or market offerings in response to the incident. This was most likely due to the difficulties they encountered in procuring spare aircraft from lessors and manufacturers on short notice. Instead, impacted carriers chose to address the situation by increasing utilization of their existing non-MAX aircraft that were predominantly less fuel-efficient than the MAX, effectively mitigating disruptions to their flight operations.

V Results

Our empirical analysis focuses on the impact of the FAA grounding of MAX aircraft on various market outcomes. We begin by examining whether the grounding led to a significant change in ticket fares within carrier-markets where the MAX had been in operation during the prior period. Henceforth, these carrier-market combinations are referred to as the *treated* group, in comparison to other carrier-markets where the MAX had never been used for flight operations (the *control* group). Secondly, we quantify the increase in fuel costs due to the grounding by also comparing treatment and control group outcomes. Lastly, we assess the degree to which carriers passed on the fuel cost increases they faced due to the grounding on to their ticket fares.

V.A Treatment Definition

To analyze these outcomes, we adopt a difference-in-differences (DiD) approach in which the treatment variable is continuous and reflects the utilization intensity of the MAX relative to other aircraft types within a carrier's fleet. Specifically, our treatment intensity is defined at the carrier-market-quarter level, as the percentage of MAX-operated flights by a carrier in a specific market during a given quarter before the grounding. According to this definition, the treatment intensity for a carrier in a market it serves ranges from 0 (during quarters when the carrier never operated the MAX) to 1 (during quarters when the carrier solely employed MAX aircraft for all its flights in that market). The treatment intensity is estimated on a quarterly basis to accommodate seasonal fluctuations in demand. This approach recognizes that a carrier's decisions on which markets to serve can vary from one quarter to another.[32] In addition to using this instrument for our analysis, we perform additional checks to ascertain its validity by empoying a binary variant of the instrument and measuring treatment intensity as the percentage of MAX-operated flights by a carrier in a specific market throughout the entire pre-grounding period.

It is important to clarify that the treatment intensity can be computed from two available samples. The first is the full sample, encompassing all markets covered by OpenSky. The second is the matched sample between OpenSky and the DB1B database, which covers only a subset of the markets included in the full sample as explained in Section IV.B. The average treatment intensity among carrier-market combinations, conditional on them being treated before the grounding, is 11% in the full sample and 7% in the matched sample. Table A4 in the internet appendix shows the treatment intensities for both samples split by each affected carrier. Panel (a) illustrates that the conditional average treatment intensities across all pre-treatment quarters for the full (matched) sample are 10% (7%) for South-

[32]Specifically, the treatment intensity calculated for a given carrier-market-quarter combination during the pre-grounding period is the treatment intensity for the same carrier-market of that same quarter in the post-grounding period. For example, the treatment intensity for the carrier-market Boston-Chicago determined during 2018'Q2 (pre-grounding period) also serves as the treatment intensity for the same carrier-market combination in 2019'Q2 (post-grounding period). A similar logic applies to the treatment intensities of carrier-markets during the third and fourth quarters of 2018 and 2019, respectively. However, it must be clarified that the treatment intensities of carrier-markets for 2018'Q1 and 2019'Q1 are estimated separately since both quarters fall under the pre-grounding period.

west, 12% (21%) for American, and 17% (11%) for United. The higher conditional average treatment intensities in the full sample, as opposed to the matched sample, imply that the MAX was active in additional markets not included in the matched sample. Since our goal is to understand the economic impact of the grounding across all domestic airline markets, we will use the conditional average treatment intensities from the full sample to interpret the economic significance of our regression estimates. Panel (b) presents the unconditional treatment estimates, considering both treated and non-treated carrier-market combinations. The unconditional treatment intensities are as anticipated—lower than the conditional treatment intensities. They closely align across both samples for all three carriers, with Southwest having the highest proportion of flights operated with grounded MAX.

V.B Summary Statistics

Table 2 provides a comprehensive overview of the characteristics pertaining to both the treated and control carrier-market groups, as defined in Section V.A, during the period prior to the grounding. In Panel (a), we present descriptive statistics related to the treatment intensities observed among all the carriers impacted by the grounding. Here each observation is weighted by the number of enplaned passengers per quarter by the corresponding carrier within that specific market. On average, the impacted carriers utilized MAX aircraft for approximately 7.3% of their total flight hours within their treated markets before the grounding occurred. However, there is significant heterogeneity in the operation of the MAX by these carriers as indicated by the differences in their treatment intensity statistics. Notably, American exhibited the highest utilization rates of the MAX before the grounding, accounting for an average of 11.7% of its total flight hours in treated markets. Following closely, United had an average treatment intensity of 10.8%. In contrast, Southwest had the lowest utilization, with only 6.8% of all its flights in treated markets involving the use of this aircraft type prior to the grounding event.

Panel B of Table 2 compares several market–level characteristics between the treatment and control groups. The comparison reveals similar flight distances, number of operating carriers, and load factors across both groups. However, some disparities exist in the degree of LCC presence in each market, the presence of carrier hubs, and markets served by only one (monopoly) or two (duopoly) carriers. Panel C illustrates the unit fuel consumption rates and related fuel costs incurred by carriers within the treatment and control groups. As expected, in the pre-treatment period the unit fuel consumption (cost) in the treated group is lower on average by 0.07 gallons ($0.14) compared to the control group. This difference can be attributed, at least partially, to the use of the fuel-efficient MAX . Panel D provides descriptive statistics for average fares and various fare percentiles, expressed in nominal US dollars. On average, these fare measures are relatively similar in both the treated and control

Table 2: Summary statistics.

	Control Carrier–Markets		Treated Carrier–Markets		All Carrier–Markets	
	Mean	SD	Mean	SD	Mean	SD
Panel (a). *Market Characteristics*						
Distance (1000'km)	1.11	0.66	1.04	0.57	1.10	0.64
Number of Carriers	2.80	1.55	3.08	1.48	2.85	1.54
Load Factor (%)	81.04	11.06	82.18	8.42	81.24	10.64
Low Cost Carrier (%)	45.59	49.81	89.06	31.22	53.38	49.89
Hub Market (%)	57.72	49.40	46.97	49.92	55.79	49.66
Monopoly Market (%)	25.78	43.74	13.28	33.94	23.54	42.42
Duopoly Market (%)	22.13	41.51	25.96	43.85	22.81	41.96
Panel (b). *Fuel Consumption*						
Fuel Burn per Seat-100km (gallons)	0.77	0.10	0.70	0.02	0.76	0.10
Fuel Cost per Seat-100km ($)	1.53	0.23	1.39	0.10	1.51	0.21
Panel (c). *Economy Fares ($)*						
Average Fare	214.04	104.79	215.56	34.18	214.31	96.03
Fare 10pct	101.72	75.61	96.22	33.74	100.74	70.01
Fare 25pct	139.32	83.15	145.08	26.23	140.35	76.17
Fare 50pct	189.90	97.79	194.34	30.38	190.70	89.54
Fare 75pct	262.43	121.91	267.61	39.78	263.36	111.74
Fare 90pct	356.34	160.61	365.91	56.63	358.06	147.51

NOTE. – Table presents summary statistics at the carrier–market–year quarter level before the grounding of the Boeing 737 MAX. Each carrier–market unit is categorized according to its treatment status prior to the grounding as defined in Section V.A. Panel A provides information on the treatment intensity for all carriers affected by the grounding at the observation level. Each observation is weighted by the number of enplaned passengers per quarter by the carrier in the corresponding market. Panel B presents the characteristics of individual markets serviced by carriers, where each market is assigned to the treatment or control group depending on whether an associated carrier operating in that market using Boeing 737 MAX aircraft prior to their grounding. Panel C compares the fuel consumption rates and unit fuel costs incurred by carriers while operating in markets assigned to the treatment and control groups, respectively. Panel D illustrates the mean and various percentiles of the fares charged by carriers to economy class passengers in markets belonging to the treated and control groups.

groups at around $215. The fares within the control group exhibit greater dispersion as the control group has less observations, thus leading to higher standard deviations.

V.C Impact on Fares

V.C.1 Econometric Specification

To estimate the overall effects of the MAX grounding on ticket fares, we use the following difference-in-differences (DiD) specification:

$$\begin{aligned} p_{cmt} = \beta_1 Treated_{cmt} + \beta_2 Treated_{cmt} \times PostBan_t + \\ \beta_3 \mathbf{X}_{cmt} + \lambda_m + \gamma_{ct} + \epsilon_{cmt} \end{aligned} \tag{1}$$

where m denotes a market, t the quarter, and c the carrier. p_{cmt} represents an outcome variable related to the ticket fares set by carriers. Our baseline outcome measure is the average economy class fare charged by carrier c in market m during time t. In subsequent analysis, we examine the effects of the grounding on specific percentiles from this fare distribution. $Treated_{cmt}$ represents the treatment intensity among carriers affected by the grounding in specific markets and time, as defined in Section V.A. $PostBan_t$ is a dummy variable that takes the value 1 for quarters following the grounding (i.e., starting from 2019'Q2) and 0 otherwise. We do not include $PostBan_t$ in the specification as it is subsumed by the time fixed effects. The coefficient β_2 captures the average change in the fare outcome within treated carrier-markets during the post-grounding period. Specifically, β_2 is the average change in the fare outcome post-grounding under full treatment for a carrier that operated all its flights in a given market using the MAX before the ban was implemented.

The vector $\mathbf{X}_{cmt}$ represents a set of time-varying controls that exhibit variation across both carriers and markets. This includes the average quarterly $Load\ Factor$ estimated from the monthly T-100 Domestic Segment Database for each carrier-market segment, $Distance$, expressed per 1000 kilometers, between the origin and destination airports, and a $Hub\ Market$ dummy equal to 1 if the market is part of the carrier's hub-and-spoke network.[33] The distance of a market significantly influences a carrier's marginal costs by impacting fuel consumption, in-flight passenger service needs, and aircraft maintenance requirements. Additionally, airports functioning as transfer hubs for the carrier's passengers tend to have lower marginal costs. This is primarily due to economies of scale, including reduced fixed costs associated with aircraft operations (such as parking/landing/hangar fees, insurance costs, and administrative expenses related to management, ticketing, and lounge facilities). Moreover, average connection times between flights are minimized, and variable costs related to aircraft maintenance and ground staff salaries are optimized at these hubs. However, stronger dominance by the carrier at its hub(s) against local competition might encourage it to mark up fares above cost (Borenstein, 1989).

All our specifications incorporate various fixed effects to account for potentially unobservable factors that may confound the analysis. We include carrier $\times$ time fixed effects γ_{ct} to absorb unobservable carrier-specific shocks that collectively vary across all its active markets over time. These fixed effects account for time-varying changes in carrier attributes such as managerial skill, fleet composition, and airport slot availability. They also help to

[33]Load factors proxy the capacity constraints faced by carriers within specific markets over time. It is crucial to recognize that load factors are endogenously determined at market equilibrium, since they depend on both passenger demand and seat capacity available with the carriers. To assess the robustness of our analysis, we conducted further tests to determine the impact of including load factors as part of $\mathbf{X}_{cmt}$ and found that their inclusion does not significantly alter our treatment effect estimates. It is also worth mentioning that one could also argue in favor of incorporating demand shifters into our analysis. However, we believe that the inclusion of time fixed effects θ_t in our specifications adequately captures the influence of demand shifters in our empirical setting.

address carrier entry and exit patterns that impact market composition, which are driven by seasonal variations in demand. Lastly, we incorporate market fixed effects λ_m in some of our specifications to capture unobserved factors specific to each market that remain constant over time, and that are not directly observable to the researcher although they are known to the carriers. By incorporating market fixed effects, our specification exclusively considers within-market variation when determining the treatment effect, restricting our control group to a subset of observations from the same markets as the treatment group. This means that we compare each treated carrier-market observation after the grounding with its own pre-grounding state, as well as with other unaffected carriers operating in the same market before and after the grounding. A possible concern could be that the true average treatment effect is underestimated if some of the carriers that are in the control group strategically increased their prices as a response to the price increase of the carriers in the treated group (in that same market). However, when excluding those competing carriers from the control group the results are almost identical, which is due to the fact that these competing carriers represent a small part of all the observations in the control group.[34]

Following the recommendations of Abadie et al. (2023), we double-cluster the standard errors by markets and carriers. This approach is justified for two reasons. First due to the sampling procedure, our matched OpenSky-DB1B/T-100 sample covers only a subset of all operational airline markets within the US. Second, carriers operated the MAX in only a subset of their markets, thereby warranting the inclusion of carriers within the clustering scheme due to the assignment. To make our study representative of consumer choices, each observation in our sample is weighted by the number of enplaned passengers. The weighting scheme aims to balance the impact of the grounding on overall fare changes experienced by passengers in bigger market to those observed in markets with fewer ones.

V.C.2 Results

Table 3 presents our primary results from the estimation of Equation (1) on mean ticket fares. The coefficients shown in panel (a) of Table 3 and in subsequent tables denote changes in the outcome under a hypothetical scenario where all flights within the treated group during a given quarter before the grounding were operated using the MAX. We refer to this scenario as *full treatment intensity*. Models 1 and 2 of panel (a) show that fares charged by carriers in markets where the MAX was operational prior to its grounding were lower than in the control group. The interaction term coefficient *Treated* × *PostBan* in models 1 and 2 indicates that, under full treatment intensity, mean economy fares in the treated group would have risen by at least \$16 on average after the grounding compared to control carrier-markets. This

[34] The treatment effect is slightly higher but the magnitude of the increase is very small relative to the size of the treatment (less than 10%)

corresponds to roughly an 8% increase in relative terms, as exhibited by the interaction term coefficients in models 4 and 5.

However, the actual effects of the grounding are best described when the we evaluate the effect at the *average treatment intensity* which stands at 11% as explained in the Section V.A. At this average treatment intensity, fares in treated carrier-markets increased by an average of at least \$1.85 compared to control carrier-markets after the grounding (model 2). Regression estimates on the $Log(Mean\ Fare)$ in models 4 and 5 indicate that this corresponds to a relative increase in mean fares of approximately 0.88%.[35]

We also run regressions using Equation (1) with the inclusion of market fixed effects to analyze mean ticket fares. Models 3 and 6 present the corresponding results for $Mean\ Fare$ and $Log(Mean\ Fare)$ as dependent variables. Both models reveal a weaker treatment effect in economic terms when accounting for unobserved market differences. However, many markets in the sample are monopolies or duopolies (refer to Table 2), implying that including market fixed effects might absorb the much needed variation to estimate the full treatment effect. We consider this issue minor since the *Treated* × *PostBan* coefficients in both models remain highly statistically significant, suggesting a substantial post-grounding fare increase in the treatment group. We consider this issue minor since the *Treated* × *PostBan* term remains statistically significant in both models, implying a substantial post-grounding fare increase in the treatment group.

In models where the dependent variable is $Log(Mean\ Fare)$ (models 4-6), we observe that the coefficients of *Treated* × *PostBan* are not only positive but also greater in magnitude than the negative coefficients of the treatment term (*Treated*) itself. This suggests that the treated group likely had lower fares before the grounding but experienced a more substantial fare increase afterwards. This pattern diverges somewhat from what we observed in models 1 and 2 for both these terms. In those models, the $Treated$ coefficients are negative and larger in comparison to the positive coefficients of *Treated* × *PostBan*. This implies that the post-grounding rise in average fares within treated carrier-markets only partially offset the pre-existing lower fares within this group. We hypothesize that these variations in the regression estimates for $Mean\ Fare$ and $Log(Mean\ Fare)$ originate from pronounced differences within the upper regions of the fare distribution between the treated and control groups. In Section V.C.4 we provide a decomposition of fares by deciles, which allows to explore the substantial differences in the price increase at the various fare percentiles, which

[35] We conduct additional robustness checks using alternative forms of the instrument: (i) a binary variant of the instrument which is equal to one for carrier-markets that had a non zero share of MAXbefore the grounding, and zero otherwise, and, (ii) treatment intensity measured as the percentage of MAX-operated flights by a carrier in a specific market during the entire pre-grounding period. These results are presented in Tables A2 and A3 in the internet appendix, respectively.

Table 3: Impact of the grounding on average ticket fares.

Panel (a): Baseline estimates

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × PostBan	23.6***	11.8	16.8***	8.10*	0.107***	0.062**	0.084***	0.043***
	(7.11)	(7.19)	(5.76)	(4.73)	(0.027)	(0.026)	(0.021)	(0.016)
Treated	23.7	26.4	-26.6***	-13.9**	0.141**	0.154**	-0.057**	-0.043
	(17.1)	(17.8)	(6.84)	(6.74)	(0.072)	(0.075)	(0.028)	(0.029)
Load Factor			10.7				0.165***	
			(9.84)				(0.048)	
Distance (1000 km)			44.3***				0.161***	
			(1.29)				(0.004)	
Hub Route			10.6***				0.046***	
			(1.62)				(0.008)	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	240.6	240.6	240.6	240.6	5.4	5.4	5.4	5.4
Observations	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320
R^2	0.69	0.69	0.84	0.93	0.80	0.80	0.89	0.95

Panel (b): Treatment by carrier

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × PostBan × Southwest	34.8***	38.2**	41.2***	19.9***	0.181***	0.161**	0.173***	0.077***
	(10.8)	(14.8)	(8.09)	(5.02)	(0.049)	(0.069)	(0.039)	(0.022)
Treated × PostBan × United	29.5*	-28.0	-8.68	-2.88	0.094*	-0.069	0.004	0.021
	(17.0)	(21.8)	(16.5)	(14.0)	(0.052)	(0.062)	(0.045)	(0.038)
Treated × PostBan × American	-7.38	9.54	8.40	4.41	-0.038**	0.036	0.041**	0.022
	(5.04)	(6.09)	(5.65)	(5.48)	(0.019)	(0.023)	(0.021)	(0.021)
Treated × Southwest	113.4***	114.5***	-30.1**	-25.5***	0.549***	0.568***	-0.005	-0.052*
	(22.5)	(20.9)	(11.8)	(7.65)	(0.112)	(0.106)	(0.053)	(0.029)
Treated × United	-5.85	6.56	-7.31	-5.01	-0.003	0.028	-0.026	-0.010
	(26.6)	(26.1)	(16.9)	(8.07)	(0.087)	(0.086)	(0.056)	(0.029)
Treated × American	-42.9***	-47.9***	-36.5***	-8.19	-0.151***	-0.174***	-0.130***	-0.055
	(14.8)	(14.9)	(9.78)	(15.3)	(0.055)	(0.056)	(0.039)	(0.067)
Controls			✓				✓	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	240.6	240.6	240.6	240.6	5.4	5.4	5.4	5.4
Observations	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320
R^2	0.69	0.70	0.84	0.93	0.80	0.81	0.89	0.95

NOTE. – Table presents OLS estimates comparing average economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (1). Separate estimates are provided for both $Mean\ Fare$ and $Log(Mean\ Fare)$ as dependent variables. Panel (a) shows the baseline regression estimates, while panel (b) presents regression estimates with treatment intensities disaggregated by carrier. Standard errors are double-clustered by carriers and markets, and are reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

are important for understanding the heterogeneity in the impact on prices of the grounding.

Coefficients of the control variables in panel (a) reveal that average fares increase with distance, driven mainly by corresponding fluctuations in fuel costs and other service expenses linked to longer flight durations. Additionally, markets characterized by higher load factors, signifying high passenger demand, also tend to have higher fares as they are closer to the capacity constraint. Fares are also higher on average in markets that feature an airport serving as a hub for the carrier, possibly because the carrier is insulated from competition in such strongholds (Borenstein, 1989).

Our next objective is to analyze how each affected carrier responded, on average, to the grounding by changing their respective fares. For this purpose, we run regressions using a modified version of Equation 1, with *Treated* decomposed as c for each impacted carrier c. This results in three $Treated_c$ terms and three $Treated_c \times PostBan$ terms in the regression specifications, as shown in panel (b) of Table 3. The findings reveal significant variability in how impacted carriers adjusted their fares, on average, within treated markets post-grounding. Notably, Southwest had the most substantial average fare increase, at \$4.12 (1.7% in relative terms) under its respective average treatment intensity level. In contrast, American and United, the other two affected carriers, did not exhibit an apparent average fare increase in response to the grounding. Individual carriers may however exhibit differential responses in setting fares following the grounding that are not captured by average fares. We investigate whether this is indeed the case by examining changes within the entire fare distributions of individual carrier-markets in Section V.C.4.

V.C.3 Robustness

We proceed by conducting a series of robustness checks. We first visually inspect the validity of the parallel-trends assumption that underpins our DiD design. To do so, we discretize the *PostBan* term in Equation 1 into eight distinct year-quarter dummies. Subsequently, we estimate the changes in fares around the grounding using the following specification:

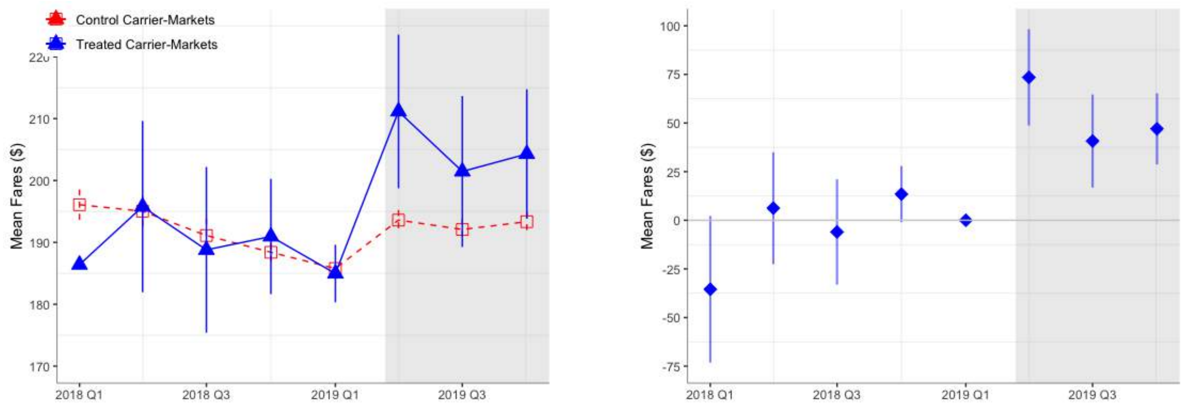
$$p_{cmt} = \beta_1 Treated_{cmt} + \beta_2 Treated_{cmt} \times \mathbf{t} + \beta_{\mathbf{3}} \mathbf{X}_{cmt} + \gamma_{ct} + \epsilon_{cmt} \tag{2}$$

where $\mathbf{t}$ is a vector of year-quarter dummies. The other terms in the equation are as described in Section V.C.1. Panel (a) of Figure 4 plots the predicted mean fares between the control and treated groups with treatment intensity set at the full sample mean of 11% as outlined in Section V.A. The treated and control groups exhibit similar trends leading up to the grounding, but then diverge afterwards with fares in the treated group markedly higher than those in the control group, which is consistent with the grounding having an effect. The relative increase in fares is most striking during the first quarter following the grounding.

We further employ an event study model to investigate the dynamic effects surrounding the treatment. The estimated differences between the treated and control groups over the sample duration are graphically shown in panel (b) of Figure 4. The event study accounts for carrier, quarter, and carrier × quarter fixed effects. The plot visually confirms the existence of a parallel trend prior to the grounding, and that the treatment effects are evident only after the MAX grounding and persisted over the ensuing period.

Figure 4: Impact of the grounding on ticket fares: dynamic estimates.

(a) Evolution of fares (b) Event study estimates



NOTE. – Figures show the dynamic time-series estimates of economy fares between treated and control carrier-markets based on Equation (2). Panel (a) shows the average fare estimates across control and treated carrier-markets over time, with the treatment intensity set at the sample mean of 11% as outlined in Section V.A. Panel (b) shows the estimated difference in average fares between the treated and control groups for each quarter. The shaded area in grey depicts the period when Boeing 737 MAX aircraft were banned from flight operations by the FAA. In all figures, the regressions include controls for carrier, year-quarter, carrier *times* year-quarter fixed effects, respectively. Vertical bars represent 95% confidence intervals clustered by carrier and quarter.

A prerequisite for the validity of our DiD design is that observations in the control group remain unaffected by the treatment, which is formally known as the *Stable Unit Treatment Values Assumption* (SUTVA). In our setting, the SUTVA would be violated if there were a consistent rotation of aircraft of a specific type between the treated and control groups, thereby introducing potentially confounding effects. We find that there are not substantial changes in fuel efficiencies separately within the treated and control carrier-markets during the periods before or after the grounding. Fuel efficiency is proxied in two ways by the *Fuel Burn* in *gps* and *Fuel Cost* in US dollars, as defined in Section IV.C. For reference, the MAX consumes 0.60 gps, which is similar to the 0.59 gps consumed by the Airbus 320 NEO, whereas the older Airbus 320 and Boeing 737 variants consume much more fuel at 0.69 gps (14% more than the MAX) and 0.79 gps (32% more than the MAX), respectively.

Table 4 presents the fuel efficiency comparisons between the treated and control groups, differentiating by individual carriers. The grounding led to substantial increments in average fuel burn rates within the treated groups of affected carriers, notably Southwest and American. Contrastingly, no such changes are evident within their respective control groups. Regarding unit fuel costs, there was a general decline across the control groups of all carriers, predominantly due to the overall decline in fuel prices during the post-grounding period (refer to Figure A7). However, despite the availability of cheaper jet fuel in the period after the grounding, a noteworthy increase in average unit fuel costs is observed within the treated groups of all the affected carriers. The consistent fuel consumption rate observed in the control group during the period surrounding the grounding indicates that there are no discernible alterations in the allocation of aircraft across treatment and control markets. However, these results are only descriptive, a causal interpretation of the grounding on fuel costs can be found in Section V.D.1.

Table 4: Fuel efficiency among carriers around the grounding.

		Fuel burn (gallons per seat–100km)		Fuel cost ($ per seat–100km)	
Carrier	Sample	Pre–Ban	Post–Ban	Pre–Ban	Post–Ban
Panel A. Affected Carriers					
Southwest (WN)	Control	0.79 (0.00)	0.79 (0.00)	1.57 (0.11)	1.49 (0.03)
	Treated	**0.70 (0.01)**	**0.79 (0.00)**	**1.38 (0.09)**	**1.49 (0.03)**
American (AA)	Control	0.81 (0.11)	0.81 (0.10)	1.61 (0.23)	1.54 (0.20)
	Treated	**0.74 (0.05)**	**0.78 (0.06)**	**1.46 (0.13)**	**1.47 (0.12)**
United (UA)	Control	0.84 (0.09)	0.86 (0.10)	1.68 (0.20)	1.63 (0.19)
	Treated	**0.79 (0.01)**	**0.79 (0.00)**	**1.38 (0.09)**	**1.49 (0.03)**
Panel B. Other Carriers					
Alaska (AS)	Control	0.77 (0.06)	0.76 (0.06)	1.51 (0.15)	1.42 (0.11)
JetBlue (B6)	Control	0.68 (0.01)	0.70 (0.04)	1.34 (0.09)	1.33 (0.08)
Delta (DL)	Control	0.84 (0.10)	0.83 (0.09)	1.66 (0.24)	1.56 (0.17)
Frontier (F9)	Control	0.65 (0.03)	0.65 (0.02)	1.31 (0.11)	1.22 (0.04)
Allegiant (G4)	Control	0.74 (0.04)	0.75 (0.04)	1.45 (0.13)	1.40 (0.07)
Hawaiian (HA)	Control	0.66 (0.11)	0.66 (0.10)	1.29 (0.25)	1.27 (0.28)
Spirit (NK)	Control	0.68 (0.05)	0.66 (0.03)	1.36 (0.13)	1.26 (0.07)
Sun Country (SY)	Control	0.79 (0.00)	0.79 (0.00)	1.54 (0.11)	1.49 (0.03)

NOTE. – Table presents fuel consumption rates and unit fuel costs incurred by individual carriers in the period surrounding the ban of the Boeing 737 MAX. Separate statistics are shown for carriers that were either affected (Panel A) or unaffected (Panel B) by the grounding. For the affected carriers, the statistics are further grouped by treatment status as defined in Section V.A, depending on whether or not a carrier operated the Boeing 737 MAX in a given market prior to the grounding. Fuel consumption rates (*Fuel Burn*) are expressed in gallons per seat–100km and unit fuel costs are expressed in dollars per seat–100km. The values shown reflect the mean and standard deviations are displayed in parenthesis.

V.C.4 Grounding Impact Heterogeneity

Examining average fares indicates whether ticket prices were impacted by the grounding at a general level. However, this approach overlooks a well-established fact in the literature that carriers strategically set different prices within the same fare class across all their flights within a market. Fares also vary substantially depending on the characteristics of each flight. For example, a long-haul flight has fewer substitutes than a comparable short-haul flight that can be covered instead by travelling in a car. Moreover, carriers tend to dynamically adjust prices for a given flight as the departure date approaches (Chandra and Lederman, 2018; Gerardi and Shapiro, 2009). Thus, relying solely on a single statistic, such as the average, presents limitations in capturing the full range of price changes across diverse markets and time. We therefore adopt a more comprehensive approach and analyse changes within different percentiles of the fare distributions for individual carrier-markets.

Table 5 shows the results for select percentiles of the distribution of economy fares set by each carrier across their respective markets in each quarter. We construct fare percentiles following the method introduced by Chetverikov, Larsen, and Palmer (2016), and later used by Chandra and Lederman (2018), and run separate regressions on the logarithm of each fare percentile as the dependent variable. In panel (a), the coefficient estimates for *Treated* $\times$ *PostBan* suggest that the grounding had a differential impact on tickets at different points along the economy fare distribution. Specifically, the grounding had the strongest influence between the middle and upper sections of the economy fare distribution. A discernible fare increase ranging from 7% to 11% is observed between the $25th$ and $90th$ percentiles under full treatment intensity, or 0.77% and 1.21% at the average treatment intensity. Conversely, there is no statistically significant effect observed at the lower end of the fare distribution, denoted by the $10th$ percentile.

In panel (b), we repeat the analysis with the treatment intensity disaggregated by carrier. The observed rise in fares along the upper regions of the distribution subsequent to the grounding varies across the impacted carriers. Notably, the fare increase is most pronounced for Southwest, and is somewhat less and much more concentrated within the upper percentiles in the case of American. However, there is no discernible impact across the various fare percentiles for United. In summary, these findings suggest that at least two out of the three affected carriers enacted price increases primarily targeting the upper sections of their respective fare distributions, which comprise a relatively higher proportion of price-inelastic passengers. Our results thus far consistently highlight notable differences in fare-related responses across carriers. For this reason, we reports results with the treatment intensities disaggregated by carrier throughout the remainder of the paper.

In this section we explore heterogeneity in the treatment effects by relating them to observable market characteristics. The results are reported in Table A5 in the Appendix. In panel (a), we analyze market structure in two ways. First, we assess whether a market is a monopoly served by a single carrier ($Monopoly\ Market$). We define a "$Monopoly\ Market$"

Table 5: Impact of the grounding on ticket fare percentiles.

Panel (a): Baseline estimates

Dependent Variables:	Log(Fare Percentile)				
	10pct	25pct	50pct	75pct	90pct
Model:	(1)	(2)	(3)	(4)	(5)
Treated × PostBan	0.01	0.10***	0.07***	0.11***	0.09***
	(0.10)	(0.02)	(0.02)	(0.02)	(0.02)
Treated	-0.12	-0.15***	-0.11***	-0.06**	0.01
	(0.11)	(0.05)	(0.03)	(0.03)	(0.03)
Controls	✓	✓	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓	✓	✓
Mean of the Fare Percentile	107.0	153.4	213.2	297.8	410.0
Observations	28,320	28,320	28,320	28,320	28,320
R^2	0.71	0.87	0.88	0.87	0.87

Panel (b): Treatment by carrier

Dependent Variables:	Log(Fare Percentile)				
	10pct	25pct	50pct	75pct	90pct
Model:	(1)	(2)	(3)	(4)	(5)
$\text{Treated}_{Southwest}$ × PostBan	-0.03	0.16***	0.18***	0.23***	0.19***
	(0.27)	(0.04)	(0.04)	(0.04)	(0.04)
$\text{Treated}_{American}$ × PostBan	-0.02	0.03*	-0.004	0.06***	0.08***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Treated_{United} × PostBan	0.05	0.04	0.008	0.01	-0.04
	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)
$\text{Treated}_{Southwest}$	0.20	0.0006	-0.07	-0.04	0.05
	(0.27)	(0.07)	(0.06)	(0.05)	(0.06)
$\text{Treated}_{American}$	-0.50***	-0.40***	-0.22***	-0.08**	-0.004
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Treated_{United}	-0.02	-0.005	-0.02	-0.04	-0.01
	(0.08)	(0.07)	(0.06)	(0.05)	(0.06)
Controls	✓	✓	✓	✓	✓
Carrier × Year-Quarter FE	✓	✓	✓	✓	✓
Mean of the Fare Percentile	107.0	153.4	213.2	297.8	410.0
Observations	28,320	28,320	28,320	28,320	28,320
R^2	0.71	0.87	0.88	0.87	0.87

NOTE. – Table presents OLS estimates comparing select percentiles of economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (1). Panel (a) shows the baseline regression estimates, while panel (b) presents regression estimates with treatment intensities disaggregated by carrier. Standard errors are double-clustered by markets and carriers, and are reported in parantheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

as one where a single carrier operated throughout every quarter of 2018.[36] Second, we assess

[36]This criterion ensures that the variable captures only sustained monopoly markets, allowing us to observe potentially distinct pricing strategies employed by sole carriers active in their markets compared to more competitive markets.

the response of competing carriers based on their utilization of MAX aircraft in the market before the grounding. The corresponding variable *Direct Competitors* reflects the combined treatment intensity of all rival carriers in a specific carrier-market during a given quarter.

Coefficients of the interaction term *Treated* × *Monopoly Market* in panel (a) indicate that fares were generally higher on average in treated markets that were monopolies. Despite an overall decline in average fares post-grounding across monopoly markets, there is no clear evidence of a different increase in fares within treated monopoly markets, relative to the rest of markets with at least one competitor. Moreover, the interaction term *Direct Competitors* × *PostBan* suggests that rival carriers employing the MAX likewise increased their fares in response to hikes initiated in markets by an incumbent carrier that had also grounded its MAX aircraft.[37] However, this fare increase by rival carriers is not statistically significant.

In panel (b), we examine the short- and long-term impacts of the grounding on average fares. Under average treatment intensity, there is a significant uptick in average fares by about 1.45% in the immediate quarter post-grounding (Q2'2019), which is nearly twice the average fare increase during the subsequent two-quarters. Furthermore, the evidence indicates that the fare increases by rival impacted carriers in response to the grounding are also most pronounced in the short-term.

Panel (c) presents results on the varying impact of the grounding by flight distances. The findings reveal a more pronounced increase in average fares for long-haul markets (exceeding 8,000 kilometres in flight distance) compared to short-haul markets. This discrepancy aligns with expectations, given that long-haul flights are typically associated with higher aggregate fuel consumption.

V.D Fuel Cost Pass-Through to Fares

Previously, we showed in the descriptive statistics reported in Table 4 that the average fuel burn of the treated group increased differently for Southwest, American and United after the grounding, and that the fuel costs increased in both the treated and control groups despite lower jet fuel prices (See Figure A7). In this section, we conduct a more thorough investigation to determine the extent to which any discernible rise in fuel expenses incurred by the affected carriers post-grounding may have contributed to the incremental change in ticket fares observed within the treated group, as shown previously in Section V.C. We achieve this using a two-step estimation procedure. In the first step, we estimate the direct effect of the grounding on fuel consumption rates and unit fuel costs incurred by the affected carriers within their treated markets. We then regress the predicted unit fuel costs (from the first step) multiplied by the corresponding market distance, representing the total fuel

[37]The control group in this context once again pertains to any competing carrier that had never operated the MAX in a given market.

cost per passenger on the route, on average ticket fares.

V.D.1 Grounding Impact on Fuel Consumption and Costs

We proceed by determining the changes in jet fuel consumption and costs that are attributable to the grounding. To achieve this, we use the DiD framework in Equation 1 to run regressions on unit fuel consumption (*Fuel Burn*, in *gps*) and unit fuel expenditure (*Fuel Cost*, in US dollars per seat-100km) as the outcomes. Recognizing the varied responses among impacted carriers in adjusting fares following the grounding, as illustrated in panel (b) of Table 3, we employ a similar methodology to evaluate the corresponding changes in fuel consumption rates and unit costs. This analysis involves disaggregating the treatment intensity by each affected carrier and control for being in the treatment group before the grounding for each of the affected carriers. The results can be found in Table 6.

We find that prior to the grounding the fuel consumption in flights operated with the MAX was consistently lower compared to the fuel consumption in the control group flights, ranging from 0.23, 0.14 to 0.25 gps less for Southwest, American and United respectively, which is 70% ($\frac{0.77-0.23}{0.77}$), 82% and 68% of the fuel consumption in the control group from before the grounding. These lower fuel consumption rates can be primarily credited to the flights operated in treated markets using the highly fuel-efficient MAX. However, as indicated by the treatment intensity, the MAX represented 10%, 12% and 17% for Southwest, American and United, implying that the respective average fuel consumption across all fleet models in the treated markets was 97%–97%–95% relative to the control group consumption from before the grounding. After the grounding, the per flight fuel consumption rose substantially for all of the carriers: from representing 70% to 115% for Southwest, from 82% to 95% for United and from 68% to 86% for United. Thus, for the average treated market, fuel consumption went from representing 97%–97%–95% for Southwest, United and American to representing 102%–99%–98%. One can also quantify the increase relative to the pre-grounding fuel consumption of the treated markets of Southwest, American and United instead of using the control group as reference. We then find that there was an increase of 4.7%, 1.6% and 3.2%.[38]

Given that the typical flight in our sample comprises 170 seats and covers an average distance of 1,040 kilometers, the fuel cost increase per flight subsequent to the grounding of

[38]The interaction terms $Treated_c \times PostBan$, where c denotes a carrier, reveal a significant surge in both unit fuel consumption and costs across all three carriers impacted by the grounding during their subsequent flights in treated markets. The post-grounding treatment effect per carrier on fuel consumption can be also quantified by juxtaposing it against the average fuel consumption rate within the control group before the grounding, which stands at 0.76 gps (see Table 2). The highest relative treatment effect compared to the control group is observed in Southwest with a 46% increase in fuel consumption (calculated as 0.35/0.76), followed by United at 18% (0.14/0.76), and American at 13% (0.10/0.76)

Table 6: Impact of the grounding on fuel consumption and costs.

Dependent Variables:	Fuel Burn	Fuel Cost
Unit:	Gallons per seat-100km	\$ per seat-100km
Model:	(1)	(2)
$\text{Treated}_{Southwest}$ × PostBan	0.35***	0.68***
	(0.04)	(0.07)
$\text{Treated}_{American}$ × PostBan	0.10***	0.24***
	(0.01)	(0.02)
Treated_{United} × PostBan	0.14***	0.23***
	(0.04)	(0.08)
$\text{Treated}_{Southwest}$	-0.23***	-0.42***
	(0.03)	(0.05)
$\text{Treated}_{American}$	-0.14***	-0.28***
	(0.03)	(0.05)
Treated_{United}	-0.25***	-0.43***
	(0.04)	(0.06)
Controls	✓	✓
Year-Quarter x Carrier FE	✓	✓
Mean of Dependent Variable	0.76	1.5
Observations	28,320	28,227
R^2	0.50	0.54

NOTE. – Table presents the first stage instrumental variable regression estimates comparing fuel consumption rates and unit fuel costs between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (1). The treatment intensities are disaggregated by carrier. Standard errors are double-clustered by markets and carriers, and are reported in parantheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

the MAX is approximately \$1,202 for Southwest ($0.68 \times 170 \times \frac{1{,}040 \text{ km}}{100}$) or \$7 per passenger, \$424 for American ($0.05 \times 170 \times \frac{1{,}040 \text{ km}}{100}$) or \$2.5 per passenger, and \$407 for United ($0.039 \times 170 \times \frac{1{,}040 \text{ km}}{100}$) or \$2.4 per passenger. Finally, the estimated increase in fuel costs that we estimated for each carrier relative to its average consumption (reported in Table 4) is 50% for Southwest (0.68/1.38), whereas it is 16% (0.24/1.46) and 17% (0.23/1.38) for American and United. Overall, these results show that the grounding led to a much more substantial increase in fuel consumption and costs Southwest's compared to the other affected carriers.

V.D.2 Grounding Impact on CO_2 Emissions

Table 6 highlights the notable upswing in jet fuel consumption from replacing the grounded MAX with less fuel-efficient aircraft. To assess the corresponding environmental ramifications stemming from the grounding, we use the regression estimates of the treatment effects on jet fuel consumption rates and covert them into CO_2 emissions.

Considering that the typical flight in our sample carries on average 170 passengers and travels 1,040 kilometers, the interaction term coefficients in model 1 of Table 6 can be used to estimate the average marginal changes in total fuel consumption per flight within the treated group after the grounding. The coefficients suggest an estimated per-flight fuel consumption increase of 61.88 gallons for Southwest (calculated as 0.35 $\times$ 10% average treatment $\times$ 170 passengers $\times$ $\frac{1{,}040\text{km}}{100}$), 30.06 gallons for American (0.10 $\times$ 21% average treatment $\times$ 170 $\times$ $\frac{1{,}040\text{km}}{100}$), and 42.08 gallons for United (0.14 $\times$ 17% average treatment $\times$ 170 $\times$ $\frac{1{,}040\text{km}}{100}$).

We leverage these estimates to perform back-of-the-envelope calculations, aiming to ascertain the collective rise in CO_2 emissions per quarter for each carrier subsequent to the grounding. Considering that every gallon of jet fuel burnt releases up to 11.96 kilograms of CO_2 (ICAO, 2017) and adjusting for the fact that the fuel consumption in our data is the 85% of the total consumption as highlighted in the introduction, the overall increase in CO_2 emissions stemming from Southwest's substitution of more fuel-efficient MAX with less efficient alternatives is estimated to be approximately 109 thousand tonnes per quarter.[39] Similar substitutions to less fuel-efficient aircraft by American and United resulted in an increase of 12 thousand and 22 thousand tonnes of CO_2 per quarter, respectively. Cumulatively, the increase in CO_2 emissions from the three impacted carriers amounts to 143 thousand tonnes of CO2 per quarter, totalling 572 thousand tonnes on an annualized basis. This increase is equivalent to the CO_2 emissions produced by more than 123,200 cars, whereby each car travels 18,500 kilometres per year and emits 250 grams of CO_2 per kilometre (EPA, 2023).

The environmental damage expected from the estimated increase in CO_2 emissions due to the grounding is estimated to incur a total social cost of around $108 million per annum. This estimate stems from the concept of the *social cost of carbon*, which quantifies the monetized value of long-term societal damages from the incremental release of one metric tonne of CO_2. Based on relevant statistics released by the US Environmental Protection Agency in 2022 under this framework, the long-term social cost of carbon at a 2% annual discount rate stands at $190 for each additional tonne of CO_2 released into the atmosphere (EPA, 2022).

V.D.3 Fuel Cost Pass-Through to Ticket Fares

Thus far, our analysis revealed a direct relationship between the MAX grounding and a notable rise in ticket fares, particularly within the upper regions of the economy fare distribution. Additionally, we found that fuel consumption rates for the affected carriers increased as a consequence of replacing the prohibited aircraft model with less fuel-efficient aircraft, contributing to a simultaneous rise in both their fuel expenses and CO_2 emissions. However, the extent to which carriers passed the increase in fuel costs experienced due to the grounding on to ticket fares remains unclear. This question holds significance because any change in unit fuel costs has a direct impact on the marginal costs incurred by a carrier.[40]

[39] Quarterly CO_2 emissions for a carrier are estimated as follows: *number of flights* $\times$ *estimated per-flight changes in jet fuel consumption* $\times$ *CO_2 emissions per gallon* $\times$ *Treatment Intensity.*

[40] The pass-through literature has considered marginal costs as an informative measure for pricing. However, a direct estimation of marginal costs is beyond the scope of this paper, as it would require the formulation

To explore this question, we utilize the unit fuel cost estimates from Table 6, which are computed from precise data that help us identify the specific type of aircraft employed for each flight in our sample and the fuel consumption characteristics of each aircraft type. We use an approach similar to Fabra and Reguant (2014) to determine the magnitude of fuel cost pass-through to ticket fares that are attributable to the grounding. The corresponding specification is as follows:

$$p_{cmt} = \rho \widehat{f_{cmt}\tau_t d_m} + \beta_0 Treated_{cmt} + \beta_1 \mathbf{X}_{cmt} + \gamma_{ct} + \epsilon_{cmt} \tag{3}$$

where ρ denotes the fuel cost pass-through rate due to the grounding on ticket fares. The dependent variable is the ticket fare, p_{cmt}, whereas f_{cmt} represents the fuel consumption rate, τ_t the average jet fuel price during quarter t, and d_m the market distance. Specific details on the computation of ticket fares and fuel costs can be found in section IV.C. The fuel cost per passenger incurred by carrier c in market m at time t is denoted by $f_{cmt}\tau_t d_m$, and is predicted from a first-stage regression of per-passenger fuel costs using the DiD specification outlined in Equation (1). The approach in Equation 3 is similar to that of Equation 1, except that we allow the grounding to affect fares only through the fuel consumption term f_{cmt} along with the prevailing jet fuel price τ_t and market distance d_m.

Table 7 reports the regression estimates based on Equation 3. Model 1 presents the results of our first-stage, showing that fuel costs per passenger in the treated markets of affected carriers increased relatively significantly following the grounding. Model 2 reports our results of the pass-through rate of fuel costs on average ticket fares, indicating a pass-through rate estimate of $\rho = 4$. This implies that for every \$1 rise in per-passenger fuel costs caused by the grounding, ticket fares could increase up to \$4, depending on the weight of fuel costs in the firms marginal cost of serving an additional ticket. This finding of a cost pass-through greater than one is an exception rather than the norm in the pass-through literature. We attribute this high pass-through rate to a discrepancy between observed cost shocks and the full spectrum of opportunity costs that carriers faced in the aftermath of the grounding. In particular supply-side capacity constraints driven by lower availability of fuel efficient fleet.

First, carriers may have sought spare aircraft from manufacturers and lessors to alleviate capacity issues caused by the grounding. However, as highlighted in Section IV.D, carriers resorted to utilizing legacy aircraft within their fleets, possibly due to a scarcity of spare

of a structural model that takes into consideration the capacity constraints of carriers, their strategic responses in relation to the grounding, as well the dynamic adjustments of fares. A recent paper by Williams (2022) explores the implications of dynamic fare adjustments by carriers and their capacity constraints. Findings reveal that optimal fares depend not only on competitor pricing responses but also on the shadow price of capacity. The paper asserts that marginal costs for additional passengers may be minimal, potentially close to zero, once a firm commits to operate a specific route. Moreover, marginal costs may be linked to factors such as luggage weight and ticket booking administrative processes.

Table 7: Impact of the grounding on fuel cost pass-through rates to mean ticket fares.

	IV (First Stage)	IV (Second Stage)	OLS
Dependent Variables:	Fuel Cost Route	Mean Fare	
Model:	(1)	(2)	(3)
$\text{Treated}_{Southwest}$ × PostBan	8.2***		
	(0.86)		
$\text{Treated}_{American}$ × PostBan	2.7***		
	(0.28)		
Treated_{United} × PostBan	3.9***		
	(0.96)		
$\text{Treated}_{Southwest}$	-5.3***	-5.7	-9.5
	(0.47)	(13.1)	(12.5)
$\text{Treated}_{American}$	-2.2***	-28.5***	-30.7***
	(0.64)	(10.4)	(9.8)
Treated_{United}	-5.2***	3.4	-3.1
	(0.53)	(14.3)	(14.4)
Fuel Cost Route		4.0***	2.2***
		(0.91)	(0.39)
Controls	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓
Observations	28,227	28,227	28,227
R^2	0.98	0.84	0.84
Mean Dep. Variable	15.1	240.6	240.6

NOTE. – Table presents the first stage estimates comparing fuel pass-through rates on average economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (3). The treatment intensities are disaggregated by carrier. The dependent variable *Fuel Cost per passenger* in model 1 are the total fuel costs incurred per passenger by carrier c operating in market m during quarter t, as denoted by the term $\widehat{f_{cmt}\tau_t d}_m$ in Equation (3). The *Fuel Cost per passenger* term in model 2 is the predicted value of $\widehat{f_{cmt}\tau_t d}_m$ from the regression estimates obtained in model 1. Standard errors are double-clustered by markets and carriers, and are reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

capacity amid high global demand for narrow-body aircraft. This would have resulted in extended usage of these legacy aircraft, leading to increased service, maintenance, and leasing expenses. Second, Boeing halted additional deliveries of the MAX until resolving and certifying issues stemming from the two fatal crashes involving this aircraft type. This significantly disrupted carriers' fleet planning and growth strategies, especially for carriers that were already operating the MAX.[41] Third, the impacted carriers were forced to store their grounded MAX aircraft, leading to increased storage and maintenance expenses. Fourth, carriers incurred significant expenses addressing software and hardware issues on their existing MAX aircraft. Pilot retraining was also necessary, contrary to earlier assurances from

[41] Following are some news articles covering the suspension of 737 MAX production by Boeing and the grounding's impact on carriers'growth plan: (i) Boeing 737 Max cancellations pile up in bleak start to the year, (ii) Southwest and American pull 737 MAX until early March, nearly a year after grounding, and (iii) Flydubai to reduce its 737 MAX order by 65 aircraft.

Table 8: Impact of the grounding on fuel cost pass-through rates to ticket fare percentiles.

Dependent Variables:	Fare Percentile				
	10pct	25pct	50pct	75pct	90pct
Model:	(1)	(2)	(3)	(4)	(5)
Fuel Cost per passenger	1.6	2.7***	3.4***	6.4***	6.3***
	(1.2)	(0.66)	(0.84)	(1.1)	(1.9)
$\text{Treated}_{Southwest}$	-0.29	0.62	-11.8	-2.4	7.4
	(8.7)	(10.1)	(12.5)	(16.6)	(23.9)
$\text{Treated}_{American}$	-60.3***	-63.2***	-50.7***	-17.3	14.3
	(5.1)	(8.2)	(9.7)	(14.1)	(18.0)
Treated_{United}	6.3	11.6	6.4	6.9	-8.4
	(11.0)	(11.7)	(13.4)	(16.4)	(29.8)
Controls	✓	✓	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓	✓	✓
Mean of Dep. Variable	107.0	153.4	213.2	297.8	410.0
Observations	28,227	28,227	28,227	28,227	28,227
R^2	0.77	0.80	0.82	0.82	0.80

NOTE. – Table presents OLS estimates comparing fuel pass-through rates on select percentiles of economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (3). The treatment intensities are disaggregated by carrier. The *Fuel Cost per passenger* term in each model is the predicted value of $\widehat{f_{cmt}\tau_t d_m}$ from the regression estimates obtained in model 1, which are shown in model 1 of Table 7. Standard errors are double-clustered by markets and carriers, and are reported in parantheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Boeing that certified pilots of older 737 models could seamlessly transition to the MAX, leading to unexpected costs. Lastly, the grounding has led to double-digit hikes in aviation insurance premiums, as underwriters had to contend with significant payouts to carriers worldwide affected by the grounding.[42] Taken together, we posit that a combination of these factors may have contributed to the high pass-through rate of jet fuel costs observed in treated carrier-markets following the grounding.

To determine whether the pass-through of jet fuel costs on ticket fares is homogenous across the fare distribution, we estimate the pass-through rates for each of the five fare percentiles as shown in Table 8. The results suggest that the pass-through rate is more substantial at higher percentiles of the fare distribution, starting at 1.6 at the 10^{th} percentile and going all the way to 6.3 at the 90^{th} percentile. Notably, the pass-through rate is strongest around the 75^{th} at about 6.4. A plausible explanation for these trends is that carriers may find it more convenient to offset incremental cost increases and related opportunity costs by setting higher fares for tickets bought by price-inelastic travellers. These individuals are more likely to make last-minute purchases, indicating a higher willingness to pay.

[42]See related news article at: Aviation industry expects double-digit insurance premium hikes after 737 MAX grounding.

VI Conclusions

In this paper we have used the unforeseen grounding of the MAXin March 2019 as a quasi-experimental setting to study pricing responses to supply shocks that affect the shadow price of existing capacity. Our empirical analysis utilized a novel dataset covering nearly all domestic flights of US carriers from 2017 to 2019. This dataset is compiled from real-time communications between aircraft in flight and ground controllers, and is thus reliably free of measurement errors.

We started by examining how the unforeseen disruption caused by the grounding to carriers' adoption and use of the MAX impacted passenger ticket fares. Carriers faced challenges securing immediate spare external capacity (aircraft from lessors and manufacturers) to replace their grounded MAX aircraft. To minimise flight disruptions and ensure continued service in their respective markets, carriers had to maximize utilization of legacy aircraft present in their fleets, despite the lower fuel efficiency of these aircraft compared to the MAX. Leveraging the grounding as a natural experiment, we employ a DiD design to compare outcomes in treated carrier-market pairs where the MAX operated before the grouding to control pairs where it never did. Our analysis shows a marginal increase of about \$1.85 (0.88% in relative terms) in average fares within treated carrier-markets post-grounding relative to the control group. The average fare increase is most substantial in the case of Southwest at \$4.12 (1.7%). In fact, had carriers utilized the MAX exclusively for all their flights in treated markets before the grounding, average fares in those markets would have risen by almost \$16 (8% in relative terms) after the grounding. We found substantial heterogeneity in the treatment effects for two primary reasons. First, fare adjustments by the affected carriers varied across the entire distribution. The higher percentiles of the fare distribution showed clear increases, while the lowest percentiles remained unchanged. Second, the three impacted carriers in our setting had adopted the MAX to different degrees in their fleets prior to the grounding. The documented rise in middle to top fare percentiles post-grounding was correspondingly most significant for Southwest, followed by American, while no noteworthy change was observed for United.

We then showed that the initial cost advantage in treated carrier-markets, attributed to the usage of fuel-efficient MAX aircraft, diminished rapidly after the grounding. This resulted in a significant increase in jet fuel consumption rates and costs, particularly affecting Southwest. Carriers impacted by the grounding swiftly adjusted prices to counter the experienced rise in fuel expenses. The corresponding pass-through rate of fuel costs to ticket fares is notably high at 4, indicating that carriers faced significant supply-side capacity constraints in addition to the observed cost shocks from the grounding. Finally, we documented a significant rise in

CO_2 emissions due to increased fuel consumption among the affected carriers. The estimated social cost of the environmental damage caused by these incremental CO_2 emissions is $108 million per annum.

Overall, this paper presents novel empirical insights on how innovation in energy-intensive industries that supports firms in cost reduction also translates into lower prices for customers. Beyond economic advantages, these innovations play a pivotal role in curbing emissions and fostering environmental well-being. From a policy standpoint, the grounding could have been avoided, unlocking the full economic and environmental benefits from MAX adoption, had regulators approved these aircraft for flying after thorough testing and certification. Instead, a combination of factors, including regulatory capture, industry lobbying, and a flawed certification process led to the MAX being cleared for flight without adequate testing.[43] This eventually led to the two fatal crashes and subsequently a prolonged twenty-month grounding of the aircraft, causing massive financial losses to carriers worldwide as well as Boeing.

We conclude by acknowledging certain limitations in our paper and propose avenues for future research. First, our study examines a supply shock impacting a subset of firms that were in the initial stages of adopting new technology. To assess the net welfare impact of technology adoption, future work should explore more established technologies like artificial intelligence, which have been in use for several years and are now widely adopted across various industries. Second, we did not assess the impact of the grounding on business class fares due to insufficient data on seat configurations by fare class and passenger occupancies for specific flights. In fact, Southwest, the main affected carrier in our setting, does not offer business class seats. Third, while our study focuses only on direct flights, future research could explore the impact of the grounding on carriers' strategic decisions regarding flight connections and code-sharing agreements. Finally, our fuel cost estimates may raise concerns about potential noise or measurement errors, as some carriers may be able to acquire jet fuel at significant discounts to the market price. We do not believe this to pose major problems as most carriers employ hedging strategies, such as securing long-term forward contracts with jet fuel vendors, to shield against oil price fluctuations.

[43]The controversy surrounding the inadequate testing of the Boeing 737 MAX by US regulators primarily stems from a combination of factors. Boeing, seeking to expedite the approval of its new MAX aircraft to remain competitive, heavily influenced the FAA through lobbying efforts and close collaboration, leading to a situation where the regulatory oversight became compromised. Additionally, the FAA delegated significant certification tasks to Boeing itself, relying on the company's assurances without conducting sufficiently independent and rigorous evaluations. This close relationship and the reliance on self-certification obscured potential safety issues, contributing to the tragic crashes of Lion Air Flight 610 and Ethiopian Airlines Flight 302. The aftermath of these incidents prompted a re-evaluation of the certification process and highlighted the need for reforms to ensure a more robust and impartial regulatory framework.

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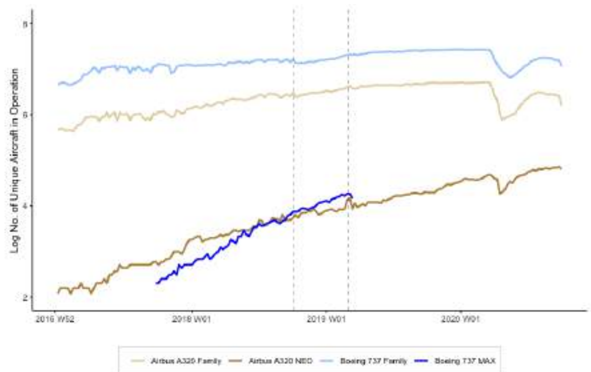
Internet Appendix

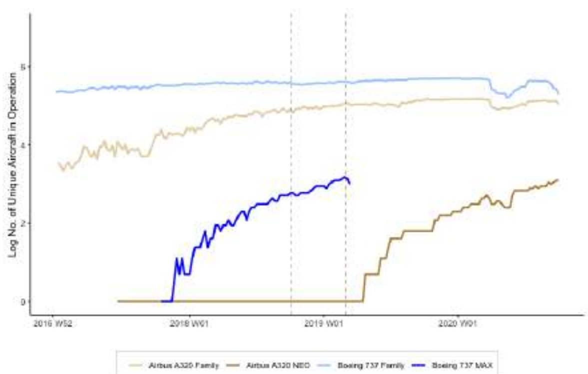
A Additional Figures and Tables

Figure A1: Inventories of narrow-body aircraft among US carriers.

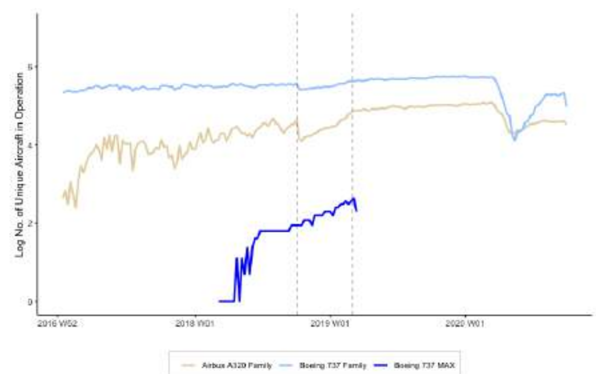
(a) All carriers



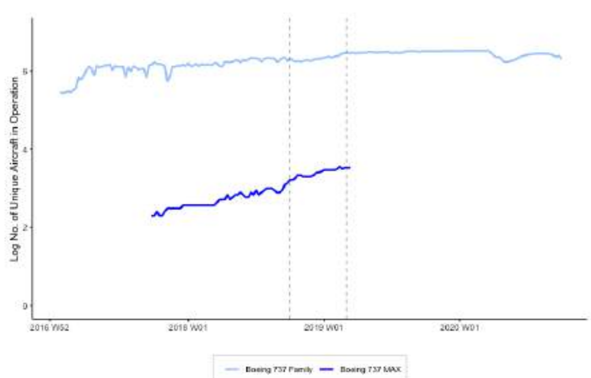
(b) American Airlines



(c) United Airlines



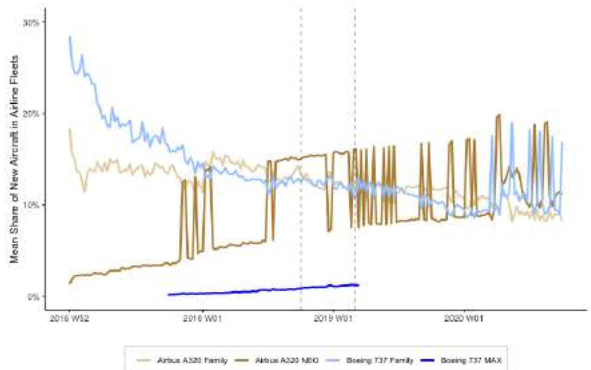
(d) Southwest



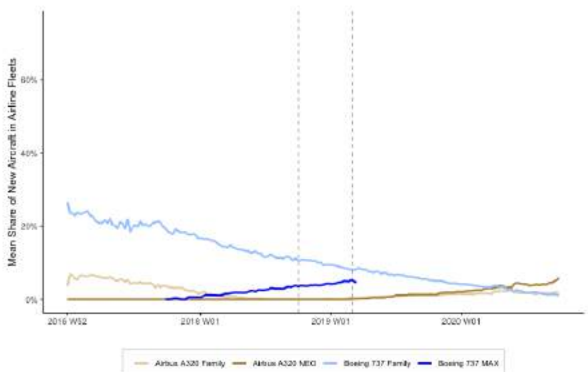
NOTE. – Figures show the log number of narrow-body aircraft operated by US carriers, grouped into four types: legacy Airbus 320 family (including all variants), Airbus 320 NEO, legacy Boeing 737 family (including all variants), and Boeing 737 MAX. *Narrow-body* aircraft have a seating configuration comprising 6 seats per row. *Smaller* and *larger* aircraft, as defined in Section IV.B, are not considered in these plots.

Figure A2: New aircraft in carrier fleets.

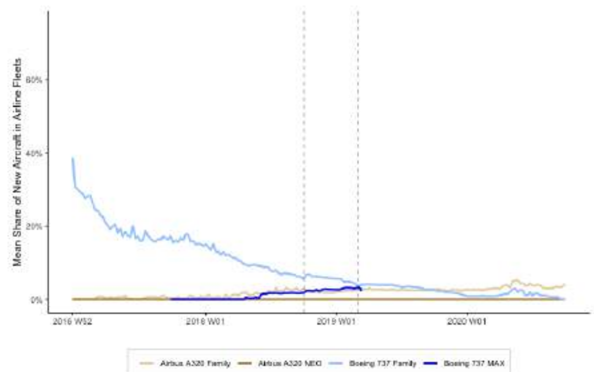
(a) All carriers



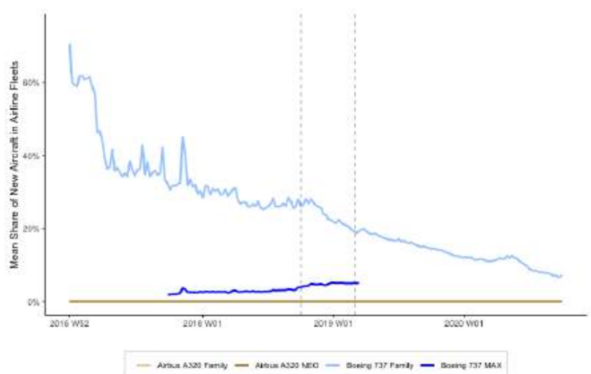
(b) American Airlines



(c) United Airlines

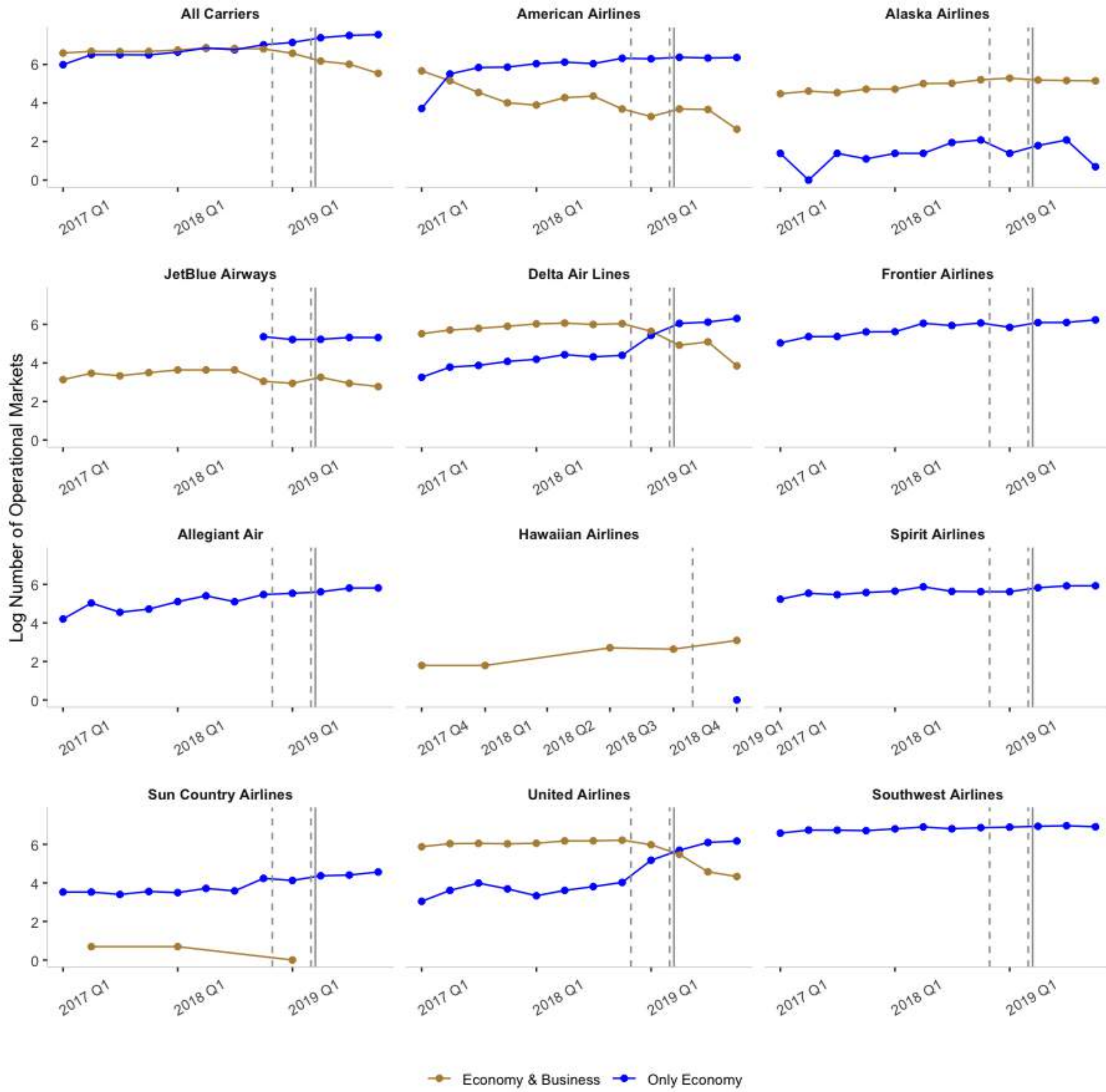


(d) Southwest



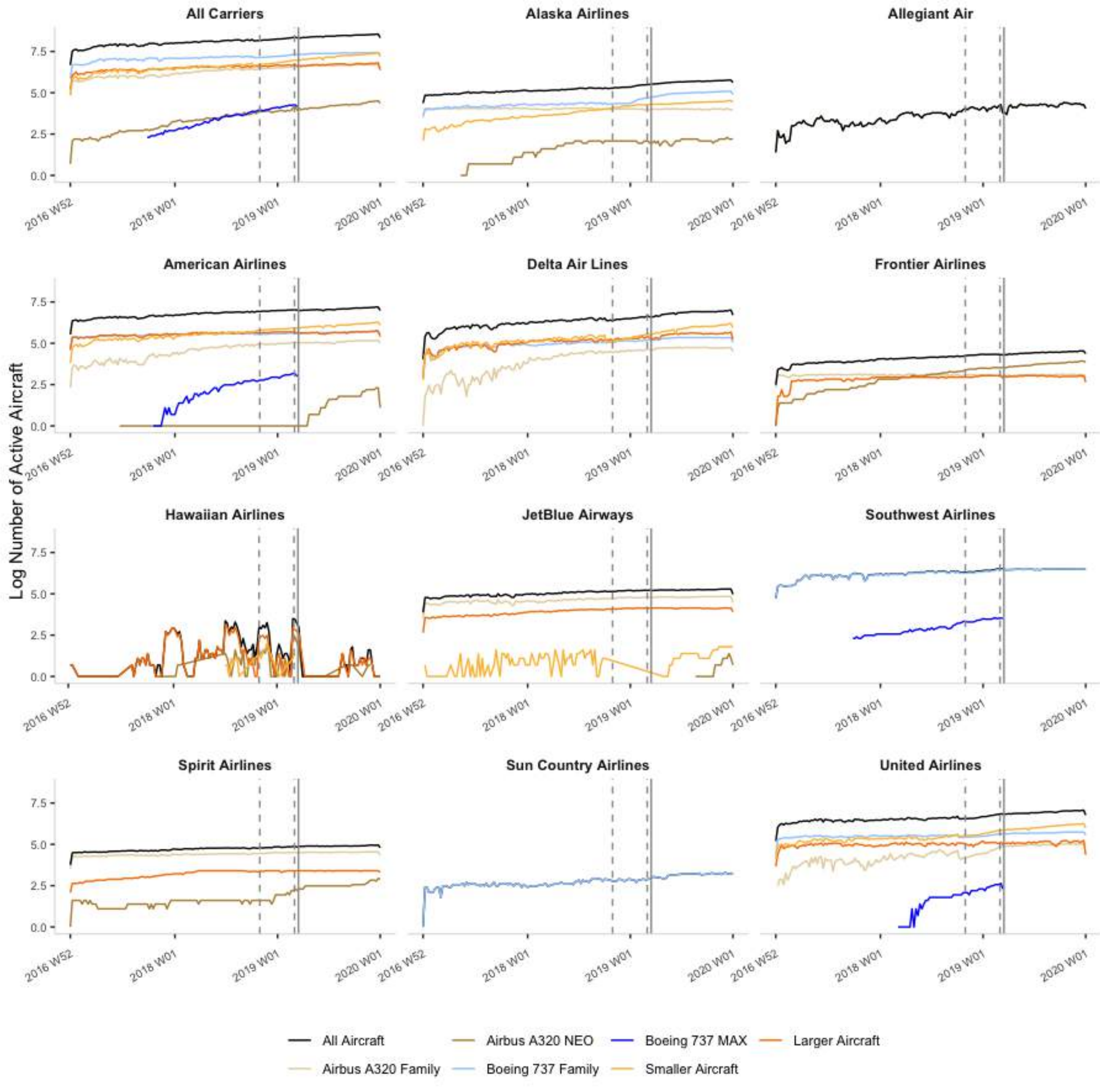
NOTE. – Figure shows the percentage of newer narrow-body aircraft (maximum 3 years since date of manufacture) present in the fleets of US carriers. Narrow-body aircraft are grouped into four types: legacy Airbus 320 family (including all variants), Airbus 320 NEO, legacy Boeing 737 family (including all variants), and Boeing 737 MAX. *Narrow-body* aircraft have a seating configuration comprising 6 seats per row. *Smaller* and *larger* aircraft, as defined in Section IV.B, are not considered in these plots.

Figure A3: Number of markets operated by carriers over time.



NOTE. – Plots show the log number of domestic markets served by US carriers. In each plot, markets are grouped into those where the carrier exclusively offers economy class seats and those where economy and business class seats are sold together. Dotted lines indicate the dates of the two crashes involding the Boeing 737 MAX aircraft. The solid vertical line in each plot represents the date on which the FAA ban on the Boeing 737 MAX was imposed.

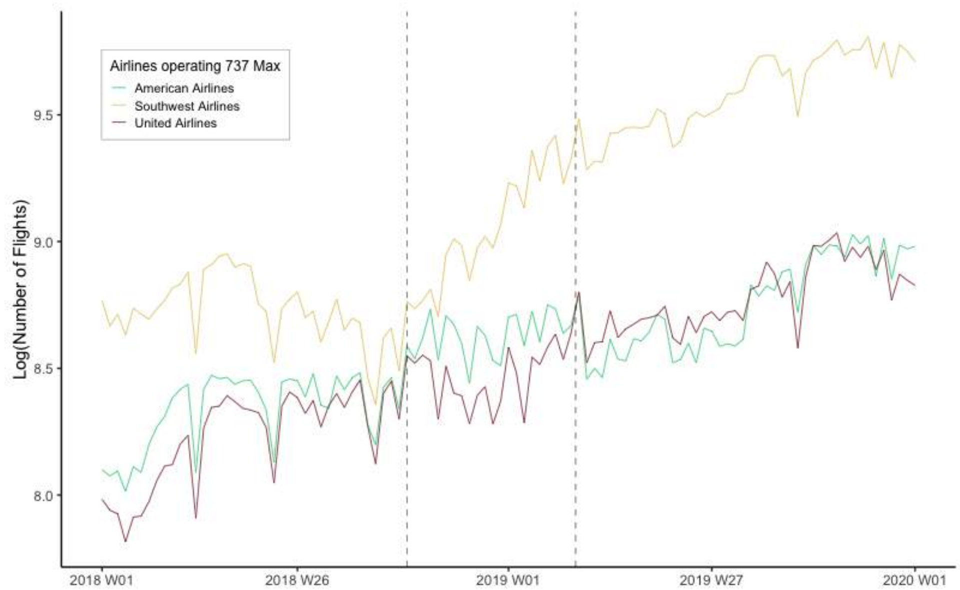
Figure A4: Fleet composition of carriers over time.



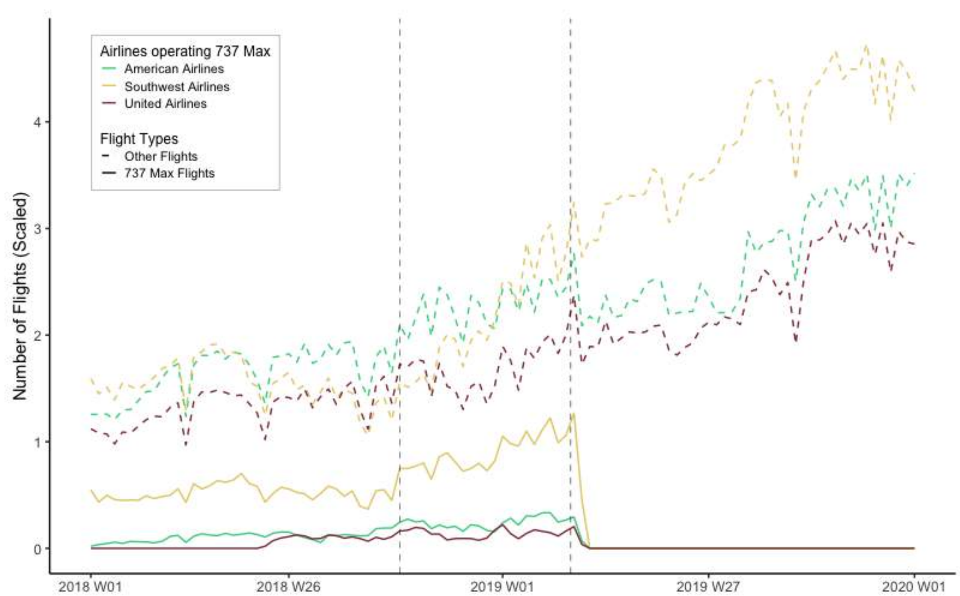
NOTE. – Plots show the log number of unique aircraft operated by US carriers. In each plot, the number of aircraft are shown in aggregate as well as grouped by the six aircraft categories defined in Section IV.B. Dotted lines indicate the dates of the two crashes involding the Boeing 737 MAX aircraft. The solid vertical line in each plot represents the date on which the FAA ban on the Boeing 737 MAX was imposed.

Figure A5: Flight statistics of carriers affected by the MAX grounding.

(a) Total flights



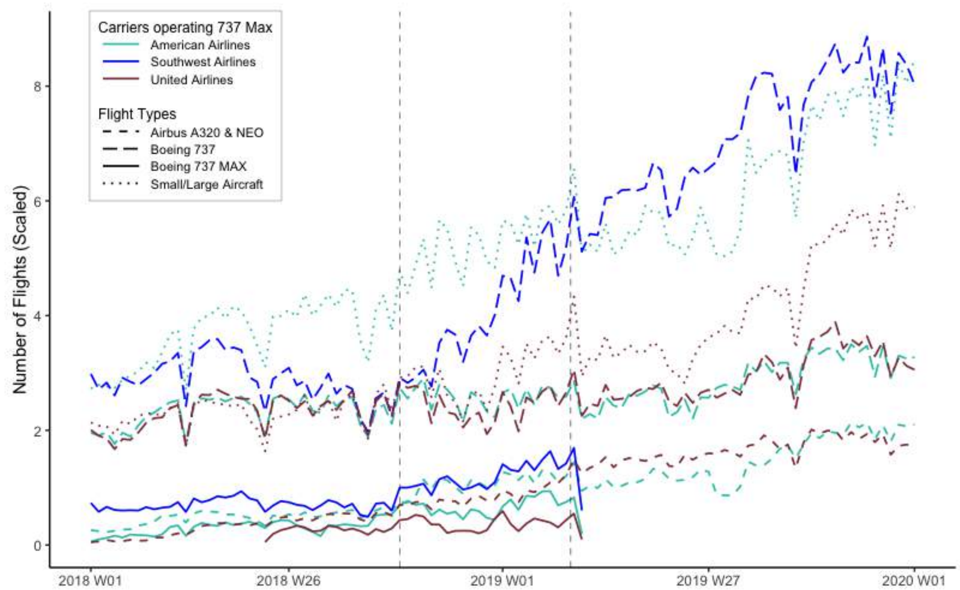
(b) Total flights (737 Max versus other aircraft)



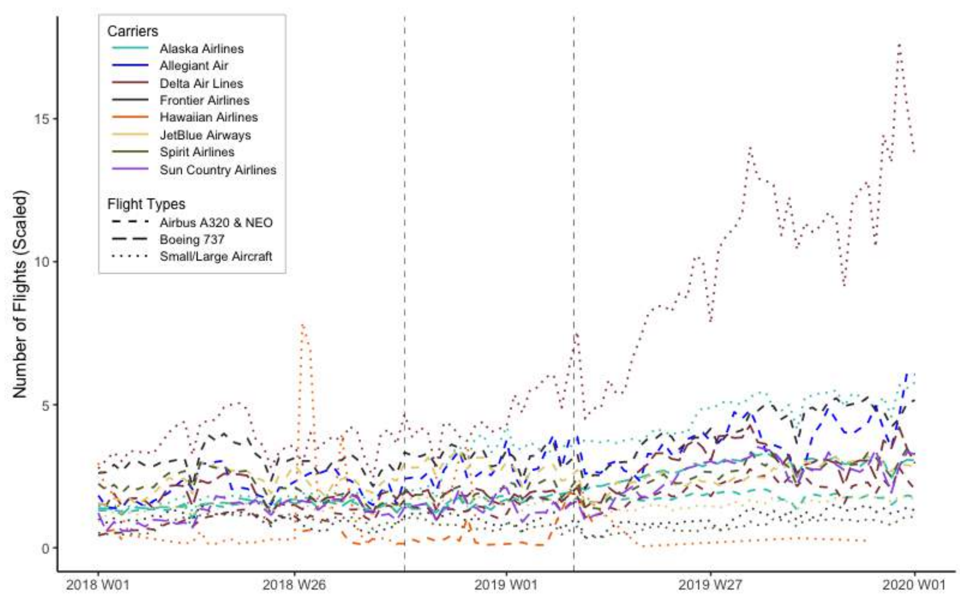
NOTE. – Figures show various flight statistics of US carriers that had the Boeing 737 MAX in their fleets, and had to stop flying these aircraft following the FAA grounding. Panel (a) shows the log number of domestic flights operated by the grounding affected carriers per week. Panel (b) shows the number of flight per week made by the grounding affected carriers using Boeing 737 MAX and other aircraft. Number of flights are scaled by the average number of non-Boeing 737 MAX flights operated by the respective carrier per week in the year 2017.

Figure A6: Flights by aircraft type around the MAX grounding.

(a) Carriers affected by the grounding



(b) Unaffected carriers



NOTE. – Figures show number of flights by US carriers. Separate plots are presented for (a) carriers that had the Boeing 737 MAX in their fleets, and had to stop flying these aircraft following the FAA grounding, and, (b) other carriers that did not operate Boeing 737 MAX aircraft and were consequently unaffected by the grounding. The number of flights are scaled by the average number of non-Boeing 737 MAX flights operated by the respective carrier per week in the year 2017.

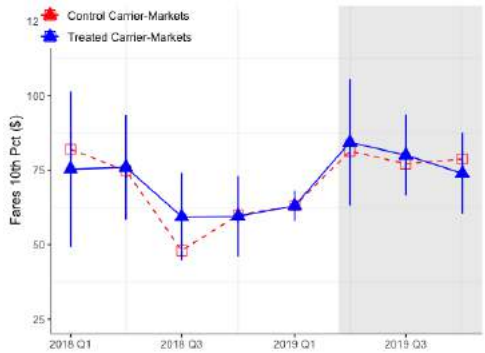
Figure A7: Jet fuel prices over time.

NOTE. – Figure shows the daily prices of aviation turbine fuel (expressed in $ per gallon) during the sample period as reported by the U.S. Energy Information Administration (EIA). The black line shows daily jet fuel prices. The red and blue dotted lines show the predicted trends in jet fuel prices during the periods before and after the grounding, respectively. Shaded areas in grey around each dotted line show the 95% confidence intervals.

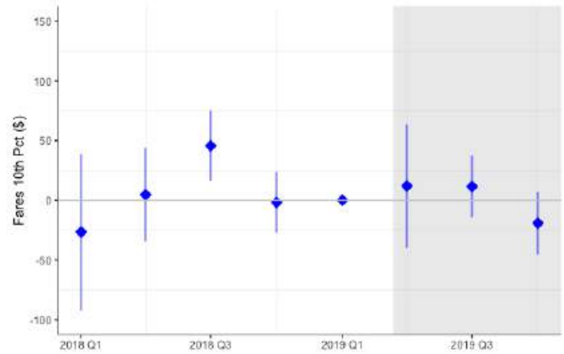
Figure A8: Changes in economy fare percentiles around the MAX grounding.

(a) Fare 10^{th} percentile

Evolution of fare percentiles

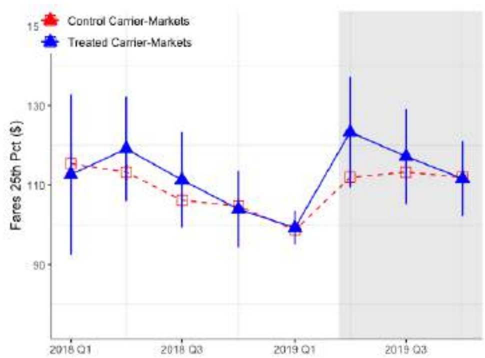


Event study estimates

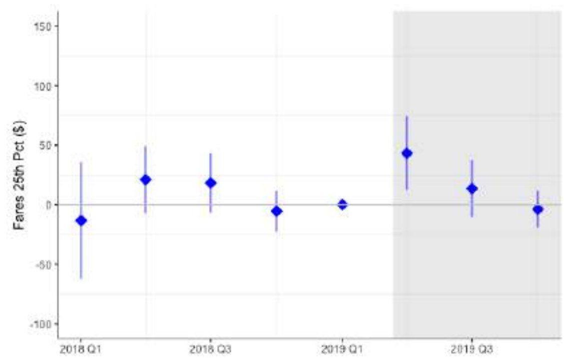


(b) Fare 25^{th} percentile

Evolution of fare percentiles

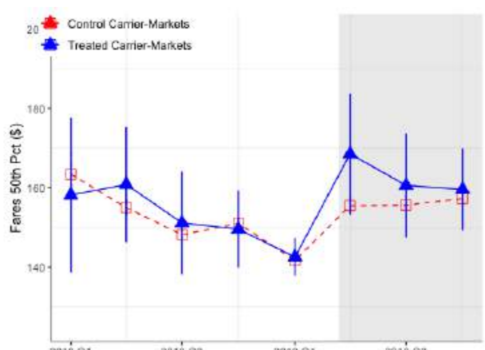


Event study estimates

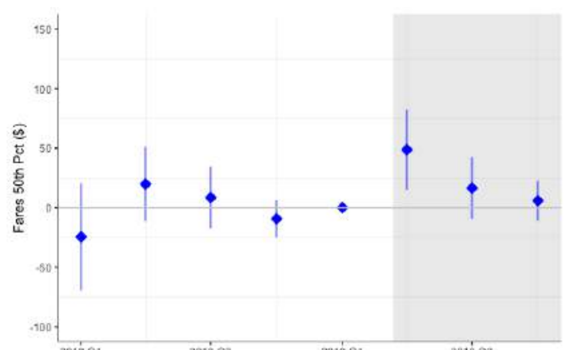


(c) Fare 50^{th} percentile

Evolution of fare percentiles

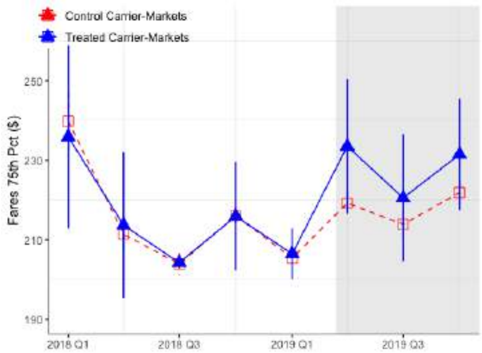


Event study estimates

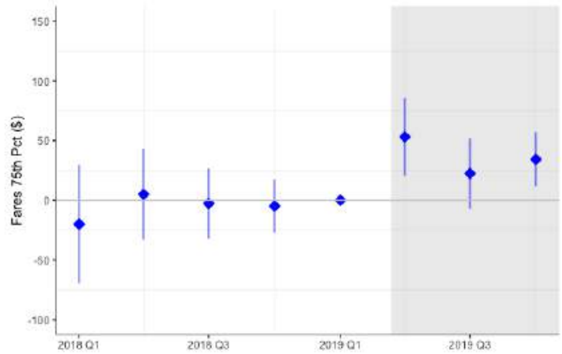


(d) Fare 75^{th} percentile

Evolution of fare percentiles

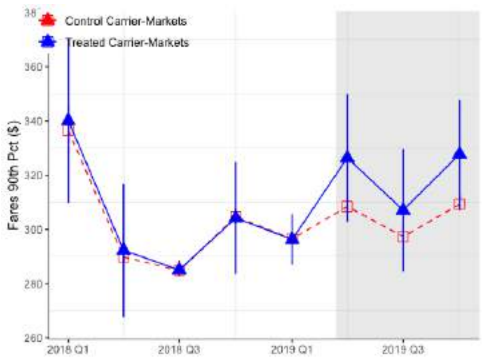


Event study estimates

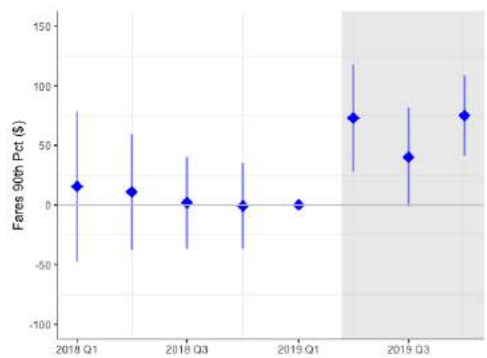


(e) Fare 90^{th} percentile

Evolution of fare percentiles



Event study estimates



NOTE. – Figures show time series estimates of mean ticket fare percentiles between treated and control carriers based on the following equation:

$$p_{cmt} = \beta_1 D_{cmt} + \beta_2 D_{cmt} \times \mathbf{t} + \beta_{\mathbf{3}} \mathbf{X}_{cmt} + \theta_t + \mu_c + \gamma_{ct} + \epsilon_{cmt}$$

where m is a market, $\mathbf{t}$ is a vector of year-quarter dummies, and c is the carrier. The outcome p_{cmt} is the average percentile (10^{th}, 25^{th}, 50^{th}, 75^{th}, or 90^{th} percentile) of the entire distribution of fares charged by a carrier c servicing market m during quarter t. D_{cm} represents treatment intensity at the carrier-market level as defined in Section V.A. $\mathbf{X}_{cmt}$ denotes a vector of market-carrier and market specific controls as specified in Equation (1) Panel (a) shows the mean fare estimates across treated ($\beta_1 + \beta_2 + \beta_3$) and control ($\beta_2$) carrier-markets over time. Panel (b) shows the coefficient estimates of the interaction terms β_3. θ_t, μ_c, and γ_{ct} denote quarter, carrier, and carrier *times* quarter fixed effects, respectively. The shaded area in grey depictes the period when Boeing 737 MAX aircraft were banned from flight operations by the FAA.

Table A1: Fleet composition by carrier.

Carrier	Narrow-body aircraft: Boeing 737 Max	Boeing 737	Airbus 320	Airbus 320 Neo	Large Aircraft	Small Aircraft	Boeing 737 Max (% of narrow-body AC)
Alaska	0	158	59	8	0	80	0
Allegiant	0	0	82	0	0	0	0
American	26	304	176	1	342	525	5.13
Delta	0	206	119	0	349	440	0
Frontier	0	0	23	35	21	0	0
Hawaiian	0	0	0	11	24	8	0
JetBlue	0	0	130	0	63	7	0
Southwest	37	701	0	0	0	0	5.01
Spirit	0	0	92	11	30	0	0
Sun Country	0	24	0	0	0	0	0
United	15	338	162	0	246	503	2.91

NOTE. – Table displays narrow-body aircraft counts by model in the fleets of our sample carriers during the period 2018'Q1 to 2019'Q4. Refer to Section IV.B for the definitions of aircraft model types.

Table A2: Impact of the grounding on average ticket fares: binary treatment.

Panel (a): Baseline estimates

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × PostBan	7.75***	7.38***	2.77	2.83	0.031***	0.028***	0.011**	0.011**
	(1.03)	(2.07)	(1.79)	(1.80)	(0.003)	(0.006)	(0.005)	(0.005)
Treated	3.27	3.46	11.7***	11.3***	0.015	0.016	0.035***	0.035***
	(3.67)	(3.63)	(1.98)	(2.12)	(0.013)	(0.013)	(0.008)	(0.008)
Load Factor			60.0***				0.296***	
			(4.10)				(0.018)	
Distance (1000 km)			-497.7***				-1.65***	
			(67.7)				(0.272)	
Hub Route			14.8***				0.073***	
			(1.38)				(0.006)	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	239.6	239.6	239.6	239.6	5.4	5.4	5.4	5.4
Observations	31,380	31,380	31,380	31,380	31,380	31,380	31,380	31,380
R^2	0.70	0.70	0.94	0.93	0.81	0.81	0.95	0.95

Panel (b): Treatment by carrier

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Treated}_{Southwest}$ × PostBan	5.14***	7.34***	2.71***	3.43***	0.025***	0.036***	0.012**	0.016***
	(0.757)	(1.52)	(0.957)	(0.962)	(0.003)	(0.008)	(0.005)	(0.005)
$\text{Treated}_{American}$ × PostBan	3.78**	7.34***	4.20***	3.88***	0.011*	0.027***	0.016***	0.014***
	(1.59)	(1.76)	(1.26)	(1.22)	(0.006)	(0.006)	(0.005)	(0.005)
Treated_{United} ×	21.2***	6.30	1.81	1.56	0.066***	0.018	0.005	0.004
	(3.71)	(4.72)	(4.03)	(4.05)	(0.010)	(0.012)	(0.010)	(0.010)
$\text{Treated}_{Southwest}$	7.23***	6.19**	4.83*	5.94**	0.036***	0.030**	0.021	0.026**
	(2.56)	(2.61)	(2.59)	(2.48)	(0.013)	(0.014)	(0.013)	(0.012)
$\text{Treated}_{American}$	-74.6***	-81.5***	25.2	-15.6	-0.266***	-0.296***	0.060	-0.103
	(17.8)	(17.5)	(24.5)	(26.2)	(0.069)	(0.068)	(0.109)	(0.118)
Treated_{United}	-51.5	-4.71	-7.79	-30.7	-0.166	-0.021	0.010	-0.089
	(73.3)	(70.0)	(25.9)	(30.2)	(0.230)	(0.223)	(0.111)	(0.117)
Controls			✓				✓	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	239.6	239.6	239.6	239.6	5.4	5.4	5.4	5.4
Observations	31,380	31,380	31,380	31,380	31,380	31,380	31,380	31,380
R^2	0.70	0.70	0.94	0.93	0.81	0.81	0.95	0.95

NOTE. – Table presents OLS estimates comparing average economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (1). *Treated* is a dummy variable equal to one if the MAX has ever been used in a carrier–market prior to the grounding, and zero otherwise. Separate estimates are provided for both *Mean Fare* and *Log*(*Mean Fare*) as dependent variables. Panel (a) shows the baseline regression estimates, while panel (b) presents regression estimates with treatment intensities disaggregated by carrier. Standard errors are double-clustered by carriers and markets, and are reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A3: Impact of the grounding on average ticket fares: treatment intensity measured over entire pre-grounding period.

Panel (a): Baseline estimates

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × PostBan	62.3***	41.2***	24.8***	21.0**	0.282***	0.177***	0.113***	0.096***
	(15.1)	(11.8)	(8.01)	(8.56)	(0.061)	(0.042)	(0.031)	(0.033)
Treated	50.9	59.6	-6.48	-35.5*	0.312*	0.353*	0.002	-0.104
	(42.1)	(44.0)	(18.4)	(19.4)	(0.187)	(0.198)	(0.076)	(0.082)
Load Factor			61.5***				0.300***	
			(4.19)				(0.018)	
Distance (1000 km)			-448.5***				-1.53***	
			(67.7)				(0.274)	
Hub Route			15.1***				0.074***	
			(1.45)				(0.006)	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	239.6	239.6	239.6	239.6	239.6	239.6	239.6	239.6
Observations	31,380	31,380	31,380	31,380	31,380	31,380	31,380	31,380
R^2	0.70	0.70	0.93	0.93	0.81	0.81	0.95	0.95

Panel (b): Treatment by carrier

Dependent Variables:	Mean Fare				Log(Mean Fare)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated_{Southwest}$ × PostBan	106.2***	118.1***	64.3***	66.4***	0.530***	0.500***	0.243***	0.255***
	(15.5)	(19.9)	(12.2)	(13.2)	(0.063)	(0.096)	(0.052)	(0.056)
$Treated_{American}$ × PostBan	1.33	19.8**	14.0*	7.05	-0.003	0.075**	0.062**	0.029
	(7.66)	(8.77)	(7.42)	(7.59)	(0.029)	(0.033)	(0.028)	(0.029)
$Treated_{United}$ × PostBan	93.6**	-10.4	-1.79	-6.86	0.323**	-0.002	0.054	0.031
	(42.5)	(46.8)	(21.3)	(21.1)	(0.131)	(0.136)	(0.070)	(0.067)
$Treated_{Southwest}$	332.1***	327.5***	-91.2***	-89.8***	1.63***	1.64***	-0.148	-0.093
	(58.0)	(57.6)	(30.4)	(32.5)	(0.294)	(0.298)	(0.133)	(0.137)
$Treated_{American}$	-74.6***	-56.4***	-15.6	-0.266***	-0.193***	-0.103		
	(17.8)	(15.1)	(26.2)	(0.069)	(0.060)	(0.118)		
$Treated_{United}$	-51.5	-9.74	-30.7	-0.166	-0.047	-0.089		
	(73.3)	(44.1)	(30.2)	(0.230)	(0.139)	(0.117)		
Controls			✓				✓	
Carrier FE	✓				✓			
Year-Quarter FE	✓				✓			
Year-Quarter x Carrier FE		✓	✓	✓		✓	✓	✓
Market FE				✓				✓
Mean Fare	239.6	239.6	239.6	239.6	239.6	239.6	239.6	239.6
Observations	31,380	31,380	31,380	31,380	31,380	31,380	31,380	31,380
R^2	0.70	0.71	0.93	0.93	0.81	0.82	0.95	0.95

NOTE. – Table presents OLS estimates comparing average economy fares between treated and control carrier-markets in the period surrounding the Boeing 737 MAX grounding, based on Equation (1). *Treated* denotes the treatment intensity measured as the percentage of MAX-operated flights by a carrier in a specific market throughout the entire pre-grounding period. Separate estimates are provided for both *Mean Fare* and *Log*(*Mean Fare*) as dependent variables. Panel (a) shows the baseline regression estimates, while panel (b) presents regression estimates with treatment intensities disaggregated by carrier. Standard errors are double-clustered by carriers and markets, and are reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A4: Average treatment intensities.

(a) Conditional average treatment intensities

	Full sample (OpenSky)			**Matched sample (OpenSky & DB1B)**		
Year-Quarter	American	United	Southwest	American	United	Southwest
All quarters (pre-grounding)	21%	17%	10%	12%	11%	7%
2018 Q1	33%	0%	8%	9%	0%	6%
2018 Q2	23%	15%	10%	11%	10%	6%
2018 Q3	19%	26%	11%	12%	23%	7%
2018 Q4	27%	18%	11%	12%	8%	7%
2019 Q1	12%	12%	10%	12%	10%	7%

(b) Unconditional average treatment intensities

	Full sample (OpenSky)			**Matched sample (OpenSky & DB1B)**		
Year-Quarter	American	United	Southwest	American	United	Southwest
All quarters (pre-grounding)	0.6%	0.6%	4.8%	0.7%	0.9%	4.2%
2018 Q1	0.4%	0%	3.6%	0.2%	0%	3.5%
2018 Q2	0.5%	0.4%	4.6%	0.5%	0.5%	3.9%
2018 Q3	0.5%	0.6%	5%	0.7%	1.2%	4.2%
2018 Q4	1%	1.1%	6%	0.9%	1.1%	5%
2019 Q1	0.5%	0.6%	4.9%	1%	1.2%	4.6%

NOTE. – Table shows the average treatment intensities during the pre-grounding period for each carrier affected by the grounding. Treatment intensities are estimated for two available sample: (i) the *full* sample encompassing all domestic airline markets in the US covered by OpenSky, and, (ii) a *matched* sample between OpenSky and the DB1B database, which covers only a subset of the markets included in the full sample as explained in Section IV.B. Panel (a) presents that the average treatment intensities across carrier-market combinations, conditional on them being treated before the grounding, across the pre-treatment quarters for both samples. Panel (b) presents the unconditional treatment estimates, taking into consideration both treated and non-treated carrier-market combinations.

Table A5: Heterogenous Impact of the MAX grounding on average ticket fares.

(a) Differential impact of the grounding by market structure

Dependent Variable:	Log(Fare Mean)	
Model:	(1)	(2)
Treated × PostBan	0.073***	0.076***
	(0.021)	(0.021)
Treated × Monopoly Market	0.119*	0.120*
	(0.067)	(0.068)
Monopoly Market × PostBan	-0.013***	-0.013***
	(0.004)	(0.004)
Treated × Monopoly Market × PostBan	0.084	0.078
	(0.063)	(0.062)
Treated	-0.054*	-0.054*
	(0.029)	(0.029)
Monopoly Market	0.037***	0.036***
	(0.006)	(0.006)
Direct Competitors		-0.024
		(0.146)
Direct Competitors × PostBan		0.137
		(0.085)
Controls	✓	✓
Year-Quarter x Carrier FE	✓	✓
Observations	28,131	28,131
R^2	0.89	0.89

(b) Short- and longer-term impact of the grounding

Dependent Variable:	Log(Fare Mean)	
Model:	(1)	(2)
Treated	-0.057**	-0.059**
	(0.028)	(0.028)
Treated × PostBan Short term (Q2'2019)	0.125**	0.132**
	(0.062)	(0.061)
Treated × PostBan Long term (Q3-Q4'2019)	0.075***	0.076***
	(0.020)	(0.020)
Direct Competitors		-0.086
		(0.146)
Direct Competitors × PostBan Short term (Q2'2019)		0.402***
		(0.114)
Direct Competitors × PostBan Long term (Q3-Q4'2019)		0.097
		(0.096)
Controls	✓	✓
Year-Quarter x Carrier FE	✓	✓
Observations	28,320	28,320
R^2	0.89	0.89

(c) Differential impact of the grounding by flight duration

Dependent Variable:	Log(Fare Mean)	
Model:	(1)	(2)
Treated × PostBan × Long Haul	0.097***	0.099***
	(0.022)	(0.022)
Treated × PostBan × Short Haul	-0.015	-0.012
	(0.047)	(0.047)
Treated × Long Haul	-0.104***	-0.103***
	(0.030)	(0.029)
Treated × Short Haul	0.236***	0.227***
	(0.075)	(0.074)
Direct Competitors × PostBan × Long Haul		0.189**
		(0.088)
Direct Competitors × PostBan × Short Haul		-0.027
		(0.136)
Direct Competitors × Long Haul		-0.055
		(0.164)
Direct Competitors × Short Haul		-0.283
		(0.239)
Long Haul	-0.004	-0.005
	(0.008)	(0.008)
Controls	✓	✓
Year-Quarter x Carrier FE	✓	✓
Observations	28,320	28,320
R^2	0.89	0.89

NOTE. – Table presents OLS estimates of heterogenous treatment effects on mean economy fares based on Equation (1). Separate estimates are shown contingent on variations in market structure, time since the grounding took effect, and flight distance variations across markets. *Monopoly Market* is a dummy variable equal to one for a given market in which only a single carrier operated throughout every quarter of 2018. *Direct Competitors* represents the combined treatment intensity of all rival carriers operating in a specific carrier-market during a given quarter. Each regression includes carrier, year-quarter, carrier × year-quarter, and market fixed effects. Standard errors are double-clustered by markets and carriers, and are reported in parantheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

B Flight tracking by OpenSky

OpenSky is a collaborative research project that aims to enhance the tracking and monitoring of aircraft movements during flight. Unlike traditional flight tracking methods that use radar-based systems, OpenSky relies on a global community network of more than 6,400 ground-based receivers to track and share aircraft data. Setting up such a receiver is very easy and costs as little as \$200. These receivers typically have a coverage radius of up to 600 kilometres. Figure B1(a) shows one such receiver set up using electronic parts ordered off online marketplaces such as Amazon. Figure B1(b) shows the number of flights tracked continuously in real time by such a receiver. Lastly, figure B1(c) depicts the extensive coverage of the US airspace (excluding Alaska, Hawaii, and its island territories) by the OpenSky receiver network as of January 1, 2018.

OpenSky leverages cutting-edge technologies to provide real-time flight tracking information, improving situational awareness for aviation stakeholders ranging from air traffic controllers and carriers to researchers and aviation enthusiasts. Researchers can use OpenSky data for studying air traffic patterns, aircraft behavior, and airspace congestion, while aviation enthusiasts can track flights in real-time and access historical data. At its core, OpenSky relies mainly on two main types of surveillance technologies, namely *Mode S* and *Automatic Dependent Surveillance-Broadcast* (ADS-B) to monitor and collect data on aircraft movements in real-time. These technologies are described in detail below.

B.1 Flight tracking with Mode S

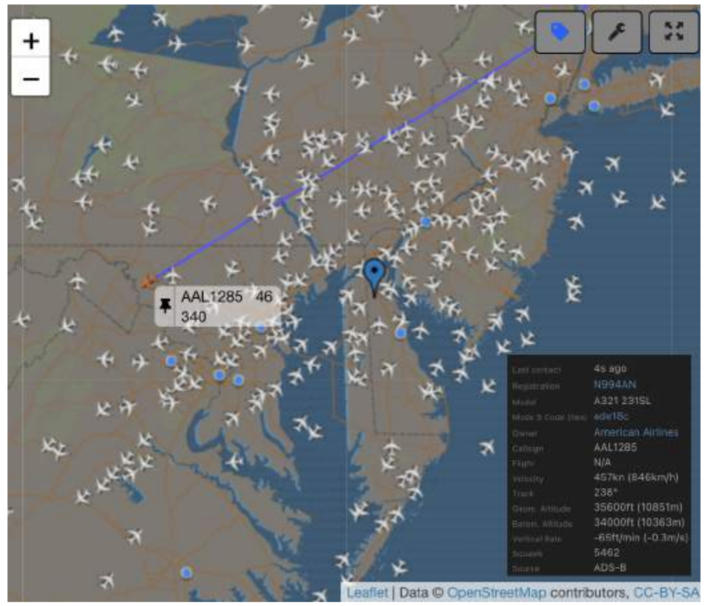
Mode S, which stands for *Mode Select*, is a crucial component of OpenSky's data collection infrastructure. Mode S is an enhancement of the traditional radar system. It was developed to overcome limitations of the earlier Mode A and Mode C transponders, which provided basic information like an aircraft's identity and altitude. Mode S, on the other hand, offers a more sophisticated and versatile way to communicate between aircraft and air traffic control (ATC) facilities. Under Part 91.215 of the FAA Regulations, Mode S transponders are mandatory for all aircraft operating in Class A airspace, which generally extends from 18,000–60,000 feet above mean sea level, as well as within 30 nautical miles around busy airports and in areas with heavy air traffic.

One of the key features of Mode S is its ability to transmit a unique 24-bit aircraft address (ICAO address). This address acts like a digital fingerprint for each aircraft, ensuring that controllers can positively identify each aircraft in their airspace. This is a significant improvement over older systems, where the same address could be assigned to multiple aircraft, leading to confusion. Mode S transponders also constantly transmit important data, including the aircraft's current position, altitude, groundspeed, and more. This information

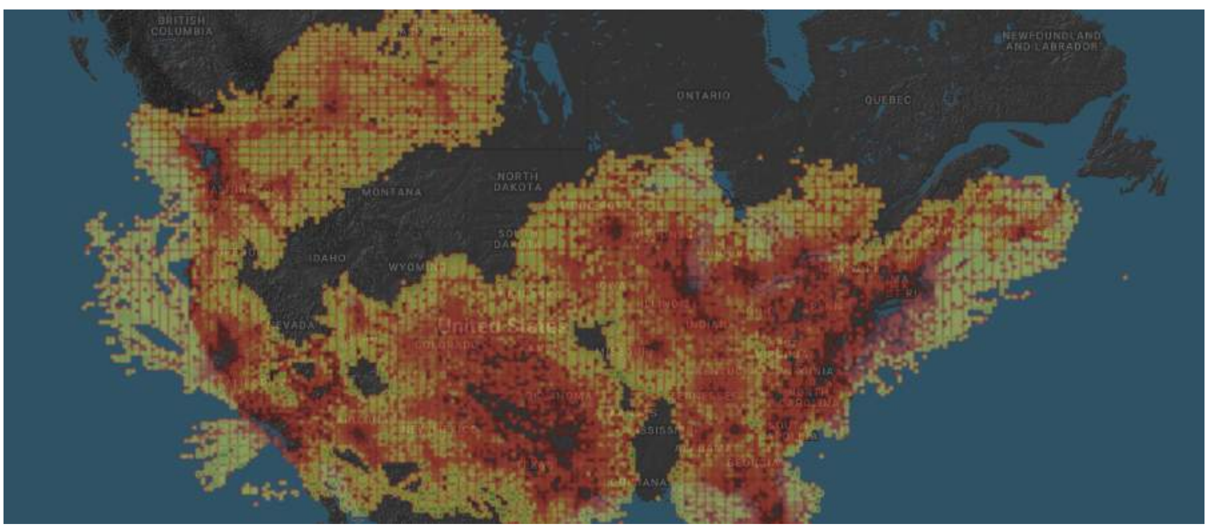
Figure B1: OpenSky receiver profile and coverage.

(a) Receiver setup

(b) Aircraft tracking by receiver



(c) OpenSky receiver coverage across US (as of January 1, 2018)



NOTE. – Panel (a) shows an OpenSky receiver made up of cheap and easily procurable electronic components. Image source: https://shorturl.at/bdnuC Panel (b) shows real-time flight tracking by one such OpenSky receiver, which can track multiple flights at once. A typical OpenSky receiver has a coverage radius of up to 600 kilometres. Panel (c) shows the extent of coverage of the US airspace by the network of OpenSky receivers.

is updated multiple times per second, allowing controllers to track the aircraft's movements with exceptional accuracy. Moreover, Mode S transponders can provide additional data, such as the aircraft's heading, rate of climb or descent, and even emergency alerts.[44] Mode S further includes a technology called *Enhanced Surveillance* (EHS). EHS provides even more detailed information about an aircraft's status, such as its vertical intent (whether it's climbing, descending, or level), the aircraft's true airspeed, and its indicated airspeed. This wealth of data is invaluable for ATCs as it enables them to manage traffic more efficiently and reduce the risk of mid-air collisions. Consquently, Mode S has transformed the way aircraft are tracked during flight. Its ability to provide unique identifiers, transmit a wealth of real-time data, and facilitate communication between aircraft make it an indispensable tool for air traffic management. Figure B2 presents a simple schematic showing how Mode S surveillance operates.

The ground-based infrastructure supporting Mode S is a network of Mode S radar stations, often referred to as *Monopulse Secondary Surveillance Radar* (MSSR). These stations are strategically located to cover large sections of airspace. They continuously interrogate aircraft in their coverage area, and when an aircraft responds, the radar decodes the Mode S transmissions, extracting vital information about the aircraft's identity and status. OpenSky tracks flights using Mode S by relying on a volunteer-driven network of MSSR receivers strategically placed around the world. These receivers continuously query each observed aircraft within their coverage area, often multiple times per second. The data collected by these receivers is then transmitted to the OpenSky platform, where it is decoded, processed, and made available to registered users.

B.2 Flight tracking with ADS-B

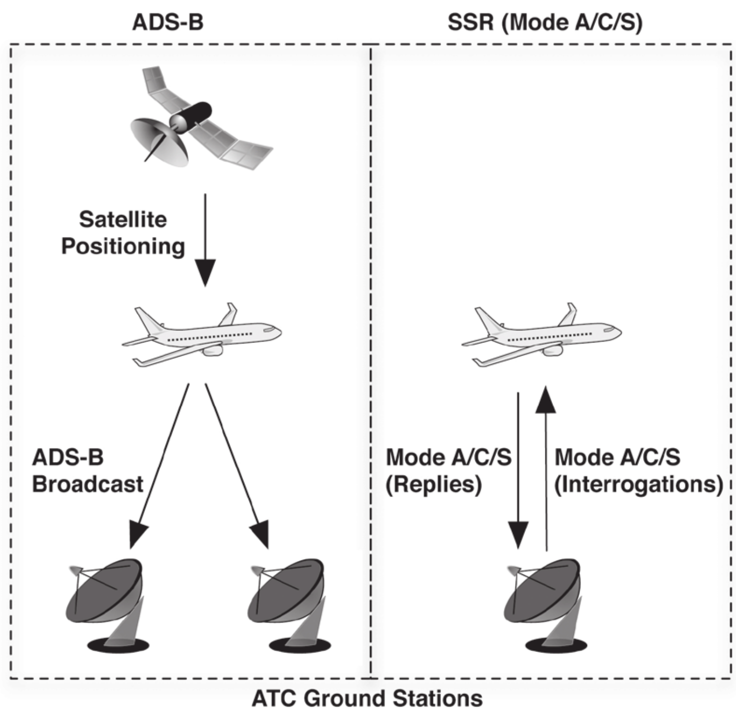
While Mode S plays a significant role in OpenSky's flight monitoring process, ADS-B is another key technology integrated into the platform. Unlike traditional radar-based systems, ADS-B relies on aircraft broadcasting their own positional data, thereby offering a more efficient, accurate, and comprehensive means of surveillance. Each aircraft equipped with ADS-B technology continuously transmits data packets, including its GPS-derived position, altitude, airspeed, heading, and more. These packets are broadcast at a high rate, typically every second, to nearby aircraft and ground receivers. OpenSky's network of receivers captures these ADS-B broadcasts, decodes them, and makes the information available to registered users.

As per FAA Regulations, specifically Parts 91.225 and 91.227, all aircraft operating within controlled US airspace at altitudes exceeding 18,000 feet above mean sea level must be

[44] An additional feature of Mode S is its ability to interrogate other nearby aircraft. This feature, known as Mode S *Interrogation*, enables aircraft to communicate with each other and share vital information. For example, if an aircraft is on a collision course with another, the Mode S transponders can automatically coordinate to initiate collision avoidance maneuvers, significantly enhancing safety in crowded skies.

equipped with ADS-B transponders by January 2020. One of the fundamental advantages of ADS-B is its accuracy and real-time nature. With precise GPS data being constantly transmitted, the system enables ATCs to track aircraft with unparalleled precision. This is a significant improvement over radar-based systems that update at a slower rate and may suffer from inaccuracies due to radar beam limitations. ADS-B also promotes situational awareness among pilots. Equipped with ADS-B receivers, aircraft can receive data from other nearby aircraft. This means that pilots can not only see their own aircraft's position but also the positions of surrounding aircraft, providing them with valuable information to enhance safety and collision avoidance. With ADS-B, it has also become possible to extend surveillance coverage to remote areas where radar coverage is limited or non-existent. This makes it an invaluable tool for tracking flights in regions like oceans, mountains, and remote forest regions. ADS-B also offers major benefits to carriers, who can use it to monitor their fleets in real-time, optimizing routes, fuel consumption, and maintenance scheduling.

Figure B2: Flight tracking via Mode S and ADS-B.



NOTE. – Figure depicts the differences in the flight tracking modes of Mode S and ADS-B. Mode S depends on selective interrogation by ground-based radars and receivers, which must first identify each aircraft and send an interrogration query requesting the aircraft's position, altitude, direction, and speed. Mode S transponders are mandatory under FAA regulations for all aircraft operating at 18,000 feet above mean sea level, as well as within 30 nautical miles around busy airports. ADS-B technology, on the other hand, involves repreated broadcasts of the position, direction, and speed by the aircraft itself. An aircraft fitted with ADS-B technology will first obtain its position from a global positioning system (GPS) satelite. This information, along with the aircraft's altitude, direction, and speed are then broadcast autonomously so that it can be picked up by ground receivers. Under FAA requirements, all aircraft operating within controlled US airspace at altitudes exceeding 18,000 feet above mean sea level must be equipped with ADS-B transponders by January 2020. Image source: (Strohmeier et al., 2017)

C What caused the Boeing 737 MAX crashes?

Boeing announced development of the 737 MAX on August 30, 2011, in response to Airbus's A320 NEO, an innovative and fuel-efficient aircraft that had been launched the previous year. Instead of designing a new aircraft from scratch, which would have been costly and time-consuming, Boeing instead opted to employ a more fuel-efficient engine and optimize existing aerodynamic features of the classic 737 and 737 NG models to reduce drag during flight. The intense competition with the A320 prompted Boeing to make extensive efforts to reduce costs and introduce the 737 MAX to the market as quickly as possible (Boeing, 2011).[45]

The 737 MAX incorporated the newly introduced CFM LEAP engine, which consumes up to 16% less fuel than older engine models (Flight Global, 2009). However, this engine needed to be installed much further forward on the aircraft wing and higher off the ground, which disrupted the 737 MAX's aerodynamic design, introducing instability (Flight Global, 2017; Forbes, 2019). To address this issue, Boeing introduced a new flight control feature called the *Maneuvering Characteristics Augmentation System* (MCAS). This system would trim the horizontal stabilizer towards the nose-down direction when the aircraft's angle of attack (AoA), as measured by the onboard AoA sensors, exceeded safety limits that could cause the aircraft to stall and crash. Figure C1 illustrates the working mechansm of the MCAS.

However, while most modern aircraft have redundant AoA sensors to ensure safety and minimize erroneous readings due to accumulation of ice or other debris, the MCAS relied upon just one sensor for its inputs. Additionally, the MCAS operated autonomously, without requiring inputs from the pilot (Sumwalt, Landsberg, and Homendy, 2019). These measures were implemented to minimize pilot training requirements and make the 737 MAX more attractive to customers. Unfortunately, these safety compromises were not adequately communicated to pilots and were even omitted from the 737 MAX's pilot handbook (Leeham News, 2018). During the MAX's certification by the FAA, the safety analysis of the MCAS was not as thorough as it should have been. The FAA relied heavily on Boeing's test flights of the MAX, which appeared to show that the MCAS was effective, even in extreme situations (Washington Post, 2019).

The MCAS had a significant flaw that made it prone to failure. It relied on a single angle of attack (AoA) sensor, which could cause it to misinterpret the aircraft's orientation and activate incorrectly. If the sensor signaled that the aircraft was ascending at an unstable

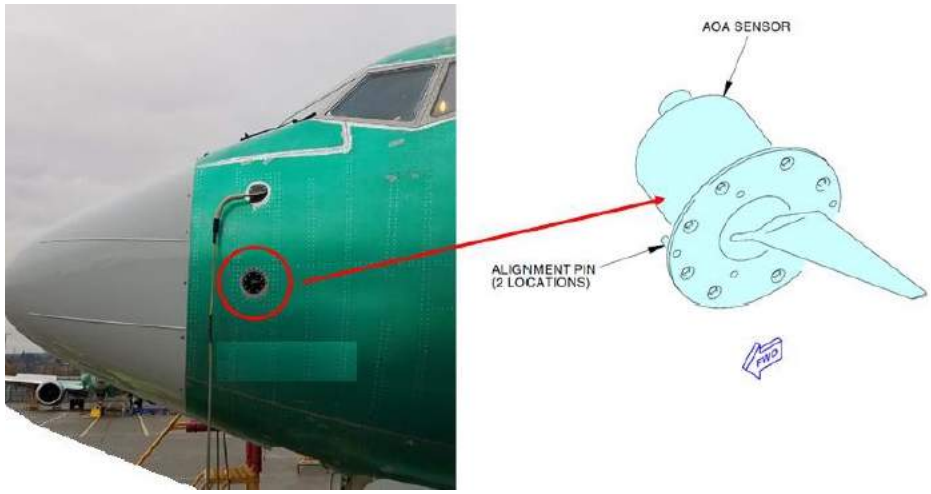
[45] Former Boeing CFO James Bell disclosed in the company's Q2 2011 earnings call that the development cost of the 737 MAX was estimated to be only 10-15% of the cost of a new aircraft development program, which was estimated to be around $10-12 billion at that time (Flight Global, 2012).

angle, the MCAS would respond by pitching the aircraft downward and cause it to dive. Even if the pilot tried to correct the angle by pulling back on the control yoke, the MCAS would continue to counteract this by moving the stabilizer trim wheel in the opposite direction, pushing the aircraft further downward. The MCAS would continue to do this as long as the AoA sensor indicated a high angle of attack, overwhelming the pilot's attempts to regain control of the aircraft (Federal Aviation Administration, 2020).

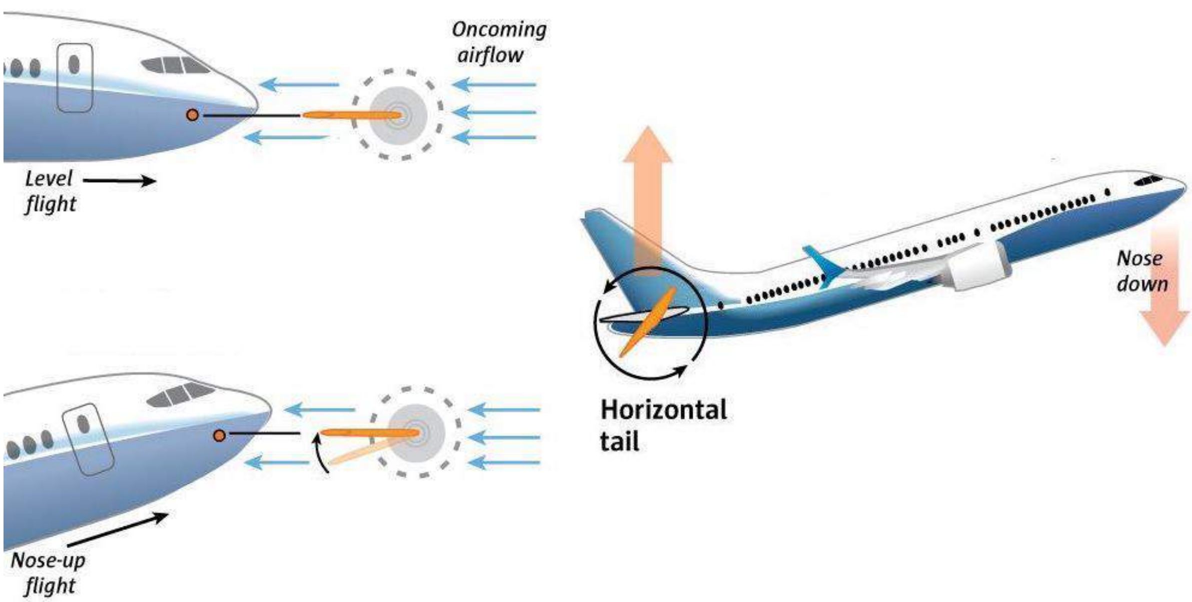
The issues with the MCAS (Maneuvering Characteristics Augmentation System) came to light after two fatal crashes involving the 737 MAX of Lion Air Flight 610 and Ethiopian Airlines Flight 302 within a short span of five months. In both instances, a faulty AoA sensor had provided incorrect data immediately after takeoff, leading to the MCAS system taking control of the flight from the pilot and causing the aircraft to stall (New York Times, 2019). Figure C2 provides a comparison of flight statistics of the 737 MAX aircraft flown as Lion Air Flight 610 and Ethiopian Airlines Flight 302 on the day they crashed with previous flights flown by these same aircraft. The figure shows unusual flight patterns by both aircraft just before crashing, which investigators later attributed to the triggering of the MCAS due to a malfunctioning AoA sensor onboard these aircraft. The pilots of these flights were not adequately trained to handle such situations, given their lack of training on the 737 MAX. They were unaware of the steps required to switch off the MCAS. In fact, as shown in Figure C3, deactivating the MCAS system required several complex steps, which would have been challenging to execute in an emergency without proper training.

Figure C1: MCAS on Boeing 737 MAX aircraft.

(a) Angle of attack (AOA) sensor



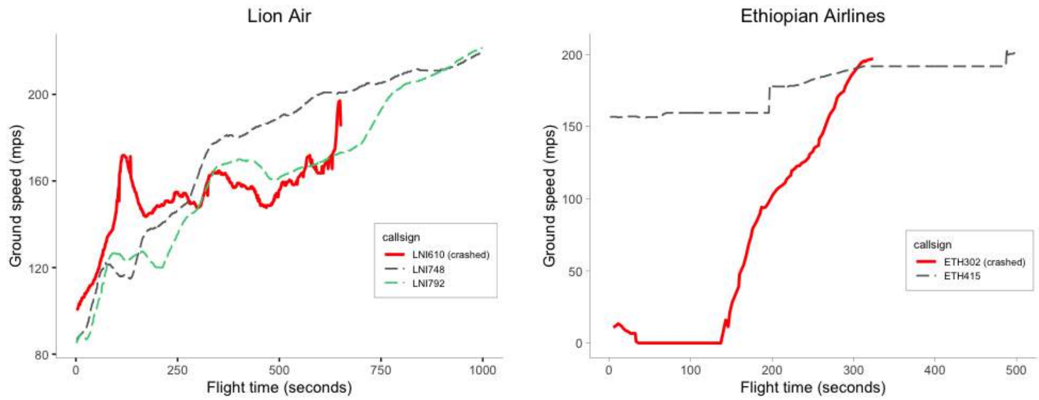
(b) Maneuvering Characteristics Augmentation System (MCAS)



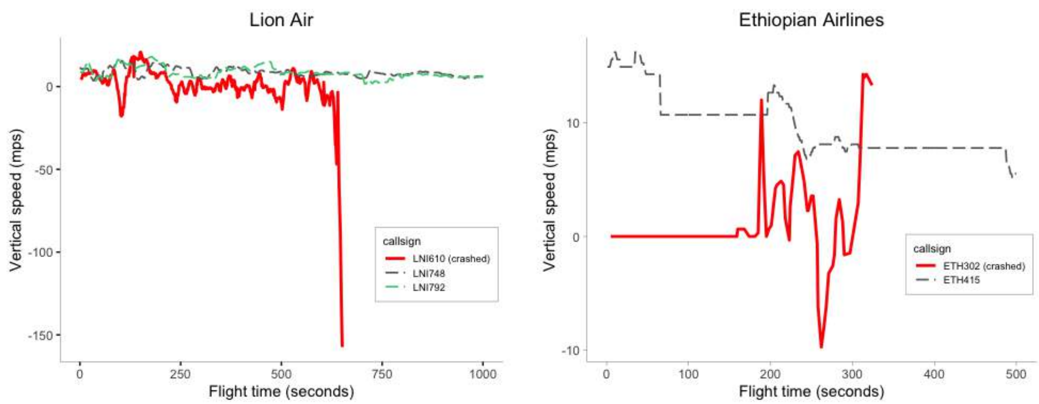
NOTE. – Panel (a) depicts the location of the Angle of Attack (AoA) sensor on a typical Boeing 737 MAX aircraft (Image source: Leeham News). Panel (b) illustrates the functioning of the *Maneuvering Characteristics Augmentation System* (MCAS) on the Boeing 737 MAX, which relies on data provided by the onboard AoA sensor. If the AoA sensor indicates that the aircraft is ascending too rapidly and could potentially stall, the MCAS takes over flight control and attempts to lower the nose of the aircraft by manipulating the horizontal tail stabilizers positioned at the rear of the plane (Image source: Seattle Times).

Figure C2: Flight statistics of 737 MAX aircraft involved in crashes.

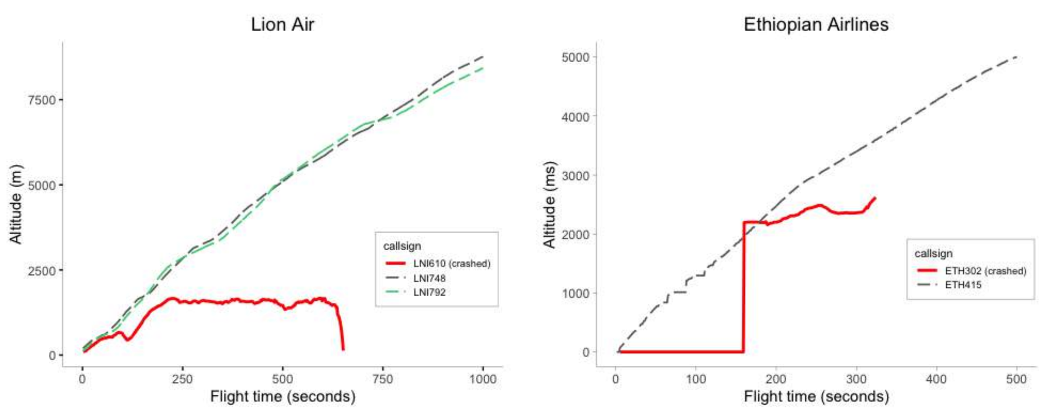
(a) Ground speed



(b) Vertical speed



(c) Altitude



NOTE. – Flight data are from Opensky and Flightradar24. In each panel, the first plot compares flight statistics of Lion Air flight LNI610 that crashed on 28^{th} October, 2018 with two other flights (LNI792 on 11^{th} September, 2018 and LNI748 on 25^{th} September, 2018) operated by the airline previously using the same 737 Max aircraft (ICAO identification 8A0711). The second plot compares flight statistics of Ethiopian Airlines flight ETH302 that crashed on 10^{th} March, 2019 with another flight (ETH415 on 31^{st} January, 2019) operated by the airlines previously using the same 737 MAX aircraft (ICAO identification 040152).

Figure C3: Steps to disable MCAS during flight.

(a) Cockpit of a 737 MAX 8 aircraft

(b) Flight controls closeup

(c) Flight controls closeup

NOTE. – Panel (a) shows a 737 MAX cockpit with the throttle levers (A), flaps (B), spoilers (C), and trim controls (D) highlighted in red. Black wheels on either side are connected to the horizontal tail and will spin if the stabilizer swivels. The instruments next to each wheel have green indicators showing the angle of the stabilizer trim, with 0 being maximum nose-down (Image source: Chicago Tribune). In Panel (b), the two switches at bottom right labeled “STAB TRIM” are the cutoff switches that will end automated movement of the horizontal tail by disabling the MCAS system (Image source: Seattle Times). Panel (c) illustrates the intricate steps that a pilot must take to deactivate the MCAS system while in flight. (Image source: New York Times).

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