Can Supply Shocks Facilitate Collusion?
Evidence from the Boeing 737 MAX Grounding

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1 Research Question

The airline industry contributes $846.3 billion (5.1%) to US GDP. From 2000 to present day, the industry heavily consolidated after a series of bankruptcies and mergers. The top four firms (American, Southwest, Delta, and United respectively) now collectively have 67% market share.

This paper exploits an exogenous shock to airline supply–the Boeing 737 MAX grounding–to understand the role of cost shocks in the airline industry. There is a large literature that studies market structure in airlines. Berry and Jia (2010) describe the evolution of the industry over time and find that consumers are more price-sensitive and low-cost carriers explain more than 80% of legacy carriers' variable profit reduction. Goolsbee and Syverson (2008) find that incumbents respond to the threat of entry by Southwest Airlines by preemptively reducing prices. There is also considerable evidence for the "Southwest Effect" before this study (See for e.g., Morrison (2001), Morrison and Winston (1995), Benett and Craun (1993)).

The Boeing 737 MAX grounding disproportionately affected Southwest Airlines (almost ten times more than other carriers). I ask two main questions. First, what is the effect of the grounding on prices, quantity, market concentration, and capacity utilization? This is primarily a descriptive question and I start by employing a flexible event study differences-in-differences framework:

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

where,

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- 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

The affected routes see price increases route level prices (see Figure 1). This price effect is higher in more concentrated and capacity constrained markets. Interestingly, there is considerable heterogeneity in carrier responses to the shock. Southwest is predictably the most affected while United and Delta are less affected; American's prices actually decrease after the shock. It is hard to come up with a story that explains these quirky responses at the carrier level which motivates the need for a pricing model.

Although this type of descriptive analysis is useful, it does not tell the full story as a key assumption of this inference strategy is the Stable Unit Treatment Value Assumption (SUTVA). This is violated as firms in concentrated markets set prices based on both own costs and rival costs. Consequently, unaffected markets (i.e. those that are not exposed to the Boeing 737 MAX) are not a valid counterfactual for the "treated" routes. This makes the reduced form estimates biased and these estimates only reflect the"net" effect of the shock.

Second, this paper tries to understand how firms respond to idiosyncratic supply shocks in a concentrated industry. There is a vast literature that studies the effects of cost shocks on pass-through in IO and trade contexts. For example, Muehlegger and Sweeney (2017) exploit a large cost shock caused by the fracking boom to isolate price responses to firm and region-specific input cost shocks. The paper also directly incorporates price setting based not only on own costs but also on rival costs. This setting is different from theirs as I do not directly observe costs and am primarily interested in market power effects. The key counterfactual in this context would be to see how outcomes would change if the shock affected all carriers similarly. There is also significant heterogeneity in what markets are affected by this shock. Airlines can also shift capacity across routes which further complicates estimation.

To deal with these endogeneity concerns described above, I will estimate demand, a la BLP, closely following Berry and Jia (2010). I will instrument for prices with the Boeing 737 MAX share at the market level before the shock.[1] These parameter estimates will measure aggregate welfare effects more precisely and perform counterfactual analysis.

Basic intuition suggests that rivals 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, carriers can reallocate aircrafts from markets where they are dominant to routes that are competitive or simply buy more planes. This

[1] This is a predictive instrument based on preliminary analysis of F-statistics following Stock and Yogo (2005).

complicates the basic story and further motivates a structural analysis that can help identify subtle market power changes even in "unaffected markets." Simple descriptive analysis suggests that the latter effect dominates as we observe that Delta and the other two relatively less affected carriers (United and American Airlines) reduce price in affected markets. Bulow et al. (1985) show that marginal cost changes in one market can change rival strategy in other markets in industries with oligopolistic competition. We see preliminary evidence of such strategic reallocation here but its hard to make strong conclusions given the small magnitude of effects and the endogeneity problem described above. This further motivates the need for structural analysis.

2 Data and Descriptive Statistics

I currently have data from two Department of Transportation data sources–(1) Origin and Destination Survey (DB1B) which is a 10% sample of passenger tickets purchased in a quarter. This gives me fares and number of passengers at the route (carrier in a market) level. (2) T-100 Domestic Segment Data which reports monthly capacity and passenger traffic at the route level. This dataset contains capacity and passengers transported for each route *and aircraft*. This allows me to identify which routes fly Boeing 737 MAXs and compute exposure at the route level. Since this data is available monthly by aircraft and the prices are only available quarterly, I aggregate to a quarter by route.

In the future, I will also attempt to add more granular plane use data which is available via commercial sources like Flight Radar. These data contain unique identifiers for each plane and we would be able to observe which (and how many) planes are reallocated across markets to deal with the shock.

3 Demand Estimation and Next Steps

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. We need instruments that vary by carrier within a market. As mentioned above, I intend to use exposure to Boeing 737 MAX *before* the shock.

The grounding disproportionately affects Southwest which will allow us to estimate substitution patterns between Southwest and other airlines. For example, American Airline prices decrease because price sensitive passengers with a preference for Southwest substitute to AA.

After demand, I will estimate supply Nash-Bertrand like 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 conduct tests 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?

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Appendix

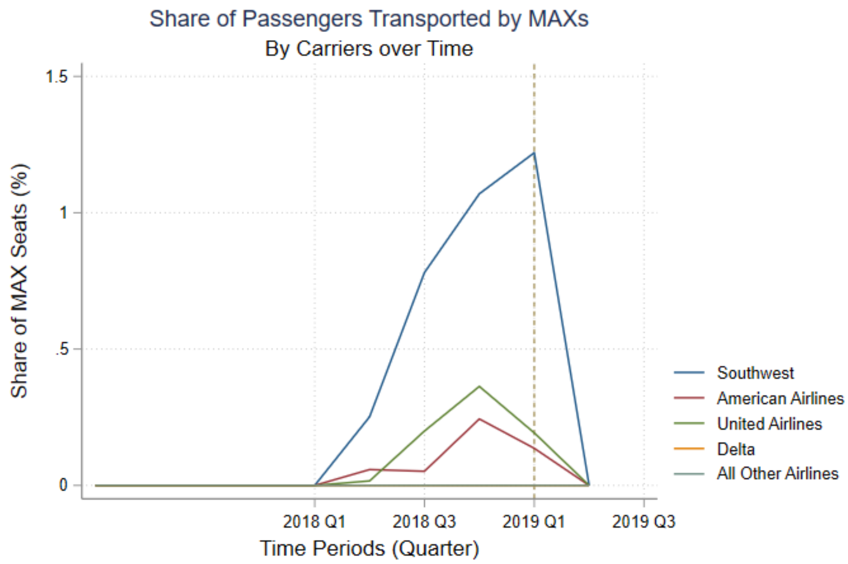

Figure 1: Share of Passengers by Carrier over time

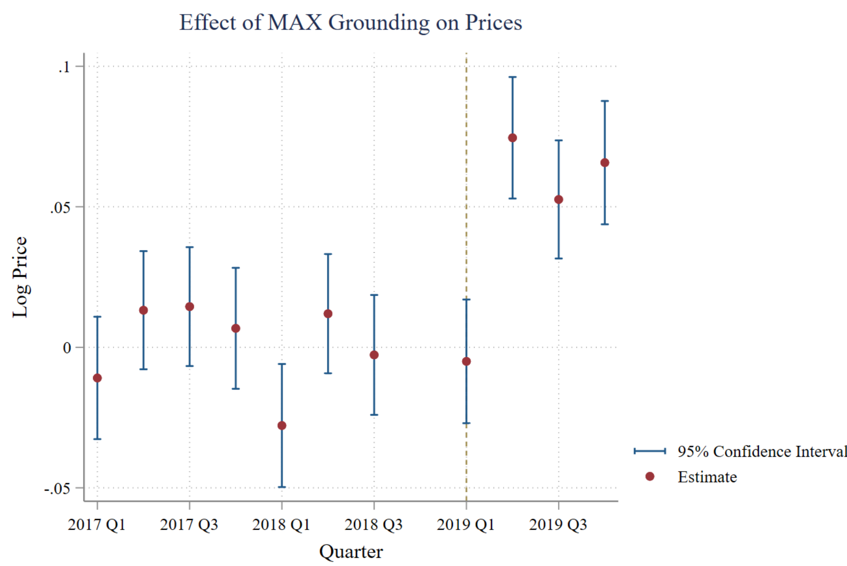

Figure 2: Event Study Graph: Price (MAX vs. Non-MAX Routes)

Table 1: Diff-in-Diff Regressions

	Log Price				
DID	0.126***	0.168***	0.174***	0.0497***	0.0295***
	(16.59)	(17.42)	(24.09)	(18.82)	(13.12)
Quarter by 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 2: HHI Heterogeneity

	Log Price
Market DID=1	-0.00459
	(-0.93)
Market DID=1 × Quantile 2	0.0403***
	(6.15)
Market DID=1 × Quantile 3	0.0237***
	(3.18)
Market DID=1 × Quantile 4	0.0330***
	(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: 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 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.

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

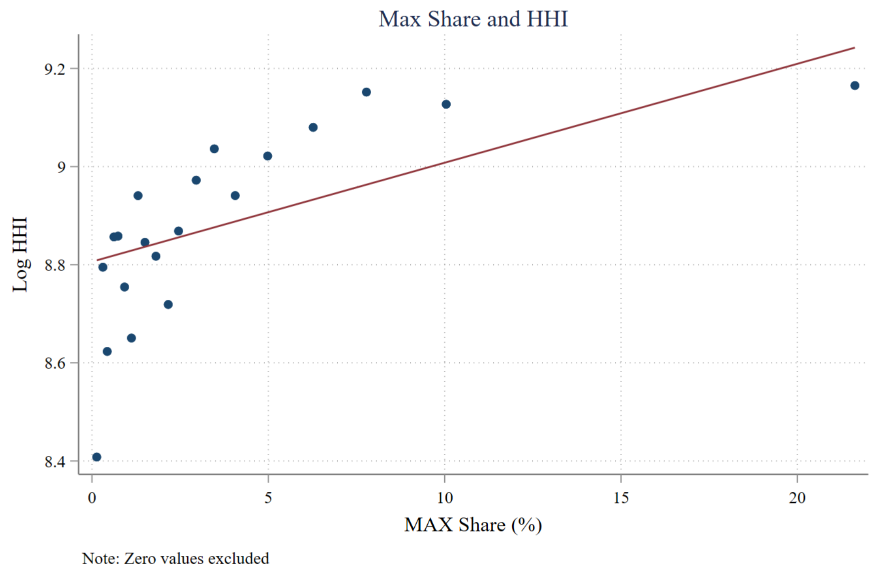

Figure 3: Binned Scatter-MAX Share and HHI (without zeros)

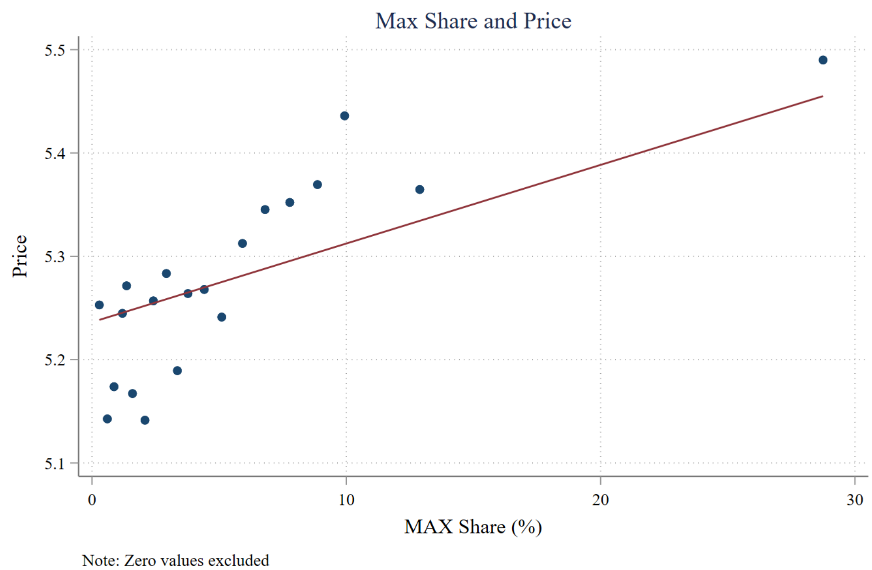

Figure 4: Binned Scatter-MAX Share and Price (without zeros)