Capacity Disruptions and Pricing: Evidence from US Airlines

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Abstract

New technology is prone to disruptions. We examine the impact of a supply disruption that simultaneously increases operational costs and reduces production capacity by removing a relatively efficient capital asset. Specifically, we analyse the unexpected regulatory decision to ground the Boeing 737 MAX in 2019, Boeing's most fuel-efficient narrow-body aircraft at the time. We use a difference-in-differences design by leveraging the differential exposure to the grounding, which we construct using novel flight frequency data in the U.S. We observe heterogeneous price and cost effects across airlines. For Southwest, the airline most affected by the disruption, the price increase is five times larger than the increase in operational costs. These findings illustrate that when firms become capacity-constrained due to a drastic reduction in the capital stock, then the cost of adjusting the capacity becomes the main driving force of the price, and not the changes in the average costs (related to efficiency).

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I Introduction

Firms invest in new generations of capital assets to benefit from efficiency gains that allow them to reduce costs. However, disruptions from various sources, such as regulatory changes, geopolitical tensions, or disputes between firms, can lead to considerable welfare losses. An extensive body of literature has focused on the effect on prices of disruptions that affect the marginal cost of production, documenting the pass-through rate of the cost shock on prices and its relation to the market structure (Amiti, Itskhoki, and Konings, 2014; Fabra and Reguant, 2014; Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010). In contrast, comparatively little is understood about shocks that simultaneously restrict productive capacity and increase firms' marginal costs. We show that when a substantial part of the capital assets suddenly become unavailable, the cost of adjusting capacity will be the dominant force increasing prices, and not the increase in the variable operating costs. Capacity constraints have important negative implications for consumer welfare as they lead to pass-through rates that are above unity, as they generate temporary increases in the cost curve with output that will drive up marginal costs.

We use the worldwide grounding of the fuel-efficient Boeing 737 MAX aircraft (henceforth MAX) in March 2019 as a unique quasi-experiment to understand how capacity utilisation affects pricing. This event stands out for being potentially one of the largest in aviation history and an incredibly costly event to airlines, consumers and manufacturers. No commercial aircraft had ever been barred from service, and it was completely unexpected that the first grounding would target a Boeing model, produced by a leading U.S. manufacturer and cleared only after full certification.[1] The policy salience of such event is further amplified by the disruption's sheer scale: within a matter of days, regulators worldwide withdrew the aircraft model, immobilizing its fleet across every market.[2]

The sudden restrictions in the fleet generated by the grounding provide us a unique source of variation in capacity that is not correlated with other factors that affect the demand of air traveling services. To conduct our analysis we have collected a novel and granular data source on all the flight hours of each aircraft model that is operated by the universe of airlines that serve the domestic market in the United States between 2017 and 2019. The data is based on real-time flight-level information tracked from mandatory communications between the

[1] In fact, the MAX emerged as a prime contender to replace the legacy aircraft due to its fuel efficiency and it had gained significant popularity among carriers with nearly 4,400 orders placed by the end of 2017 (Boeing, 2023).

[2] 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 United States, through the Federal Aviation Administration (the regulatory agency), was among the last to enact the MAX ban on March 13, 2019 (Herkert, Borenstein, and Miller, 2020).

aircraft and the airport's ground control. This data is not only novel due to its granularity and full coverage of the market, but also because it is free of measurement errors and self-reporting bias. Other studies have used information contained in DoT databases, such as the T-100 Domestic Segment, which is self-reported by carriers to the DoT's Office of Airline Information, possibly resulting in incomplete or missing data due to inconsistent reporting practices of carriers.[3] We combine the flight frequency and fleet utilitsation dataset with the characteristics of the aircraft, including the seating capacity and the average per-flight fuel consumption rate. For prices we rely on the (DB1B), the price survey from the Department of Transport in the United States (DoT). As a result, we can measure the fleet utilization before and after the grounding, thereby allowing estimation of jet fuel consumption patterns by route and for each of the aircraft of an airline.

We use a Difference-in-Difference (DiD) approach with continuous treatment, differentiating by airline. We quantify the cost of this disruption by assessing its impact for consumers (prices) and firms (costs). Our findings reveal that firms coped with the disruption by relying on their existing idle capacity, which led to a price adjustment. Prices were adjusted according to the shadow price of the capacity, which was higher for airlines with a more intensive usage of their aircraft fleet. For simplicity, these price increases can be decomposed into a capacity effect, and an operational cost increase. The first relates to the production capacity of firms, which diminishes when capital is being disrupted. In this particular setting, the airlines had fewer aircraft to operate, implying that the shadow price of capacity increased. The second channel is related to changes in marginal cost due to changes in the technology that is being operated. Since the most fuel-efficient capital asset is being removed, the changes in marginal costs will depend on the differences in fuel consumption of grounded aircraft with respect to the second most efficient one.[4]

While the choice of capital is endogenous, the grounding provides quasi-experimental setting for assessing the level and the degree of disruption in the capital of a firm. As a result, these short-term price adjustments reflect market frictions that preclude firms from easily acquiring additional capital. These frictions are not only exclusive to the airline industry, they are also present in other markets with high levels of specialisation in the input market, fixed costs related to entry or exit, or facing uncertainty. In the specific setting of this study, the uncertainty over the duration of the grounding, combined with the

[3]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.

[4]Fuel expenses have been documented to account for up to one-third of the operating costs (Csereklyei and Stern, 2020; Kahn and Nickelsburg, 2016) and Boeing claimed that the innovations introduced in the MAX enabled it to achieve fuel consumption reductions ranging from 14% to 32% compared to legacy aircraft models of similar size, such as Airbus 320 and the Boeing 737 (Boeing, 2024).

difficulties in acquiring capital in the short term, impeded firms from utilising other channels of adjustment that would be available in the long term.

One central aspect of this paper is to explore the asymmetric impact on the firms, as capacity creates non-linearities in the price response. In the United States domestic market, three airlines (Southwest, United, and American) had started to operate the aircraft that had been certified in 2017, and many more were waiting for their delivery. We use the utilization rate of the aircraft for each carrier as the treatment intensity measure in the DiD analysis. Southwest had adopted a strategy that relied on a low diversification of the fleet, potentially to benefit from economies of scale in costs. It operated 3000 routes with 10% of MAX aircraft (on average), and the remaining routes with older and less fuel-efficient Boeing 737 models. Southwest Airlines operated two-thirds of all MAX flights. In contrast, the legacy carriers had several aircraft models. American operated the in only 150 routes and United in 210, at 12% and 17% respectively. Southwest, which operated with less excess/idle capacity, had invested more heavily in the MAX, which was the only other model used other than the older Boeing 737 models (with 30% more fuel consumption).

We find that the average increase in the ticket price in Southwest MAX-operated markets was 5 times higher than the operational cost increase from using the second most efficient aircraft. This corresponds to a 1.7%, which is $4. We show that this was because their capacity to operate with their fleet was substantially reduced, and they had to operate much closer to the limit of their existing capacity. In contrast, for United and American, the increase in fares was in line with operational cost increases from subsituting the grounded aircraft by operating more intensively the idle capacity. Additionally, we find large differences in the change in operational cost, which refers to the change in marginal cost from replacing a flight that was previously operated with a MAX with other aircraft models. More specifically, we find that it is around $8 per passenger for Southwest flights, and $3 and $4 per passenger for American and United. Using our detail data we can show that both American and United used their fleet less intensively, and that they had other spare aircraft that consumed less, whereas Southwest had to rely exclusively on the older Boeing 737 models.

While there is a broad literature studying pricing in airlines, or pass-through, to the best of our knowledge, no other study has documented the price effect of short-term capacity changes resulting from supply disruptions using detailed data on capital utilisation. Instead, the existing literature has mainly focused on the role of market structure and market power (Bailey, Graham, and Kaplan, 1985; Berry, 1992; Berry, 1990; Borenstein, 1989; Borenstein, 1990; Borenstein, 1991; Borenstein, 1992; Borenstein and Rose, 1994; Brueckner, Dyer, and Spiller, 1992; Brueckner and Spiller, 1994; Call and Keeler, 1985; Ciliberto and Tamer, 2009; Dai, Liu, and Serfes, 2014; Evans and Kessides, 1993; Evans and Kessides, 1994; Gerardi and Shapiro, 2009; Graham, Kaplan, and Sibley, 1983; Hurdle et al., 1989; Morrison and Winston, 2010a; Morrison and Winston, 2010b; Morrison et al., 1989). There is also a growing literature that focuses on second- and third-degree price discrimination strategies that carriers practice, as well as intertemporal price discrimination, mainly on peak load pricing and dynamic pricing (Alderighi, Nicolini, and Piga, 2015; Aryal, Murry, and Williams, 2023; Chandra and Lederman, 2018; Chen, 2018; Escobari, 2012; Gaggero and Piga, 2011; Lazarev, 2013; Williams, 2022). Our study also broadly relates to Ferrer and Perrone, 2023 and Jin and Leslie, 2003, who study the consequences of unexpected events that caused a product harm crisis that raises firms' costs. However, the main difference is that the grounding did not affect the product demand other than through its effect on price, it only affected the supply.

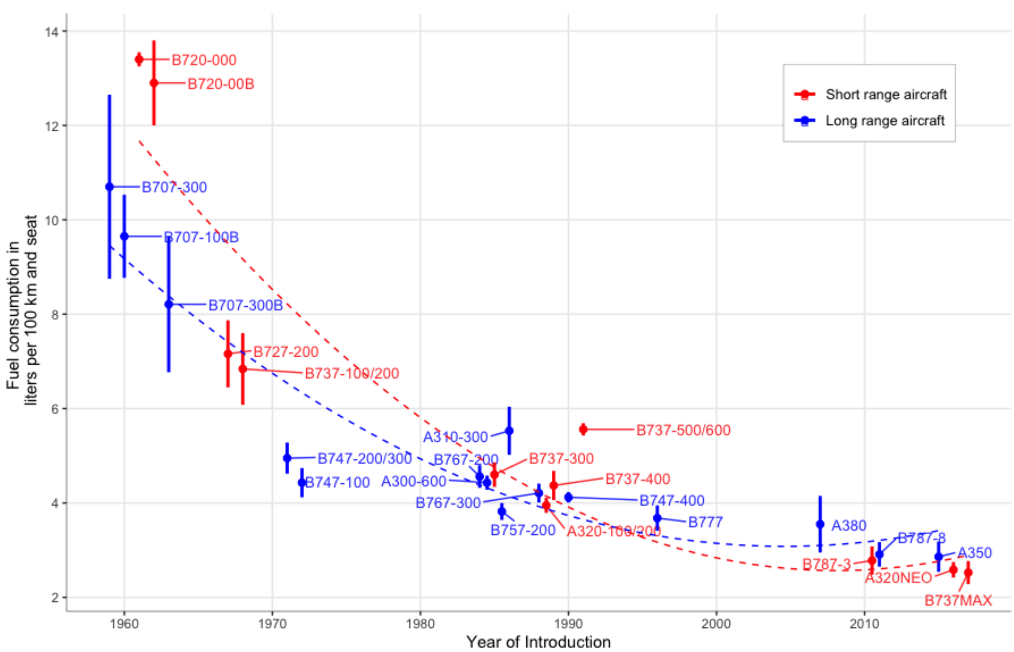
As highlighted in a recent article, supply disruptions are also relevant for the shipping industry, and descriptive evidence shows that theoretically they could be explained by capacity constraints and demand fluctuations (Brancaccio, Kalouptsidi, and Papageorgiou, 2025). Additionally, the effect of the grounding of the Boeing 737 MAX on air travel prices has not been studied either, despite being one of the largest disruptions in aviation history. Isidore, 2020 estimated that Boeing incurred a huge financial cost: $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. Disruptions with the aircraft model continued after the grounding was lifted by the FAA in November 2020 (CBS News, 2020; Gates, 2020), and the MAX resumed commercial flights (December 2020), and was re-certified for use in Europe and Canada in January 2021 (American Machinist, 2020).

Overall, this study aims to complement the existing literature on airline pricing, cost shocks, and supply disruptions by using quasi-experimental evidence. We draw these conclusions based on detailed data on capacity utilisation, that shows more than full pass-through when a firm's capacity is suddenly (and severely) constrained, and simultaneously, it faces limited substitution possibilities for the disrupted inputs. Therefore, the effect of such shocks can be quite heterogeneous if the firms make very different capacity choices. As shown in this study, the prices of firms with less constrained capacity will only rise at the same scale as the operating costs. Therefore, for these firms, the change in prices is determined by the cost differences from using the idle capacity compared to the disrupted capacity. The remainder of the article is organized as follows. Section II describes the industry. Section III describes the data used. Section IV presents the empirical strategy used and the estimation results, and Section V concludes.

II Industry

The fuel efficiency of an aircraft allows airlines to reduce operating costs. As shown in Figure 1, between 1971 and 1998 (International Energy Agency, 2009), a 60% reduction in the average fuel consumption has been achieved, driven by innovation in areas such as engine technology, aerodynamic design, and weight reduction through the development of lighter airframes made from carbon composites.

Figure 1: Fuel efficiency of commercial aircraft. NOTE. – 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 the 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.



Already in 1967, Boeing's 737 model emerged to compete with Airbus in the narrow-body aircraft segment. It represented a major breakthrough in fuel efficiency, utilising only two engines compared to the four and three engines required by its predecessors, the 707 and 727. Improvements in the fuel efficiency of the Boeing 737 followed in the 1990s with the development of the Next Generation (NG) engine and a fly-by-wire control system, which replaced conventional manual flight controls with a fully electronic cockpit. This allowed the 737 model to maintain its position as a popular narrow-body aircraft for decades.

In 2011, Boeing started developing the 737 MAX series to respond to Airbus' announcement of the Airbus 320 Neo, its most fuel-efficient narrow-body aircraft. The MAX featured significant improvements in engine performance and fuel efficiency (CFM LEAP engine), as well as new aerodynamic improvements, such as unique split winglets that further enhanced fuel efficiency and optimised existing aerodynamic features to reduce drag during flight. 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.[5]

The plans to develop the 737 MAX aircraft were announced on August 30, 2011, in response to the launch of the Airbus's 320 NEO in the previous year. The Boeing 737 MAX was certified by the Federal Aviation Administration (FAA) in 2017, which is two years before the grounding that preceded the two fatal crashes. The causes of the accident have been attributed to design failures in incorporating the new and more efficient engines. These new engines 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).[6] To solve this Boeing introduced a new flight control feature called the *Maneuvering Characteristics Augmentation System* (MCAS) which operated autonomously, without requiring inputs from the pilot. These measures were implemented to minimise pilot training requirements. Unfortunately, these safety compromises were not adequately communicated to pilots and were even omitted from the pilot handbook.

Furthermore, the FAA's safety analysis of the MCAS that was conducted during the MAX's certification had some flaws. The reason is that they relied heavily on Boeing's test flights, which showed that the MCAS were effective, even in extreme situations. However, they failed to detect that 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. Appendix C provides a detailed description of these issues that led to the two fatal MAX crashes.

III Short-Term Disruptions and Optimal Pricing

It is essential to distinguish between the short-term adjustment mechanisms that are the focus of this paper and the long-term adjustment, which goes beyond the scope of this study. In the long term, there would be adjustments in the extensive margin through entry and exit

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

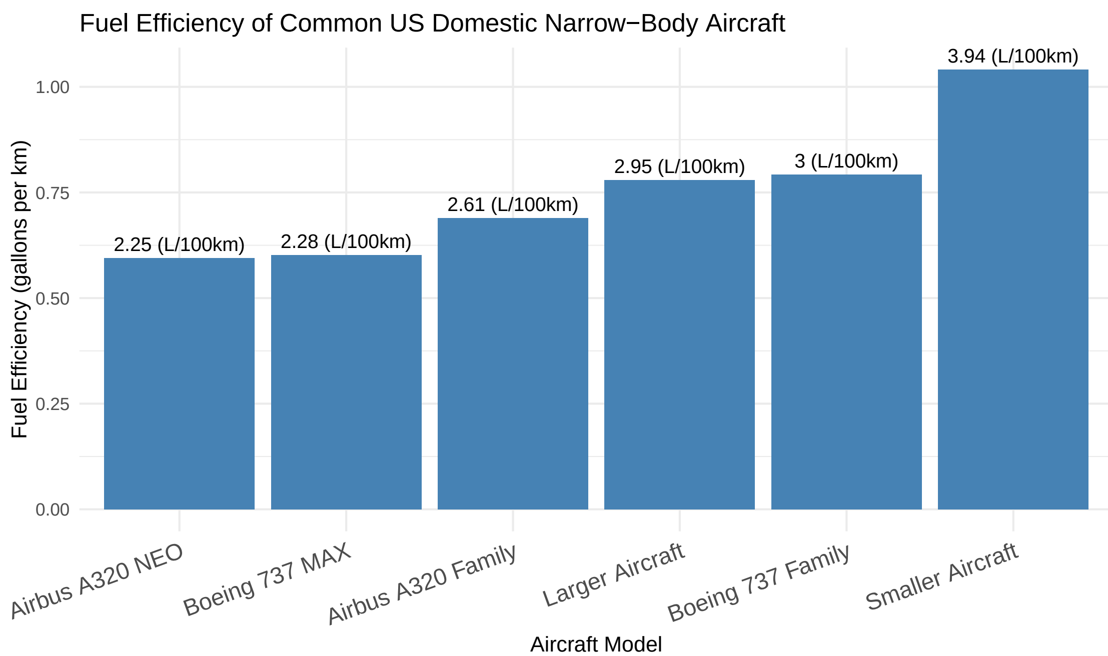
[6]Former Boeing CFO James Bell disclosed in the company's Q2 2011 earnings call that the development cost of the 737 MAX was estimated to be only 10-15% of the cost of a new aircraft development program, which was estimated to be around $10-12 billion at that time (Flight Global, 2012).

(Berry and Jia, 2010), changes in the network structure or in the leasing contracts, which are long-term arrangements. Additionally, our data reveals no noticeable deviations from the existing trend in the number of new routes (see Figure A2 in the Appendix).

The effect of capacity (K) on prices can be understood as operating through the firms' cost function, $C(K)$. In Ryan (2012), and subsequently in Jeon (2022), capacity curves are modelled as increasing non-linearly, making costs follow a "hockey stick" shape with respect to output. Goldberg (1995) model trade quotas that restrict capacity as Lagrange multipliers. However, firm-specific multipliers can not be identified in her study, and they are assumed to be identical across firms. In this setting, we show that these constraints vary substantially across firm. The closest representation of capacity is Williams, 2022, who models how seating capacity affects flight ticket prices for different passengers. When modelling flight prices, there is a more explicit physical capacity limitation, since each aircraft has a fixed number of seats available. For modelling the fleet, the limit is more diffuse, since the firm can always purchase capacity in the market, although the price will explode as capacity becomes scarce. Additionally, the increasing transaction costs associated to purchasing additional capacity effectively act as constraints for acquiring unlimited units of capacity.

To incorporate capacity costs into the airline profit maximisation it is convenient to split costs into two components. The first is c_m, the marginal cost of serving an additional passenger at a given capacity level in that market (m), which can be seen as a change in the production function. For our purpose, we do not explicitly need to estimate the form of the production function of the airlines as in Bet (2021). Still, it can be useful to imagine the production function of an airline as a function of the capital (the fleet), the labour (pilots, and other flight and administrative staff). The capital used, which is the aircraft model used, affects the marginal costs through the different input requirements (mainly fuel), and leads to different maintenance costs, which reflects part of the cost of capital. Therefore, removing an airline model will generate a change in the fuel consumption of the aircraft mix allocated to one route, which drives changes in c_m. It is worth noting that changes in the cost of labour would, in principle, also affect the cost. Still, these are unlikely to be relevant in the short term, as airlines have little incentive to change their pilot composition as a response to the grounding, and there are frictions to acquire and use new pilots or other labour. Additionally, we assume that the fuel market is competitive and airlines are price takers. As discussed in Bet (2021), jet fuel price is strongly correlated with oil prices, and the fact that airlines often hedge against jet fuel prices provides additional support for the hypothesis of limited bargaining power when ordering jet fuel. As illustrated in Figure 1 and in Figure 2, the MAX stands out as the narrow-body aircraft with the highest fuel efficiency, consuming 0.60 gallons per seat–100km (gps). As a comparison, the older Airbus 320 and

Figure 2: Fuel consumption for the main aircraft models, in gallons and litres per 100km. Source: Aircraft fuel economy, Wikipedia, and small-emitters tool from EUROCONTROL.



Boeing 737 models respectively consume 0.69 (14% more) and 0.79 (32% more) gps than the MAX. Although the Airbus 320 NEO has a similar fuel efficiency to the MAX, it has a limited presence in the sample period, with only one affected carrier, American, operating a single aircraft of this type. Other costs, such as storage costs, are fixed costs from the grounding, but they do not affect the marginal cost of serving a passenger.

The second component of the cost comes from the cost of obtaining additional capacity, $K(q_m)$. As it will be documented in the *Results section* through the DiD analysis, this "capacity channel" is fundamental to explain pass-through rates vastly exceeding full pass-through. In the aviation context, the main channel through which an airline can increase its capacity is by using additional aircraft that were not being fully used before (idle capacity). Replacing the disrupted capital with the idle capacity has implications for costs. Such implications go beyond the change in the marginal cost that originates due to differences in the fuel requirements of each aircraft, which can be understood as changes in the production technology. We represent these other costs related to adjusting the capacity with $\frac{\partial K(q_m)}{\partial q_m}$. As capacity is closer to some limitation (potentially related to the physical limits of idle capacity), the opportunity (or shadow) cost of capacity rises, since each unit of capacity is allocated to its more profitable use. The cost of adjusting the capacity can include fixed cost changes such as (i) the cost from operating a higher level of capital (e.g. higher maintenance costs, and administrative changes during the transition to operate a non-MAX model), or

(ii) from potential labour adjustments that are related to a higher capacity.

While the latter are not relevant in this setting, they could be important in others with a more flexible labour market. As a result, capacity constraints will generate an upward sloping cost curve with respect to quantity due to the rising adjustment cost of increasing capacity, and the optimal price ($p^\star_m$) becomes,

$$p^\star_m(q_m) = c_m + \frac{\partial K(q_m)}{\partial q_m} - q_m \left(\frac{\partial q_m(\mathbf{p_m})}{\partial p_m} \right)^{-1}.$$

The markup term is represented by $q_m \left(\frac{\partial q_m(\mathbf{p_m})}{\partial p_m} \right)^{-1}$. In this study, we use the DiD model to recover the change in c_m due to the grounding. We will show that the changes in c_m can explain the changes in prices reasonably well for some firms but are insufficient for explaining the changes in prices that are experienced in the treated markets of Southwest. Additionally, to be more precise and differentiate the markup changes from the capacity-driven price increases, we provide estimates of the changes in markup in each market based on a model following Berry (1994).

IV Data

To understand pricing decisions in the US airline industry after the grounding, we use publicly accessible data on ticket fares from the DoT's DB1B database that has been used extensively in past research (Bontemps, Gualdani, and Remmy, 2023; Borenstein and Rose, 1994; Brueckner, Dyer, and Spiller, 1992; Dai, Liu, and Serfes, 2014; Gerardi and Shapiro, 2009). Our analysis focuses exclusively on economy class fares, as the carrier that was most affected by the grounding (Southwest) offers only economy class seats, and economy fares have been reported to be more reliable compared to the business class ones. Since the fare data is available only quarterly, we conduct our analysis at that level, while using the flight level information to compute the MAX utilisation rates. The utilisation rate of the grounded aircraft (in terms of flight hours) is fundamental for our study since it is our treatment intensity measure. This variable reflects the usage of the grounded aircraft by a carrier in a market relative to the total fleet, and it is described in more detail in the section containing the identification strategy. Therefore, our unit of analysis is the carrier, market (unidirectional origin-destination airport pairs) and quarter year.

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 the Bureau of Transportation Statistics (BTS).[7] 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).[8] 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. The OpenSky Network presents significant improvements in coverage and reliability relative to the T100 Domestic Segment Database maintained by the BTS that has been typically used in this literature to measure flight activity. 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. Table A2 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 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 maintained by the OpenSky network continuously interrogate aircraft within their coverage area spanning up to a radius of 600 km, and collect data 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 OpenSky captures through its receiver network.[9] Under either system, the positional information relayed back to Open-

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

[8] 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.

[9] Access to OpenSky data is subject to approval by the platform's administrators. Although commercial 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.

Sky 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.[10] 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.[11] 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 against these lookup tables to obtain its national registration ID and aircraft type. These are cross-checked with the aircraft registries of different countries, including the FAA, wherever possible, to remove any outstanding errors. We then manually collect specifications of each aircraft type from manufacturer 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.

[10] 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.

[11] 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.

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.[12] 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

Aircraft models covered. 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. *Narrow-body aircraft*, which includes single aisle, medium- to long-range aircraft that can seat between 130 and 200 passengers and have a flying range of up to 7,130 kilometres. We distinguish between four major categories based on manufacturer and fuel efficiency: *Boeing 737*, *Boeing 737 MAX*, *Airbus 320*, and *Airbus 320 NEO*. The remaining two categories are *Large aircraft* and *Small aircraft*. Large aircraft includes 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 (e.g. the Boeing 757/767/777/787 Dreamliner, and the Airbus 330/340/350 series).[13] *Small aircraft* include single aisle, short-range aircraft that can seat up to 120 passengers and have a flying range of up to 4,300 kilometres (e.g. Embraer 170/195 and Bombarder CRJ series)

Flights covered. 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. To avoid including such non-scheduled flights involving the MAX, we excluded all observations involving flights made during 2017 or before. We also 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 carriers. 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.

Merging the price and utilisation data. To understand aircraft utilisation, we aggregate the OpenSky flights data at the carrier–market–date level. We calculate the number of flights and flight hours operated by each airline 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. Given that the DB1B database constitutes a 10 percent random sample of domestic tickets issued by carriers, merging the

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

[13]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.

OpenSky sample with it leads to a reduction in the markets that can be covered in this study.

IV.C Main Variables Definition

The main variables used in our analysis are ticket fares, jet fuel consumption, and costs. These are calculated at market–carrier–date level, which we detail as follows.

Date (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 before 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 A1. 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.[14] 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.[15] In every such 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

[14] 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.

[15] For instance, flights departing from or arriving into Chicago O'Hare (ORD) and Chicago Midway (MDW) airports are considered to both serve the greater Chicago metropolitan area, and both are hence treated as a single airport.

operational costs that differ significantly from larger markets, which can make it difficult to obtain consistent estimates.[16] 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 the economy fare class and are reported at a quarterly frequency (carrier–market–date average economy fares). 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. The prices of round-trip itineraries are divided by two. Tickets priced below $20 are excluded, as these are typically issued to frequent passengers. 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, and data quality issues. As depicted in Figure A2, legacy carriers such as American, United, and Delta (which never operated a MAX) have been reducing their business class offerings on various markets prior to the grounding. In contrast, low-cost carriers like Southwest, Spirit, and Frontier do not provide business class seats. 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 the US. The variation in fares across itineraries occurs because passengers traveling 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 unobservable service-related costs, fuel costs represent a tangible component of carriers' marginal costs that we can accurately observe. 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, which represent the fuel consumed during the flight by an aircraft per passenger and unit distance traveled. 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 kilometers at cruising altitude from the official websites of aircraft manufacturers for

[16]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.

each aircraft type in our study.[17] 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.[18] 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.[19]

IV.D Descriptive Statistics on Capacity Utilisation

Usage of the fleet. Each airline follows different strategies in terms of fleet diversification, as illustrated in Figure A4. Since each aircraft model has a different operating cost at a given capacity, we can write cost curves that resemble the dispatch curves used for analysing the electricity market. As discussed in Section III, when firms are far from the capacity constraint (i.e., increasing capacity is not costly), then changes in c_m will mainly reflect changes in technology. In contrast, when the capacity adjustment cost increases, then the cost increase will also reflect the opportunity cost (or shadow price) of adjusting the capacity. Using our detailed data on fleet utilisation shows the costs of operating with different capital inputs (aircraft models), which can be interpreted as cost curves.

Impact of the grounding on flight activity. Figure A1 in the internet appendix presents the total number of flights and flight hours by carriers over time, categorised 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.

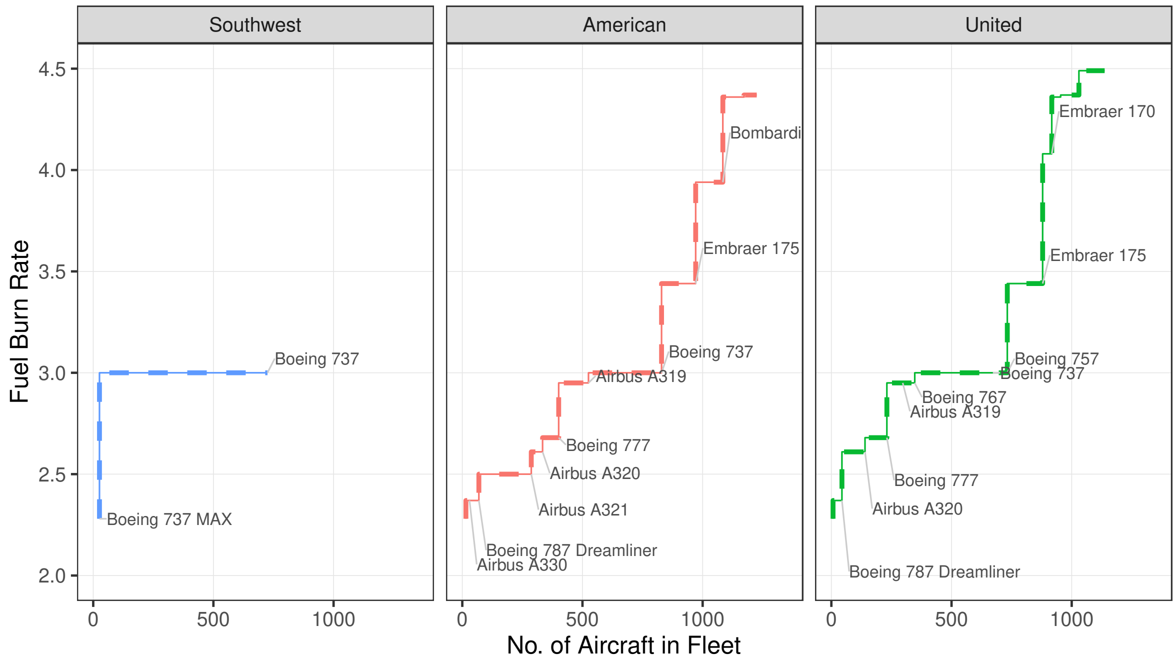
Short-term frictions to replace the disrupted capital inputs. Acquiring new aircraft takes time, and only American Airlines could expand its capacity after the grounding. It received some Airbus 320 that had been ordered long before this event. The airlines had to replace the grounded model by increasing the intensity of usage of their existing idle fleet. A fundamental feature of these aircraft used for replacement is that they are less fuel-efficient compared to the MAX. Figure 3 shows the fuel burn by each of the aircraft models in the fleet, ordered from most efficient to least efficient.

[17] The estimation of *Fuel Burn* excludes fuel consumption during takeoff and landing.

[18] *Fuel Burn* values are expressed in gallons, which are the units in which the EIA reports jet fuel prices.

[19] 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 the total available seat capacity is expected to yields similar results.

Figure 3: Capacity curves approximation based on the observed aircraft. NOTE. – Snapshot of the fleet of Boeing 737 MAX operating carriers in Q3 2018. The y-axis contains the fuel burn rate in liters per 100km, the x-axis contains the number of aircraft that were used in any route during that period.



A broader representation of capacity across time can be found in Figure A3(a), which shows that airlines make different choices of fleet. While the focus of this paper is not on understanding differences in fleet composition, our data show that full-service and low-cost carriers differ in their risk management strategies, which impact the availability of idle capacity. Legacy full-service carriers such as American, Delta, and United diversify they fleet by employing 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 minimise the operating costs related to maintenance and pilot training. Thus, they benefit from economies of scale at the cost of being exposed to higher costs in the event of aircraft failure. For example, Southwest exclusively uses the Boeing 737 while Allegiant operates only the Airbus 320.[20] LCCs have played an important role in the expansion of the US airline industry in recent decades (Chandra and Lederman, 2018), and they have actively incorporated the latest narrow-body aircraft into their fleets, such as the Boeing 737 MAX and Airbus A320 NEO. These models are attractive as they represent the most fuel-efficient aircraft models available, and they

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

are cheaper to operate in terms of pilot training, maintenance, and crew service costs per passenger (Camilleri, 2018).

V Results

Our empirical analysis focuses on the impact on various market outcomes of the FAA grounding of MAX aircraft. 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 previous 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). Second, we quantify the effect of the grounding on fuel costs by comparing the treatment and control group. Third, we examine the heterogeneity in treatment effects, showing mainly that accounting for direct competitors operating the MAX does not change our main findings. 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 it reflects the utilization intensity of the MAX , i.e. the percentage of MAX-operated flight hours relative to the flight hours with other aircraft types within a carrier's fleet in that route, and during a given quarter before the grounding. Specifically, our treatment intensity is defined at the carrier-market-quarter level. According to this definition, the treatment intensity for a carrier–market pair can range 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). In order to accommodate seasonal fluctuations in demand from carrier's decisions on which markets to serve in each quarter, the treatment intensity is estimated on a quarterly basis.[21] In addition to using this measure for our analysis, we perform additional robustness checks to ascertain its validity by employing 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.

[21] Specifically, the treatment intensity calculated for a given carrier-market-quarter combination during the pre-grounding period (we use all of 2018) 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).

Table 1: Average treatment intensities in all of the pre-grounding quarters

NOTE. – This table shows the average treatment intensities during the pre-grounding period for each carrier affected by the grounding. "Conditional" represents the average treatment intensities across carrier-market combinations that belong to the treated group before, i.e. the average utilisation of the MAX for those that were using it. "Unconditional" represents the flight hours of the MAX relative to all the flights in any market of that carrier.

	Full sample (OpenSky)			**Matched sample (OpenSky & DB1B)**		
Carrier	American	United	Southwest	American	United	Southwest
Conditional	21%	17%	10%	12%	11%	7%
Unconditional	0.6%	0.6%	4.8%	0.7%	0.9%	4.2%

It is important to clarify that the treatment intensity can be computed from either the full sample, encompassing all markets covered by OpenSky but with no prices, or the matched sample between OpenSky and the price data from the DB1B database, as reflected in A3. The latter covers only a subset of the markets included in the full sample as explained in Section IV.B. We find that the average utilization of the MAX (the treatment intensity) among carrier-market combinations that were using the MAX before the grounding is 11% in the full sample, and 7% in the matched sample. Since our goal is to understand the economic impact of the grounding across all domestic airline markets (and the price data from the DB1B survey is representative of the whole domestic market), we will use the conditional average treatment intensities from the full sample to scale our regression estimates. More details on how the treatment intensities for both samples varies split by carrier can be found in Table A3. The table shows that American and United concentrated the usage of the MAX in fewer markets than Southwest, but they also used the MAX more intensively (around 20% of the flights in those markets). In contrast, the usage of Southwest was, on average, around 10% of the flights in the markets in which the aircraft was being operated but the aircraft was used in more markets, representing roughly 5% of all the flight hours in all the markets. For a more detailed split of the treatment intensity across each of the pre-grounding years see Table A3 in the internet Appendix.

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. Since most of the observations in the sample belong to the control group, the mean of the full sample strongly resembles the control group. In Panel A, we present descriptive statistics related to the market characteristics of both treatment and control. The comparison reveals similar flight distances, number of operating carriers, and load factors across both groups.

Table 2: Summary statistics. NOTE. – This table shows market, fuel and fares at the firm–market level averaged during the period prior to the grounding and by treatment status, as defined in Section V.A.

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

Panel B 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 C 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 groups at around $215.

V.C Grounding Impact on Fares: Differences in Differences

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

$$p_{cmt} = \beta_1 Treated_{cmt} + \beta_2 Treated_{cmt} \times PostBan_t + \beta_3 \mathbf{X}_{cmt} + \gamma_{ct} + \epsilon_{cmt} \quad (1)$$

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.[22] 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 × 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 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. One motivation to include market fixed effects would be to capture unobserved factors, specific to each market and constant over time. However, it would comes at a large cost of restricting the cross sectional (across markets) variation from our sample, and importantly, it

[22]Load factors are commonly used in the literature to capture efficiencies in carriers' demand forecasting and capacity utilization (Aryal, Murry, and Williams, 2023; Berry and Jia, 2010). However, they are endogenous, depending on carriers' fleet choices. We find that their inclusion as controls in our regressions does not significantly alter our treatment effect estimates. Additionally, we account for other demand shifters affecting each carrier over time with carrier×time fixed effects.

captures endogenous strategic responses from the carriers operating in the same market. In other words, it is equivalent to comparing each of the treated carrier-market observation after the grounding with its own pre-grounding prices, as well as with the pre-grounding prices of the other unaffected competing carriers operating in the same market. Nonetheless, the interest for providing this specification is that it allows quantifying the additional increase in fares (in the treated carrier-markets pairs) relative to the competitors in that market. The results provide evidence of an important role of strategic interactions. It is worth noting that while in the regression results without market fixed effects, the control group also contains the observations from the same market as the treated, these observations represent less than 5% of the total observations in the control group. However, for interested readers, we also provide a complete assessment of the results, completely separating the observations that are from the same market, forming an additional treatment. These results show no sizeable changes in the treatment effect, and they can be found in Table A9 in the Appendix.[23]

Following Abadie et al. (2023), we cluster the standard errors by market and carrier. 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, due to the assignment, only some carriers operated the grounded aircraft, and correlation across markets is expected. 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 make the treatment effect more representative of the size of the markets.

Table 3 reports our baseline estimates from Equation (1) for average ticket fares. Throughout the paper, we scale the treatment indicator to one when all pre-grounding flights in a carrier–market were operated with the MAX; we refer to this counterfactual as *full treatment intensity*. Panel (a) treats exposure as homogeneous, whereas panel (b) allows the effect to vary by carrier, revealing substantial heterogeneity. We show how the gradual inclusion of fixed effects and controls affects the treatment effect, distance and hub are important controls whereas including or excluding load factor makes no significant changes to the treatment estimates. Comparing Panel B to Panel A highlights the importance of disaggregating the analysis, as the effects of the grounding vary substantially across carriers. Panel B provides several insights that support the use of log-transformed fares and the inclusion of controls

[23]The true average treatment effect is not significantly underestimated when competitors are included in the treatment compared to when they are excluded, as in Table A9 in the Appendix. The main regression tables show that some of the carriers in the control group strategically increased their prices in 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 because these competing carriers represent a small part of all the observations in the control group. 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%)

Table 3: Impact of the grounding on average ticket fares. NOTE. – OLS estimates comparing average economy fares of treated and control carrier-markets, based on Equation (1). Separate estimates are provided with *Mean Fare* and *Log(Mean Fare)* as dependent variables. Panel (a) shows the baseline regression estimates. Panel (b) the regression estimates with treatment intensities disaggregated by carrier. Standard errors (in parenthesis) are clustered by carrier and market. Significance levels 1%, 5%, 10% correspond to ***, **, *.

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)	
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			✓				✓	
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

and fixed effects to construct a similar control group. Regarding the treatment effect of the grounding it suggests that it led to sizable fare increases—up to 17% for Southwest on routes that would have been exclusively operated by grounded aircraft, and approximately 4% for American.

In addition to measuring the treatment effect, several conclusions can be drawn on the control and treatment group fares Table 3. First, the inclusion of year and carrier fixed effects—whether separately (models 1 and 5) or jointly (models 2 and 6)—substantially alters the estimated treatment effects, as well as the magnitude and sign of the pre-treatment fare differentials between treated and control markets. In several specifications, the sign of the pre-treatment coefficient reverses, underscoring the importance of accounting for firm-date-specific trends While models 1 and 5 help assess changes in fares relative to broader market trends, specifications that include carrier-by-date fixed effects yield a more refined comparison: fare differences are then measured relative to the same carrier's fares on other routes on the same date. Further, adding observable controls (models 3 and 7) markedly affects both the magnitude and statistical significance of the estimates, generally reducing the gap between treated and control markets.

The divergence in results between models using fares in levels and those using log-transformed fares points to heterogeneity across the fare distribution. Specifically, fare differentials in treated markets appear to be driven by relatively higher prices at the top end of the distribution. That is, absolute fare differences are more pronounced among the most expensive tickets. This distinction becomes clearer when comparing model 3 (levels) and model 7 (logs): after logging fares, which reduces the influence of extreme values, the treated and control groups appear more comparable. For Southwest and United in particular, the treated routes had substantially lower pre-grounding fares than control routes, especially at the upper end of the distribution, as indicated by the large negative coefficients in columns 1–3. As a result, when fares are measured in levels, treatment effects tend to show lower average prices for treated routes. In contrast, for American, the fare differences in the treatment group are more pronounced in the higher percentiles, with initial fare gaps of up to 13%, suggesting a different pattern of heterogeneity in response to the grounding.

To gauge the magnitude of the grounding on fares, it is most informative to evaluate the coefficient at the mean treatment intensity—11 percent (see Section V.A). At this average exposure, fares in treated carrier–markets rose by $1.85 relative to the control group (model 2). In logarithms, the estimate in model 7 implies a 0.84 percent increase in mean fares. Robustness exercises using alternative instruments yield comparable results although with lower magnitude. First, with a binary indicator equal to one for carrier–markets with any pre-grounding MAX exposure and zero otherwise; second, with treatment intensity defined as the share of MAX -operated flights over the entire pre-grounding period. Full results appear in Tables A7 and A8 of the online appendix.

We also run regressions using Equation (1) with the inclusion of market fixed effects to analyze mean ticket fares. Models 4 and 8 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 Section V.E 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 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 $Treated_c$ × *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.E.

V.D Grounding Impact on Fares: Event Study

We conduct an event study to further assess whether the fares in our control and treatment groups statistically differed before the grounding. As a result, the variable that denoted the period following the grounding (*PostBan*) is discretised into eight distinct year-quarter dummies and used to estimate whether there are significant differences in the fares between the treatment and control groups. The specification used is as follows:

$$\begin{aligned} p_{cmt} = &\beta_1 Treated_{cmt} + \beta_2 Treated_{cmt} \times t \\ &+ \beta_3 \mathbf{X}_{cmt} + \gamma_{ct} + \epsilon_{cmt} \end{aligned} \tag{2}$$

where $\mathbf{t}$ is a vector of year-quarter dummies. The other terms in the equation are as described in Section V.C. Panel (a) of Figure A5 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. We find evidence supporting parallel pre-trends in average fares between the treated and control groups before the grounding event, followed by a pronounced divergence thereafter. In the post-grounding period, fares in the treated group rise significantly relative to those in the control group, suggesting a causal impact of the grounding. This effect is most pronounced in the first quarter following the grounding, during which the relative increase in fares is particularly salient. 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 A5. 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.

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 A5 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 A6). 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.F.

V.E Grounding Impact: Heterogeneity and Competition

Examining average carrier×market-level 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 A6 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* × *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 (a), we show 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 more 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.[24]

We next explore heterogeneity in the treatment effects by relating them to observable market- and carrier×market-specific characteristics. The results are reported in Table A9 in the Appendix. For each of these analyses, along with the standard results using the previously defined control group, we include a new variable, *Direct Competitors*, defined as the percentage of flights by all competing carriers in a market that operated the MAX in that market during the given quarter. *Direct Competitors* is a continuous variable reflecting the fact that the grounding affected some markets more than others, as direct competitors operating a similar aircraft model in a given market are expected to respond more intensely when a larger proportion of flights are grounded in that market and less so when fewer flights are affected. The corresponding results in panel (a) show the interaction term *Direct Competitors* × *PostBan* has a positive coefficient but is not very statistically significant, implying that rival MAX -operating carriers did not differentially raise their fares post-grounding relative to a treated carrier. Furthermore, the significance of the main treatment coefficients (disaggregated by carrier) remains unchanged upon including *Direct Competitors*, reinforcing our main findings.

In panel (b) we assess whether a market is a monopoly served by a single carrier (*Monopoly Market*). We define a *Monopoly Market* as one where a single carrier operated throughout every quarter of 2018.[25] Coefficients of the interaction term *Treated* × *Monopoly Market* 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

[24]Figure A7 provides a visual depiction of these results for different fare percentiles.

[25]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.

to the rest of markets with at least one competitor. In panel (c), 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 fare increases by rival impacted carriers in response to the grounding are also most pronounced in the short-term. Finally, panel (d) presents results on the varying impact of the grounding by flight duration. The findings reveal a more pronounced increase in average fares for long-haul markets (flights exceeding an hour (≈800 kilometres in flight distance) compared to short-haul markets. This discrepancy aligns with expectations, given that long-haul flights are associated with higher aggregate fuel consumption.

V.F 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. Our analysis involves disaggregating the treatment intensity by each affected carrier.

Results from our analysis are reported in Table 4. Model 1 shows that, before the grounding, MAX-operated flights consistently demonstrated lower fuel consumption rates. On average, Southwest, American, and United experienced reductions of 0.23, 0.14, and 0.25 gps, respectively, in their MAX-operated flights compared to the control group flights that had an average fuel consumption rate of 0.77 gps. This would imply that carriers achieved significantly reduced fuel consumption rates, in percentage terms, when utilizing MAX aircraft compared to similar legacy aircraft in the control group: 30% ($\frac{0.23}{0.77}$) in the case of Southwest, 18% ($\frac{0.14}{0.77}$) for American, and, 32.5% ($\frac{0.25}{0.77}$) for United. However, since Southwest operated only 10% of its flights in treated markets with MAX aircraft, the resulting average reduction in fuel consumption rate across all its treated markets relative to the control group is modest at just 3% ($\frac{0.23\times0.10}{0.77}$). The fuel consumption rates across all treated markets of American and United were correspondingly lower on average by 2% ($\frac{0.14\times0.12}{0.77}$) and 5.5% ($\frac{0.25\times0.17}{0.77}$), respectively, in comparison to the control group. The three carriers experienced increases in fuel consumption rates within their treated markets after the grounding. In the case of Southwest, its average fuel consumption rate rose by 5%, from being 3% below the control group pre-grounding to 2% above in the grounding's aftermath. American and United also faced similar increases in average fuel consumption rates of 1% and 3%, respectively, between the pre- and post-grounding periods.[26]

Table 4: Impact of the grounding on fuel consumption and costs.

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 clustered by markets and carriers, and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables: Unit: Model:	Fuel Burn Gallons/seat-100km (1)	Fuel Cost $/seat-100km (2)	Fuel Cost Route $/seat at route distance (3)
$\text{Treated}_{Southwest} \times \text{PostBan}$	0.35***	0.68***	8.2***
	(0.04)	(0.07)	(0.86)
$\text{Treated}_{American} \times \text{PostBan}$	0.10***	0.24***	2.7***
	(0.01)	(0.02)	(0.28)
$\text{Treated}_{United} \times \text{PostBan}$	0.14***	0.23***	3.9***
	(0.04)	(0.08)	(0.96)
$\text{Treated}_{Southwest}$	-0.23***	-0.42***	-5.3***
	(0.03)	(0.05)	(0.47)
$\text{Treated}_{American}$	-0.14***	-0.28***	-2.2***
	(0.03)	(0.05)	(0.64)
Treated_{United}	-0.25***	-0.43***	-5.2***
	(0.04)	(0.06)	(0.53)
Controls	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓
Mean of Dependent Variable	0.76	1.5	15.1
Observations	28,320	28,227	28,227
R^2	0.50	0.54	0.98

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 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 A5) 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.

[26] 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)

VI Conclusions

We use the unforeseen grounding of the MAX in 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 relies on 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. The unforeseen disruption caused by the grounding forced carriers to replace their grounded MAX aircraft with less fuel-efficient aircraft. Leveraging the grounding as a natural experiment, we employ a DiD design to compare outcomes in treated carrier-market pairs where the MAX was operational before the grounding to control pairs where it was not. 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 utilised the MAX exclusively for all their flights in treated markets before the grounding, average fares in those markets could 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 before 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. The initial cost advantage in treated carrier-markets, attributed to the use of fuel-efficient MAX aircraft, quickly disappeared 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, indicating that some carriers faced significant supply-side capacity constraints in addition to the observed cost shocks from the grounding. We find evidence of strategic behaviour from the competitors, who also raised their prices.

We conclude by acknowledging certain limitations in our paper and proposing avenues for future research. First, our study examines a supply shock impacting a subset of firms that were in the initial stage of adopting new technology. To assess the impact of technology adoption, future work could explore more established technologies. 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. Finally, 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.

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Internet Appendix

A Additional tables and figures

Figure A1: US domestic flight activity by aicraft type. 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.

(a) Number of flights

(b) Total flight hours

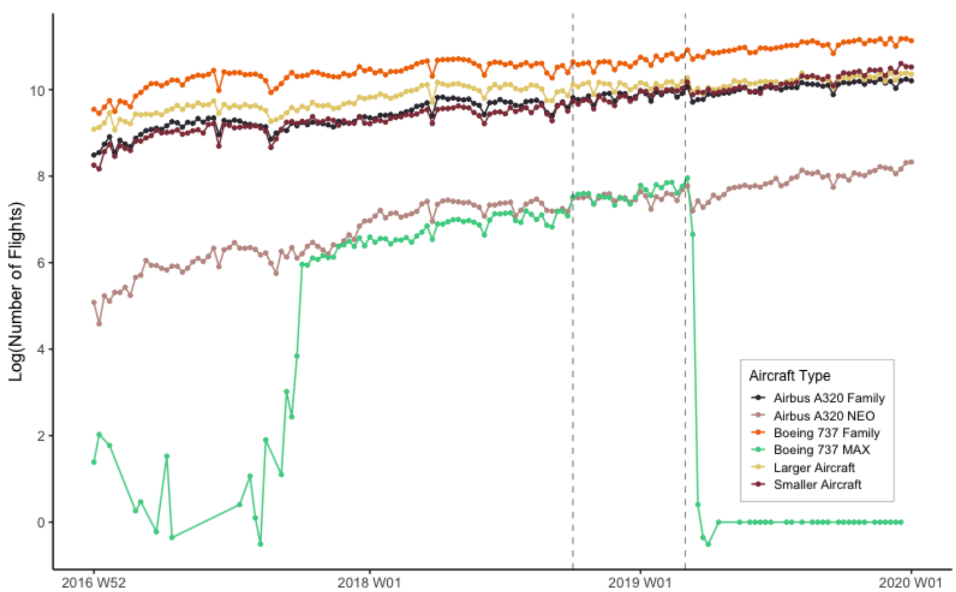


Figure A2: Number of markets operated by carriers over time. NOTE. – Plots show the log number of domestic markets served by US carriers. In each plot, markets are grouped into those where the carrier exclusively offers economy class seats and those where economy and business class seats are sold together. 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.

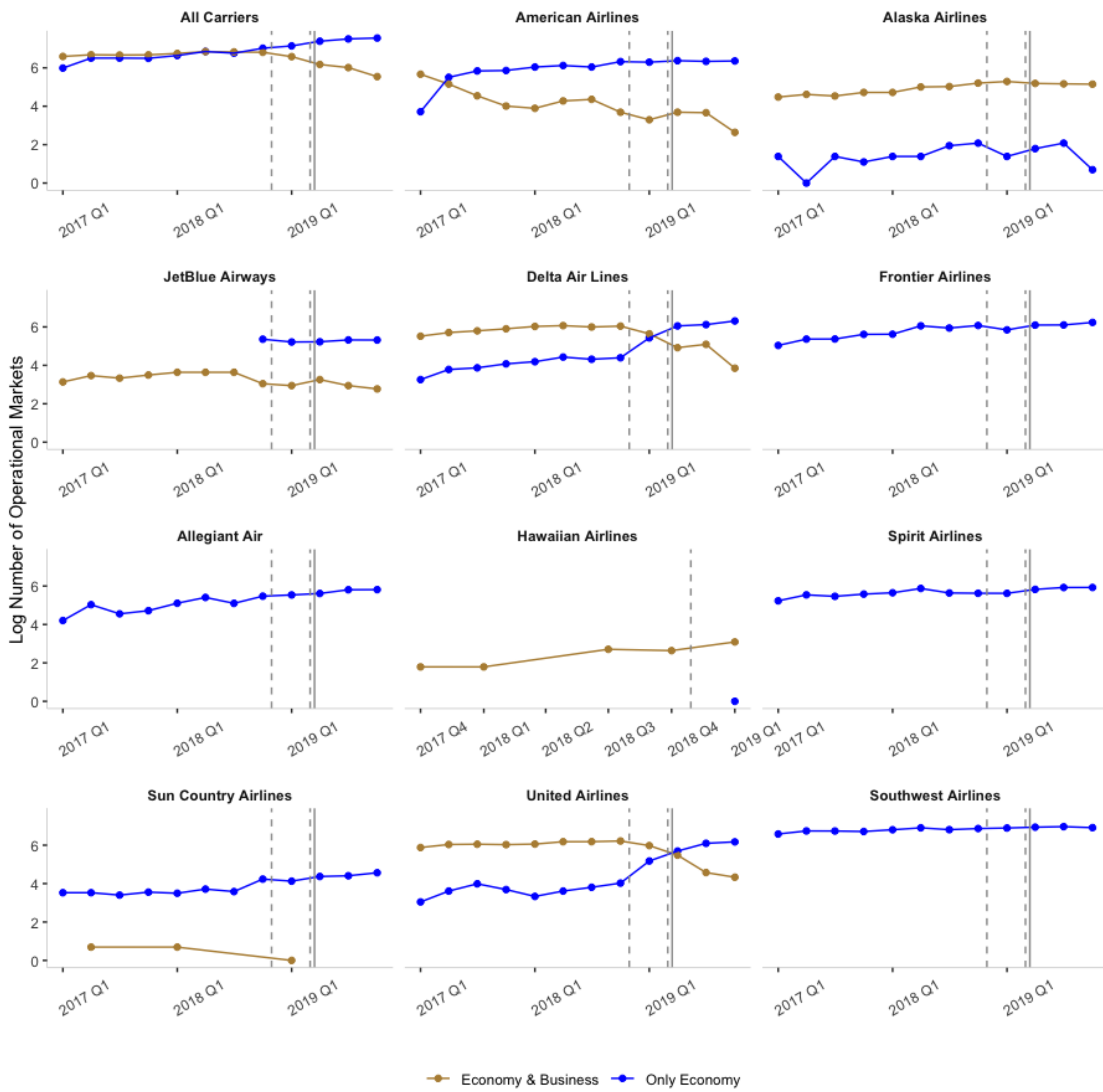
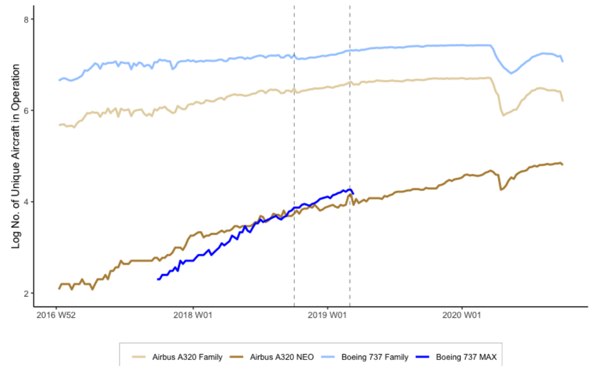
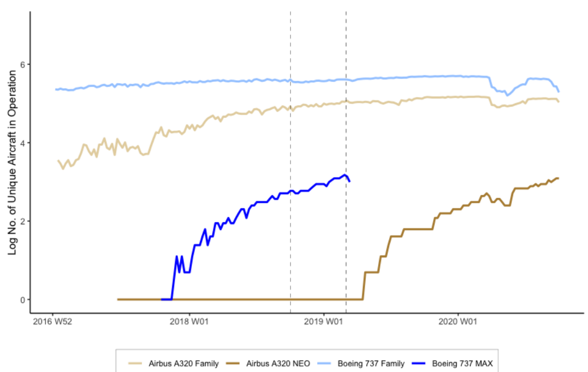


Figure A3: Inventories of narrow-body aircraft among US carriers. NOTE. – Log number of narrow-body aircraft operated by US carriers, grouped into four types: legacy Airbus 320 family (including all variants), Airbus 320 NEO, legacy Boeing 737 family (including all variants), and Boeing 737 MAX. Each aircraft is counted only once based on its unique hexcode*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.

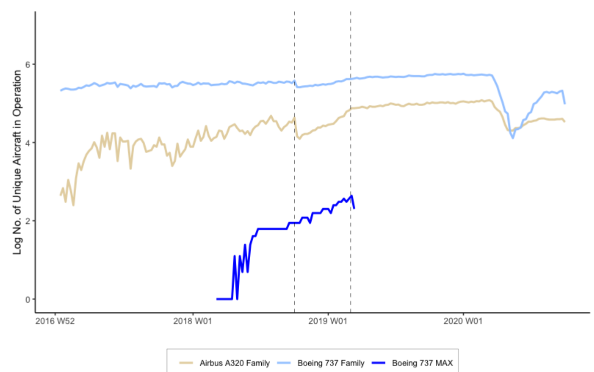
(a) All carriers



(b) American Airlines



(c) United Airlines



(d) Southwest

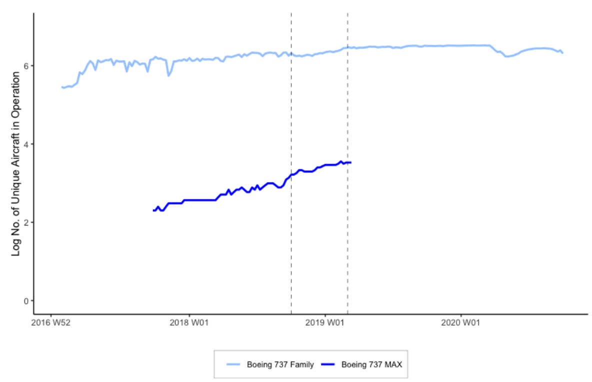


Figure A4: Fleet composition of carriers over time. NOTE. – Log number of unique aircraft operated by US carriers. In each plot, the number of aircraft are shown in aggregate as well as grouped by the six aircraft categories defined in Section IV.B. Dotted lines indicate the dates of the two crashes 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.

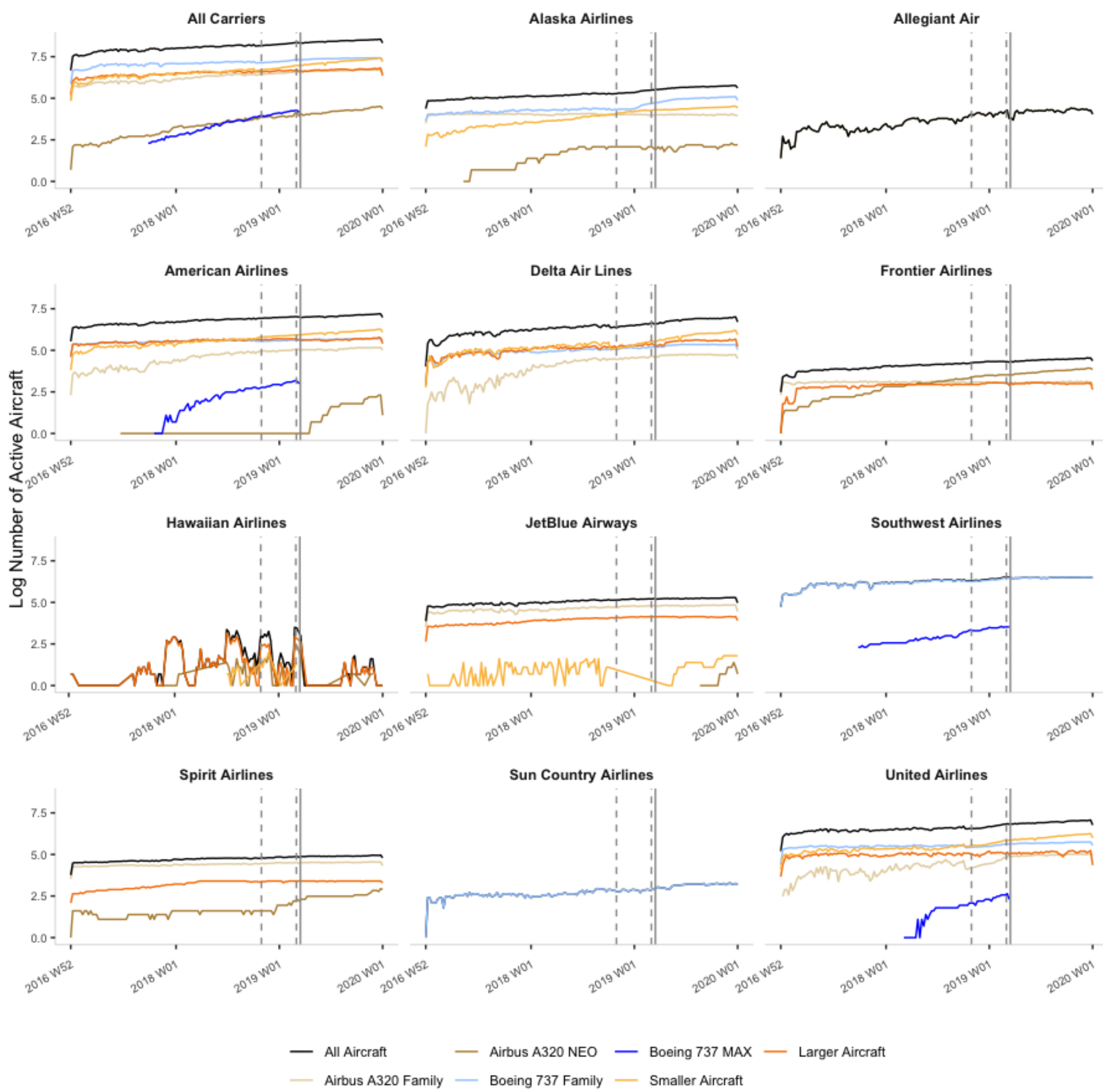


Figure A5: Impact of the grounding on ticket fares: dynamic estimates.NOTE. – figures show the dynamic time-series estimates of economy fares between treated and control carrier-markets based on Equation (2). Panel (a) shows the average fare estimates across control and treated carrier-markets over time, 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) Evolution of fares (b) Event study estimates

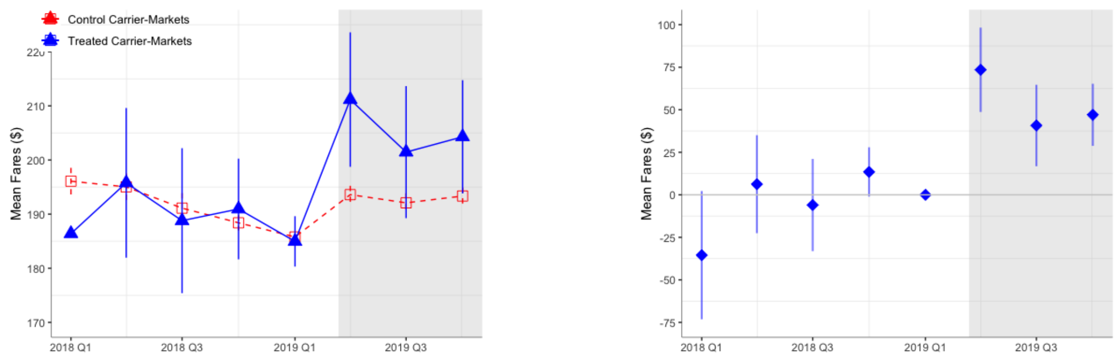
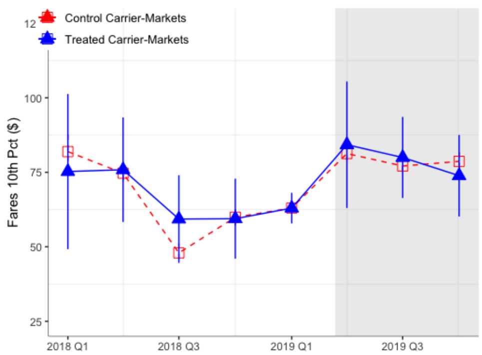


Figure A6: Jet fuel prices over time. NOTE. – Daily prices of aviation turbine fuel (expressed in $ per gallon) during the sample period as reported by the U.S. Energy Information Administration (EIA). The black line shows daily jet fuel prices. The red and blue dotted lines show the predicted trends 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.

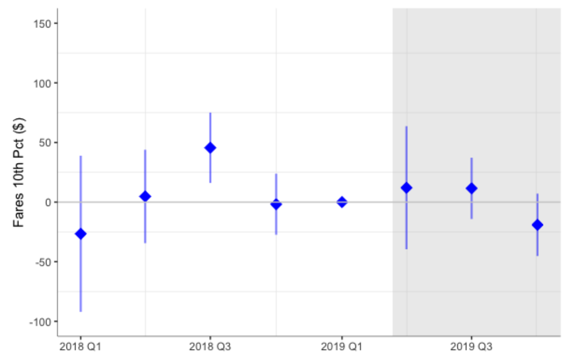
Figure A7: Changes in economy fare percentiles around the MAX grounding.

(a) Fare 10^{th} percentile

Evolution of fare percentiles

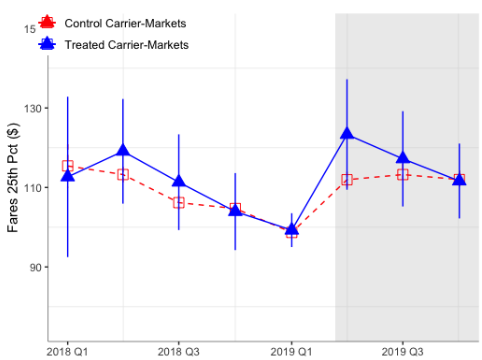


Event study estimates

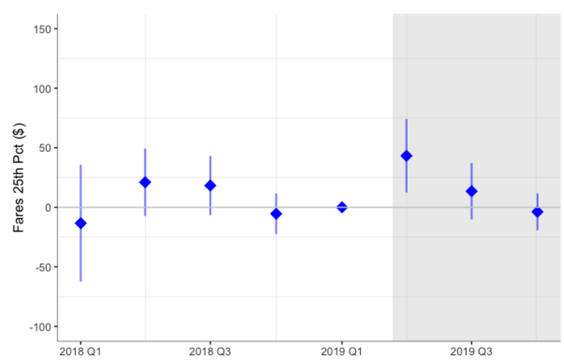


(b) Fare 25^{th} percentile

Evolution of fare percentiles

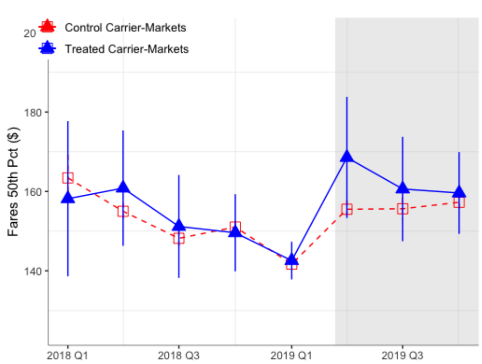


Event study estimates



(c) Fare 50^{th} percentile

Evolution of fare percentiles



Event study estimates

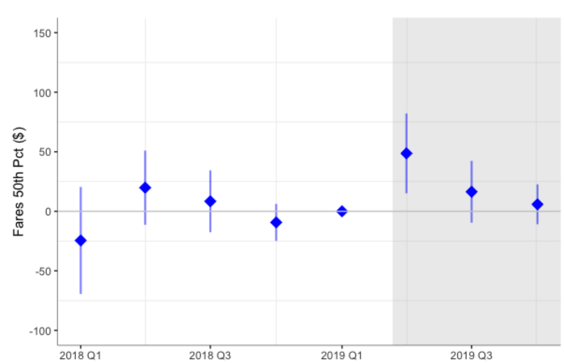
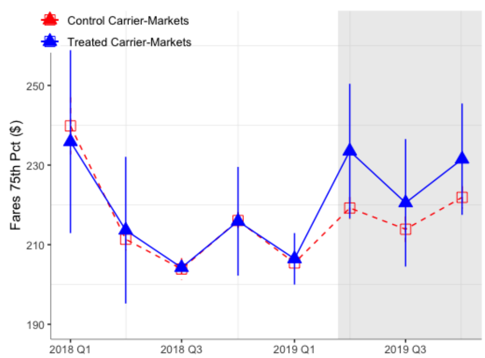


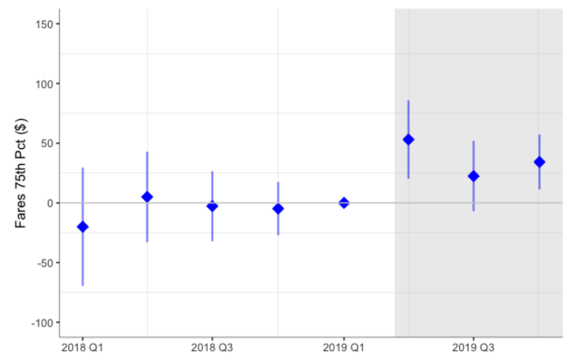
Figure A8: Fare changes by percentiles. NOTE. – Time series estimates of mean ticket fare percentiles between treated and control carriers based on the following equation $p_{cmt} = \beta_1 D_{cmt} + \beta_2 D_{cmt} \times \mathbf{t} + \beta_{\mathbf{3}} \mathbf{X}_{cmt} + \gamma_{ct} + \epsilon_{cmt}$, 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 depicts the period when Boeing 737 MAX aircraft were banned from flight operations by the FAA.

(a) Fare 75^{th} percentile

Evolution of fare percentiles

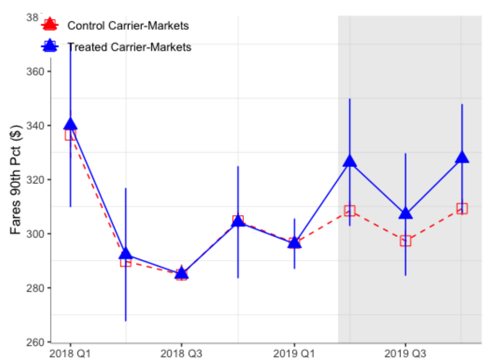


Event study estimates



(b) Fare 90^{th} percentile

Evolution of fare percentiles



Event study estimates

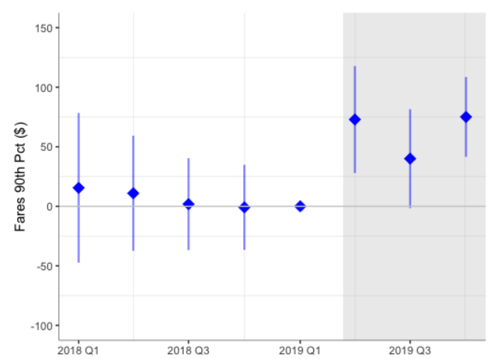


Table A1: Fleet composition by carrier. NOTE. – Narrow-body aircraft counts by model in the fleets of the sample carriers during the period 2018'Q1 to 2019'Q4. Refer to Section IV.B for the definitions of aircraft model types.

Carrier	**Narrow-body aircraft**				Large Aircraft	Small Aircraft	Boeing 737 Max (% of narrow-body AC)
	Boeing 737 Max	Boeing 737	Airbus 320	Airbus 320 Neo			
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

Table A2: Differences in flight coverage between OpenSky and T-100 domestic segment. 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.

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

Table A3: Average treatment intensities.

NOTE. – 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 that contains the prices for a subset of routes, 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.

(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%

Table A4: Impact of the grounding on average ticket fares: matched sample analysis.
NOTE. TBC. 1:3 matching without replacement

(a) Bseline estimates

Dependent Variables:	Mean Fare		Log(Fare Mean)	
Model:	(1)	(2)	(3)	(4)
Treated × PostBan	33.2**	37.3***	0.167***	0.136***
	(14.1)	(9.69)	(0.054)	(0.034)
Treated	-37.0**	-27.6***	-0.066	-0.056*
	(15.6)	(7.78)	(0.069)	(0.030)
Load Factor	23.0*		0.230***	
	(13.6)		(0.076)	
Distance (1000 km)	44.1***		0.161***	
	(1.71)		(0.006)	
Hub Route	4.31		0.038**	
	(2.68)		(0.015)	
Year-Quarter x Carrier FE	✓	✓	✓	✓
Market FE		✓		✓
Observations	12,756	12,756	12,756	12,756
R^2	0.85	0.95	0.89	0.96
Dependent variable mean	204.0	204.0	5.2	5.2
Mean DV (weighted)	236.8	236.8	5.4	5.4

(b) Treatment by carrier

Dependent Variables:	Mean Fare		Log(Fare Mean)	
Model:	(1)	(2)	(3)	(4)
Treated × PostBan × Southwest	43.9***	23.5***	0.205***	0.097***
	(13.5)	(8.05)	(0.067)	(0.036)
Treated × PostBan × United	12.2	77.5***	0.044	0.246***
	(33.8)	(12.4)	(0.102)	(0.032)
Treated × PostBan × American	-772.9	-1,586.4	-2.67	-6.18
	(1,792.3)	(1,003.5)	(6.92)	(4.02)
Treated × Southwest	-47.7***	-33.1***	-0.049	-0.064
	(18.2)	(10.1)	(0.089)	(0.044)
Treated × United	-16.6	-20.5*	-0.092	-0.048
	(33.4)	(11.3)	(0.101)	(0.031)
Treated × American	-691.4**	-332.8**	-2.38**	-1.29**
	(281.1)	(155.6)	(1.14)	(0.627)
Load Factor	23.5*		0.228***	
	(13.4)		(0.074)	
Distance (1000 km)	44.1***		0.161***	
	(1.71)		(0.006)	
Hub Route	4.33		0.038**	
	(2.69)		(0.015)	
Year-Quarter x Carrier FE	✓	✓	✓	✓
Market FE		✓		✓
Observations	12,756	12,756	12,756	12,756
R^2	0.85	0.95	0.89	0.96
Dependent variable mean	204.0	204.0	5.2	5.2
Mean DV (weighted)	236.8	236.8	5.4	5.4

Table A5: Fuel efficiency among carriers around the grounding. NOTE. – 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.

		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)

Table A6: Impact of the grounding on ticket fare percentiles. 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.

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

Table A7: Impact of the grounding on average ticket fares: binary treatment. NOTE. – OLS estimates comparing average economy fares in treated and control carrier-markets for 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 with *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 clustered by carriers and markets, and reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10% levels.

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)	
Controls			✓				✓	
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} × PostBan	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			✓				✓	
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

Table A8: Impact of the grounding on average ticket fares: treatment intensity measured over entire pre-grounding period. NOTE. – OLS estimates comparing average economy fares of treated and control carrier-markets, based on Equation (1). *Treated* is the treatment intensity measured as the percentage of MAX-operated flights by a carrier in a market throughout the entire pre-grounding period. Separate estimates are provided for *Mean Fare* and *Log(Mean Fare)* as dependent variables. Panel (a) shows the baseline regression estimates, and panel (b) presents regression estimates with treatment intensities disaggregated by carrier. Standard errors are clustered by carrier and market, and reported in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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)	
Controls			✓				✓	
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)
$\text{Treated}_{Southwest}$ × 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)
$\text{Treated}_{American}$ × 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)
$\text{Treated}_{Southwest}$	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)
$\text{Treated}_{American}$	-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			✓				✓	
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

Table A9: Heterogenous impact of the MAX grounding on average ticket fares.

(a) Differential impact of the grounding by market structure: heterogeneity by carrier

Dependent Variable:	Log(Fare Mean)			
Model:	(1)	(2)	(3)	(4)
Treated × PostBan × Southwest	0.161**	0.173***	0.162**	0.173***
	(0.069)	(0.039)	(0.069)	(0.039)
Treated × PostBan × American	0.036	0.041**	0.037	0.044**
	(0.023)	(0.021)	(0.023)	(0.021)
Treated × PostBan × United	-0.069	0.004	-0.066	0.008
	(0.062)	(0.045)	(0.062)	(0.045)
PostBan × Direct Competitors			0.080	0.158*
			(0.098)	(0.083)
Treated × Southwest	0.568***	-0.005	0.568***	-0.005
	(0.106)	(0.053)	(0.106)	(0.053)
Treated × American	-0.174***	-0.130***	-0.172***	-0.132***
	(0.056)	(0.039)	(0.056)	(0.039)
Treated × United	0.028	-0.026	0.030	-0.029
	(0.086)	(0.056)	(0.086)	(0.056)
Direct Competitors			0.052	-0.089
			(0.181)	(0.146)
Controls		✓		✓
Year-Quarter x Carrier FE	✓	✓	✓	✓
Observations	28,320	28,320	28,320	28,320
R^2	0.81	0.89	0.81	0.89

(b) Differential impact of the grounding by market structure

Dependent Variable:	Log(Fare Mean)			
Model:	(1)	(2)	(3)	(4)
Treated × PostBan	0.051*	0.073***	0.052*	0.076***
	(0.027)	(0.021)	(0.027)	(0.021)
Treated × PostBan × Monopoly	0.098	0.084	0.095	0.078
	(0.082)	(0.063)	(0.082)	(0.062)
PostBan × Monopoly	-0.017***	-0.013***	-0.016***	-0.013***
	(0.005)	(0.004)	(0.005)	(0.004)
PostBan × Direct Competitors			0.063	0.137
			(0.099)	(0.085)
Treated	0.151*	-0.054*	0.153**	-0.054*
	(0.078)	(0.029)	(0.078)	(0.029)
Treated × Monopoly	0.132	0.119*	0.127	0.120*
	(0.128)	(0.067)	(0.128)	(0.068)
Monopoly	0.018**	0.037***	0.019**	0.036***
	(0.009)	(0.006)	(0.009)	(0.006)
Controls		✓		✓
Year-Quarter x Carrier FE	✓	✓	✓	✓
Observations	28,131	28,131	28,131	28,131
R^2	0.80	0.89	0.80	0.89

Table A10: Heterogenous Impact of the MAX grounding on fares.

NOTE. – OLS estimates of heterogeneous treatment effects on mean economy fares based on Equation (1). Separate estimates are shown including the competitors, the time since the grounding or and flight distance variation. *Monopoly Market* is a dummy variable equal to one when a single carrier operated throughout every quarter of 2018. *Direct Competitors* represents the combined treatment intensity at the route. Carrier × year-quarter fixed effects are included. Standard errors are clustered by market and carrier, and reported in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%.

(a) Differential impact of the grounding by market structure: short- and longer-term impact

Dependent Variable:	Log(Fare Mean)			
Model:	(1)	(2)	(3)	(4)
Treated	0.154**	-0.057**	0.155**	-0.059**
	(0.075)	(0.028)	(0.075)	(0.028)
Treated × Short term (Q2'2019)	0.195*	0.125**	0.197*	0.132**
	(0.114)	(0.062)	(0.114)	(0.061)
Treated × Long term (Q3-Q4'2019)	0.033	0.075***	0.035	0.076***
	(0.028)	(0.020)	(0.029)	(0.020)
Direct Competitors × Short term (Q2'2019)			0.144	0.402***
			(0.125)	(0.114)
Direct Competitors × Long term (Q3-Q4'2019)			0.069	0.097
			(0.118)	(0.096)
Direct Competitors			0.074	-0.086
			(0.182)	(0.146)
Controls	✓	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓	✓
Observations	28,320	28,320	28,320	28,320
R^2	0.80	0.89	0.80	0.89

(b) Differential impact of the grounding by market structure: heterogeneity by flight duration

Dependent Variable:	Log(Fare Mean)			
Model:	(1)	(2)	(3)	(4)
Treated × PostBan × Long Haul	0.065***	0.097***	0.065***	0.099***
	(0.024)	(0.022)	(0.024)	(0.022)
Treated × PostBan × Short Haul	-0.048	-0.015	-0.049	-0.012
	(0.048)	(0.047)	(0.048)	(0.047)
PostBan × Direct Competitors			-0.092	-0.027
			(0.159)	(0.136)
PostBan × Direct Competitors × Long Haul			0.167	0.215
			(0.175)	(0.152)
Treated × Long Haul	-0.149**	-0.104***	-0.158***	-0.103***
	(0.059)	(0.030)	(0.058)	(0.029)
Treated × Short Haul	0.294***	0.236***	0.300***	0.227***
	(0.100)	(0.075)	(0.101)	(0.074)
Direct Competitors × Long Haul			-0.214	0.228
			(0.327)	(0.293)
Long Haul	0.159***	-0.004	0.161***	-0.005
	(0.007)	(0.008)	(0.007)	(0.008)
Direct Competitors			-0.121	-0.283
			(0.251)	(0.239)
Controls	✓	✓	✓	✓
Year-Quarter x Carrier FE	✓	✓	✓	✓
Observations	28,320	28,320	28,320	28,320
R^2	0.85	0.89	0.85	0.89

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 such a receiver tracked continuously in real time. 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.

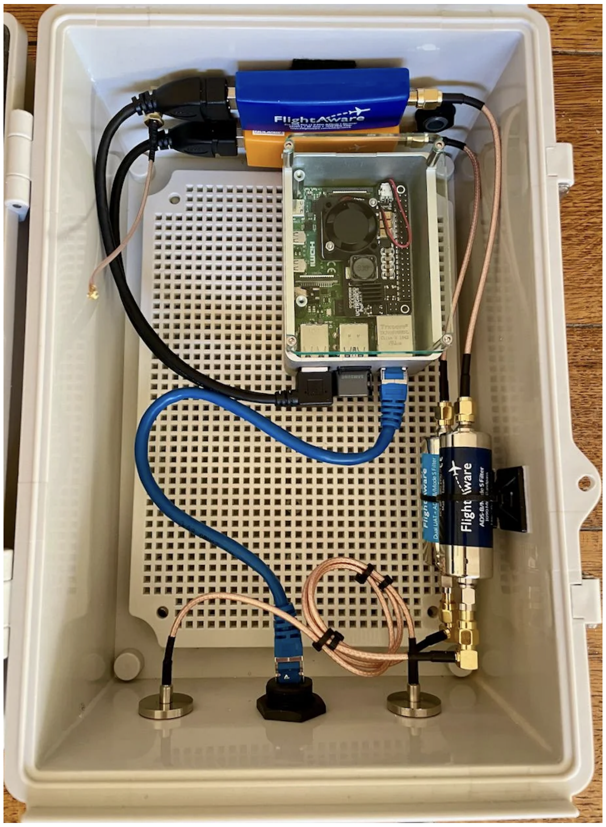
B.1 Flight tracking with Mode S

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.

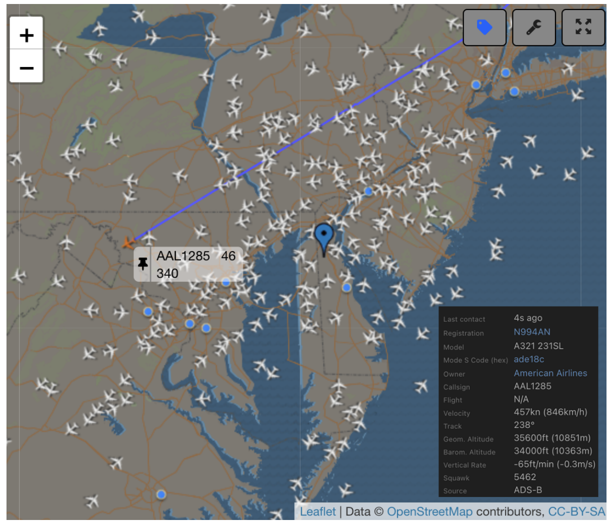
One of the key features of Mode S is its ability to transmit a unique 24-bit aircraft address (ICAO address). This address acts like a digital fingerprint for each aircraft, ensuring that controllers can positively identify each aircraft in their airspace. This is a significant improvement over older 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.
NOTE. Panel (a) shows an OpenSky receiver built from inexpensive, easily procurable electronic components. Panel (b) shows real-time flight tracking by one such receiver, capable of tracking multiple flights simultaneously; the typical coverage radius is up to 600 km. Panel (c) maps the extent of US air-space coverage provided by the full OpenSky receiver network.

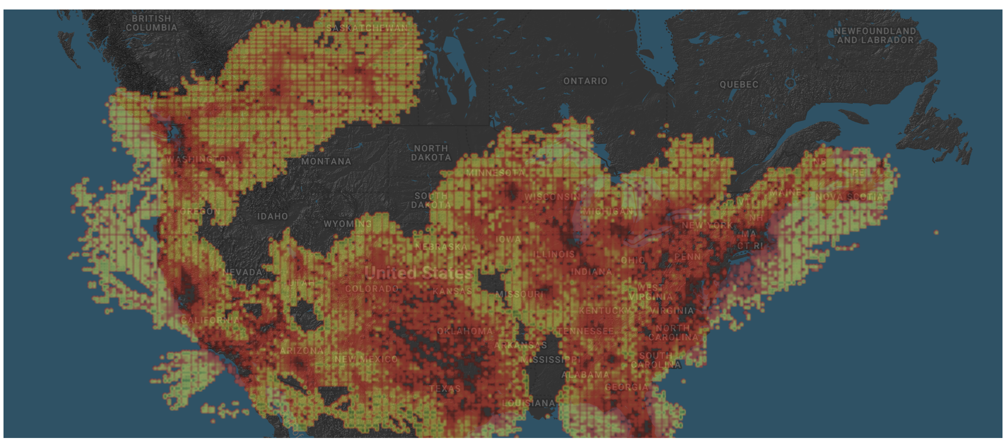
(a) Receiver setup



(b) Aircraft tracking receiver



(c) OpenSky receiver coverage across US (1 Jan 2018)



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.[27] 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

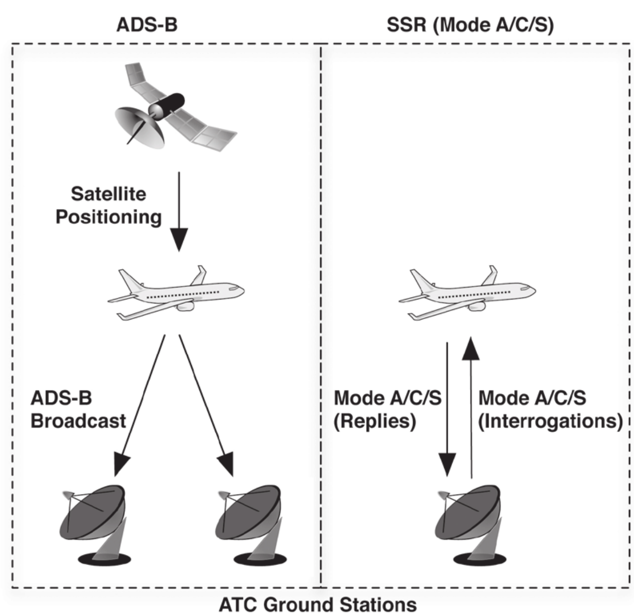
While Mode S plays a significant role in OpenSky's flight monitoring process, ADS-B is another key technology integrated into the platform. Unlike traditional radar-based systems, ADS-B relies on aircraft broadcasting their own positional data, thereby offering a more efficient, accurate, and comprehensive 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

[27] 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?

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 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), which was another notable innovation developed by Boeing for the MAX series. The crashes were attributed to erroneous readings from onboard aircraft sensors and malfunctioning of the MCAS system. 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 mechanism of the MCAS.

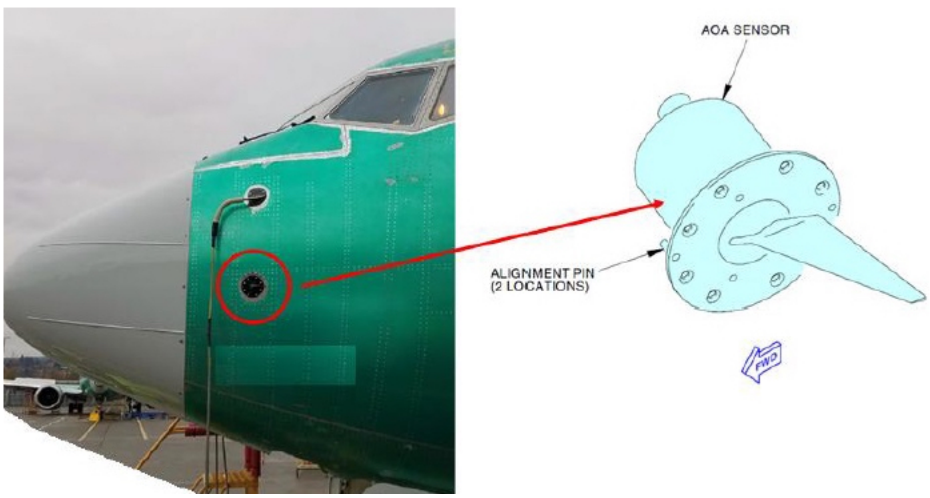
However, while most modern aircraft have redundant AoA sensors to ensure safety and minimize erroneous readings due to accumulation of ice or other debris, the MCAS relied upon just one sensor for its inputs. Additionally, the MCAS operated autonomously, without requiring inputs from the pilot (Sumwalt, 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 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. 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).

(a) Angle of attack (AOA) sensor



(b) Maneuvering Characteristics Augmentation System (MCAS)

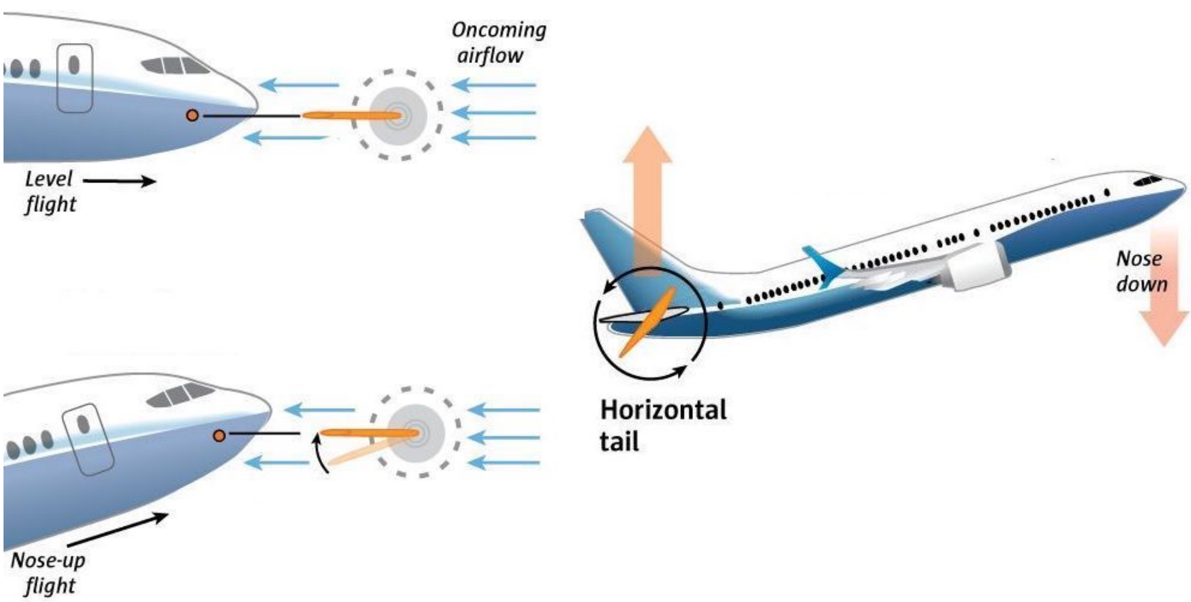
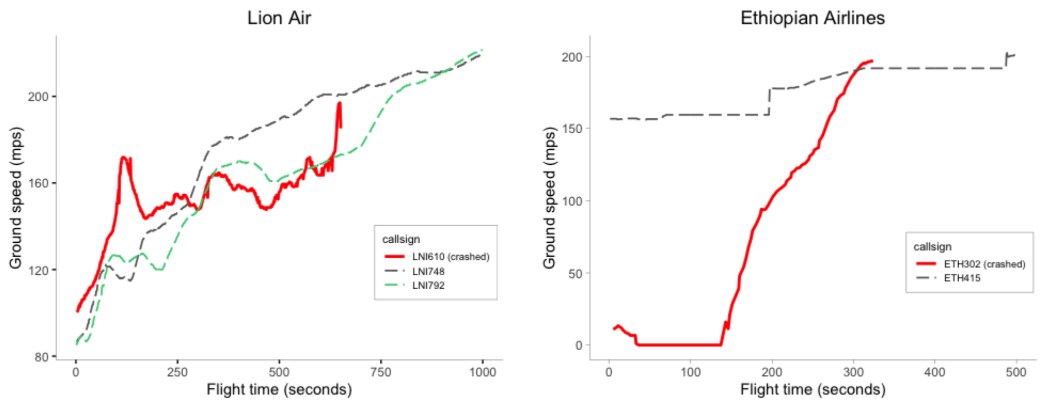
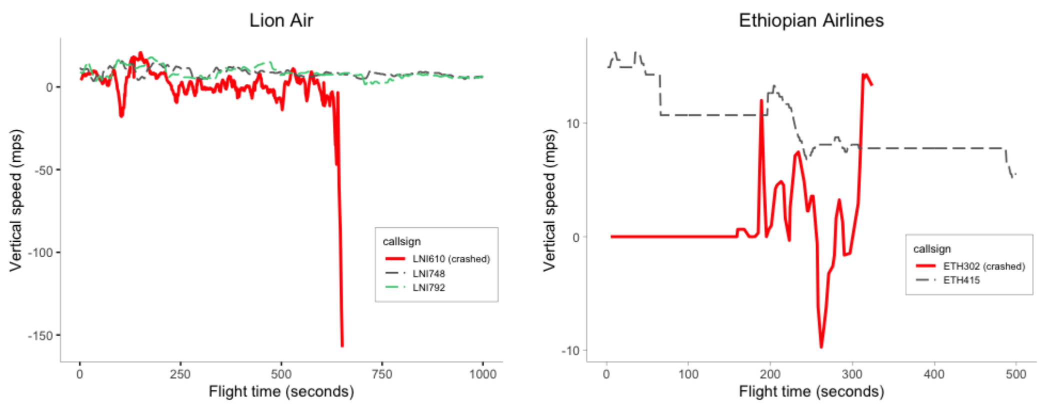


Figure C2: Flight statistics of 737 MAX aircraft involved in crashes. NOTE. – Flight data are from Opensky and Flightradar24. In each panel, the first plot compares flight statistics of Lion Air flight LNI610 that crashed on 28^{th} October, 2018 with two other flights (LNI792 on 11^{th} September, 2018 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).

(a) Ground speed



(b) Vertical speed



(c) Altitude

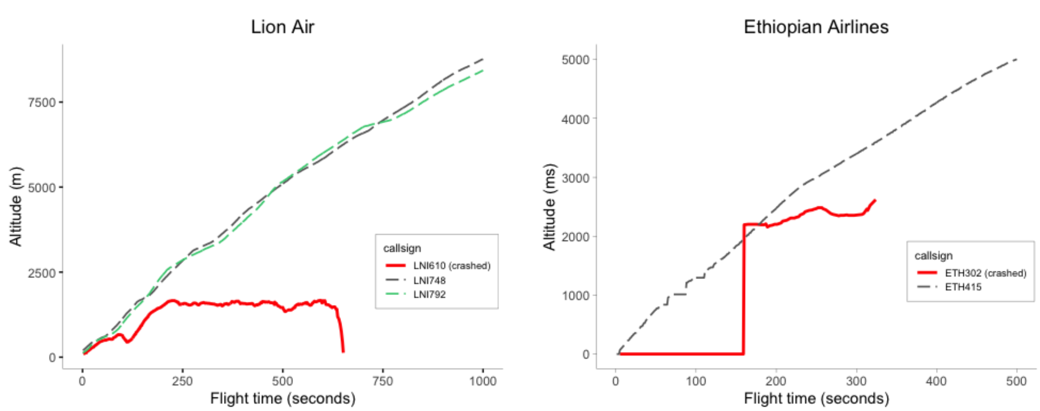
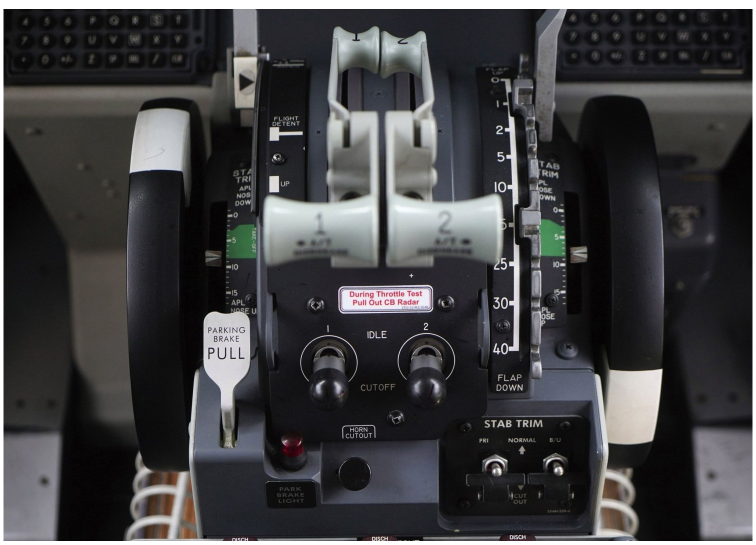


Figure C3: Steps to disable MCAS during flight.
NOTE. – Panel (a) shows a 737 MAX cockpit with the throttle levers (A), flaps (B), spoilers (C), and trim controls (D) highlighted in red. Black wheels on either side are connected to the horizontal tail and will spin if the stabilizer swivels. The instruments 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).

(a) Cockpit of a 737 MAX 8 aircraft

(b) Flight controls closeup



(c) Flight controls closeup

Appendix References

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