Firm Conduct in the Airline Industry: Evidence from the 737 Max Grounding

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Abstract

Through the lens of a structural model I measure the pricing and welfare effects of the grounding of the 737 Max, and identify a level of coordination among airlines. A discrete choice demand system is estimated with supply moments, the conduct assumption takes the form of a constant and is similar to Miller and Weinberg (2017) and Ciliberto and Williams (2014). The system is estimated jointly via optimal GMM. I find evidence for a moderate level of coordination between airlines. I find that products that had exposure to the 737 Max saw increased prices, though generally prices did not increase as much as marginal costs did. Total profits for products that used the 737 Max decreased by around $400 million and $1.3 billion for the industry as a whole, welfare fell by around 1.5%.

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Introduction

In 2011 Boeing began work on the 737 Max, a family of fuel-efficient aircraft designed to compete with Airbus's existing A320Neo family. Boeing and Airbus designed these two families of long-range narrow-body aircraft to reduce fuel costs and allow airlines to serve smaller long-distance markets. A few major US-based carriers, such as American Airlines, United, and Southwest, made large orders of the 737 Max. The first airframes were delivered and in service in 2017, seven years after the aircraft was announced. However, in October 2018, a Lion Air 737 Max out of Indonesia crashed. While initially believed to be an isolated incident, in March 2019, a second 737 Max crashed on a flight from Ethiopia under similar circumstances that pointed to a design flaw in the 737 Max. Within two days, most of the world's air regulators, including the Federal Aviation Administration (FAA), had grounded all 737 Max aircraft indefinitely over safety concerns.

The sudden disruptions meant airlines that used the 737 Max had to either replace the lost capacity with less fuel-efficient aircraft or reduce operations. As a result, the average marginal cost increased for routes that the 737 Max operated on. In addition to the supply shock, the Max crashes potentially caused a demand shock. As a result, potential passengers might seek to avoid flying on the 737 Max or a 737 thereafter. There is anecdotal evidence that this is the case. For example, after the famous American Flight 191 crash at O'Hare Airport in Chicago, passengers told reporters that they tried to reschedule flights to avoid the DC-10. The accidents and grounding caused large efficiency losses to the carriers that used them.

While the direct effects of the grounding are of interest, the grounding also provides exogenous variation to measure coordination in the airline industry. The literature on coordination or firm conduct goes back to the 1980s and much earlier with the Structure-Conduct-Performance paradigm. Firm conduct is a long-standing question in economics Bresnahan (1989) provides a good overview of early work trying to measure firm conduct, and Gandhi and Nevo (2021) provide an overview of the more recent work. There were two ways to measure conduct: first, estimating a conduct parameter like Bresnahan (1982) , Ashenfelter and Sullivan (1987) , and Porter (1983) , and second, by comparing outcomes from different conduct assumptions to observed outcomes. Nevo (2001) uses the second identification strategy. He measures the price-cost margin implied by different conduct assumptions to actual price-cost margins. The analysis requires the econometrician to know something about marginal costs. The grounding of the 737 Max is a lens to measure coordination and test for collusion because the cost shock affects known carriers and routes. To understand how the grounding helps measure conduct, consider two airlines competing in three markets. In the first market, neither uses the 737 Max; in the second market, both use the 737 Max; in the third market, one uses the 737 Max, and the other airline does not. Given only the first two markets, any conduct assumption can rationalize a common cost shock to explain the observed price changes. The inclusion of the third market adds a restriction such that only one conduct parameter will generate a cost shock that explains the observed prices. The contribution to this literature is exploiting the grounding of the 737 Max to get a measure of coordination in the airline industry.

Bearing these questions in mind, this paper develops and estimates a structural equation model to explore how the 737 Max's crashes and subsequent grounding affected prices, costs, and markups in the airline industry. Demand is estimated as a nested logit with three branches: outside or inside good, the choice of low cost or legacy carrier, and finally, nonstop or connecting. Airlines are assumed to be profit-maximizing multiproduct firms and face a constant marginal cost. I model the grounding with a demand shock and a marginal cost shock. The demand shock is an interaction of a dummy variable for the LionAir accident and the percentage of flights on the route using the Boeing 737. I chose this specification because passengers might avoid flying any Boeing 737 as they might not be able to determine if they would be on a 737 Max or not. The marginal cost shock is an interaction term between a dummy variable for the grounding and the percent of flights that used the 737 Max prior to the grounding. Firm conduct is assumed to be a constant conduct parameter κ following

Ciliberto and Williams (2014) and Miller and Weinberg (2017). The parameter represents how much a carrier takes into account the profits of rival airlines. This specification nests both Bertrand-Nash and perfect collusion. Bertrand-Nash is implied by $\kappa = 0$, and perfect collusion would be $\kappa = 1$.

I use a dataset of flights derived from the DB1B from Quarter 1 of 2018 to Quarter 4 of 2019 and the T-100 Domestic Segment to measure route level usage of the 737 and 737 Max. The DB1B is a 10% random sample of all US ticket sales. The primary source of identification of the demand curve is the 737 Max usage. The exclusion restriction is that the usage of the 737 Max only affects consumer choices through their effect on prices. The assumption is reasonable given that the average consumer has no preference for specific aircraft models; thus, usage of the 737 Max should only affect utility through price. The grounding is a plausibly exogenous cost shock. Airlines did not have enough time to react strategically between the second crash and the grounding. A threat to identification would be if airlines knew there was a problem with the aircraft after the first crash and moved them to routes to minimize grounding effects. The demand and supply system is estimated with GMM. Following the literature, I employ a two-stage procedure to use the optimal weighting matrix.

The point estimate of the conduct parameter is .38. I reject the assumption of Bertrand-Nash competition; more importantly, the coordination parameter suggests a moderate degree of coordination between airlines. This finding is in line with previous work. Specifically, Ciliberto and Williams (2014) found parameter values between major carriers to be between .69 and .8 and values much closer to .1 for smaller carriers. The cost shock was fairly small, with the median increase being $2.81 and some routes having costs increased by $70 or more. Prices with and without the grounding are be compared using estimates of the structural parameters. Most carriers that used the 737 Max passed through between 94% and 100% of marginal costs to prices. Airlines that did not use the 737 Max saw slight increases in prices. Welfare is measured to have fallen by .5% for the median route.

A limitation of the paper comes from the static nature of the model. A fundamental assumption is that the flight network would have been the same absent the grounding. While this is unlikely to be accurate, the analysis still provides insight into the direct effects of the grounding. The first-order pricing effects are still of interest.

This work also contributes to the literature on competition in the airline industry. One strand focuses on the pricing effects of the entry of low-cost carriers. Tan (2015) , Morrison (2001), and Vowes (2001) all find that entry of low-cost carriers drives down airfares. Another strand of research is on sources of market power for airlines. Specifically, there is literature on the hub premium, which is the additional price associated with flying out of a hub airport. Ciliberto and Williams (2009) find a positive relationship between access to airport facilities and the hub premium, and Lederman (2008) links frequent-flyer programs with higher prices. They find that 25% of the hub measured hub premium can be explained by frequent-flyer programs. There is also a large literature on effects of mergers: pricing and welfare effects such as Park (2019) , Ali (2019) , Li et al (2022) , and Ciliberto et al (2019) . My contribution to this literature is examining how the grounding of the 737 Max affected the airline's pricing decisions.

Institutional Background

The 737 Max is a family of aircraft designed to replace older 737s with one of the main selling points being an increase in the fuel efficiency of the engines. The 737 Max consisted of two sub-models: the 737-8 and the 737-9. For the purposes of the paper both variants will be referred to as the 737 Max.[1] The 737 Max program began as a strategic reaction by Boeing to the Airbus A320Neo family. Specifically the program entered an accelerated development after American Airlines placed a large order for 130 A320Neos in 2013. In 2017 the first 737 Max aircraft were being delivered. The three major airlines that used the 737 Max in the United States are Southwest Airlines, American Airlines, and United

[1] The difference between the sub-models is seating capacity.

Airlines. As of January 2019 these three airlines had 31, 24, and 14 aircraft in their fleets respectively. To put this in context in March of 2019 Southwest had 754 aircraft in service, so the 737 Max made up 4%. Table 2 shows the size of 737 Max fleet and Total fleet size for the airlines that used the Max. The key flaw in the aircraft was related to a system known as the Maneuvering Characteristics Augmentation System (MCAS). The system was designed to protect the aircraft from pilots pitching up to much and preventing a stall. Boeing is alleged to have hidden some of these features from the FAA and other regulators so it would be type certified the same as other 737s. They wanted this because it would mean faster adoption and less investment for initial training of pilots. According to reports of the investigation airlines had no knowledge of any possible problems with the MCAS or related warning systems . By the end of 2019 it came out in December of 2018 the FAA kept silent their predictions of 15 accidents if the MCAS flaw was not fixed. As of May 2022 there is on going litigation against Boeing and accusations that Southwest might have helped Boeing hide the initial faults in the 737 Max.

Data

For this paper, a market is a unidirectional origin-destination pair and a quarter-year triple. A product is a specific routing-carrier pair on the market. For example, a flight could be nonstop or connect via a single airport. I define the carrier as the ticketing carrier. A ticketing carrier is a carrier that markets and sells the ticket. The operating carrier is the airline that operated the leg of the trip, and the reporting carrier is the carrier that reported the data to the Department of Transportation. For nonstop flights, this is straightforward, but for flights with a layover, this becomes more complicated. Commuter carriers commonly operate one leg of a flight with a layover. Larger carriers usually own or contract commuter carriers for more minor routes. For example, Republic Airways operates as American Eagle, Delta Connection, or United Express when flying for American Airlines, Delta Airlines, or United Airlines. The ticket carrier will be the larger airline for these products. The carriers that appear in the dataset are American Airlines (AA), Alaskan Airlines (AS), JetBlue (B6), Delta Airlines (DL), Frontier (F9), Allegiant (G4), Hawaiian Airlines (HA), Spirit (NK), Skywest (OO), Sun Country (SY), United Airlines (UA), Virgin (VX), and SouthWest (WN).

The origin and Destination Survey (DB1B) from the US Department of Transportation is the primary data source. The DB1B is a 10% random sample of all domestic tickets in the United States at the quarterly level. A round-trip coupon is broken down into two one-way ticket. Tickets where the Bureau of Transportation Statistics believes the reported fare is not credible are dropped, along with outlier fares. Outliers are defined as having fares below $25 as they are most likely entry errors or frequent flier mile redemption. For the upper end, for each observed ticket for a routing-carrier-year-quarter I drop those with fares greater then the $95th$ percentile. These are fares that on average much greater than $\$2,000$. The coupon level data is aggregated up to the product level. I measure the total observed passengers on the route at a given year-quarter pair and the passenger weighted average fare.

Following the literature, I will drop products with two or more connections. Only a tiny proportion of flights have more than one connection. Around 8% of products have 2 connections and that proportion is even smaller for 3 or more connections. The total number of passengers is calculated, and products with less than ten passengers in a quarter are dropped. [2] This leaves 478,412 different products from Quarter 1 of 2018 to Quarter 4 of 2019. The product's fare is the passenger-weighted prices observed in the data. Nonstop is a dummy variable =1 if the product is nonstop. The product distance is defined as the distance flown from origin to destination if the flight is nonstop, and origin to connecting the airport to destination for other flights. As Chen and Gayle (2017) used, route quality is a variable defined as the ratio of the product's distance divided by the nonstop distance between the origin and destination. This variable represents how close the product is to the

[2]This represents less than 100 passengers and is most likely not an effective competitor.

nonstop distance. [3] Prices in the airline market are dynamic; buying a ticket six months in advance would have a different price if bought six days in advance. The date the ticket is purchased is not observed; only the quarter-year of the flight is observed. To account for this, I create a variable that is the standard deviation of the observed fares for a product. The higher the standard deviation, the higher the chance the passenger can purchase the ticket for a lower price.

The T-100 domestic segment is all flights aggregated up to the carrier-aircraft-month level known as segments. Usage of either 737 or 737 Max is defined as the percentage of flights that used the aircraft. For nonstop flights this is straight forward as the route and product are the same. For flights with a connection the product is now two distinct segments. The first segment and second segment. The usage variable for flights with a connection is defined as the distance weighted average first and second-leg usage. Putting more weight on longer segments makes sense as those segments would be more exposed to the cost shock. LionAir is a binary =1 for quarter 4 2018 and on, and the variable grounding is =1 quarter 1 of 2019 and on-wards. These two variables represent when the demand and supply shock hit, respectively. The interaction term between the 737 usage variable and LionAir represents the demand shock. The coefficient represents the differential change in mean utility after the crash of Lion Air Flight 610. By the definition of an aircraft being grounded, the 737 Max usage variable is zero for the quarters after the grounding occurred. I define a variable called SupplyShock, which is equal to the 737 Max usage up to the grounding, and after, I assume each product's use would have been the same as it was in quarter 1 of 2019 in the remainder of 2019 if the grounding did not occur. The interaction between the SupplyShock and a dummy variable for the grounding will be used to measure the differential change in marginal cost after the grounding. The variable DemandShock if a dummy variable =1 if the current year-quarter is Quarter 4 of 2018 or Quarter 1 of 2019. The two periods the demand shock is expected to be in effect.

[3] By definition, a nonstop flight has a route quality of 1, and connecting flights have a route quality > 1.

The average jet fuel price for a carrier in a given quarter-year is calculated from the P-12a database. The variable is calculated as the total expenditure of jet fuel divided by the total fuel consumption in a given quarter year. The jet fuel price is merged into the dataset based on the operating carrier. The national average jet fuel price is used for carriers where the data is unavailable. For carriers where the expenditure is 0, I use the fuel price for the ticketing carrier. [4]

I break markets into three categories: no firms use the 737 Max, some firms use the 737 Max, and all firms use the 737 Max. The second type of market is the market of interest for the counterfactuals because these markets have 737 Max users and non-users interacting. I break products down into two groups: 737 Max users and non-users. A breakdown of the number of observations in each category is reported in Table 5. A market is said to have high exposure to the 737 Max if the average exposure in the market is greater than the 95^{th} percentile. The number of observations for each product type in markets with high exposure is reported in Table 6.

Reduced Form Analysis

To motivate the structural analysis, I estimate a reduced form model to show the price effects of the 737 Max grounding. This simple difference-in-difference regression will illuminate the price dynamics of the 737 Max grounding. I will estimate the following regression.

$$Y_j = \beta_1 737MaxExpose_j + \beta_2 \mathbb{1}(PostGround) + \beta_3 737MaxExpose_j \times \mathbb{1}(PostGround) + c_m + c_c + c_t + \epsilon_j \tag{1}$$

The coefficient β_3 represents the differential price effect of the grounding based on the product's exposure to the 737 Max. The equation is estimated with market, carrier, and quarter-year fixed effects. The standard errors are clustered at the market level. The results are

[4] Zero expenditure only existed for commuter carriers in the dataset. For example, Republic Airways operates as American Eagle, Delta Connection, and United Express. The fuel prices will be from American, Delta, and United.

reported in Table 3. A product with 10% exposure to the 737 Max saw an increase in prices of $6.40. The effect does not represent a very economically significant price change, given that the average fare is $472.49. That is a change of around 1.3% increase in price. The more interesting question is how prices changed compared to costs, and a measure of the change in marginal cost is needed. A structural model will be constructed with a discrete choice demand model and airline pricing model based on profit maximization. The remainder of the paper will focus on the structural analysis.

The Model

Demand

Following the demand estimation literature, I assume each consumer makes a discrete choice of an outside good, not flying, and one of the available inside goods. Specifically, I assume the following is the indirect utility function for consumer i consuming product j.

$$u_{ij} = X_j \beta_d + \alpha P_j + \xi_j + \epsilon_j^d = \delta_j + \epsilon_{ij}^d \tag{2}$$

The utility from choosing product j, with carrier c, on the market m, at quarter-year t, is a function of product characteristics, the price, the unobserved product-level utility, and the idiosyncratic error. The outside option is not flying. It is assumed that consumers will choose product j if $u_ij > u_ik, \forall k \neq j$. The error term is assumed to be a Generalized Type I Extreme Value distribution—specifically the nested logit form with correlation coefficient σ. The nesting structure will have three layers. Following the literature, the first branch is a choice of the outside good or inside goods. If the inside good is chosen, there are two limbs to take: flying on a legacy or a low-cost carrier. Then conditional on the carrier type, there are two final twigs for flying a nonstop or connecting flight. There are five possible nests: the outside good, flying a nonstop flight from a low-cost carrier, flying a connecting flight from a low-cost carrier, flying nonstop from a legacy carrier, or flying connecting from a legacy carrier. Figure 1 is a visual representation of the nesting structure. I choose this structure because it should provide robust substitution patterns. This structure implies that consumer chooses between lowcost or legacy carrier and then decide on nonstop or connecting. It is possible that the exact opposite is true where the nonstop/connecting branch is before the lowcost/legacy branch. As robustness check the I will estimate the model with this alternative structure in Appendix A. There is the usual logit choice probability from the distributional assumptions on ϵ_{ij}^d.

$$s_j = \frac{exp(\delta_j/(1-\sigma_1))}{exp(I_{rcg}/(1-\sigma_1))} * \frac{exp(I_{rcg}/(1-\sigma_2))}{exp(I_{cg}/(1-\sigma_2))} * \frac{exp(I_{cg}/(1-\sigma_3))}{exp(I_g/(1-\sigma_3))} * \frac{exp(I_g)}{exp(I)} \tag{3}$$

Where δ_j is the mean utility for product j, I_{rcg}, I_{cg}, I_g, and I are the inclusive values for each nest, the two intermediate branches, and the overall inclusive values, respectively. The mean utility for the outside good will be normalized to zero. Following the demand estimation literature, the market share expression will be inverted. Berry (1994) shows that the inverted market share can be expressed in the following form.

$$log(s_j/s_0) = X_j\beta^d + \alpha P_j + \sigma_1 log(s_{j|rcg}) + \sigma_2 log(s_{r|cg}) + \sigma_3 log(s_{r|g}) + \xi_j \tag{4}$$

Equation 4 will be the basis of estimation for the demand parameters. The product characteristics include a binary variable for a non-stop versus a flight with a connection, the product distance flown by the flight, the origin presence of the carrier, the flight frequency, and the standard deviation of the fare. The origin presence measures the proportion of non-stop flights that carrier c operates out of the origin airport. The flight frequency is the number of times a specific routing is offered in a given quarter-year. A rich set of fixed effects are also estimated, including quarter-year, carrier, origin, and destination fixed effects.

Marginal Cost

I assume that airlines will choose some vector of prices to maximize their profits. Following the literature, I assume that the marginal cost for one additional passenger is constant. The marginal cost represents the cost for an additional passenger on that specific routing. The marginal cost can be thought of as the costs of each leg and any efficiencies from the network. The network assumed to be exogenous and fixed within a year-quarter. Assuming marginal costs are additively separable and constant is a useful simplification. This assumption on marginal costs means the profit function for the carrier is additively separable. Specifically, carrier c at time t chooses a vector of prices, P_{ct}, to maximize their profits.

$$\max_{P_{ct}} \pi_{ct} = \sum_{j \in \mathcal{C}} \omega_{jk}(P_{icmt} - MC_{jcmt}) s_{jcmt}(P_{mt}) \tag{5}$$

The following equation is the first order necessary conditions for the price of product i on market m. Where ω_{jk} is equal to 1 if the if product the same firm owns j as product k or is equal to a constant $\kappa \in [0, 1]$—the specification nests both perfect collusion and Bertrand-Nash competition with $\kappa = 1$ and $\kappa = 0$.

$$\frac{\partial \pi_{ct}}{\partial P_{jcmt}} = s_{jcmt} + \sum_{k \neq j} \omega_{jk}(P_{jcmt} - MC_{jcmt}) \frac{\partial s_{jcmt}}{P_{jcmt}} = 0 \tag{6}$$

Following the methodology in the literature, including Berry (1995) Berry [1994], the set of first-order conditions can be stacked and written in matrix form.

$$\mathbf{MC} = P + (\Omega \circ \frac{\partial \mathbf{s}}{\partial \mathbf{p}})^{-1} \mathbf{s} \tag{7}$$

Where Ω is the ownership matrix, and $\circ$ is an element-by-element multiplication. The ownership matrix is where the assumption of the firm's conduct will enter. The element ω_{ij} is equal to 1 if $i = j$ or if i and j are owned by the same carrier. Bertrand-Nash's assumption would imply that the other elements of Ω are equal to 0. Consider an example market where

Delta owns products 1 and 2, product 3 is owned by Southwest, and product 4 is owned by Spirit. The ownership matrix would be the following.

$$\begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{8}$$

Following the work of Miller and Weinberg (2017) and Ciliberto and Williams (2014) alternative firm conduct will be added via a parameter κ.

The term $\partial s/\partial p$ is the matrix of derivatives of the market share with respect to price. Given the nest logit structure assumption there is a closed form solution to these derivatives.

$$\frac{\partial s_j}{\partial p_j} = \alpha s_j(\frac{1}{1-\sigma_1} - \frac{\sigma_1 - \sigma_2}{(1-\sigma_1)(1-\sigma_2)} s_{j|rcg} - \frac{\sigma_2 - \sigma_3}{(1-\sigma_2)(1-\sigma_3)} s_{j|cg} - \frac{\sigma_3}{1-\sigma_3} s_{j|g} - s_j) \tag{9}$$

$$\frac{\partial s_j}{\partial p_k} = -\alpha s_j(\frac{\sigma_1 - \sigma_2}{(1-\sigma_1)(1-\sigma_2)} s_{k|rcg} + \frac{\sigma_2 - \sigma_3}{(1-\sigma_2)(1-\sigma_3)} s_{k|cg} + \frac{\sigma_3}{1-\sigma_3} s_{k|g} + s_k), \forall j \neq k \tag{10}$$

$$\frac{\partial s_j}{\partial p_k} = -\alpha s_j(\frac{\sigma_2 - \sigma_3}{(1-\sigma_2)(1-\sigma_3)} s_{k|cg} + \frac{\sigma_3}{1-\sigma_3} s_{k|g} + s_k), \forall j \neq k \tag{11}$$

$$\frac{\partial s_j}{\partial p_k} = -\alpha s_j(\frac{\sigma_3}{1-\sigma_3} s_{k|g} + s_k), \forall j \neq k \tag{12}$$

The cross-price derivatives are defined for three possibilities: if the product j and k are in the same nest, the same branch (both low cost or legacy carriers), or inside goods. Given the demand parameters, markups can be estimated. Marginal costs will be assumed to take a linear form and be a function of distance, distance squared, the grounding and 737 Max shocks, and a robust set of fixed effects.

$$\begin{aligned} MC_{jcmt} = \beta_1^s Dist_{jcmt} + \beta_2^s Dist_{jcmt}^2 + \beta_3^s Grounding_t + \beta_4^s 737MaxFlightExpose_{jcm} \\ + beta_5^s Grounding * 737MaxExpose_{jcmt} + \zeta_{origin} + \zeta_{dest} + \zeta_c + \zeta_t + \eta_{jcmt}^s \end{aligned} \tag{13}$$

The marginal cost for one passenger is a function of the distance flown, the distance squared, and a rich set of origin, destination, carrier, and quarter-year fixed effects. The distance square term is common in the transportation literature. The term represents that flying further costs more in a nonlinear fashion [5]. The coefficient β_4^s represents the differential cost shock that is faced by airlines that use the 737 Max.

Identification

Price and the within nest market share are endogenous variables, and for identification, instruments are required. The ideal instruments for price are a set of cost shifters. Variables that shift the marginal cost but do not affect demand are often hard to find in practice. The primary source of identification is the grounding of the 737 Max. The cost shock caused by the grounding is used to trace the demand curve. The cost shock is the interaction between a binary variable for the grounding and the product's exposure to the 737 Max. That requires that cost shock does not affect the demand curve. The assumption is that cost shock from grounding is uncorrelated with the unobserved product characteristic, ξ_j. The cost shock is defined by the interaction between the exposure to the 737 Max and the Grounding variable. I also use the instruments proposed in Berry, Levinsohn, and Pakes (1995) . The instruments are the sum of each product characteristic of products in the market owned by the same firm and the sum of product characteristics owned by rival firms. The argument is that the firm's pricing decisions should be affected by the characteristics of products owned by the firm and those owned by rival firms. These instruments require the assumption that the product characteristics are exogenous. The price of jet fuel is employed as a cost shifter. The jet fuel price varies by quarter and by the airline. Jet fuel costs differ by the airline based on long-term contracts and hedging strategies. [6] The log conditional market shares are also mechanically correlated to the error term. To address this, I will also use the instruments

[5] Flying further requires more fuel, more fuel adds weight, and increases the fuel required due to lowered fuel economy.

[6] Most US airlines have some hedging strategy in place. Jet fuel hedging usually involves purchasing futures for crude oil or kerosene gas. A review of the theory and practice of jet fuel hedging can be found in Morrell and Swan (2006)

proposed by Berry (1994) . The sum of product characteristics of products within the same nest. After the grounding, all products have an exposure of 0 by definition. The 737 Max exposure will be measured as the proportion of flights for a given product that used the 737 Max. For periods after the grounding, the value assigned is the value for that product during quarter 1 of 2019. This assumes that if the grounding never occurred, the 737 Max usage would have remained constant. This is a conservative estimate given that over time, more 737 Max's would have been delivered, and thus, exposure should be expected to increase.

Firm conduct is endogenous, and the measured parameter κ will require instruments. A natural instrument makes use of the exogenous nature of the grounding. For each product, I measure the average exposure to the 737 Max of the rival firms. For the exclusion restriction, it is reasonable to assume that the rival's exposure to the cost shock is exogenous to the marginal cost error. It is expected that airline conduct should be correlated with rival exposure.

Estimation

The structural parameters will be estimated via joint GMM. The moment conditions take the following form.

$$Z'\epsilon = \begin{pmatrix} Z_d & 0 \\ 0 & Z_s \end{pmatrix}' \begin{pmatrix} \xi_j \\ \eta_j \end{pmatrix} = \begin{pmatrix} Z_d'\xi_j \\ Z_s'\eta_j \end{pmatrix} \tag{14}$$

There are more instruments than endogenous variables, so the system is over-identified. The vector of parameters θ will be chosen to minimize the value of the quadratic form of the moments. That is, it solves the following problem.

$$\hat{\theta} = \arg\min_{\theta}(Z'\epsilon)'\hat{W}(Z'\epsilon) \tag{15}$$

Where W are some positive definite weighting matrix, the weighting matrix chosen will be the optimal weighting matrix, $\hat{W} = (\hat{S})^{-1}$. Where $\hat{S}$ is the estimated moment variance matrix from the first stage estimation. The standard errors will be from the following variance-covariance matrix.

$$Var[\hat{\theta}] = n(\hat{D}'Z(\hat{S})^{-1}Z'\hat{D})^{-1} \tag{16}$$

Where $\hat{D}$ is the jacobian of the residuals with respect to the vector of parameters θ

$$\hat{D} = \frac{\partial \epsilon}{\partial \theta'} \tag{17}$$

$\hat{S}$ is the estimated variance of the residuals. This specification is robust to heteroskedasticity.

$$\hat{S} = \frac{1}{n}\sum_{i=1}^{n} \epsilon_i'\epsilon_i Z_i' Z_i \tag{18}$$

Results

Demand

The estimates of the demand parameters are reported in Table 4. As expected, an increase in a price decrease the probability of choosing the product, ceteris paribus. All parameters are statistically significant and have the expected signs. An increase in the standard deviation of the fare of a product by $100 increases the log odds ratio by 1.4267. The higher the standard deviation means there is a chance of purchasing a ticket at a lower price. Consumers prefer flights closer to nonstop, given by the coefficient of route quality. The longer a specific flight is compared to the nonstop distance decreases the chance of consumers choosing that product. The interaction term between the product's exposure to the Boeing 737 and the Lion Air crash represents the demand shock. After the 737 Max crashed in Indonesia, passengers preferred products with a lower chance of being on a 737.

Supply

The conduct parameter is estimated at .38 with a standard error of .004. I can easily reject both Bertrand-Nash and perfect collusion at normal confidence levels. A value of .38 implies a moderate level of coordination between airlines. Ciliberto and Williams (2014) find values between .6 and .8 for κ for major carriers and values around .1 for coordination between major and minor carriers. This parameter is constant and the same for all carriers so the value of .38 makes sense.

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Counterfactual Analysis

The crash of Lion Air in October 2018 and the grounding of the 737 Max in March 2019 represent two shocks. A demand shock and a supply shock. The demand shock represents the change in consumer behavior. In reality, it is expected that there will be three distinct demand shocks: the crash of Lion Air in October 2018, the Ethiopian Air crash on March 11, 2019, and the grounding by the FAA on March 12, 2019. Due to the structure of the data, one over shock will be considered. The demand shock will be defined as a product's exposure to the Boeing 737. This is done for a few reasons. First, by definition, the 737 Max exposure is 0 after the grounding. The second reason is based on the fact that passengers might not be able to tell the difference between a 737 Max and a non-Max 737. There are some physical differences between the aircraft types [7]. The demand shock will be defined as the percentage of flights on a specific route using the Boeing 737. There is anecdotal evidence that passengers will change their flying behavior to avoid an aircraft after a major accident. After the crash of American Airlines Flight 191 in 1979 at O'Hare Airport, passengers told

[7] The 737 Max -8 and -9 have engines that are higher off the ground and forward compared to other 737s. The engines also make use of noise mitigation technology from the 787 and have a chevron pattern on the rear of the engine nacelle.

reporters they changed or tried to change their flight plans to avoid flying on the DC-10. After the shock, passengers in a specific market may change which airlines they fly to avoid the 737.

Given the structural parameters, counterfactual marginal costs can be calculated. The new equilibrium is the solution to the following system of equations given some vector of marginal costs.

$$\delta_i^{CF} = X_{jcmt}\beta^d + \alpha P_{jcmt} + \sigma s_{j|g} + \hat{\xi}_j - \beta^{DemandShock}\nu_d \tag{19}$$

$$MC_{jcmt}^{CF} = X_{jcmt}^s\beta^s - \beta^{SupplyShock}\nu_s \tag{20}$$

Where $\beta^{DemandShock}$ is the coefficient for the interaction between the product's use of the Boeing 737 and the Lion Air Accident in Quarter 4 of 2018; and $\beta^{SupplyShock}$ is the coefficient for the interaction of the $737MaxExposeGrounding$ interaction term in the pricing equation, and ν_d and ν_s are the interaction terms respectively. Given these shocks and the estimated parameters, we are presented with a nonlinear system of two equations and two unknowns.

$$s_{jcmt} = exp(\delta_{jcmt}^{CF})s_0 \tag{21}$$

$$P_{jcmt} = MC_{jcmt}^{CF} - (\Omega \circ \frac{\partial s}{\partial P})^{-1} s_j \tag{22}$$

The system will be rewritten as a fixed point problem. Given an initial vector of market shares, the equation will be iterated until a fixed point is reached. Using the Brauer Fixed Point Theorem, this leads to the equilibrium market share and can be used to solve for the equilibrium vector of prices.

$$\begin{gathered} S_{new} = exp(X_{jcmt}\beta^d + \alpha(MC_{jcmt}^{CF} - (\Omega \circ \frac{\partial \mathbf{s}}{\partial \mathbf{P}})^{-1} S_{old}) \\ +\sigma \frac{s_j}{\sum_{k\in\mathcal{F}(mt)} s_k} + \hat{\xi}_j - \beta^{DemandShock}\nu_d)(1 - \sum_{k\in\mathcal{F}(mt)} s_k) \end{gathered} \tag{23}$$

Where $sum_{j\in\mathcal{F}(mt)} s_j$ is the sum market shares for all products k in market m at time t.

I am assuming that product characteristics remain the same in both cases. Expressly, the assumption even if the average price changes on a product, the dispersion of prices remains the same. The unobserved product quality would have been the same, absent the shock. The assumption is that all the demand effects of the shock can be explained by the demand shock and the fixed effects. Also, the implicit assumption that products observed being offered would have been offered absent the merger; there was no entry or exit. A strong assumption but necessary for the static model.

Profits and welfare are calculated for the world where the grounding did and did not occur. Welfare is calculated as the nested logit inclusive values, which take the following form.

$$I_{rcg} = (1-\sigma_1)ln(\sum exp(\delta_k/(1-\sigma_1)) \tag{24}$$

$$I_{cg} = (1-\sigma_2)ln(\sum exp(I_{rcg}/(1-\sigma_2)) \tag{25}$$

$$I_{g} = (1-\sigma_3)ln(\sum exp(I_{cg}/(1-\sigma_3)) \tag{26}$$

$$I = ln(1+I_g) \tag{27}$$

The markets of interest are markets where some firms used the 737 Max and others did not. We can think of the firms that used the 737 Max and firms that did not use the 737 Max, which I refer to as 737 Max Users and Non-users, respectively. The solution is a vector of market shares and prices for the world where the shock occurred and did not occur. The results are presented regarding how the values changed due to the shock. For example $P_{base} - P_{counterfact}$.

Looking at price changes first: Figure 3 shows the change in price due to the grounding for users of the 737 Max. As expected, there is a definite upward trend. Increasing usage of the 737 Max by ten percentage points implies price on average increases by \$14.45. The naive difference-in-difference estimate provided a similar but smaller price effect. For non-users of the 737 Max, the price changes are plotted against rival 737 Max Usage in Figure 6.

Again, there is no strong relationship between rival usage and price change. In Table 8 the changes in price are broken down by 737 Max exposure level. The results are from a simple OLS regression of change in price on 737 Max usage and a constant for the products that used the 737 Max in Quarter 1 of 2019. On average, airlines that saw minimal usage around 1% only saw increased prices of 19 cents from an increase of marginal costs of \$1.41. Where carriers with 25% usage saw price increases of \$34.84, this represents around an 8% increase compared to the average fare for these products.

The results for the Lerner index are reported in Figure 2 and 5. For airlines that used the 737 Max, Figure 2 shows the change in the Lerner index. As expected for airlines with little exposure to the 737 Max, there was little change to markups. Usage between 0 and 10% changes the Lerner index between 0 and $-.026$. There is also a general downward trend, and the regression line has a slope of -.39. Products with higher usage of the 737 Max saw increased costs, and not all those costs were passed onto consumers. The Lerner index is one measure of market power, suggesting that users of the 737 Max saw decreased market power due to the grounding.

The product level profits were calculated. Figure 4 reports the changes in profits plotted against 737 Max usage on the x-axis. There is a noticeable downward trend in profits; products with heavier usage of the 737 Max saw larger decreases in their profits. The median change in profits is around $-\$3,000$. A histogram of the change in profits is reported in Figure 19. Airlines who did not use the 737 Max saw higher and lower profits, as reported in Figure 7. The trend appears to be flat compared to the rival 737 Max usage. This suggests there is no obvious linear relationship between rival exposure and the change in profits for these airlines. The histogram in Figure 18 shows almost equal weight above 0 and below 0. The median change in profit is \$44. More than half of the airlines in this group saw an increase in profits.

Cost pass-through was also calculated for the airlines that used the 737 Max. I define the measure of cost pass-through as the change in imputed marginal costs divided by the change in price for the base and counterfactual cases.

$$PassThrough = \frac{P_{base} - P_{counterfactual}}{MC_{base} - MC_{counterfactual}} \tag{28}$$

Table 7 shows some summary statistics on the cost pass-through. The median pass-through was .9443, meaning that for a dollar increase in costs, \$.9443 were passed on to fliers. The full distribution of the estimated pass-through is reported in Figure 17. Outliers were removed when plotting to make the histogram easier to read, and values greater than 5 in absolute value were not plotted. As can be seen, the majority of the mass is between 0 and 1, with the largest bin of observations being around near-perfect pass-through.

Other Counterfactuals

Bertrand-Nash ($\kappa = 0$)

A natural counterfactual is to think about how the counterfactual results would look if κ were forced to be 0. Comparing these results to the previous can illuminate the importance of price coordination on the results. The full system is estimated again with GMM with an added constraint forcing $\kappa = 0$. Given the new vector of parameters, a new vector of marginal costs and unobserved product characteristic ξ_j is calculated. The estimated cost shock in this model comes out to be around 97. The cost shock is smaller than the one implied by the more flexible conduct assumption. Then the new base and counterfactual results are formulated with the new parameters. The question is how the assumption of Bertrand-Nash changes the results of the counterfactual. The results are reported in Figure 10 in terms of the difference between the change in the Lerner index in the main counterfactual minus the counterfactual in the $\kappa = 0$ case. The higher the exposure to the 737 Max, the more significant the difference between the two conduct assumptions. Specifically, the decrease in the Lerner index was smaller for the more flexible compared to the Bertrand-Nash Case. At 50% exposure, the difference between the two counterfactuals is around .05; for the flexible conduct model, the Lerner index change at this exposure level is around $-.1$. This suggests that if we assume, Bertrand-Nash will overestimate the change in markups by around a factor of 2, which is a significant difference. The results agree with the prior literature that conduct assumptions matter for this analysis, and merely assuming Bertrand-Nash will give us drastically different results.

Relative Importance of Demand and Cost Shocks

What was the relative importance of the shocks in terms of the outcomes observed? Two sets of counterfactuals were additionally computed, where one only had the demand shock in quarter 4 of 2018, and the other only grounded in quarter 1 of 2019. As with the previous, the results are reported as how the new counterfactuals compared to the main counterfactual. Figure 8 shows the demand shock case results. The figure is the difference in the change in the Lerner index. This figure suggests that the demand shock had little effect on the counterfactual. Where for the supply shock, the difference between the main counterfactual and it is minimal, as seen in Figure 9. The figure suggests that the cost shock was more important in explaining the changes in the Lerner index than the demand shock.

Conclusion

The FAA's grounding of the 737 Max in 2019 offered a unique opportunity to measure airline coordination. Previous work used instruments measuring potential competition or mergers to identify a conduct parameter. The grounding of the 737 Max is helpful because the exposure to the ground varies significantly between airlines and products. Specifically, the product level variation in usage allows the identification of the conduct parameter. Jointly estimating the system with GMM, κ is estimated to be around .38 and statistically significant. Bertrand-Nash conduct can be ruled out, but the parameter does not have a natural interpretation as the traditional conduct parameter. This value suggests a moderate level of coordination between carriers that aligns with the existing literature.

The grounding of the 737 Max had heterogeneous pricing and welfare effects. The grounding caused airlines to replace the more fuel efficient 737 Max aircraft with less fuel-efficient variants. The sudden grounding also caused disruption and a potential demand shock as passengers tried to avoid flying on the aircraft. As expected, products with higher usage of the 737 Max faced more significant increases in marginal costs, had higher prices, and lost more profits on average. I estimate the total decrease in profits for products using the 737 Max to be around $400 million dollars and the loss in profits for the industry to be around $1.3 billion.

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Table 1: Notation

i	Consumer index
j	Route-carrier (product) index
m	Origin-destination pair (market) index
c	Carrier index
t	Quarter-year index
α	Price coefficient
ξ_j	Unobserved product quality
κ	Price coordination parameter
$s_{j\vert rcg}$	Conditional Probability of selecting product j conditional on being in the nest
$S_{r\vert cg}$	Probability of selecting a nonstop flight conditional on carrier type and consuming an inside good
$S_{c\vert g}$	Probability of selecting carrier-type conditional on consuming an inside good
S_g	Probability of consuming the inside good
π_{ct}	Profit for firm c at time t
Ω	Ownership matrix
ν_d	$\beta^{5,d}\mathbb{1}(LionAir)_t * 737Usage_{jcmt}$
ν_s	$\beta^{5,s}\mathbb{1}(Grounding)_t * 737MaxExpose_{jcmt}$

Airline	737 Maxes (delivered)	Narrow-body Fleet Size	Proportion
Southwest Airlines	31	754	4.11%
American Airlines	24	802	2.99%
United Airlines	14	591	2.37%
WestJet	12	120	10%

Table 2: Size of Aircraft Fleets and 737 Max Deliveries

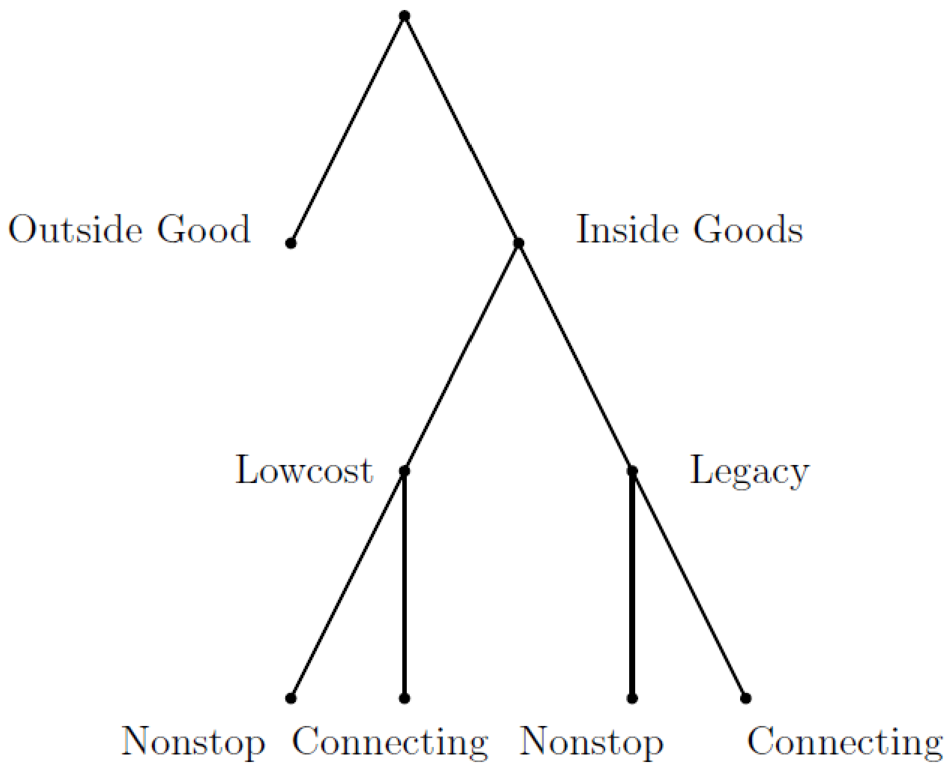

Figure 1: Nesting Structure

VARIABLES	(1) AvgFare
B737Usage	105.8***
	(0.899)
Grounding	1.515*
	(0.811)
B737MaxUsageGround	63.98***
	(21.93)
Observations	478,412

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Diff-in-diff results. Quarter-year, Ticket Carrier, City Market Fixed Effects

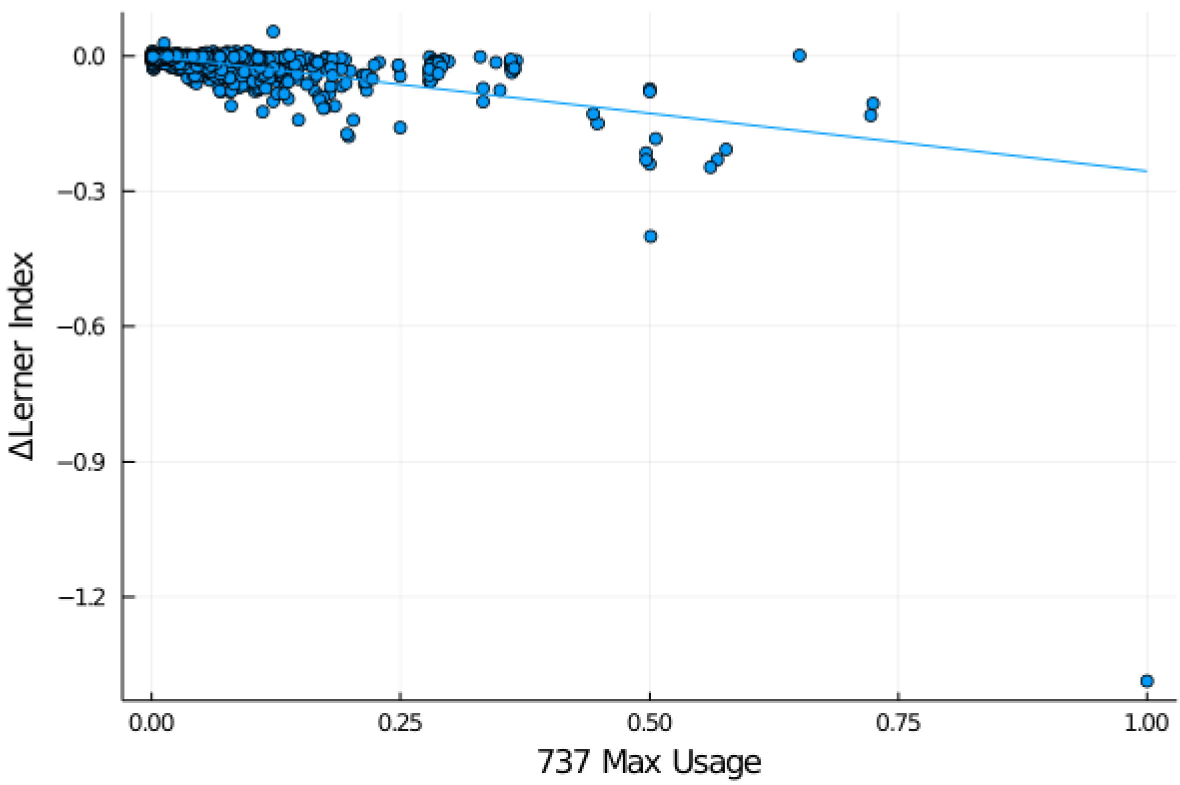

Figure 2: Change in the Lerner index for firms that use the 737 Max in Quarter 1 of 2019.

Demand		
Variable	Nested Logit with κ	Nested Logit with $\kappa = 0$
α	-0.01212 (5.26e-7)	-0.01194 (.00017)
σ_1	0.43546 (7.61e-6)	.52475 (.00506)
σ_2	0.15923 (1.63e-5)	0.11021 (.02024)
σ_3	.25766 (.00012)	.25109 (.01605)
Fare Standard Deviation ($100s)	1.14267 (00011)	1.14267 (.02214)
Route Quality	-0.17930 (8e-5)	-0.17930 (.01709)
737 Usage	0.58072 (1.65e-5)	0.58072 (.01037)
737 Usage × dDemandShock	-0.10205 (1.33e-5)	-0.10205 (.00863)
Market Distance (1000s Miles)	0.69348 (5.89e-6)	0.69348 (.01292)
Supply		
κ	0.38139 (.00444)	-
737 Max Usage	-102.68783 (.23017)	-47.49246 (18.39426)
737 Max Usage × Grounding	141.28840 (.46633)	97.23668 (19.41605)
Product Distance (1000s Miles)	96.32407 (.30511)	116.05958 (3.02197)
Product Distance Squared	-3.39936 (.02606)	-5.26972 (.35922)

Table 4:

Quarter-Year	Product Type 1	Product Type 2	Product Type 3	Product Type 4
1	16,283	25,972	11,448	111
2	19,989	29,004	11,971	120
3	20,364	28,254	11,693	120
4	19,699	27,584	12,239	130
5	17,545	23,909	14,910	145
6	21,539	29,746	12,541	129
7	21,774	28,485	11,745	116
8	20,540	28,412	11,771	124

Table 5: The number of products in each product type by Quarter-Year. 1 is all products aren't exposed, 2 has no exposure, but rivals have exposure, 3 has exposure and rivals without exposure, and 4 all products have exposure.

Quarter-Year	Product Type 2	Product Type 3	Product Type 4
1	1,936	927	4
2	2,098	947	7
3	2,009	898	6
4	2,006	963	7
5	1,760	1,221	8
6	2,224	982	6
7	2,036	892	6
8	2,075	902	6

Table 6: The number of products in each product type by Quarter-Year for markets with 95th percentile exposure. 1 is all products aren't exposed, 2 has no exposure, but rivals have exposure, 3 has exposure and rivals without exposure, and 4 all products have exposure.

25th Percentile	.7108
Median	.9443
75th Percentile	.9994
Mean	.6677

Table 7: Cost Pass-Through for carriers that used the 737 Max during Q1 2019

737 Max Usage	ΔPrice	ΔLerner Index	Δ Product Profits
1%	\$0.19	-.003	\$4,421
5%	\$5.97	-.0128	−\$85,478
10%	\$13.18	-.026	−\$197,852
25%	\$34.84	-.064	−\$534,975
50%	\$70.92	-.128	−\$1,096,846

Table 8: Counterfactual results for 737 Max Users in Quarter 1 of 2019.

	Product Types
1	No firms use the 737 Max
2	Product doesn't use the 737 Max, but has rivals use the 737 Max
3	Product use the 737 Max, and rivals that do not use the 737 Max
4	All Products in the market use the 737 Max

Table 9: Product Types

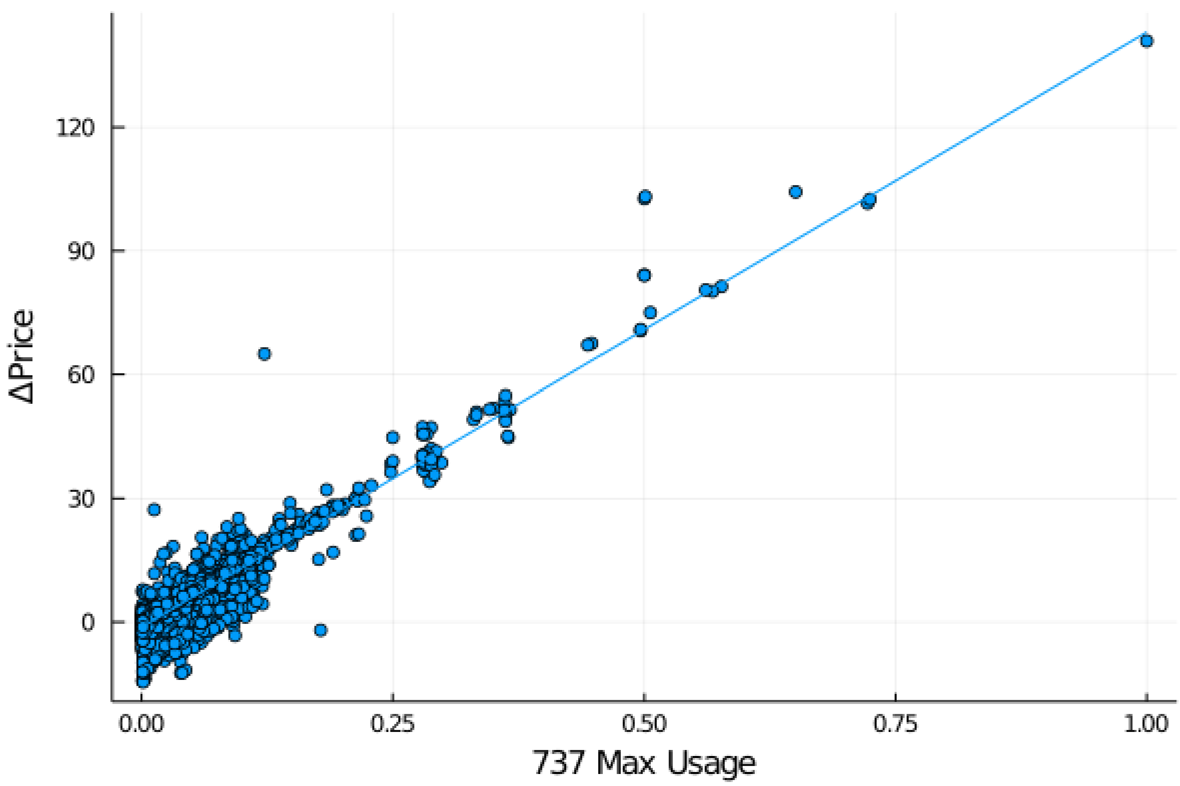

Figure 3: Change in the Price for firms that use the 737 Max in Quarter 1 of 2019.

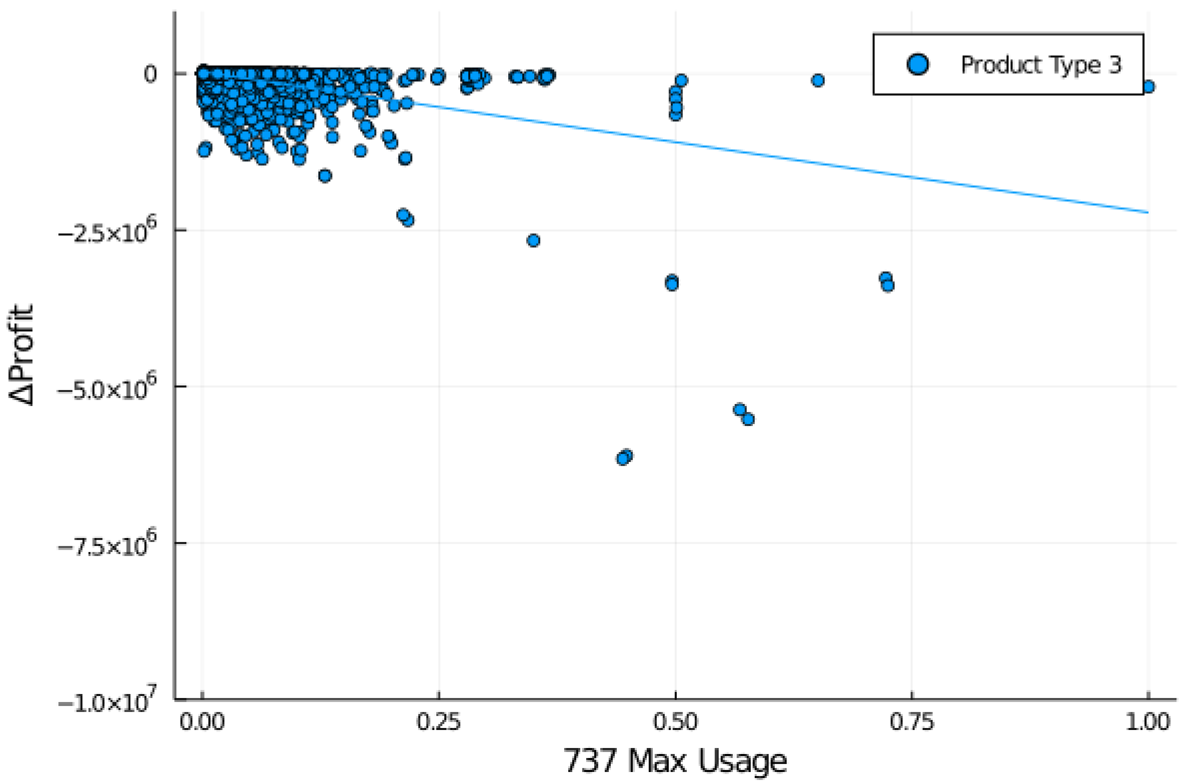

Figure 4: Change in the profit for firms that use the 737 Max in Quarter 1 of 2019.

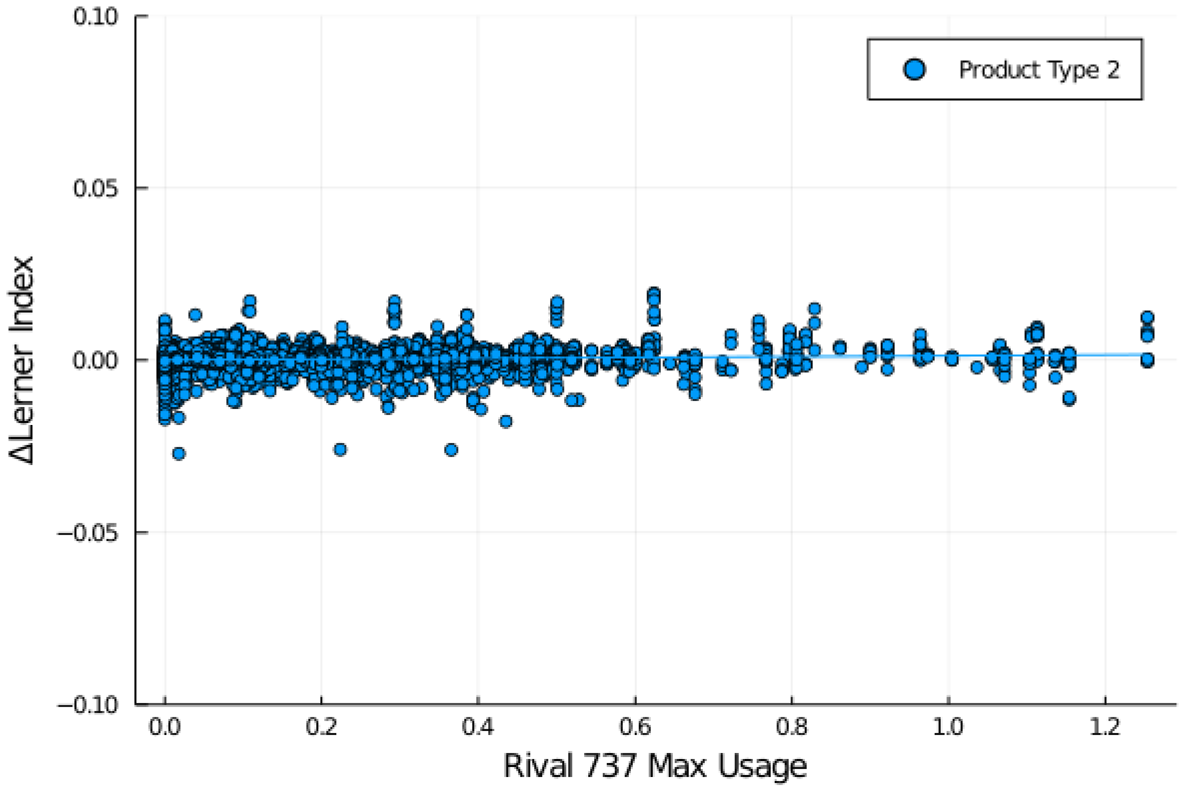

Figure 5: Change in the Lerner index for firms that had rivals that used the 737 Max in Quarter 1 of 2019.

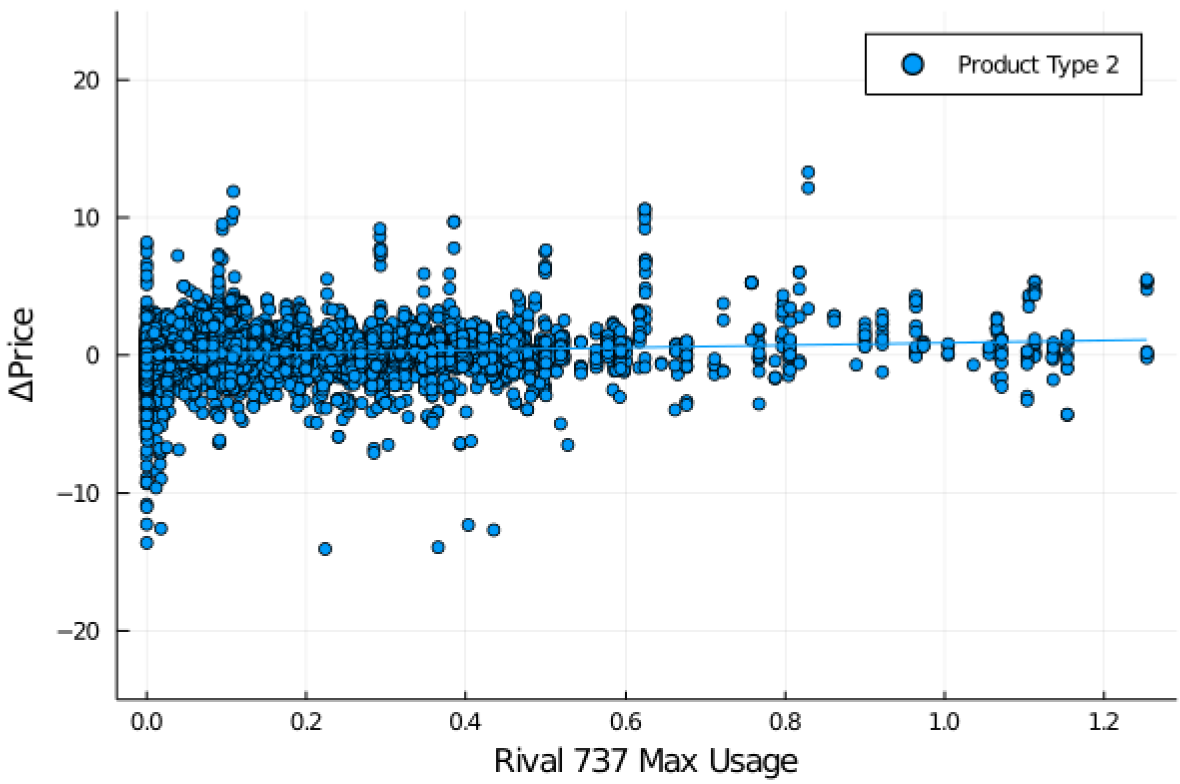

Figure 6: Change in the Price index for firms that had rivals that used the 737 Max in Quarter 1 of 2019.

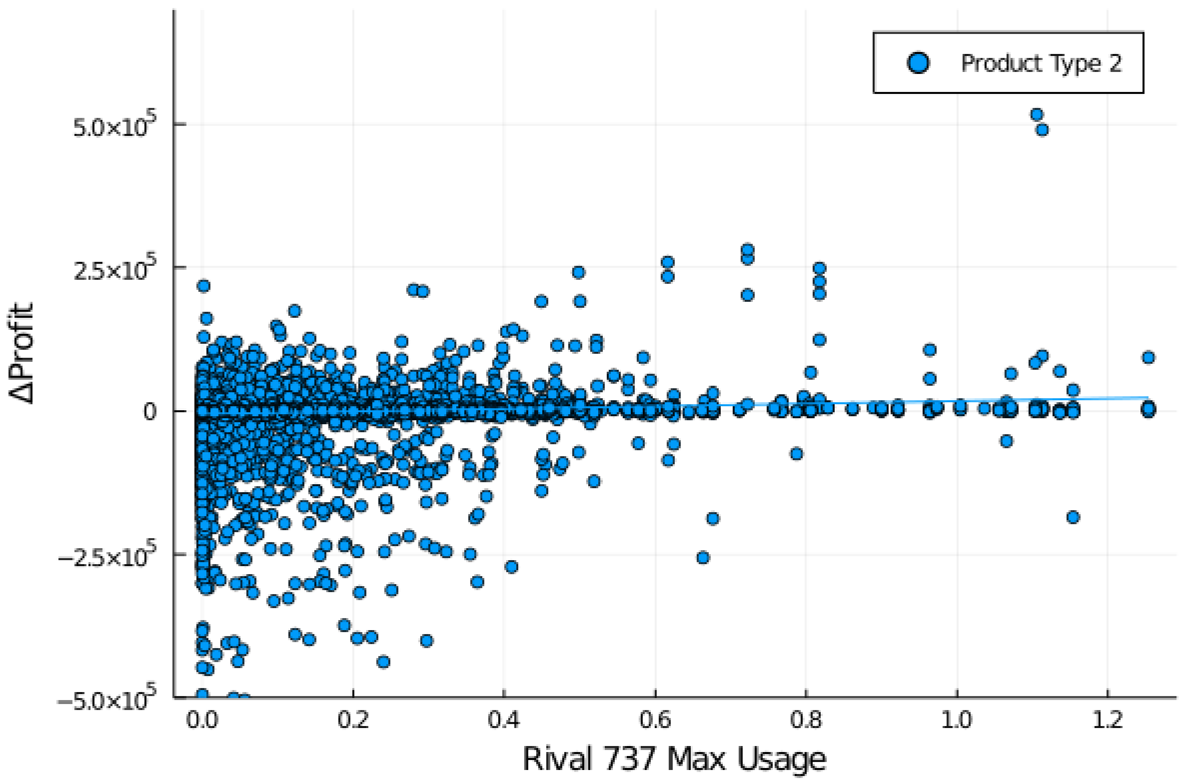

Figure 7: Change in the profit for firms that had rivals that used the 737 Max in Quarter 1 of 2019.

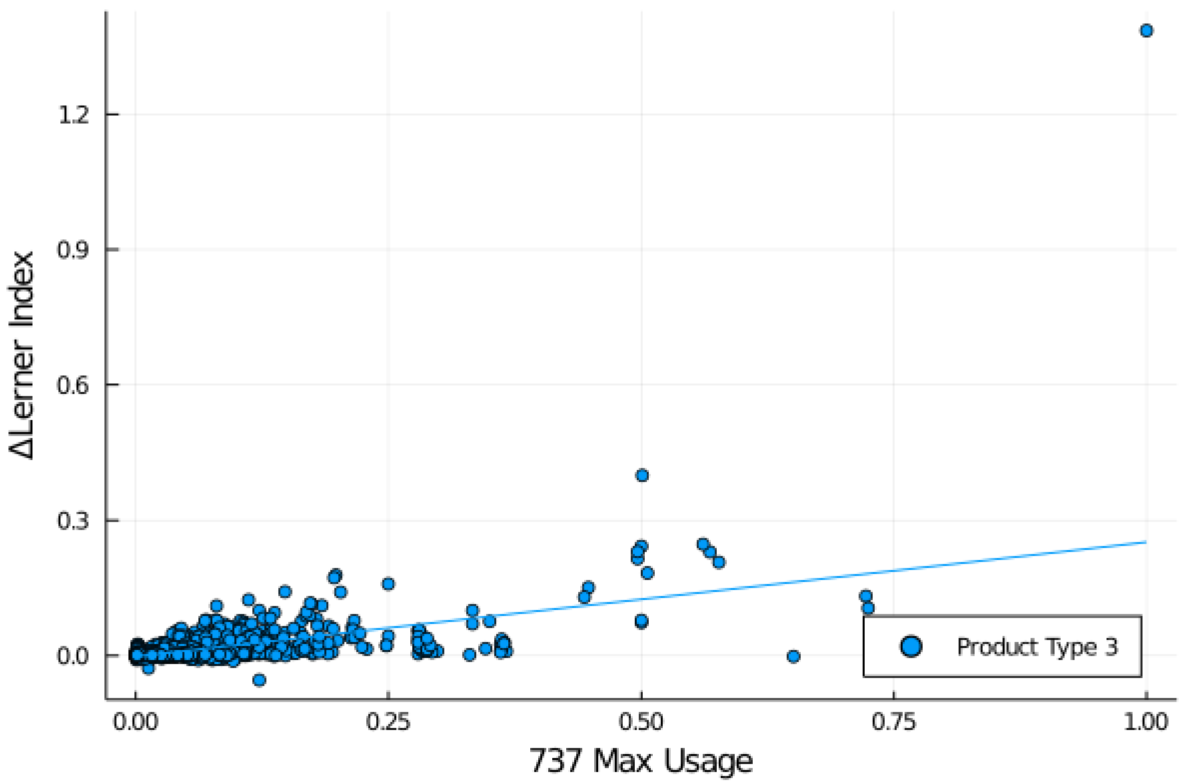

Figure 8: Difference in the change in Lerner Index for the the first counterfactual and the counterfactual where only the demand shock occurred.

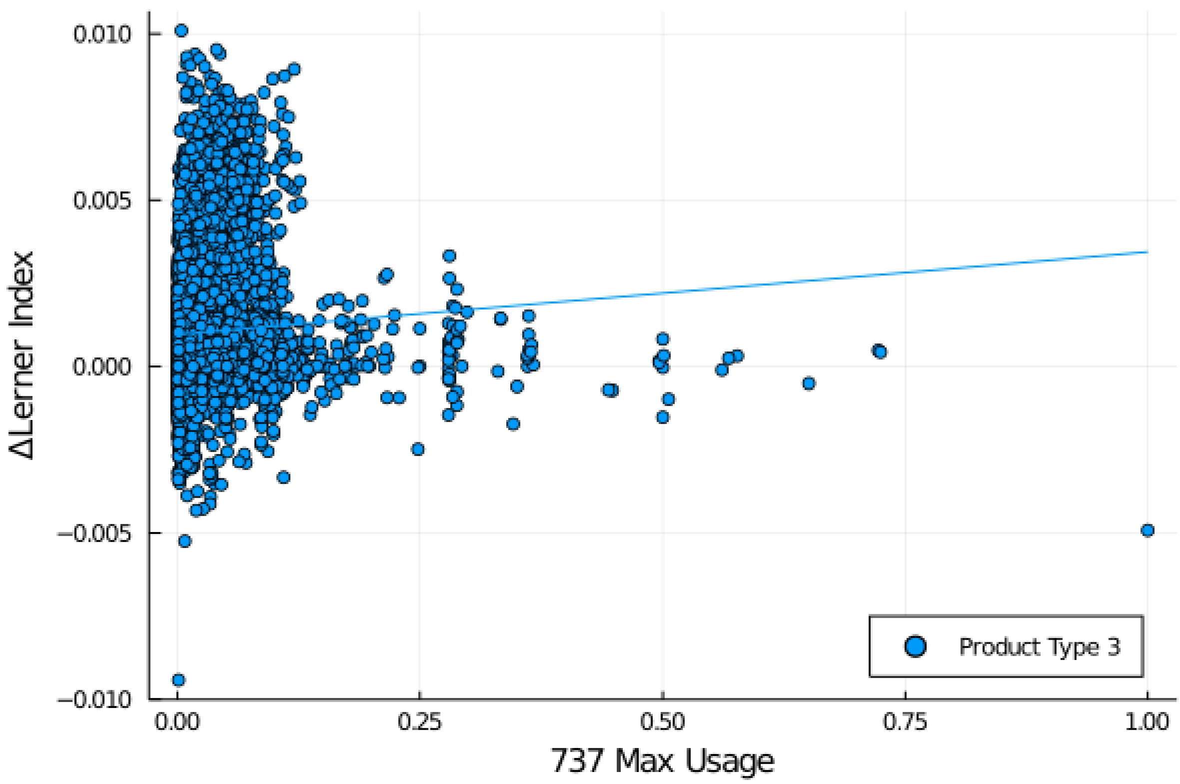

Figure 9: Difference in the change in Lerner Index for the the first counterfactual and the counterfactual where only the cost shock occurred.

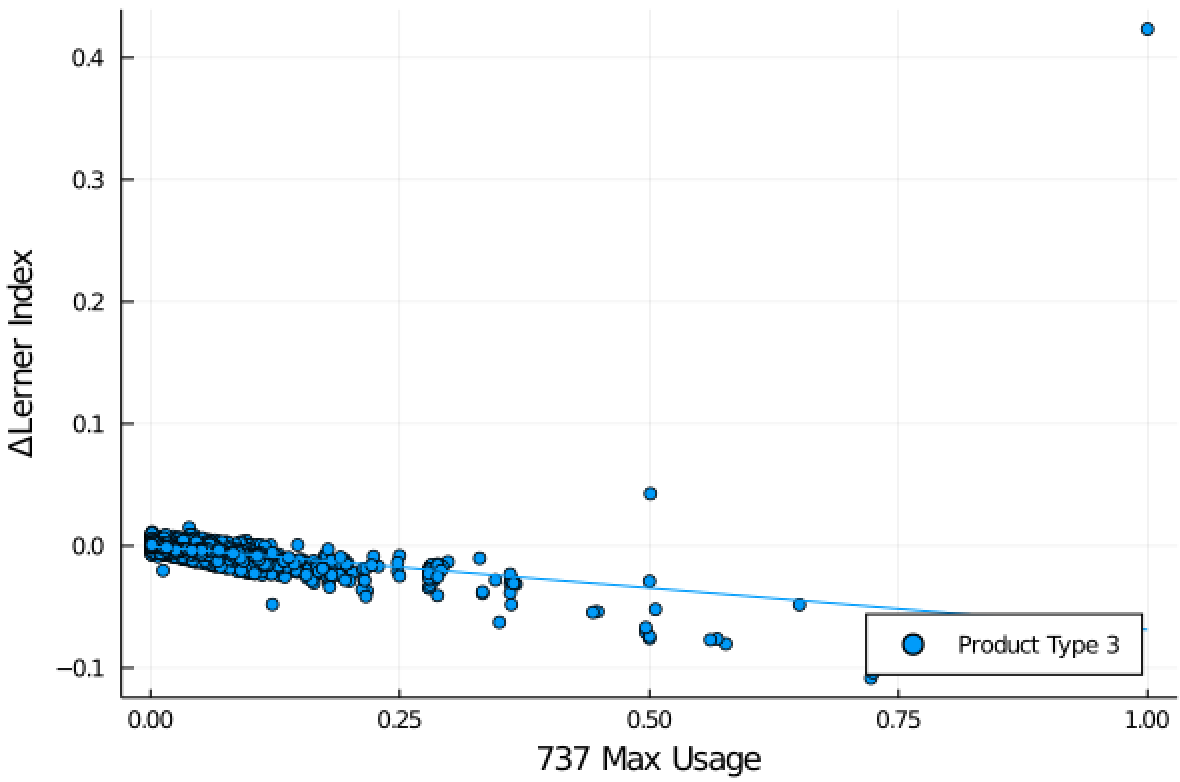

Figure 10: Difference in the change in Lerner Index for the the first counterfactual and the counterfactual where κ is forced to be 0.

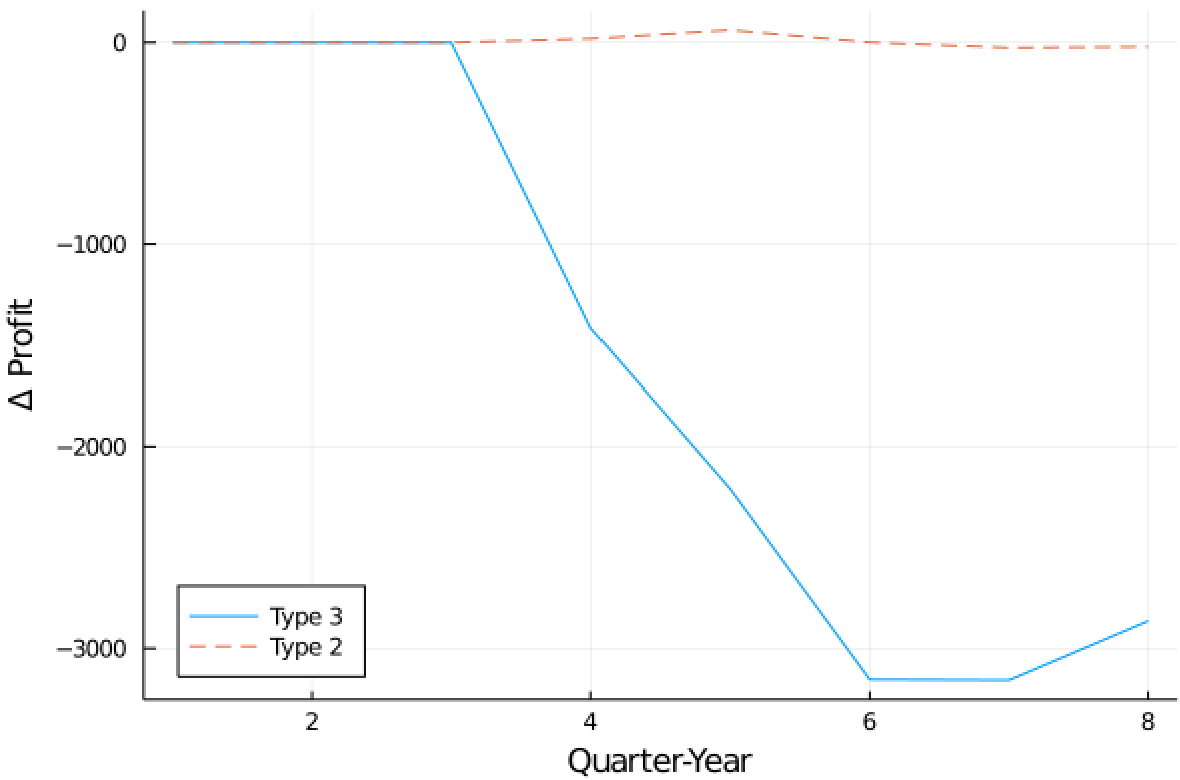

Figure 11: Median change in product profit in Quarter 1 of 2019

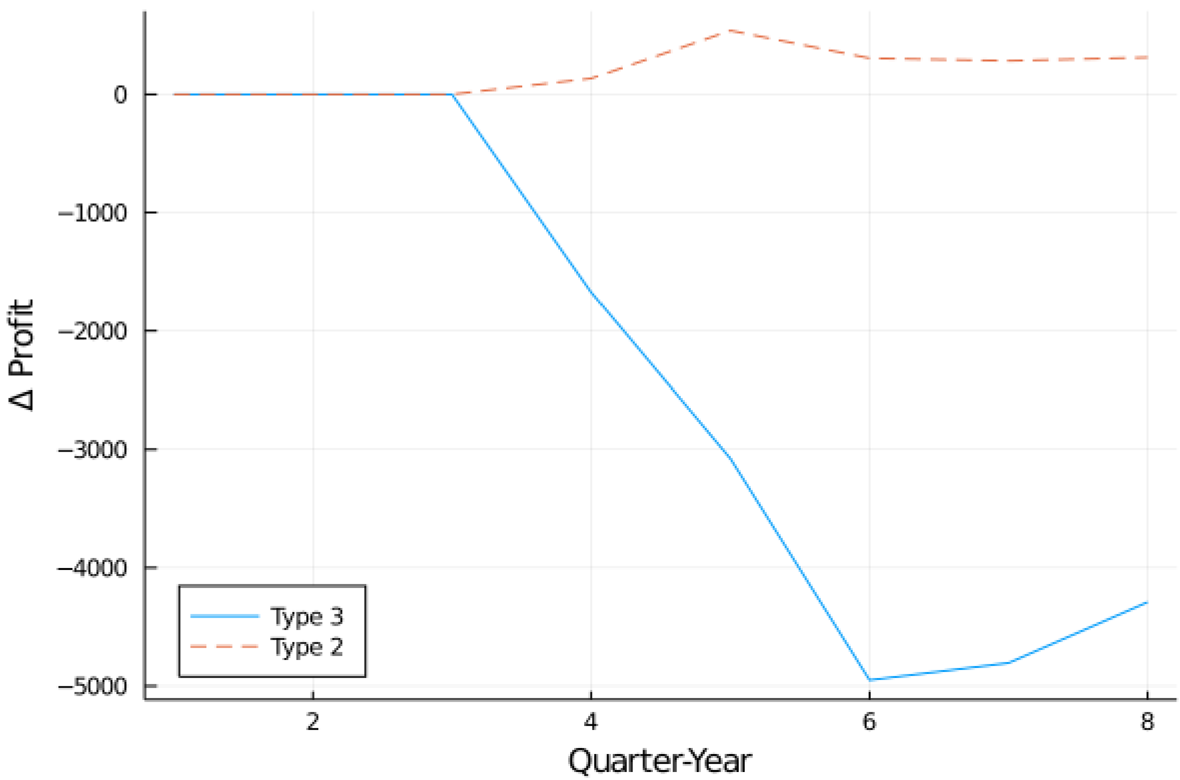

Figure 12: Median change in product profit in Quarter 1 of 2019 for markets with 95th percentile exposure to the grounding.

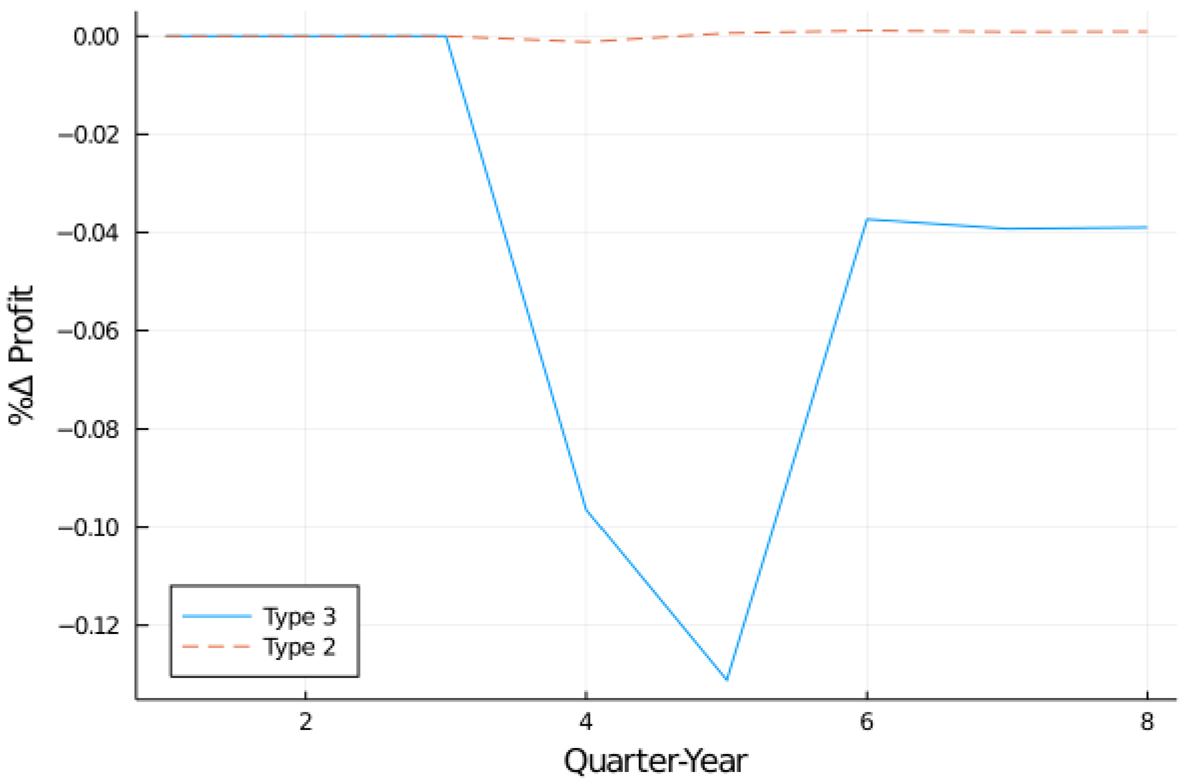

Figure 13: Median percent change in product profit

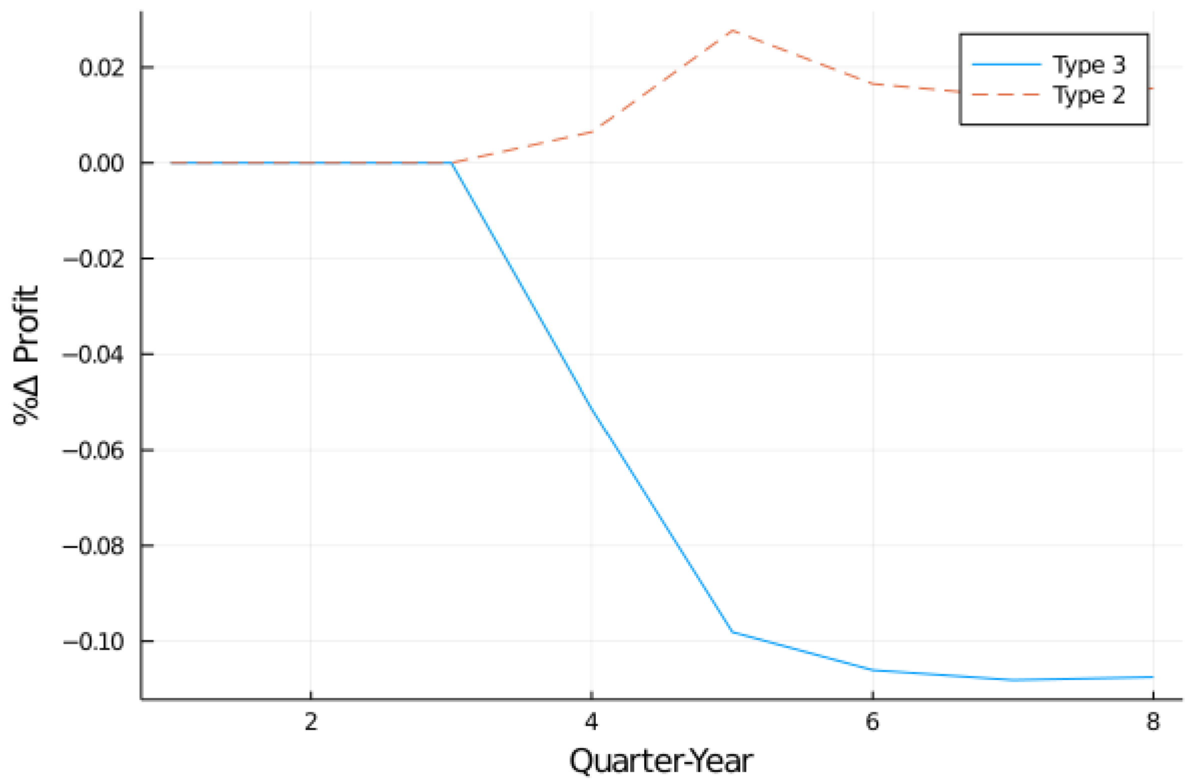

Figure 14: Median percent change in product profit for markets with 95th percentile exposure to the grounding.

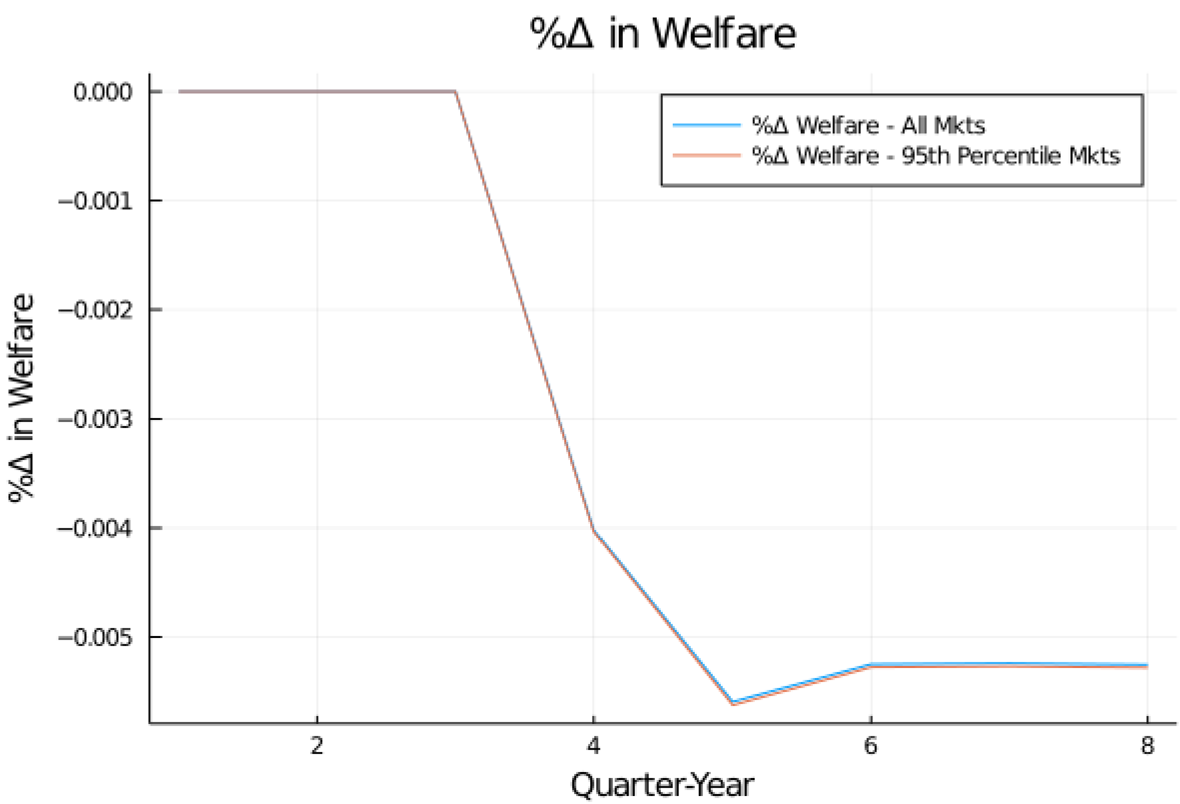

Figure 15: Median percent change in welfare as defined by inclusive values.

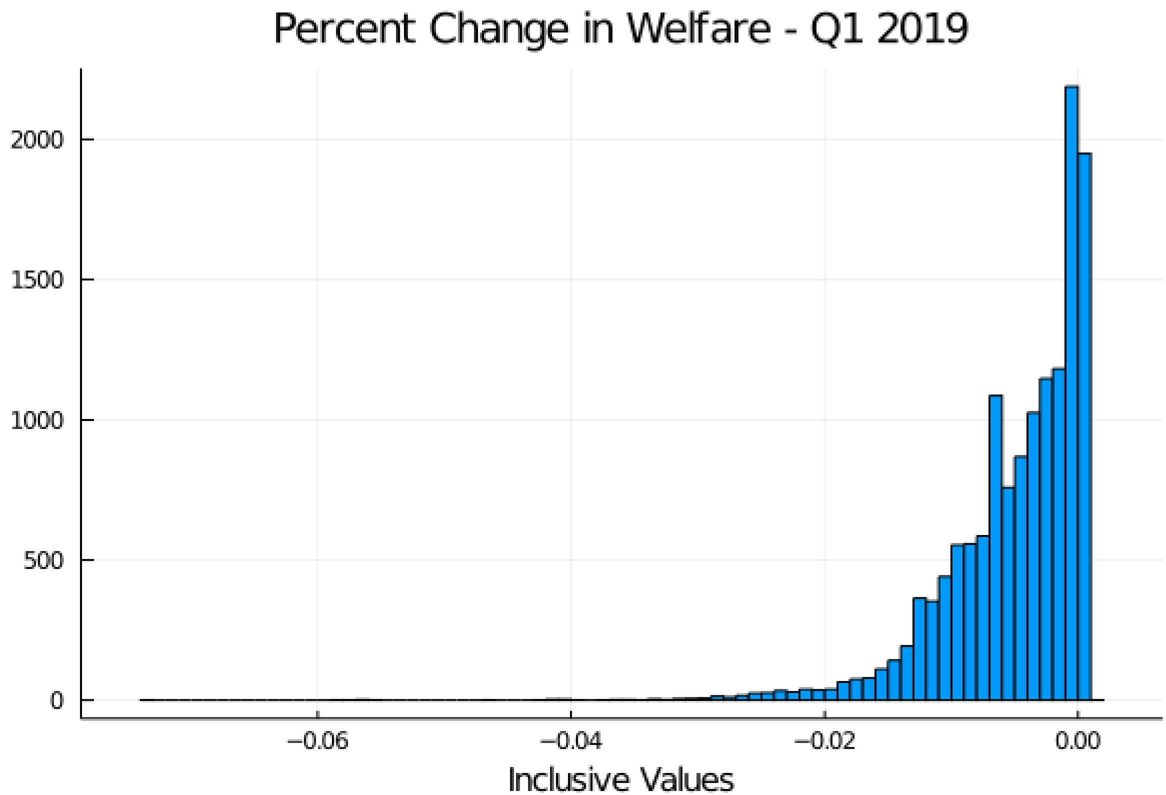

Figure 16: Change in Welfare for all products Quarter 1 of 2019.

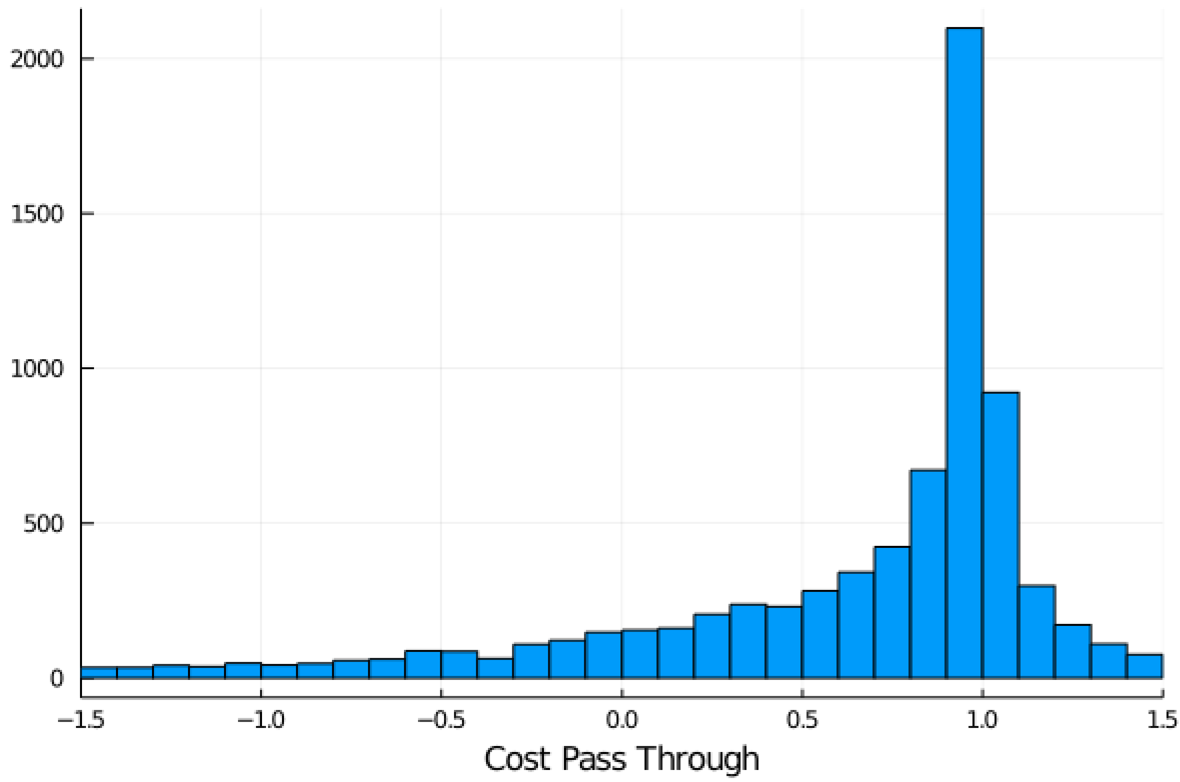

Figure 17: Cost pass-through for quarter 1 of 2019. Defined as $\frac{\Delta P}{\Delta MC}$.

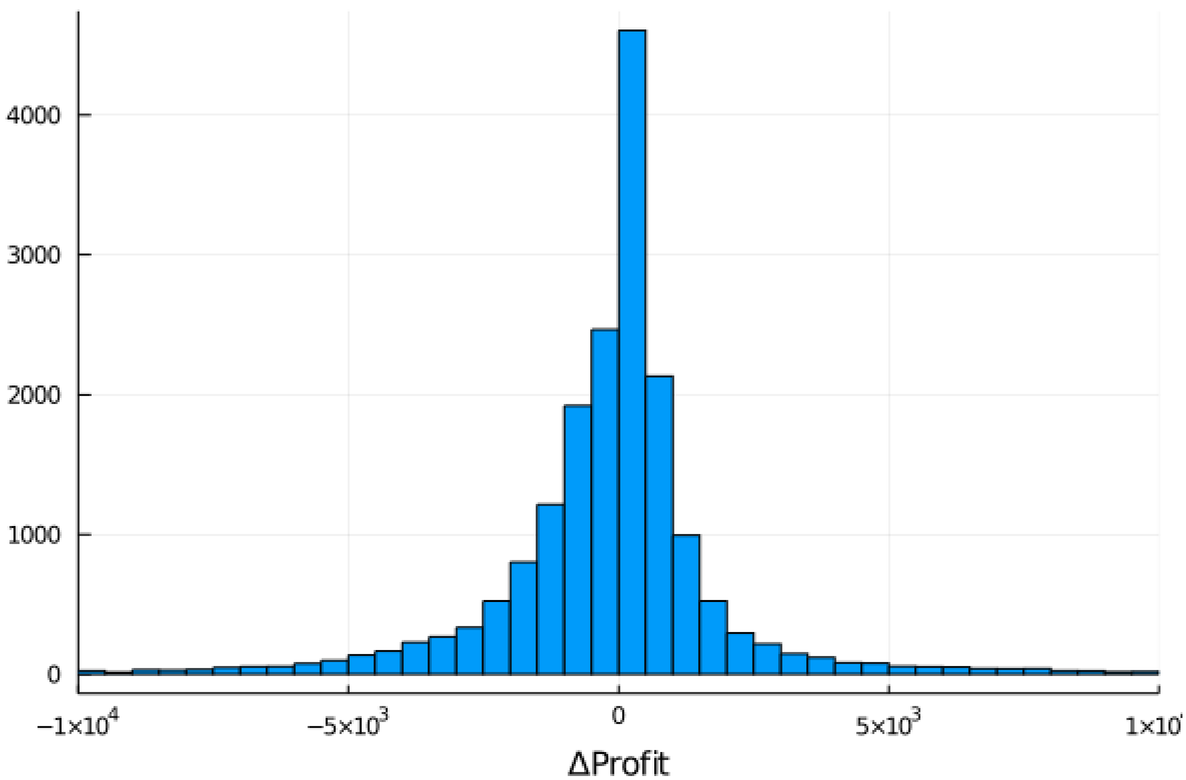

Figure 18: Change in Profits for airlines who didn't use the 737 Max in Quarter 1 of 2019.

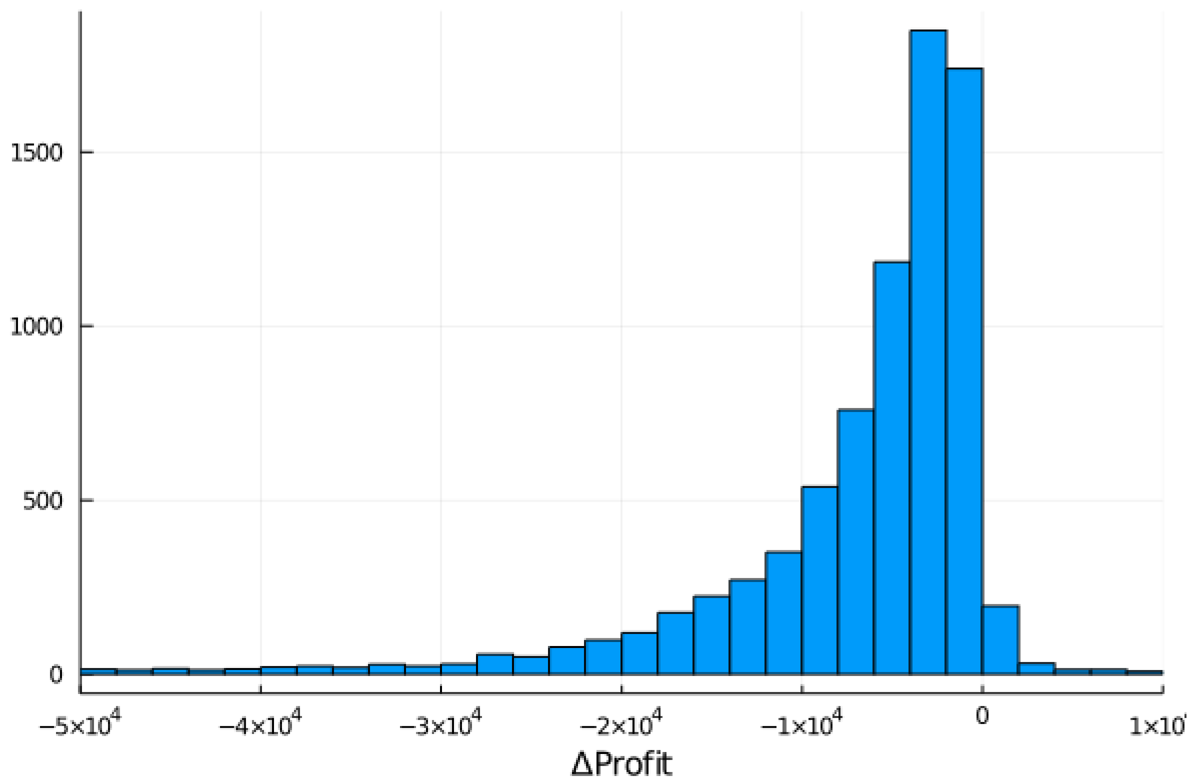

Figure 19: Change in Profits for airlines who used the 737 Max in Quarter 1 of 2019.