The invisible costs of competition : insights from demand estimation in the airline industry

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Abstract

Ever since the Airline Deregulation Act in 1978, the airline industry drastically transitioned from the most condensed and regulated industry to one of the most competitive one. Severe competition makes airline industry's profit margin among the lowest at 8.2% in 2018, only slightly more than half of U.S. average (15.2%). The introduction of electronic booking and budget airlines increased the competition in this market to an unparalleled degree. How would such competition affect airline's behavior, market structure, and ultimately, the future of aviation? This paper explores the effects of airline industry competition on the firms' costs and operations behavior. Specifically, the effects of competition on airline's safety expense, product-differentiation expense, route choices and fleets.

This article begins by deriving an estimate for the degree of competition, employing the discrete choice techniques with differentiated product to estimate the demand for air travel in the U.S. domestic markets. A substitution matrix and a vector of preferences for observable characteristics are obtained for each quarter from 1993Q1 to 2018Q4. A measure for competition in the industry is formulated for each airline during the period. This competition index is then used to evaluate the effect of competition on the multiple costs and characteristics of airlines, using the instrumented difference in differences method. My result shows that, the expense for safety does not change significantly, but the expenses for product differentiation decreases as the markets become more competitive. Airlines fly longer routes on average, and air fleets gravitates towards homogeneously narrow-body, long-distance airplanes as airlines face more competition.

JEL Classification: R41, H22, L11

Key words: Demand Estimation, Competition, Airline, Safety, Transportation

1 Introduction

Before 1978, air travel was one of the most regulated industries in America, with limited licenses to only a small group of airlines. The government decided the routes, which airline to operate a route, airport security, and pricing. The Airline Deregulation Act in 1978 drastically transformed this industry from the most regulated to one of the most competitive ones. From 1990 to 2018, scheduled passenger enplanement almost doubled from 460 million to 888 million customers per year, while average inflation-adjusted fare plummeted from around \$500 to \$350. Severe competition makes airline industry's profit margin among the lowest at 8.2% in 2018, only slightly more than half of that of U.S. average at 15.2%. This is obviously good from the view point of customers, since they can enjoy lower prices and more route diversity. It is also empirically better for interregional economic activities(Brueckner 2003) . However, competition comes with a cost. This paper explores how competition in the industry would affect airline's cost and operations behavior. Specifically, the airlines' safety expenses, product-differentiation expenses, and changes of route, fleet, and flying models.

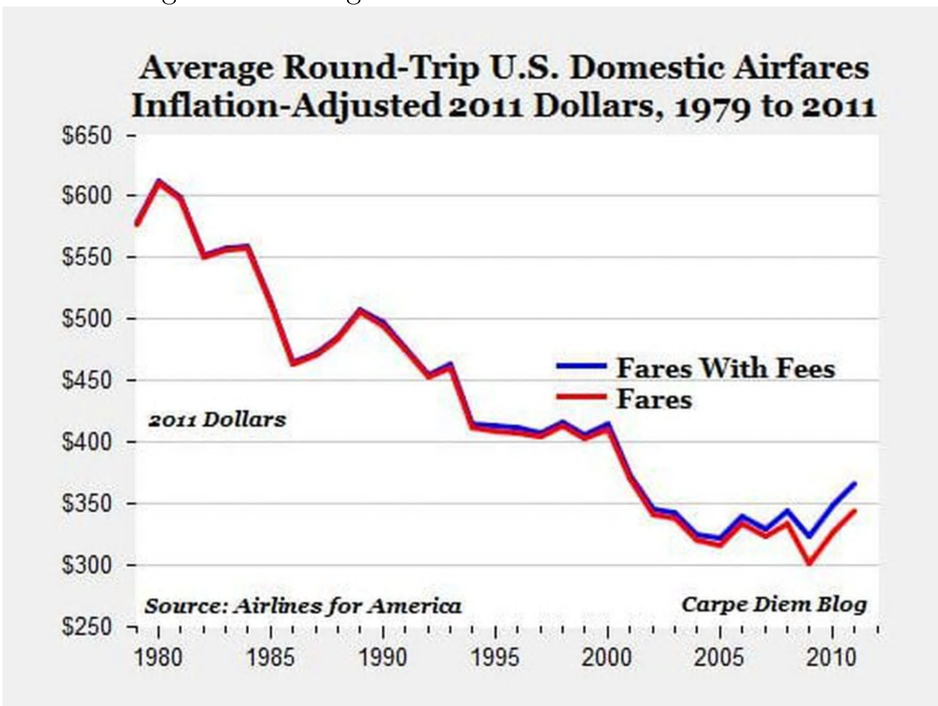
The airline industry: history and literature

Although the industry is still highly condensed, prices are extremely competitive. Market power is not manifested through high prices. A series of mergers of major airlines and the overwhelming 65% market share of the big four airlines suggested that fares should have climbed in the past three decades. On the contrary, figure 1 from Airlines for America suggests that inflation-adjusted prices have decreased in the past thirty years.

The declining profitability of airlines are well documented throughout the years. After liberalization, the industry as a whole lost \$10 billion in the decade following 1979, gained back \$5 billion in the 1990s and lost \$54 in the 2000s (Borenstein 2011). Borenstein (2011) listed some notable reasons: demand shocks, entrance of low cost carriers, and tax and fuel costs[1]. Among these reasons, taxes and the existence of budget airlines are crucial, since they made airline product differentiation futile and airlines had to be extremely competitive in prices. The tickets are taxed at 7.5%, on top of \$6.2 per segment flown. Multiple airport service and security surcharges, and the decline in fare

[1] For airline prices estimation, see Snider and Williams(2015) ,Borenstein and Rose(1994),Goolsbee and Syverson (2008), Borenstein(1989), Borenstein (1989), Brueckner (1994)

Figure 1: Average US Domestic air fare 1980-2012



Blue = not inflation adjusted. Orange = inflation adjusted with base year 2017. Source: Bureau of Transportation Statistics

makes the tax portion keep their uptrend on a ticket. The growth of online booking and the prevalence of budget airlines also contribute largely to the competitiveness of air travel.

Competition in the airlines industry has been analyzed extensively throughout the years. Borenstein discussed the industrial organization aspect of airline competition, pointing out that a series of mergers following deregulation would condense the market. Potentially, consumers will be the one at a disadvantage due to loss in welfare along with competition. In a series of later articles, Borenstein discusses the thin profit margin by the airlines, and the role of hubs in determining market power and Oum et al.(1995) pointed out the reasons for airline industry to be so competitive. Berry (1990) provided a model to estimate airport presence as product differentiation.

Regarding air travel as a consumer welfare, Olivier (2008) recently investigates the impacts of airline alliances on consumer well-being. Brueckner (2003) also provided empirical evidence to the positive impact of increased air travel to the urban economic development. Graham et al. (1983) provided a discussion about the effects of competition on welfare post the 1978 deregulation. These papers all pointed towards the positive aspects of deregulation: increased airline competition decreases prices, increase volume traveled, increase technology, increase the degree of connections between cities, etc.

This paper contributes to the existing discussion of pros and cons following the airline deregulation by adding the argument that: competition in the industry also drives down the cost of airlines and creates disutility to consumers. It also adds a projection of how the aviation industry is going to shape in the near future with increasing competition.

Article agenda

The airline industry is notorious for being price-sensitive (Oum et al 1993, Ruben 2005). Since airlines cannot freely adjust their pricing, it is intuitive to expect them to cut its costs to cope with competition, but which costs to get cut? Different costs have different effects on the industry. If the costs for gates and ground control gets cut, it means the airline will shift its transportation model or exit entirely from certain airports, increasing market shares of existing airlines. If the cost for in-flight amenities (food, entertainment, reclined seats, etc) gets cut, it means airlines are prepared to engage in price competition, and the firms then pay much less attention to differentiating their products. If the crew training cost or maintenance cost gets cut, it would pose some safety concerns to the public.

This paper explores the effects of competition in the airline industry in two steps. In the first step, I constructed an index for competition for each of the airlines in the industry[2]. Following the discrete choice framework proposed by Berry(1994), and Berry-Lehvinson-Pakes(1995), I estimate the demand elasticity between products in the markets, then come up with a volume-weighted average of the own price elasticity for each airline in a given year-quarter in the period of 1993Q1-2018Q4. The model allows that a consumer can choose to not participate in the market. The first step produces the necessary proxies of competition needed for the second step. This step reveals that competition in the industry has increased throughout the last quarter of a century: own price elasticity uniformly decreases during the mentioned time period. The result is consistent throughout different carriers and the industry average.

The second step uses the level of competition from the first step to evaluate the effects

[2]For more demand estimation styles, see Brueckner 1994, McFadden 1989

of competition on costs and operations behavior. The costs discussed in this paper are maintenance expenses (safety cost) and "other operating" expenses, which involves in-flight entertainment, ground service, etc (product differentiation costs). The paper also explores if competition shifts the transportation model by airlines: it examines wherther airlines are more inclined to fly longer or shorter routes, and if airlines' fleets are more or less homogeneous. The main identification issue that discourages any inferences from an ordinary least square (OLS) is that there may exist endogeneity, reverse causality to be specific, between costs/operations and the level of competition: a decrease in costs may cause more firms to enter a given market, and more firms entering the market may also decrease costs. Therefore, OLS might be an overmeasurement of causal effects between competition and costs/operations by airlines. To address this issue, I employ the method of instrumented differences in differences (DDIV) and performed two stage least squares. The instrumental variable is the presence of nonstop flights offered by rival budget airlines, which are proxies of increased competition. The first stage shows that airlines with more market shares that face nonstop budget rivals are more competitive. The second stage result shows that in presence of increased competition, airlines tend to cut costs related to product differentiation. The maintenance costs related to safety does not vary significantly. Airlines fly longer routes on average, and air fleets gravitates towards homogeneously small, long-distance, narrow-body airplanes as airlines face more competition. This signals the transition away from the traditional hub-to-spoke model and towards the point-to-point model.

This paper is organized as follows: section 2 discusses the data that were used in my analysis, section 3 describes the demand estimation procedure and its output, section 4 presents the empirical model that evaluates the effects of competition on costs and its results, and section 5 gives policy suggestions and concludes.

2 Data

The primary data source this article utilizes is the quarterly Origin-Destination Survey Data Bank 1B (DB1B) published by the Bureau of Transportation Statistics. The data contains 10% of all U.S. domestic itineraries within a quarter of a year. DB1B dates back to the first quarter of 1993, replacing the old version DB1A, which is no longer available to the public. The data set contains the essential information on individual itinerary: after tax prices, yield (price per mile flown), the ticketing carrier, the number of stops, plane load factor, coupons, and miles flown. Ticket class, one of the important identification factor for elasticity of demand, is reported in the DB1B Coupon data table. Customer demographics (age, income, education,etc) are not reported in the survey data. This data is used to construct the demand estimation (step 1 between the two steps) discussed in Section 3.

The financial information are obtained through the Air Carrier Financial Reports form 41, Schedule P-1.2, P-7,B-4.3. Schedule P-1.2 is the quarterly profit-loss financial statement for carriers with operating revenues at least $20 million. The data contains multiple operating revenues and costs. Schedule P-7 contains detailed quarterly aircraft operating expenses for large aircrafts. Schedule B-4.3 lists aircraft inventories (airline fleets) by airlines in a given year.

2.1 Sample selection

As per tradition in the literature, this paper defines a market m=1,2,...M as a unidirectional origin-destination pair. This means a trip from point A to point B is, by definition, in a different market than a trip from point B to point A. Each market has different routes that different carriers operate. Each route can be understood as a "product" that belongs to a carrier in the context of a differentiated product market. For consistency, I use "products" to refer to routes henceforth. The index for product in each market is j=1,2,...J. Time t=1,...T is each quarter in the data. In this paper, I choose the time period from 1993Q1 to 2018Q4.

The sample is restricted along the following dimensions: price, routes, airport, and carrier (firms). For prices, I omit the observations with price less than $40 or greater than $1500. This is a more conservative restriction of data than the standard Department of Transportation "unreliable" range. These fares are rare within the dataset and it might be a result of data collection error or a redemption of the frequent flyer miles. For routes, I omit the observations that uses more than one carrier and open-jaw itineraries (ones with different returning tickets). At the aggregate route level, I omit routes with less than 1 flight per week, or 13 flights in a quarter, since this might represent test flights or very small markets that does not provide valuable variation in competition. For carriers, I omit small airlines that has less than 100 passengers per week, or 1300 passengers in a year-quarter. In the remaining sample, all the major

Table 1: Airlines included

Airline	Code
American	AA
Alaska	AS
Jet Blue	B6
Continental	CO
Delta	DL
Frontier	F9
ATA	TZ
Allegiant	G4
Spirit	NK
NorthWest	NW
AirTran	FL
United	UA
USAir	US
SouthWest	SW
Trans World	TW
Hawaiian	HA
Virgin Atlantic	VX

airlines are retained, plus some regional airlines.

The data are aggregated to the product level for each of the year-quarter. It contains the volume traveled in each route by each carrier in a time period. The final data set has 13,142,196 observations in 19,675 origin-destination pair markets.

2.2 Descriptive Statistics

Market concentration is reflected through the dominance of major airlines. The big four airlines in 2018 serve more than 60% of all passenger enplanement domestically. We can project the trend that airlines now condense their routes to profitable ones, which increases the volume that they serve and also the homogeneity of aircraft fleet that they employ. Table2 below describes an example of the market volume in terms of passenger enplanement by airlines. We can observe that the top airlines occupy a volume significantly higher than others.

Average air fares for domestic flights has been stable around $250. This number has not been adjusted to reflect the change in distance preference by airlines.

The number of markets has increased consistently along with the number of products

Table 2: Airline traffic and average fare 2015Q1

Airline	Average fare	# passengers(million)(%total passengers)
Southwest Airlines	$189	2.3 (17%)
Delta Air Lines	$270	1.8 (13%)
United Air Lines	$266	1.35 (10%)
American Airlines	$273	1.08 (7%)
US Airways	$253	1.06 (7%)
JetBlue Airways	$197	0.55 (3%)
Alaska Airlines	$209	0.43(3%)
Spirit Air Lines	$90	0.31(2%)
Source: Bureau of Transportation statistics		

offered by the airlines. At the end of the last century (from 1993 to 1999), there were around 16,000 airport pair markets with around 87,000 routes (an average of around 5 routes for each market). These numbers increased substantially to more than 120,000 routes and 18,000 markets in 2018.

Figure 2: Markets 1993-2018

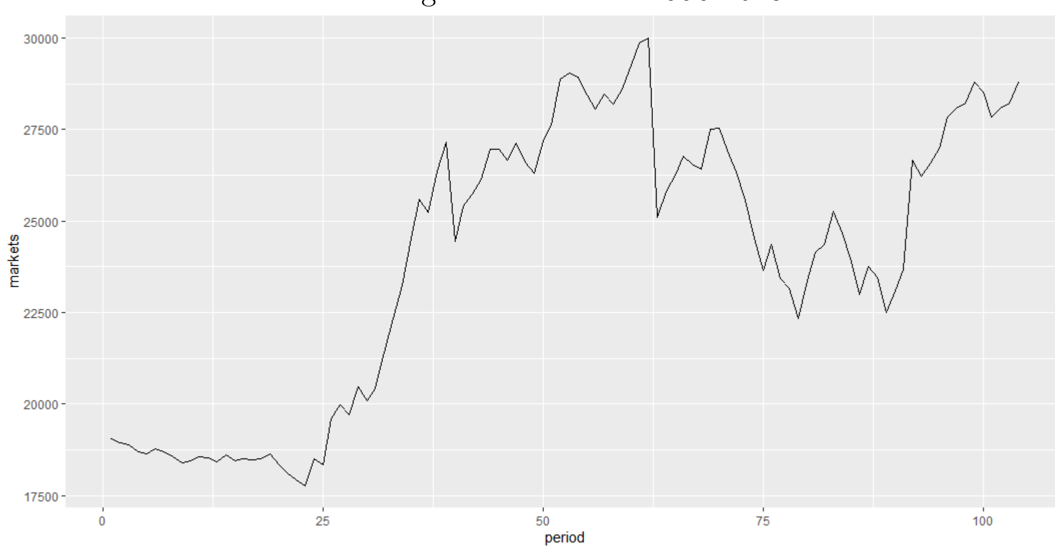


Table 3 presents the summary statistics of the data, including the mean, standard deviation, minimum, and maximum of main variables in the data sets. Fare is the average price of the flight for ticketing airline a for product j in market m. Nonstop is a dummy variable assigned to a product if it offers no transit in market m. Distance is the one-way route distance between the origin and destination airports. Distance can be different in one market, since the number of stops are different. Within-carrier origin share measures the percentage of flights originated from an airport as a percent of all airports that the carrier operates. Nonstop rivals is the number of rivals in a market that offers nonstop flights, which is a proxy for competition within a market m. Budget_airlines is the number of budget airlines operating in market m. Budget airline is one of the following: Allegiant, Frontier, Jet Blue, Southwest, Spirit, Sun Country. Southwest gets the most attention due to its prevalent presence and rapid growth. Number of routes per market represents the number of differentiated products within a market m. It has slightly increased over the years, suggesting that consumers now have more choices to fly in a market.

Maintenance cost per aircraft is extracted from two different sources. Schedule P-7 provides the quarterly maintenance expense, and schedule B-4.3 provides the list of aircrafts that belongs to different carriers. Food and other operating costs are obtained from schedule P-7.

3 Demand Estimation

This section employs discrete choice methods to estimate the demand for air travel. I will present some different measures of demand, each with a different methodology and slightly different assumptions. First, a simple reduced form OLS result will be introduced, regressing market shares on prices, then multinominal logit, and a full BLP model is estimated. The main results is from heterogeneous discrete choice (BLP) model.

In this section, I assume away the supply side of the market, since I am specifically interested in the competitiveness of the industry. In the literature, markups can be estimated using the models of Ciliberto and Williams(2014), Berry, Carnall and Spiller(2006).

3.1 Empirical strategy & identification

The demand estimation model in this paper is mainly following Berry-Lehvinson-Pakes (1995) and Nevo (2001). The reason for this model choice is to address the endogeneity in pricing behavior, as well as to generate a realistic substitution pattern between carriers within each year-quarter.

Model

First, the model includes utility-maximizing consumers. Each choose a route in a given origin-destination pair market and derive the following random utility:

$$U_{ijm} = -\beta_{1i}.P_{jm} + \beta_{2i}x_{jm} + \varepsilon_{ijm} \tag{1}$$

Where $\varepsilon_{ijm} = \xi_{jm} + \epsilon_{ijm}$, the unobservable individual deviation term consists of two parts: the average market-product specific characteristic $\xi_{jm}$and the mean zero individual deviation $\epsilon_{ijm}$from that average.

i=1,2,...,I is an index for individual i, j=1,2,...,J is an index for product j. and m=1,2,...,M is an index for market m. Consumers are exogenously sorted into different markets m's. They derive their utility from budget $Y_i$and pay price P_{jm}if choose product j, in this case, the choice of airline. $x_{jm}$is the vector of market-product characteristics that are observed by the economist.$\beta_{1i}$is the marginal utility of income, specific to each individual, and $\beta_{2i}$is the vector of parameters indicating the marginal utility of each of the observed characteristics from x_{jm}.

The utility choice indicates that the nature of product differentiation is vertical, since the coefficient $\beta_1$of prices is allowed to vary with individuals, while everyone in the same market m observes the same price P_{jm}

Market is defined as a pair of origin-destination, in which a flight from A to B is counted as a different market than the flight from B to A. This obviously assumes that the customers in region A (origin) only choose from airline choices within that region. This assumption might not hold if the airport lies in between two states, so that a customer might have a larger choice set than assumed. I assume that such cases do not exist.

Individual characteristics that shape the choices are categorized into two major types: observed characteristics O_i and unobserved characteristics θ_i. In a traditional BLP model, no individual data is observed, so demographics variables are drawn from the outside datasets such as the Current Population Survey (CPS). In our case, the dataset DB1B does provide individual ticket characteristics, but no demographics are recorded. As a result, we cannot observe basic variables that potentially significantly affect individual choices such as income, age, sex, education, etc. Therefore, in each of these two cases, $O_i$will consist of different information set. On the other hand, $\theta_i$is in no way observable, therefore we would have to make a parametric assumptions about it.

$$\begin{pmatrix} \beta_{1i} \\ \beta_{2i} \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \Omega O_i + \Theta\theta_i \tag{2}$$

Where $O_i \sim F_O(O)$, $\theta_i \sim F_\theta(\theta)$

Where $\beta_1$and $\beta_2$are the average preferences of prices and product-market characteristics, respectively. Ω and Θ are matrices that indicate observable and unobservable individual deviation from the mean. The distribution of observables, $F_O(O)$, can be taken nonparametrically from other data sources, or can be parametric with parameters estimated from a different source. In this paper, I employ both multinominal logit estimation and the BLP estimation with demographics drawn from demographic parametric distribution provided by the Bureau of Labor Statistics(BLS). The BLS extracted and aggregated data from CPS for each of the states in a given year-quarter. The demographic I got from each state in a year-quarter are GDP per capita, average age, and gender composition.The distribution of unobservables, $F_\theta(\theta)$ is a parametric multivariable normal distribution.

Next, we discuss the modelling of the outside good, or choice 0. Consumers will compare utility across every choices, including to step out of a market, to decide on their consumption. By choosing to stay out of a market, in our context, it means that consumers either choose an international airline that operates on the same route that the dataset does not contain, choose other transportation modes(car, train, boat, etc) or just completely does not make the trip. If the origin and destination is within driving/train distance, flying may not be an optimal choice. The outside choice is needed since it would create a realistic consumption pattern, because otherwise everyone will unrealistically consume the same amount of the good when prices are proportionately increased throughout the market. Normally, we would expect consumers to exit the market when there is an uniform inflation. I will later use an assumption on this to simplify the computation of demand. The utility for an outside choice is as follows:

$$u_{i0m} = -\beta_{2i}.0 + \omega_0 O_i + \Theta_0\theta_{i0} + \varepsilon_{i0m} \tag{3}$$

The outside choice is normalized to have a zero utility by setting $\Theta_0, \omega_0, \xi_{0m}$to 0.

For estimation purpose, we can rewrite equation (1) into:

$$U_{ijm} = \underbrace{[x_{jm}\beta_2 - \beta_1 P_{jm} + \xi_{jm}]}_{\mu_{jm}} + \underbrace{[[-P_{jm}, x_{jm}](\Omega O_i + \Theta\theta_i)]}_{\delta_{ijm}} + \varepsilon_{ijm} \tag{4}$$

Where $\mu_{jm}$is the mean utility faced by everyone, and $\delta_{ijm} + \varepsilon_{ijm}$is the individual deviation from the mean.

Consumers are assumed to consume only one unit of the good that gives the highest utility. This is relevant in our context, since it is reasonable to expect a person to travel about once every quarter. Market share is therefore determined by the proportion of customers who choose to buy good j in market m. This has to come from the individual deviation of preferences from the mean. Therefore, market share is inversely mapped to the set of individual characteristics that makes a person choose a given good j. The set of individual characteristics that makes a person i choose good j in market m is:

$$S_{jm}(x_m, P_m, \mu_m; \Omega, \Theta) = \{(O_i, \theta_i, \varepsilon_{i0m}, \varepsilon_{i1m}, ..., \varepsilon_{iJm}) | U_{ijm} \geq U_{ikm}, \forall k \epsilon \{0, 1, ..., J\}\} \tag{5}$$

The market share of good j in market m is then simply the weighted sum of people who buy good j out of the total market m. Since a consumer is defined by the joint characteristics of $(O_i, \theta_i, \varepsilon_{ijm})$,we can get market share $Q_{jm}$for each good j in market m by integrating the joint distribution function of $(O_i, \theta_i, \varepsilon_{ijm})$ over the region of S_{jm}.

$$Q_{jm}(x_m, P_m, \mu_m; \Omega, \Theta) = \int_{S_{jm}} dF(O_i, \theta_i, \varepsilon_{ijm}) \tag{6}$$

Applying Bayes' Rule, we get

$$Q_{jm}(x_m, P_m, \mu_m; \Omega, \Theta) = \int_{S_{jm}} dF(O_i, \theta_i, \varepsilon_{ijm}) = \int_{S_{jm}} dF(\varepsilon|O, \theta) dF(O|\theta) dF(\theta) \tag{7}$$

From independence of O, θ, ε, we have:

$$Q_{jm}(x_m, P_m, \mu_m; \Omega, \Theta) = \int_{S_{jm}} dF_\varepsilon(\varepsilon) dF_O(O) dF_\theta(\theta) \tag{8}$$

With the assumed parametric distributions mentioned above, we can integrate equation 8. As a result, a given set of parameters will be mapped to a specific market share. We can minimize the distance between the predicted market share given by equation 8, and the true market share from data set. This estimation strategy, however, does not address the endogeneity issue of pricing of a product.

Logit model vs full model

The simplest case we can think of in estimating the demand in this case is by assuming there is no individual preferences, so everyone has the average preference towards the price vector and product characteristics. In other words, $\beta_{1i} = \beta_1, \beta_{2i} = \beta_2, \Omega = \Theta = 0$. The only variable that varies among individual that makes a difference in choice is ε_{ijm}. Assuming a type I extreme value distribution, market share of good j in market m is:

$$Q_{jm} = \frac{e^{x_{jm}\beta_2 - p_{jm}\beta_1 + \xi_{jm}}}{\sum_{k=0}^{J} e^{x_{km}\beta_2 - p_{km}\beta_1 + \xi_{km}}} \tag{9}$$

The logit model will pose an undesirable feature, since its elasticity of substitution pattern is unrealistic:

The own-price elasticity is:

$$\zeta_{jm} = \frac{\partial Q_{jm}/\partial P_{jm}}{Q_{jm}/P_{jm}} = Q_{jm}\beta_1 P_{jm} - \beta_1 P_{jm} \tag{10}$$

and cross price elasticity is

$$\zeta_{jm} = \frac{\partial Q_{jm}/\partial P_{km}}{Q_{jm}/P_{km}} = Q_{km}\beta_1 P_{km} \tag{11}$$

As has been discussed by Nevo(2001), the functional form immediately determines the pattern of elasticity: small market shareQ_{jm}means that the elasticity will largely be based on price. Goods with low prices automatically has more elastic market and therefore higher markup. In the airline case, this is only partially relevant, since lower fare airlines do have better competitive edge and market power, although we do not see the markup.

Another problem lies in the cross-price elasticity. From the cross price equation, we clearly observe that substitution pattern will be gravitated towards the big airlines. This is very plausible in the airline case, but will not be true if small airlines differentiate their product better and suffer smaller markup. One would expect to see older and richer people to prefer more leg space and smoother ticketing/boarding process and somewhat indifferent about prices, as opposed to the younger/poorer public who would respond more to prices.

In the full model, however, differences in choice are also drawn from differences in demographics and individual preferences δ_{ijm}.

In the full model, equation8 becomes:

$$Q_{jm} = \frac{e^{\mu_{jm}+\delta_{ijm}}}{\sum_{k=0}^{J} e^{\mu_{km}+\delta_{ikm}}} \tag{12}$$

The own price elasticity is

$$\zeta_{jm} = \frac{\partial Q_{jm}/\partial P_{jm}}{Q_{jm}/P_{jm}} = \frac{-P_{jm}}{Q_{jm}} \int \beta_{1i} Q_{ijm} - \beta_{1i} Q_{ijm}^2 dF_O(O) dF_\theta(\theta) \tag{13}$$

And the cross price elasticity is

$$\zeta_{jm} = \frac{\partial Q_{jm}/\partial P_{jm}}{Q_{jm}/P_{jm}} = \frac{P_{jm}}{Q_{jm}} \int \beta_{1i} Q_{ijm} Q_{ikm} dF_O(O) dF_\theta(\theta) \tag{14}$$

These elasticity equations does not posess the potential bias of the pure logit model. If the price of an airline increases, old and rich customers will switch to similar airlines which offer better services, rather than to switch to the most major airline who dominates the route.

3.2 Estimation

In this section, I will discuss the estimation procedures and results for three different specifications. First, I simply run a reduced form OLS to make a benchmark of the estimates on preferences parameters and elasticity of demand for each of the good. In this section, I also employ instrumental varibale to address the concern that pricing behavior correlates to unobservable product characteristics. After that, I run a logit estimation of demand, assuming that there is no unobservable preferences for product characteristics. Finally, I run a full model estimation of parameters. Results are reported for each year-quarter. This is different from the literature since traditionally, every origin-destination pair in each year-quarter can be treated as a different market. For example, the market from New York JFK to Buffalo BUF in 2018Q1 and 2018Q2 can be treated as two different markets, and the data can be regarded as a large cross-sectional dataset. However, since this paper is interested in competition in the industry in each year-quarter, the same procedure is applied repeatedly for the 104 year-quarters that were used (from 1993Q1 to 2018Q4). Each year quarter then provides a competition index for each airline and thus the industry in general.

Airlines are mapped into product characteristics $p_{jm,}x_{jm},\xi_{jm}$. The observable product-market characteristics are prices, whether the flight is straight, whether the airline is a budget airlines, and if the airline is major in the airport. Unobservables include the quality of service, seat space, boarding process, whether the flight takes place at midnight or early morning, etc.

Demographics are not included at all in the dataset, except for the indicator whether the flight is business class or not. Demographics and individual characteristics are parameterized to have a multivariate normal distribution. Each variable's mean and standard deviation is obtained from the origin state's demographics data. The variables include income, age, and gender.

The entire market size is defined by the total above-16-years population of the origin state in a year-quarter. As a result, the "market size" of choice zero (the percentage of people who choose not to participate in a market) is the entire market size minus the people who has chosen to air travel. A weak point of this is it neglects the possibility that one person travels more than once in a year-quarter. In a setting where airlines have data about the number of people searching for a trip available, that can be used as a perfect measure of the total market size.

Instruments

As addressed earlier, prices are likely endogenous and correlates with the product characteristics. The instruments must be orthogonal to the structural errors of the estimation model. In other words, an instrument must be a cost shifter[3] in order to identify

[3]Within the airline literature, cost shifters and other firm characteristics are common instruments for prices and qithin-market shares. For more instruments choice, see [?, ?, ?]Ciliberto Williams 2014, Gayle 2007, Berry 2010

the slope of the demand curve. One set of instrument is standard for BLP estimation, in which prices by airline j in market m are instrumented by the average price or airline j outside of the market m. This is under the assumption that prices are set independently across states, and the average price in other states indicate the overall shift in costs of the airlines. Besides, I use airline fixed effect, which can account for the general cost of a carrier across markets in a year-quarter, and a lot of un observable product characteristics that does not get reported in the dataset.

OLS and Multinomial Logit

OLS

To explore the dataset, I first employed OLS and simple logit for the entire year-quater dataset. Furthermore, using DB1B Coupon dataframe, I segment markets for airlines into two major categories: business flyers and leisure flyers. This segmentation is to address the concern that different types of travelers have different preferences and hence fundamentally different in choice behavior. The business flyers (classes C,D,F,G) are about 11% of the remaining data, and leisure (classes X,Y) are 89%. This segmentation is not done in the full model, since the cost observations cannot be attributed towards business or leisure class, and hence cannot be used in the next section.

The OLS specification simply measures the cross-sectional elasticity of demand according to this empirical model

$$lnQ_{jm} - lnQ_{0m} = \beta_1 lnP_{jm} + \beta_{jk} ln[(\prod_{k \neq j} P_{km})^{\frac{1}{K_m - 1}}] + x_{jm}\beta_2 + \varepsilon_{jm} \tag{15}$$

Where $\beta_1$is the own price elasticity of airline j in market m, $\beta_{jk}$is the average cross price elasticity between airline j and airline k, and $\beta_2$is the preference towards observable characteristics of airline j in market m. In this case, I treat the average fare of other products(routes) within the market as a product characteristic (part of x_{jm}).$\beta_{jk}$is constructed this way because the number of airlines that operates in each market (K) is different. This specification implies that there are no individual variation in valuation of price vector and characteristics.

Logit

In the logit specification, no demographics matter in airline choice. Endogeneity in this specification is adressed again through a set of instrumental variables Z.

$$U_{ijm} = -\beta_1 P_{jm} + x_{jm}\beta_2 + \xi_{jm} + \varepsilon_{ijm} = \mu_{jm} + \varepsilon_{ijm} \tag{16}$$

Instrumentals Z satisfy:

$E(Z.\xi) = 0$

That is, instruments are independent of the unobservable product characteristics.[4]

The GMM estimation is therefore:

$$\beta^* = \underset{\beta^*}{argmin} \xi' Z \Phi^{-1} Z' \xi \tag{17}$$

Where

- $\Phi$is an estimation of $E[Z'\xi\xi'Z]$, the weighting matrix of the GMM calculation.
- $\xi = \mu_{jm} - (-\beta_1 P_{jm} + \beta_2 x_{jm})$
- And $\beta^* = (\beta_1, \beta_2, \Omega, \Theta)$

In the logit specification, finding $\mu_{jm}$is simply taking the difference: $\mu_{jm} = lnQ_{jm} - lnQ_{0m} = Q_{jm}$= observed market share

Given the above functions, we can rewrite ξ_{jm}entirely as a function of $\beta^*$and perform the GMM estimation

The result in table 4is quite intuitive: airlines will lose customers or market share to opponents if their prices are increased. The group of business class travelers does not have significant coefficients on prices , although the signs are as expected. Business travelers are much less price sensitive than leisure travelers. Business class has a strong

[4]There are a lot of unobservable characteristics that the literature has discussed but I did not have the data on. Such are whether the flight is at late night or early morning, whether it has code shares with other airlines and so on.

and consistently significant distaste towards transiting throughout different models. This is intuitive, since this group has more opportunity cost of time. Major airlines are strongly preffered by business travelers while leisure travelers are quite indifferent exept in two specifications. This is consistent with Borenstein 1989, who indicates that airlines that has major control of an airport will be able to attract more frequent flyers who are often business travelers and have more income than average.

Main demand estimation results

The main results from the model is summarized in table 5 . The result shows a strong distaste for price in the utility function. In 2018, there seems to be a significantly stronger disutility for high prices, which points towards a more competitive market. A flight through a hub (a non-direct flight) and budget airlines also create disutility to the consumer. The dummy variable budget airline = 1 captures variation in in-flight service and ticketing service. We can expect budget airlines to have minimal airport employees, therefore a lack of assistance service from the airline; they also serve minimal to no in-flight meal, and the seats are often not reclinable. Routes with major airline operating can imply more access to information and less delay, leading to a higher utility to consumers. This can simply the major airline's dominance in the airport leads to their ability to advertise their products.

The heterogeneity captured through income, age and gender. From the results, wealthier passengers care less about prices and more about product characteristics, especially about whether the flight is nonstop. This is intuitive since we expect higher income individuals to have higher opportunity costs of time. Higher income and older individuals also care more about comfort (whether the airline is budget). Females have strong distaste towards both higher prices and discomfort.

Further market segmentation shows more interesting results. Long haul flights(flights with nonstop distance more than 2200 nmiles) customers experience less disutility from prices than short haul flyers (nonstop distance less than 600 miles). This is intuitive since short haul flyers faces more choices of transportation and can choose choice zero. Prices relatively matter less and comfort matters more for longhaul market. The opposite is true for short-haul flights. We can project that competition is different along each of the distance type of markets. Product differentiation matters more in longhaul markets, and less in shorthaul ones.

Given the results for marginal utility of income and product characteristics, we can derive a substitution matrix between different products, then aggregate these own and cross price elasticities for each airlines. We can observe coefficients with absolute values higher than one across the diagonal. Substitution towards the choice zero is quite inelastic. This means that travel demand will be substituted between airlines and hardly out of the market. The implication of this points towards a very agressive pricing behavior between airlines.

The results from table6 with 8 different types of products are translated into a substitution matrix between airlines, so as to observe the competition between airlines, which is relevant to the section that follows. For each market, I compute own price elasticity by adding up the own price elasticity of all its product types offerred in the market, weighted by its market share within market, then add back the cross-price elasticity, also weighted by market share within market. This is to address that consumers can switch from one product type to the other within a carrier. The resulting estimated elasticity is reported below:

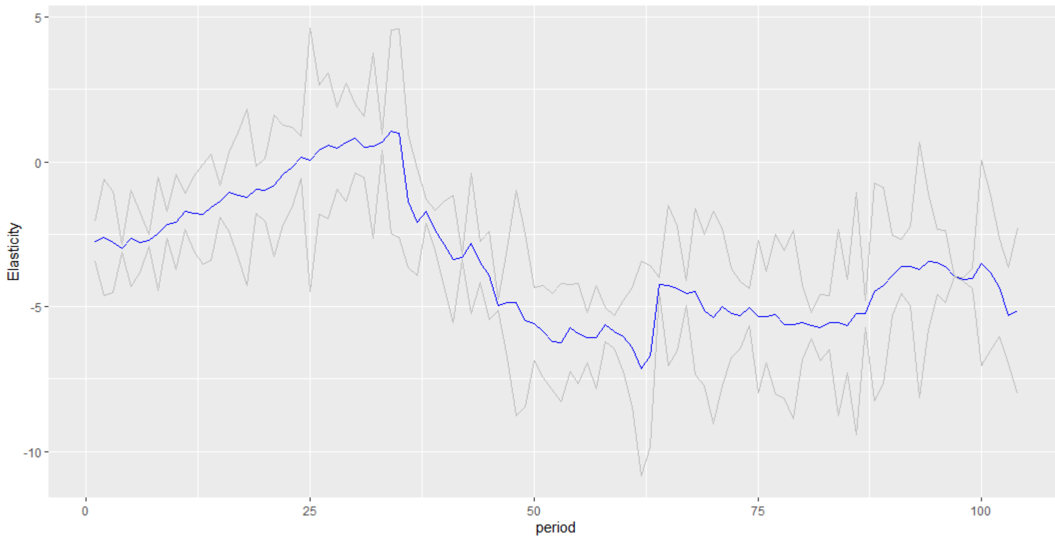
The matrix in table7 indicates a quite elastic own price elasticity of demand for domestic airlines in 2018Q4. For each of the year-quarter, we can then obtain the weighted average own-price elasticity.

In figures 4 and 3, we can see the trend for the own-price elasticity for industry average and also select carriers in the US in the period from the first quarter of 1993 to the end of 2018. The figures suggest an increasingly elastic market for the industry: the absolute value of own-price elasticity is significantly higher than 1993 for every one of the graphs. The whole market uniformly face with an increasingly competitive market. This variations in average industry elasticity is used in the next section to examine the effects of such increased competition on the cost behavior of airlines.

4 The effects of competition on costs and market structure

As we can see from the previous section, the US airline competition has become more competitive over the last quarter of the century. In this section, I will explore the effects

Figure 3: Average own-price elasticity from 1993Q1 to 2018Q4

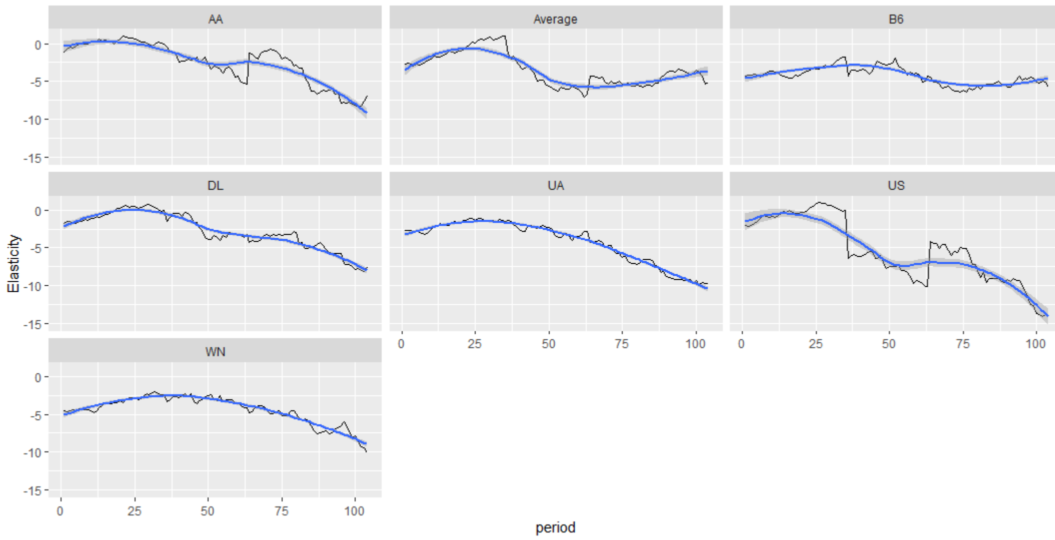


of such changes in the market on the cost behavior and the market structre . The result from section 3 gives us a panel with 24 major airlines over 104 periods (year-quarter).

In a fiercely competitive market, it is expected that the markup for each airline is minimal , and the market is so elastic that raising price is not an option. This would expectedly push the firm to reduce its marginal cost to maintain a competitive edge with its industry rivals. But which costs to cut is the question. In this section, I explore the effects of competition on safety expenses and product-differentiating expenses.

The measure of market structure that I use in this article is the average nonstop distance and the homogeneity of airline fleets. The nonstop distance and the airplane fleets give us information on the preference of airlines on which type of routes they want to operate. The fleet homogeneity is a measure if the airlines are using the same type of plane across their fleets. It is measured by the sum of squared differences of plane characteristics (capacity, manufacturer, model), normalized to a range from 0 to 1. For example, a 0 in homogeneity index means that every airplanes that the airline owns are different, while 1 means the airline has the same planes for operation everywhere . The combination of information regarding airlines' nonstop distance and fleet homogeneity gives us some insights to the future of aviation: is it transitioning from the traditional hub-to-spoke model to point-to-point model? The hub-to-spoke model connects local flights to a hub first, therefore it often includes a short flight and a fleet that consists of small planes to connect local airports to hubs and big planes to connect between big hubs. We will

Figure 4: Ownprice elasticities for specific airlines, 1993Q1-2018Q3



see at the end of this section that the traditional transportation model is changing.

OLS

The costs chosen to make this analysis are the quarterly airline maintenance cost, the quarterly total food costs, and the "other" operating expenses. The maintenance cost relates to our safety interest of the story. The food cost and operating costs are often related to the degree of differentiated product, since at the same price and safety preference, consumers choose an airline that offers better in-flight and airport service. A naive way to answer the question is to take a simple ordinary least square with respect to costs as a dependent variable and the degree of competition, the average ζ_{at} as the independent variable:

$$C_{at} = \gamma_1 + \gamma_2 \zeta_{at} + l_a + X_{at}\gamma_3 + e_{at} \tag{18}$$

Where a={AA,DL,US,..} is the index for an airline, t=1,2,...104 is the index for the year-quater. Since the variation in costs is only observed at each airline's year-quarter level, it is hard to assign these costs to different products in different markets.$l_a$is the fixed effect for airline a, which captures the characteristic of an airline across the time periods. l_t is the period fixed effects. $X_{at}$is a vector of other controls such as labor cost, average flight distance of the airlines, percentage of flights from a hub, and percentage of direct nonstop flights. The independent variable of interest, ζ_{at}, is an absolute value of the own-price elasticity of an airline in a year-quarter.

A concern over the ordinary least squares is that, there might exist endogeneity within the regression in equation 18. Specifically, reverse causality may be severe: not only can an airline cut costs due to more competition, competition also could increase due to an observation of lower costs. A decreased cost in a period can make airlines expand their operation, not necessarily by ordering new planes, but could be utilizing idle ones or underused ones. This makes the market increasingly competitive for more origin-destination pair, and thus the own price elasticity is going to become more elastic. To address this endogeneity issue, I employ a couple of indentification strategies that exploit the natural experiment nature of the data: Difference in difference and Instrumental variable.

Instrumented Difference in Differences

I address endogeneity in this model by applying the instrumented difference in differences method, which gives an estimation of the weighted average causal effects[5]. The assumption to be met in this specification is quite standard in the difference in difference as well as the instrumental variable literature: (1) exclusion restriction, the instrument only affects the outcome through the treatment, and (2) parallel trend, both difference of treatment values and outcomes are mean independent of treatment.

The instrument in our case is the volume-weighted percentage of markets of an airline with a presence of a budget airline's nonstop route. A dummy variable Post={0,1} is assigned such that an entrance or exit of a budget airline (defined in section 2) switches it from Post=0 to Post=1 for every existing airlines in each of the markets in a year-quarter. The number of markets with Post=1 is then aggregated accross markets for each ariline in a year-quarter.

$$C_{at} = l_a + \pi T_t + \gamma_2 \zeta_{at} + X_{at}\gamma_3 + \varepsilon_{at} \tag{19}$$

$$\zeta_{at} = k_a + \delta_1 T_t + \delta_2 Z_{at} T_t + \eta_{at} \tag{20}$$

Where ζ_{at} is the treatment (competition), $Z_{at}$is the instrument (weighted percentage of markets that has a nonstop budget rival), and $T_t$is the period indicator for when the

[5]Method was widely used but not discussed as much formally. See Duflo 2001, Angrist 1995

level of instrument jumps.

Exclusion restriction requires that the percentage of presence of nonstop budget competitor in an airline's market has no effect on its cost decision. It is reasonable to expect that the decision to enter a given market and offer a nonstop route by a budget airline has little to do with existing carrier's costs. It is rather by the firm's connection, available type of plane, and risk tolerance, which is independent of the costs of an existing airline.

The first stage in the two stage least square is, as usual, to measure equation20 above. This is measured by a standard difference in difference procedure. The second stage returns the average causal effect of competition on the firms' cost:

$$\gamma_2 = \frac{E[C_{a1} - C_{a0}|Z_a = z_1] - E[C_{a1} - C_{a0}|Z_a = z_0]}{E[\zeta_{a1} - \zeta_{a0}|Z_a = z_1] - E[\zeta_{a1} - \zeta_{a0}|Z_a = z_0]} \tag{21}$$

where $z_1 > z_0$, which represents a discrete jump in percentage of market of an airline faced with nostop budget competition.

The first stage result shows that, a 10% jump in the percentage of markets faced by nonstop rival rises an airline's absolute average own-price elasticity by 1.37 percentage points.

Table 8 presents the estimation result for the two models with three different choices of dependent variable.

The OLS specification result shows that a 1 percentage point increase in absolute own price elasticity would also increase the maintenance cost, but not statistically significant. The OLS estimation of Food cost and Other operating cost is more statistically significant, both pointing out that the airlines are cutting Food and Operating costs when facing more competition. This is also confirmed by the DDIV estimations for both Food and Operating expenses. The result suggests that when firms face more competition, their willingness to spend for product differentiation decreases. This is specific to the airline industry and might not be extrapolated to a different technology-oriented consumer experience industry like smart phone or computer.

The DDIV estimate shows a slightly negative but statistically insinificant coefficient for maintenance cost. This is reassuring regarding the concern over safety. The airlines may be aware that an accident would be detrimental to its market power and thus safety costs like maintenance is inelastic even with more severe competition. It is also because the government rule on maintenance is extremely strict. Airplanes would have to undergo small maintenance after a fixed number of flying hours and grand maintenance after a fixed period of time.

Other coefficients also provide interesting insights: the Average Nonstop distance uniformly increases every types of costs under every models. However, it may be misleading to think that airlines should shift to shorter markets and be local, since this increase in total maintenance, food, and operating cost might be subject to economies of scale. By flying longer haul, the airlines keep their planes flying and making more profit instead of having to transit a lot. From an engineering standpoint, a plane's age counts not by the miles flown, but by the number of times it takes off and lands, so having a plane to fly longer route would depreciate it less than to fly short routes and take off multiple times.

The results in both OLS and DDIV shows that with more competition, airlines fly longer nonstop routes and employ more homogeneous fleets. Since competition makes airline more aware about cost saving and revenue maximizing, they would want the airplanes to spend as much time flying and as little time on the ground as possible. On top of that, fuel efficiency for new small, narrow-body planes allows them to travel longer, point-to-point routes without going through costly and densely populated hubs. This allows airlines to operate more locally and serve a smaller demand without having to connect. Therefore, it is intuitive that we see an increasing nonstop distance as a result of more competition. The gravitation towards a homogeneous fleet of planes is also justfied, since airlines would only have to train one type of pilot and hire one type of engineer to perform maintenance on their fleets, exploiting economies of scale. One more justification for a homogeneous fleet goes back to the observation that airlines now prefer longer, poin-to-point routes. It is very intuitive to see their fleet transitioning towards a homogeneous fleet of small efficient planes.

5 Conclusion

In this paper, I estimated the effects of competition on cost behavior and market structure of the airline industry. The estimation is broken into two steps: step one estimates the demand elasticicities for the airlines, while step two takes the elasticity derived from step one to evaluate the effect of more competition on costs behavior of the firm and the market structure.

In step one, this paper used the Berry-Lehvinson-Pakes (1995) method to estimate the demand for a differentiated product airline market. For each of an year-quarter from 1993Q1 to 2018Q4, an own-price elasticity is derived for each airline. The result shows that, during the period of the estimation, own-price elasticity has increased significantly throughout the United States aviation market. The whole industry uniformly faces more competition.

In step two, I estimated the effects of increased competition on different costs by the airlines and how airline change their structures. The costs chosen were maintenance cost, food cost, and other operating costs. Maintenance cost addresses the concern over safety that might be compromised by airlines. The coefficient, however, does not indicate that airlines changed their safety cost behavior significantly. Instead, airlines might be strongly willing to compromise customer comfort and airline's differentiated product, as they decrease food cost and other operating expenses when faced with more competition. This also implies that they are more prepared to engage in price competition, since the differentiated product aspect is gradually being removed. Airlines are flying longer nonstop routes with a more homogeneous fleets as a result of competition. This signals a transition of the transportation model from the traditional hub-to-spoke to point-to point model. The new plane orders are mostly small, efficient narrow-body planes which can fly longer distance and serve a lower demand market without connecting through costly, populated hubs.

In order to address the increasing competitiveness in the industry, in a future research, it would be interesting to examine the effects of different government subsidies in order to maintain consumer experience in air travel. I would also like to see the effects of competition on overbooking and delay behavior of airlines, and develop a model to explore which policy to be derived.

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Table 3: Summary

	mean	sd	min	max	Source
Fare	218.19	146.23	40	1500	DB1B
Nonstop	0.101		0	1	DB1B
Distance (miles)	1,560	75	45	7550	DB1B
Within-carrier origin share	0.15	0.11	0	1	DB1B
Nonstop rivals	1.22	1.43	0	12	DB1B
Budget airlines	1.75		0	5	DB1B
Number of routes per market	10.47	6.55	1	81	DB1B
Number of carriers per market	4.98	2.33	1	14	DB1B
Maintenance costs per aircraft (x1000)	3,145	1.23	0	19.23	P-7.B-4.3
Food costs per aircraft(x1000)	64.12	9.93	0	172.62	P-7,B-4.3
Operating costs(x1000)	517,132	417.76	2	2,934	P-7
N	13,142,196				

Table 4: OLS estimation of demand

Demand estimation-OLS vs Multinomial Logit				
	OLS		Multinomial Logit	
	Business	Leisure	Business	Leisure
Price β_1	-0.32	-3.87	-0.09	-3.21***
	(0.42)	(2.38)	(0.54)	(1.39)
Average competitor price β_{jm}	0.06	0.86	0.04	1.37***
	(1.80)	(0.65)	(0.12)	(0.55)
Nonstop=0	-10.36***	-2.98*	-2.25***	0.08
	(2.00)	(1.72)	(0.33)	(0.59)
Budget =1	0.004	1.47**	-0.076	1.66***
	(1.13)	(0.64)	(0.32)	(0.42)
Major	6.4***	0.657	1.11**	0.73***
	(1.05)	(2.88)	(0.60)	(0.17)
R^2	0.09	0.17	0.14	0.20

Table 5: Logit estimation

Full model estimation								
	All year-quater		1993Q1		2018Q4		Long haul	Short haul
	Mean	Stdv	Mean	Stdv	Mean	Stdv	Mean	Mean
Constant	71.45***	30.12***	72.12***	27.98***	82.92***	29.19***	62.55***	82.92***
	(1.26)	(6.37)	(20.29)	(8.43)	(13.75)	(11.12)	(20.19)	(13.75)
Price	-44.05***	2.86	-20.24***	1.72	-79.75***	6.12***	-11.24***	-36.75***
	(3.08)	(2.45)	(2.43)	(1.98)	(4.16)	(0.87)	(1.43)	(4.95)
Nonstop=0	-4.17***	1.17	0.04	0.02	-7.88***	3.98***	-1.47***	-3.68*
	(0.15)	(2.12)	(0.11)	(1.64)	(0.04)	(1.82)	(0.11)	(2.14)
Major at origin	8.14***	3.11***	13.11***	5.44	6.09**	3.12*	11.81***	3.90*
	(1.03)	(1.10)	(1.71)	(4.32)	(2.97)	(2.45)	(1.88)	(2.05)
Budget=1	-9.72***	1.45***	-15.44***	3.23***	-18.45	1.04*	-26.74***	-1.64***
	(2.11)	(0.42)	(1.20)	(0.67)	(1.99)	(0.66)	(6.56)	(0.59)
Income * Price	31.69***		17.42***		23.42***			
	(5.76)		(1.28)		(6.72)			
Age*Price	1.45***		6.28***		5.45***			
	(0.14)		(1.12)		(1.42)			
Female * Price	-1.45***		-3.14***		-0.95			
	(0.16)		(0.89)		(0.75)			
Income*(Nonstop=0)	-18.12***		-16.42***		-31.78***			
	(1.94)		(3.65)		(4.42)			
Income * Budget	0.45		1.88		-2.16			
	(1.72)		(1.64)		(3.49)			
Female*Budget	-7.25*		-7.28***		-17.45***			
	(4.53)		(2.55)		(4.76)			
GMM objective	688.9		1,277.95		877.38			

Table 6: Average own- and cross-price elasticity

Elasticity-calculation from GMM BLP estimation -2018Q4											
Product type	Characteristics			1	2	3	4	5	6	7	8
	Nonstop	Budget	Major at origin								
1	0	0	0	-3.468	0.421	1.488	0.089	0.124	0.236	2.445	0.143
2	1	0	0	0.251	-2.515	0.644	0.378	0.223	0.420	0.975	0.128
3	0	1	0	0.124	0.141	-7.257	1.644	0.015	2.057	2.689	0.045
4	0	0	1	0.339	0.321	0.348	-5.988	0.029	0.701	1.084	0.012
5	1	1	0	0.434	0.039	1.12	0.475	-2.756	0.096	0.992	0.001
6	1	0	1	0.211	0.110	1.021	0.493	0.086	-4.779	1.104	0.556
7	0	1	1	0.121	0.450	2.667	1.748	0.324	1.799	-8.75	0.425
8	1	1	1	0.421	0.199	0.145	0.001	0.103	0.212	0.345	-1.454
0-Outside good	-	-	-	0.020	0.015	0.042	0.075	0.142	0.037	0.987	0.137

Table 7: Average own- price elasticity

Elasticity-calculation from GMM logit estimation 2018Q4	
Airlines	Own price elasticity
WN	-5.277
DL	-4.251
UA	-4.164
AA	-2.339
US	-3.144
B6	-5.921

Table 8: Empirical results-Costs

Summary: Effect of competition on different costs						
	Maintenance		Food		Other operating expenses	
	OLS	DDIV	OLS	DDIV	OLS	DDIV
Absolute Own price elasticity	1.04	-0.76	-1.36**	-0.43***	-3.17*	-0.17***
	(1.42)	(3.81)	(0.72)	(0.014)	(1.92)	(0.061)
Labor costs	3.26***	2.17*	-	-	-	-
	(1.05)	(1.43)	-	-	-	-
Hub %	-	-	-1.08***	1.03*	1.64*	1.35*
	-	-	(0.35)	(0.68)	(0.98)	(0.77)
Average Nonstop Distance	5.72**	7.69***	0.86	1.46***	4.29*	1.86***
	(2.01)	(1.64)	(0.32)	(0.45)	(2.87)	(0.15)
Nonstop %	4.22***	5.12***	0.44	1.77***	-2.12*	-1.75***
	(1.02)	(1.86)	(1.19)	(0.41)	(1.65)	(0.47)
R^2	0.14	0.08	0.18	0.21	0.10	0.14

Table 9: Empirical results- nonstop distance and fleet homogeneity

Summary: Effect of competition on different airlines				
	Nonstop distance		Fleet Homogeneity	
	OLS	DDIV	OLS	DDIV
Absolute Own price elasticity	0.318***	0.157***	0.110***	0.014***
	(0.092)	(0.048)	(0.034)	(0.002)
Labor costs	-	-	0.032	0.041***
	-	-	(0.025)	(0.009)
Hub %	-0.151***	-0.271***	-	-
	(0.022)	(0.485)	-	-
Average Nonstop Distance	-	-	-	-
	-	-	-	-
Nonstop %	-	-	-	-
	-	-	-	-
R^2				