A Note on Aircraft Age and Airfares

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Abstract

This paper finds that airlines charge higher fares on flights operated by older aircraft. The results show how airline fleet costs can ultimately affect consumers through airfares. Data on over five million domestic flights are collapsed into a quarterly panel that tracks fares and operating aircraft attributes across various nonstop markets within the United States. The fare impacts of aircraft age are estimated using a reduced-form fare regression, which controls for competition and other market characteristics that affect ticket prices. While fares are found to generally increase with older aircraft, the results show that the relationship between aircraft age and fares is more nuanced. Prices decrease with age on markets served by brand-new aircraft, but increase with age on markets where the average aircraft age is over nine years old.

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1 Introduction

Over the past decade, U.S. airlines have restructured through mergers and bankruptcies amid growing competition from low-cost carriers and international airlines. Volatile fuel prices and high labor costs have led carriers to adopt various cost-reducing strategies, including modernizing their aging fleets to improve operational efficiencies and to potentially lessen their burden of meeting environmental protection targets (Kwan & Rutherford, 2015). Airlines with younger fleets realize cost savings from operating new generation aircraft that are more fuel efficient and less expensive to maintain (Antoniou, 1992; Dixon, 2006; Ryerson & Hansen, 2013). The high cost of ownership for newer aircraft, however, can also outweigh their lower operating and maintenance costs (Swan & Adler, 2006; Zuidberg, 2014). Thus, airlines pay close attention to the age distribution of their fleets when making both aircraft-acquisition and operational decisions.

Various studies have addressed the efficiency and cost-competitiveness of airlines (Caves et al., 1984; Gillen et al., 1990; Distexhe & Perelman, 1994; Good et al., 1993, 1995; Oum & You, 1998; Barbot et al., 2008), while Brueckner et al. (1992) specifically showed that carrier costs and airfares decline as passenger traffic density increases on airline routes. More recent works studied the operational costs associated with airline fleet characteristics (Merkert & Hensher, 2011; Barros et al., 2013; Ryerson & Hansen, 2013), and examined how airlines plan aircraft size and cabin seat configurations (Givoni & Rietveld, 2009). Research on the role of aircraft age in airline revenue management, however, is sparse. Understanding the fare impacts of aircraft age is timely, as major U.S. carriers are renewing their fleets with the latest generation aircraft.[1] While efficiency improvements of modern fleets are well-documented, little is known about the mechanisms airlines may use to pass through costs of owning and operating their new aircraft. This paper fills some of these knowledge gaps by investigating the impact of aircraft age on airfares.

Airlines make significant capital investments when purchasing or leasing new airplanes, and they typically incur depreciation costs of new equipment for 10-to-15 years (Belobaba, 2009). These high ownership costs, which account for 32 percent of new airplane expenditures, are partly offset by reductions in fuel burn and maintenance costs (Swan & Adler, 2006). Although airlines manage their fleet costs by making decisions on the age, size and composition of their aircraft, fleet changes are expensive and slow to implement. Thus, in the short term, airlines make operational decisions for their pre-planned networks and routes, including aircraft assignments, crew and maintenance schedules, and airfares. As these decisions are constrained by fleet capacity and efficiency factors, the age of available aircraft is likely to be considered by flight planners. To the extent that cost-

[1] New aircraft accounted for around 6 percent of the U.S. commercial fleet in 2013, while aircraft under five years old accounted for approximately 13 percent of the existing fleet.

savings from more fuel-efficient aircraft outweigh their ownership costs, and are passed through to consumers, cheaper airfares would be expected on markets served by younger airplanes.[2]

Aircraft age can also affect airfares through demand-side drivers. New airplanes, indicating better service quality, may increase travel demand and drive up fares (Borenstein, 1989). Although passengers are not likely to pay attention to aircraft vintage when purchasing tickets, the novelty of new aircraft types (e.g., the Airbus A380 and Boeing 787) can generate sufficient interest for carriers to raise fares on flights specifically operated by those airplanes (Belobaba, 2009). The airline literature, however, suggests that passengers care more about other service attributes, such as flight frequency and on-time records (Mazzeo, 2003).

This paper examines the effect of aircraft age on airfares by estimating a reduced-form regression model, using quarterly data from 2013. The relationship between aircraft age and airfares is examined by joining itinerary fares on nonstop domestic flights with the frequency-weighted average age of operating aircraft. Airfares are regressed on aircraft age and key controls for airline competition, network characteristics, and travel demand. The results show that fares generally increase with aircraft age. However, fares are also found to decrease on markets served by new aircraft, where the average aircraft age is under nine years old.

The next section describes the data used for this study, the construction of variables from various data sources, and the methodology. Section 3 presents the regression results, including those from an alternative specification of the empirical model. Section 4 provides some conclusions.

2 Data and Variables

This study uses itinerary data on nonstop domestic markets served by mainline U.S. carriers in the four quarters of calendar year 2013.[3] Regional carriers are left out because they have a different business model, operate different aircraft types, and have much higher aircraft-utilization rates. The analysis combines flight-level data from the U.S. Department of Transportation's (DOT's) Airline On-time performance data base and passenger traffic data from their Form 41 Traffic, T-100 Segment tables. Flight records in the On-time performance data base provide an aircraft tail ("N") number field, which is used to join the data base to aircraft information provided in the Federal Aviation Administration's (FAA) aircraft registry. The FAA's aircraft registry provides a variety of data on aircraft including registered owners, manufacturers, year of production, number of

[2] See Koopmans & Lieshout (2016) on airline pass-through costs, which they find vary by market structures and types of cost increases.

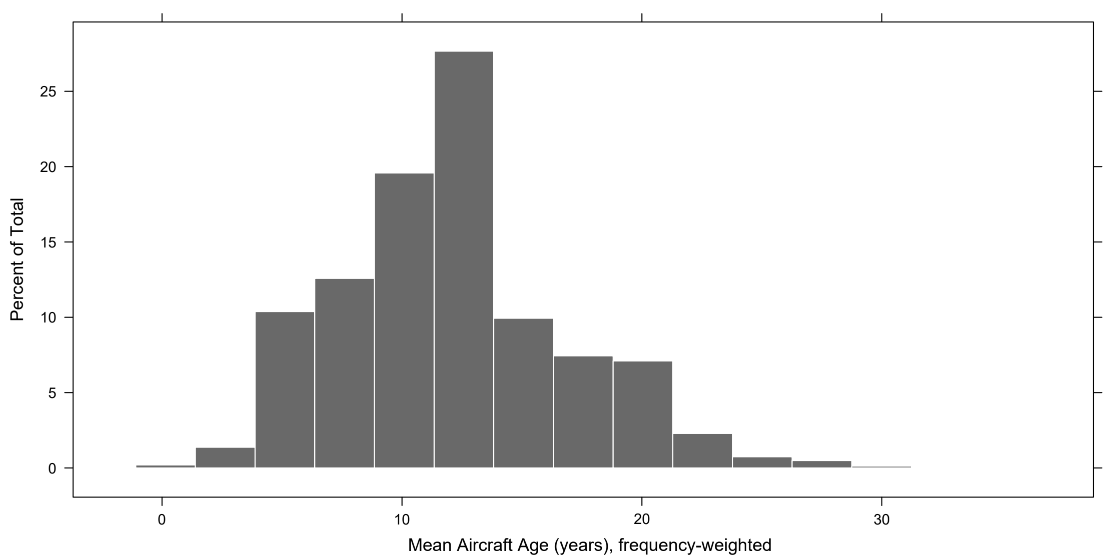
[3] The mainline carriers that operated in 2013 include AirTran Airways (FL), Alaska Airlines (AS), American Airlines (AA), Delta Air Lines (DL), Frontier Airlines (F9), Hawaiian Airlines (HA), JetBlue Airways (B6), Southwest Airlines (WN), United Airlines (UA), US Airways (US), and Virgin America (VX).

seats, and engine types.[4] The DOT also provides an inventory of aircraft owned by U.S. carriers in their Schedule B-43 inventory, but the FAA's aircraft registry provides more accurate and complete information.

2.1 Aircraft Characteristics

The On-time performance data provide detailed information on gate-to-gate airline operations, including measures of flight delays, cancellations, and diversions of certified U.S. major carriers. The data also include registration tail numbers of operating aircraft, which can be used as unique identifiers of the airplanes. Cleaned tail numbers reported for 2013 are used to join the FAA aircraft registry information with flight records in the On-time performance data base. Using reported aircraft manufacturing dates, the market-specific average aircraft age is calculated for each carrier. Figure 1 shows the average age distribution of aircraft operated by mainline carriers on nonstop flights in 2013. For each carrier, the average age is weighted by flight frequency on both the outbound and inbound segments of the sample's nonstop markets. The average aircraft age for the carriers ranges from less than 1 to almost 35 years, with the mean at around 11 years. Figure 3 in the appendix shows the average age distribution of operating aircraft by carrier.

Figure 1: Aircraft Age of Mainline US Carriers on Nonstop Markets, 2013 (A)



[4] For complete coverage of aircraft that operated in 2013, three data sets (registered aircraft, de-registered aircraft, and an aircraft reference file) are downloaded from the FAA's aircraft registry website. Registered and de-registered aircraft are then joined with the aircraft reference file.

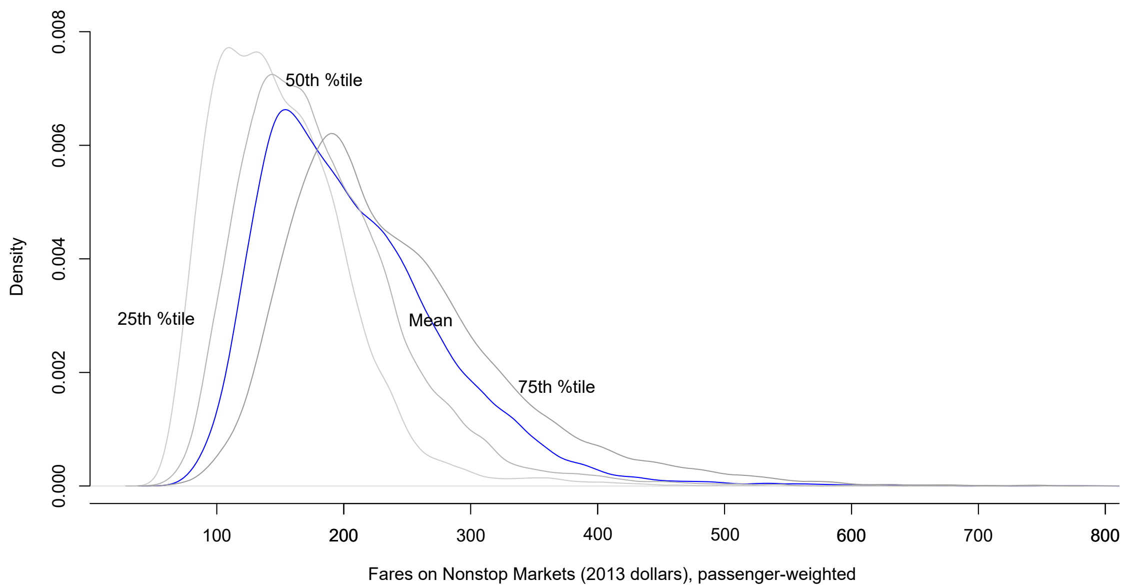
2.2 Fares

Fare data are obtained from the DOT's Airline Origin and Destination Survey (DB1B Market). These data are based on a 10-percent sample of passenger tickets sold by reporting U.S. carriers. For each itinerary record, the DB1B Market data provide the operating, ticketing and reporting carrier, the origin and destination airports, the prorated airfare, the number of flights, and other directional market attributes of the sample itineraries. This study focuses on roundtrip nonstop markets to accurately match operating aircraft characteristics with corresponding fare data. Hence, the DB1B data are filtered to exclude one-way tickets and records with more than one market coupon (two itinerary coupons). Records for the return trip of the nonstop markets are linked to the outbound trips by matching itinerary codes. Given that the operations data taken from the On-time performance data base are provided by a reporting carrier, the DB1B Market data used in this study are restricted to cases where the reporting and operating carriers are the same, and where the operating airline flies both the outbound and inbound flights between market airports.[5]

Figure 2 shows the distribution of passenger-weighted average fares on nonstop markets included in the study's sample. The quartile average fare distributions show price dispersion in the nonstop sample, and the market average fares are generally skewed to the right, with the mean fares falling between the median and 75th percentile. Figure 4 in the appendix exhibits the average fare distributions by carrier.

[5] The sample is based on nonstop domestic flights between 100 and 10,000 nautical miles, including flights between the contiguous US, Hawaii, and Alaska. Observations with directional fares that are less $50 or greater than $5,000 are dropped, and records with ticket prices higher than five times the 2013 Standard Industry Fare Level (SIFL) are also omitted.

Figure 2: Fare Distribution on Nonstop Markets, 2013 (A)



2.3 Controls for Competition and Market Characteristics

The DOT's T-100 Segment data on passenger traffic and flight distances are used to construct controls for competition and market characteristics. These controls account for time-invariant factors that are likely to affect airfares.

Market concentration

Airport- and route-level competition is measured by the Herfindahl-Hirschman Index (HHI), an indicator of market concentration that is used in competition and merger studies. HHI is calculated by summing the squares of each carrier's enplanement shares at the airport- and route-levels. Markets with unobservable characteristics that foster higher fares naturally attract more entry. Thus, it could be argued that these measures of competition are endogenous. While attempts to instrument for these variables could reduce the bias in their estimated coefficients, the bias is not expected to be substantial. Hence, following Morrison (2001) and Brueckner et al. (2013), this paper does not attempt to correct for the potential endogeneity of the competition measures.

Flight distance

Long-distance flights are costlier for carriers to operate, compared with shorter flights. Given that operating-cost differences due to flight distance are reflected in airfares, a control measuring the distance between market airports (stage length), is used in the analysis.

Market size

Larger markets generate greater demand for airline services than smaller markets. Using the U.S. Census Bureau's 2013 population estimates, the average endpoint MSA populations are calculated for nonstop markets in the regression sample.

Income

The demand for air transport increases with income (Brueckner, 1985). The mean income of market cities is computed from 2013 demographic estimates provided by the U.S. Census Bureau.

Weather

Warmer destinations (Sunbelt locations) are generally more attractive for leisure travel. The regression model includes a variable measuring differences in the highest daily-average January temperature between market cities. Data on weather conditions are obtained from the National Oceanic and Atmospheric Administration's (NOAA) data base.

2.4 Model Specification

A reduced form linear regression model is used to examine the relationship between aircraft age and ticket prices. For a given carrier i in quarter t, the average itinerary fares of nonstop markets (indexed m) are regressed on the average age of aircraft operated on those trips. Including other market-specific controls in the regressions, the reduced-form regressions are represented by:

$$\begin{aligned} \ln FARE_{itm} = \beta_o + \beta_1 AGE_{itm} + \gamma_2 HHIAIRP_{tm} + \gamma_3 HHIROUTE_{tm} + \gamma_4 \ln DIST_{tm} \\ + \delta_5 POP_m + \delta_6 INC_m + \delta_7 JANTEMP_m + \sum \rho_i CAR_i + \sum \theta_t QTR_t + \varepsilon_{itm}, \end{aligned} \tag{1}$$

where $FARE$ is the average itinerary fare (in 2013 dollars) for the sample nonstop markets; AGE is the average age (in years) of aircraft operating both outbound and inbound trips; $HHIAIRP$ and $HHIROUTE$ are the airport and route Herfindahl-Hirschman indexes, respectively; $DIST$ is the nonstop distance between market airports (in nautical miles); POP and INC are the mean populations and incomes (in 2013 dollars) of market endpoint MSAs, respectively;[6] and $JANTEMP$ is the January temperature difference between market endpoint airports (in degrees Celsius).

Carrier dummies (CAR) are included in the regressions to control for price impacts from unobserved, airline-specific differences that are constant over time. Differences in fleet size, types and commonality, for example, can have a strong bearing on a carrier's cost structure. Lastly, quarter dummies are used to control for seasonal variations in the time series. Table 1 provides descriptive statistics for the regression variables. The expected signs for the regression coefficient estimates are shown in parentheses.

[6] Both the arithmetic and geometric means of endpoint MSA populations and incomes are examined. Given their similarity, the arithmetic mean is selected arbitrarily for this study.

Table 1: Variable Definitions and Summary

Variable	Definition	Min	Median	Mean	Max
ln *FARE*	Natural log of passenger-weighted average fare on nonstop markets (2013 dollars)	69.0	194.9	208.5	861.4
	25th percentile	51.5	143.5	151.3	759.5
	50th percentile	52.0	172.0	183.5	759.5
	75th percentile	69.0	222.8	241.2	1,133.5
AGE (+/-)	Mean age (years from production date) of aircraft operating on nonstop markets, frequency-weighted	0.29	11.74	12.06	34.83
HHI AIRP (+)	Airport Herfindahl-Hirschman index (airport-level concentration)	0.10	0.25	0.28	0.91
HHI ROUTE (+)	Route Herfindahl-Hirschman index (route-level concentration)	<0.00	0.61	0.66	1.00
ln *DIST (+)*	Natural log of average nonstop, directional distance between market endpoint airports (nautical miles)	101	952	1,113	4,983
POP (-)	Arithmetic mean of endpoint MSA populations (millions), 2013 estimates	0.11	3.72	4.70	16.54
INC (+)	Arithmetic mean of endpoint MSA per-capita incomes (2013 dollars, thousands), 2013 estimates	19.93	29.95	30.47	42.80
JANTEMP (-)	Difference of average maximum January temperatures recorded at market endpoint MSAs (degrees Celsius), 2013	0.02	8.68	9.92	30.41

3 Results

Table 2 exhibits the regression results. The second column (column 1) shows the results for the regression of average age on all of the covariates in the analysis. Recall that the panel for this analysis is constructed by aggregating data to the market level for each carrier in the four quarters of 2013. Markets with higher levels of airline concentration, particularly at endpoint airports, tend to be served by older airplanes, controlling for flight distances and other market characteristics.

The coefficient on flight distance exhibits the expected negative sign, as airlines would choose to operate newer and more fuel-efficient equipment on longer routes.

An interesting finding, which supports some anecdotal observations, is that markets between affluent endpoints are served by younger airline fleets. This result lends some credence to the existence of demand-side drivers of aircraft age, such that newer, more-reliable airplanes are used to serve passengers with a high value of time. The carrier dummies in the first regression reflect the average vintage of the airline fleets, relative to the average age of aircraft operated by American Airlines (the baseline carrier omitted from the list of covariates). With the exception of Delta Air Lines, all of the carriers in the sample operated younger fleets than American's. Notably, Virgin America and JetBlue flew the newest airplanes in 2013, followed by Alaskan and Frontier.

3.1 Linear model

The next three columns (columns 2 through 4) show results of fare regressions, assuming a linear relationship with aircraft age (AGE). Linear restriction tests confirm that the estimated coefficients on AGE are significantly different from zero. In column (2), the average fare is regressed on AGE and control variables. The statistically-significant coefficient on AGE implies that average fares rise by 0.7 percent for a single-year increase in AGE. Thus, for a 10-year increase in the average age, fares would rise by 6.7 percent. This outcome holds across various distributions of airline fares, as shown by the results of columns (3) and (4). The average aircraft age appears to have a weaker relation with the lower quartile airfares, such that fares increase only by about 0.4 percent for every year AGE increases.

The other variables included in these fare regressions exhibit the expected signs. Controls for airline competition indicate that fares rise with increased airline concentration (decreased competition), both at the airport and route levels. The coefficient on ln $DIST$ confirms that average fares are higher on flights with longer stage lengths, all else equal. Since price does not increase in direct proportion to stage length, the distance coefficient is less than one. Consistent with findings in the relevant literature (Brueckner et al., 2013), the POP coefficients suggest that airline fares for flights between large cities are lower, presumably due to economies of traffic density on those markets. The average income of endpoint cities in the sample markets increases with fares for the mean and upper-quartile ranges of fares, while decreasing with fares in the lower, 25th percentile range. This outcome is consistent with the theory that markets connecting wealthier cities have stronger demand for air travel. The differential impact on lower and mid- to high-quartile fares may also reflect the presence of time-sensitive business travelers who are willing to pay higher fares for air travel (Brueckner et al., 2013). The coefficient on $JANTEMP$ implies that larger differences in endpoint city temperatures (usually on leisure markets) are associated with lower fares.

The dummy coefficients for airlines show how their average fares compare to that of American Airlines. As would be expected, the traditional low-cost carriers (Frontier, Airtran, JetBlue, and Southwest) exhibit the largest fare reductions relative to American, followed by Alaskan, Hawaiian and Virgin America. Legacy carriers — US Airways, United and Delta — have higher average fares compared with American. Lastly, coefficient estimates of the quarter dummies confirm the expected higher demand for air travel during the summer months in the third quarter, followed by the holiday season that spans the fourth and first quarters of the calendar year.

Returning to the AGE regression results (column 1), the statistically-significant coefficient on $HHIAIRP$ suggests that network carriers use older aircraft at their hubs. Given the established links between airport concentration and airfares,[7] the fare impacts of aircraft age might be, to some extent, driven by airline competition. Network carriers possibly schedule older airplanes on markets connecting concentrated airports, where they can also exercise their market power and charge higher fares. Similarly, market distance ($\ln DIST$) may also affect airfares through aircraft age. If airlines inherently fly older planes on short-distance markets, the observed fare impacts of AGE might partly reflect the higher price carriers charge on shorter routes. Preliminary fare regressions that introduce interactions of AGE with $HHIAIRP$ and $\ln DIST$ provide some support to the theory that airport concentration and market distance indirectly affect fares through aircraft age. However, more rigorous tests are needed to measure the strength and significance of such indirect effects.

3.2 Curvilinear model

The relationship between fleet costs and aircraft age is likely to change over the life-cycle and mix of aircraft in airline fleets. Newly-manufactured airplanes of the latest designs allow carriers to enjoy low operating costs but incur high ownership costs from leasing and deprecation.[8] While new aircraft with older designs have lower acquisition costs, they require relatively high operating costs. Used aircraft of current designs have even lower acquisition costs, but introduce a risk of high maintenance costs as their manufacturer warranties phase out. Lastly, airlines enjoy relatively low ownership costs from used fleet of older models. These aircraft, however, typically require higher operating and maintenance costs (Swan & Adler, 2006).[9]

[7] See Borenstein (1989) for the seminal econometric analysis.

[8] New generation aircraft, such as the Airbus A320neo series and the Boeing 737MAX, use advanced-technology engines, and are constructed with light-weight materials to reduce fuel burn. Manufacturers have also redesigned the airframes and wings of commercial aircraft to improve aerodynamic performance. Additionally, the latest cabin designs support relatively dense seating configurations, which inherently lowers unit costs for airlines.

[9] Note that commercial aircraft approach their useful life after operating for around 26 years. See Forsberg (2015) for a report on the retirement age and storage trends of commercial aircraft.

For a given fleet mix, airlines are likely to adjust the relative utilization rates of their new and old aircraft to minimize operating costs. Specifically, while preferring older aircraft for low ownership costs, carriers would operate their newest planes more often, particularly on long-distance routes. Assuming that fleet costs are passed through to passengers, airfares would be expected to decrease with aircraft age when ownership costs are greater than cost-savings from operations and maintenance, and they would be expected to increase with aircraft age when ownership costs are outweighed by operating and maintenance costs. To explore how the fare impact of aircraft age may change over fleet vintages, a quadratic AGE term is added to the regression analysis. Columns (5) through (7) in Table 2 provide the results for estimations including the squared AGE term. These regressions model the following modification of Equation 1:

$$\ln FARE_{itm} = \beta_o + \beta_1 AGE_{itm} + \beta_2 AGE_{itm}^2 + \gamma_3 HHIAIRP_{tm} + \gamma_4 HHIROUTE_{tm} + \gamma_5 \ln DIST_{tm} \\ + \delta_6 POP_m + \delta_7 INC_m + \delta_8 JANTEMP_m + \sum \rho_i CAR_i + \sum \theta_t QTR_t + \varepsilon_{itm}. \quad (2)$$

Across all fare percentiles, the estimated coefficients for AGE and AGE^2 are statistically significant. However, unlike the results for Equation 1 (columns 2-4), the signs on these coefficients suggest that airfares initially decrease with aging aircraft, albeit at a decreasing rate. At a certain point, fares stop decreasing with aircraft age, and begin increasing with aircraft age. This turning point (minimum) is calculated by differentiating Equation 2 with respect to AGE, and setting it equal to 0:

$$AGE = \frac{-\beta_1}{2\beta_2}.$$

From the estimated coefficients in columns (5) through (7), Table 3 provides the average aircraft ages at which point airfares increase with aging aircraft. The remaining variables in columns (5) through (7) have comparable coefficient estimates presented in columns (2) through (4), for which the implications are discussed earlier in this section.

Table 2: Results

Dependent Variable:	*AGE* (1)	ln *FARE* (2) Mean	(3) 25th pctile	(4) 75th pctile	(5) Mean	(6) 25th pctile	(7) 75th pctile
INTERCEPT	24.6927^a	3.0727^a	2.6453^a	3.5435^a	3.1960^a	2.7620^a	3.6681a
	(0.8546)	(0.0531)	(0.053)	(0.0586)	(0.0551)	(0.0577)	(0.0606)
AGE	—	0.006501^a	0.003933^a	0.007284^a	-0.012484^a	-0.014022^a	-0.011905a
		(0.000939)	(0.000937)	(0.000979)	(0.002931)	(0.003314)	(0.003151)
AGE^2	—	—	—	—	0.000690^a	0.000653^a	0.000698a
					(0.000109)	(0.000121)	(0.000115)
HHI AIRP	2.8109^a	0.0968^a	0.1134^a	0.1322^a	0.0811^a	0.0985^a	0.1163a
	(0.4849)	(0.0279)	(0.0294)	(0.0313)	(0.0279)	(0.0294)	(0.0314)
HHI ROUTE	0.1561	0.1297^a	0.1095^a	0.1414^a	0.1305^a	0.1102^a	0.1421a
	(0.2014)	(0.0119)	(0.0119)	(0.0136)	(0.0118)	(0.0119)	(0.0135)
ln *DIST*	-1.1091^a	0.3130^a	0.3535^a	0.2517^a	0.3092^a	0.3500^a	0.2479a
	(0.1068)	(0.0059)	(0.0062)	(0.0064)	(0.0059)	(0.0062)	(0.0063)
POP	-0.1373^a	-0.0053^a	-0.0135^a	-0.0057^a	-0.0054^a	-0.0136^a	-0.0058a
	(0.0204)	(0.0012)	(0.0011)	(0.0014)	(0.0012)	(0.0011)	(0.0014)
INC	-0.1011^a	0.0007	-0.0042^a	0.0033^a	0.001	-0.0039^a	0.0036a
	(0.0185)	(0.001)	(0.001)	(0.0011)	(0.001)	(0.001)	(0.0011)
JANTEMP	-0.0015	-0.0063^a	-0.0060^a	-0.0068^a	-0.0060^a	-0.0057^a	-0.0065a
	(0.0082)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
AS	-5.9836^a	-0.0867^a	-0.1098^a	-0.0526^b	-0.0969^a	-0.1194^a	-0.0629a
	(0.3862)	(0.0178)	(0.0195)	(0.0209)	(0.0176)	(0.0193)	(0.0005)
B6	-6.2806^a	-0.1812^a	-0.1261^a	-0.1568^a	-0.1934^a	-0.1376^a	-0.1629a
	(0.3451)	(0.0151)	(0.015)	(0.0173)	(0.015)	(0.0149)	(0.0207)
DL	3.4992^a	0.0978^a	0.1061^a	0.1173^a	0.1000^a	0.1082^a	0.1195a
	(0.3337)	(0.014)	(0.0136)	(0.0158)	(0.0139)	(0.0135)	(0.0157)
F9	-5.9841^a	-0.4219^a	-0.3762^a	-0.4193^a	-0.4198^a	-0.3743^a	-0.4173a
	(0.326)	(0.0179)	(0.0191)	(0.0201)	(0.0178)	(0.019)	(0.02)
FL	-3.3317^a	-0.2189^a	-0.1560^a	-0.2674^a	-0.2016^a	-0.1396^a	-0.2499a
	(0.3231)	(0.0131)	(0.014)	(0.0148)	(0.0139)	(0.0145)	(0.0153)
HA	-1.7131	-0.0725^b	0.0042	-0.1158^a	-0.0818^a	-0.0046	-0.1252a
	(1.0697)	(0.0321)	(0.0232)	(0.0442)	(0.0294)	(0.0222)	(0.0413)
UA	-0.4554	0.0968^a	0.0769^a	0.0949^a	0.1168^a	0.0959^a	0.1151a
	(0.3324)	(0.0134)	(0.013)	(0.0154)	(0.0139)	(0.0136)	(0.0159)
US	-2.0192^a	0.0622^a	0.0816^a	0.0720^a	0.0727^a	0.0916^a	0.0827a
	(0.3832)	(0.1772)	(0.0175)	(0.0199)	(0.0177)	(0.0175)	(0.0199)
VX	-8.5144^a	-0.0565^b	-0.1142^a	-0.0908^a	-0.0995^a	-0.1548^a	-0.1342a
	(0.3806)	(0.0263)	(0.0197)	(0.0284)	(0.0266)	(0.0205)	(0.0287)
WN	-3.5486^a	-0.1565^a	-0.1058^a	-0.1604^a	-0.1423^a	-0.0924^a	-0.1461a
	(0.3121)	(0.011)	(0.0111)	(0.0127)	(0.0113)	(0.0115)	(0.013)
Q2	-0.1881^a	-0.0097^a	0.0169^a	-0.0262^a	-0.0098^a	0.0169^a	-0.0263a
	(0.0345)	(0.0028)	(0.0033)	(0.0034)	(0.0028)	(0.0033)	(0.0034)
Q3	-0.3882^a	0.0460^a	0.1051^a	0.0229^a	0.0452^a	0.1044^a	0.0221a
	(0.0443)	(0.0033)	(0.0037)	(0.004)	(0.0033)	(0.0037)	(0.0041)
Q4	-0.5671^a	0.0373^a	0.0601^a	0.0304^a	0.0361^a	0.0589^a	0.0291a
	(0.0469)	(0.0031)	(0.0037)	(0.0304)	(0.0031)	(0.0037)	(0.0037)
Obs.	13,836	13,836	13,836	13,836	13,836	13,836	13,836
Adj. R-Squared	0.4999	0.6285	0.6040	0.5136	0.6321	0.6070	0.5171

White period standard errors, clustered at the market-level, are shown in parentheses.
Baseline carrier (AA) and quarter (Q1) are not shown.
Fares are passenger-weighted.
^{a} $p < 0.01$.
^{b} $p < 0.05$.

Table 3: Turning Point for AGE-FARE Relationship (Years)

	Mean	25th pctile	75th pctile
AGE	9.0	10.7	8.5

The turning-point estimates in Table 3 show that fares decrease with aircraft age on markets where the average aircraft age is less than nine years old. Assuming carriers pass costs through to passengers through airfares, this finding suggests that the ownership costs (leasing and depreciation) of aircraft under this age are potentially high enough to outweigh cost-savings associated with operating a young fleet. After nine years, airfares increase on flights operated by older aircraft, potentially to offset their higher operating and maintenance costs. The estimated turning point in the aircraft age and fare relationship occurs earlier at around 8.5 years for the highest quartile of airfares (75th percentile), compared to the lowest quartile of fares (nearly 11 years). Although ownership costs of brand-new commercial aircraft decrease over time, their operations and maintenance costs can increase significantly. Airlines face a substantial increase in maintenance costs as their aircraft come off manufacturer warranties, and the maintenance cost burdens are transferred from manufacturers to owners (Dixon, 2006).[10] Aircraft also go through their first depot-level heavy maintenance check (D check) after being in service for six-to-twelve years.

4 Conclusions

This paper examines the impact of aircraft age on airfares using data on nonstop domestic flights operated by U.S. airlines in 2013. Average airfares and aircraft ages across various markets serviced by mainline carriers are tracked for four quarters in a panel. The fare effects of aircraft age are then estimated using standard fare regressions, which include controls for travel demand, airport- and route-level airline competition, and other network characteristics.

The study shows that airfares generally increase with aging aircraft, consistent with the assumption that airlines would pass through the increasing costs of operating and maintaining older equipment. However, fares are found to be higher on flights that operate the newest airplanes, possibly as a price premium to offset their relatively high ownership costs (leasing and depreciation). Specifically, airfares decrease with aircraft age on markets where the average aircraft age is under nine years old. After this age, airfares increase with aircraft age, potentially reflecting when airlines face operating and maintenance costs that outweigh the ownership costs of their fleet. This estimated turning point coincides with the age that aircraft are phased out from manufacturer

[10] Commercial aircraft and engine warranties provide a range of coverage on equipment, including manufacturing defects, parts, and airframe structures. Manufacturers also guarantee seat-mile and maintenance cost targets over the first decade of an aircraft's life.

warranties, and go through their first round of heavy maintenance. Further research could employ similar econometric techniques on a longer panel, which would allow the estimation of market fixed effects. Such an approach would provide insights into how aging aircraft affect fares on specific markets, over time. A closer examination of the turning point in the aircraft age and fares relationship would also be a timely contribution to the relevant literature.

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5 Appendix

Figure 3: Aircraft Age of Mainline US Carriers on Nonstop Markets, 2013 (B)

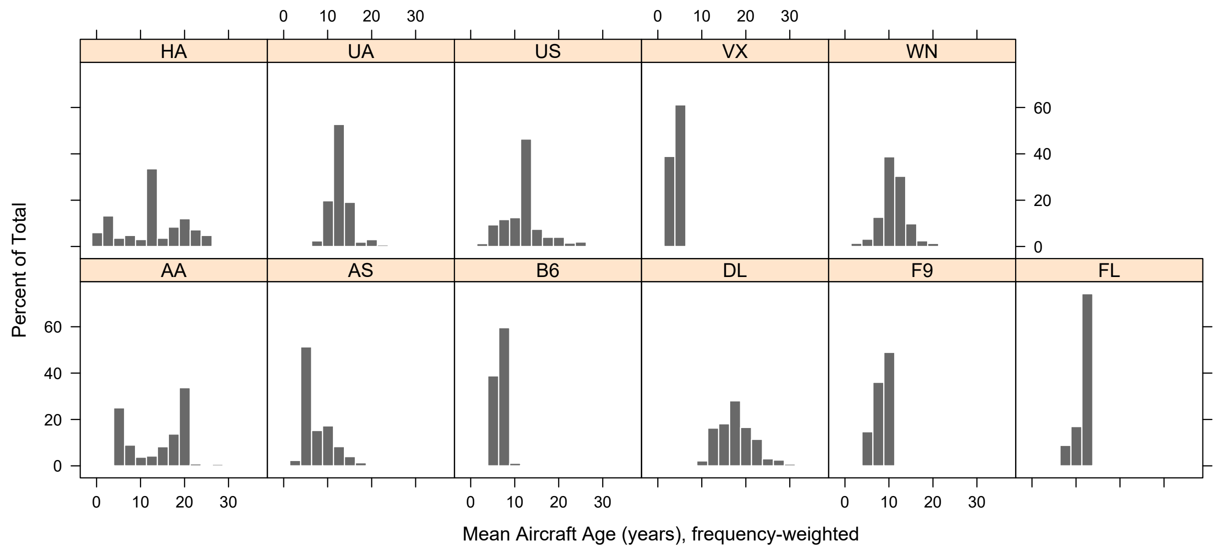

Figure 4: Fare Distribution of Mainline US Carriers on Nonstop Markets, 2013 (B)