Boeing Interrupted - The impact of the grounding of the 737 MAX aircraft on ticket prices and routes

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Abstract

The grounding of the Boeing 737 MAX aircraft by the FAA and other regulators worldwide after two fatal crashes caused a significant supply shock in both the domestic US air travel market and elsewhere. We exploit the different fleet compositions of the largest domestic carriers in the US and particularly the differential effect this regulatory grounding had on American, Southwest and United Airlines to calculate price and quantity effects on affected routes, as well as spillover effects on other routes served by these carriers using a difference-in-differences approach. We further investigate the heterogeneous effect on different routes, based on route characteristics including presence of hubs, and competition. Our analysis suggests that the affected airlines make adjustment to their schedules and fleet deployment to account for this supply shock leading to spillover effects even on routes where the 737 MAX aircraft is not regularly deployed. We find sizable and significant increases in ticket prices between 3% to 7% on non-MAX carriers, and smaller or negligible increase in prices on Max carriers.

1. Introduction

On the 18th of November 2020, the US Federal Aviation Agency (FAA) cleared the Boeing 737 MAX aircraft for commercial flights almost 20 months after grounding it[1]. The original regulatory decision to impose a ban on flying the aircraft came as a result of two fatal crashes: Lion Air Flight 610, which crashed into the Java Sea on October 29, 2018, killing

[1] FAA Updates on Boeing 737 MAX "https://www.faa.gov/news/updates/?newsId=93206". Retrieved on 12/05/2020

all 189 passengers and crew, and Ethiopian Airlines Flight 302, which crashed near Bishoftu, Ethiopia on March 10, 2019, killing all 157 people aboard. A joint investigation by Boeing and aviation regulators worldwide, including the FAA, ensued and found that the crashes were a result of a combination of faulty design, malfunctioning sensors and Maneuvering Characteristics Augmentation System (MCAS) technology. These factors forced an auto-pilot response from the plane's avionics system that resulted in steep nosedives by the plane leading to the two crashes. This automated flight control system was designed to enhance aircraft stability but instead forced an auto-pilot response from the plane's avionics system that resulted in steep nosedives by the plane leading to the two crashes. These findings, along with reports of lax regulatory oversight by the FAA during the original certification period, resulted in a significant loss of confidence in the aircraft and led to its unprecedented grounding by major aviation regulators across the globe including the FAA in the immediate aftermath of the second crash.

By March 10^{th} 2019, when the second of the two 737 MAX crashes took place and more than two years after the first delivery to a commercial customer, there were more than 380 Boeing 737 MAX aircraft flying worldwide, with 72 operating in the domestic market in the United States. Although Boeing and the FAA pushed an optimistic message and promised a quick software fix within weeks, it became apparent that there were significant systemic concerns regarding both the aircraft design and certification process that required a lengthy regulatory review (Committee on Transportation and Infrastructure, House of Representatives [13], Federal Aviation Administration [15]).

This was a significant disruption in the plans of the three MAX carriers - American, United and Southwest (collectively referred to as MAX carriers henceforth) who were all pursuing a "fleet modernization" strategy that involved retiring older aircraft and replacing them with the new fuel-efficient narrow-bodied Boeing 737 MAX planes. The MAX aircraft represented a major cost improvement, offering up to 20% better fuel efficiency compared to prior 737 models and approximately 14% lower maintenance costs per seat as advertised by the manufacturer The Boeing Company [23]. The grounding meant that not only were a fraction of their planes grounded and not being flown, but planned future deliveries would also not be able to join the fleet until the regulatory restrictions were lifted. On the other hand, Delta Airlines and JetBlue, who had chosen to replace their older planes with the Airbus 220s and 320neos instead, would face no such supply constraint in the midst of an otherwise industry-wide trend toward fleet renewal and efficiency improvements.

We hypothesize that there were several consequences of the Boeing 737 MAX grounding in the US domestic airline market. While basic economic theory suggests that average fares would rise on routes that MAX carriers flew the 737 MAX aircraft because of the supply shock, there are likely to be heterogeneous and complex dynamic effects on other routes as well. First, we examine direct price effects on routes previously served by 737 MAX aircraft. Second, we analyze spillover effects throughout carrier networks as airlines reallocated their remaining aircraft across routes, potentially affecting prices and service levels even on routes where the MAX aircraft never operated but the MAX carriers did. Third, we explore heterogeneous effects, including how responses varied based on the presence of hubs, level of competition, route distance, and carrier market shares on ticket prices of Max carriers versus non-MAX carriers. Lastly, because aircraft can be moved around and re-positioned, there likely were spillover effects throughout the network from the MAX ban as the affected carriers readjusted their networks leading to a reduction in seats flown, frequency (departures) or even exits from some markets (routes) once it became clear that the 737 MAX would be undergoing a lengthy review process.

The airline industry provides an ideal setting to study the effects of this Boeing 737 MAX supply shock in a network industry with complex market structures. Unlike many other industries where supply constraints affect all markets similarly, airlines can make reallocation decisions across their networks in the medium-term, if not the short-term when faced with fleet constraints. This creates variation in how the shock propagates through the system, allowing us to identify both direct and indirect effects in our quasi-experimental setting. Thus it allows us to compare how constraint-affected carriers (MAX carriers) and unconstrained carriers (non-MAX carriers) respond within the same affected markets, providing insights into strategic behavior under asymmetric supply constraints.

1.1. How was the 737 MAX aircraft being used by the MAX carriers?

	Boeing 737 MAX delivered by March 2019	Boeing 737 MAX expected by Dec 2020
non-MAX carriers		
Alaska	0	4**
Delta	0	0
Jetblue	0	0
Max carriers		
American	24	15**
Southwest	34	13-18**
United	14	13**

Table 1: Boeing 737 MAX deliveries to domestic US carriers.
Note **: Indicates expected deliveries by December 2020. However, these are estimated, and aren't always firm deadlines. There can occasionally be delays of a few months.

The Boeing 737 MAX aircraft was a boon for the MAX carriers who had already deployed them in their fleet as noted by several press statements and industry trade associations:

- Lower costs per seat to operate compared to the older 737NG and older models because of larger and more efficient engines
- Boeing advertised that the new aircraft required no additional pilot training
- Longer fuselage compared to the older generations so more seats and more passengers
- Longer range which gave the new planes an advantage in long transcontinental flights between the coasts.

As we will discuss in a later section, the MAX carriers deployed the MAX planes extensively and in the case of American and United, on longer routes as can be seen in Figures 3, 4 and 5.

1.2. Was the demand for domestic air travel in the US affected by the first crash?

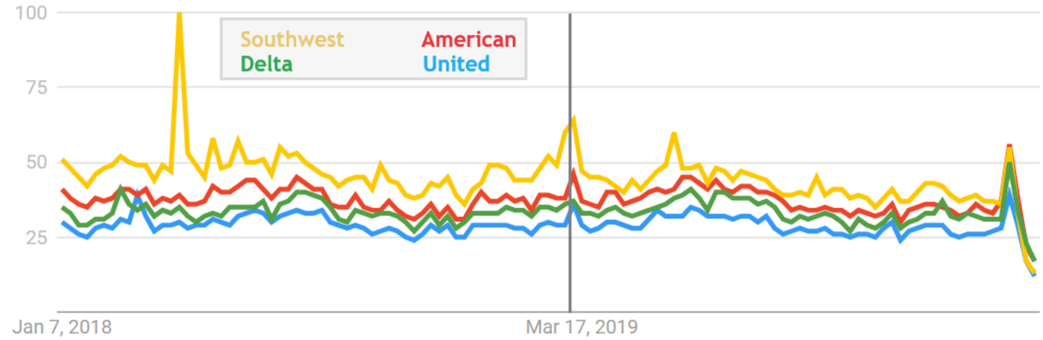
Reviewing past literature on major airline crashes, several papers find effects on the demand for air travel - a persistent negative effect on the specific carrier that suffered a crash, and a smaller transitory contagion effect on competitors along with an opposing switching effect. In particular, Zotova [24] finds that the crash of an Alaska Airlines flight off the coast of California led to a decline in Alaska Airlines fares - a discount to compensate for the perceived risk associated with flying with the airline in question. This matches earlier findings by Bosch et al. [7] and Squalli and Saad [22] that find some switching and contagion effect in the local market. However, since foreign carriers flew both of the 737 MAX planes that crashed with no presence on US soil, it is unclear what effects that this might have since neither Lion Air or Ethiopian Air are likely to have been encountered by a typical American consumer and are unlikely to be considered to be in the same market or as competitors to the domestic carriers.

Brueckner [8] investigates this exact question to see if the first Boeing 737 MAX crash in Indonesia in October 2018 led to US consumers perceiving a higher risk associated with flying on the 737 MAX aircraft on Southwest airlines which had deployed the highest number of them in US on many routes. He concludes that even after significant media coverage, consumers do not shy away from flying on Southwest and there is no effect on fares.

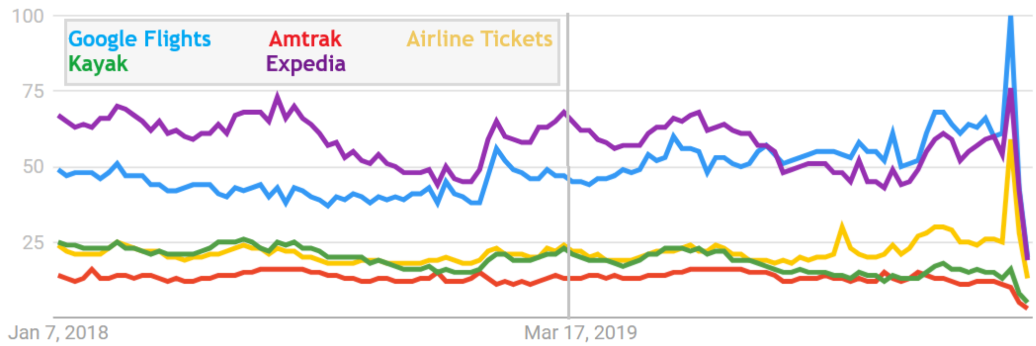
We supplement this analysis by providing further supporting evidence from Google Trends on web searches performed in the US between February 11, 2018 and March 11 2020 for related relevant search terms including the four largest domestic carriers including the three MAX Carriers and Delta. This is because most airline tickets are purchased online through the carrier's own websites or through third party travel agencies/websites like Expedia, Google Flights and Kayak.

As the data shows, while there is a small spike in searches for Southwest and American Airlines, there is very little persistent change post-ban.

Bilotkach and Hüschelrath [3] find that carriers typically schedule routes and aircraft



(a) Google trends data on web searches on the four largest domestic carriers in the US



(b) Google trends data on web searches relevant to domestic air travel in the US

on specific routes 47-48 weeks ahead of time. In their analysis of schedule and departure data, they conclude that on routes that MAX aircraft flew, MAX carriers increased their departures and seats while non-MAX Carriers made no significant changes to their departures or fleet utilization in response to the disruption caused by the grounding of the MAX aircraft. Our results differ from theirs as we find that controlling for route characteristics, there is significant heterogeneity in the responses of Max carriers and non-MAX carriers in terms of ticket prices, departures and seats offered on the routes that were affected.

1.3. Supply Shocks in Airline Markets - A History

The study of supply shocks in airline markets has a substantial history in economics literature. Seminal work by Borenstein and Rose [6] established that carrier-specific supply constraints can lead to significant price effects even in previously competitive markets. Research on airline pricing behavior following shocks has typically focused on either industry-wide shocks (such as the airline crashes on 9/11) or carrier-specific disruptions. Berry et al.

[1] and Berry and Jia [2] developed structural models of airline competition that demonstrate how capacity constraints affect equilibrium prices. Their research shows that when carriers face binding capacity constraints on specific routes, this leads to higher equilibrium prices not only for the constrained carrier but also potentially for competitors. Gerardi and Shapiro [16] further emphasizes that competition restrains price discrimination by airlines, but this effect varies across different market conditions.

Ciliberto and Williams [12] find that multimarket contact facilitates tacit collusion in the airline industry, suggesting that strategic responses to competitors' supply constraints may be influenced by broader competitive relationships. This is particularly relevant to our study, as MAX and non-MAX carriers compete across multiple route markets simultaneously.

1.4. Fleet Constraints and Network Adjustments

The mechanics of how airlines adjust to fleet constraints is explored by Bilotkach and Hüschelrath [3], who find that carriers optimize fleet assignment to preserve their most profitable routes while potentially abandoning marginal markets. Similarly, Gil and Kim [17] demonstrate that incumbents adjust flight frequency in response to competitive pressures, including supply constraints faced by rivals. Network structure plays a crucial role in how airlines respond to capacity constraints. Brueckner and Luo [10] show that flight frequency decisions are strategically influenced by competition, while Pita et al. [21] present optimization models demonstrating how airlines integrate flight scheduling and fleet assignment decisions under competitive pressure.

Airline hubs create particularly unique dynamics in response to supply shocks. Borenstein [5] established the "hub premium" phenomenon, where dominant carriers at hub airports charge higher fares due to market power. Building on this, we expect differential responses to the MAX grounding depending on whether routes touch carrier hubs, where airlines may have greater flexibility to reallocate capacity.

1.5. Prior Research on Aircraft Groundings

Research specifically addressing asymmetric aircraft groundings is more limited. Most similar to our study, Bilotkach et al. [4] examine schedule and departure data after the MAX grounding and conclude that on routes where MAX aircraft flew, MAX carriers increased their departures and seats while non-MAX carriers made no significant changes to their departures or fleet utilization. Our analysis differs, as we find significant heterogeneity in responses when controlling for route characteristics.

Brueckner [8] investigates consumer response to the first 737 MAX crash, finding limited demand effects, which suggests that our supply-side analysis addresses the primary economic mechanism at work in this case. This aligns with earlier findings from Zotova [24] and other studies of airline crashes showing that consumer responses are typically limited to the specific carrier involved in an incident.

Our study builds upon this literature by examining the unique supply shock that affected multiple carriers differently based on their fleet composition and network structure. The extended nature of the 737 MAX grounding provides an opportunity to study not just immediate pricing responses but also medium-term network adjustments. We contribute to the literature by analyzing both direct effects on routes where MAX aircraft operated and spillover effects across carrier networks, while accounting for heterogeneity in market structure and hub presence.

2. Data

The main source of our data is collected from the Airline Origin and Destination Survey (DB1B) and the Air Carrier Statistics database (T-100 Domestic Segment). DB1B reports a 10% random sample of airline tickets from reporting carriers and includes origin, destination, segments, and its sequence, ticket fare, number of passengers and etc. T-100 Domestic Segment reports monthly air carrier traffic information using Form T-100. All three data sources are collected and made available by the Bureau of Transportation Statistics.

For the purpose of this paper, we are restricting our data to the 48 contiguous states in the U.S. as flights from or to non-contiguous states (Hawaii and Alaska) and international destinations are subject to significantly different market dynamics and policies. Our data consists of quarterly observations for the years 2018 and 2019. Following established conventions from earlier papers in the airlines literature (Brueckner and Spiller [11]), we restrict our sample further by dropping tickets cheaper than $25 and those with multiple carriers.

In our analysis, we include controls for capacity constraints (slot-controls), airport congestion, competition including HHI at origin and destination, carrier hub status (Morrison and Winston [20]) and the level of effective competition on a given route. Connecting itineraries with less than 4 coupons are used for constructing Herfindahl–Hirschman index (HHI) within the route to capture the competitiveness of the market. The route characteristics are sourced from the T-100 and the Department of Transportation's Origin and Destination Survey (2001).

The sample itinerary fares data is aggregated for each route i, carrier c, quarter q to obtain route-carrier-quarter observations. Routes (markets) are defined as directional airport pairs that are served on a nonstop basis. This implies that flights from airport A to airport B are treated separately from flights from airport B to airport A. This is particularly important in the case of Southwest Airlines, which does not follow the traditional hub and spoke model of the three other large legacy US carriers (United, American and Delta).

As is common in the airlines literature (Brueckner [8]; Brueckner et al. [9]; Morrison [19] Kwoka et al. [18]), we additionally restrict our sample only to include a carrier on a given route if it has 12 or more flights operated and at least 90 passengers flown in a given quarter and consider the carrier as "present" on that route. Average fares are passenger-weighted fares calculated using non-stop itineraries. Itineraries with fares being flagged as not credible or marked as bulk and those with one-way fares less than $25 or more than $5000 are dropped (Kwoka et al. [18]; Brueckner and Spiller [11]). After aggregating and filtering our sample data, we are left with 42,677 observations. Table 1 summarizes some of these key variables in our data for all routes showing the mean, standard deviation, minimum and maximum values too.

For our analysis of the grounding of the 737 MAX aircraft we carefully define treatment variables to capture both direct and spillover effects. We define a 'MAX route' if any of the three MAX carriers (American, Southwest and United) flew a Boeing 737 MAX aircraft on that route in any quarter, and operated at least 12 flights. We then create a new variable, a carrier's *MAX ratio* which is the ratio of the MAX carrier's 737 MAX flights to the carrier's total flights on that route. We define a route i to be a MAX route if any of the MAX carriers have a *MAX ratio* of 5%. While the 5% threshold was chosen somewhat

Table 2: Summary Statistics – All Carriers

	Mean	S.D.	Min	MAX
Avg. Fare	193.670	80.147	31.030	587.070
Departures	249.352	221.806	12.000	2151
Passengers	25998	28813	275.000	279810
Carrier Max Ratio - Cont.	0.019	0.055	0.000	0.852
Route Max Ratio	0.006	0.018	0.000	0.272
Max Carrier on Route	0.752	0.432	0.000	1.000
Distance	915.441	565.502	67.000	2724
log(Distance)	6.617	0.672	4.205	7.910
Slot Controlled	0.284	0.451	0.000	1.000
Tourist	0.258	0.438	0.000	1.000
Hub	0.844	0.363	0.000	1.000
Airport Congestion	1.180	0.799	0.007	5.052
Carrier's Overall Network	1139.875	423.917	48.000	1555
Carrier's Mean Network	21.925	13.741	0.000	152
Origin HHI	0.288	0.198	0.082	1.000
Destination HHI	0.288	0.198	0.082	1.000
Route HHI	0.636	0.252	0.171	1.000
Marketshares' S.D.	0.235	0.180	0.000	0.704
Low-Cost HHI	0.646	0.393	0.000	1.000
Connecting HHI	0.414	0.322	0.000	1.000
Potential Comp	3.536	1.788	0.000	9.000
Mean Income	54044	5504	39530	76246
Mean Population	3392272	2369286	192355	15981652
Quarter	2.997	0.816	2	4
Year	2018.507	0.500	2018	2019
Observations	42677			

arbitrarily, we conduct robustness checks relaxing the definition and varying this threshold and using alternative specifications including treating MAX ratio as a continuous variable in our analysis, and categorizing it into data-drive bins of specific sizes, and find broadly similar results. Figures 3, 4, and 5 illustrate the geographic distribution of the MAX routes for each of the affected MAX carriers in 2018 Q4, revealing distinctly different deployment patterns. It is clear that while American (AA) and United (UA) focused on a few specific routes, Southwest (WN) deployed the MAX planes far more broadly throughout its network. Interestingly, our exploration of the data shows that almost none of the MAX carriers used their MAX aircraft on the same routes as another MAX carrier - there was no overlap. This means that routes where American flew the 737 MAX-8 aircraft, for example LAX-MIA, no other MAX carrier flew their MAX aircraft on the route. This lack of overlap and distinct pattern of deployment enables cleaner identification of the effect of the grounding and suggests potential for heterogeneous impacts across carriers based on their distinct network strategies.

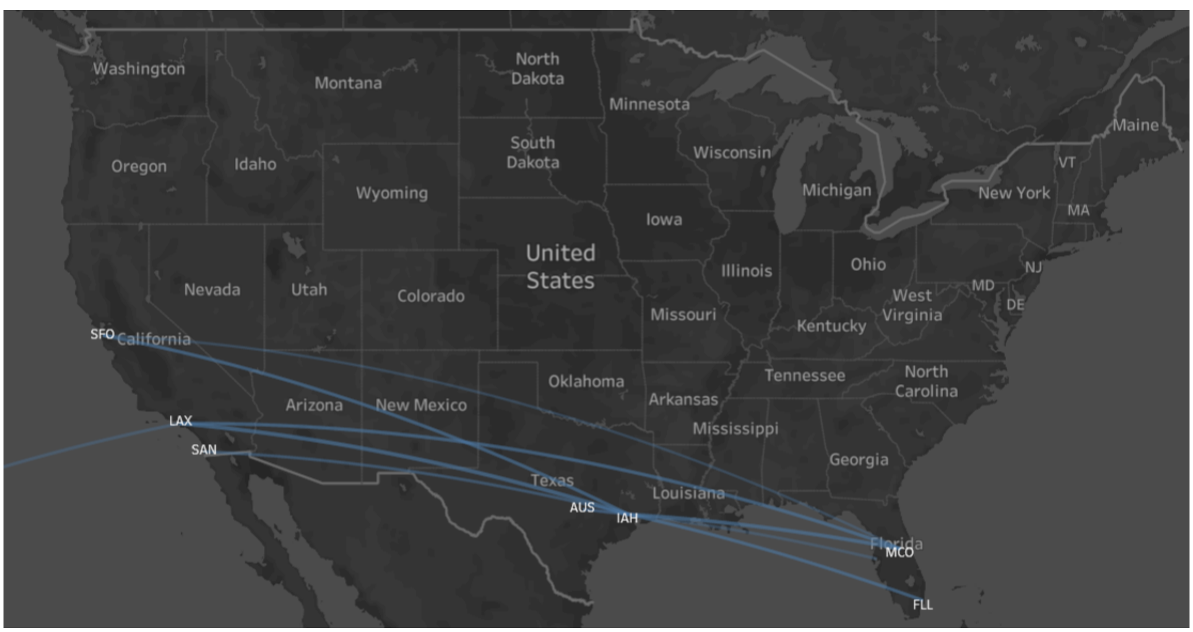


Figure 2: United Airlines

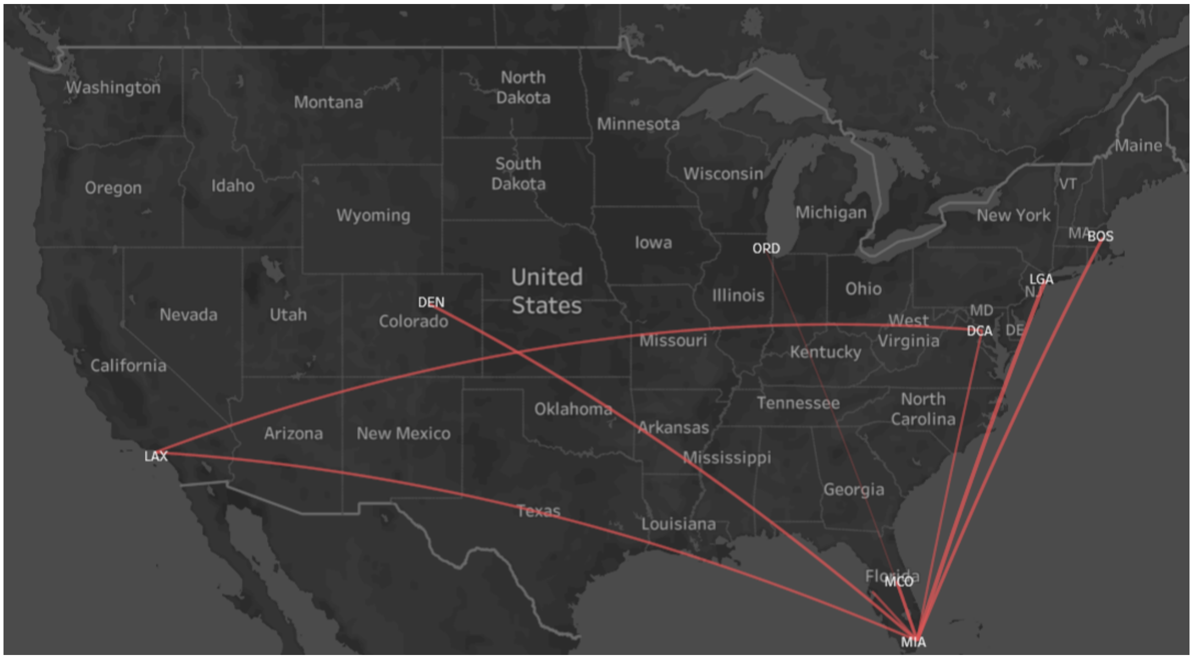


Figure 3: American Airlines

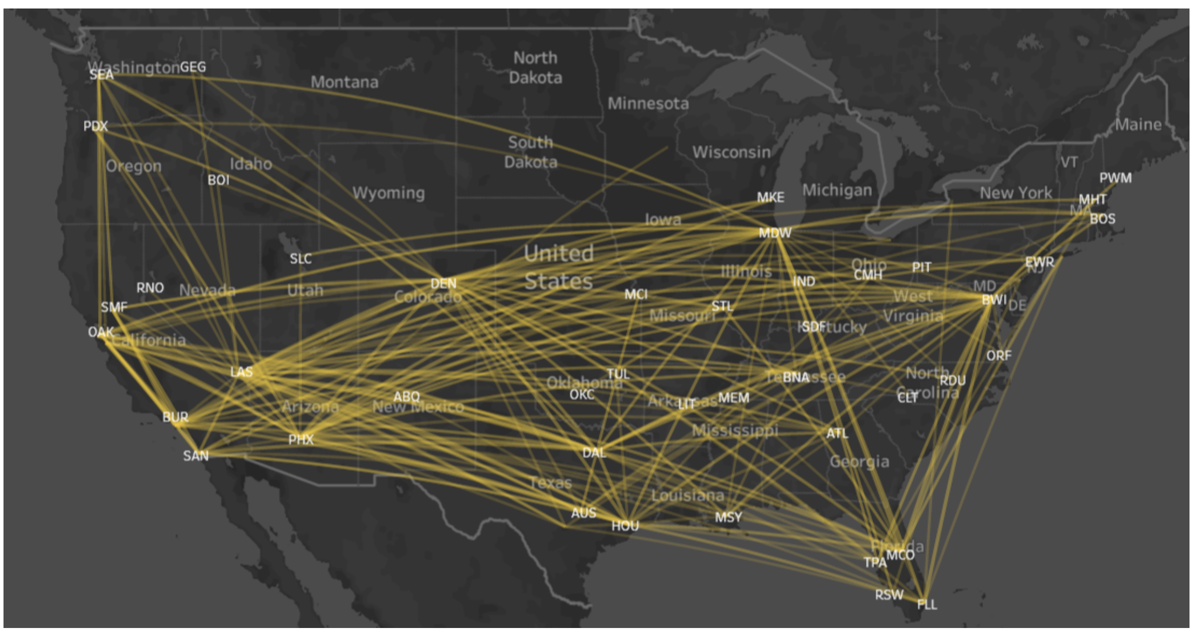
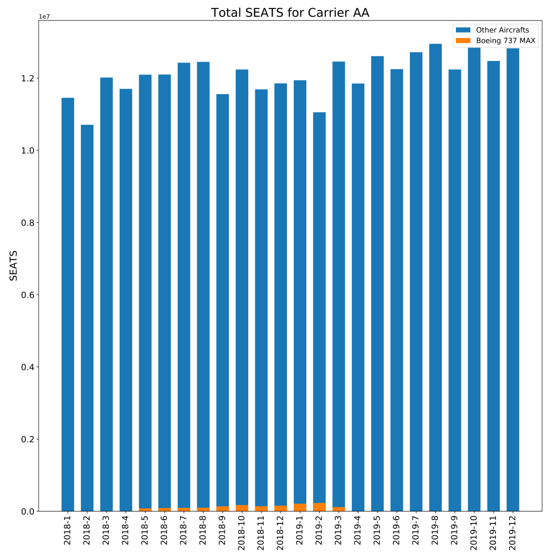
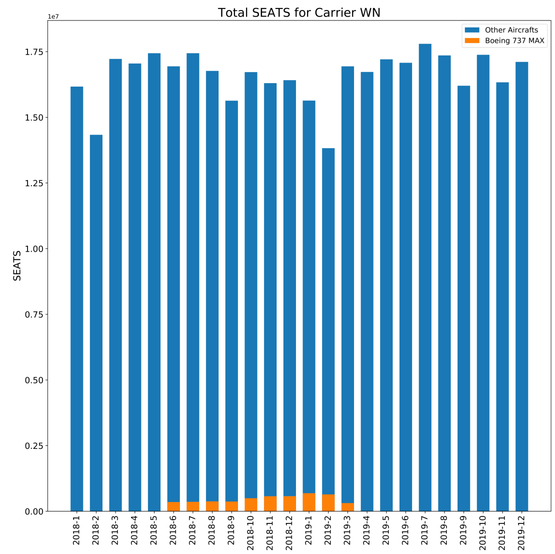


Figure 4: Southwest Airlines

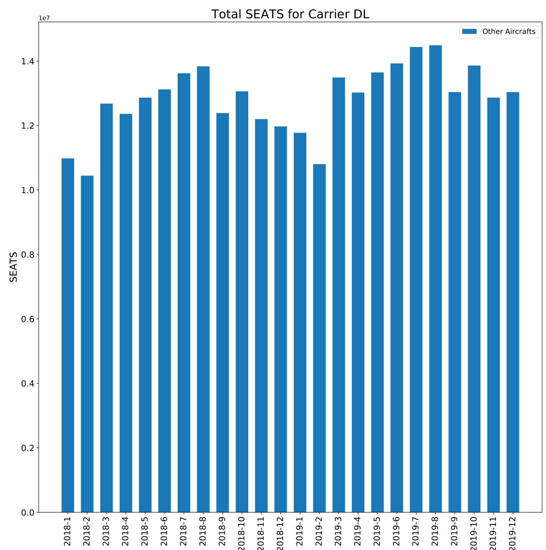
The following charts in Figure 2.6 show how the grounding of the 737 MAX aircraft affected Southwest and American and to a smaller degree United Airlines whereas Delta which has no 737 MAX aircrafts in its fleet had no forced reduction in the number of seats and flights it could fly.



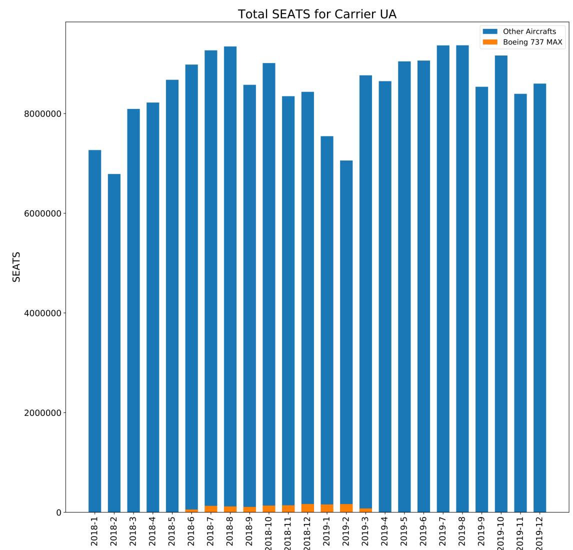
(a) American Airlines



(b) Southwest Airlines



(c) Delta Airlines



(d) United Airlines

Figure 5: The four carriers and the seats flown by the Boeing 737 aircraft in orange

As the graphs show, the grounding of the 737 MAX aircraft in March 2019 came at the same time as domestic air travel picks up after the doldrum travel months of January and February, and came at an inopportune time for the three large carriers. A reduction in the number of planes available to the carriers put a constraint on the amount of routes and passengers it could fly at the same time as the seasonal demand for air travel picked up towards the summer. However it is unlikely that even among the Max carriers they would all be affected the same way, and we believe that there might be some heterogeneity in the effect of the grounding on the different carriers due to fleet composition. United Airlines and American Airlines have large diversified fleets - they have a mix of different aircraft - unlike Southwest which flies an all 737 fleet and has the largest number of 737 MAX aircraft deployed.

We have several hypotheses that we will put to test in our analysis. As evidenced by past literature and theory, it is expected that a reduction in supply (fewer aircraft flying will result in fewer departures and fewer seats all things held constant) will raise prices on affected routes. However, we hypothesize that the MAX carriers (UA, AA, WN) are likely to respond to the ban by making changes across their overall network. As multi-product profit-maximizers, the MAX carriers are likely to choose to adjust their schedule and frequency not only on those routes that they flew the 737 MAX aircraft, but on other routes too as they reposition aircraft and adjust schedules. Thus, there are likely to be spillover effects and higher prices even on routes on which they never flew the 737 MAX aircraft. Additionally, we believe that these effects are not likely to be distributed equally throughout the network and there likely is significant heterogeneity in their effects on certain types of routes. We will focus our analysis in the latter part of the paper to see if there are differential effects in response by both MAX carriers and non-MAX carriers due to the presence of hubs (own or rivals), route competition and market shares, and number of daily MAX flights.The grounded Boeing 737 MAX aircraft is a fuel-efficient and higher density aircraft compared to its predecessors and other similar narrow-body competitors from Airbus. This was one of the major publicized factors that legacy carriers claimed would enable a cost advantage, allowing them to compete with LCCs like Spirit and Frontier, which usually fly out of secondary airports (Daraban and Fournier [14]). Thus, it is quite clear that although the 737 MAX aircraft formed a small portion of the overall fleet of the MAX carriers (American, United, and Southwest) before the MAX ban, the regulatory grounding was likely to have a significant impact on fares all across the industry as the MAX carriers have a presence on almost 70% of all routes flown in the US.

We begin our analysis by presenting the summary statistics for our control and treated routes in Table 2. Although, all routes across all carriers can be impacted by the grounding of MAX planes, we expect to see the least impact on routes where MAX carriers are not present and the largest impact on the routes where MAX carriers' fleet is affected. We categorize the routes into three categories to also differentiate between the two types of routes that are likely affected. "DirectTreat" routes are MAX routes, where the MAX carrier's MAX ratio (proportion of 737 MAX departures) for a given carrier is above 0.05 in at least one quarter in 2018. "Spillover" routes are all other routes where MAX carriers (American, Southwest or United) are present, but the MAX carrier's MAX ratio is less than 0.05. This is done out of convenience and to simplify our analysis. In a later section, we do run a series of robustness checks by expanding the number of bins (degrees of treatments) by their MAX ratios - and even using MAX ratio as a continuous variable - and we find very similar effects. Our control group includes all routes where MAX carriers are not present and are expected to be impacted the least - if at all. Our focus is on how DirectTreat and Spillover routes have been impacted relative to the control group.

Table 3 shows that there are a few differences in between the control and the treatment routes. However, this is not wholly unexpected as this partly arises from the fact that our control group only consists of routes flown by one major legacy carrier (Delta) and along smaller carriers like Alaska or JetBlue - and have no MAX carriers. This is in contrast to our treated group, which consists of any routes flown by three of the four largest domestic carriers - American, Southwest and United. As a result we find differences when comparing Avg. Fare, Departures, Passengers, and Distance between the three groups. Additionally, we see in our summary tables that there are fewer non-stop major carriers and more non-stop

Table 3: A comparison of the Control, DirecTreat and Spillover routes

	Mean(Control)	Mean(DirectTreat)	Diff.	Mean(Spillover)	Diff.
Avg. Fare	166.419	196.988	-30.569***	203.628	-37.209***
Departures	166.629	204.526	-37.897***	289.068	-122.439***
Passengers	16086.272	28458.145	-12371.873***	29403.290	-13317.018***
Distance	918.072	1405.569	-487.497***	829.723	88.349***
Slot Controlled	0.101	0.199	-0.098***	0.369	-0.268***
Tourist	0.162	0.379	-0.218***	0.274	-0.113***
Hub	0.659	0.834	-0.175***	0.918	-0.259***
Airport Congestion	0.690	1.516	-0.826***	1.312	-0.622***
Carrier's Overall Network	909.698	1170.057	-260.359***	1222.054	-312.357***
Carrier's Mean Network	17.001	27.324	-10.323***	22.896	-5.895***
Origin HHI	0.333	0.291	0.041***	0.270	0.062***
Destination HHI	0.333	0.298	0.035***	0.269	0.063***
Route HHI	0.759	0.516	0.243***	0.609	0.150***
Marketshares' S.D.	0.184	0.250	-0.066***	0.252	-0.068***
Low-Cost HHI	0.685	0.776	-0.091***	0.608	0.078***
Connecting HHI	0.318	0.438	-0.121***	0.447	-0.130***
Potential Comp	2.986	4.199	-1.213***	3.633	-0.647***
Mean Income	51994.251	54753.773	-2759.523***	54714.281	-2720.030***
Mean Population	2274011	3941989	-1667978***	3729434	-1455423***
Observations	10582	4732		27382	

regional carriers flying on these routes versus the treated routes. However, this is not a concern for our identification strategy in the differences-in-differences framework since we do control for these observed differences in these observed characteristics and include route, quarter and carrier fixed effects while our analysis spans a short time frame of six quarters. Lastly, it is quite obvious that the Boeing 737 MAX ban was very much an exogenous shock with fleet composition and new aircraft purchase decisions made by the domestic carriers several years prior to it happening and as such we can consider it a quasi-experimental design.

3. Methodology

We investigate the effect of the Boeing 737 MAX groundings using a difference-in-difference approach analyzing two different groups of treated routes using route, carrier, and quarter-year fixed effects. Though the main focus of our paper is to investigate the effect of the MAX ban on the log(Avg. Fares) on a treated route, for a majority of our analysis we also investigate the effects of the ban on three other dependent variables - departures, seats and passengers. This is important as it provides a comprehensive view of the effect of the MAX ban on the supply response of the carriers themselves (both MAX and non-MAX carriers) after the grounding.

Our identification strategy relies on the exogenous timing of the MAX grounding, which was determined by regulatory action following the second crash in March 2019. This regulatory decision was not anticipated by carriers and was independent of market conditions, demand factors, or carrier-specific strategies (routes, low-cost carriers versus full-cost carriers etc.). The grounding constitutes a well-defined supply shock affecting only carriers operating 737 MAX aircraft (American, Southwest, and United), creating a quasi-random natural experiment.

Since the other aircraft in the affected MAX carriers are not perfect substitutes, there are likely readjustments in the schedules and routes flown by the MAX carriers. This is why we extend our analysis by not only looking at the changes in log(Avg. Fares) but also investigating changes in departures, seats offered, and actual passengers flown by each carrier c on a given route i in a quarter q as our dependent variable of interest. Additionally, for the sake of clarity and consistency, we will refer to the effect on the routes that the 737 MAX aircraft operated on before March 2019 as the direct treatment effect - and the effect on fares on other routes flown by the MAX carriers (American, Southwest, and United) but with **no** 737 MAX planes as the spillover effect using a carrier's MAX ratio of 0.05 as a cutoff to separate the two types of routes. In subsequent analysis, we then calculate the heterogeneous spillover effects on other routes flown by carriers (American, Southwest and United), presence of hubs and degree of competition. Our main estimating equation is as follows:

$$\begin{aligned} \mathrm{Y}_{icq} = \alpha_0 &+ \beta_{\text{diff1}} \text{ Post Ban}_q \times \mathit{Spillover}_i + \beta_{\text{diff2}} \text{ Post Ban}_q \times \mathit{DirectTreat}_i \\ &+ \sum_{i=0}^{k} \beta_k \text{Controls}_{icq}^{k} + \pi_i + \mu_c + \zeta_q + \epsilon_{icq} \end{aligned} \tag{1}$$

where i, c, q are observations by route, carrier and quarter-year. Spillover and DirectTreat are dummy variables that are equal to 1 on our treated routes. Routes where a MAX

Carrier (American, Southwest, United) operates few or no 737 MAX planes are classified as Spillover. Routes where a MAX Carrier operates at least 5% of their actual departures using the grounded 737 MAX planes in at least one quarter prior to 2019 Q1 and the MAX ban are designated as DirectTreat routes. Post is a dummy variable that is equal to 1 representing the time, after the MAX 737 ban went into effect from 2019 Q2 onward. Our dependent variable Y is the log(Avg. Fares), log(Departures), log(Deats), or log(Passenger) for each carrier c on a given route i in a quarter q. We undertake our primary difference-in-difference analysis by regressing on all four of our dependent variables: log(Avg Fare.), log(Departures), log(Seats), log(passengers) using a full sample that includes all carriers and two other restricted samples where we regress on MAX carriers and non-MAX carriers separately using clustered robust standard errors.

X_k's are time varying controls that are not captured by route fixed effects (π_i), carrier fixed effects (μ_c), and time fixed effects (ζ_q), including capacity constraints (slot-controls); airport congestion; measures of competition such as HHI at origin and destination, and the level of effective competition on a given route.

Additionally, it is important to note that since the FAA imposed the ban on flying MAX 737s on March 13, 2019, we drop our 2019 Q1 observations - and consequently 2018 Q1 - from our regressions to exclude the possibility of picking up the partial effects of the regulatory action. Our estimate of the treatment effect is obtained from the coefficients of the interaction terms - $\text{post}_q \times \text{Spillover}_i$ and $\text{post}_q \times \text{DirectTreat}_i$ and we expect this to be positive in the case of both types of treated routes (i.e. the average fares will rise on routes flown by MAX carriers (American, United, Southwest) after the regulatory action compared to routes where they do not fly). Additionally, we expect the size of the DirectTreatment coefficient and the effect on routes that the MAX aircraft was flown to be larger than the size of the spillover effect because of imperfect substitution of aircraft.

In Section 4, we also present the results of our examination into the heterogeneity of the treatment effects of the Boeing 737 MAX ban degree of competition on routes, presence of carrier hubs on either nodes of the route, and number of MAX daily flights. We accomplish this by interacting post-ban affected routes with Htr (heterogeneity variable). Htr represents carrier hubs - a vector of binary variables to represent hubs - which is equal to 1 when either the origin or destination airport is a hub for one of the MAX carriers or other carriers, route HHI in 2018, and sum of average MAX daily flights.

Our estimating equation for these series of regressions is given as follows:

$$
\begin{aligned}
\mathit{log(Avg.Fare)}_{icq} = {} & \beta_{\text{diff1}}\text{Post Ban}_q \times \text{Spillover}_i + \beta_{\text{diff2}}\text{Post Ban}_q \times \mathit{DirectTreat}_i + \\
& \beta_{\text{diffHtr1}}\text{Post Ban}_q \times \mathit{Spillover}_i \times \text{Htr}_{ic} + \\
& \beta_{\text{diffHtr2}}\text{Post Ban}_q \times \mathit{DirectTreat}_i \times \text{Htr}_{ic} + \\
& \sum_{i=0}^{k} \beta_k \text{Controls}^k_{icq} + \text{Route FE}_i + \text{Carrier FE}_c + \text{Quarter FE}_q + \epsilon_{icq}
\end{aligned}
\tag{2}
$$

4. Results

As expected based on our initial hypothesis, we find an increase in the log(Avg. Fares) on both types of routes that are affected (treated) by the regulatory grounding of the 737 MAX aircraft as reported in Table 2.3 when compared to routes where the MAX carriers do not fly. The results in Table 2.4 are grouped together where columns (1) to (3) are regressions on the log(Avg. Fares) for all carriers while columns (4) to (6) and columns (7) to (9) are regressions on the restricted samples of only non-MAX carrier fares and MAX carrier fares respectively.

Focusing on column (3) which shows the results from our preferred full model that includes quarter, carrier and route fixed effects, we find an approximately 1.1% increase in fares on the Spillover routes and a substantially larger 2.6% increase in average fares in DirecTreat routes as expected. However, columns (6) and (9) are even more illuminating as they show that much of the increase in fares is actually driven by the non-MAX carriers more so than the MAX carriers. All our primary specifications report the expected effect on fares, with coefficients on the DirectTreat routes (i.e. on routes that used to fly the 737 MAX planes more than 5% of the departures) are more than twice as large as the effect on Spillover effects (routes where the MAX carriers are present, but never or infrequently flew the 737 MAX planes) and the results are significant at the 0.1% level.

The much smaller price effects for all carrier fares and MAX carrier fares on Spillover routes also imply that the MAX carriers were not able to significantly re-adjust their schedules. This implies that there was some imperfect substitution of other aircraft to replace the grounded MAX aircraft on these routes. This is not very surprising as scheduling decisions often take place 24-48 weeks ahead of flights (Bilotkach, 2020) and a major readjustment is not always feasible. The regression results in Table 5 and Table 6, where we regress on log(departures) and log(seats flown) provide further evidence of this. Columns (6) and (9) of both these tables show that there was negligible change in the departures and seats offered by MAX carriers on spillover routes - but a large and significant decline of about 5% to 6% on DirecTreat routes. Interestingly, rival non-MAX carriers do not show significant changes in departures or seats offered, indicating no systematic opportunistic response to the MAX grounding in terms of supply on routes, where non-MAX carriers compete with MAX carriers.

Lastly, Table 7 shows the effect of the grounding on actual passengers flown. When we compare columns (6) and (9), we see that although there was a small decrease of 1.5% in in number of passengers flown by MAX carriers on Spillover routes, there is an almost 7% decrease in passengers flown on DirectTreat routes - a larger decrease than the number of seats offered and departures by the MAX carriers. It is not clear why this is so, but two potential reasons could be a decrease in quality (more cancellations, delays, older and less comfortable aircraft) and a perceived decline in quality (trust and reputation).

Table 4: Regression Results on log(Avg. Fares) - DirectTreat and Spillover

Variable	All Carriers			non-MAX Carriers			Max Carriers		
Treatment Type									
Spillover	-0.0358***	0.0342***	-	-0.0405***	-0.0280***	-	1.040***	0.0280***	-
	(0.00881)	(0.00673)	-	(0.00908)	(0.00739)	-	(0.0119)	(0.00671)	-
DirectTreat	0.0978***	0.0106	-	0.0861***	-0.0413***	-	1.179***	-	-
	(0.0109)	(0.00817)	-	(0.0144)	(0.0107)	-	(0.0147)	-	-
Treatment Effect									
Spillover x Post Ban	**0.00871****	**0.0125*****	**0.0109*****	**0.0189*****	**0.0191*****	**0.0177*****	**0.00435**	**0.01000*****	**0.0105*****
	(0.00267)	(0.00269)	(0.00273)	(0.00349)	(0.00362)	(0.00373)	(0.00280)	(0.00282)	(0.00287)
DirectTreat x Post Ban	**0.0255*****	**0.0286*****	**0.0266*****	**0.0391*****	**0.0386*****	**0.0374*****	**0.0187*****	**0.0235*****	**0.0227*****
	(0.00358)	(0.00361)	(0.00366)	(0.00638)	(0.00668)	(0.00680)	(0.00363)	(0.00361)	(0.00367)
Confounders									
log(Distance)	-	-1.095***	0	-	-0.881***	-	-	-1.019***	-
	-	(0.0533)	(.)	-	(0.0840)	-	-	(0.0588)	-
log(Distance)^2	-	0.103***	0	-	0.0881***	-	-	0.0973***	-
	-	(0.00407)	(.)	-	(0.00634)	-	-	(0.00452)	-
Slot Controlled	-	0.0178**	0	-	0.0280**	-	-	0.00164	-
	-	(0.00577)	(.)	-	(0.00906)	-	-	(0.00665)	-
Tourist	-	-0.0433***	0	-	0.0116	-	-	-0.0718***	-
	-	(0.00501)	(.)	-	(0.00716)	-	-	(0.00610)	-
Carrier's Network	-	-0.000418***	-0.000398***	-	-0.000591***	-0.000556***	-	-0.000460***	-0.000448***
	-	(0.0000182)	(0.0000190)	-	(0.0000256)	(0.0000273)	-	(0.0000205)	(0.0000214)
Carrier's Mean Network	-	0.00285***	0.00243***	-	0.00326***	0.00262***	-	0.00280***	0.00254***
	-	(0.000157)	(0.000382)	-	(0.000270)	(0.000633)	-	(0.000175)	(0.000426)
Hub	-	0.0638***	-	-	0.0768***	-	-	0.0470***	-
	-	(0.00647)	-	-	(0.00858)	-	-	(0.00748)	-
Airport Congestion	-	-0.0158***	0.120***	-	0.0153**	0.268***	-	-0.0278***	0.0932***
	-	(0.00370)	(0.0181)	-	(0.00519)	(0.0274)	-	(0.00456)	(0.0227)
log(Origin HHI)	-	-0.0104**	-0.0133	-	-0.0117*	-0.0203	-	-0.0173***	-0.0119
	-	(0.00404)	(0.0101)	-	(0.00540)	(0.0151)	-	(0.00439)	(0.0106)
log(Destination HHI)	-	-0.0148***	-0.0281**	-	-0.0141**	-0.0424**	-	-0.0212***	-0.0199
	-	(0.00408)	(0.0104)	-	(0.00542)	(0.0160)	-	(0.00444)	(0.0109)
Potential Comp	-	0.00596***	0.00897***	-	0.00554***	0.0106***	-	0.00643***	0.00696***
	-	(0.00104)	(0.00142)	-	(0.00156)	(0.00227)	-	(0.00118)	(0.00161)
log(Route HHI)	-	0.0916***	0.0157	-	0.0694***	-0.0313*	-	0.107***	0.0517***
	-	(0.00563)	(0.00849)	-	(0.00825)	(0.0139)	-	(0.00657)	(0.00947)
log(Mean Income)	-	-0.178***	0.324*	-	-0.0550	-0.102	-	-0.237***	0.533**
	-	(0.0259)	(0.162)	-	(0.0390)	(0.293)	-	(0.0294)	(0.175)
log(Mean Pop)	-	-0.0324***	-0.377	-	-0.0338***	-1.629***	-	-0.0269***	0.248
	-	(0.00468)	(0.205)	-	(0.00634)	(0.350)	-	(0.00511)	(0.220)
Low-Cost HHI	-	-0.0208***	-0.00654	-	-0.0572***	-0.0199*	-	-0.00639	0.00284
	-	(0.00354)	(0.00405)	-	(0.00743)	(0.00922)	-	(0.00370)	(0.00421)
Connecting HHI	-	-0.0115***	-0.0109***	-	-0.0158**	-0.0121*	-	-0.00968***	-0.0101**
	-	(0.00275)	(0.00293)	-	(0.00491)	(0.00523)	-	(0.00291)	(0.00308)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	42677	42677	42677	20616	20616	20616	32643	32643	32643
No. Clusters	8035	8035	8035	4035	4035	4035	6096	6096	6096

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Regression Results on log(Departures) - DirectTreat and Spillover

Variable	**All Carriers**			**non-MAX Carriers**			**Max Carriers**		
Treatment Type									
Spillover	0.325***	-0.0449*	-	0.324***	-0.0290	-	2.173***	-0.121***	-
	(0.0249)	(0.0215)	-	(0.0254)	(0.0244)	-	(0.0298)	(0.0289)	-
DirectTreat	0.259***	0.0458	-	0.233***	0.00843	-	2.118***	-	-
	(0.0338)	(0.0285)	-	(0.0430)	(0.0373)	-	(0.0452)	-	-
Treatment Effect									
Spillover x Post Ban	**-0.00816**	**-0.00244**	**-0.00276**	**-0.00739**	**-0.00854**	**-0.00101**	**-0.00862**	**-0.000974**	**-0.00414**
	(0.00573)	(0.00561)	(0.00563)	(0.00720)	(0.00714)	(0.00745)	(0.00635)	(0.00627)	(0.00628)
DirectTreat x Post Ban	**-0.0486*** **	**-0.0408*** **	**-0.0322*** **	**0.0113**	**0.00438**	**0.00940**	**-0.0786*** **	**-0.0628*** **	**-0.0508*** **
	(0.00898)	(0.00883)	(0.00906)	(0.0130)	(0.0130)	(0.0137)	(0.0107)	(0.0105)	(0.0107)
Confounders									
log(Distance)	-	0.434**	-	-	0.228	-	-	0.697***	-
	-	(0.151)	-	-	(0.236)	-	-	(0.159)	-
log(Distance)^2	-	-0.0790***	-	-	-0.0539**	-	-	-0.104***	-
	-	(0.0117)	-	-	(0.0180)	-	-	(0.0125)	-
Slot Controlled	-	-0.216***	-	-	-0.164***	-	-	-0.228***	-
	-	(0.0209)	-	-	(0.0326)	-	-	(0.0240)	-
Tourist	-	0.170***	-	-	0.250***	-	-	0.126***	-
	-	(0.0192)	-	-	(0.0250)	-	-	(0.0239)	-
Hub	-	0.0147	-	-	-0.00106	-	-	0.0269	-
	-	(0.0239)	-	-	(0.0253)	-	-	(0.0297)	-
Airport Congestion	-	0.470***	1.528***	-	0.395***	1.419***	-	0.593***	1.833***
	-	(0.0151)	(0.0533)	-	(0.0192)	(0.0732)	-	(0.0215)	(0.0735)
Carrier's Overall Network	-	-0.000556***	-0.000493***	-	-0.000878***	-0.000790***	-	-0.000374***	-0.000321***
	-	(0.0000410)	(0.0000421)	-	(0.0000565)	(0.0000596)	-	(0.0000470)	(0.0000478)
Carrier's Mean Network	-	0.0172***	0.0131***	-	0.0217***	0.0187***	-	0.0144***	0.0113***
	-	(0.000712)	(0.000997)	-	(0.00111)	(0.00151)	-	(0.000832)	(0.00115)
log(Origin HHI)	-	0.00949	-0.0344	-	0.0371*	-0.0674	-	0.0151	0.0110
	-	(0.0137)	(0.0272)	-	(0.0174)	(0.0371)	-	(0.0149)	(0.0285)
log(Destination HHI)	-	0.00397	-0.0524	-	0.0357*	-0.0784*	-	0.00924	-0.00815
	-	(0.0138)	(0.0282)	-	(0.0174)	(0.0379)	-	(0.0150)	(0.0297)
Potential Comp	-	-0.00950***	-0.0112***	-	-0.0132***	-0.00231	-	-0.0107**	-0.0167***
	-	(0.00287)	(0.00328)	-	(0.00400)	(0.00464)	-	(0.00350)	(0.00411)
log(Route HHI)	-	0.150***	0.114***	-	0.0156	-0.0477	-	0.292***	0.266***
	-	(0.0224)	(0.0283)	-	(0.0308)	(0.0420)	-	(0.0260)	(0.0322)
Low-Cost HHI	-	-0.00685	-0.0194*	-	-0.119***	-0.117***	-	0.0188	0.00288
	-	(0.00904)	(0.00954)	-	(0.0169)	(0.0187)	-	(0.00978)	(0.0103)
Connecting HHI	-	-0.0197**	-0.00362	-	-0.00257	0.0190	-	-0.0211**	-0.00906
	-	(0.00706)	(0.00711)	-	(0.0115)	(0.0118)	-	(0.00746)	(0.00746)
log(Mean Income)	-	0.527***	0.404	-	0.683***	0.388	-	0.319**	0.526
	-	(0.0934)	(0.378)	-	(0.125)	(0.561)	-	(0.110)	(0.413)
log(Mean Pop)	-	0.0544***	-1.465**	-	-0.0182	-2.228**	-	0.0580**	-1.808**
	-	(0.0164)	(0.538)	-	(0.0208)	(0.720)	-	(0.0181)	(0.618)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	42677	42677	42677	20616	20616	20616	32643	32643	32643
No. Clusters	8035	8035	8035	4035	4035	4035	6096	6096	6096

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Regression Results on log(Seats) - DirectTreat and Spillover

Variable	All Carriers			non-MAX Carriers			Max Carriers		
Treatment Type									
Spillover	0.403***	-0.0774**	-	0.414***	-0.0318	-	1.479***	0.895***	-
	(0.0280)	(0.0243)	-	(0.0287)	(0.0273)	-	(0.0340)	(0.0534)	-
DirectTreat	0.487***	-0.0294	-	0.367***	-0.0591	-	1.645***	0.989***	-
	(0.0373)	(0.0312)	-	(0.0462)	(0.0394)	-	(0.0510)	(0.0602)	-
Spillover x Post Ban	**-0.0100**	**-0.00471**	**-0.00360**	**-0.000148**	**-0.000297**	**0.00694**	**-0.0145***	**-0.00740**	**-0.00882**
	(0.00600)	(0.00584)	(0.00589)	(0.00761)	(0.00755)	(0.00785)	(0.00662)	(0.00647)	(0.00651)
DirectTreat x PostBan	**-0.0513*****	**-0.0437*****	**-0.0336*****	**0.0214**	**0.0122**	**0.0192**	**-0.0878*****	**-0.0706*****	**-0.0581*****
	(0.00969)	(0.00948)	(0.00970)	(0.0146)	(0.0146)	(0.0151)	(0.0113)	(0.0111)	(0.0113)
Confounders									
log(Distance)	-	0.0179	-	-	0.0730	-	-	0.198	-
	-	(0.173)	-	-	(0.259)	-	-	(0.186)	-
log(Distance)^2	-	-0.0324*	-	-	-0.0279	-	-	-0.0510***	-
	-	(0.0134)	-	-	(0.0197)	-	-	(0.0146)	-
Slot Controlled	-	-0.333***	-	-	-0.218***	-	-	-0.347***	-
	-	(0.0230)	-	-	(0.0348)	-	-	(0.0265)	-
Tourist	-	0.168***	-	-	0.243***	-	-	0.112***	-
	-	(0.0209)	-	-	(0.0265)	-	-	(0.0260)	-
Hub	-	-0.0582*	-	-	-0.0136	-	-	-0.0716*	-
	-	(0.0256)	-	-	(0.0280)	-	-	(0.0314)	-
Airport Congestion	-	0.622***	1.595***	-	0.499***	1.490***	-	0.793***	1.898***
	-	(0.0175)	(0.0543)	-	(0.0213)	(0.0738)	-	(0.0258)	(0.0748)
Carrier's Overall Network	-	-0.000601***	-0.000505***	-	-0.000954***	-0.000823***	-	-0.000421***	-0.000350***
	-	(0.0000418)	(0.0000429)	-	(0.0000569)	(0.0000601)	-	(0.0000480)	(0.0000489)
Carrier's Mean Network	-	0.0202***	0.0139***	-	0.0259***	0.0199***	-	0.0168***	0.0123***
	-	(0.000733)	(0.00102)	-	(0.00116)	(0.00159)	-	(0.000867)	(0.00116)
log(Origin HHI)	-	0.0117	-0.0347	-	0.0432*	-0.0687	-	0.0232	0.0106
	-	(0.0148)	(0.0276)	-	(0.0186)	(0.0379)	-	(0.0160)	(0.0290)
log(Destination HHI)	-	0.00593	-0.0531	-	0.0419*	-0.0806*	-	0.0170	-0.00862
	-	(0.0149)	(0.0286)	-	(0.0187)	(0.0387)	-	(0.0161)	(0.0301)
Potential Comp	-	-0.00521	-0.0145***	-	-0.00886*	-0.00314	-	-0.00538	-0.0199***
	-	(0.00304)	(0.00343)	-	(0.00413)	(0.00470)	-	(0.00373)	(0.00432)
log(Route HHI)	-	0.146***	0.132***	-	-0.00813	-0.0490	-	0.305***	0.296***
	-	(0.0236)	(0.0290)	-	(0.0321)	(0.0425)	-	(0.0274)	(0.0331)
Low-Cost HHI	-	0.0209*	-0.0123	-	-0.0860***	-0.113***	-	0.0466***	0.0120
	-	(0.00946)	(0.00995)	-	(0.0178)	(0.0199)	-	(0.0103)	(0.0108)
Connecting HHI	-	-0.0135	-0.00262	-	0.00505	0.0192	-	-0.0143	-0.00721
	-	(0.00747)	(0.00757)	-	(0.0120)	(0.0124)	-	(0.00787)	(0.00797)
log(Mean Income)	-	0.403***	0.603	-	0.378**	0.791	-	0.220	0.594
	-	(0.103)	(0.410)	-	(0.136)	(0.597)	-	(0.122)	(0.447)
log(Mean Pop)	-	0.120***	-1.199*	-	0.0182	-1.709*	-	0.121***	-1.587*
	-	(0.0183)	(0.551)	-	(0.0227)	(0.751)	-	(0.0203)	(0.625)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	42677	42677	42677	20616	20616	20616	32643	32643	32643
No. Clusters	8035	8035	8035	4035	4035	4035	6096	6096	6096

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression Results on log(Passengers) - DirectTreat and Spillover

Variable	**All Carriers**			**non-MAX Carriers**			**Max Carriers**		
Treatment Type									
Spillover	0.432***	-0.0774**	-	0.447***	-0.0359	-	-0.236***	-0.107**	-
	(0.0294)	(0.0255)	-	(0.0301)	(0.0286)	-	(0.0410)	(0.0336)	-
DirectTreat	0.572***	-0.0190	-	0.434***	-0.0603	-	-	-	-
	(0.0387)	(0.0324)	-	(0.0482)	(0.0410)	-	-	-	-
Treatment Effect									
Spillover x Post Ban	**-0.0164****	**-0.0113**	**-0.0101**	**-0.00848**	**-0.00782**	**-0.000217**	**-0.0201****	**-0.0135***	**-0.0148***
	(0.00594)	(0.00579)	(0.00585)	(0.00756)	(0.00749)	(0.00785)	(0.00655)	(0.00643)	(0.00647)
DirectTreat x Post Ban	**-0.0613*****	**-0.0537*****	**-0.0438*****	**0.0106**	**0.00222**	**0.00942**	**-0.0973*****	**-0.0803*****	**-0.0682*****
	(0.00949)	(0.00929)	(0.00954)	(0.0144)	(0.0144)	(0.0151)	(0.0110)	(0.0108)	(0.0110)
Confounders									
log(Distance)	-	0.0420	-	-	0.258	-	-	0.164	-
	-	(0.180)	-	-	(0.278)	-	-	(0.193)	-
log(Distance)^2	-	-0.0303*	-	-	-0.0379	-	-	-0.0443**	-
	-	(0.0139)	-	-	(0.0210)	-	-	(0.0151)	-
Slot Controlled	-	-0.364***	-	-	-0.245***	-	-	-0.381***	-
	-	(0.0237)	-	-	(0.0360)	-	-	(0.0274)	-
Tourist	-	0.180***	-	-	0.271***	-	-	0.118***	-
	-	(0.0216)	-	-	(0.0275)	-	-	(0.0270)	-
Hub	-	-0.0287	-	-	0.0197	-	-	-0.0497	-
	-	(0.0264)	-	-	(0.0297)	-	-	(0.0324)	-
Airport Congestion	-	0.662***	1.662***	-	0.545***	1.581***	-	0.831***	1.958***
	-	(0.0182)	(0.0564)	-	(0.0221)	(0.0769)	-	(0.0270)	(0.0783)
Carrier's Overall Network	-	-0.000586***	-0.000480***	-	-0.000911***	-0.000771***	-	-0.000399***	-0.000320***
	-	(0.0000421)	(0.0000432)	-	(0.0000582)	(0.0000612)	-	(0.0000483)	(0.0000491)
Carrier's Mean Network	-	0.0202***	0.0133***	-	0.0259***	0.0193***	-	0.0169***	0.0117***
	-	(0.000748)	(0.00104)	-	(0.00119)	(0.00162)	-	(0.000885)	(0.00118)
log(Origin HHI)	-	0.0185	-0.0228	-	0.0559**	-0.0473	-	0.0275	0.0159
	-	(0.0152)	(0.0278)	-	(0.0194)	(0.0378)	-	(0.0166)	(0.0293)
log(Destination HHI)	-	0.00990	-0.0506	-	0.0514**	-0.0714	-	0.0216	-0.00252
	-	(0.0154)	(0.0289)	-	(0.0195)	(0.0391)	-	(0.0167)	(0.0303)
Potential Comp	-	-0.00323	-0.0107**	-	-0.00820	-0.000675	-	-0.00359	-0.0158***
	-	(0.00306)	(0.00344)	-	(0.00421)	(0.00477)	-	(0.00377)	(0.00433)
log(Route HHI)	-	0.140***	0.118***	-	-0.00131	-0.0472	-	0.300***	0.282***
	-	(0.0240)	(0.0294)	-	(0.0332)	(0.0434)	-	(0.0279)	(0.0333)
Low-Cost HHI	-	0.0150	-0.0152	-	-0.0954***	-0.115***	-	0.0401***	0.00856
	-	(0.00983)	(0.0103)	-	(0.0186)	(0.0207)	-	(0.0107)	(0.0112)
Connecting HHI	-	-0.0127	-0.00183	-	0.00284	0.0182	-	-0.0121	-0.00511
	-	(0.00760)	(0.00770)	-	(0.0121)	(0.0124)	-	(0.00800)	(0.00809)
log(Mean Income)	-	0.373***	0.912*	-	0.351*	1.030	-	0.206	0.879*
	-	(0.105)	(0.403)	-	(0.141)	(0.594)	-	(0.124)	(0.438)
log(Mean Pop)	-	0.122***	-1.155*	-	0.0190	-1.514*	-	0.124***	-1.621**
	-	(0.0190)	(0.550)	-	(0.0240)	(0.761)	-	(0.0211)	(0.624)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	42677	42677	42677	20616	20616	20616	32643	32643	32643
No. Clusters	8035	8035	8035	4035	4035	4035	6096	6096	6096

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.1. A more circumspect approach to treatment types

For most of our analysis in this paper so far, we have somewhat arbitrarily treated routes flown by the three MAX carriers - American, Southwest and United as DirectTreat or Spillover routes using a cut-off based on a carrier's MAX ratio of 0.05 on a given route. In this part of the paper, we confirm the robustness of our results by taking a more heuristic data-driven approach by considering the histogram of MAX ratio for the routes that MAX carriers flew prior to the ban. From the histogram in Figure 2.7, we identify several possible clusters, and so we expand the number of treatment types by grouping the routes MAX carriers flew into five bins and rerun our analysis.[2]

The five types of treated routes defined by their carrier MAX ratios are listed below.

1. Routes with a MAX ratio below 0.02
2. Routes with a MAX ratio between 0.02 and 0.05
3. Routes with a MAX ratio between 0.05 and 0.10
4. Routes with a MAX ratio between 0.10 and 0.20
5. Routes with a MAX ratio greater than 0.20

We supplement this analysis further with another robustness check by using two different measures of MAX ratio - carrier MAX ratio and route MAX ratio as a continuous treatment variable. One caveat with this approach is that this requires the assumption of a functional form for MAX ratio instead of the categorical treatment types we used in our earlier analysis. The results are shown in Tables 8, 9 and 10. Using the more heuristic data-driven approach to categorizing treatment types by carrier MAX ratios, we find qualitatively similar results as our first approach with our results echoing much of what we had already presented. In particular, Table 8 results show that routes with carrier MAX ratios lower than 0.02 see increases in average fares of about 2% to 5%, with larger fares rises for non-MAX carriers

[2]We also ran our analysis using four MAX route types, and there was no perceptible differences in our treatment effects

than MAX carriers. One curious and interesting result comes from column (9) where we see that on routes with carrier MAX ratios greater than 0.02, non-MAX carriers raise the average fares by almost 5.5%, whereas MAX carriers show no increase in fares. This is likely a consequence of imperfect substitution as the MAX carriers are unable to account for the loss of the MAX aircraft on these routes with enough seats/departures. Tables 9 and 10 present results using a continuous carrier MAX ratio and route MAX ratio as our driving variable assuming a linear functional form. Echoing our previous results, we find that route with higher route and carrier MAX ratio see an increase in fares of 0.2% and 0.1% for each 0.01 increase in MAX ratio with the non-MAX carriers raising fares more than MAX carriers. Running the same regressions assuming a quadratic functional form, we find that fares increase with higher carrier MAX ratios until 0.53, before declining. Similarly using a quadratic functional form for route MAX ratio, this peak happens at 0.11, before fares start declining.

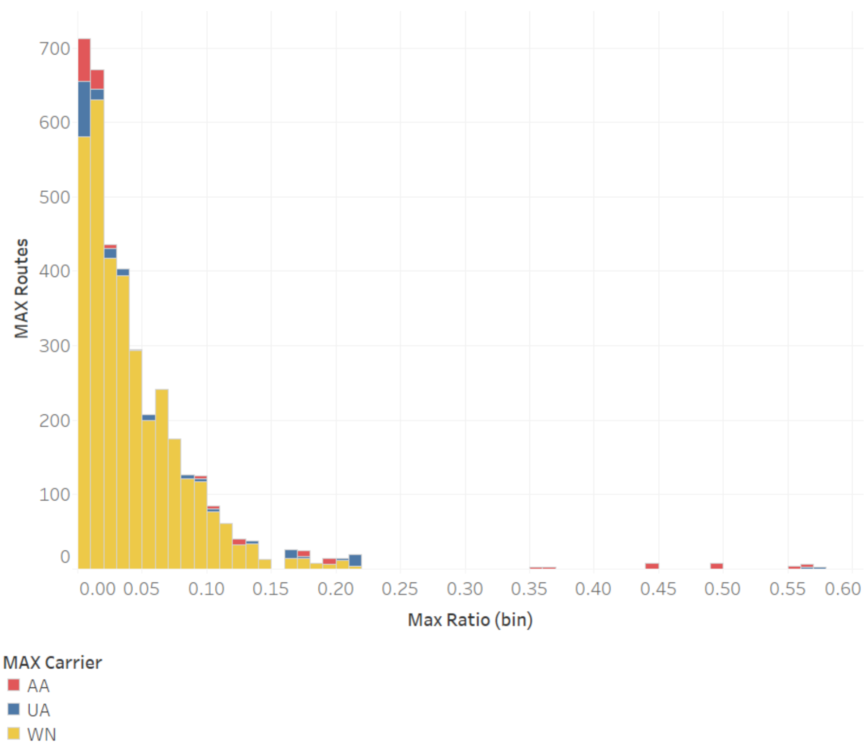


Figure 6: Histogram of Carrier-Routes by Carrier MAX Ratio

Table 8: Regression Results on log(Avg. Fares) - Carrier's Max Ratio Categories

Variable	**All Carriers**			**non-MAX Carriers**			**Max Carriers**		
Max Ratio Cat: <0.02 x Post Ban	**0.0255*** **	**0.0292*** **	**0.0266*** **	**0.0170* **	**0.0197* **	**0.0185* **	**0.0301*** **	**0.0351*** **	**0.0347*** **
	(0.00473)	(0.00480)	(0.00495)	(0.00812)	(0.00846)	(0.00865)	(0.00525)	(0.00528)	(0.00548)
Max Ratio Cat: 0.02 - 0.05 x Post Ban	**0.0300*** **	**0.0337*** **	**0.0308*** **	**0.0408*** **	**0.0424*** **	**0.0410*** **	**0.0241*** **	**0.0297*** **	**0.0284*** **
	(0.00351)	(0.00355)	(0.00362)	(0.00602)	(0.00627)	(0.00640)	(0.00356)	(0.00361)	(0.00370)
Max Ratio Cat: 0.05 - 0.10 x Post Ban	**0.0222*** **	**0.0250*** **	**0.0227*** **	**0.0340*** **	**0.0339*** **	**0.0328*** **	**0.0164*** **	**0.0215*** **	**0.0201*** **
	(0.00374)	(0.00377)	(0.00384)	(0.00694)	(0.00722)	(0.00732)	(0.00376)	(0.00376)	(0.00388)
Max Ratio Cat: 0.10- 0.20 x Post Ban	**0.0277*** **	**0.0312*** **	**0.0286*** **	**0.0469*** **	**0.0444** **	**0.0425** **	**0.0196*** **	**0.0259*** **	**0.0254*** **
	(0.00583)	(0.00588)	(0.00598)	(0.0130)	(0.0138)	(0.0141)	(0.00577)	(0.00571)	(0.00585)
Max Ratio Cat: 0.20 - 0.86 x Post Ban	**0.0240* **	**0.0315** **	**0.0269** **	**0.0521*** **	**0.0600*** **	**0.0543*** **	**0.00217**	**0.00958**	**0.0118**
	(0.00986)	(0.00964)	(0.00998)	(0.0133)	(0.0137)	(0.0140)	(0.0128)	(0.0126)	(0.0129)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	22741	22741	22741	14953	14953	14953	18370	18370	18370
No. Clusters	4263	4263	4263	2935	2935	2935	3424	3424	3424

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Regression Results on log(Avg. Fares) - Continuous Carrier's Max Ratio

Variable	All Carriers			non-MAX Carriers			Max Carriers		
Cont. Carrier Max Ratio x Post Ban	**0.00102***** (0.000190)	**0.00111***** (0.000194)	**0.000991***** (0.000198)	**0.00180***** (0.000354)	**0.00178***** (0.000371)	**0.00165***** (0.000374)	**0.000823***** (0.000216)	**0.00106***** (0.000222)	**0.00103***** (0.000228)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
No. Observations	22741	22741	22741	14953	14953	14953	18370	18370	18370
No. Clusters	4263	4263	4263	2935	2935	2935	3424	3424	3424

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Regression Results on log(Avg. Fares) - Continuous Route MAX Ratio

Variable	All Carriers			non-MAX Carriers			MAX Carriers		
Cont. Route Max Ratio x Post Ban	**0.00257***** (0.000621)	**0.00328***** (0.000633)	**0.00242***** (0.000628)	**0.00667***** (0.00155)	**0.00734***** (0.00159)	**0.00596***** (0.00154)	**0.00224***** (0.000663)	**0.00303***** (0.000692)	**0.00268***** (0.000701)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	22391	22391	22391	14953	14831	14831	18142	18142	18142
No. Clusters	4263	4263	4263	2935	2935	2935	3424	3424	3424

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2. The heterogeneous treatment effects by route concentration, presence of airline hubs, and number of daily flights

From Figures 3, 4 and 5, we have seen that the MAX carriers pursued different strategies when deploying the 737 MAX aircraft. This implies that even among the MAX carriers, there is potential for significant heterogeneity in the effect on their strategy and the impact of the grounding. This is because not only do the MAX carriers have varied fleet composition (Southwest has an all-Boeing 737 fleet including older generations of the 737 aircraft, whereas both American and United have a more diverse fleet that include smaller single-aisle narrow-bodied aircraft and wide-bodied aircraft that is more frequently used on international routes), they also have different network strategies (American and United employ a hub-spoke model whereas Southwest flies point to point).

We continue our analysis by considering how the presence of an airline hub (and a MAX carrier hub in particular) on either the origin or destination is differently affected by the 737 MAX ban. Since airline hubs usually imply significant market power on routes that originate or end at these hubs, and also the capacity to accommodate supply shocks such as the one from the Boeing 737 MAX grounding, we hypothesize that MAX carriers will often be able to absorb the supply shocks on these routes without raising fares significantly. Table 11 reports the regression results on how the 737 MAX ban affects routes where at least one node is a carrier hub with the results grouped by all carriers, non-MAX carriers, and MAX carriers for our four dependent variables we have presented earlier: log(average fares), log(Departures), log(Seats) and log(Passengers). As expected, there are small and negligible price effects for Southwest hubs when we look at log(Avg. Fares) for MAX carriers. This is not unexpected because of the network strategy that Southwest employs - flying point-to-point rather than a hub and spoke model like American and United. Thus, in the case of American and United hubs, we see large and significant increases in average fares of 5% and 25%, respectively, for Spillover routes that originate or end in those hubs. As we have consistently found before, non-MAX carriers raised their fares more than MAX carriers, likely in response to a reduction in seats being offered by AA and UA on these routes from their hubs. The large increase in fares seems to be particularly an issue that UA faced with a significant decline in the number of seats of between 13% and 22% on both Spillover and DirectTreat routes. One likely reason that explains why United was affected more than American and Southwest is because United used the 737-MAX 9 aircraft which had more seats and carried even more passengers. Thus a shift to smaller aircraft likely resulted in a significant reduction in capacity. Curiously, there are also small decreases in average fares on DirecTreat routes that originate from Southwest hubs. But with their all-Boeing 737 fleet, Southwest was best placed to substitute older 737 aircraft and thus minimize the effects of the MAX ban. The presence of hubs usually indicates significant market power and flexibility. Thus, it is clear that American and Southwest were able to leverage this into maintaining seats, and departures for flights to and from their hubs. However, United shows the limits of what a carrier can do even at a hub. There is also an interesting, if expected decline in the number of seats and departures that MAX carriers offer from other non-MAX carrier hubs, reducing their capacity on those routes as they adjust their networks.

In Table 12, we report the regression results on the differential effect of the 737 MAX ban based on the pre-treatment average route HHI in 2018. The results are again grouped by all carriers, non-MAX carriers, and MAX carriers for our four dependent variables we have presented earlier: log(average fares), log(Passengers), log(Seats) and log(Departures). Similar to the results from Table 11, we hypothesize that on routes that are highly competitive (both DirectTreat and Spillover routes), MAX carriers are likely to be less competitive and reduce the number of seats and departures as they readjust the way they are deploying their planes to routes where they have higher market power and are able to extract higher fares. Table 2.12 shows that this holds true. On highly concentrated routes with high average route HHIs and thus less competition, both MAX carriers and non-MAX carriers are increasing fares even though there are no significant changes in seats or departures in the case of Spillover routes.

Table 11: Regression Results at Carriers' Hubs - DirectTreat and Spillover

	log(Avg. Fare)			log(Seats)			log(Departures)			log(Passengers)		
Variable	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**
Non-Hub												
Spillover x Post Ban	0.00397	-0.0160	0.0123*	0.0313	-0.0312	0.0647**	0.0309	-0.0402	0.0698***	0.0182	-0.0284	0.0454*
	(0.00573)	(0.0107)	(0.00575)	(0.0171)	(0.0284)	(0.0199)	(0.0168)	(0.0267)	(0.0198)	(0.0168)	(0.0284)	(0.0195)
DirectTreat x Post Ban	0.0426***	0.0546**	0.0362***	-0.0460*	-0.0320	-0.0527*	-0.0510**	-0.0635*	-0.0414	-0.0440*	-0.0244	-0.0527*
	(0.00793)	(0.0172)	(0.00678)	(0.0212)	(0.0337)	(0.0250)	(0.0192)	(0.0259)	(0.0245)	(0.0203)	(0.0322)	(0.0239)
American Hub												
Spillover x Post Ban x AA	0.0490**	0.0763***	0.0409*	0.000423	-0.0157	-0.0224	-0.0154	-0.0109	-0.0460	0.125***	0.0766	0.110***
	(0.0153)	(0.0198)	(0.0165)	(0.0233)	(0.0518)	(0.0261)	(0.0229)	(0.0488)	(0.0259)	(0.0215)	(0.0510)	(0.0237)
DirectTreat x Post Ban x AA	0.0189	0.0448*	0.0161	0.0551	0.0278	0.0602	0.0692*	0.0548	0.0607	0.150***	0.0410	0.171***
	(0.0253)	(0.0228)	(0.0275)	(0.0291)	(0.0392)	(0.0326)	(0.0306)	(0.0351)	(0.0340)	(0.0280)	(0.0337)	(0.0303)
Southwest Hub												
Spillover x Post Ban x WN	-0.0330	-0.0514*	-0.0311	0.0204	0.0482	0.00617	-0.00335	0.0456	-0.0258	0.0264	0.0367	0.0186
	(0.0206)	(0.0249)	(0.0208)	(0.0399)	(0.0503)	(0.0405)	(0.0385)	(0.0483)	(0.0395)	(0.0366)	(0.0476)	(0.0375)
DirectTreat x Post Ban x WN	-0.0678**	-0.130***	-0.0490*	0.0660	0.00898	0.0955*	0.0500	0.00625	0.0660	0.0602	-0.00226	0.0917*
	(0.0216)	(0.0321)	(0.0213)	(0.0434)	(0.0656)	(0.0448)	(0.0411)	(0.0606)	(0.0433)	(0.0400)	(0.0634)	(0.0415)
United Hub												
Spillover x Post Ban x UA	0.250***	0.299***	0.228***	-0.143***	-0.1000	-0.220***	0.0696**	0.0908	-0.00614	-0.0847*	-0.0695	-0.156**
	(0.00848)	(0.0194)	(0.00792)	(0.0259)	(0.0550)	(0.0260)	(0.0269)	(0.0544)	(0.0251)	(0.0361)	(0.0470)	(0.0502)
DirectTreat x Post Ban x UA	0.229***	0.294***	0.190***	-0.0993*	-0.107*	-0.139**	0.108**	0.126**	0.0546	-0.0586	-0.0503	-0.108
	(0.0199)	(0.0322)	(0.0199)	(0.0388)	(0.0480)	(0.0501)	(0.0370)	(0.0454)	(0.0475)	(0.0475)	(0.0394)	(0.0675)
Other Carriers' Hub												
Spillover x Post Ban x Others	0.0193**	0.0525***	-0.000152	-0.0390*	0.0599*	-0.116***	-0.0387*	0.0597*	-0.111***	-0.0336	0.0484	-0.102***
	(0.00684)	(0.0116)	(0.00723)	(0.0189)	(0.0296)	(0.0226)	(0.0184)	(0.0280)	(0.0223)	(0.0186)	(0.0297)	(0.0223)
DirectTreat x Post Ban x Others	-0.00437	0.00142	-0.00769	0.0264	0.0933*	-0.0292	0.0343	0.122***	-0.0333	0.00946	0.0691	-0.0426
	(0.00931)	(0.0188)	(0.00857)	(0.0257)	(0.0376)	(0.0323)	(0.0235)	(0.0298)	(0.0312)	(0.0249)	(0.0363)	(0.0312)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	42677	20616	32643	42677	20616	32643	42677	20616	32643	42677	20616	32643

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Regression Results Based on Avg. Route HHI in 2018 - DirectTreat and Spillover

	log(Avg. Fare)			log(Seats)			log(Departures)			log(Passengers)		
Variable	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**	**All**	**Non-MAX**	**MAX**
Treatment Effect at Base												
Spillover x Post Ban	**-0.391*****	**-0.408*****	**-0.478*****	**-0.233**	**-0.246**	**-0.375***	**-0.159**	**-0.300**	**-0.202**	**-0.356****	**-0.381**	**-0.470****
	(0.0610)	(0.0979)	(0.0643)	(0.137)	(0.221)	(0.150)	(0.131)	(0.204)	(0.145)	(0.136)	(0.221)	(0.149)
DirectTreat x Post Ban	**-0.318*****	**-0.457***	**-0.372*****	**-0.316**	**-0.212**	**-0.902*****	**-0.392***	**-0.225**	**-0.937*****	**-0.434***	**-0.416**	**-0.984*****
	(0.0803)	(0.179)	(0.0828)	(0.196)	(0.374)	(0.243)	(0.184)	(0.347)	(0.225)	(0.191)	(0.371)	(0.235)
Treatment Effect By log(Avg. HHI)												
Spillover x Post Ban x log(Avg. HHI)	**0.0456*****	**0.0487*****	**0.0553*****	**0.0249**	**0.0282**	**0.0404***	**0.0169**	**0.0343**	**0.0215**	**0.0380***	**0.0424**	**0.0504****
	(0.00688)	(0.0115)	(0.00725)	(0.0155)	(0.0260)	(0.0169)	(0.0149)	(0.0240)	(0.0164)	(0.0154)	(0.0259)	(0.0169)
DirectTreat x Post Ban x log(Avg. HHI)	**0.0390*****	**0.0571****	**0.0447*****	**0.0308**	**0.0256**	**0.0958*****	**0.0406**	**0.0268**	**0.101*****	**0.0428**	**0.0477**	**0.104*****
	(0.00919)	(0.0214)	(0.00947)	(0.0225)	(0.0452)	(0.0277)	(0.0213)	(0.0419)	(0.0258)	(0.0220)	(0.0449)	(0.0268)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	42043	20274	32033	42043	20274	32033	42043	20274	32033	42043	20274	32033

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Lastly, we look at average daily flights of MAX carriers on routes, which we calculate as the sum of average of $\frac{MAXcarrierdepartures}{91}$ over the three quarters (2018 Q2, Q3, Q4) prior to the ban. We categorize the routes into three bins *0-2, 2-5, and 5-32*[3] and compare it to our control group of routes where there are no MAX carriers present. Table 2.13 presents our results showing the largest increases in fares on spillover routes with a high number of daily flights from MAX carriers. For DirectTreat routes, there are increases in fares across all route categories - although curiously the largest fare increases come on routes where the MAX carriers have few flights and seem to be a strategic response from the non-MAX rivals. Tables 2.14, 2.15 and 2.16 show the same regressions using our other dependent variables of interest - log(Departures), log(Seats) and log(Passengers) and provide further evidence that there is little change in the number of seats or departures from non-MAX carriers on these routes, but rather MAX carriers are forced to readjust their schedules with the lowest frequency DirecTreat routes seeing the biggest decrease in number of seats and departures offered and thus these routes see the largest increase in fares.

[3] 0-2 could also mean 0.14, which is one flight a week.

Table 13: Regression Results of log(Avg. Fare) on MAX Carriers' Daily Flights - DirectTreat and Spillover

	log(Avg. Fare)			log(Avg. Fare)			log(Avg. Fare)		
	All Carriers			Non-MAX Carriers			MAX Carriers		
Variable	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**
Spillover x Post Ban	**0.00775***	**0.0108****	**0.0153*****	**0.0118***	**0.0162***	**0.0289*****	**0.00699**	**0.0102***	**0.0120*****
	(0.00357)	(0.00380)	(0.00305)	(0.00582)	(0.00726)	(0.00466)	(0.00399)	(0.00410)	(0.00330)
DirectTreat x Post Ban	**0.0355*****	**0.0230*****	**0.0200*****	**0.0561*****	**0.0181**	**0.0327****	**0.0270*****	**0.0265*****	**0.0160****
	(0.00511)	(0.00632)	(0.00520)	(0.0101)	(0.0129)	(0.0118)	(0.00525)	(0.00639)	(0.00506)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	21493	20284	20992	14041	13224	13827	18034	17642	17747

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Regression Results of log(Seats) Based on MAX Carriers' Daily Flights - DirectTreat and Spillover

	log(Seats)			log(Seats)			log(Seats)		
	All Carriers			Non-MAX Carriers			MAX Carriers		
Variable	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**
Spillover x Post Ban	**0.0448*****	**-0.0312*****	**-0.0241*****	**0.0215**	**-0.00857**	**0.0123**	**0.0524*****	**-0.0407*****	**-0.0370*****
	(0.00951)	(0.00817)	(0.00634)	(0.0117)	(0.0153)	(0.0107)	(0.0120)	(0.00894)	(0.00671)
DirectTreat x Post Ban	**-0.0251**	**-0.0383***	**-0.0233**	**0.0510***	**0.00177**	**0.0209**	**-0.0648*****	**-0.0591****	**-0.0388****
	(0.0157)	(0.0168)	(0.0132)	(0.0245)	(0.0251)	(0.0263)	(0.0187)	(0.0212)	(0.0142)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	21493	20284	20992	14041	13224	13827	18034	17642	17747

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Regression Results of log(Departures) Based on MAX Carriers' Daily Flights - DirectTreat and Spillover

	log(Departures)			**log(Departures)**			**log(Departures)**		
	All Carriers			**Non-MAX Carriers**			**MAX Carriers**		
Variable	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**
Spillover x Post Ban	**0.0462*** **	**-0.0299*** **	**-0.0246*** **	**0.0113**	**-0.0112**	**0.000789**	**0.0592*** **	**-0.0383*** **	**-0.0326*** **
	(0.00906)	(0.00795)	(0.00608)	(0.0110)	(0.0148)	(0.0101)	(0.0115)	(0.00877)	(0.00652)
DirectTreat x Post Ban	**-0.0260**	**-0.0320***	**-0.0227**	**0.0396**	**-0.000654**	**0.00740**	**-0.0599*** **	**-0.0475***	**-0.0311***
	(0.0146)	(0.0157)	(0.0122)	(0.0219)	(0.0223)	(0.0252)	(0.0179)	(0.0203)	(0.0130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	21493	20284	20992	14041	13224	13827	18034	17642	17747

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Regression Results of log(Passengers) Based on MAX Carriers' Daily Flights - DirectTreat and Spillover

	log(Passengers)			**log(Passenger)**			**log(Passenger)**		
	All Carriers			**Non-MAX Carriers**			**MAX Carriers**		
Variable	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**	**0-2**	**2-5**	**5-32**
Spillover x Post Ban	**0.0374*** **	**-0.0367*** **	**-0.0294*** **	**0.0185**	**-0.0122**	**0.00147**	**0.0428*** **	**-0.0467*** **	**-0.0392*** **
	(0.00947)	(0.00818)	(0.00630)	(0.0118)	(0.0156)	(0.0109)	(0.0119)	(0.00895)	(0.00664)
DirectTreat x Post Ban	**-0.0371***	**-0.0465** **	**-0.0304***	**0.0421**	**-0.00697**	**0.0109**	**-0.0780*** **	**-0.0670** **	**-0.0440** **
	(0.0154)	(0.0163)	(0.0131)	(0.0244)	(0.0248)	(0.0269)	(0.0182)	(0.0205)	(0.0141)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route, Carrier, Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	21493	20284	20992	14041	13224	13827	18034	17642	17747

Standard errors are clustered and shown in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Conclusions

Our analysis shows that the MAX carriers responded to the regulatory grounding by switching to other aircraft when possible, but this substitution is imperfect. The Boeing 737 MAX ban thus became an effective constraint on supply for the MAX carriers with both Spillover and DirectTreat routes seeing an increase in average fares of between 1% to 2% and 4% to 6%, respectively, for all carriers. But there is significant heterogeneity in these results, with often non-MAX carriers seeing an increase in average fares that are larger than the increase in MAX carrier fares.

Additionally, we expected there to be significant heterogeneity in the supply response and the fares of the two legacy MAX carriers (American and United) versus that of Southwest because of how the latter's network strategy combines with their all-Boeing 737 fleet, which implies that the ban would have differing effects on the carriers. This is especially true because both United and American fly most of their MAX aircraft from their hubs. So whereas Southwest would find it easy to substitute the new 737 MAX aircraft with the older 737 aircraft, American and United would have to substitute in with other aircraft - both smaller and larger. As we had expected, Southwest was able to respond and maintain supply (seats, departures) from their hubs, unlike United, which saw a significant decrease in the number of seats and passengers and a large increase in fares of nearly 25%, suggesting that imperfect substitution of supply was a significant factor for United.

This interesting heterogeneity and the differences in the impact of the MAX ban among the three MAX carriers suggest that there are several compelling new research questions we plan on pursuing, including taking a further look at the fleet composition and network strategy (including exiting or reducing frequency in certain types of routes). We would also like to revisit this paper in the future to include the additional class fare data that has been completely overlooked in the current airline literature along with propensity score matching models to create a better control group for the treated routes.

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