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Abstract

This paper estimates a Frequent Flyer Programs (FFP) price premium—higher fares associated with a larger proportion of travelers using FFP. The results show that FFP affect the entire price distribution, but the effect is larger on lower end fares. In addition, airport dominance increases the premium on less expensive fares but has no effect on the premium associated with the right tail of the price distribution.

Keywords: Frequent Flyer Programs; Pricing; Airlines; Panel Data.

JEL Classifications: C23; L11; L93.

1 Introduction

Frequent Flyer Programs (FFP) have grown significantly since the introduction of AAdvantage in 1981, the deregulation of the industry and the introduction of computer reservation systems. It is calculated that FFP have more that 80 million participants. The largest FFP in the U.S. are AAdvantage from American Airlines, Mileage Plus from United, and Sky Miles from Delta, each having more than 20 million members.[1] On the other hand, deregulation also replaced the traditional point-to-point service with the hub-and-spoke system raising the importance of hubs and airport dominance on pricing.

Existing empirical evidence, e.g. Borenstein (1989), shows how airport dominance influences the carriers ability to charge higher prices. In a related paper, Lederman (2008) uses

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[1]For more on the description of these programs see www.frequentflier.com.

the formation of partnerships to estimate that at least 25% of the 'hub premium'—higher fares charged by hub airlines for flights originating at its hub—can be accounted by FFP. Other papers on FFP include Lederman (2007) who looks at the effect of international partnerships on domestic demand and Bilotkach (2009) who looks at partnerships and frequency. Despite the importance of FFP, research in this area is scarce mainly because information on individual miles balances are not available to researchers. This paper uses a novel way to measure the extent of FFP to overcome this obstacle.

The current paper extends existing literature in three aspects. First, it provides an estimate of the FFP premium—higher fares associated with FFP. Second, it assesses the effect of FFP on the distribution of fares, and third, it evaluates the role of airport dominance on the effect of FFP on different percentiles of fares. The results show that a one percent increase in the proportion of travelers that use frequent flyer programs increases average fares by 1.16%. The effect is larger on the lower end of the price distribution than on more expensive tickets. Moreover, the effect of FFP on lower end fares was found to be greater when the carrier has a dominant position in the departing airport.

The rest of the paper is structured as follows. Section 2 describes the construction of the data, Section 3 presents the empirical model and Section 4 provides the results. Finally, Section 5 concludes.

2 Data

The data set for this paper comes from the market and the ticket sub-sections of the DB1B database and the segment sub-section of the T-100 database from the Bureau of Transportation and Statistics (BTS). The DB1B is a 10% random sample quarterly data of airline passenger ticket transactions with information on the ticket price, origin, destination and any connecting airports, carrier, type of ticket and service class. The T-100 has information on number of performed departures as well as number of seats and transported passengers between an origin and destination airport pair.

The paper focuses on domestic, round-trip, coach class tickets between the first quarter of 2000 and the third quarter of 2009. We restrict the analysis to round-trip tickets because these tickets allow us to identify the originating airport of the ticket. To restrict the analysis to economically significant routes, the sample includes only routes that had at least one carrier transporting an average of 40 passengers per week, by either direct or connecting service. The construction of the data set is such that each observation in the sample corresponds to a route—a pair of origin and destination airports—served by a carrier on a quarter. The carriers considered are AirTran, Alaska, American, Continental, Delta, Frontier, JetBlue, Northwest, Spirit, Trans World Airlines, United, and US Airways, each with its corresponding FFP partners. Because frequent flyer miles can also be obtained by traveling with a carrier's FFP partner, we identified the partners of each of the main carriers and considered those tickets as belonging to the main carrier. e.g. American Eagle miles count towards American Airlines' frequent flyer program.

3 Empirical Model

To investigate the relationship between pricing and the extent of frequent flyer programs, we estimate the following reduced-form pricing equation:

$$\log \textsc{Meanfare}_{ijt} = \delta \cdot \textsc{Ffp}_{ijt} + X'_{ijt}\beta + \nu_t + \varepsilon_{ij} + \mu_{ijt} \tag{1}$$

where each observation refers to route i, carrier j during quarter t. The dependent variable log MEANFARE is the logarithm of the average of fares. To further analyze the effect of loyalty programs on the tails of the price distribution we will also use the log 20th and the log 80th percentiles of fares as dependent variables, log 20PCTFARE and log 80PCTFARE, respectively. The main variable of interest is FFP, a measure of FFP. It is obtained as the ratio of frequent flyer tickets to the total number of tickets, where the number of frequent flyer tickets is the number of tickets with a price equal to zero as recorded in the DB1B database.[2] The vector of controls X'_{ijt} includes time-variant carrier-route characteristics not captured by the fixed effects. It includes $\textsc{Propdepa}_{ijt}$, a measure of airport dominance that is constructed as the proportion of departures out of the departing airport in route j that belong to carrier i during time t. Constructed in the same fashion, $\textsc{Propdest}_{ijt}$ is the proportion of nonstop destinations of carrier i out of the departing airport in route j and

[2]The typical approach in empirical studies that use the DB1B database is to control for tickets sold through frequent flyer programs by eliminating tickets prices below \$10 or \$20. See, for example, Borenstein and Rose (1994) or more recently Gerardi and Shapiro (2009).

PROPDIRECT_{ijt} is the proportion of direct flights. Also in X'_{ijt}, NUMDEST_{ijt} is the total number of destination of carrier i out of the departing airport on route j and LOADFACT_{ijt} is the load factor or capacity utilization. Finally, ν_t denotes the unobservable time specific effect, ε_{ij} captures any unobservable carrier-route time-invariant specific effect and μ_{ijt} is the remaining disturbance. The fixed effects control, for example, for changes over time in industry-level prices and for time-invariant hub effects on pricing.

A positive δ coefficient will be evidence of a positive FFP premium. To analyze the role of airport dominance on the FFP premium we present two additional specifications. The first includes the interaction term $\text{FFP}_{ijt} \times \text{PROPDEPA}_{ijt}$ in Equation 1 to see how the premium changes as a carrier increases its presence at the departing airport. The second approach separates the effect of FFT_{ijt} on fares in two, when the proportion of departures is below its median and when it is above its median:

$$\begin{aligned} \log \text{MEANFARE}_{ijt} \quad &= \quad \delta_1 \cdot \text{FFP}_{ijt} \times 1_{[\text{PROPDEPA} > \text{med(PROPDEPA)}]} \\ &+ \quad \delta_2 \cdot \text{FFP}_{ijt} \times 1_{[\text{PROPDEPA} \leq \text{med(PROPDEPA)}]} + X'_{ijt}\beta + \nu_t + \varepsilon_{ij} + \mu_{ijt}. \end{aligned} \tag{2}$$

The indicator variable $1_{[\text{PROPDEPA} > \text{med(PROPDEPA)}]}$ is equal to one when PROPDEPA_{ijt} is above its median, zero otherwise. The estimation of Equations 1 and 2 will additionally consider various log percentiles of fares as dependent variables.

4 Estimation Results

The summary statistics of the variables is presented in Table 1 and the results from the estimation of Equation 1 are presented in Table 2. All specifications include time and carrier-route fixed effects. The figures in parentheses are cluster-robust standard errors, clustered by airline. The positive coefficient on FFP in Column 1, that has log MEANFARE as the dependent variable, indicates that average fares are higher when the fraction of frequent flyer travelers is larger—positive FFP premium. In particular, this highly statatistically significant effect indicates that a one percent increase in the proportion of travelers who use FFP increases average fares by 1.16%. To assess the effect of the programs on the tails of the pricing distribution, Columns 2 and 3 present the estimates when the logs of the 20th and the 80th percentiles of fares are used as dependent variables. The results show that a one percent increase in the proportion of travelers who use FFP increases the 80th percentile of fares by 1.03%, but increases the 20th percentile by 3.06%. This is evidence that the programs have a larger effect on the lower tail of the price distribution.

To provide additional insights on the effect of the programs on the distribution of fares, Figure 1 provides the estimates of δ in the estimation of Equation 1 with the log of percentiles 5 through 95 of fares (with increments of 5) as the dependent variable. The shaded area is the 95% confidence interval, * denotes significance at 1% and the numbers in parentheses are clustered robust standard errors. While the effect is fairly constant for the 30th percentile and more expensive fares, the effect on the lower tail of fares is larger.

We now turn to the analysis of the role of airport dominance on the effect of the programs on fares. The positive and highly significant coefficient on the interaction term in Column 4 indicates that the effect of the programs on average fares is larger when the carrier has a larger proportion of departing flights from the originating airport. Columns 5 and 6 show that the effect is larger for the lower tail of fares and that airport dominance plays no role in the effect of the programs on more expensive fares. Figure 2 takes an additional step and shows the estimated $\hat{\delta}_1$ and $\hat{\delta}_2$ from Equation 2 at various log of percentiles of fares as the dependent variable. While the left-hand-side axis shows the values of the estimates, the right-hand-side axis show the p-values for the null of $\delta_1 = \delta_2$. The results indicate that the effect of the programs on the lower tail of fares is larger when the proportion of departures is larger than its median. There is no statistically significant difference between δ_1 and δ_2 for higher end fares.

5 Conclusions

Our measure of frequent flyer programs shows an intuitive positive and highly statistically significant FFP premium. While the positive premium affects the entire price distribution, the effect was found to be larger for lower end fares. A one percent increase in the proportion of travelers who use frequent flyer miles increases average fares by 1.16% and increases the 20th percentile and the 80th percentile of fares by 3.06% and 1.03%, respectively. Airport dominance showed to play an important role by increasing the FFP premium only on lower end fares.

Table 1: Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Ffp	0.024	0.042	0.000	0.699
Meanfare	173.4	57.52	27.37	774.9
20Pctfare	110.5	41.37	1.000	676.0
80Pctfare	225.4	92.45	33.00	1,150
Propdepa	0.136	0.146	0.000	1.000
Propdest	0.411	0.270	0.007	1.000
Propdirect	0.459	0.462	0.000	1.000
Numdest	29.60	31.02	1.000	135.0
Loadfact	0.745	0.101	0.000	1.000

Notes: Number of observations: 236,919.

Table 2: Regression Results

VARIABLES	(1) log of Meanfare	(2) log of 20Pctfare	(3) log of 80Pctfare	(4) log of Meanfare	(5) log of 20Pctfare	(6) log of 80Pctfare
Ffp	1.158*	3.057*	1.029*	0.981*	1.541*	0.929*
	(0.0959)	(0.596)	(0.0965)	(0.125)	(0.436)	(0.129)
Ffp × Propdepa				0.874*	7.494*	0.496
				(0.243)	(1.831)	(0.374)
Propdepa	0.132	0.369†	0.137	0.0713	-0.148	0.103
	(0.134)	(0.132)	(0.165)	(0.129)	(0.0904)	(0.159)
Propdest	0.0321	0.110	0.0218	0.0303	0.0948	0.0208
	(0.0481)	(0.0959)	(0.0572)	(0.0479)	(0.0991)	(0.0571)
Propdirect	-0.0159	0.0925‡	-0.0460*	-0.0158	0.0933‡	-0.0459*
	(0.0158)	(0.0428)	(0.0147)	(0.0158)	(0.0438)	(0.0147)
Numdest/10^3	-0.0430	-1.430	0.179	0.0522	-0.613	0.233
	(0.437)	(1.820)	(0.453)	(0.403)	(1.850)	(0.423)
Loadfact	-0.131†	0.356*	-0.231†	-0.134†	0.337*	-0.232†
	(0.0471)	(0.0910)	(0.0751)	(0.0465)	(0.0928)	(0.0748)
Within R-squared	0.190	0.051	0.132	0.192	0.060	0.132

Notes: The dependent variable is the log of Meanfare in Columns 1 and 4, the log of 20Pctfare in Columns 2 and 5 and the log of 80Pctfare in Columns 3 and 6. Number of observations: 236,919. Figures in parentheses are cluster-robust standard errors, clustered by airline. ‡ significant at 10%; † significant at 5%; * significant at 1%.

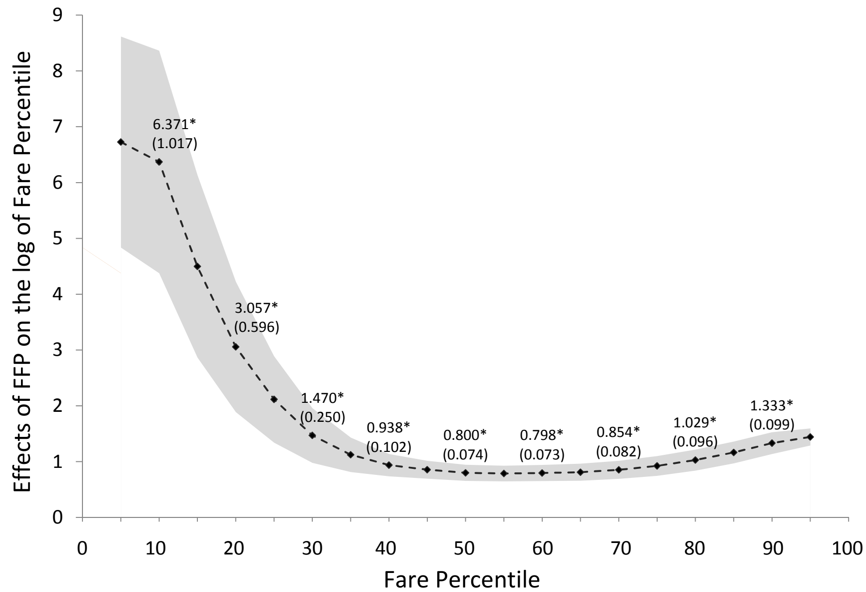

Figure 1: Effects of FFT on the log of fare percentiles. The shaded area is the 95% confidence interval. * significant at 1%. The numbers in parentheses are cluster-robust standard errors, clustered by airline.

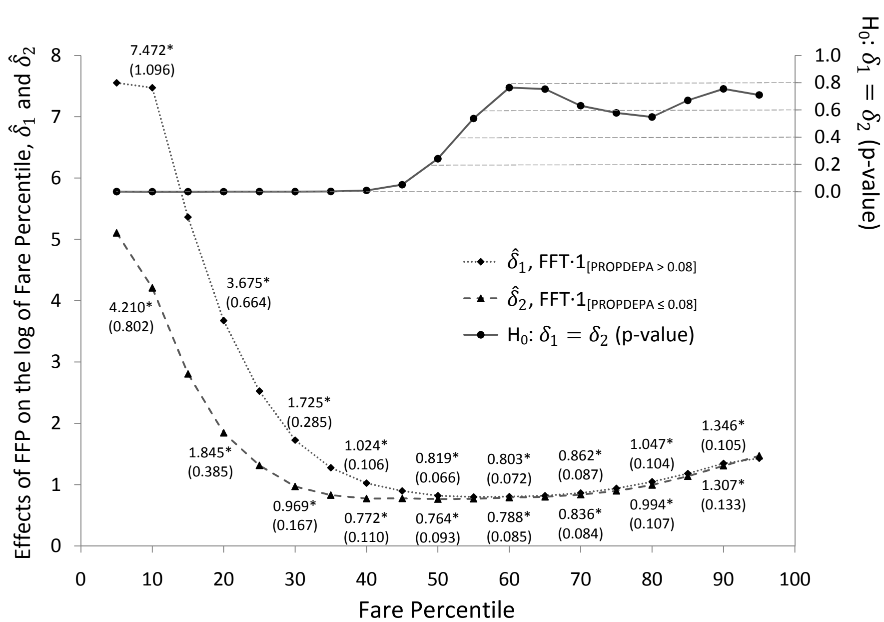

Figure 2: Effects of FFT on the log of fare percentiles. * significant at 1%. The numbers in parentheses are cluster-robust standard errors, clustered by airline.

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