Zoom Calls and Revenge Travel: Pandemic-induced Changes to Demand for US Domestic Air Travel

Sean Ewen

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Abstract

The market for air travel was among the industries most affected by the COVID-19 pandemic. Business and media commentators have speculated about numerous changes to the industry including the decline of business travel and the rise of pandemic-induced "revenge travel." Empirical investigation of these claims is complicated by carriers' rising fuel and labor costs and the endogeneity of flight frequency decisions. I analyze these claims in US domestic air travel in 2022 relative to 2019 using a structural model of air travel demand that assumes heterogeneity in consumers takes two forms: business travellers and leisure travellers. I endogenize the number of daily departures on a given route to account for changes in fuel cost that may affect carriers' flight frequency decisions. I use this model to analyze claims of decreasing business travel and "revenge travel" in the wake of the COVID-19 pandemic, and their effect on airline profits. I find that both consumer "types" became less price-sensitive and average price elasticity decreased in absolute value. There was a large shift in the share of passengers from "leisure"-type to "business"-type. I interpret this as evidence that many leisure travellers behaved as business travellers during 2022 – forgoing their usual concerns about price to partake in revenge travel. I also conduct counterfactual analyses to examine the effects of these changes on airlines' profits. I show that the change in demand was relatively more important than the change in cost to for airline profits in 2022.

1 Introduction

The market for air travel was among the industries most affected by the COVID-19 pandemic. Global travel decreased drastically as many practiced social distancing to limit their exposure to the virus. Additionally, governments worldwide imposed travel restrictions into and out of their countries. The result was a 50% decrease in available airplane seats and 2.7 billion less passengers flown in the year 2020 than in 2019.[1] In the US, domestic enplanements decreased 28% between 2019 and 2020[2], provoking Congress to pass several pieces of legislation aimed at supporting the struggling industry. Over the course of 2020 and 2021, Congress authorized the Treasury to issue over $50 billion in loans to US airlines.[3] Figure 1 plots US domestic enplanements over the years 2019-2023. By 2022, enplanements had not yet fully recovered. In the last three quarters of the year, the number of enplaned domestic passengers was still 5.8% lower than the corresponding quarters in 2019 and major airlines such as American, United, and Southwest reported negative net income.[4]

On its face, this appears to be an, as yet, incomplete recovery. However, many attribute the continued weak demand and poor financial performance not only to lingering effects of pandemic restrictions, but also to a permanent change in the behavior and preferences of business travellers. These travellers are now said to substitute "Zoom" or other videoconferencing calls for meetings where travel may have once been prominent. Since the pandemic induced mass adoption of videoconferencing technology, many believe this has permanently altered the nature of business travel demand.

Decreased business travel demand is a problem for airlines, as business travellers are observed to have lower price-sensitivity than leisure travellers. On the other hand, easing of pandemic restrictions and widespread vaccination status has precipitated discussions of so-called "revenge travel."[5] This describes a phenomenon where consumers, prevented from vacationing over a long period, suddenly increase their consumption of travel to "make up for" lost vacation experiences. This suggests there may be two countervailing effects of the post-lockdown environment on air travel demand: one of decreasing price-insensitive business travel, and one of increasing price-sensitive leisure travel.

Disentangling these effects is further complicated by the fact that airlines faced significantly higher operating costs during and after the pandemic. Fuel costs rose due to geopolitical instability and carriers experienced labor shortages. The labor shortages were due in part to a pre-existing pilot shortage and in part to layoffs during the pandemic. These costs are likely to significantly effect carriers' decisions of how much to fly on a given route (their flight frequency), all else equal, so any empirical investigation needs to account for this.

In this paper, I investigate the substantial differences in the market for US domestic air travel in 2022 relative to 2019 using a structural model of air travel demand that assumes heterogeneity in consumers takes two forms: business travellers and leisure travellers. I endogenize the number of daily departures on a given route to account for changes in fuel and labor costs that may affect carriers' flight frequency decisions. I use this model to analyze claims of decreasing business travel and "revenge travel" in the wake of the COVID-19 pandemic, and their effect on airline profits. I find that both consumer "types"

[1]Source: International Civil Aviation Organization
[2]Source: Bureau of Transportation Statistics
[3]Source: US Department of the Treasury
[4]Source: Bureau of Transportation Statistics
[5]See, for example, "'Revenge travel' is surging. Here's what you need to know" by Manuela López Restrepo, from *NPR.org* (2022)

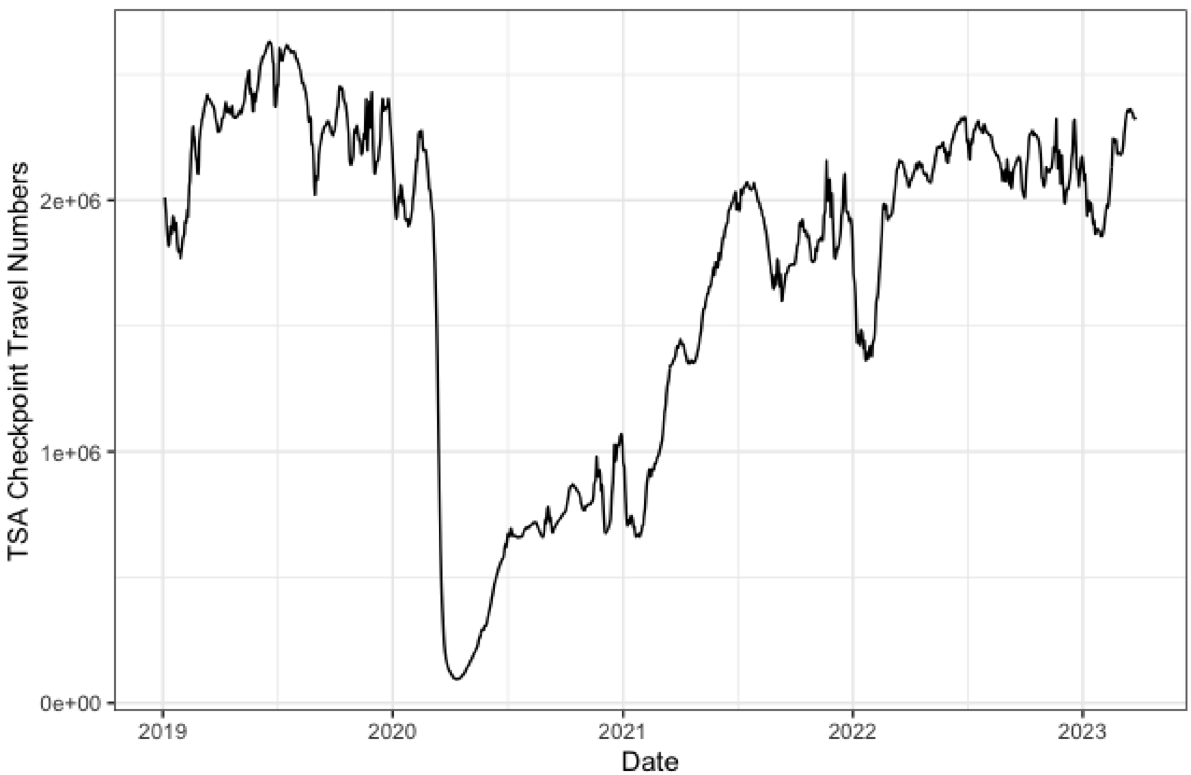

Figure 1: TSA Checkpoint Travel Numbers (7-day moving average), 2019-2023
Source: Transportation Security Administration

became less price-sensitive and average price elasticity decreased in absolute value. There was a large shift in the share of passengers from "leisure"-type to "business"-type. I interpret this as evidence that many leisure travellers behaved as business travellers during 2022 – forgoing their usual concerns about price to partake in revenge travel. I also conduct counterfactual analyses to examine the effects of these changes on airlines' profits. I show that the change in demand was relatively more important than the change in cost to for airline profits in 2022.

The paper is organized as follows: Section 2 reviews the literature, Section 3 develops the model, Section 4 describes the data, Section 5 reports results and counterfactual estimates, and Section 6 concludes.

2 Related Literature

My work contributes to two distinct strands of literature: structural models of demand and competition in air travel markets and studies concerning the impacts of the COVID-19 pandemic on economic activity. I consider each of these in turn.

Several papers have investigated demand for air travel using structural estimation methods. Most studies in this field rely on a key insight due to Berry (1990) that a carrier's presence at an airport (measured by the number of markets they serve out of that airport) is an important determinant of demand for their flights in that market. This allows researchers to use airport presence as a measure of product differentiation, facilitating the use of structural demand models. One of the seminal works in this vein is Berry, Carnall, and Spiller (2006) (BCS) who applied a random coefficients logit model in the style of Berry, Levinsohn, and Pakes (1995) (BLP) to aggregate US ticket data. Using this model, they find an airline can charge a premium for flights out of their hubs because of price-insensitive business travellers who value the airline's airport presence. They also find evidence of considerable economies of density from airlines' hub-and-spoke networks.

BCS employed two techniques that would become widely used in air travel demand estimation. The first was their decision to model consumer heterogeneity as coming from differences between two discrete types of consumers, which they interpret as business and leisure travellers. This interpretation comes from the widely documented observation that business travellers are relatively less price-sensitive and relatively more connection-averse than leisure travellers. Business travellers do not generally pay for tickets themselves, instead they may book a flight and bill their company, hence their lower responsiveness to price. The second technique used by BCS was to allow for correlation between price and unobserved ticket characteristics like advance-purchase requirements and Saturday night stayover rules (more common in the 1990's than today) by incorporating an unobserved product characteristic term into the consumer's utility function. In estimation, this is treated as a product-specific econometric error (see Berry (1994)).

My paper closely resembles work by Berry and Jia (2010). These authors estimate demand for US domestic air travel in two years, 1999 and 2006, and compare the estimates in between the two. They seek to explain the causes of legacy carriers' low profits in the first decade of the 21st century. They find that consumers became more price sensitive and more connection averse and that this accounts for most of the decrease in airlines' profits. The entry and expansion of several low-cost carriers such as Southwest and JetBlue was another contributing factor.

Ciliberto and Williams (2014) use a similar structural demand model to estimate the competition softening effects of multi-market contact. They relax the Bertrand-Nash pricing assumption common in BLP-style models and instead allow the markup to depend on an estimated "conduct parameter." This parameter summarizes the extent to which firms internalize the effects of their own pricing decisions on rivals' products. They find that this conduct parameter is positively correlated with the number of markets in which two firms compete and conclude that multi-market contact facilitates tacit collusion.

Several papers find that fixed costs and entry decisions are important aspects of competition and price setting in airline markets. This literature has roots in Berry (1992) but several developments have been made since then. For instance, Ciliberto and Tamer (2009) develop a model of entry where firms with unique identities make simultaneous entry decisions in travel markets. They estimate the payoff functions of carriers and find that legacy carriers have different "competitive effects" on rivals' profits than low-cost carriers. Ciliberto, Murry, and Tamer (2021) extend this model to one of simultaneous entry and price setting. They show that if there exists correlation between firms' fixed cost and demand unobservables, traditional demand estimation will be biased. Li et al. (2022) estimate a model of sequential product choice and price competition in airline markets. They allow firms to first choose whether to offer nonstop or connecting service, then decide on prices. They use the estimated parameters to conduct merger simulations that closely match results of observed mergers. Finally, Aguirregabiria and Ho (2012) use a dynamic model of oligopolistic competition to show that the sunk entry cost in an airline market declines with the number of flights offered out of the endpoint airports.

My model does not estimate fixed costs but rather the slope of fixed cost with respect to product characteristics. I use the method described in Fan (2013), who endogenizes product characteristic decisions in the US newspaper industry. To my knowledge, this is the first study to incorporate endogenous product characteristics to a static demand model in the airline industry. For a more general treatment of endogenous product characteristics in static demand models, see Boyoung, Seo, and Ponder (2022).

My research also relates to work on the COVID-19 pandemic and its impact on economic activity. Recent years have produced an especially large amount of work on this topic and I do not attempt a complete review here. Instead, I highlight work related to consumption during and after the lockdown phases of the pandemic. For an extensive literature review, refer to Brodeur et al. (2021).

Much pandemic-related literature has focused on the effects of the virus on consumption. Chetty et al. (2020) analyze the heterogeneity of changes in consumption at the onset of the pandemic and find that high-income individuals reduced their consumption sharply in 2020. This led to revenue and job losses for many businesses. High-wage employment experienced a sharp decline, followed by a relatively quick recovery, whereas low-wage job losses persisted into 2022.

Kapetanios et al. (2022) study policy interventions intended to encourage social distance during the pandemic and their effect on consumption. They find that, for Dutch citizens, the spread of the virus caused a drop in consumption early in the pandemic, but this effect disappears as the pandemic went on. Coibion et al. (2020) find that differential lockdown policies across US counties explain differences in expected employment, inflation, and mortgage rates. Bounie et al. (2020) use transaction and bank data from France to document virus-induced changes in consumption in the country. They find a sharp reduction in consumption in the early stages of the pandemic but a strong recovery over the following year.

Several papers from travel and marketing disciplines have also considered the specific phenomenon of "revenge spending" after social distancing phases of the pandemic. For instance, Zaman et al. (2021) survey a sample of international travellers and find a positive association between pandemic fatigue and "revenge travel" motivations. These are motivations for travel that include "escape from the psychological pressure, daily routines, and rules that resulted from the pandemic." Additionally, Gupta and Mukherjee (2022) survey a sample of Indian consumers and find that revenge buying was associated with feelings of autonomy need frustration in consumers during the pandemic.

3 Model

I consider a structural model of oligopolistic competition between airlines in the style of Berry, Levinsohn, and Pakes (1995). My model follows other demand analyses of air travel, namely BCS (2006), Berry and Jia (2010), and Ciliberto and Williams (2014). Airlines compete for travellers in markets composed of an origin and destination pair. Flight products are differentiated by fare, nonstop status, and frequency. Other variables that affect demand such as time of departure and number of days until departure at the time of purchase are unobserved and are thus modelled as a product-level unobservable. The specifics of the model are outlined below.

3.1 Demand

In what follows, consumers are indexed by i, products by j, markets by m, and time periods by t. Let J_{mt} denote the number of products in market m in time period t. There are two discrete types of consumers, with types indexed by r. For consumer i of type r in market m, at time t, utility for product j is given by

$$u_{ijmt} = x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt} + \nu_{jmt}(\lambda) + \lambda\varepsilon_{ijmt},$$

where x_{jmt} is a vector of product characteristics for product j, p_{jmt} is product fare, β_r and α_r are consumer type r's taste parameters for nonprice characteristics and price, respectively, ξ_{jm} is an unobserved (to the researcher) product characteristic, and $\nu_{jmt}(\lambda) + \lambda\varepsilon_{ijmt}$ is an error term that generates nested-logit preferences. The nesting parameter $\lambda \in [0, 1]$ governs substitution between product nests. There are two nests: one that comprises all products in a market and another that consists only of the outside good of not purchasing a flight. The deterministic portion of utility for the outside good is normalized to zero. Hence, utility from not purchasing a flight is given by

$$u_{i0mt} = \varepsilon_{i0mt},$$

where ε_{i0mt} is a logit error.

Conditional on flying, the share of type r consumers who purchase product j is

$$\frac{e^{(x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt})/\lambda}}{D_{rmt}}, \tag{1}$$

where

$$D_{rmt} = \sum_{k=1}^{J_{mt}} e^{(x_{kmt}\beta_r - \alpha_r p_{kmt} + \xi_{kmt})/\lambda}.$$

The share of type r consumers who purchase a flight is

$$\frac{D_{rmt}^{\lambda}}{1 + D_{rmt}^{\lambda}}. \tag{2}$$

Putting together equations (1) and (2) and aggregating across consumer types, the market share of product j in market m is given by

$$s_{jmt}(\mathbf{x}_{mt}, \mathbf{p}_{mt}, \xi_{jmt}, \theta_d) \equiv \sum_{r=1}^{2} \gamma_r \frac{e^{(x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt})/\lambda}}{D_{rmt}} \frac{D_{rmt}^{\lambda}}{1 + D_{rmt}^{\lambda}},$$

where γ_r is the proportion of consumers of type r in market m and $\theta_d \equiv (\beta, \alpha, \lambda, \gamma)$ is the vector of demand parameters. Following BCS (2006) and Berry and Jia (2010), γ_r is assumed to be constant across all markets.

I add carrier and time fixed effects to control for correlation in consumers' preferences within the same carrier and across time. Thus the unobserved component of mean utility for product j can be represented as

$$\Delta\xi_{jmt} = \xi_{jmt} - d_{jmt}\phi,$$

where d_{jmt} is a vector of carrier and time period dummy variables.

I can then invert the market share equation to obtain the vector of demand unobservables, $\Delta\xi_{jmt}$. Because preferences are specified as a random coefficients nested logit model, I use a modification of the BLP contraction mapping (see Grigolon and Verboven (2014) for details). Specifically, each step $T+1$ of the iteration is "dampened" by the nesting parameter, λ. For example, the $T+1$ step is calculated as

$$\Delta\xi_{jmt}^{T+1} = \Delta\xi_{jmt}^{T} + \lambda[\ln s_{jmt} - \ln s_{jmt}(\mathbf{x}_{jmt}, \mathbf{p}_{jmt}, \xi_{jmt}^{T}, \theta_d)].$$

Let z_{jmt} denote a vector of instruments. The model satisfies the moment condition

$$\mathbb{E}[\Delta\xi_{jmt}|z_{jmt}] = 0,$$

which, in turn, implies

$$\mathbb{E}[h(z_{jmt})\Delta\xi_{jmt}] = 0, \tag{3}$$

for some function $h(\cdot)$ of the instruments. Ticket fare, p_{jm}, is endogenous in this model and hence left out of the instrument vector, z_{jm}.

3.2 Supply

Airlines are assumed to compete in a static Bertrand-Nash price game. This implies that prices are set at a markup above marginal costs:

$$\mathbf{p}_{mt} = \mathbf{mc}_{mt} + \Delta^{-1}\mathbf{s}_{mt}, \tag{4}$$

where Δ is a matrix whose (j,k)-th element corresponds to

$$\Delta_{j,k} = -\frac{\partial s_j}{\partial p_k} \cdot \mathbf{1}\{\text{product } j \text{ and } k \text{ are produced by the same firm}\}.$$

Thus I can recover the market-level vector of marginal costs from the equation

$$\mathbf{mc}_{mt} = \mathbf{p}_{mt} - \Delta^{-1}\mathbf{s}_{mt}.$$

Marginal costs are then parameterized as

$$mc_{jmt} = [w_{jmt}, d_{jmt}]'\psi + \omega_{jmt},$$

where w_{jmt} is a vector of observable cost-shifters, ψ is a vector of parameters, and ω_{jmt} is a product-level structural error term.

The model implies the following moment conditions:

$$\mathbb{E}[\omega_{jmt}|z_{jmt}] = 0,$$

which, as in the demand side, are used to construct

$$\mathbb{E}[h(z_{jmt})\omega_{jmt}] = 0. \tag{5}$$

Finally, carriers' flight frequency decisions are endogenous. Let x^f_{jmt} be flight frequency for carrier j in market-quarter mt. I assume that they choose their flight frequency for each market before choosing prices, thus their first order condition for frequency sets the derivative of the profit function equal to 0. I further assume that fixed costs, FC, are a quadratic function of frequency. The optimality condition is given by

$$\frac{d\pi_{jmt}}{dx^f_{jmt}} = \sum_{k\in\mathbb{J}_\daleth}\left[\left(\frac{\partial p_{kmt}}{\partial x^f_{jmt}} - \frac{\partial mc_{jmt}}{\partial x^f_{jmt}}\right)M_{mt}s_{kmt} + (p_{kmt} - mc_{kmt})\,M_{mt}\frac{\partial s_{kmt}}{\partial x^f_{jmt}}\right] - \frac{\partial FC_{jmt}}{\partial x^f_{jmt}} \tag{6}$$

$$= \sum_{k\in\mathbb{J}_\daleth}\left[\left(\frac{\partial p_{kmt}}{\partial x^f_{jmt}} - \frac{\partial mc_{jmt}}{\partial x^f_{jmt}}\right)M_{mt}s_{kmt} + (p_{kmt} - mc_{kmt})\,M_{mt}\frac{\partial s_{kmt}}{\partial x^f_{jmt}}\right] - \tau_0 - \tau_1 x^f_{jmt} - \upsilon_{jmt} \tag{7}$$

$$= 0, \tag{8}$$

where M_{mt} is market size in market-quarter mt, τ_0 and τ_1 are fixed cost parameters to be estimated, and υ_{jmt} is a structural error. These first-order conditions imply the third and final moment condition

$$\mathbb{E}[\upsilon_{jmt}|z_{jmt}] = 0,$$

which can be taken to data with the following unconditional moment:

$$\mathbb{E}[h(z_{jmt})\upsilon_{jmt}] = 0. \tag{9}$$

Calculating the gradient $\frac{\partial p_{kmt}}{\partial x^f_{jmt}}$ in 6 is not straightforward. To do this, I follow Fan (2013) and assume the pricing function is smooth in response to changes in characteristics. I then take the derivative of 4 with respect to frequency. Since 6 is the first-order condition for the observed product characteristics, the derivative only needs to be calculated at the values of these observed characteristics.

3.3 Consumer Type Interpretation

Consumer heterogeneity is modelled by assuming each consumer is one of two types. In the air travel demand literature (BCS (2006), Berry and Jia (2010), Ciliberto and Williams (2014)), these types are interpreted as leisure and business travellers. This assumption derives from a desire to fit a documented difference in preferences between the two consumers in a parsimonious way. Leisure travellers are generally considered to be more price sensitive than business travellers and business travellers more connection averse. Thus I allow coefficients on three variables to vary with type: fare, nonstop status, and a constant.

Note that while this interpretation is convenient for my purposes, I do not have data on the actual share of business and leisure travellers. More generally, the types can be considered price sensitive and non-price sensitive types, respectively.

4 Data

The data I use comes from three sources. The first is the DB1B Origin and Destination Survey, a 10% sample of all domestic airline tickets in the US for a given quarter published by the Bureau of Transportation Statistics (BTS). The DB1B contains data on individual tickets including the fare, connection, and ticketing and operating carriers. The second source is the Airline On-Time Performance Data, also published by the BTS, from which I derive a measure of flight frequency. Finally, demographic data comes from US Census Bureau.

4.1 Sample Selection

I use data from the second, third, and fourth quarters of 2019 and 2022. This allows me to compare demand from before the pandemic, with demand after leisure travel is said to have mostly recovered.[6] Using data from multiple quarters allows for more heterogeneity in choice sets, which aids in identifying the type parameter, γ_r.

I drop tickets with unrealistic fares such as those below \$30 or above \$3000 or whose credibility has been questioned by the BTS. I also drop itineraries with more than one ticketing carrier, more than 2 connections on a leg, or those that include ground transportation. Finally, I drop carriers from markets that do not represent a competitive presence in that market. In practice, this means I drop carriers that transport less than 100 passengers in a market-quarter.

I define a market as a directional trip between two airports. Thus SEA-JFK is a different market than JFK-SEA. I restrict attention to airports in metropolitan areas with populations greater than 1 million. I also focus on markets whose endpoints are at least 150 miles apart. On-Time Performance Data contains carriers with at least 0.5% of all domestic service scheduled passenger revenue. The only carrier that

[6] See Belaich and Pisani-Ferry (2022) for evidence of this claim

does not meet this threshold but has a significant market share in the data is Sun Country, which has a hub at the Minneapolis-St. Paul airport. Thus I drop markets that involve Minneapolis-St.Paul as one of the endpoints. Finally, if a metropolitan area has more than one airport, I treat each as part of a separate market.

4.2 Product Definition

A product is a unique combination of carrier, fare, and nonstop status. A carrier can offer at most two products in a market, a nonstop flight and a connecting flight. Unlike Berry and Jia (2010), products are not differentiated by connecting airport. Also unlike Berry and Jia (2010), who account for product heterogeneity by creating separate products for different fare values, I follow Ciliberto and Williams (2014) and define a product's fare to be the mean fare over all tickets sold by the carrier in the market for a given nonstop status. I use this definition because the Berry and Jia (2010) definition is prone to a selection problem where demand shocks induce entry for certain products. Thus, due to Ciliberto, Murry, and Tamer (2021), estimation will be biased under this product definition.

4.3 Exogenous Variables

Nonprice variables are flight frequency, the size of a carrier's network, market distance, hub status of the endpoint airports, whether either of the endpoint airports is slot-controlled, and the number of nonstop markets served out of the endpoint airports. Flight frequency is measured as the number of daily departures in a quarter, as reported in the BTS Airline On-Time Performance data. For connecting flights, I measure frequency as follows: for an observed itinerary leg between airports A and C, connecting through airport B, if a flight departs B for C at least 45 minutes and no more than 4 hours after a flight arrives at B from A, I count it as one connecting departure from A to C. I then sum over all such combinations to find a measure of connecting frequency. If there are multiple possible connections after the flight from A to B, I only count one.

As is well documented in the air travel literature (see e.g. Berry (1992)), the size of a carrier's network at a particular airport is an important determinant of demand for that carrier. This is due to the value of frequent flyer miles for that carrier operating out of that airport. Thus I incorporate network size into consumers' utility. In constructing the network size variable for a particular carrier-airport pair, I follow Aguirregabiria and Ho (2012) and sum over the populations of the endpoints of every market served by the carrier out of that airport. Defining network size in this way serves two purposes: 1) higher population areas are likely to be visited more frequently and thus matter more as a destination to consumers who may be deciding which frequent flyer program to join, and 2) it is less correlated with the number of nonstop destinations served out of an airport than is the number of total markets served. This second point allows me to use the number of nonstop destinations served out of the endpoint airports in a market as supply side cost shifters.

I include both distance and its square. It is widely recognized in air travel demand estimation that air travel demand's response to distance is hump-shaped (see e.g. Berry and Jia (2010)). At short distances, air travel competes more heavily with other forms of transportation, such as bus and rail, than at long distances. In addition, when the length of travel is too long, travel itself becomes less desirable.

Hub status and slot-controlled status are dummy variables equal to one if either endpoint is a hub or slot-controlled, respectively. Flying through a hub airport could plausibly impact the marginal cost of a product either positively or negatively. If hubs are very congested, flying through a hub may increase marginal cost. If hubs lead to economies of density (as estimated in BCS (2006)), flying through one could decrease marginal cost. If an airport is slot-controlled, this means the Federal Aviation Administration assigns carriers certain time slots to take off and land. Slot-controlled airports have high traffic and are capacity-constrained, thus flying through one should increase marginal cost.

I use the number of nonstop destinations served out of the endpoint airports as determinants of supply. The justification for this is that the more destinations offered at a certain airport, the more the carrier must pay in personnel costs and gates. I also include a dummy variable in the cost equation that is equal to one when a market is less than 1,500 miles. This is because carriers use different planes and perhaps regional codeshare partners for short distance flights (Forbes and Lederman (2007)).

Finally, I follow standard practice in transportation demand studies and define the market size as the geometric mean of the metropolitan populations at the endpoints in the market.[7]

I take all nonprice variables as exogenous.[8] This assumption is true when equilibrium is a result of a game where carriers first decide on product characteristics and then decide on price. This also assumes that carriers take the network structure as given. This assumption seems reasonable given the large fixed costs that go into creating and maintaining a hub. A carrier is unlikely to substantially change its network in response to a competitor's price change in a single market.

Tables 1 and 2 report summary statistics by year for products and markets, respectively. Means and standard deviations are broadly similar between both years. The exceptions are the daily departures and passengers variables, which decreased significantly from 2019 to 2022. There are 55,150 total products in 13,129 market-quarters in 2019 and 58,152 products in 13,580 market-quarters in 2022.

Table 3 reports summary statistics by carrier. Most carriers increased their fares slightly from 2019 to 2022 with small increases in dispersion. Carriers entered about the same number of markets, except for Southwest, which enters considerably more markets in 2022.

[7]For an alternative measure of market size, see Li et al. (2022)

[8]Berry and Jia (2010) model flight frequency as an endogenous variable. I find this assumption does not make a significant difference in my parameter estimates

	2019		2022	
Statistic	Mean	SD	Mean	SD
Fare (2022 $100)	2.83	0.92	2.82	1.02
Market share	0.001	0.002	0.001	0.002
Daily departures	7.66	7.80	5.98	6.25
Origin network size (10 million people)	27.82	7.93	27.79	7.49
Dest. network size (10 million people)	27.84	7.90	27.79	7.48
Nonstop	0.23	0.42	0.23	0.42
Distance (thousands of miles)	1.26	0.66	1.26	0.65
Hub	0.24	0.42	0.23	0.42
Slot	0.08	0.27	0.08	0.27
Obs.	65,016		65,610	

Table 1: Product characteristics means and standard deviations.
Notes: Network size is the sum of populations at the endpoints of each market the carrier serves out of that airport. Hub = 1 if either endpoint is a hub for the carrier that owns the product. Slot = 1 if either endpoint is a slot-controlled airport.

	2019		2022	
Statistic	Mean	SD	Mean	SD
Products	3.85	2.14	3.99	2.23
Carriers	3.29	1.59	3.41	1.66
Passengers (thousands)	16.59	28.92	15.79	26.70
Nonstop passengers (thousands)	13.99	28.31	13.28	26.13
Market size (millions)	3.54	2.45	3.60	2.48
Market-Quarters	16,866		16,445	

Table 2: Market characteristics means and standard deviations

4.4 Instruments

Price is an endogenous variable in my model and must be instrumented for. As instruments, I use BLP-style "markup shifters" that serve as measures of a product's isolation in the characteristics space. These are:

- The exogenous product characteristics, x_j
- The exogenous cost shifters, w_j
- The sums of rival network size, nonstop frequency, and connecting frequency
- Route-level variables such as the number of carriers in a market, the number of low-cost carriers in a market, the number of nonstop products in a market, and the market size

These are correlated with price through their competitive impact on a product's markup, but are uncorrelated with the unobserved component of utility, thus valid instruments.

Carrier	2019			2022		
	# of Markets	Mean Fare	SD Fare	# of Markets	Mean Fare	SD Fare
American	13,824	2.79	0.74	13,125	2.81	0.79
Alaska	1,301	2.22	0.70	1,293	2.49	0.76
JetBlue	1,480	2.35	0.78	1,663	2.29	0.90
Delta	12,551	2.75	0.81	12,112	2.85	0.93
Frontier	2,850	0.98	0.24	2,992	1.06	0.32
Allegiant	660	0.95	0.22	747	0.95	0.24
Spirit	2,059	0.93	0.23	2,700	1.18	0.38
United	10,713	2.85	0.76	10,078	2.80	0.88
Southwest	10,096	2.13	0.51	11,393	1.95	0.61

Table 3: Carrier summary statistics
Note: Mean and standard deviation of fare is weighted by passenger

4.5 Model Limitations

The model has several limitations. One, pointed out by Berry and Jia (2010), is it cannot account for differences in price due to airlines' revenue management pricing strategies. In short, revenue management implies that airlines intertemporally price discriminate – they sell a fixed number of seats for a low price, then raise the price as more seats are sold.[9]. This, along with other ticket characteristics that certainly affect demand, such as time and day of the week of the flight, are not observed in my dataset. Thus, I assume that any impact this has on mean fares is captured by the unobserved product characteristic term, ξ_j.

Second, I do not observe the consumer's choice set. It is probable that all products observed in a market will not be available to a consumer at the time of purchase. Furthermore, the prices in a consumer's choice set likely differ from the mean fares I calculate in my dataset. Unobserved product availability will likely bias my coefficient estimates. I follow Berry and Jia (2010) and assume that product availability is also captured by the unobserved product characterisitics term. Those authors show that the bias due to this assumption is likely to be small when the share of the outside good is large, as is the case here.

Finally, my model does not allow me to estimate fixed costs. Only the slope of the fixed cost equation with respect to frequency is estimable. This is problematic for two reasons. The first is that estimates of profit can only be interpreted as variable profits. The second and more substantial concern is that if fixed costs are correlated with the demand shock, ξ_j, parameter estimates will be biased. This is due to a selection problem where firms with both low fixed costs and high demand shocks enter the market. Assuming ξ_j is conditionally mean zero is hence violated. Although this is a concern in airline markets,[10] I have roughly the same number of products per market in 2019 and 2022 with about the same amount

[9]For an empirical investigation of the welfare effects of these strategies, see Lazarev (2013)
[10]See Ciliberto et al. (2021) for a discussion on this point.

of dispersion. This suggests that entry rates are not significantly different between the two years and that parameter estimates should still be broadly comparable.

5 Results

In this section, I present estimates of the parameters of the model in Section 3, along with elasticities and profits, followed by counterfactual analyses. I estimate the model by first forming the sample analogues of the moments in (3) and (9). I then stack the moments and perform two-step GMM to recover the parameter estimates. I allow for arbitrary correlation between the demand and supply unobservables within markets. In practice, this affects the construction of the second step weight matrix and calculation of the standard errors. In what follows, I interpret the first consumer type as the "leisure" or price-sensitive type.

5.1 Demand Parameters

Corresponding with the conventional wisdom that business travel demand has weakened since the pandemic, I expect the coefficient on fare for the business type to be larger in absolute value in 2022. I also expect the type parameter, γ, which is interpreted as the share of leisure travellers, to be larger in 2022. This is associated with a scenario where business-type consumers drop out of the market and leisure-types enter the market.

I also expect results to be similar to previous demand estimation studies in finding that utility for all consumers increases with a nonstop flight, network size, and the number of daily departures. Utility is expected to respond to distance following an upside-down parabola, as air travel competes with ground travel at short distances, and travel becomes undesirable at long distances.

Finally, note that coefficient estimates are, in general, not comparable across logit models estimated on different data. This is because the parameters indicate the importance of a variable to a consumer's decision *relative to the unexplained variance in their decision.* Since I estimate two models in broadly the same markets for different time periods, I expect the magnitudes of the coefficients to be similar. However, comparisons should be interpreted as rough approximations to the actual differences. I report more rigorous comparisons below using elasticity estimates.

Columns 2 and 3 of Table **??** report demand parameter estimates for 2019 and 2022, respectively. For both consumer types, the fare coefficient decreased. Leisure-type consumers saw a drop from -4.48 to -5.38 and business-type from -0.51 to -0.34. This suggests that consumers across the board became more price sensitive. The coefficient on nonstop is positive for both types in both years but decreases significantly between the years for the leisure type.

Estimates of the type parameter, γ, differ significantly from my expectations. While the values of the coefficients of the share equation are not particularly informative, they imply that 31% of passengers were leisure travellers in 2019 and only 8% were leisure travellers in 2022. The Bureau of Transportation Statistics reports thatn roughly 20% of domestic air travellers are traveling for business so this result casts doubt on the interpretation of the two types as leisure and business travellers. Instead, this can be rationalized with a situation where both business and leisure types were relatively price insensitive in the strong macroeconomic environment of 2019. After the pandemic shock, a small group of travellers became much more price sensitive, whereas another group of travellers undertook "revenge spending," which is described by Nguyen and Chao (2021) as a "situation in which the demand for specific goods and services suddenly skyrockets and remains high for an extended period of time." This is commonly attributed to demand for goods and services after the pandemic as consumers who saved during the lockdown phases of the pandemic increase their consumption heavily after the lockdown phases end. In this scenario, the consumer types lose their interpretation as leisure and business travellers and are more appropriately described as price-sensitive and price-insensitive types, respectively.

The nesting parameter changed significantly, as well. In 2019, it was 0.72 while in 2022 it was 0.84, suggesting that flight products became less close substitutes for each other in 2022. This, along with a decrease in the magnitude of the coefficient on flight frequency, may be because of carriers offering less flights in 2022. Consumers may have a particular flight schedule in mind and only purchase flights on that schedule.

Other demand parameters – network size, distance, and its square – all had the expected sign. Marginal utility from distance became negative at around 5,400 miles in 2019 and around 2,100 miles in 2022, suggesting consumers valued shorter trips in 2022.

5.2 Cost Parameters

Marginal cost is specified as a linear function of eight variables: distance, nonstop status, the number of daily departures, the number of nonstop destinations the carrier flies to out of both endpoints and short-distance, hub, and slot-controlled dummy variables. I have strong expectations for the signs of three cost-side parameters: distance, slot-controlled dummy variable, and short dummy variable. I expect marginal cost to increase with distance and slot-controlled airports as the amount of fuel required is higher for longer distance flights and slot-controlled airports are more highly congested so there are probably higher landing fees.

Fixed costs are assumed to be quadratic in the number of daily departures. I estimate the slope of the fixed cost function at the observed characteristics, which is expected to be positive. Carriers are expected to have higher costs of maintaining airport gates, higher payroll, and higher opportunity cost of the use of planes when they have higher flight frequency on a given route.

Marginal costs may either increase or decrease with hub, daily departures, destinations, and nonstop status. Carriers may be able to capture higher economies of density with hubs and other airports where they have large operations but they may also have higher personnel and/or gate costs at these airports. Similarly, economies of density may also be captured from connecting flights or increased flight frequency but a large fraction fuel is consumed during takeoff and landing. So increased flights – whether by the scale of operation or through more connections – may increase marginal costs.

Cost-side parameter estimates are reported in columns 4 and 5 of Table **??**. Signs are largely as expected, save for short, which one would expect to decrease marginal costs. Coefficients on distance, nonstop, daily departures, and extra miles increased from 2019 to 2022. This is expected if fuel costs are higher in 2022 than 2019. Interestingly, signs change the constant and slot-controlled airports between 2019 and 2022. The coefficient on hub is also not significant in 2022. Together, these tell a story of flights out of large, connected airports becoming less costly in 2022. Finally, the coefficients for the slope of fixed costs are small but significant. In addition, increasing daily departures increases fixed costs over the relevant range for both years. The effect is small, most likely due to the fact that most of the cost of daily departures is conceptualized as moarginal cost.

5.3 Elasticities and Marginal Costs

Elasticity estimates are given in the first three rows of Table 6. Two price elasticities are reported: the aggregate price elasticity, which is the percent change in demand for all products if the price of all products rise by 1%, and the median product price elasticity. These largely confirm the findings discussed over the demand parameters. Aggregate price elasticity rose from -2.87 to -1.17. Type 1 elasticity increased from -6.48 to -5.24 and the corresponding values for the type 2 consumer are -1.32 and -0.81. Median price elasticities are much smaller, as we would expect due to the effect of competition. My overall price elasticities are within the range of those found in Berry and Jia (2010) and Ciliberto and Williams (2014).

Nonstop semielasticity is defined as the percentage change in demand when the nonstop variable of a flight product is changed from 0 to 1 and estimates are reported in rows 4-6 of Table 6. An increase in overall nonstop semielasticity from 2.32 in 2019 to 5.25 in 2022 indicates that consumers cared relatively more about taking nonstop flights in 2022 than they did in 2019. This could perhaps be explained by consumers being more averse to spending time in airports in 2022. Consumers may perceive airports as places with a large risk of COVID-19 transmission and so wish to avoid exposure by taking more nonstop flights. Broken down by type, the more price sensitive consumer was relatively less likely to value nonstop flights than the price-insensitive consumer (semielasticities of 0.20 and 13.26 in 2019 and 0.79 and 10.57 in 2022). It is apparent that the increase in willingness-to-pay for nonstop flights in 2022 is driven primarily by the shift from price-sensitive to price-insensitive consumers.

Estimates of marginal costs are reported in the last three rows of Table 6. Average marginal costs decreased from 2019 to 2022 from 181 to 53. Marginal costs are higher for connecting flights than for nonstop flights. The decrease in marginal costs as well as the presence of a large number of negative marginal costs in 2022 raises the concern of misspecification of the markup equation for that year. It's plausible that in the high fuel cost, labor-constrained environment of 2022, costs are not well fit by the supply side of the model. More research is needed to investigate this finding.

5.4 Profits

Estimated average variable profits per market for both years are reported by carrier in Table 7. Despite large changes to demand and supply during the period, average profits increased 118% across all carriers between 2019 and 2022. Most of the legacy carriers[11] and Southwest experienced increases in average profit between the two years. Low-cost carriers saw only small changes in average profits. Note, however, that profits cannot be interpreted as total profits, as I do not observe fixed costs. If higher fuel and labor costs can be interpreted as fixed over this time period, it is likely that carriers' true profits were much lower in 2022.

6 Conclusion

This study employs a differentiated products discrete choice model to estimate demand for air travel between 2019 and 2022. To account for the endogenous nature of flight frequency, I allow for carriers to choose flight frequency before making price decisions. This is incorporated via the method described in Fan (2013).

I find that consumers became less price sensitive in 2022 relative to 2019, before the COVID-19 pandemic. Moreover, changes in demand are explained by large changes in the types of consumers traveling. In 2019, 31% of consumers were relatively price sensitive (elasticity of -6.48) compared to 69% who were less so (elasticity of -1.32). In 2022, both consumers became less price-sensitive (elasticities of -5.24 and -0.81, respectively) and the share of the most price sensitive consumers dropped to 8%. I attribute this change to one in which many leisure travellers partake in "revenge travel" after staying home for long periods during the pandemic the pandemic, thus decreasing their price-sensitivity. In addition, consumers value nonstop flights more in 2022 than in 2019, which I attribute to decreased willingness to be in crowded airports. Despite these changes, carrier variable profits grew 118% between the two years, although counterfactuals show profits would have been much higher in 2022 under 2019 demand. I also raise concerns about the ability of the BLP-style model I use to capture the cost dynamics of airlines in 2022. Negative marginal costs in 2022 – a year marked by high fuel costs and capacity constraints for

[11]Legacy carriers are those that were in operation before airline deregulation and are composed of American, Alaska, Delta, and United. They are defined in contrast to low-cost carriers who entered the air travel industry since deregulation and are generally associated with cheaper fares and lower quality service.

airline – cast doubt on the pricing equation of my model. More research is needed to investigate how to appropriately model these costs.

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Nonlinear Variables	2019	2022	Linear Variables	2019	2022
Fare 1	-4.478^{***}	-5.381^{***}	Origin Network size	0.086^{***}	0.090^{***}
	(0.008)	(0.040)		(0.001)	(0.001)
Nonstop 1	1.394^{***}	0.508^{***}	Destination Network size	0.086^{***}	0.089^{***}
	(0.015)	(0.040)		(0.001)	(0.001)
Constant 1	-2.458^{***}	-4.880^{***}	Daily departures	0.021^{***}	0.010^{***}
	(0.043)	(0.106)		(0.000)	(0.000)
Fare 2	-0.513^{***}	-0.341^{***}	Distance	0.941^{***}	0.758^{***}
	(0.003)	(0.005)		(0.018)	(0.016)
Nonstop 2	2.018^{***}	2.112^{***}	Distance^2	-0.087^{***}	-0.179^{***}
	(0.014)	(0.013)		(0.006)	(0.006)
Constant 2	-9.755^{***}	-11.081^{***}	Extra Miles	-0.416^{***}	-0.683^{***}
	(0.001)	(0.072)		(0.013)	(0.010)
Nest param. (λ)	0.720^{***}	0.835^{***}	Tour	-0.019	0.030^{***}
	(0.001)	(0.003)		(0.010)	(0.009)
			Hub	-0.141^{***}	-0.317^{***}
				(0.007)	(0.007)
Type function (γ)					
Constant	0.630^{***}	-1.078^{***}			
	(0.044)	(0.188)			
Personal Income	0.157^{***}	0.171^{***}			
	(0.004)	(0.010)			
Type 1 share	0.308	0.084			
Function value	6173	7894			

Table 4: Demand parameter estimates for 2019 and 2022
Notes: Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Carrier and Quarter dummy variables are included in both regressions. Their coefficient estimates are omitted here.

Cost Variables	2019	2022
Constant	1.245***	−0.522***
	(0.017)	(0.026)
Short	0.203***	0.055***
	(0.015)	(0.024)
Distance	0.341***	0.613***
	(0.008)	(0.014)
Nonstop	−0.468***	−0.227***
	(0.004)	(0.006)
Short×Distance	−0.139***	−0.163***
	(0.008)	(0.013)
Daily departures	0.001***	0.008***
	(0.001)	(0.001)
Extra Miles	0.143***	0.201***
	(0.005)	(0.009)
Hub	0.033***	0.016
	(0.005)	(0.008)
Slot-control airports	0.060***	−0.086***
	(0.005)	(0.008)
Origin destinations	−0.000***	−0.002***
	(0.000)	(0.000)
Dest. destinations	−0.000***	−0.002***
	(0.000)	(0.000)
Slope of Fixed Cost		
Constant	0.000***	−0.000***
	(0.000)	(0.000)
Daily departures	0.000***	0.000***
	(0.000)	(0.000)

Table 5: Cost parameter estimates for 2019 and 2022
Notes: Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Carrier and Quarter dummy variables are included in both regressions. Their coefficient estimates are omitted here.

Elasticity	2019	2022
Price (Aggregate)	-2.87	-1.17
Type 1	-6.48	-5.24
Type 2	-1.32	-0.81
Price (Product Median)	-14.01	-9.53
Type 1	-16.52	-17.26
Type 2	-1.87	-1.08
Nonstop semielasticity	2.32	5.25
Type 1	0.20	0.79
Type 2	13.26	10.57
Marginal Costs	181	53
Nonstop	125	52
Connecting	198	67

Table 6: Median elasticities and average marginal costs
Notes: Nonstop semielasticity is the percent change in demand when a product's nonstop status changes from 0 to 1

	Profit ($100k)	
Carrier	2019	2022
American	4.11	7.84
Alaska	0.76	2.11
JetBlue	0.80	2.05
Delta	3.39	7.12
Frontier	0.12	0.46
Allegiant	0.05	0.10
Spirit	0.18	0.76
United	3.15	6.28
Southwest	3.13	8.15
Total	1.06	2.31

Table 7: Carrier average variable profit per market

	Observed		Counterfactual	
Carrier	2019	2022	1	2
American	3.96	5.06	28.28	4.26
Delta	3.24	4.46	22.64	4.14
United	3.03	3.89	18.70	3.69
Southwest	2.83	3.67	29.80	3.16

Table 8: Counterfactual profits under 2 different scenarios
Notes: Scenario 1: 2022 product characteristics and marginal costs, 2019 demand parameters.
Scenario 2: 2022 product characteristics and demand, 2019 cost parameters.