Market Power and Supply Shocks
Evidence from the Boeing 737 MAX Grounding

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Abstract

I use the grounding of the Boeing 737 MAX to study the impact of cost shocks in airlines. By exploiting the disproportionate exposure of the grounding on certain carriers (such as Southwest) and routes, I am able to credibly measure the impact of this cost shock. My differences-in-difference and event study analysis shows that the grounding led to a 5% increase in prices at the market level, with the effect being particularly pronounced in more concentrated and capacity-constrained markets. Interestingly, I also observe that while Southwest was forced to raise prices, its rival legacy airlines actually reduced prices on affected routes. In future work, I will use a structural approach to better disentangle the effects of market power and capacity reduction on prices.

*Pre-Doctoral Fellow, Becker-Friedman Institute at the University of Chicago. Email: pdrall@uchicago.edu. This is very early stage work that builds off an undergraduate paper. I would like to thank Eric Ohrn, Katja Seim, Charles Hodgson, Ryan Kellogg, and Rich Sweeney for thoughtful feedback. Comments are welcome and all errors are my own.

1 Introduction

The airline industry plays a significant role in the US economy, contributing over $846 billion to the country's GDP. In recent years, the industry has undergone significant consolidation, with the top four firms holding a 67% market share.

Boeing introduced the 737 MAX in August of 2011. This aircraft offered improved fuel efficiency by ∼15% and could carry ∼20% more passengers than its predecessors, making it attractive to low-cost carriers like Southwest and Ryanair. However, the aircraft was grounded by the Federal Aviation Administration (FAA) following two fatal crashes in Ethiopia and Indonesia. The airplane was grounded from late March 2019 to November 2020.

This paper examines the impact of the grounding on the airline industry. In the US domestic market, only three airlines used the MAX, with Southwest being the most affected carrier (see Figure 1). The grounding also had a disproportionate impact at the route level. Southwest used it for certain medium-distance routes like Boston to Miami while legacy airlines used it on longer haul flights like Los Angeles to Hawaii.

To estimate the grounding's impact on prices, I exploit this variation at the the market (bi-directional airport pair) and route (carrier in a market) level. I use a differences-in-difference model with a range of fixed effects to control for time, market, and carrier-level trends. I also use a more flexible event study design to measure the impact of the grounding in each quarter. The "treatment" in this study is an indicator for routes with any MAX presence before the grounding, or a continuous measure of exposure to the MAX at the route or market level.

I find that the grounding resulted in an average price increase of 5% on routes where the aircraft was in use before the shock. This increase was particularly pronounced in more concentrated and capacity-constrained markets. These findings align with basic theories of conduct in the airline industry, but more interestingly, they also show considerable heterogeneity in how carriers responded to the shock. Southwest raised prices, while the other three major airlines (United, Delta, and American) reduced prices on more affected routes, despite being affected by the shock.

By examining the impact of the 737 MAX grounding which mostly affected Southwest, a significant low-cost carrier in the airline industry, I contribute to the existing literature on the role of such carriers in the industry. Berry and Jia (2010) found that increased price sensitivity and the rise of low-cost carriers have played a major role in the industry's evolution. In a seminal study, Goolsbee and Syverson (2008) show that incumbents responded to the threat of entry by Southwest Airlines by preemptively reducing prices. There is also a wealth of earlier evidence, albeit less well identified, for this so-called "Southwest Effect" going back to the 1990s and 2000s (See for e.g., Benett and Craun (1993), Morrison and Winston (1995), and Morrison (2001)). My analysis further contributes to this body of literature by examining the specific impact of a supply shock on Southwest and its competitors.

This descriptive analysis motivates a careful structural approach. I am primarily interested in studying how market power interacts with the cost shock. A counterfactual that can get at this is how would prices change if all carriers were equally affected by the shock. The difference in response observed here also motivates conduct testing for collusion Ciliberto and Williams (2014); Miller and Weinberg (2017) as firms appear to be "squeezing out" Southwest.

Building on this evidence, I aim to use a structural approach to analyze the interaction between market power and supply shocks in the industry. I can better understand the effects of market power on prices by estimating a counterfactual scenario in which all carriers are equally affected by the shock. The observed differences in how carriers responded to the grounding of the 737 MAX also suggest the need for conduct testing to determine whether collusion is taking place (Ciliberto and Williams (2014); Miller and Weinberg (2017)). Legacy airlines may be attempting to ”squeeze out” Southwest in more exposes routes. A key challenge with this approach requires explicitly modelling MAX share for each carrier-route as firms can easily reallocate capacity across routes.

Rest of the paper proceeds as follows. In Section 2, I describe the data and empirical strategy. I don't discuss results in detail here. In section 3, I describe the structural analysis in more detail.

2 Data and Empirical Strategy

I use data from two sources within the Department of Transportation: the Origin and Destination Survey (DB1B) and the T-100 Domestic Segment Survey. The DB1B is a 10% sample of passenger tickets purchased in a quarter, which provides me with fares and the number of passengers at the route (carrier in a market) level. The T-100 Domestic Segment Survey reports monthly capacity and passenger traffic at the route level, and also includes data on the aircraft used on each route.

By combining data from these two sources, I am able to identify routes that use Boeing 737 MAX aircraft and calculate the exposure at the route level. Since the T-100 data is available monthly by aircraft and the DB1B data is only available quarterly, I aggregate the data to the quarter level and weight the results by the number of passengers flown on each route when taking averages. This allows me to accurately assess the impact of the 737 MAX on a route-by-route basis.

I estimate two main specifications. First, a differences-in-difference model where I simply compare the average price before and after the shock on affected routes. Second, a flexible event study design where I estimate a “treatment effect” in each quarter:

$$ln(Y)_{ijt} = \alpha + \sum_{t \neq -1} \gamma DD_{ijt} + \sigma_{ij} + \chi_t + \epsilon_{ijt}$$

where,

- i indexes markets, j indexes airlines and t indexes time (quarters)
- Y are prices at the route (market-carrier) level
- DD is a route level dummy for exposed routes; this is a continuous variable in alternative specifications
- σ_j are airline and market fixed effects
- χ_t are year and quarter fixed effects
- standard errors are clustered at the route level

In the future, I plan to incorporate more detailed airplane usage data from commercial sources like Flight Radar. This data includes unique identifiers for each plane, allowing me to track which planes are reallocated across markets in response to the shock.

3 Next Steps: Demand Estimation and Conduct Testing

Basic intuition suggests that legacy airlines that are not affected by the shock (for e.g., Delta) would try to earn *supra* normal profits in markets where affected carriers (primarily Southwest) was relatively more reliant on the Boeing 737 MAX. However, airlines can also adjust their aircraft allocation to more competitive routes or purchase additional planes, making it difficult to predict their behavior. This complicates the basic story and further motivates a structural analysis that can help identify subtle market power changes even in "unaffected markets." This highlights the need for a structural analysis to identify potential changes in market power, even in "unaffected" markets. Initial analysis shows that Delta and other less affected carriers, such as United and American Airlines, reduced prices in affected markets. Bulow et al. (1985) has shown that changes in marginal costs in one market can influence the strategies of competitors in oligopolistic industries. While there is some evidence of this in this situation, it is difficult to draw strong conclusions due to the small scale of the effects and the endogeneity problem mentioned earlier.

In this section, I'll sketch out an early analysis plan. Demand model follows Berry and Jia (2010) and Ciliberto and Williams (2014) closely:

$$u^r_{ijmt} = x_{jmt}\beta_r + p_{jmt}\alpha_r + \xi_{jmt} + \nu_{itm}(\lambda) + \lambda\epsilon_{ijmt}$$

where,

- u_{ijmt} is the utility of a consumer j of type r buying product j in market m at time t
- β is a vector of taste coefficients for each consumer type r
- α is the disutility of a marginal price increase
- ξ_{jmt} are unobserved product market characteristics
- ν_{itm} is the nested logit taste shock to differentiate air travel from the outside good
- λ is the nested logit parameter varies from 0 to 1
- ϵ_{ijmt} is an i.i.d logit error

Since, there is a nested logit parameter λ, the contract mapping is slightly different to that of BLP. The discrete consumer types make the market share formula closed form which means we don't have to integrate over consumer characteristics; this makes computation much faster. I plan to follow the estimation route from Berry et al. (1996). I will also include fixed effects for airlines, and time (year-quarter) to account for consumer tastes for carriers and seasonality.

In order to perform this estimation, I require instruments that vary by carrier within a particular market. As a predictive instrument, I will use the exposure to the Boeing 737 MAX in each market prior to the grounding of the aircraft. This instrument will allow us to estimate substitution patterns between Southwest and other airlines, as the grounding of the aircraft disproportionately affected Southwest. For instance, we can observe the decrease in American Airlines prices as price-sensitive passengers with a preference for Southwest shift to AA.

I will estimate Nash-Bertrand supply similar to Ciliberto and Williams (2014) (and possibly explicitly model Boeing 737 MAX Share). Once I model supply, I will simulate a counterfactual with post-shock demand with pre-shock marginal costs. It would also be interesting to do conduct tests a la Ciliberto and Williams (2014) and Miller and Weinberg (2017) style in affected markets. Table 3 suggests that legacy airlines are trying to "squeeze out" Southwest. Can the reduction in prices by legacy airlines rationalized by Nash-Bertrand? Or do other conduct models explain this better?

I plan to use a similar approach to Ciliberto and Williams (2014) to estimate supply. This may include explicitly modeling the supply of Boeing 737 MAX planes. I will then use this supply model to simulate a counterfactual with post-shock demand and pre-shock marginal costs. This will help shed light on how prices would have looked in absence of the shock. Additionally, I will consider conducting tests similar to those in Ciliberto and Williams (2014) and Miller and Weinberg (2017) to determine whether the supply shock "tips" markets from Nash-Bertrand to Collusive pricing.

Appendix

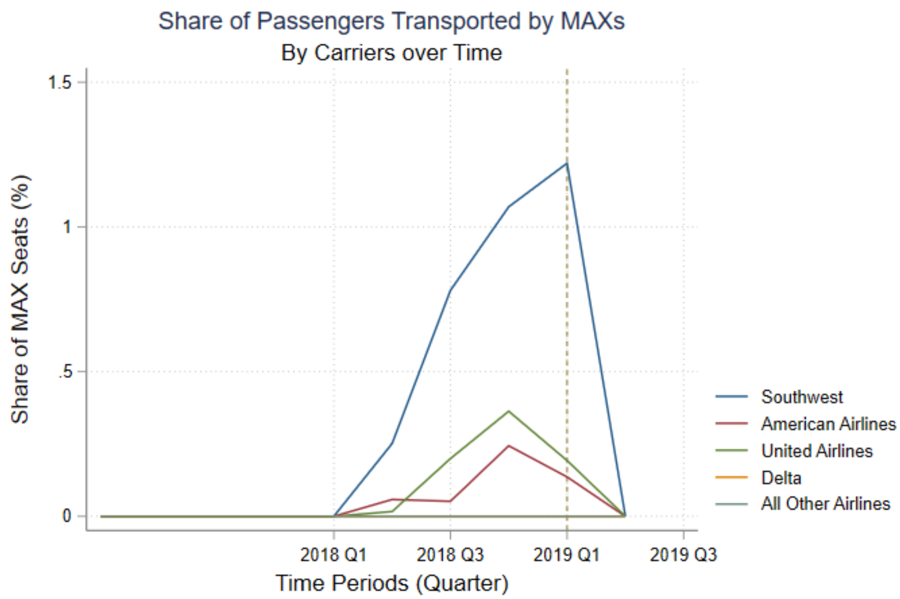

Figure 1: Share of Passengers by Carrier over time

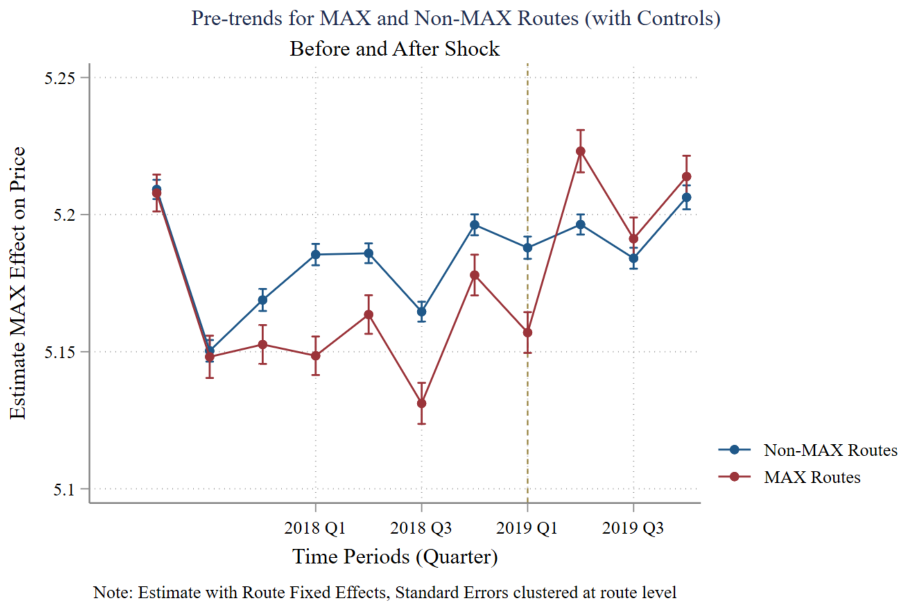

Figure 2: Differences-in-Difference Trends (MAX vs. Non-MAX Routes)

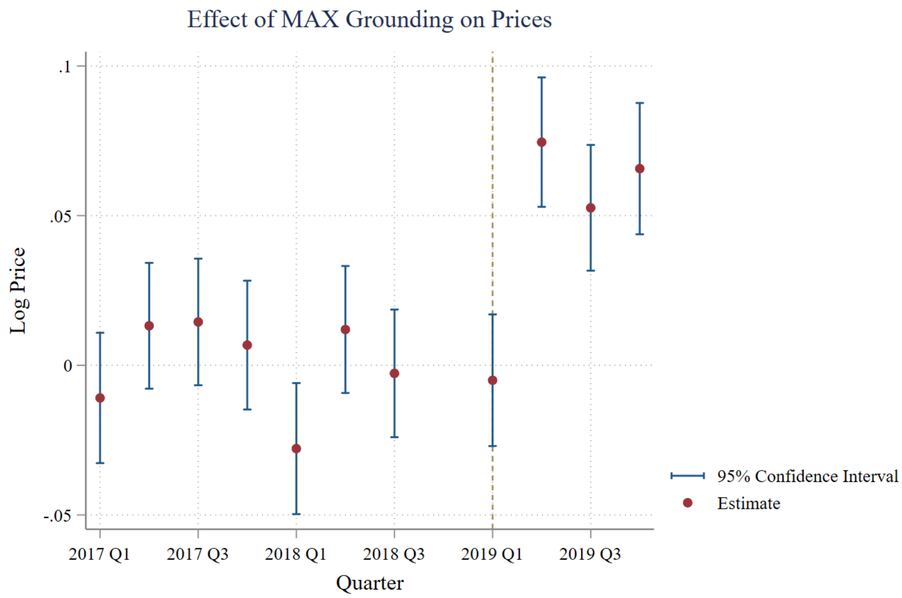

Figure 3: Event Study Graph: Price (MAX vs. Non-MAX Routes)

Table 3.1: Impact of Grounding on Ticket Prices

	(1) Log Prices	(2) Log Prices	(3) Log Prices	(4) Log Prices	(5) Log Prices
MAX Route x Post	0.126***	0.168***	0.174***	0.0497***	0.0295***
	(0.00760)	(0.00965)	(0.00723)	(0.00264)	(0.00225)
Quarter in Year FE	No	Yes	Yes	Yes	Yes
Market FE	No	No	Yes	Yes	No
Airline FE	No	No	No	Yes	No
Airline in Market FE	No	No	No	No	Yes
Adjusted R-squared	0.00317	0.00639	0.600	0.915	0.952
N	79926	79926	79831	79828	78072

Standard Errors are clustered at the route level.

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

Table 3.2: HHI Heterogeneity

	Log Price
Market DID=1	-0.00459
	(-0.93)
Market DID=1 × Quantile 2	0.0203***
	(6.15)
Market DID=1 × Quantile 3	0.0337***
	(3.18)
Market DID=1 × Quantile 4	0.0530***
	(6.00)
Constant	5.187***
	(5207.87)
Airline FE	Yes
Quarter by Year FE	Yes
Market FE	Yes
Adjusted R-squared	0.915
N	79828

Standard Errors are clustered at the route level.

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

Table 3.3: Airline Heterogeneity

	Log Price
Market DID=1	0.0474***
	(16.86)
Market DID=1 × 0	0
	(.)
Market DID=1 × American	-0.0617***
	(-8.93)
Market DID=1 × United	-0.0328***
	(-4.92)
Market DID=1 × Delta	-0.0272***
	(-3.45)
Market DID=1 × Other	-0.0551***
	(-8.96)
Constant	5.187***
	(5210.58)
Airline FE	Yes
Quarter by Year FE	Yes
Market FE	Yes
Adjusted R-squared	0.915
N	79828

Standard Errors are clustered at the route level.

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

Table 3.4: Capacity Utilization Heterogeneity

	Log Price
DID=1	0.0803***
	(11.67)
DID=1 × Load Factor=1	0
	(.)
DID=1 × Load Factor=2	0.0740***
	(6.11)
DID=1 × Load Factor=3	0.132***
	(9.68)
DID=1 × Load Factor=4	0.176***
	(11.99)
Constant	5.179***
	(1520.68)
Quarter by Year FE	Yes
Market FE	Yes
Adjusted R-squared	0.601
N	79831

Standard Errors are clustered at the route level.

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

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