Market Power in Airlines: Evidence from the Boeing 737 MAX Grounding

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Abstract

This paper exploits an exogenous shock to airline supply, the Boeing 737 MAX grounding in the United States, to determine the effect of market share on airline prices using an instrumental variable empirical strategy. I find that a 1% increase in the Herfindahl–Hirschman Index (HHI), at the market level, increases prices by 3.06% for affected routes. I also find that a 10% exposure to MAXs, at the route level, increased prices by 7%. These results directly contribute to the reduced form empirical industrial organization literature and inform competition policy by estimating a price-concentration relationship using a natural experiment.

Keywords: Prices, Concentration, Supply Shock, Airlines

JEL Codes: L11, D24, L93

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1 Introduction

The airline industry, an important part of the American economy, contributes $846.3 billion (5.1%) to US GDP (America, 2019). It is typically characterized as an oligopoly as new entrants face strong barriers to entry due to high fixed costs and network effects. Moreover, there is little product differentiation and non-price competition which supports the oligopoly characterization (Wolla and Backus, 2018). From 2000 to 2013, the industry heavily consolidated after a series of bankruptcies and mergers (CNNMoney, 2013). The top four firms (American, Southwest, Delta, and United respectively) now collectively have 67% market share (Mazareanu, 2020). As concentration in the airlines industry has increased, it is important to study its effect on prices and consumer welfare.

There is a large structural literature that studies the effects of consolidation and market structure on outcomes for airlines (see e.g.: Berry and Jia (2010), Peters (2006), Armantier and Richard (2008)). These papers use demand models to simulate the impact of horizontal mergers by recovering post merger outcomes. There is also significant work on entry (Berry, 1992a), product quality (Chen and Gayle, 2019), dynamic effects (Benkard et al., 2010), and networks (Ciliberto et al., 2019). These approaches allow researchers to estimate important unobserved and behavioural parameters, perform counterfactual analysis (predict the effect of future mergers and policy changes), and empirically test predictions of competing theories (Reiss and Wolak, 2007). However, they also have to make trade-offs, that sacrifice realism, by making distributional assumptions and putting restrictions on firm conduct for computational and analytical tractability (Reiss and Wolak (2007) and Angrist and Pischke (2010)). In the context of horizontal mergers, there is *some* evidence that merger simulation studies sometimes predict outcomes significantly different from observed price effects (ex: Peters (2006) and Ashenfelter et al. (2013)).

There is a complimentary literature that uses quasi-experimental approaches to directly answer questions about market structure and outcomes (see e.g.: Hastings (2004), Dafny

(2009), Yan et al. (2019)).[1] Such approaches are far from infallible and don't always estimate causal relationships. As Evans et al. (1993) identified, there are important endogeneity problems when estimating price-concentration relationships using observational data as performance feeds into structure (reverse causality) and unobserved factors affect both concentration and price (omitted variable bias). Some papers compare outcomes for merging entities directly to those that didn't. This line of papers suffers from classic selection problems as the decision to merge is endogenous to prices (or its determinants) and merging firms are likely fundamentally different from non-merging firms (Bresnahan, 1989). Other, perhaps more severe, problems emerge when there are no mergers as firms compete on quality and market share can bias estimates. Therefore, causal concentration-price studies are few and far between (Angrist and Krueger, 2001).

This paper helps close this gap in the literature by exploiting a plausibly exogenous shock to airline supply—the Boeing 737 MAX grounding in the United States that disproportionately affects certain carriers and markets—to estimate a price-concentration relationship. The grounding is a capacity shock and is likely uncorrelated with consumer demand. It affects market structure (concentration) by reducing the supply (capacity) of certain carriers in certain markets. I argue that this change in market share leads to changes in equilibrium prices.

My estimates inform policy in a direct way by estimating the *causal* relationship between concentration and prices. This is an important relationship for competition policy, especially merger analysis. Moreover, Boeing 737 MAX exposure varies considerably across airlines and Southwest Airlines is exposed to the 737 MAX (1.46% of total ASMs) roughly three times more than the average across all other carriers (0.53% of total ASMs) in the first quarter of 2019. The intuition here is fairly clear. If Southwest loses capacity on a route, legacy high-cost airlines like Delta, that aren't affected by the shock are able to gain market share

[1] These are sometimes termed "reduced form" studies as well. For an important discussion on the correct terminology for this distinction. See "Structural vs. Reduced Form" Language and Models in Empirical Economics (Haile, 2019)

and charge higher prices due to decreased competition.

This paper makes three main contributions. First, it provides causal estimates for concentration and price for routes affected by the shock using a parsimonious reduced form empirical design without relying on structural and distributional assumptions. The severity of these welfare effects directly informs competition policy as the relationship between the Herfindahl–Hirschman Index (HHI) and prices is regularly used in antitrust proceedings. Second, I estimate the relationship between capacity and prices which informs aviation safety policy as regulators can weigh the cost and benefits of grounding certain aircraft for safety reasons in the future. Third, I estimate the direct effect of the grounding on prices which directly affects consumer welfare.

I find that a 1% increase in the HHI, at the market level, increases prices by 3.06% for affected routes. The reduced form suggests that affected routes saw an increase in prices of 0.8% on average and a 10% exposure to MAXs caused a 7% increase in prices. I also estimate the relationship between capacity and prices and find that a 10% decrease in capacity increases prices by 2-5% depending on my IV specification.

2 Background

2.1 Boeing 737 MAX Groundings

Boeing introduced the 737 MAX on August 30, 2011 as the fourth generation of the Boeing 737 which entered service in 1967 (Press, 2019). The 737 series was the highest selling commercial aircraft until October 2019 when the Airbus A320 surpassed it (Kaminski-Morrow, 2019). This shift is largely attributed to the MAX grounding (Cameron, 2019). The MAX variants of the 737 is also Boeing's fastest selling plane (Company, 2016). As of November 2019, 4932 MAXs had been ordered and only 387 have been delivered (8%) (Company, 2019).

The Boeing 737 MAX promised improved fuel efficiency of 14-20%, according to Boeing, relative to 737 NGs (the third generation of the 737 series) (Topham, 2019). At the same time, it carried upto 20% more passengers (Campbell, 2019). This represented significant cost savings for airlines and low-cost airlines like Southwest and RyanAir (a low-cost airline in Europe) planned to heavily use the MAX (Kingsley-Jones, 2019).

On March 13, 2019, the Federal Aviation Administration (FAA) ordered the grounding of the Boeing 737 MAXs after fatal crashes in Ethiopia (October 29, 2018) and Indonesia (March 11, 2019). The FAA had reaffirmed the "airworthiness" of the MAX aircrafts just two days prior (March 11, 2019) but grounded the planes after some security concerns were raised. The airlines could have anticipated that FAA was going to ground the MAXs because regulators in other countries had done so one or two days prior. This means the shock was purely exogenous as airlines had no time to adjust.

2.2 Airline Competition and The Southwest Effect

Exposure to the Boeing 737 MAX varies considerably by airline and Southwest is disproportionately affected. Moreover, only three carriers are affected (See Figure 1). Southwest Airlines is the most affected with 1.13% of its total ASMs carried by Boeing 737 MAXs followed by American (0.7%) and United Airlines (0.23%). Southwest planned to increase its reliance on the MAX even more with some analysts suggesting that by July 2019, it planned to have 8% of its ASMs on the MAX (Sumers et al., 2019). It is also important to note that United's reliance on the MAX seems inflated because they utilized the MAX for flights to Hawaii which artificially inflates ASMs. In summary, Southwest is considerably more exposed to the MAX relative to United and American which allows us up to ask questions about concentration and competition directly.

There is an extensive work on the impact of Southwest entry and threat of entry at the route level on airline competition. Morrison (2001) finds that Southwest lowered aggregate fares by $12.9 billion in 1998 which amounts to 20% of the airline industry's total revenue. These estimates are based on Southwest's actual, adjacent, and potential competition. Similar work that examines the effect over a longer time span finds price reductions ranging between 5.610.2% on routes actually served, 4.7% on adjacent routes, and 5.2% from potential competition (Morrison and Winston, 1995; Benett and Craun, 1993).

However, these estimates are not causal as the decision to enter or potentially enter routes is not exogenous. Southwest likely targets routes where airlines are already making supranormal profits. Goolsbee and Syverson (2008) provide some causal estimates of the "Southwest Effect" by examining the behavior of incumbents in response to the threat of entry at the route level while dealing with endogeneity concerns. These results are more robust as they do not extend to routes into neighboring airports in the same MSA where SW isn't threatening entry. The results indicate that incumbents react by dropping prices and drop them even further after entry occurs.

As I discuss in the introduction, there is an extensive "New Empirical Industrial Organization" literature that applies structural models to the airline industry and measures the impact of a variety of conduct including mergers, entry and exit and collusion (see e.g., Berry (1992b); Berry and Jia (2010); Ciliberto and Williams (2014). This work is mostly estimating parameters and performing counter-factuals.

However, there is compelling evidence that structural predictions are often wrong. In the merger context, Peters (2006) employs a variety of widely accepted structural models, like Berry et al. (1995), to first estimate demand and then recover post-merger parameters to predict prices. The results suggest that structural models systematically underestimate the effect of mergers. Ashenfelter et al. (2013) finds similar results for the cereal industry, in contrast, to Nevo (2001). Moreover, as Angrist and Pischke (2010) point out, these models usually rely on restrictive substitution assumptions and heavy distributional assumptions. However, there are other good reasons to use structural models as Nevo and Whinston (2010) points out, especially, for studying counterfactuals and endogeneity concerns.

Dana and Orlov (2014), in perhaps the closest paper to mine, examine the impact of the adoption of the internet on capacity utilization from 1993 to 2007 at the metropolitan statistical area (MSA) level. They use the DOT's DB1B dataset to construct a panel over this time period and utilize rich fixed effects to control for unobserved market, airport, airline, and time-specific characteristics. They find that differences in internet penetration across MSAs are strongly correlated with "differences in rate of changes of airlines' airport-pair load factors" as online tickets reduce market frictions and allow airlines to meet demand with less capacity. However, they are unable to produce truly causal estimates as omitted variables can be correlated to both internet penetration and load factors despite the use of fixed effects and ample controls.

2.3 Capacity (Utilization) and Prices

Capacity, defined as available seat miles (ASMs), is a significant cost to airlines and maximizing capacity utilization is a priority. Airline Capacity Utilization is measured by load factor and indicates the percentage of total capacity utilized by an airline. It is calculated by dividing revenue passenger miles (RPM) with available seat miles (ASM). There is considerable work on the relationship between capacity utilization, demand uncertainty, and airline profits.

Escobari (2012) estimates the effect of changes in capacity utilization on prices using a unique panel data set from Expedia. This data set contains prices and seat inventories at the ticket level for 103 days prior to flights. The majority of paper the deals with the relatively short term relationship between fares, departure dates, and inventories. However, it also finds that a unit standard deviation increase in utilized capacity corresponds to a 49.09% ($38.65) within flight standard deviations of fares. This variation in capacity utilization is largely driven by aggregate demand uncertainty and not long term shock.

Escobari and Lee (2014) builds on this work and uses a theoretical model and structural estimation to examine the relationship between unexpected demand and capacity utilization and finds that a unit increase in standard deviation of unexpected demand decreases utilization by 21 percentage points. They also utilize a unique panel dataset from Expedia and observe nonstop one-way flights in the domestic US market across time (days) which gives them a measure of capacity utilization as the same planes fly the route keeping the ASM constant. The day-to-day fluctuations in demand lead to variation in RPM across different flights and over various departure dates which allows them to capture demand uncertainty.

Since both of these papers rely on demand uncertainty for identification, their results are not relevant to competition policy because carriers face similar levels of demand uncertainty. This paper, on the other hand, relies on an exogenous shock to overall capacity for identification. One of the core assumptions of this strategy here is that capacity decisions are costly and largely dependent on long term considerations which is well supported by the literature (Berry and Jia (2010) & Escobari (2012)). By utilizing an exogenous shock to carrier capacity, I am able to produce parsimonious estimates for the causal relationship between capacity and equilibrium prices and quantity. This has broader implications for industrial organization as the relationship between capacity and welfare is well-documented (see e.g., Gaynor and Anderson (1995); Kim (1999)). It is likely that airlines shift capacity across routes in response to this capacity shock but since this should not be a problem as the lack of total capacity will likely have negative spillover effects at *some* routes assuming airlines are utilizing capacity efficiently.

3 Data and Descriptive Statistics

3.1 Data Sources and Description

This paper utilizes two different data sets from the Department of Transportation. I utilize the Origin and Destination Survey (DB1B) market database. This is a 10% sample of all passenger tickets purchased in each quarter for each year. It includes the airline, the quarter in which the ticket was used, the number of passengers on the ticket, the fare, and the origin and destination airport. I define a "market" as a unidirectional airport pair; that is ORD-LAX and LAX-ORD are two different markets. A "route" is a combination of a unique carrier in a market; that is Southwest in LAX-ORD and Delta in LAX-ORD are two different routes.

I first remove outliers by removing the bottom 1st and 99th percentile of prices. This removes tickets below $20 and above $1000. I then aggregate prices to a route by quarter level by taking means. It is computationally very difficult to deal with this dataset without aggregating to a route level as each quarter in a year has about 7 million observations. Moreover, having aggregated prices by route are more useful to answer my question as it more effectively deals with within group variation.

I also utilize the T-100 Domestic Segment Data which reports monthly capacity and passenger traffic by airline, by origin-destination Airport pair (hereafter referred to as market), and by aircraft for all flights in the US. I have this data for all of 2017 and 2018 and up to December for 2019. This is a natural stopping point for the analysis as the pandemic essentially crushed the demand for airlines. This dataset contains capacity and passengers transported for each route (carrier in a market) by aircraft used to fly on that route. This allows me to identify which routes fly Boeing 737 MAXs. Since this data is available monthly by aircraft and the prices are only available quarterly, I aggregate to a quarter by route. I also observe number of passengers transported by Boeing 737 MAX 8 and MAX 9 which allows me to compute exposure of each carrier, market, and route to the MAX aircrafts. I then merge these datasets by route, quarter, and year. Observations that do match are thrown out and I'm left with 77,000 observations in my sample from the first quarter of 2017 to the third quarter of 2019.

It is important to note that I examine aggregate prices at the route level because price dispersion and demand uncertainty likely vary by routes and can be endogenous to capacity and prices. This is supported by the literature (Escobari and Lee, 2014). By meaning prices across routes, I am able to ignore price dispersion.

3.2 Descriptive Statistics

I will motivate my empirical methodology using descriptive statistics. Figure 2 shows that the mean difference in prices between BA 737 MAX Routes vs. Non-MAX routes was \$5.8 before the shock i.e. MAX routes were cheaper by \$5.8 on average. This completely flips after the shock. Routes that were previously exposed to MAXs became considerably more expensive by \$5.38 on average.

Tables 1 and 2 and show this in more detail. It is clear that the MAX and non-MAX routes differ in many ways. Non-MAX routes tend be longer distance, offer less capacity, seats, and utilize less capacity on average. More importantly, MAX routes are cheaper before the shock but get significantly more expensive after the shock. It is also informative that the only sign that flips from Table 1 and Table 2 is that of prices. This shows that the route characteristics don't change over time but prices simply increase for MAX routes. These tables do not control for seasonality so it is hard to draw strong conclusions about these variables but they do motivate the core empirical strategy of this paper.

I also present binned scatter plots to highlight the effect of the shock on concentration, capacity, and prices. I exclude all zero values for max share as they are 96% of my sample which makes my plots biased; simply excluding them shows us the variation in how increasing share affects our variables for interest. Figure 3 provides further support to the key motivation of this paper as an increase in MAX Share increases prices significantly. This effect flows through two channels: Capacity and Concentration. Figure 4 shows the relationship between MAX Share and HHI. A higher exposure to MAX increases concentration, however, the relationship isn't linear. This can be explained by how airlines substitute capacity as routes with a very high exposure likely see substitution from carriers like Southwest as they do not want to lose a lot of customers. This also makes sense because capacity is costly to move. When MAX share is low, airlines possibly substitute less as those routes do not produce as much revenues (Berry and Jia, 2010). I also produce scatter plots for Southwest's Market Share which confirms this story as Southwest sees a marked decline in market shares in routes with high exposure (See Figure 6). As expected, an increase in capacity reduces market share which further motivates my secondary empirical specification (Figure 5).

4 Empirical Methodology

A fundamental challenge in identifying models of supply and demand is that firms can adjust prices to reflect demand shocks. The econometrician observes equilibrium prices and quantity, thus, making it difficult to accurately measure the relationship between supply-side variables like capacity and observed prices and quantity (Angrist and Krueger, 2001). I utilize an instrumented differences-in-difference empirical strategy to deal with this simultaneous equation (reverse causality) problem.

My primary empirical specification for measuring the relationship between concentration and prices is:

$$ln(Y)_{jt} = \alpha + \beta X_{jt} + \sigma_j + \chi_t + \mu_T + \epsilon_{jt}$$

where, j indexes markets, and t indexes time (quarters), Y represents prices at the route level, X represents the logged HHI (concentration), σ_j are market fixed effects, and χ_t and μ_T are quarter and year fixed effects respectively. The HHI is instrumented with two different types of instruments that are related to the shock. In this specification, we interpret any difference in prices for exposed markets as the causal effect of the change in concentration. First, I use a binary variable to identify routes with *any* MAX exposure and I then compare them to routes with no exposure. Second, I define the instrument as percentage of seats serviced by 737s at the route level. Both of these instruments are interacted with a binary variable that turns on after the first quarter of 2019. This DDIV methodology is similar to the one used in Duflo (2001).

I go on to estimate the relationship between capacity and prices:

$$ln(Y)_{ijt} = \alpha + \beta C_{ijt} + \sigma_{i \times t} + \chi_T + \epsilon_{ijt}$$

where, i indexes markets, j indexes airlines and t indexes time (quarters), Y are prices at the route level, C is the route level capacity, $\sigma_{i \times t}$ are market by quarter level fixed effects, and χ_T are year fixed effects. The capacity is instrumented with three different types of instruments that are related to the shock. In this specification, we interpret any difference in the price for exposed route as the causal effect of the change in capacity at the route level. In addition to using the two instruments mentioned above, I also run a specification that looks at exposure by airline within each distance group. The groups range from 1-18 with one representing routes that are 0-500 miles, this number then steadily progresses at 500 intervals. 85% of all routes are less than 2000 miles and thus are represented by groups 1-4. The MAX aircraft is suitable to specific distances and this specification exploits this set-up to look at price effects within groups of routes.

For these model to be well-identified, I need to satisfy the assumptions for both the instrument and the differences-in-difference framework. I will start by discussing IV assumptions. The first stage requires me to show that exposure to MAXs affects HHI/capacity at the route level. I test this by regressing HHI/Capacity on my instrument (See Table 3). I find that the percent MAX share instrument isn't strong for either capacity or concentration so those results should be interpreted with caution. The exclusion restriction requires me to show that the instrument affects equilibrium prices/quantity *only* through capacity. I argue this is the only channel because products in the airline industry exhibit little product differentiation and there is almost no non-price competition (Wolla and Backus, 2018).

Figure 1 provides motivation for the second differences-in-difference identification strategy which relies on variation in MAX exposure across carriers. The figure illustrates the considerable difference in exposure across carriers. Southwest is clearly the most exposed in Q1 2019, followed by American and United. Delta and all other providers are simply not exposed to the 737 MAXs. The slow ramp-up prior to the shock is due to the deliveries of 737 MAXs catching up to orders as orders are made years prior to deliveries.

The key differences-in-difference assumption in this context requires that MAX routes would exhibit similar behaviour as non-MAX routes in absence of the shock. I am able to test pre-trends by comparing routes with *any* MAX exposure to those with non exposure which offers support for this assumption. Figure 7 depicts trends of mean price on MAX and non-MAX routes. This picture shows that there is opposite movement during many quarters and right before the treatment which would violate our assumption. However, this differential movement in prices goes away after I add market and time fixed effects. I estimate price coefficients for each quarter with route-level fixed effects and clustered standard errors (Figure 8). The trends look much closer after this and support the parallel trends assumption.

The second assumption requires that there is no other treatment at the exact same time of the shock (mid-March, 2019). After some preliminary research, there appears to be no evidence of any structural changes in airlines around this time period. Seasonality could be a concern but my rich route and time fixed effects should take care some of this problem.

5 Results

I will start by discussing the most parsimonious specification–a binary variable as the treatment. This is also the main instrument as it satisfies first stage requirements for both capacity and concentration (See Tables 4 & 5). The reduced form estimates suggest that MAX routes see price increases of 0.8% on average after the shock. The final regression suggests that a 1% increase in concentration increases prices by 3.062%. For capacity, I see an increase of 2% for every 10% reduction in capacity.

Tables 4 and 6 show the results of my the specification with the continuous IV. The first stage is not satisfied for this instrument but I do find significant relationships for all the specifications. The reduced form estimates suggest that a 1% exposure to the Boeing 737 MAX at the route level increased prices by 0.16%. Although, this estimate seems small, it is significant if interpreted with context. The mean exposure to this plane within the treated group is 5.30% which implies prices increase by 0.9% for the mean treated route. Moreover, the top 75th percentile of routes range from 7.19% to 69.86% so price effects can be quite large for these highly exposed routes. My preferred 2SLS estimate suggests that for a 1% increase in HHI, prices increase by 1.75%. For capacity, this estimate is 2.53% for every 10% reduction in capacity which is close to our first estimate.

Table 7 reports results for my carrier and distance group specification where exposure is measured within each carrier-distance group pair. A 10% increase in exposure to MAXs increases prices by 1.58%. This exposure ranges from 0.002% to 2.34% so the effect ranges from close to null to about 3.78%. The final estimate for the capacity-price relationship using this IV is 4.8%. I don't run this for HHI as it doesn't make intuitive sense.

6 Conclusion

This paper exploits the exogenous grounding of Boeing 737 MAX planes to measure the relationship between airline capacity and prices. I first estimate the effect of this shock on equilibrium prices using a reduced form design. I then estimate the relationship between concentration and prices and capacity and prices. These results show that the grounding significantly increased prices and that the effect is considerable especially when exposure was high. My estimate for the effect of capacity remains largely consistent across specifications.

This is one of the first estimates for concentration and price for the airline industry which informs competition policy directly. Previous merger specific work is unable to come up with such estimates as post prices are recovered based on product and firm characteristics which makes them less generalizable. This estimate is also robust to distributional assumptions for consumers, information asymmetry, and rationality.

The significant decrease in prices suggests that Federal regulators should carefully weigh the costs and benefits of grounding planes. The results also suggest that airlines are capacity constrained and even a 1% reduction in capacity can reduce prices significantly. There are two core limitations of this paper. First, I fail to disentangle the channels for the price increases.

Do price effects come from reduced capacity for airlines or increased market power? I intend to add capacity as a control, however, since capacity is endogenous to prices, it is unclear if this is reasonable. Second, I only have two post treatment periods which decreases my confidence in these results. As more data is released, I will update my results.

Future drafts of this paper will add a more careful discussion of the price-concentration literature and its relevance in antitrust, add controls for airline quality and market demographics, add descriptive work about which types of routes are affected by this shock, and use price dispersion as an alternate outcome.

7 Appendix

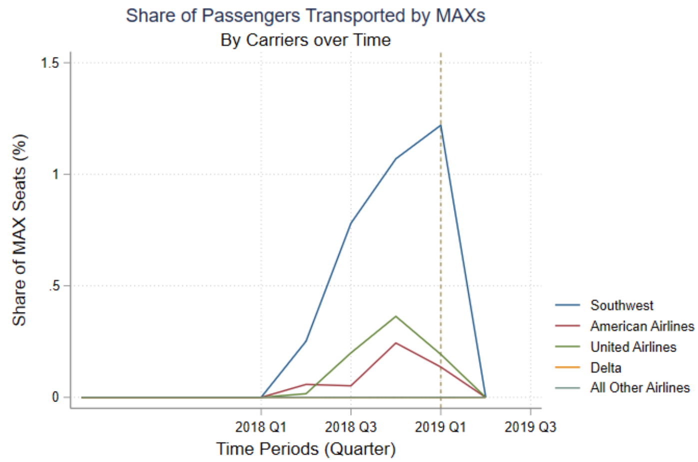

Figure 1: Difference in mean prices for MAX & Non-MAX routes; Pre and Post shock

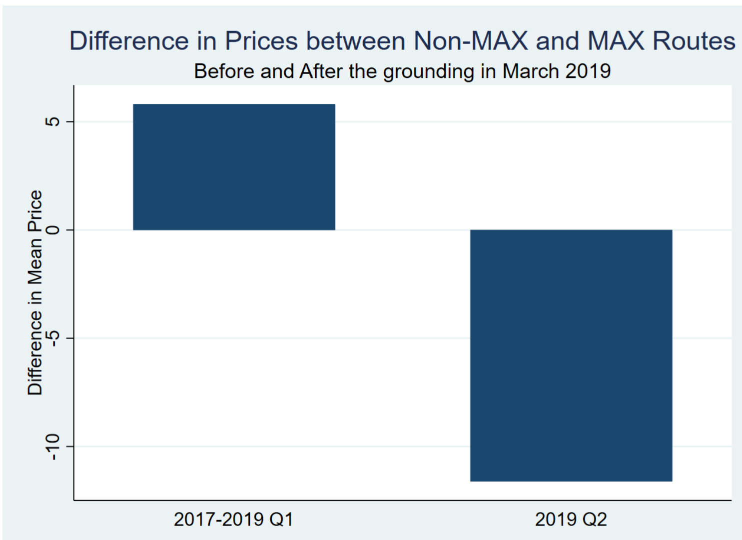

Figure 2: Difference in mean prices for MAX & Non-MAX routes; Pre and Post shock

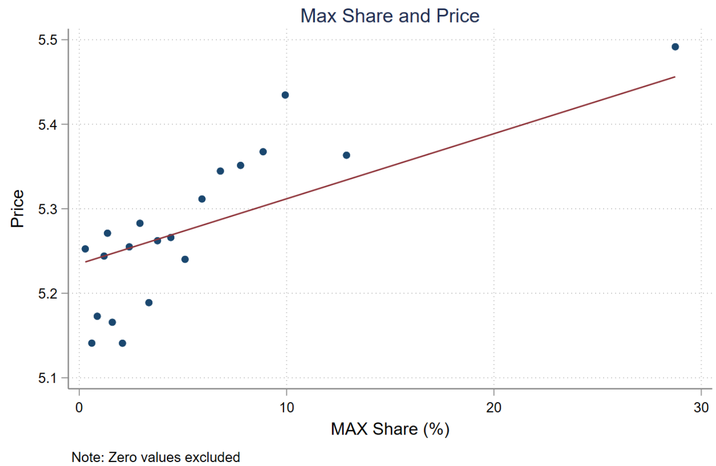

Figure 3: Binned Scatter-MAX Share and Price (without zeros)

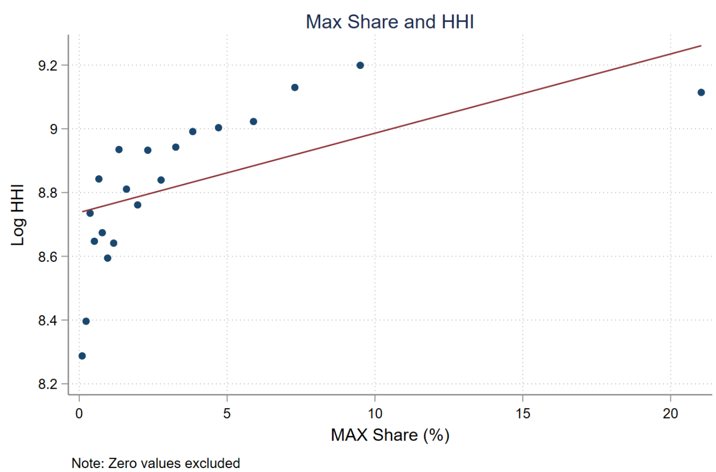

Figure 4: Binned Scatter-MAX Share and Concentration (log HHI) (without zeros)

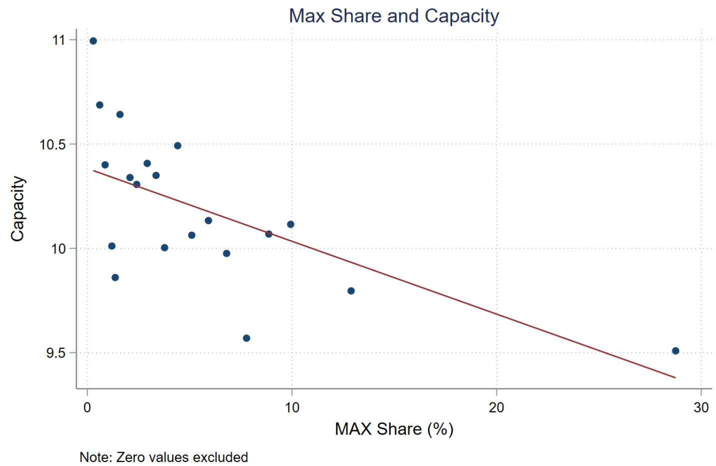

Figure 5: Binned Scatter-MAX Share and Capacity (without zeros)

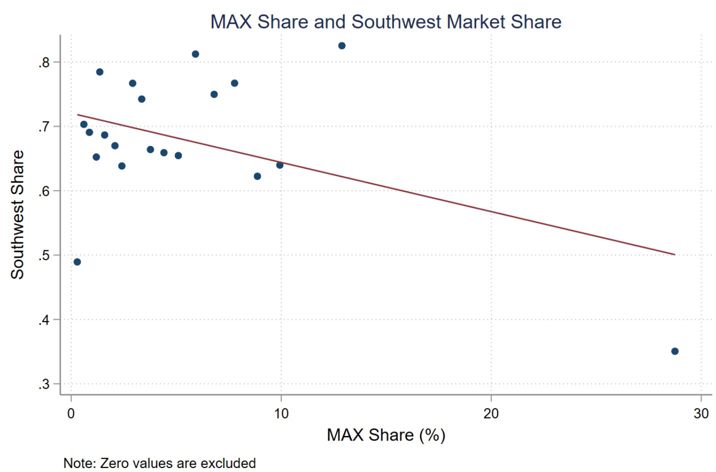

Figure 6: Binned Scatter-MAX Share and Southwest Share (without zeros)

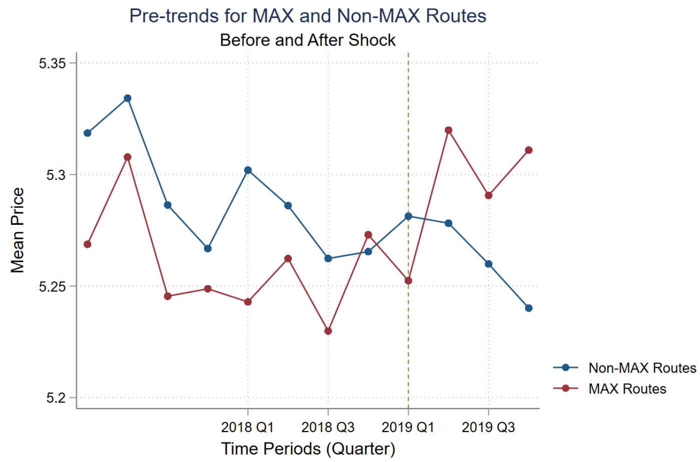

Figure 7: Parallel Trends Graph (without Controls)

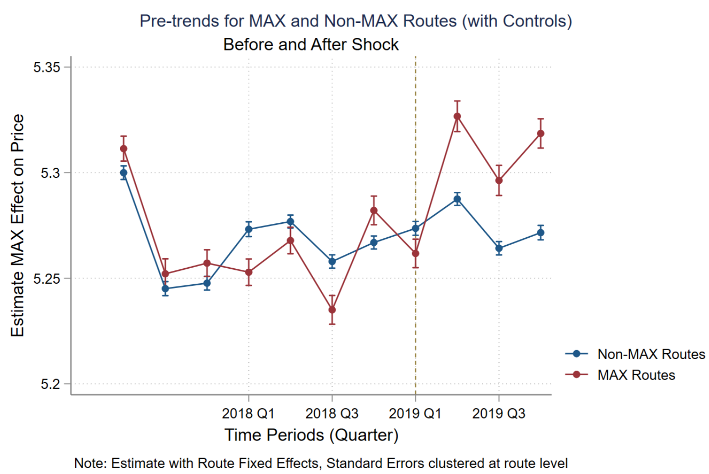

Figure 8: Parallel Trends Graph (with Controls)

Figure 9: Effect of Grounding on Prices (DD: % Exposure to 737 MAX)

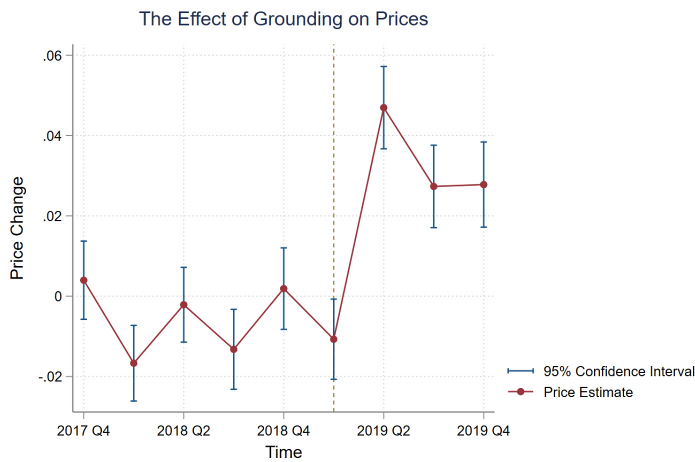

Figure 10: Effect of Grounding on Passengers (DD: % Exposure to 737 MAX)

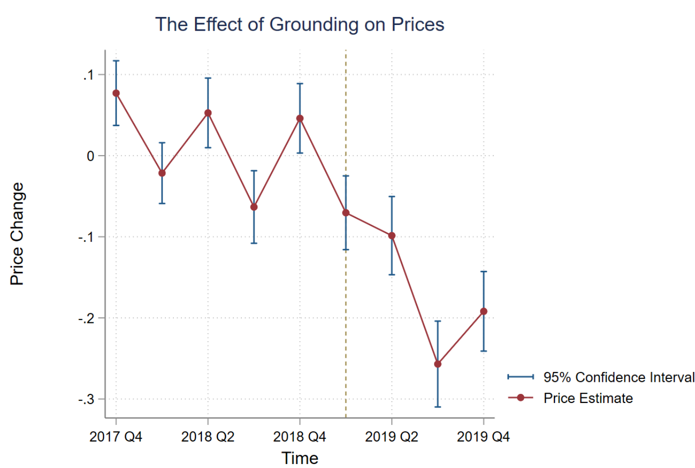

Table 1: MAX versus Non-MAX Routes (Before Shock)

	Non-MAX Routes		MAX Routes		T-Test
	Mean	St. Dev.	Mean	St. Dev.	Difference
Price	205.23	98.30	199.44	56.03	5.79***
Distance	1075.53	681.20	977.15	555.77	98.38***
Passengers	16930.04	26956.10	36406.81	31196.99	-19476.78***
Capacity	20343.32	31755.69	44272.72	37250.52	-23929.40***
Load Factor	80.36	14.09	82.16	8.83	-1.80***
Seats	20343.32	31755.69	44272.72	37250.52	-23929.40***
Logged HHI	8.89	0.39	8.86	0.41	0.03***
Observations	53632		13388		67020

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: MAX versus Non-MAX Routes (After Shock)

	Non-MAX Routes		MAX Routes		T-Test
	Mean	St. Dev.	Mean	St. Dev.	Difference
Price	202.61	99.91	207.99	53.86	-5.38***
Distance	1069.55	672.88	988.05	562.83	81.51***
Passengers	16626.96	27613.24	37026.41	32956.54	-20399.45***
Capacity	19386.43	31681.86	44321.58	38967.86	-24935.14***
Load Factor	83.49	13.10	83.89	8.32	-0.40**
Seats	19386.43	31681.86	44321.58	38967.86	-24935.14***
Logged HHI	8.88	0.40	8.84	0.42	0.04***
Observations	14007		3049		17056

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: F-Statistics for Instruments

Instrument Specification	**Log HHI**	**Log Capacity**
Binary Variable	31.76	531.77
% Exposure at Route	2.27	3.32
% Exposure by Carrier by Distance Group	-	42.66

Table 4: Concentration and Price (Binary and Continous IV)

	First Stage (IV1)	Log Price (IV1)	First Stage (IV2)	Log Price (IV2)
MAX Binary	0.0203***			
	(5.64)			
Log of HHI		3.062***		1.752**
		(5.75)		(2.10)
MAX Exposure (%)			0.00188	
			(1.51)	
Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.869	-	0.869	-
N	52858	52858	52858	52858

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Capacity and Price (Binary Instrument)

	First Stage	Log Price (Reduced Form)	Log Price (IV)
Route Dummy * Post	0.166***	0.802***	
	(21.16)	(23.06)	
Log Capacity			0.207***
			(16.78)
Year FE	Yes	Yes	Yes
Market by Quarter FE	Yes	Yes	Yes
Adjusted R-squared	0.643	0.542	-
N	77638	77638	77638

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Capacity and Price (Continuous Exposure Instrument)

	First Stage	Log Price (Reduced Form)	Log Price (IV)
Route Exposure * Post	0.0261*	0.00707***	
	(1.82)	(3.05)	
Log Capacity			0.253***
			(2.72)
Year FE	Yes	Yes	No
Market by Quarter FE	Yes	Yes	Yes
Adjusted R-squared	0.537	0.641	-
N	77638	77638	77638

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Capacity and Price (Carrier Exposure Instrument)

	First Stage	Log Price (Reduced Form)	Log Price (IV)
Carrier-Route Type Exposure * Post	0.158***	0.0757***	
	(6.53)	(15.34)	
Log Capacity			0.480***
			(6.54)
Year FE	Yes	Yes	Yes
Market by Quarter FE	Yes	Yes	Yes
Adjusted R-squared	0.538	0.642	-
N	77097	77097	77097

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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