Loyalty rewards and redemption behavior: Stylized facts for the U.S. airline industry

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Abstract

Over the past forty years, one of the most important datasets in industrial organization has been the Airline Origin and Destination Survey (DB1B). Most studies relying on these data remove tickets with fares less than \$20, assuming that these are heavily discounted frequent flyer awards (FFAs). We investigate the validity of this approach by first defining the size of the frequent flyer market using annual Form 10-K filings. Exploiting a federal regulation, we then outline a novel approach to identify FFAs in the DB1B. Our method indicates that the \$20 cutoff used by researchers is too high and may be lowered to \$12 for tickets appearing in the DB1B after February 1, 2002. Using the FFAs we identify, we show how the characteristics of award tickets differ from paid tickets and how these characteristics have changed over time. We then demonstrate how various market and product quality characteristics influence the share of passengers traveling on FFAs. Finally, we find that price dispersion increases on routes with higher shares of frequent flyer passengers, implying that airline loyalty programs enhance market power.

JEL Codes: L11, L13, L14, L93, M31, R40, R49

Keywords: Airlines, competition, loyalty rewards, frequent flyer tickets, product quality

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1 Introduction

Loyalty programs that reward consumers for repeat purchases are common in a variety of retail markets including airlines, car rentals, clothing, credit cards, hotels, restaurants, and supermarkets. By implementing loyalty programs, firms exercise a degree of market power over repeat customers by introducing a cost of switching to a competitor's product. These switching costs often include foregoing future rewards in addition to transaction costs associated with switching suppliers, learning to use new brands, and uncertainty about the quality of the competing product (Klemperer, 1995).

Although the typical consumer is a member of several different rewards programs, it is unclear whether these programs enhance or reduce competition in markets where they are present. For example, many have argued that loyalty programs are anticompetitive because switching costs generally raise prices, create barriers to entry, generate deadweight losses, facilitate tacit collusion, and reduce product variety (Banerjee and Summers, 1987; Cairns and Galbraith, 1990; Fong and Liu, 2011; Kim et al., 2001; Klemperer, 1995). Others argue that loyalty programs are "business stealing devices" that enhance competition and increase total surplus (Caminal, 2012; Caminal and Claici, 2007; Caminal and Matutes, 1990).[1]

Despite the importance of determining whether loyalty programs increase consumer welfare, empirical evidence on the effects of these programs are limited. Data on program membership and redemption behavior are often proprietary, and thus researchers have struggled to obtain appropriate data. However, there are some exceptions for the airline industry. Due to regulatory reporting requirements, airline data is often available to researchers. Using geocoded data from a major European frequent flyer program (FFP), De Jong et al. (2019) find that national airlines enjoy a substantial loyalty advantage in their home country.[2] Lederman (2007) used airline mergers to

[1]In addition, Basso et al. (2009) argue that within the airline industry, firms create frequent flyer programs to take advantage of the principal-agent problem between employers who pay for airline tickets and the employees who book them. In their theoretical model, they find that while these programs likely raise prices, airlines may end up worse off than if they had not created the programs due to intensified competition in the form of frequent flyer benefits.

[2]In particular, De Jong et al. (2019) find that foreign consumers earn about 60% less miles and are 70% less likely to be FFP members than domestic consumers.

instrument for enhancements to an airline's FFP and found that these enhancements are associated with increases in demand on routes that depart from an airline's hub airports (i.e., airports where the airline is dominant). In a follow-up paper, Lederman (2008) finds that FFPs enable airlines to charge higher fares on routes that depart from its hubs.

Nevertheless, many questions surrounding the economics of loyalty programs remain unexplored. For example, are consumers encouraged to redeem rewards on high or low quality products when the firm operating the loyalty program vertically differentiates its products? Do consumers disproportionately redeem rewards on high or low price products when multiple redemption options are available? How do loyalty programs affect price dispersion in differentiated product markets? In this paper, we shed light on these questions by presenting empirical evidence on frequent flyer redemption behavior for the U.S. airline industry.

Empirical questions concerning the economics of loyalty programs have been difficult to answer due to difficulties in identifying award redemptions in public and proprietary datasets. Our first contribution outlines an approach to credibly identify frequent flyer awards in one of the most widely used datasets in empirical industrial organization and transportation economics, the Department of Transportation's Airline Origin and Destination Survey (referred to as database DB1B). Released quarterly, the DB1B data are a 10% random sample of all airline tickets that originate in the United States on domestic carriers.[3] Over the past forty years, researchers relying on these data have provided empirical evidence on important questions surrounding competition policy and the functioning of oligopolistic markets. For example, the DB1B have been used to examine topics such as how incumbents respond to the threat of entry[4], the relationship between competition and price dispersion[5], how competition affects prices and profitability[6], the price effects of merg-

[3]The Department of Transportation relies on these data to determine air traffic patterns, air carrier market shares, and passenger flows.

[4]E.g., see Goolsbee and Syverson (2008), Gayle and Wu (2013), Gayle and Xie (2018), Morrison (2001), and Tan (2016).

[5]E.g., see Borenstein and Rose (1994), Gerardi and Shapiro (2009), Dai et al. (2014), Luttmann (2019), and Kim et al. (2023).

[6]E.g., see Berry and Jia (2010), Brueckner et al. (2013), and Kwoka et al. (2016).

ers[7], the price effects of granting antitrust immunity in international markets[8], the price effects of domestic alliances[9], how multimarket contact may facilitate tacit collusion[10], how capacity constraints affect prices[11], the revenue effects of product unbundling[12], and the competitive effects of common ownership[13], among others.[14]

A common theme among papers relying on DB1B data are their approaches towards removing low-fare tickets. Almost all papers remove observations with fares below a $20 or $25 cutoff, assuming that these fares represent heavily discounted frequent flyer award (FFA) tickets.[15] We focus on this portion of the dataset and find that researchers are removing approximately 7%-10% of observations (tickets) when applying a $20 cutoff. We then investigate the validity of this approach by comparing these dropped ticket counts to the number of FFAs reported by airlines in their annual Form 10-K filings, finding that FFAs account for roughly 7%-8% of revenue passenger miles in a given year.[16]

To identify frequent flyer tickets in the DB1B data, we exploit a February 1, 2002 federal regulation that established the Passenger Fee, also known as the September 11 Security Fee. This fee is collected by all commercial air carriers at the time airfare is purchased, *including when passengers redeem frequent flyer awards*. Although not the focus of this paper, the method of identifying frequent flyer tickets that we describe in Section 3 can serve as a starting point for empirical researchers interested in exploring questions such as the effects of mergers and codesharing on FFAs,

[7] E.g., see Luo (2014), Carlton et al. (2017), Shen (2017), and Li et al. (2022).

[8] E.g., see Brueckner and Whalen (2000), Whalen (2007), Brueckner et al. (2011), Gayle and Thomas (2016), Calzaretta Jr et al. (2017), Brueckner and Singer (2019), and Gayle and Xie (2019).

[9] E.g., see Gayle (2013).

[10] E.g., see Ciliberto and Williams (2014), Ciliberto et al. (2019), and Kim et al. (2021).

[11] E.g., see Fukui (2019).

[12] E.g., see Brueckner et al. (2015) and He et al. (2022).

[13] E.g., see Azar et al. (2018).

[14] The DB1B data have also been used to investigate how the internet influences price dispersion (Orlov, 2011) and how government legislation affects fares (Luttmann and Nehiba, 2020; Snider and Williams, 2015), among others.

[15] For example, Severin Borenstein has graciously posted raw and summary versions of the 1979Q1-2016Q3 DB1A/DB1B data on NBER's website. The summary files at the airline-route-quarter level are generated after removing tickets with fares below $20 and fares above $9,998. These datasets are available at `http://data.nber.org/data/dot-db1a/`.

[16] A revenue passenger mile is a standard industry metric that summarizes the number of miles flown by paying (revenue) passengers. For example, a revenue passenger mile is flown when a revenue passenger is transported one mile.

how the timing and introduction of airline branded credit cards impacts reward redemptions, and how frequent flyer program devaluations over time have affected consumer welfare, among others. Overall, our approach indicates that FFAs can be credibly identified in the DB1B and that the $20 cutoff used by most researchers is too high. In particular, the cutoff may be lowered to $12 for any tickets appearing in the DB1B after the establishment of the Passenger Fee in 2002.

Using the FFAs we identify from 2005-2019, our second contribution establishes how the characteristics of FFA tickets differ from paid tickets and how these differences have changed over time. Foremost, we find that FFAs are disproportionately redeemed on less concentrated (i.e., more competitive) routes to leisure destinations, suggesting that passengers either have a preference for redeeming award tickets for travel to vacation destinations or airlines are successful in restricting capacity on more concentrated routes where price markups are expected to be higher. Second, FFAs are also found to be disproportionately redeemed on seasonal routes (i.e., routes that are not served continuously throughout the year).[17] In comparison to paid tickets, we also find that FFAs have more flight segments, are longer on average, and more likely to be roundtrip. However, these differences have declined over time. By 2019, FFAs are generally not statistically distinguishable from paid tickets in terms of these observable characteristics. This finding suggests that devaluations of frequent flyer programs and airline consolidation during our sample period have resulted in consumers treating reward redemptions more like cash.[18]

Additionally, we tie our results to the extensive literature on the hub premium.[19] In particular, we find that FFAs are disproportionately redeemed on routes from origins with higher carrier specific concentrations of passengers. This finding supports the classic hub premium story that fares for routes leaving from hub airports are higher due to the value of frequent flyer miles.

[17]Examples of seasonal routes are airport-pairs involving Aspen, Colorado that are only served during the winter ski season (e.g., Delta's seasonal Los Angeles (LAX)-Aspen (ASE) or Atlanta (ATL)-Aspen (ASE) services).

[18]It is also possible that it is the airlines themselves who start treating frequent flyer miles more like cash. Historically, airline rewards programs awarded miles based on actual distance flown and set thresholds for award redemptions (i.e., 25,000 miles for a domestic round trip). More recently, airlines have moved to awarding points based on the amount paid for a consumer's flight and redemption thresholds now vary by route, season, and schedule. Additionally, with the growth in rewards credit cards, airlines now derive comparable revenue from selling their miles to credit card companies than to passengers flying their routes.

[19]For more on the hub premium, see Borenstein (1989), Lederman (2007), Lederman (2008), Lee and Luengo-Prado (2005), Ciliberto and Williams (2010), Escobari (2011), and Bilotkach and Pai (2016).

Our third contribution establishes how various market structure and product quality characteristics affect the share of an airline's passengers traveling on FFAs. We find that high fare routes do not have larger shares of frequent flyer awards. In contrast, we find that measures of competition and routing quality have larger effects on frequent flyer passenger shares. Airlines appear to limit FFAs on more competitive routes and more direct routes. Moreover, we also find that routes with low load factors have higher shares of FFAs, suggesting that airlines may restrict a customer's ability to redeem awards on densely traveled routes.

Finally, our results show that price dispersion increases on routes with higher shares of frequent flyer passengers. The increase in price dispersion is driven by both higher prices at the 10th percentile of fares and larger price increases at the 90th percentile of fares. These increases suggest that airlines reduce the availability of lower fare tickets for paying customers when more frequent flyer passengers are present on a route.

The rest of this paper is organized as follows. Section 2 provides details on the size of the frequent flyer market. Section 3 describes the Department of Transportation (DOT) data used in the analysis and describes the method used to identify frequent flyer tickets. After identifying these award tickets, Section 4 outlines the descriptive analysis used to identify how FFAs differ from paid tickets and presents results from this ticket level analysis. Section 5 outlines the empirical strategy used to determine how various market structure and product quality characteristics affect the share of frequent flyer passengers and presents results from this market level analysis. Section 6 provides evidence on how FFAs affect price dispersion. Finally, Section 7 concludes.

2 Size of the frequent flyer market

To provide statistics on the size of the frequent flyer market, we compiled data from annual Form 10-K filings for each of the major U.S. airlines from 2005-2019. Since 1934, publicly-traded U.S. companies are required to submit an annual report to the Securities and Exchange Commission providing a comprehensive overview of the company's business and financial condition.[20] Typical information reported on the Form 10-K include a company's organizational structure, risk factors, subsidiaries, and audited financial statements. Because frequent flyer programs are an important aspect of an airline's business strategy, many of the major airlines also report details on the size of their loyalty programs in these annual filings.

By airline and year, Table 1 reports the percentage of revenue passenger miles that are due to passengers traveling on frequent flyer awards. A revenue passenger mile is a standard industry metric summarizing the number of miles flown by paying (revenue) passengers.[21] The numbers in Table 1 indicate that passengers traveling on frequent flyer awards account for a sizeable fraction of total passenger traffic. Depending on carrier, award passengers accounted for between 6.0% and 14.1% of revenue passenger miles in 2019. For the two low-cost carriers in the table, there is a clear trend of increasing award traffic over time. For Southwest, award passengers accounted for 6.6% of revenue passenger miles in 2005 compared to 14.1% in 2019. For JetBlue, award passengers accounted for just 2.0% of revenue passenger miles in 2005 compared to 6.0% in 2019. In contrast, the trend for the three major legacy carriers remained relatively constant from 2005-2019. On American, Delta, and United, passengers traveling on frequent flyer awards accounted for 7%-9% of revenue passenger miles in most years.

[20]The Form 10-K reporting requirement was established as a result of the Securities and Exchange Act of 1934. For more information on the Form 10-K, see `https://www.sec.gov/fast-answers/answers-form10khtm.html`.

[21]A revenue passenger mile is flown when a paying (revenue) passenger is transported one mile.

Table 1: Frequent Flyer Award Traffic
(% of revenue passenger miles)

Airline	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alaska (AS)	7.9%	8.6%	9.7%	12.4%	15.0%	9.0%	*	*	*	*	*	*	*	*	*
American (AA)	7.2%	7.5%	7.5%	9.7%	8.9%	8.8%	8.8%	8.6%	8.2%	5.5%	6.5%	6.3%	6.1%	7.6%	8.0%
Continental (CO)	7.0%	6.8%	7.2%	8.5%	6.0%	5.7%	5.6%	Acquired by United (UA)							
Delta (DL)	9.0%	*	*	*	*	8.3%	8.2%	8.0%	7.3%	7.4%	7.2%	7.9%	7.9%	8.2%	8.9%
Hawaiian (HA)	*	*	*	6.0%	5.0%	6.0%	5.7%	5.2%	4.8%	5.3%	5.0%	5.0%	5.0%	6.0%	6.0%
JetBlue (B6)	2.0%	2.0%	3.0%	4.0%	3.7%	3.0%	2.0%	3.0%	3.0%	3.0%	4.0%	4.0%	5.0%	5.0%	6.0%
Northwest (NW)	7.3%	7.3%	*	*	Acquired by Delta (DL)										
Southwest (WN)	6.6%	6.4%	6.2%	6.4%	7.7%	7.9%	8.6%	9.0%	9.5%	11.0%	12.0%	12.7%	13.8%	13.8%	14.1%
United (UA)	7.4%	8.1%	8.0%	9.1%	8.3%	7.5%	8.2%	7.1%	7.7%	7.1%	7.5%	7.7%	7.5%	7.1%	7.2%
U.S. Airways (US)	9.1%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	3.5%	Acquired by American (AA)					

Source: 2005-2019 Form 10-K filings for Alaska, American, Continental, Delta, Hawaiian, JetBlue, Northwest, Southwest, United, and U.S. Airways.

Notes: *Number not reported in Form 10-K filing. A revenue passenger mile is flown when a paying (revenue) passenger is transported one mile. AirTran (FL), Frontier (F9), Spirit (NK), and Virgin America (VX) are not included because they do not report the number of frequent flyer awards in their annual Form 10-K filings. Allegiant (G4) introduced their frequent flyer program in August 2023.

By airline and year, Table A1 reports the number of frequent flyer award tickets redeemed. Across all airlines, there is a clear increasing trend in the number of award tickets redeemed over time with number of award flights across reporting carriers, increasing from just over 18 million in 2005 to more than 50 million in 2019. This increasing trend is likely a result of a combination of factors including the introduction of airline branded credit cards that allowed reward program members to accrue frequent flyer miles, the completion of several mergers, and increasing travel demand over time.

Using data from 2019 Form 10-K filings, Table 2 compares airline revenue from loyalty programs to net income and liabilities accrued through their loyalty programs to the airline's long term debt. In 2019, each major domestic carrier reported frequent flyer program revenue that exceeded their net income. Additionally, carrier's liabilities from their frequent flyer programs are comparable to or exceed that of their long term debt.[22] Overall, the statistics presented in Tables 1 and 2 indicate that passengers traveling on frequent flyer awards represent a large and non-trivial fraction of total passenger traffic and play an important role in airline profitability.

Investors also immensely value loyalty programs given that several airlines collateralized the future cash flows of their frequent flyer programs to raise billions of dollars in loans during the Covid-19 pandemic. For example, United raised $6.8 billion in July 2020, Spirit $850 million in September 2020, Delta $9 billion in September 2020, and American $10 billion in March 2021.[23]

Table 2: Airline Loyalty Revenues and Liabilities 2019
(millions of dollars)

Airline	Loyalty Revenue	Net Income	Loyalty Liabilities	Long Term Debt
Alaska (AS)	$1,169	$769	$1,990	$1,264
American (AA)	$5,540	$1,972	$8,615	$22,372
Delta (DL)	$4,862	$4,767	$6,728	$8,052
Hawaiian (HA)	$244	$224	$350	$547
JetBlue (B6)	$592	$569	$661	$1,990
Southwest (WN)	$3,787	$2,300	$3,385	$1,846
United (UA)	$4,350	$3,009	$5,276	$13,145

Source: 2019 Form 10-K filings for Alaska, American, Delta, Hawaiian, JetBlue, Southwest, and United.

[22] Loyalty liabilities are not included in Form 10-K reports of Long Term Debt but are reported separately under other liabilities.

[23] For additional information on how loyalty programs helped save airlines during the Covid-19 pandemic, see `https://hbr.org/2021/04/how-loyalty-programs-are-saving-airlines`.

3 Method for identifying frequent flyer tickets in the DB1B database

In order to identify airline frequent flyer awards, itinerary and price data (inclusive of all ticket taxes and fees) are taken from the U.S. Department of Transportation's Airline Origin and Destination Survey (referred to as database DB1B). Data from this survey are released quarterly and generated from a 10% random sample of all airline tickets that originate in the United States on U.S. based carriers. Information from this survey include ticket characteristics such as the total fare, fareclass, origin and destination airports, operating and ticketing carriers, distance flown, number of route segments, connecting airports (if any), and an indicator specifying if the ticket is roundtrip.

To identify frequent flyer tickets in the DB1B data, we exploit a February 1, 2002 federal regulation that established the Passenger Fee, also known as the September 11 Security Fee.[24] This fee is collected by all commercial air carriers at the time airfare is purchased, *including when passengers redeem frequent flyer awards*.[25] Airlines then remit these fees to the Transportation Security Administration (TSA). Between February 1, 2002 and July 20, 2014, the TSA imposed a security fee of $2.50 per flight segment for a maximum of $5.00 per one-way trip or $10.00 per roundtrip. On July 21, 2014, the Passenger Fee was changed to $5.60 per one-way trip and $11.20 per roundtrip (i.e., fees no longer applied on a flight segment basis). Table 3 summarizes this regulation and the amendment made on July 21, 2014.

[24]The Passenger Fee was initially authorized under the Aviation and Transportation Security Act. For more information on this fee, see `https://www.tsa.gov/for-industry/security-fees`.

[25]Specifically, the original legislation states that "Direct air carriers and foreign air carriers must collect the security service fees imposed on air transportation sold on or after February 1, 2002. *The security service fee imposed by this interim final rule applies to passengers using frequent flyer awards for air transportation, but is not applicable to other nonrevenue passengers.*" See Federal Register Vol. 66, No. 250 available at `https://www.govinfo.gov/content/pkg/FR-2001-12-31/pdf/01-32254.pdf`.

Table 3: Passenger Fee Summary

Legislation	Effective Fee Date	Fee for one-way trips: One segment	Fee for one-way trips: Two segments	Fee for one-way trips: Three or more	Fee for Roundtrips: Two segments	Fee for Roundtrips: Three segments	Fee for Roundtrips: Four or more
Public Law 107–71	Feb. 1, 2002	$2.50	$5.00	$5.00	$5.00	$7.50	$10.00
Public Law 113–67/113–294	Jul. 21, 2014	$5.60	$5.60	$5.60	$11.20	$11.20	$11.20

Source: Federal Register Vol. 66, No. 250, Federal Register Vol. 79, No. 119, and Federal Register Vol. 80, No. 107. More information on the Passenger Fee is located at `https://www.tsa.gov/for-industry/security-fees`.
Notes: "The security service fee must be imposed on passengers who obtained the ticket for air transportation with a frequent flyer award, but may not be imposed on other nonrevenue passengers." Federal Register Vol. 79, No. 119.

Because passengers redeeming frequent flyer awards (FFAs) are required to pay the Passenger Fee, we identify FFAs in the DB1B by classifying tickets according to the fee structure in Table 3. Prior to July 21, 2014, one segment trips with $2.50 fares are identified as FFAs.[26] One-way trips with two or more segments and roundtrips with two segments are identified as FFAs if the fare charged was $5. For roundtrips with three segments, tickets with $7.50 fares are identified as FFAs.[27] For roundtrips with four or more segments, tickets with $10 fares are identified as FFAs. After July 20, 2014, one-way trips with $5.60 fares and roundtrips with $11.20 fares are identified as FFAs.[28]

Figures 1, 2, and 3 illustrate our strategy for identifying FFAs. In Figure 1, the distribution of DB1B fares under $20 in 2005, 2010, 2015, and 2018 are presented. In line with the Passenger

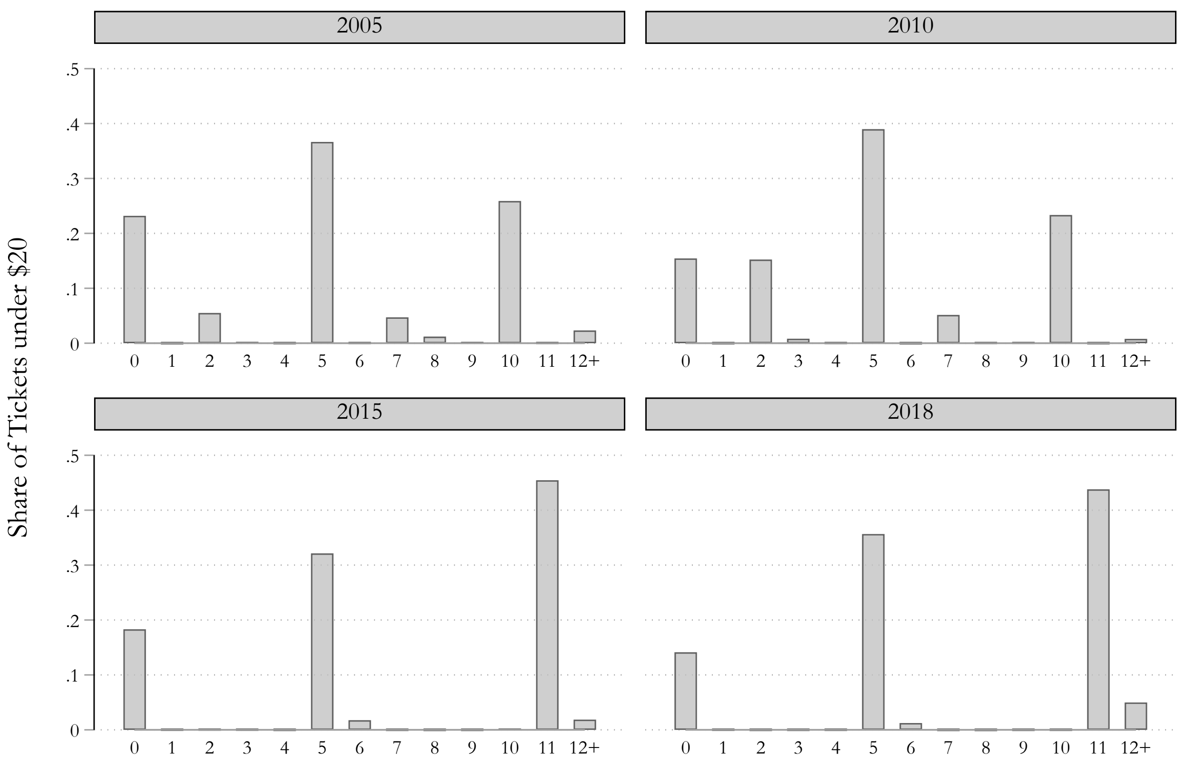
[26]Since fares in the DB1B are expressed as whole numbers, one segment trips with fares of $2 or $3 are classified as FFAs prior to July 21, 2014.

[27]Since fares in the DB1B are expressed as whole numbers, three segment roundtrips with fares of $7 or $8 are identified as FFAs prior to July 21, 2014.

[28]Since fares in the DB1B are expressed as whole numbers, one-way trips with fares of $5 or $6 are identified as FFAs after July 20, 2014. Similarly, roundtrips with $11 or $12 fares are identified as FFAs after July 20, 2014.

Fees in effect prior to July 21, 2014, spikes in the distribution occur at $2, $5, $7, and $10 in 2005 and 2010.[29] Reflecting the Passenger Fee change in 2014, spikes occur at $5 and $11 in 2015 and 2018. However, not all tickets with fares less than $20 are FFAs. For example, the spikes observed at $0 in Figure 1 reflect nonrevenue passengers such as airline employees and friends and family of airline employees flying standby. In addition, some fares under $20 are actual paid fares (e.g., Allegiant's $9 flight sales and Frontier's $15 and $19 flash sales).

Figure 1: Distribution of DB1B Fares Under $20 in 2005, 2010, 2015, and 2018



Notes: Data from DB1B files for 2005, 2010, 2015 and 2018. Bars represent the share of passengers with tickets under $20 that reported that exact itinerary fare. Data are limited to one-way itineraries with three or fewer segments and round trip itineraries with six or fewer segments.

Figure 2 displays the distribution of DB1B fares under $20 in 2013 (red bars) and 2015 (blue bars) for American (Panel A) and Delta (Panel B). The four charts in each panel correspond to the Passenger Fees charged to that itinerary under the 2013 fee regime. The chart titled "$2.50"

[29] Itinerary prices in DB1B are reported in whole dollar increments.

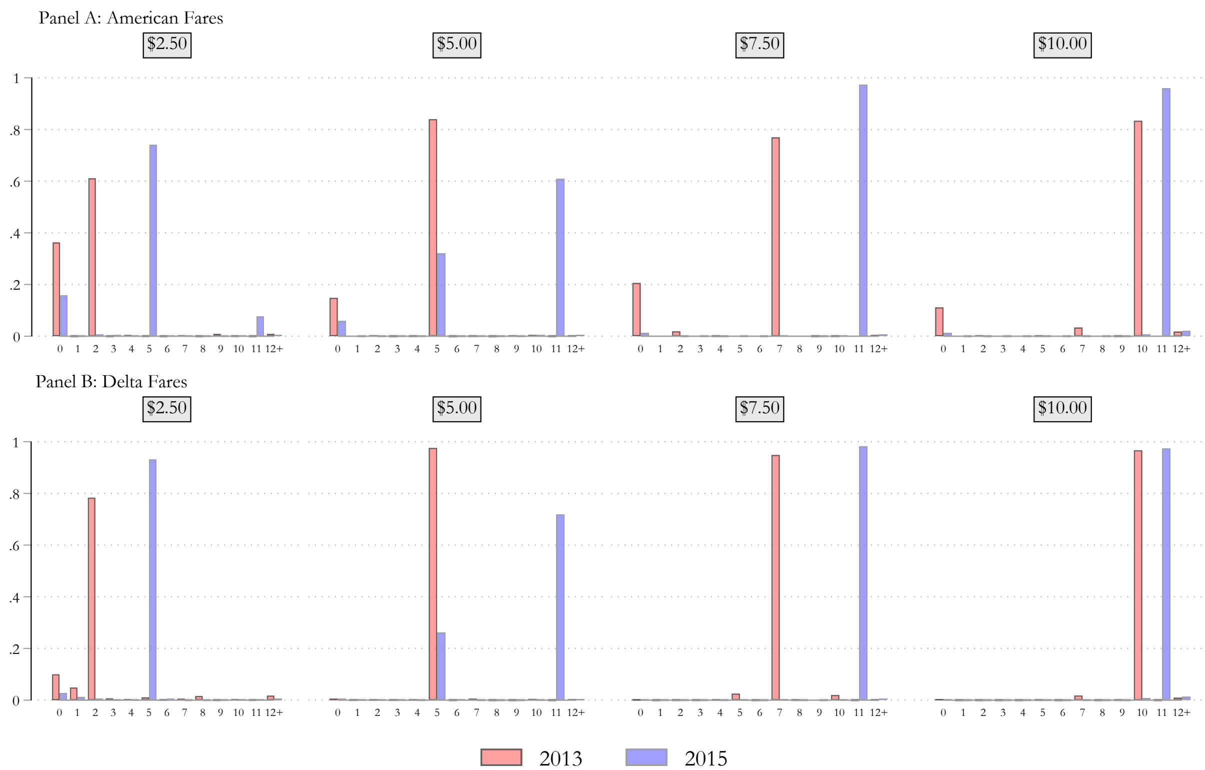
in each panel displays the distribution of fares under $20 for one segment trips as these trips were subject to a Passenger Fee of $2.50 in 2013. With the change in the Passenger Fee in 2014, these itineraries were then subject to a Passenger Fee of $5.60 in 2015. Consistent with Table 3, spikes in the distribution of American and Delta's fares occur at $2 in 2013 and $5 in 2015 for these trips. Our approach classifies all one segment trips with $2 fares before July 2014 and $5 fares after July 2014 as FFAs. All other one segment trips are not identified as FFAs (e.g., one segment trips with $0 fares are not identified as FFAs).

The "$5.00" charts in Figure 2 display the distribution of American (Panel A) and Delta's (Panel B) fares under $20 for multi-segment one-way trips and two segment roundtrips in 2013 and 2015. The Passenger Fee for one-way trips with multiple segments was $5 in 2013 and $5.60 in 2015 while the Passenger Fee for roundtrips with two segments was $5 in 2013 and $11.20 in 2015. Consistent with Table 3, fare spikes for these trips occur at $5 in 2013 (red bars) and at $5 and $11 in 2015 (blue bars). Accordingly, two segment trips with $5 fares before July 2014 and two segment trips with $5 (one-way trips) or $11 (roundtrips) fares after July 2014 are identified as FFAs. All other trips with two segments are not identified as FFAs.

The "$7.50" charts in Figure 2 display the distribution of American (Panel A) and Delta's (Panel B) fares under $20 for three segment roundtrips in 2013 and 2015. The Passenger Fee for roundtrips with three segments was $7.50 in 2013 and $11.20 in 2015. As expected, large spikes in the distribution of American and Delta's fares for three segment trips occur at $7 in 2013 (red bars) and $11 in 2015 (blue bars). In line with Table 3, we classify three segment one-way trips with $5 fares in addition to three segment roundtrips with $7 fares before July 2014 and $11 fares after July 2014 as FFAs. All other trips with three segments are not identified as FFAs.

The "$10.00" charts in Figure 2 display the distribution of American (Panel A) and Delta's (Panel B) fares under $20 for roundtrips with four or more segments in 2013 and 2015. The Passenger Fee for roundtrips with four or more segments was $10 in 2013 and $11.20 in 2015. As expected, large spikes in the distribution of American and Delta's fares for these trips occur at $10 in 2013 and $11 in 2015. In line with Table 3, roundtrips with four or more segments and $10 fares before July 2014 and $11 fares after July 2014 are classified as FFAs. All other trips with four or more segments are not identified as FFAs.

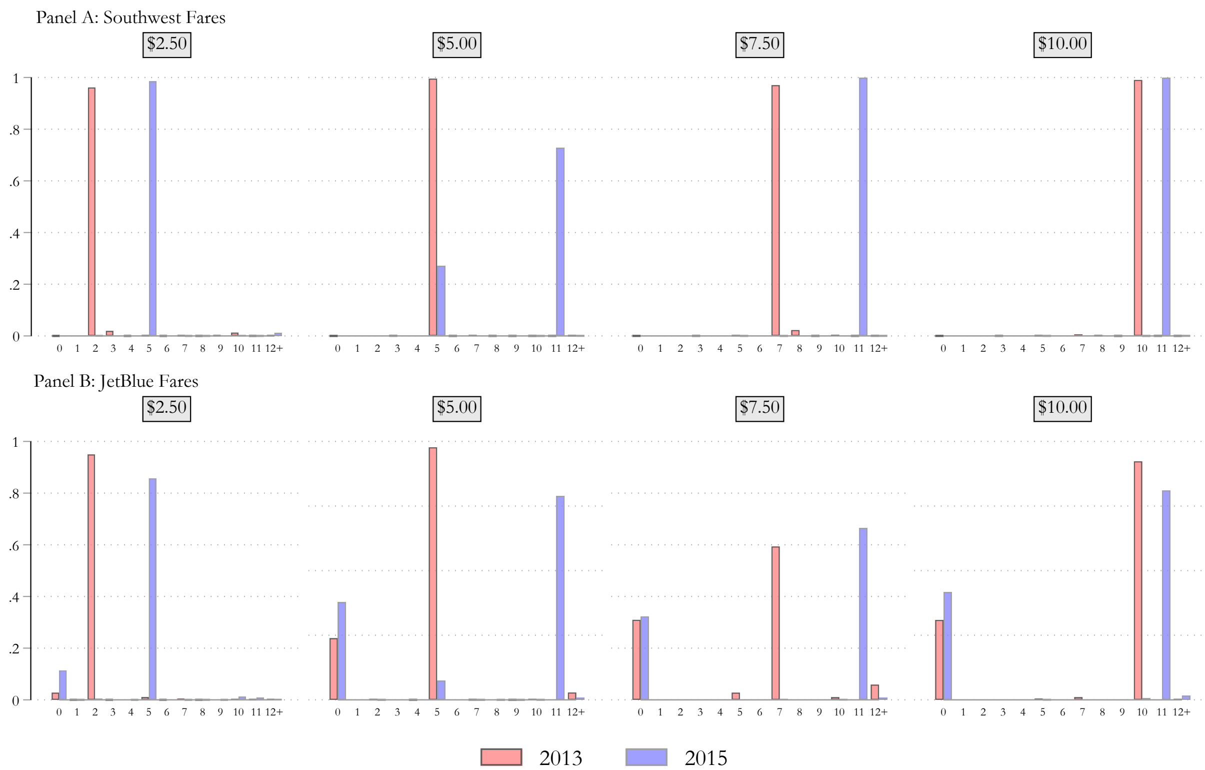
Figure 2: American and Delta Fares Under $20 by Expected Passenger Fee in 2013



Notes: Data from DB1B files for 2013 and 2015 are limited to observations on American or Delta Flights. Bars represent the share of passengers with tickets under $20 and the expected Passenger Fee in 2013 that reported that exact itinerary fare. Passenger Fees of $2.50 expected for one segment one-way flights. Passenger Fees of $5.00 expected for two or three segment one-way flights or two segment roundtrip flights. Passenger Fees of $7.50 expected for roundtrip flights with one leg having two or three segments while the other leg has only one. Passenger Fees of $10.00 expected for roundtrip flights with both legs having two or three segments.

Figure 3 is analogous to Figure 2, except that the distribution of fares under $20 in 2013 (red bars) and 2015 (blue bars) are displayed for Southwest (Panel A) and JetBlue (Panel B). Consistent with Figure 2, fare spikes for one segment trips ("$2.50" charts) occur at $2 in 2013 and $5 in 2015, at $5 in 2013 and at $5 and $11 in 2015 for two segment trips ("$5.00" charts), at $7 in 2013 and $11 in 2015 for three segment trips ("$7.50" charts), and at $10 in 2013 and $11 in 2015 for trips with four or more segments ("$10.00" charts).

Figure 3: Southwest and JetBlue Fares Under $20 by Expected Passenger Fee in 2013



Notes: Data from DB1B files for 2013 and 2015 are limited to observations on Southwest or JetBlue Flights. Bars represent the share of passengers with tickets under $20 and the expected Passenger fee in 2013 that reported that exact itinerary fare. Passenger fees of $2.50 expected for one segment one-way flights. Passenger fees of $5.00 expected for two or three segment one-way flights or two segment roundtrip flights. Passenger fees of $7.50 expected for roundtrip flights with one leg having two or three segments while the other leg has only one. Passenger fees of $10.00 expected for roundtrip flights with both legs having two or three segments.

Table 4 compares the results from using this method to identify FFAs with those reported in each airline's annual Form 10-K filings. Panel A of Table 4 is analogous to Table 1 except with revenue passenger mile calculations that are derived from our method of identifying FFAs in the DB1B data. Panel B gives the percentage point difference between Panel A and Table 1. Our method appears to identify similar proportions of FFA tickets, though there are some airline specific over and under estimate of awards. The observed differences between FFA revenue passenger miles in the DB1B data and those reported in the Form 10-Ks could be due to differences both in the number of FFAs identified and the total number of revenue passenger miles to compare to.[30] Our method of identifying frequent flyer awards is conservative as we likely underestimate the number of FFAs present in the DB1B data. For example, American and United used to charge their award program members a "close-in booking fee" to redeem frequent flyer miles for travel very close to the date of departure. Those passengers would have fares exceeding the passenger fee and would not be identified with our method. These close-in booking fees were recently eliminated by United on November 15, 2019 and American on January 15, 2020.[31] Additionally, we are not able to observe FFAs redeemed for international travel or total international revenue passenger miles as our analysis relies on the publicly available domestic version of the DB1B database.[32] If customers redeem awards disproportionately on domestic routes, then not including international data may lead to an overestimate of the percentage of revenue passenger miles from FFAs.[33] Despite these limitations, our method still appears to be identifying a decent share of FFAs.[34]

[30]It is important to note that the numbers reported in 10-K filings appear to be rounded for some airlines (e.g., Alaska, Hawaiian, JetBlue, and U.S. Airways).

[31]For more information on the elimination of these "close-in" booking fees, see `https://thepointsguy.com/news/united-pulling-award-chart/` and `https://thepointsguy.com/news/aa-eliminates-close-in-booking-fee/`.

[32]Access to the international version of the DB1B database is restricted to U.S. citizens. To access these data, U.S. citizens must submit an application to the Office of Airline Information within the Bureau of Transportation Statistics. The restricted data is unlikely to alleviate the problem of identification of international FFAs as many international itineraries include additional fees for customs, fuel, and landing.

[33]Similarly, any airline that has customers disproportionately redeeming FFAs for international trips would have a lower FFA share as a percentage of revenue passenger miles in the DB1B data.

[34]Our large overestimates of FFA share on Hawaiian Airlines may be due to not including their long distance international travel (26% of revenue in 2019). If Hawaiian Airlines has relatively few passengers that redeem FFAs for international trips then excluding them would increase the denominator for the percentage revenue passenger miles calculation while not changing the numerator. For reference, Hawaiian Airlines reported 720,000 total frequent flyer awards in 2019 (see Table A1) while we identify approximately 512,000 frequent flyer awards in the DB1B.

Table 4: Frequent Flyer Award Traffic From DB1B
(% of revenue passenger miles)

Panel A: Estimated Frequent Flyer Award Traffic From DB1B

Airline	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alaska (AS)	9.3%	10.7%	11.2%	12.5%	11.3%	10.6%	9.7%	10.0%	10.0%	9.5%	9.1%	9.2%	8.3%	7.7%	7.2%
American (AA)	7.1%	7.1%	7.4%	8.3%	7.7%	7.9%	8.0%	7.9%	7.5%	7.0%	6.8%	5.7%	5.9%	6.8%	7.0%
Continental (CO)†	—	—	—	—	—	—	—	Acquired by United (UA)							
Delta (DL)	4.8%	4.2%	8.8%	7.0%	8.2%	7.7%	7.9%	7.8%	7.6%	7.6%	7.4%	8.2%	8.2%	8.2%	8.2%
Hawaiian (HA)	6.7%	7.7%	7.3%	9.7%	9.1%	10.0%	9.9%	9.7%	8.5%	8.1%	7.9%	8.3%	8.4%	8.6%	8.8%
JetBlue (B6)	1.5%	2.2%	2.5%	3.5%	3.6%	2.5%	2.7%	3.0%	3.4%	3.9%	4.2%	4.8%	5.6%	6.4%	7.2%
Northwest (NW)	6.2%	6.3%	6.4%	6.4%	Acquired by Delta (DL)										
Southwest (WN)	9.2%	8.6%	8.9%	9.2%	8.8%	8.9%	9.8%	10.8%	11.4%	12.4%	12.7%	13.6%	14.9%	15.5%	16.4%
United (UA)‡	8.5%	8.3%	8.7%	10.1%	9.2%	8.9%	8.9%	—	—	—	—	—	—	—	—
U.S. Airways (US)	5.3%	2.5%	3.5%	3.7%	3.2%	4.4%	4.3%	4.0%	4.1%	Acquired by American (AA)					

Panel B: Difference in Frequent Flyer Award Traffic From DB1B Compared to Reported Numbers from 10-K Filings (Table 1)

Airline	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alaska (AS)	1.4%	2.1%	1.5%	0.1%	−3.7%	1.6%	*	*	*	*	*	*	*	*	*
American (AA)	−0.1%	−0.4%	−0.1%	−1.4%	−1.2%	−0.9%	−0.8%	−0.7%	−0.7%	1.5%	0.3%	−0.6%	−0.2%	−0.8%	−1.0%
Continental (CO)†	—	—	—	—	—	—	—	Acquired by United (UA)							
Delta (DL)	−4.2%	*	*	*	*	−0.6%	−0.3%	−0.2%	0.3%	0.2%	0.2%	0.3%	0.3%	0.0%	−0.7%
Hawaiian (HA)	*	*	*	3.7%	4.1%	4.0%	4.2%	4.5%	3.7%	2.8%	2.9%	3.3%	3.4%	2.6%	2.8%
JetBlue (B6)	−0.5%	0.2%	−0.5%	−0.5%	−0.1%	−0.5%	0.7%	0.0%	0.4%	0.9%	0.2%	0.8%	0.6%	1.4%	1.2%
Northwest (NW)	−1.4%	−1.3%	*	*	Acquired by Delta (DL)										
Southwest (WN)	2.6%	2.2%	2.7%	2.8%	1.1%	1.0%	1.2%	1.8%	1.9%	1.4%	0.7%	0.9%	1.1%	1.7%	2.3%
United (UA)‡	1.1%	0.2%	0.7%	1.0%	0.9%	1.4%	0.7%	—	—	—	—	—	—	—	—
U.S. Airways (US)	−3.8%	−1.5%	−0.5%	−0.3%	−0.8%	0.4%	0.3%	0.0%	0.6%	Acquired by American (AA)					

Source: 2005-2019 DB1B and 2005-2019 Form 10-K filings for Alaska, American, Continental, Delta, Hawaiian, JetBlue, Northwest, Southwest, United, and U.S. Airways.

Notes: *Number not reported in Form 10-K filing. —Number not calculated in DB1B. A revenue passenger mile is flown when a paying (revenue) passenger is transported one mile. † Continental appears to report FFA tickets in DB1B with an itinerary fare of zero. ‡ United also reports FFA tickets with an itinerary fare of zero after their merger with Continental (2012-2019). See Appendix B for a more detailed discussion.

4 Characteristics of frequent flyer tickets

Using the frequent flyer awards we identify, the goal of our descriptive analysis is to determine how the characteristics of frequent flyer awards differ from paid tickets. In Section 4.1, we outline the fixed effects model used to examine how FFAs differ from paid tickets. In Section 4.2, we present results from our ticket level analysis.

4.1 Descriptive analysis at the ticket level

To determine how the characteristics of frequent flyer tickets differ from paid tickets, we estimate equation (1) below,

$$y_{ijktn} = \beta_0 + \beta_1 \cdot \text{FrequentFlyer}_n + \beta_2 \cdot \text{Roundtrip}_n + \gamma_{ki} + \delta_{kj} + \theta_t + \epsilon_{ijktn} \qquad (1),$$

where y_{ijktn} is the dependent variable measured at the origin i, destination j, ticketing carrier k, quarter t, and ticket n, level. γ is an airline-origin fixed effect and δ an airline-destination fixed effect. These fixed effects control for the airline's level of dominance at the origin and destination airports. θ_t is a quarter-of-year fixed effect that controls for seasonality in our dependent variables. Dependent variables are (i) one-way distance traveled (including stopovers if any) (ii) the number of flight segments on the itinerary, (iii) indicator specifying if the ticket is nonstop, (iv) a measure of the number of competing airlines operating in the same market in that quarter, (v) the Herfindahl-Hirschman Index (HHI) for travel between origin airport i and destination airport j in quarter t, (vi) the average paid fare for travel between origin airport i and destination airport j on ticketing carrier k in quarter t, (vii) the maximum Seasonal Variation in Demand Index (SVID)[35] of the origin airport i and destination airport j, and (viii) a measure of the share of passengers on carrier k for the origin airport i and destination airport j. The coefficient of interest in our analysis is β_1, as this coefficient measures how frequent flyer award tickets differ from paid tickets with respect to the dependent variables.

[35]Following Appendix A of Li et al. (2022), SVID is calculated using monthly T100 data on passenger traffic as $\frac{\sum_{m=1,\ldots,M=12}(\frac{100*Traffic_{a,m}}{Traffic_a}-100)^2}{1000}$ where a refers to the airport. Large values of SVID indicate airports with considerable seasonality in passenger traffic.

During our fifteen year sample period, several airlines merged with other carriers, changed the structure of their frequent flyer programs, and introduced airline branded credit cards that enabled frequent flyer program members to accrue reward miles outside of flying. To allow the estimated effects to differ over time, equation (1) is estimated separately for each year across our sample period. All regressions are weighted by the number of passengers and standard errors are two-way clustered at the airport-pair and airline level.[36]

4.2 Results of ticket level analysis

Figure 4 displays the yearly coefficients on $FrequentFlyer$ when distance flown, number of flight segments, and the nonstop trip indicator are the dependent variables in equation (1). The blue lines in the figure display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are included (our preferred specification) while the red lines display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are excluded. The bars stemming from the yearly coefficients indicates the 95$\%$ confidence interval.

As demonstrated in panel (a), passengers redeeming frequent flyer awards (FFAs) traveled approximately 250 more miles than passengers traveling on paid tickets in 2005. However, this difference has steadily declined over time. By 2019, the average distance flown on FFAs was only 50 miles more than the distance flown on non-FFAs.

Panel (b) of Figure 4 displays the coefficients on $FrequentFlyer$ when the number of flight segments is the dependent variable. In 2005, FFAs had an average of 0.12 more flight segments than non-FFAs. This difference has also steadily declined over time. By 2019, FFAs involved an average of only 0.04 more segments.

Panel (c) of Figure 4 displays the coefficients on $FrequentFlyer$ when the nonstop trip indicator is the dependent variable. In 2005, FFAs were about 5$\%$ more likely to involve connecting flights. Since nonstop flights are of higher quality than connecting flights, this finding—along with the increase in flight segments found in Panel (b)–suggests that FFAs are redeemed on lower qual-

[36]Each ticket in the DB1B data contains a passenger count.

ity flights. However, this difference has also steadily declined over time. By 2019, FFAs were only 1% more likely to involve connecting flights than paid fares.

Figure 5 displays the coefficients on $FrequentFlyer$ when the number of competitors (top panel) and HHI (bottom panel) are the dependent variables in equation (1). As both panels illustrate, FFAs were redeemed on less concentrated routes with approximately 0.20 more competitors in 2005. However, these differences have steadily declined over time. Relative to non-FFAs, FFAs were reedemed on routes with only 0.05 more nonstop competitors in 2019. Furthermore, FFAs and non-FFAs are not statistically different from each other in terms of the route's market concentration or the number of nonstop competitors in the specification without airline-origin and airline-destination fixed effects during a large portion of our sample period.

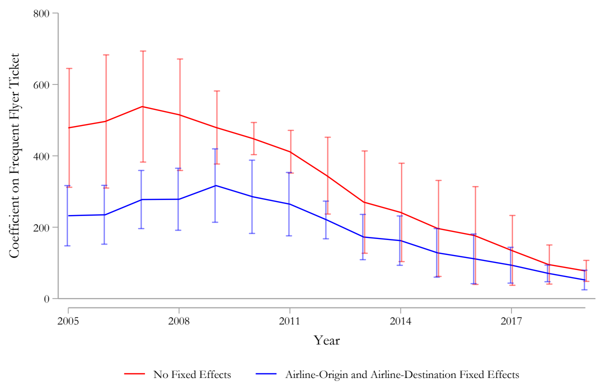
Panel (a) of Figure 6 displays $FrequentFlyer$ coefficients when the average paid fare is the dependent variable. In the specification with airline-origin and airline-destination fixed effects, FFAs and non-FFAs are not statistically different from each other in terms of the average fare on routes where FFAs are redeemed. In the specification without airline-origin and airline-destination fixed effects, FFAs are redeemed on higher fare routes from 2005-2015 (routes that are $7.50-$13.50 more expensive). However, consistent with the specification with airline-origin and airline-destination fixed effects, FFAs and non-FFAs are not statistically different from each other in terms of the average paid fare by the end of our sample period (2016-2019). The disagreement between the models with and without airline-origin and airline-destination fixed effects in the pre-2016 period suggest that FFAs are disproportionately on routes to or from particular cities.

Panel (b) of Figure 6 displays $FrequentFlyer$ coefficients when the maximum value of the Seasonal Variation In Demand (SVID) measure between the origin and destination airports is the dependent variable. High values of SVID indicate airports with substantial seasonal variation in demand (e.g., ski destinations such as Aspen (ASE), Eagle County (EGE), Jackson Hole (JAC), and Telluride (MTJ) where demand spikes during the winter). As demonstrated in panel (b), FFAs are disproportionately redeemed on more seasonal routes.

Panel (c) of Figure 6 displays $FrequentFlyer$ coefficients when the carrier share at the origin

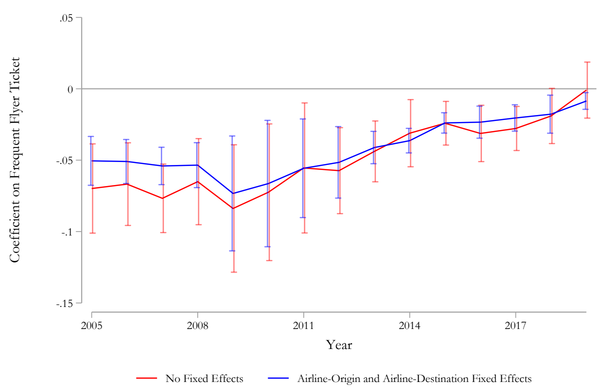
Figure 4: Difference in Distance, Flight Segments, and Fraction of Nonstop Tickets

(a) Difference in Number of Miles Flown



(b) Difference in the Number of Flight Segments

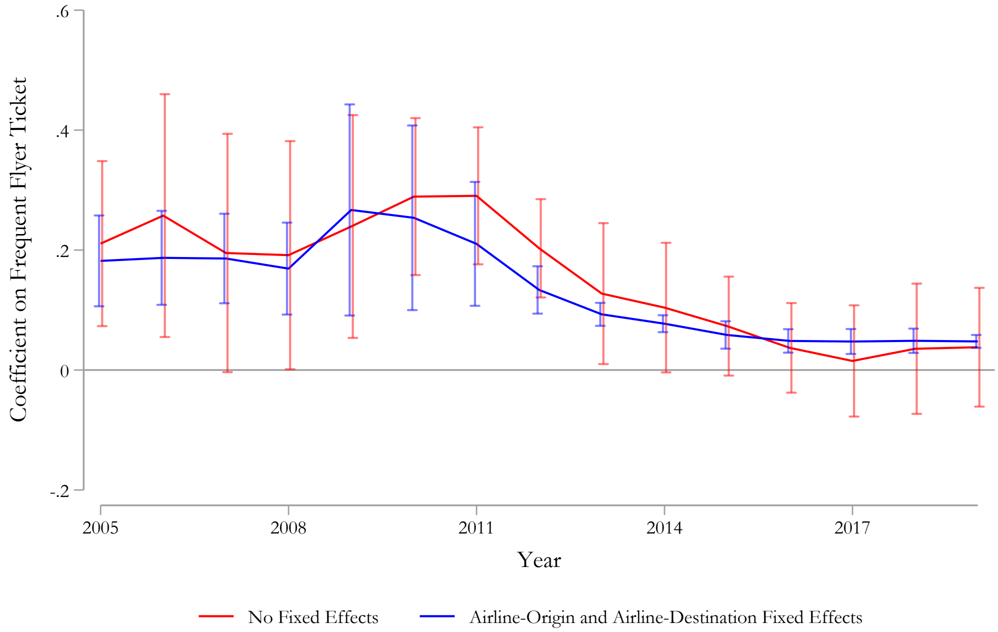
(c) Difference in the Fraction of Nonstop Tickets



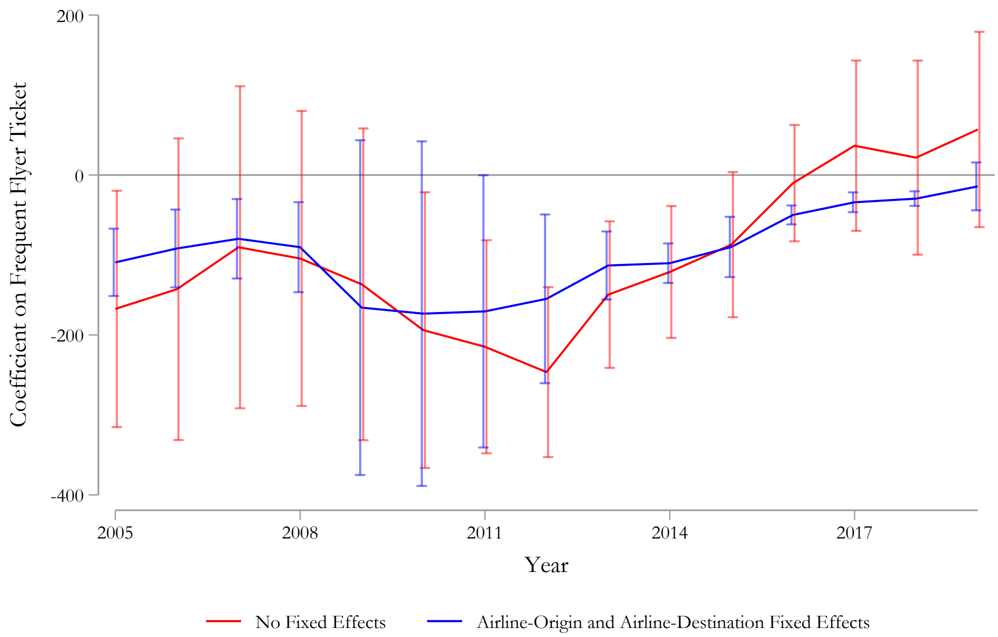
Notes: Charts display the yearly coefficients on $FrequentFlyer$ for regressions with the respective dependent variable for each panel. All regressions include controls for roundtrip status and airline. The blue lines in the figure display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are included (our preferred specification) while the red lines display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are excluded. The bars stemming from the yearly coefficients indicates the 95% confidence interval. Data are from the DB1B (2005-2019) and limited to one-way tickets with three or fewer segments and round-trip tickets with six or fewer segments.

Figure 5: Difference in Market Structure

(a) Difference in the Number of Competitors



(b) Difference in the Herfindahl-Hirschman Index (HHI)



Notes: Charts display the yearly coefficients on $FrequentFlyer$ for regressions with the respective dependent variable for each panel. All regressions include controls for round-trip status and airline. The blue lines in the figure display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are included (our preferred specification) while the red lines display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are excluded. The bars stemming from the yearly coefficients indicates the 95% confidence interval. Data are from the DB1B (2005-2019) and limited to one-way tickets with three or fewer segments and round-trip tickets with six or fewer segments.

and destination airports are the dependent variables. In this panel, the red line displays the results when the dependent variable is the origin airport own-carrier share while the blue line displays the results from the destination airport own-carrier share. This specification suggests that FFAs are more likely to originate at airports with higher own-carrier shares (e.g., hub airports) where it may be easier for consumers to accrue frequent flyer miles. These FFAs are disproportionately used to travel to destinations with lower own-carrier shares which may reflect more leisure or seasonal destinations.

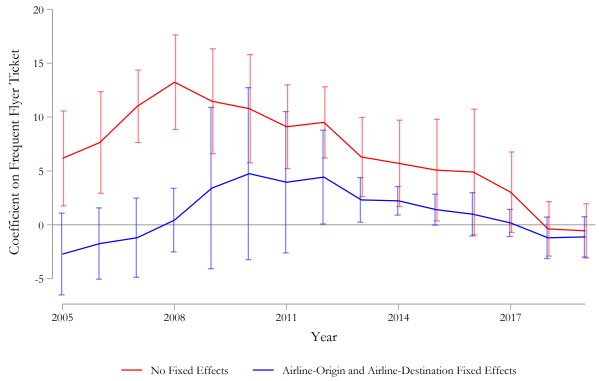
To further illustrate that FFAs are disproportionately redeemed on seasonal routes to leisure destinations, Figure 7 displays Delta's route segments with large shares of frequent flyer passengers ($\geq 15\%$) in the first (January-March) and third quarters (July-September) of 2016. In the first quarter of 2016, these segments include routes from Delta's hubs in Atlanta (ATL), Los Angeles (LAX), Minneapolis (MSP), and New York City (JFK) to winter vacation destinations such as Honolulu (HNL), Maui (OGG), Kauai (LIH), and Kona (KOA) in Hawaii in addition to ski destinations such as Aspen (ASE), Eagle County (EGE), Gunnison (GUC), and Telluride (MTJ) in Colorado (see panel (a)). In the third quarter of 2016, these segments shifted further north from ski destinations in Colorado to summer vacation destinations near Glacier, Grand Teton, and Yellowstone National Parks in Montana and Wyoming (see panel (b)). For example, these third quarter segments include routes from Delta's largest hub in Atlanta (ATL) to Bozeman Yellowstone (BZN), Glacier Park (FCA), Jackson Hole (JAC), and Missoula (MSO).

5 Characteristics of markets with large shares of frequent flyer passengers

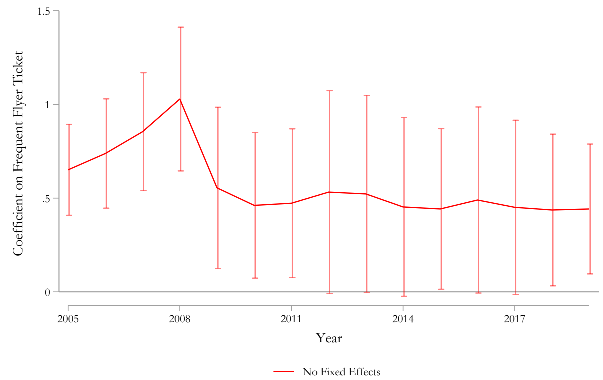
Using the FFAs we identify, our market level analysis examines how various market structure and product quality characteristics affect the share of an airline's passengers traveling on FFAs. In Section 5.1, we outline the instrumental variables strategy used to identify how market and product quality characteristics affect the share of frequent flyer passengers. In Section 5.2, we

Figure 6: Difference in Average Fare, SVID, and Carrier Share

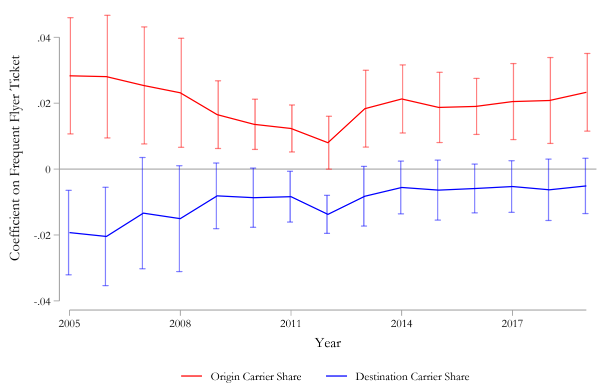
(a) Difference in the Average Fare



(b) Difference in the Seasonal Variation in Demand (SVID) of the Destination Airport



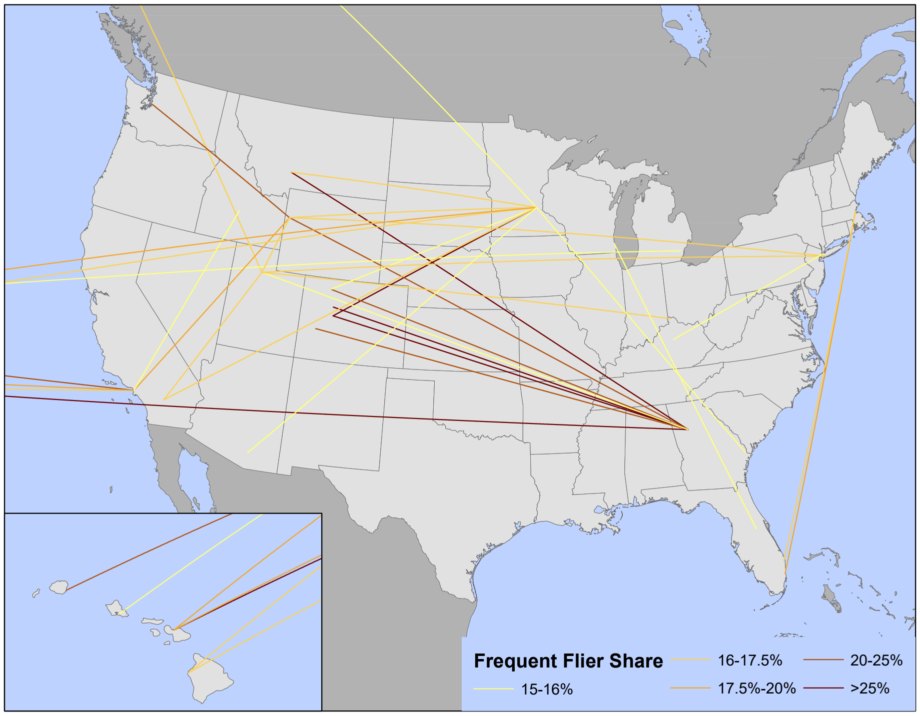
(c) Difference in Carrier Share



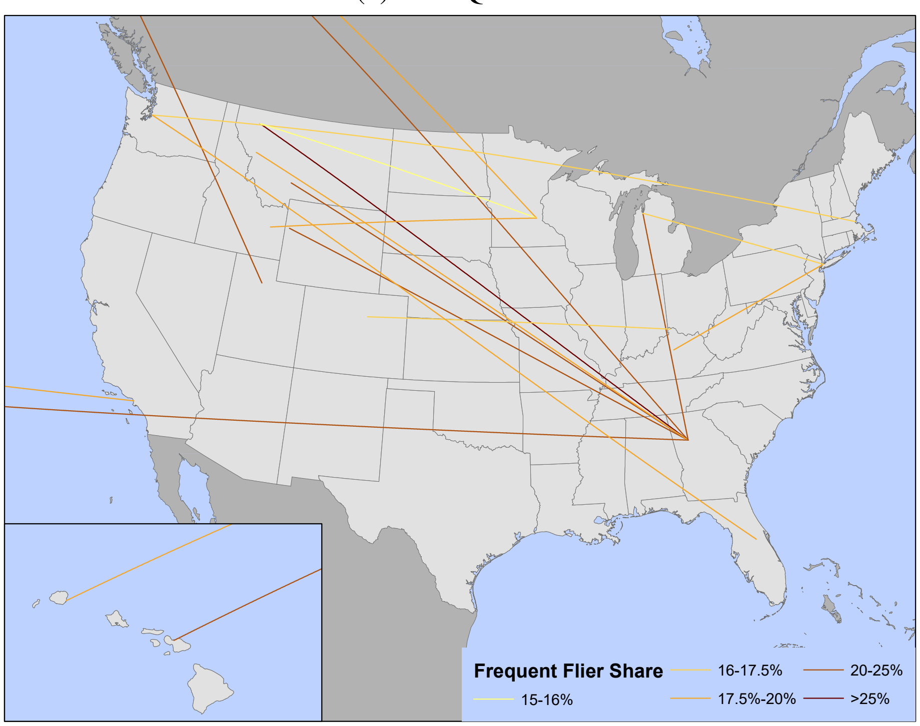
Notes: Charts display the yearly coefficients on $FrequentFlyer$ for regressions with the respective dependent variable for each panel. All regressions include controls for round-trip status and airline. The blue line in Panel (a) displays $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are included (our preferred specification) while the red lines in Panel (a) and (b) display $FrequentFlyer$ coefficients when airline-origin and airline-destination fixed effects are excluded. The bars stemming from the yearly coefficients indicates the 95% confidence interval. In Panel (c), the red line displays $FrequentFlyer$ coefficients for the regressions with origin airport own-carrier share as the dependent variable. The blue line in Panel (c) displays $FrequentFlyer$ coefficients for the regressions with destination airport own-carrier share as the dependent variable. Data for all panels are from the DB1B (2005-2019) and limited to one-way tickets three or fewer segments and round-trip tickets with six or fewer segments.

Figure 7: Delta Routes with Large Shares of Frequent Flyer Passengers in 2016

(a) 2016 Quarter 1



(b) 2016 Quarter 3



Notes: Data are from the DB1B and limited to one-way tickets with three or fewer segments and round-trip tickets with six or fewer segments on Delta flights. Only segments with more than 15% of Delta passengers in that quarter identified as traveling on FFAs on routes with at least 500 passengers are included.

present results from our market level analysis.

5.1 Empirical strategy

We define a market m, as a unique combination of origin airport i, and destination airport j. This definition is directional, meaning that flights between Los Angeles (LAX) and New York (JFK) constitute two different markets depending on the direction flown. We define a product p, as a specific routing (nonstop or sequence of connecting airport(s)) in a market. Letting k denote the ticketing carrier and t the quarter of travel, an observation in our market level analysis is a unique combination of product, market, ticketing carrier, and quarter.

To determine how various market and product quality characteristics affect the share of an airline's passengers traveling on FFAs, we employ a fixed effects strategy to control for unobservable confounders that may influence demand. We estimate our empirical model using two sets of fixed effects.

Foremost, we include airline-quarter-year fixed effects to control for unobserved time-varying airline-specific effects. These fixed effects control for changes in an airline's service quality or operating costs that occur during our sample period such as changes in frequent flyer programs, onboard amenities, formation of codeshare alliances, and mergers.

We also include airline-market fixed effects to control for unobserved time-invariant factors that affect an airline's demand on particular routes. Additionally, this fixed effect controls for the underlying effect of an airline's level of dominance at the origin and destination airports.

Incorporating both of these fixed effects, we estimate the following reduced-form demand equation,

$$\text{FF\_SHARE}_{pmkt} = \beta_0+\beta_1\cdot\text{FARE}_{pmkt}+\beta_2\cdot\text{FARE}_{pmkt}\cdot\text{HUB\_ORIGIN}_{ikt}+\beta_3\cdot\text{HHI}_{mt}+\beta_4\cdot\text{NONSTOP}_{pmkt}+ \beta_5\cdot\text{ROUNDTRIP}_{pmkt} + \beta_6\cdot\text{ROUTING\_QUALITY}_{pmkt} + \beta_7\cdot\text{LOAD\_FACTOR}_{pmkt} + \gamma_{kt} + \delta_{km} + \epsilon_{pmkt} \qquad (2),$$

where FF_SHARE_{pmkt} is the share of passengers redeeming frequent flyer awards for product p, in market m, on ticketing carrier k, and quarter t. γ an airline-quarter fixed effect and δ is an airline-market fixed effect. FARE is the average fare paid by revenue (i.e., non-frequent flyer) passengers for product p on carrier k in quarter t. HUB_ORIGIN is an indicator specifying if origin airport i is a hub for carrier k in quarter t. NONSTOP is an indicator specifying if product p is nonstop (i.e., ticket does not involve a connection) while ROUNDTRIP is an indicator specifying if product p is for roundtrip travel. HHI is the Herfindahl-Hirschman Index for that market and quarter calculated on a scale from 0 to 1.

Following Chen and Gayle (2019), ROUTING_QUALITY is defined as the percentage ratio of the product's itinerary flight distance to the minimum flight distance in the market. Assuming that passengers prefer shorter travel times to longer travel times, the closer the product's distance to the minimum flight distance, the more desirable the product is to passengers.[37] Finally, LOAD_FACTOR is defined as the percentage ratio of seats filled to the total number of available seats for product p on carrier k in quarter t. Load factors are constructed using the T-100 domestic segment database available from the Bureau of Transportation Statistics. For products involving multiple flight segments, the maximum load factor across all trip segments is used.

FARE and FARE·HUB_ORIGIN in equation (2) are likely endogenous. For example, frequent flyer promotions that apply to a particular city will be correlated with both an airline's fares and the number of frequent flyer passengers that depart from that city. In addition, airlines may intentionally restrict frequent flyer award capacity on high fare routes to encourage passengers to redeem awards on low fare routes. In an analogous manner, passengers who wish to extract the maximum value from their frequent flyer miles may self-select into high fare routes when redeeming reward tickets. To correct for the likely endogeneity of fare, we estimate equation (2) using two-stage least squares (2SLS). Following Gayle and Xie (2019), we instrument for fare using (i) the number of competing products offered by other carriers with an equivalent number of connections and (ii) the interaction between the product's distance and the quarterly jet fuel price.[38]

Our first instrument measures the degree of market competition a product faces, which affects

[37] The lowest value ROUTING_QUALITY can take is 100 when the flight distance is the same as that of a nonstop flight. Higher values for ROUTING_QUALITY thus indicate more circuitous (and longer) routes.

[38] U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price (dollars per gallon) data come from the Energy Information Administration.

the size of the price markup over cost. The rationale for our second instrument is that jet fuel prices and distance are correlated with the marginal cost of providing airline service, which in turn affects the overall fare.

The validity of our instruments rely on the fact that the number of products offered by carriers in a market is predetermined at the time demand shocks occur, which implies that the instruments are uncorrelated with the error term. Moreover, the number of products offered and their associated non-price characteristics are not easily adjusted in the short-run, which mitigates the influence of demand shocks on the number of products and their non-price characteristics.

5.2 Results of market level analysis

Table 5 presents results from the model specified by equation (2). To prevent airline markets and airline products with low amounts of passenger traffic from disproportionately affecting our results, we limit our analysis to airline markets with at least 500 passengers in a quarter and airline products with at least 50 passengers in a quarter.

In column (1), the endogeneity of FARE and FARE·HUB_ORIGIN are ignored as equation (2) is estimated using ordinary least squares (OLS). In this specification, the coefficients on our market variables (FARE, FARE·HUB_ORIGIN, HHI) are statistically insignificant. Several of our product quality variables (ROUNDTRIP and LOAD_FACTOR) are also statistically insignificant. However, two measures of product quality display negative and statistically significant coefficients. The negative and statistically significant coefficient on NONSTOP indicates fewer frequent flyer passengers are present on direct flights. Conversely, the negative coefficient on ROUTING_QUALITY indicates that products with higher routing quality have larger shares of frequent flyer awards (FFAs).[39] These results are consistent with the idea that airlines may limit the number of FFAs that can be redeemed on direct flights to below that of market demand. Once those seats are filled

[39]Because ROUTING_QUALITY is defined as the ratio of the product's itinerary distance to the minimum distance in the market, a ratio equal to one indicates that the product's distance equals the minimum distance (i.e., highest routing quality). A ratio larger than one indicates that the product is not the highest routing quality option in the market.

by frequent flyer passengers, individuals are forced to redeem awards on connecting itineraries. Frequent flyer passengers on connecting routes still prefer more efficient routing, and thus we find higher shares of FFAs on these routes once we limit to connecting itineraries.

In column (2), we correct for the endogeneity of FARE and FARE·HUB_ORIGIN by estimating equation (2) using 2SLS. The magnitude of the coefficient on FARE is now statistically significant at the 10% level, proving suggestive evidence that unobserved factors that affect both an airline's fares and its share of FFAs are biasing the estimates presented in column (1). Moreover, the positive coefficient on FARE indicates that high fare products have larger shares of FFAs. In particular, a \$100 increase in fare increases an airline's share of FFAs on routes by 1.04%.[40]

The coefficients on NONSTOP and LOAD_FACTOR are also statistically significant at conventional levels once FARE and FARE·HUB_ORIGIN are instrumented for in column (2) of Table 5. The negative coefficient on NONSTOP implies that connecting airline products have larger shares of FFAs. This finding suggests that passengers may prefer to redeem reward tickets on routes that require connections (e.g., trips to outlying Hawaiian islands) or that carriers are effective at ensuring that passengers redeem reward tickets on lower quality connecting products. In addition, the negative coefficient on LOAD_FACTOR indicates that routes with high load factors have lower shares of FFAs. A 10% increase in load factor implies a 0.45% decrease in an airline's share of FFAs.[41] This finding suggests that airlines may restrict reward capacity on routes with high load factors. Finally, the positive and statistically significant coefficient on HHI shows that less competitive routes have higher shares of FFAs. This finding is consistent with passengers redeeming FFAs on more seasonal routes which often have fewer competitors.[42] It is also possible that passengers who routinely fly on less competitive routes may accrue rewards faster than passengers flying more competitive routes as individuals are more likely to fly the same carrier repeatedly, thereby accruing a particular airline's frequent flyer miles faster.

[40]This result is roughly a 15.7% increase over the mean frequent flyer share (1.04/6.63).

[41]This result is roughly a 6.8% increase over the mean frequent flyer share (0.45/6.63).

[42]As shown in Figure 7, many segments with high shares of frequent flyer passengers go from airline hubs to vacation destinations. These routes likely have less competition.

Table 5: Share of Frequent Flyer Passenger Results

Dependent variable: FF Share (Mean=6.63%)	OLS (1)	2SLS (2)
FARE	0.0022	0.0227*
	(0.0019)	(0.0117)
FARE·HUB_ORIGIN	0.0014	-0.0557
	(0.0017)	(0.0341)
HHI	-0.6466	1.7408**
	(0.4544)	(0.7425)
NONSTOP	-0.5653***	-1.0060***
	(0.1184)	(0.2306)
ROUNDTRIP	0.2217	-1.0765
	(1.2409)	(2.1417)
ROUTING_QUALITY	-0.0236***	-0.0301***
	(0.0050)	(0.0045)
LOAD_FACTOR	-0.0204	-0.0454***
	(0.0142)	(0.0093)
Observations	4,708,692	4,708,692

Notes: All regressions include airline-quarter-year, and airline-market (i.e., airport-pair) fixed effects. Two-way clustered standard errors at the airline and market level are reported in parentheses. The sampling period is 2005Q1-2019Q4. Fares are deflated using the Bureau of Economic Analysis Gross Domestic Product: Implicit Price Deflator (GDPDEF) indexed to quarter 4 of 2019. In column (2), FARE and FARE·HUB_ORIGIN are treated as endogenous variables. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

There is a concern that HHI is endogenous in columns (1) and (2) of Table 5. For example, markets with high fares due to a lack of competition may be attractive for entry. These markets may also be unattractive for entry if high fares are a result of entry barriers such as slot controls or limited access to gates at the endpoint airports (Luttmann and Nehiba, 2020). For two reasons, we believe that the simultaneity bias that results from an airline's decision to enter or exit a given route is not substantially biasing our results. Foremost, Gayle and Wu (2013) show that this simultaneity bias is negligible in their model that accounts for endogenous entry in U.S. airline markets. Second, the inclusion of airline-quarter-year and airline-market fixed effects likely eliminates a large degree of bias associated with the correlation between HHI and the regression error term.

Based on the descriptive analysis in Section 4, we have reason to believe that the relationship between these variables and frequent flyer shares may change over time. Table 6 breaks our fifteen year sample period into three different five year subsamples and presents results for each subsample. Comparing the 2SLS specifications across these three subsamples (columns 2, 4 and 6) indicates that the sign of the effects are consistent, but the coefficients decline in magnitude and significance over time. In the 2005 to 2009 subsample, the fare coefficients (FARE and FARE·HUB_ORIGIN) suggest that carriers are effective at steering passengers towards redeeming reward tickets on low fare routes in markets where the carrier has substantial market power (i.e., its hub airports). In markets where the carrier is not dominant, passengers are able to redeem reward tickets on higher fare routes. In later subsamples, these fare coefficients become statistically insignificant. Across all three subsamples, the coefficient on ROUTING_QUALITY is negative and statistically significant, indicating that products with higher routing quality have larger shares of frequent flyer awards (FFAs).[43] These results provide further evidence of airlines and consumers altering their approaches towards FFAs over the past fifteen years.

[43]Because ROUTING_QUALITY is defined as the ratio of the product's itinerary distance to the minimum distance in the market, a ratio equal to one indicates that the product's distance equals the minimum distance (i.e., highest routing quality). A ratio larger than one indicates that the product is not the highest routing quality option in the market.

Table 6: Share of Frequent Flyer Passenger Results By Subsample

	2005-2009		2010-2014		2015-2019	
Dependent variable:	OLS	2SLS	OLS	2SLS	OLS	2SLS
FF Share	(1)	(2)	(3)	(4)	(5)	(6)
FARE	0.0022*	0.0482*	0.0022	0.0232	0.0019	0.0074
	(0.0011)	(0.0227)	(0.0021)	(0.0179)	(0.0024)	(0.0238)
FARE·HUB_ORIGIN	0.0020*	-0.1016*	0.0010	-0.0984	0.0036	-0.0445
	(0.0010)	(0.0489)	(0.0016)	(0.06234)	(0.0037)	(0.0715)
HHI	-1.4438***	-0.2665	-0.9601	0.9860	-0.7265*	-1.2932
	(0.3814)	(0.9852)	(0.6652)	(1.0783)	(0.3981)	(0.8461)
NONSTOP	-0.9421***	-2.3758***	-0.7633***	-1.7938***	0.0641	-0.5199
	(0.1567)	(0.7191)	(0.2387)	(0.3101)	(0.2034)	(0.3387)
ROUNDTRIP	3.3500***	1.7159	-0.1564	-0.6996	-0.8425	-0.1370
	(0.7952)	(1.0148)	(1.5140)	(3.1756)	(1.0887)	(3.6122)
ROUTING_QUALITY	-0.0171***	-0.0494***	-0.0187**	-0.0202***	-0.0422***	-0.0381***
	(0.0054)	(0.0161)	(0.0077)	(0.0489)	(0.0065)	(0.0053)
LOAD_FACTOR	-0.0452***	-0.0774***	-0.0166	-0.0774**	-0.0135	-0.0234
	(0.0079)	(0.0243)	(0.0146)	(0.0059)	(0.0227)	(0.0199)
Observations	1,167,753	1,167,753	1,655,743	1,655,743	1,884,922	1,884,922

Notes: All regressions include airline-quarter-year, and airline-market (i.e., airport-pair) fixed effects. Two-way clustered standard errors at the airline and market level are reported in parentheses. Fares are deflated using the Bureau of Economic Analysis Gross Domestic Product: Implicit Price Deflator (GDPDEF) indexed to quarter 4 of 2019. In columns (2, 4 and 6), FARE and FARE·HUB_ORIGIN are treated as endogenous variables. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

6 Frequent flyer redemptions and price dispersion

As discussed in Section 1, it is ambiguous whether loyalty programs increase or decrease competition in markets where they are present. While many argue that these programs are anticompetitive because introducing switching costs generally raises prices, creates barriers to entry, and generates deadweight losses (Banerjee and Summers, 1987; Cairns and Galbraith, 1990; Fong and Liu, 2011; Kim et al., 2001; Klemperer, 1995), others argue that loyalty programs are "business stealing devices" that enhance competition and increase total surplus (Caminal, 2012; Caminal and Claici, 2007; Caminal and Matutes, 1990).

Similar to the large body of literature that examines the relationship between competition and price discrimination, we examine whether the share of passengers traveling on frequent flyer awards in a market increases or decreases an airline's ability to price discriminate. If loyalty programs enhance market power, then an increase in the share of frequent flyer passengers in a market should increase an airline's ability to price discriminate (i.e., the dispersion of that carrier's fares in the market should increase). However, if loyalty programs enhance competition, then an increase in the share of frequent flyer passengers should decrease an airline's ability to price discriminate (i.e., the dispersion of that carrier's fares in the market should decrease).

6.1 Price dispersion regression specification

Following Borenstein and Rose (1994), Gerardi and Shapiro (2009), Dai et al. (2014) and several other previous studies of airline pricing, we rely on the Gini coefficient as our measure of price dispersion.[44] Consistent with prior literature (and in an effort to focus on the effect of FFAs on paid tickets), we calculate the gini coefficient for each nonstop route excluding all fares under \$20. The median Gini coefficient we find for 2005-2019 is 0.24, which is similar to the median coefficients for nonstop routes in Gerardi and Shapiro (2009) (0.22) and Dai et al. (2014) (0.23). To determine how competition and the share of frequent flyer passengers affects price dispersion, we estimate equation (3) below,

$$\text{GINI}_{mkt} = \beta_0 + \beta_1 \cdot \text{HHI}_{mt} + \beta_2 \cdot \text{FREQUENT FLYER SHARE}_{mkt} + \gamma_{kt} + \delta_{km} + \epsilon_{mkt} \qquad (3),$$

where GINI_{mkt} is the Gini coefficient of ticketing carrier k's fares in market m and quarter t. γ is an airline-year-quarter fixed effect that controls for any unobserved time-varying airline-specific effects (e.g., carrier-specific demand shocks). δ is an airline-market fixed effect that controls for unobserved time-invariant factors that affect an airline's demand in a given market. HHI is the Herfindahl-Hirschman Index for the market measured on a scale from 0 to 1. The coefficient of interest in our analysis is β_2, as this coefficient measures how the share of frequent flyer passengers on a carrier in a given market affects that carrier's fare dispersion. In addition, we estimate the

[44] In our context, the Gini coefficient measures how far the distribution of an airline's fares on a route deviates from a completely equal distribution. Specifically, the Gini coefficient is equal to twice the expected absolute difference between two fares that are randomly drawn from the population. For example, a Gini coefficient of 0.20 for a given carrier and route implies an expected absolute difference of 40 percent of the mean fare for two randomly selected passengers traveling on that carrier and route.

same equation with the natural log of the 10th and 90th percentile fares as the dependent variable to better understand how competition and the share of frequent flyer passengers affect prices across the distribution.

HHI in equation (3) is likely endogenous. For example, an airline may be more likely to enter a route that has higher levels of price dispersion as they anticipate the ability to undercut some of the prices. To address this endogeneity, we estimate equation (3) using two-state least squares (2SLS). Following Borenstein and Rose (1994), Gerardi and Shapiro (2009), and Dai et al. (2014), we instrument for HHI using (i) measures of passengers enplaned on the route[45] and (ii) measures of the end-point city populations.[46] Collectively, these instruments are likely unrelated to the price dispersion of a particular route, but capture the effect on competition between airlines through their entry and exit decisions.

6.2 Results of price dispersion regression

Table 7 presents results from the model specified by equation (3) in column (1) as well as the same model estimated on the log of the 10th percentile fare (column (2)) and the log of the 90th percentile fare (column (3)). Consistent with prior literature (Gerardi and Shapiro (2009) and Dai et al. (2014)) we limit our analyses exclusively to nonstop flights. To prevent airline markets with low amounts of passenger traffic from disproportionately affecting our results and to ensure a large enough dispersion of prices to calculate a gini coefficient, we limit our analysis to airline markets with at least 1000 passengers in a quarter.[47]

In column (1), our results indicate that higher levels of Frequent Flyer passengers on a route increase the price dispersion of paying passengers. Comparing columns (2) and (3) indicates that this increase in price dispersion is driven by larger fare increases in the 90th percentile of fares as opposed to the 10th percentile of fares. This finding supports the theory that loyalty programs may

[45] Specifically, we use the natural log of the total passenger traffic in the market across all carriers and the "genp" measure introduced by Borenstein and Rose (1994).

[46] We use the natural log of both the geometric and arithmetic means of Metropolitan Statistical Area (MSA) populations of the endpoint airports.

[47] As the DB1B is a 10% sample of all tickets, this corresponds to at least 100 observations in each quarter.

enhance market power, as increases in the share of frequent flyers passengers on a route increases an airline's ability to price discriminate. Additionally, these results show higher levels of FFAs increase fares across the price distribution supporting the assertion that FFAs serve as quantity discounts for customers who exhibit brand loyalty. Thus, consumers are helping to subsidize increasing their own switching costs by paying higher ticket prices in the hopes of receiving future free travel.

Table 7: Price Dispersion Results

Dependent variable:	Gini Coefficient	ln 10th Percentile Fare	ln 90th Percentile Fare
	(1)	(2)	(3)
FREQUENT FLYER SHARE	0.0003***	0.0054***	0.0084***
	(0.0000)	(0.0003)	(0.0003)
HHI	-0.0270***	0.8750***	0.8296***
	(0.0035)	(0.0270)	(0.0249)
Observations	405,568	405,568	405,568

Notes: All regressions include airline-quarter-year, and airline-market (i.e., airport-pair) fixed effects. The analysis sample is limited to nonstop routes with at least 100 passengers in the DB1B for that quarter. Standard errors clustered at the market level are reported in parentheses. The sampling period is 2005Q1-2019Q4. Fares are deflated using the Bureau of Economic Analysis Gross Domestic Product: Implicit Price Deflator (GDPDEF) indexed to quarter 4 of 2019. In all regressions, HHI is treated as endogenous. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

7 Conclusion

Firms introduce loyalty programs to attract and retain customers, but it is unclear whether these programs enhance or reduce competition in markets where they are present. This paper introduces a novel method to identify rewards for one of the most prominent industries that employ loyalty programs, airlines. Using this new method, we find that frequent flyer awards (FFAs) are disproportionately redeemed on less concentrated (i.e., more competitive) routes to leisure and seasonal destinations, suggesting that passengers either have a preference for redeeming award tickets for travel to vacation destinations or airlines are successful in restricting capacity on more concentrated routes where price markups are expected to be higher. In comparison to paid tickets, we also find that FFAs have more flight segments, are longer on average, and more likely to be roundtrip. However, these differences appear to have declined over time. Additionally, we find that FFAs are disproportionately redeemed on routes from origins with higher carrier specific concentrations of passengers, supporting the classic hub premium story that fares for routes leaving from hub airports are higher due to the value of frequent flyer miles.

We also show that airlines appear to limit FFAs on more competitive and more direct routes. Moreover, we find that routes with low load factors have higher shares of frequent flyer passengers, suggesting that airlines may restrict a customer's ability to redeem awards on densely traveled routes. Finally, we also find that price dispersion increases on routes with higher shares of frequent flyer passengers. This finding suggests that airline loyalty programs may enhance market power, as they appear to increase an airline's ability to price discriminate.

Our paper contributes to the literature on both loyalty programs and the airline industry in general. Our novel approach for identifying loyalty rewards could be used to shed more light on the role of loyalty programs and their impact on market structure, individual decisions, competition, and consumer welfare. For example, our method could serve as a starting point for empirical researchers interested in exploring questions such as the effects of mergers and codesharing on FFAs, how the timing and introduction of airline branded credit cards impacts reward redemptions, and how frequent flyer program devaluations over time have affected consumer welfare, among others.

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APPENDIX A: Number of Frequent Flyer Awards

Table A1: Number of Frequent Flyer Awards Redeemed
(millions of tickets)

Airline	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alaska (AS)	0.8	0.9	1.1	1.4	1.4	1.7	*	*	*	*	*	*	*	*	*
American (AA)	5.2	5.2	5.2	6.2	5.2	5.6	6.0	6.0	6.1	7.9	8.3	10.0	11.0	13.0	14.0
Continental (CO)	1.4	1.5	1.5	1.6	1.3	1.6	1.9	Acquired by United (UA)							
Delta (DL)	3.3	*	*	*	*	12.0	12.0	11.0	11.0	12.5	13.3	13.4	14.9	17.2	20.0
Hawaiian (HA)	*	*	*	0.5	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.7	0.7
JetBlue (B6)	0.1	0.2	0.2	0.3	0.3	0.6	0.6	0.8	0.9	1.1	1.4	1.6	2.0	2.0	3.0
Northwest (NW)	1.5	1.5	*	*	Acquired by Delta (DL)										
Southwest (WN)	2.6	2.7	2.8	2.8	3.0	3.2	3.7	4.5	5.4	6.2	7.3	8.3	9.6	10.4	10.7
United (UA)	2.2	2.3	2.2	2.3	2.1	2.4	2.5	4.7	5.0	4.8	5.0	5.2	5.4	5.6	6.1
U.S. Airways (US)	1.3	0.5	0.9	0.9	0.8	0.8	0.8	0.8	1.8	Acquired by American (AA)					

Source: 2005-2019 Form 10-K filings for Alaska, American, Continental, Delta, Hawaiian, JetBlue, Northwest, Southwest, United, and U.S. Airways.

Notes: *Number not reported in Form 10-K filing. Numbers are reported in millions. AirTran (FL), Frontier (F9), Spirit (NK), and Virgin America (VX) are not included because they do not report the number of frequent flyer awards in their annual Form 10-K filings. Allegiant (G4) introduced their frequent flyer program in August 2023.

APPENDIX B: Continental and United

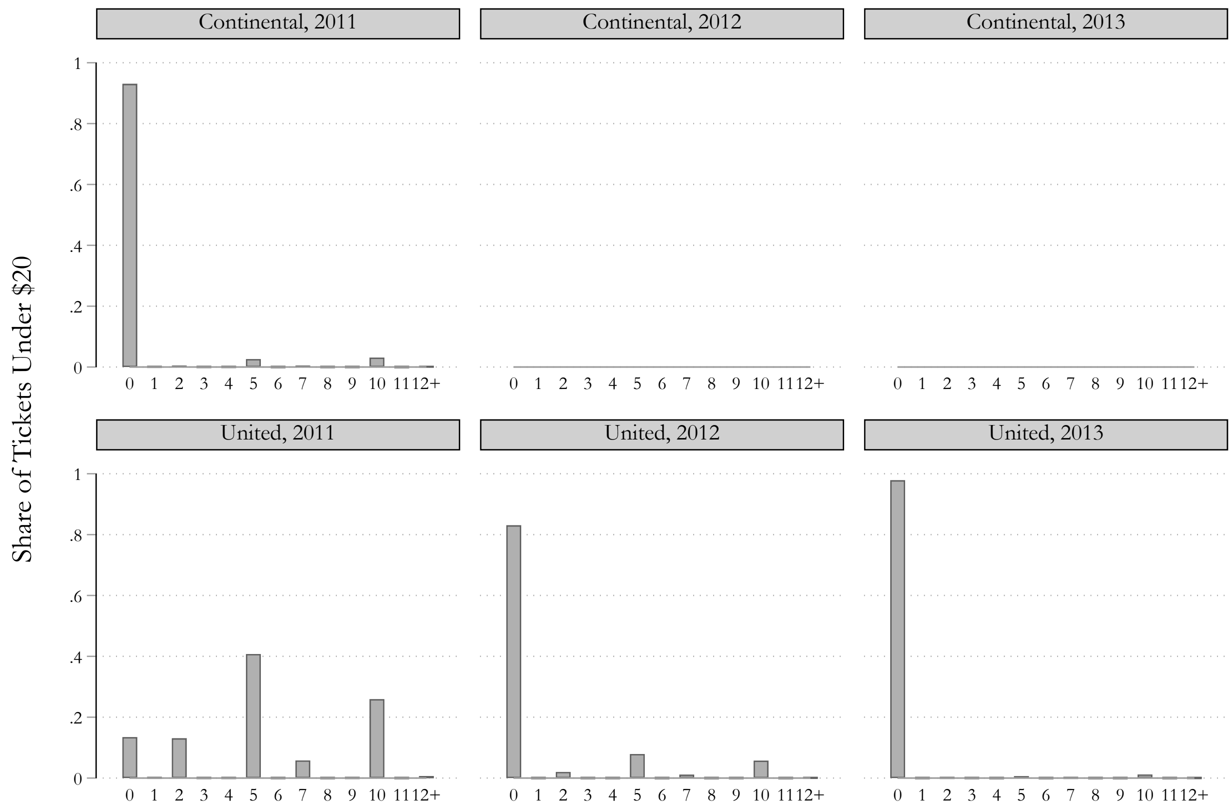
As mentioned in Table 4, Continental appears to report frequent flyer award (FFA) tickets in the Airline Origin and Destination Survey (DB1B) with an itinerary fare of zero. United also appears to report FFA tickets with a fare of zero after their merger with Continental (2012-2019). To illustrate this phenomenon, Figure B1 plots the distribution of DB1B fares under \$20 for Continental and United in 2011, 2012, and 2013.

Consistent with our FFA identification strategy described in Section 3, spikes in the distribution of United's fares occur at \$2, \$5, \$7, and \$10 in 2011. However, these spikes largely disappear in the 2012 and 2013 plots after Continental's reservation system and frequent flyer program were merged into United's on March 3, 2012.[48] Additionally, the distribution of Continental's fares in 2011 has a large spike at \$0 but no spikes at \$2, \$5, \$7, and \$10. These plots suggest that Continental reports FFA tickets in the DB1B with an itinerary fare of zero. Furthermore, researchers should be aware that all Continental tickets in addition to United tickets after March 3, 2012 are likely not inclusive of ticket taxes and fees since the Passenger Fee does not appear to be reflected in their DB1B observations. Accordingly, researchers should consider adding the applicable Passenger Fee to all reported Continental fares and United fares after March 3, 2012 or include the appropriate level of fixed effects (e.g., airline-time and airline-route) in their empirical analyses.

Finally, we do not classify Continental or United tickets with an itinerary fare of \$0 as FFAs in the analysis presented in Sections 4, 5, and 6. However, the results presented in this paper do not materially change if all Continental tickets with a fare of \$0 and all United tickets after March 3, 2012 with a fare of \$0 are classified as FFAs (results from these robustness checks are available upon request).

[48] Although the United-Continental merger closed on October 1, 2011, the Federal Aviation Administration did not grant a single operating certificate to United until November 30, 2011. Continental's reservation system and OnePass Frequent Flyer miles program were officially merged into United's on March 3, 2012.

Figure B1: Distribution of DB1B Fares Under $20 for Continental and United in 2011, 2012, and 2013



Notes: Data from DB1B files for 2011, 2012, and 2013. Bars represent the share of passengers with tickets under $20 that reported that exact itinerary fare. Data are limited to one-way itineraries with three or fewer segments and round trip itineraries with six or fewer segments.