Purchase discounts on federal holidays and adjacent shopping holidays: Evidence from the airline industry

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Purchase discounts on federal holidays and adjacent shopping holidays: Evidence from the airline industry[*]

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Abstract

Discounts during Thanksgiving and Christmas are common in a variety of retail markets. In this article, we examine whether holiday discounts extend to the airline industry. In contrast to many retail markets where purchased goods are meant for immediate consumption (e.g., groceries), goods in airline markets are often consumed in the future due to advance purchases. Exploiting a unique panel of almost 22 million fares, we find that fares purchased on a holiday for flights in the sixty-day period following the holiday are 1.9% cheaper, supporting the conjecture that airlines price discriminate when demand is lower than average or when the mix of purchasing passengers makes demand more elastic. These holiday discounts also do not vary with the level of competition, indicating that market structure has no impact on the magnitude of the holiday purchase discount.

JEL classification: L11, L13, L93, D40.

Keywords: advance-purchase discounts, airline pricing, competition, price discrimination, sales.

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1 Introduction

Sales during holiday periods are common in a variety of retail markets. For example, Chevalier et al. (2003) and MacDonald (2000) document that grocery prices are lower during the Thanksgiving and Christmas holidays while Warner and Barsky (1995) find that prices for consumer appliances are lower in the period preceding Christmas.[1] Moreover, Levy et al. (2010) find that price decreases are more common than price increases during holiday periods.

Although classical economic theory predicts that prices should increase during periods of high aggregate demand (such as the period surrounding Thanksgiving and Christmas), previous studies assert that prices fall during these seasonal demand peaks because consumers are more price elastic.[2] For example, MacDonald (2000) argues that high seasonal demand reduces the cost of informative advertising, which in turn increases buyers' price sensitivity. Warner and Barsky (1995) suggest that consumers are better informed in high demand states, resulting in retailers perceiving their demand to be more elastic. Similarly, Chevalier et al. (2003) argue that consumers may search more intensively for low prices during periods of high demand because the expected returns from search are larger during these periods.[3]

In this article, we examine whether holiday discounts extend to the airline industry. In contrast to many retail markets where purchased goods are meant for immediate consumption (e.g., the consumer appliance and grocery markets mentioned above), goods in airline markets are often consumed in the future because consumers purchase tickets in advance of departure. Hence, the holiday occurs prior to the actual date of travel in our setting due to advance purchase behavior.

[1] For a witty review of the economics surrounding Christmas, see Birg and Goeddeke (2016).

[2] Other explanations have also been offered. For example, Rotemberg and Saloner (1986) suggest that prices fall because firms are not able to sustain tacit collusion in high demand periods. In other words, the temptation to cheat from a collusive agreement is highest during a temporary demand spike because the gain from cheating is increasing in current demand whereas the loss from punishment is increasing in future demand. Alternatively, Lal and Matutes (1994) and Hosken and Reiffen (2004) suggest that multiproduct retailers may discount highly demanded products during peak periods to facilitate greater store traffic.

[3] This explanation is consistent with Varian (1980), who argues that sales are a form of price discrimination in which firms effectively offer lower prices to consumers with superior information or lower search costs.

We offer two explanations for why airlines may discount fares on federal holidays. Foremost, demand may be more elastic on holidays because price inelastic business travelers are unlikely to purchase outside of normal business hours.[4] Second (and in contrast to the retail case), holidays may coincide with lower than average airline demand. For example, Thanksgiving and Christmas are holidays when consumers typically travel to visit family. Because individuals away from home may not be ready to plan another vacation after having just incurred significant travel expenses, airlines may have to offer substantial discounts to entice consumers to purchase at these times. As a result, federal holidays provide an opportunity for airlines to price discriminate by offering discounts to passengers who purchase on these dates.

Price discrimination may result in higher profits if firms are able to agree on which types of consumers are price elastic (Borenstein, 1985; Colombo, 2018; Holmes, 1989; Liu and Serfes, 2004). However, even if airlines agree that passengers purchasing on a federal holiday are more price elastic or that demand is lower on federal holidays, they may still avoid discriminatory pricing. For example, Corts (1998) shows that price discrimination may result in "all-out competition" where prices are lower for all consumers than under uniform pricing. In this competitive environment, the ability to price discriminate results in a prisoner's dilemma in which each firm has a dominant strategy to price discriminate even though profits would be higher for all firms if discrimination were not possible.

Furthermore, recent work by Ciliberto and Williams (2014) and Ciliberto et al. (2019) suggests that airlines may be tacitly colluding when setting fares. If airlines are colluding, they may coordinate to avoid certain types of discriminatory pricing. For example, if fewer airline tickets are purchased on holidays relative to other periods, the theoretical models in Haltiwanger and Harrington Jr (1991) and Rotemberg and Saloner (1986) suggest that collu-

[4]Escobari et al. (2019) find that airfares are higher during business hours and lower in the evening. We also expect demand to be more elastic on adjacent "shopping holidays" such as Black Friday, Christmas Eve, and New Year's Eve because many public and private sector employees either receive or request these days off from work.

sive prices may increase. Coordination is also expected to be easier in the consolidated United States airline industry where American, Delta, Southwest, and United currently control over 80% of the domestic market. Therefore, although we hypothesize that federal holidays provide an opportunity to price discriminate by discounting fares, it is also possible that fares may increase.

To determine if airlines offer discounts on federal holidays, we exploit a unique panel of almost 22 million fares collected over a seven-month period. Our fare data is comprehensive, encompassing many densely traveled routes across the continental United States (U.S.). Tracking the price of each flight in the sixty-day period prior to departure, we find that fares published on a major holiday for flights in the sixty-day period following the holiday are 1.9% cheaper on average. Allowing for heterogeneity in discounts across holidays, we find that the holiday booking discount ranges from 1.5% on Thanksgiving to 5.9% on Christmas Day. Moreover, we find that the largest holiday discounts are offered for flights that are within one-week of departure (flights typically purchased by business travelers), consistent with the conjecture that airlines discount fares on federal holidays because price inelastic business travelers are unlikely to purchase on these dates. However, because we do not find evidence that holiday discounts are larger on routes with more business travel and because the largest discounts occur on Christmas when many consumers are away from home, lower than average airline demand may explain the majority of holiday purchase discounts observed in our sample.

Further decomposing our results, we examine how holiday booking discounts are affected by market structure. As discussed in Borenstein (1985), Holmes (1989), and Chandra and Lederman (2018), the relationship between competition and price discrimination is ambiguous in oligopolistic markets when consumers differ both in their underlying willingness-to-pay and their degree of brand loyalty. We find that the level of competition (measured by either the number of competitors or the Herfindahl-Hirschman Index) has no statistically measurable impact on the magnitude of the holiday purchase discount.

The rest of this article is organized as follows. Section 2 summarizes previous literature on price discrimination in oligopolistic markets, with a particular emphasis on empirical studies of the airline industry. Section 3 describes the fare and itinerary data collected for the empirical analysis. Section 4 presents a descriptive analysis of dynamic pricing in the sixty-day period leading up to a flight's departure. Section 5 outlines the empirical model used to identify holiday booking discounts. Section 6 presents empirical results. Finally, Section 7 concludes.

2 Price Discrimination and Price Dispersion in Oligopolistic Markets

Firms in a variety of industries including automobiles, Broadway theater, energy, hospitality, retail, and specialty coffee engage in price discrimination (Chevalier and Kashyap, 2019; Ivaldi and Martimort, 1994; Leslie, 2004; Möller and Watanabe, 2010; McManus, 2007; Verboven, 1996, 2002). In the airline industry, a sizable literature has developed examining the various ways in which airlines practice second and third-degree price discrimination.[5] Dana (1998) and Gale and Holmes (1993) show that advance-purchase restrictions enable airlines to reduce fares for price-elastic leisure travelers. Other ticket restrictions such as Saturday-night stay, length of stay, and non-refundability are designed to discourage price-inelastic passengers from buying cheaper tickets (Escobari and Jindapon, 2014; Stavins, 2001).[6] Puller and Taylor (2012) find that fares purchased on weekends are 5% cheaper, supporting the conjecture that

[5]Second-degree price discrimination occurs when firms offer a menu of prices that induce consumers to differentiate themselves. Non-linear pricing strategies such as quantity discounts and charging different prices for refundable and non-refundable tickets are examples of second-degree price discrimination. In contrast, third-degree price discrimination occurs when firms directly segment consumers according to some observable metric. Student discounts, senior citizen discounts, and prices that vary by location are examples of third-degree price discrimination.

[6]Escobari and Jindapon (2014) present a theoretical model examining how airlines use refundable and non-refundable tickets to screen consumers who are uncertain about their demand. Empirically, they show that the difference in fare between refundable and non-refundable tickets declines as the departure date approaches.

airlines price discriminate when the mix of purchasing passengers makes demand more elastic. Applying a similar argument, Escobari et al. (2019) find that fares are higher during business hours and lower in the evening. Additionally, Luttmann (2019b) and Lewis (2020) offer conflicting evidence on the existence of directional price discrimination in the domestic U.S. market.[7]

The empirical analysis presented in this article is also motivated by the extensive theoretical literature on the relationship between competition and price dispersion when firms practice third-degree price discrimination.[8] In particular, the relationship between competition and price discrimination is ambiguous when consumers differ both in their degree of brand loyalty and their underlying willingness-to-pay (Borenstein, 1985; Holmes, 1989; Chandra and Lederman, 2018).

Consistent with theory, previous empirical studies of the airline industry that examine this relationship provide conflicting results. Borenstein and Rose (1994) and Stavins (2001) find that competition increases price dispersion while Gaggero and Piga (2011), Gerardi and Shapiro (2009), and Siegert and Ulbricht (2020) find that competition reduces price dispersion. Furthermore, Dai et al. (2014) find a nonmonotonic relationship, with competition increasing dispersion in concentrated markets and reducing it in competitive markets. Examining the Canadian airline industry, Chandra and Lederman (2018) find that competition has little impact at the top or bottom of the price distribution but a significant impact in the middle of the distribution, with competition increasing some price differentials and decreasing others.

[7] Directional price discrimination occurs when airlines charge different prices on the same flights to passengers who originate from different endpoints. This form of price discrimination is feasible if demand elasticities substantially differ between endpoint cities. Using aggregated transacted fare data from 2015, Luttmann (2019b) finds evidence consistent with airlines practicing directional price discrimination. Using published fare data, Lewis (2020) finds that airlines do not directionally price discriminate on domestic routes but do directionally discriminate on international routes.

[8] See Stole (2007) for a comprehensive review of price discrimination under oligopoly.

3 Fare and Itinerary Data

Previous empirical studies that examine airline price dispersion and price discrimination in the U.S. have typically relied on the U.S. Department of Transportation's Airline Origin and Destination Survey (DB1B).[9] Data from this survey are released quarterly and represent a 10% random sample of all airline tickets sold for U.S. domestic travel. However, the DB1B data do not include information on the specific flight(s) purchased or the exact purchase and departure dates (only the quarter of travel is reported). As a result, the DB1B cannot be used to examine holiday pricing or control for other factors that may affect fares, such as advance-purchase requirements or the specific date of travel. With these shortcomings in mind, we constructed our own dataset using published fare and itinerary information from a major online travel agency.[10]

In lieu of collecting published fares for all possible routes in the U.S. market, we relied on DB1B data from the third and fourth quarters of 2018 to identify the 98 major airport-pairs within the continental U.S. ranked by total passenger traffic.[11] These routes were supplemented with 17 monopoly, 24 duopoly, and 16 airport-pairs without nonstop service (these are routes where passengers must take a connecting flight to reach their destination).[12] Due to overlap between the 98 major and 24 duopoly airport-pairs, our analysis covers a total of 148 directional airport-pairs instead of 155. A detailed list of these routes is provided in Appendix Table A1.

Figure 1 displays a map of the routes included in our analysis. As the map illustrates, our route coverage is fairly comprehensive across the continental U.S.

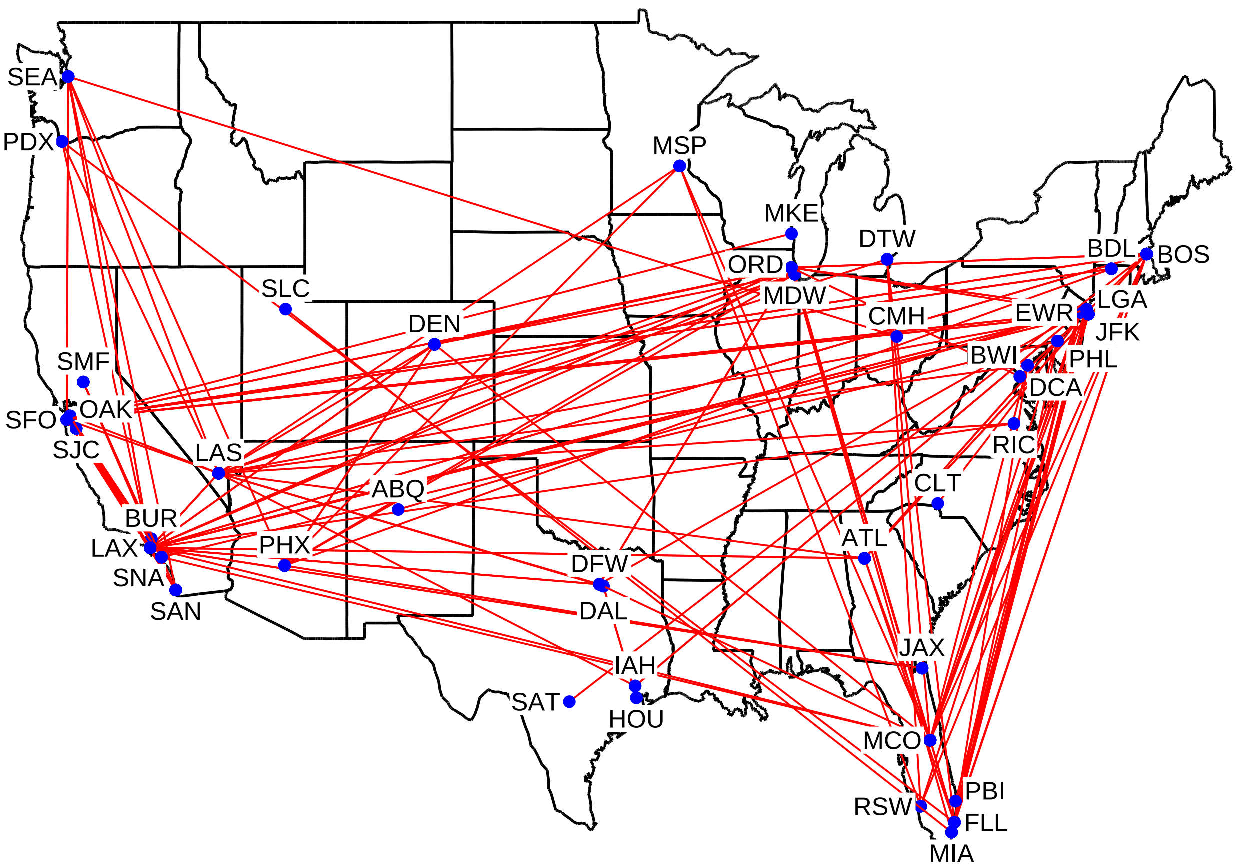
[9]These studies include Borenstein and Rose (1994), Hayes and Ross (1998), Gerardi and Shapiro (2009), Dai et al. (2014), and Luttmann (2019b), among others.

[10]Major online travel agencies (OTAs) and aggregator websites include Expedia, Google Flights, Kayak, Priceline, Skyscanner, and Travelocity. This article is not the first to analyze data from a major OTA. For example, see Escobari (2009), Escobari et al. (2019), Luttmann (2019a), and Williams (2022), among others.

[11]A market in our analysis is defined as a directional pair of origin and destination airports. Therefore, Los Angeles (LAX)-New York (JFK) and New York (JFK)-Los Angeles (LAX) are treated as separate markets.

[12]The list of monopoly, duopoly, and connecting airport-pairs were also ranked by total passenger traffic.

Figure 1: U.S. domestic routes included in our analysis sample



To construct our analysis sample, data were collected over a seven-month period for flights departing between October 1st, 2019 and February 29th, 2020.[13] Fare quotes were obtained daily, for one-way travel between the airport-pairs listed in Appendix Table A1.[14] For each flight option on a given route, the lowest observed economy-class fare for each of the next sixty travel days were collected, allowing us to track the price of an individual flight (or sequence of flights for connecting trips) over the sixty-day period prior to departure.[15] We

[13]Because our analysis sample ends on February 29th, 2020, the COVID-19 pandemic has a negligible impact on our results. In the U.S., COVID-19 was declared a national emergency on March 13th, 2020. Moreover, California became the first state to issue a statewide stay-at-home order on March 19th, 2020.

[14]We focus on one-way trips due to difficulties in specifying trip duration. For any given departure date, there are a substantial number of roundtrip fares that could potentially be gathered, each depending on trip duration. For example, fares for three-day trips are likely different from seven and fourteen-day trips. Similar articles using published fare and itinerary data also focus on one-way trips due to this duration issue. Examples include Bilotkach (2005), Bilotkach et al. (2010), Escobari et al. (2019), and Luttmann (2019a).

[15]For example, fare quotes for a flight departing on January 1st, 2020 were collected daily between November

focus on a sixty-day window to capture leisure travelers who purchase flights well in advance of the departure date in addition to business travelers who purchase flights closer to the date of departure.[16]

Our sampling procedure resulted in a unique sample of 21,829,963 observations. 30.8% of our observations are for connecting trips. The airlines included in our sample are Alaska, Allegiant, American, Delta, Frontier, JetBlue, Spirit, Sun Country, and United.[17]

4 Descriptive Analysis of Dynamic Pricing During the Booking Period

To illustrate how fares evolve in the sixty-day period prior to departure, Figure 2 displays the average fare per mile by number of days to departure for each of the nine airlines in our analysis sample.[18] The top panel of Figure 2 displays averages for the four legacy carriers (Alaska, American, Delta, and United) while the bottom panel displays averages for the five low-cost carriers (Allegiant, Frontier, JetBlue, Spirit, and Sun Country). For both legacy carriers and low-cost carriers (LCCs), the fare per mile remains relatively stable during the early part of the booking period, starts to increase three weeks before departure, and substantially increases in the last seven days to departure.

For legacy carriers, there are four well-defined fare hikes that occur from twenty-one to twenty, fourteen to thirteen, seven to six, and three to two days prior to departure. In

3rd, 2019 and December 31st, 2019. Our data collection began in August 2019 to ensure that fare quotes were obtained over the full sixty-day period before departure for flights departing on October 1st, 2019. If an airline offers multiple flight options on a given day, the lowest economy-class fare for each of the flight options were collected (e.g., if Delta operates three flights from Atlanta to Boston on a given departure date, the lowest observed economy-class fare for each of the three flights would be collected).

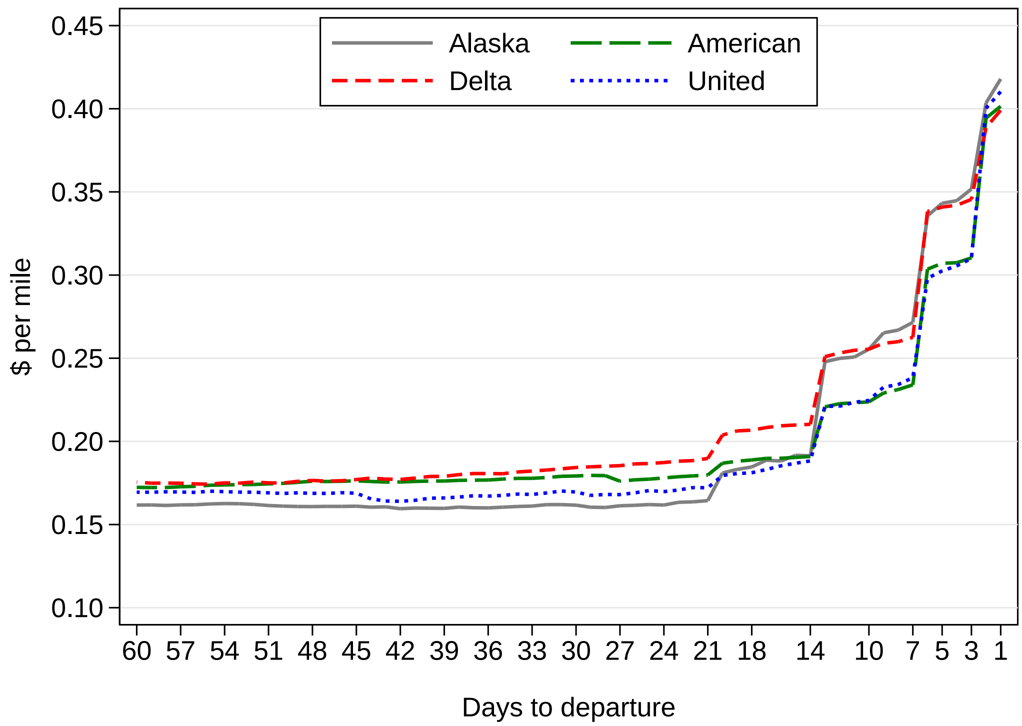
[16] In his analysis of intertemporal price discrimination in monopoly airline markets, Lazarev (2013) employs a six-week data collection window.

[17] Fare quotes for Southwest Airlines are not available on travel aggregator websites such as Expedia, Google Flights, and Kayak. However, Southwest is accounted for in our empirical analysis when we construct market structure variables such as the number of competitors or the Herfindahl-Hirschman Index.

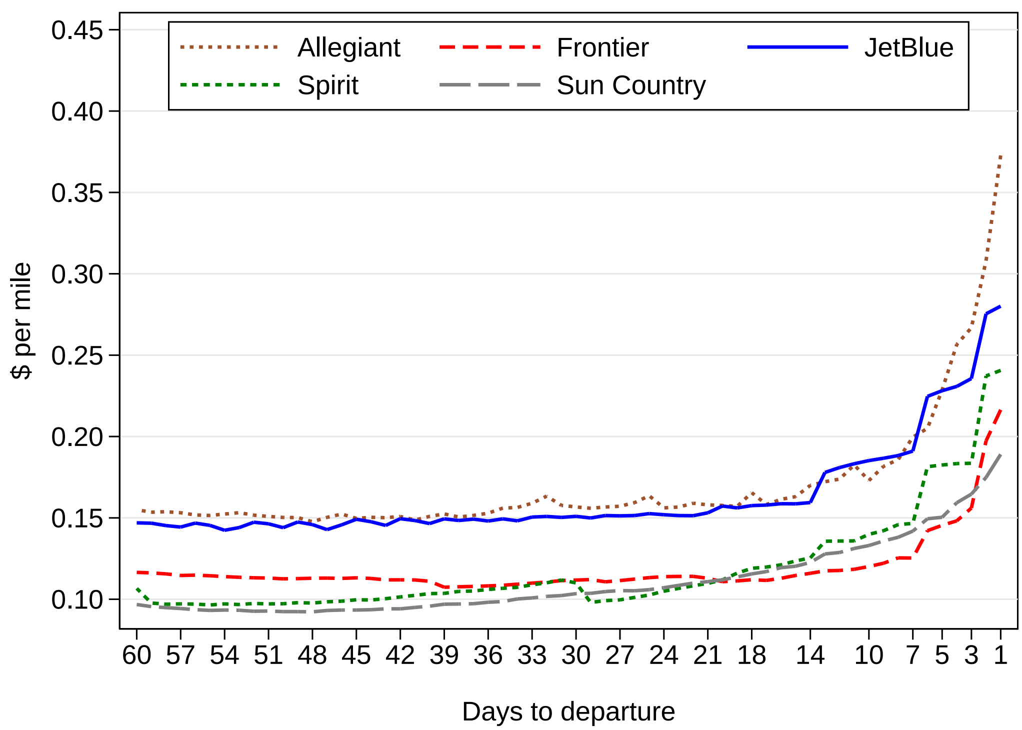
[18] Only nonstop flights were used to generate Figure 2. Of the 21,829,963 observations in our sample, 69.2% (15,106,864) are for nonstop travel.

Figure 2: Average fare per mile during the booking period for nonstop flights

(a) Legacy carriers



(b) Low-cost carriers



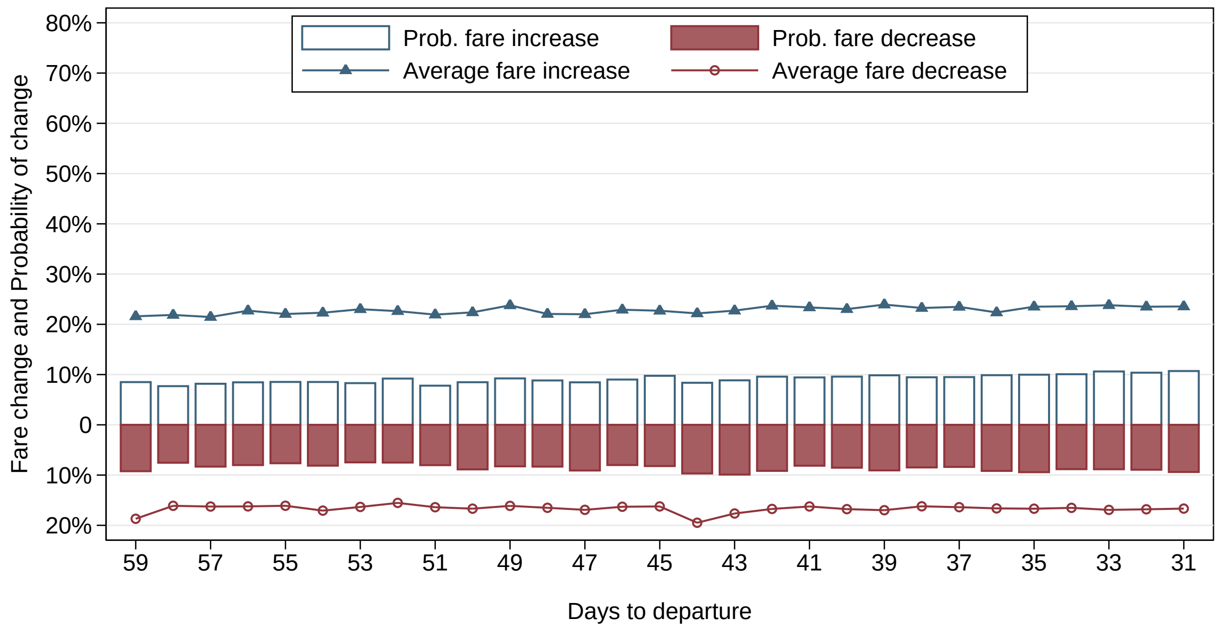
other words, legacy carriers sharply increase fares at specific three-week, two-week, one-week, and three-day milestones prior to departure. The first three milestones likely reflect the expiration of discount fare classes attached to three-week, two-week, and one-week advance-purchase requirements. The last milestone likely reflects intertemporal price discrimination for late booking passengers who have a lower price elasticity of demand (Gaggero, 2010). Furthermore, consistent with the expectation that purchasing passengers are more price inelastic as the departure date approaches, the magnitude of the fare jump monotonically increases as we move across the three-week, two-week, one-week, and three-day fare hike milestones.

Consistent with their status as a LCC, Allegiant, Frontier, JetBlue, Spirit, and Sun Country all have a lower average fare per mile than the four legacy carriers (see bottom panel of Figure 2). Allegiant and JetBlue fares are also consistently higher than Frontier, Spirit, and Sun Country fares across the entire sixty-day booking period. Nevertheless, both legacy and LCCs display similar patterns. Fares are relatively stable until three weeks before departure when fares begin to monotonically increase. In addition, JetBlue and Spirit sharply increase fares at three-week, two-week, one-week, and three-day milestones prior to departure, behavior consistent with Alaska, American, Delta, and United.

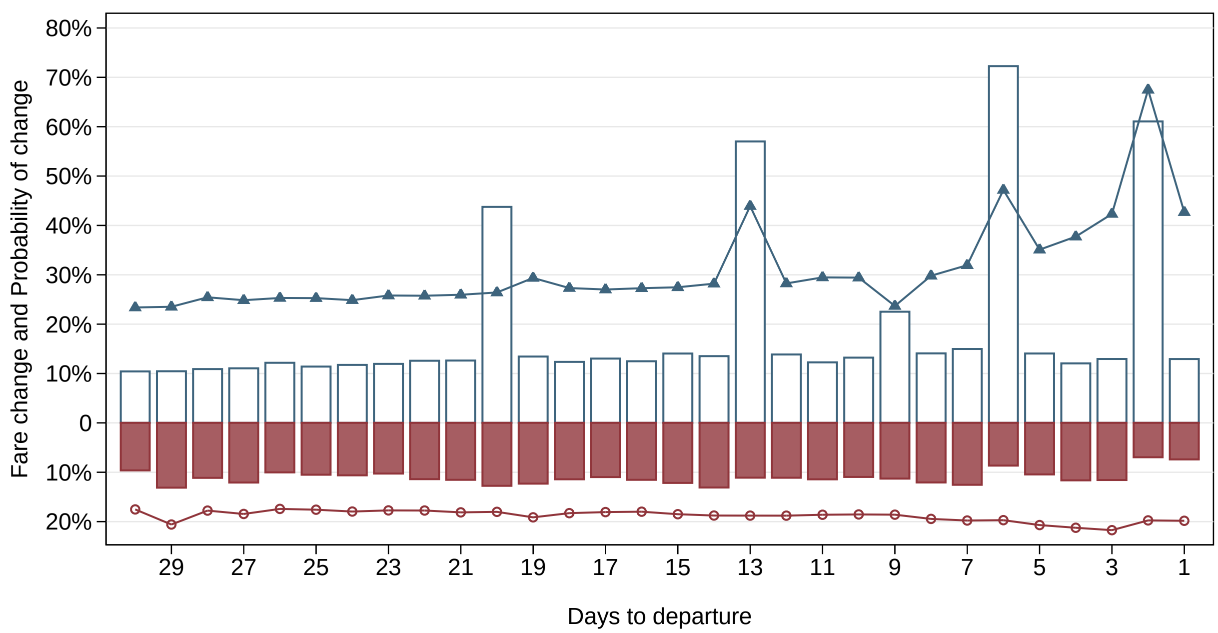
To further illustrate how fares evolve in the sixty-day period before departure, Figure 3 displays the probability of observing a fare increase (denoted by a white bar) or fare decrease (denoted by a red bar) for each day to departure. The blue line above each white bar displays the average percentage fare increase, while the red line below each red bar displays the average percentage fare decrease. For example, the white bar at 31 days to departure in the top panel of Figure 3 indicates that the fare for 11% of the flights in our sample increased 31 days before departure and the blue line indicates that the average fare increase was 24%. Similarly, the white bar at 31 days to departure indicates that the fare for 9% of the flights in our sample decreased 31 days before departure and the red line indicates that the average fare decrease was 17%.

Figure 3: Probability of observing a fare increase or decrease during the booking period and average fare increase or decrease

(a) Early booking period



(b) Late booking period



As depicted in the top panel of Figure 3, fares are relatively stable during the early booking period, with the probability of a fare increase hovering around 10% and the probability of a fare decrease at 8% on average. The magnitude of fare increases and decreases are also stable during the early booking period, ranging from 21%-24% for fare increases and 16%-19% for fare decreases.

The bottom panel of Figure 3 demonstrates that fare increases and decreases are larger in magnitude and more likely to occur in the last thirty days to departure. Consistent with the fare hikes observed in Figure 2, the probability of observing a fare increase jumps at twenty (44%), thirteen (57%), six (72%), and two (61%) days prior to departure. Moreover, in line with the expectation that demand is more inelastic closer to the date of departure, the average percentage fare increase, in general, monotonically increases from 26% twenty days before departure to 67% two days before departure.

Similar to the early booking period, the probability of observing a fare decrease and the magnitude of the decrease are relatively stable in the last thirty days to departure. During this late booking period, the probability of a fare decrease hovers around 10% with the average fare decrease ranging from 17% to 22%.

Overall, the descriptive analysis of dynamic pricing presented in Figures 2 and 3 reveals two key insights. Foremost, it is important to control for advance-purchase requirements in our empirical analysis of holiday pricing. Most importantly however, if airlines discount flights on major holidays, these discounts are likely to differ with the advance-purchase requirement. For example, if airlines discount flights on federal holidays because price inelastic business travelers are not purchasing tickets when offices are closed, then holiday purchase discounts are likely to be larger in magnitude for flights closer to the date of departure (Bilotkach et al., 2015). In other words, because passengers shopping on a holiday are more likely to be price elastic, high fares that are typically reserved for late arriving business travelers may be heavily discounted to stimulate purchases from these price elastic customers.

5 Empirical Strategy

To identify holiday booking discounts, we estimate a flight fixed effects model where the variables of interest are the set of dummies that identify each of the eleven major federal and shopping holidays that occur during our sample period (see Table 1 for a detailed list). We estimate equation (1) below,

$$ln(fare)_{fjt} = \alpha + \sum_{i=1}^{4} \delta_i \cdot DaysToDeparture_{ft} + \gamma \cdot WeekendBook_{ft} + \sum_{i=1}^{12} \beta_i \cdot HolidayBook_{ft} + \rho_{fj} + \varepsilon_{fjt} \quad (1)$$

where $ln(fare)_{fjt}$ is the natural logarithm of the published fare measured at the flight or flight-pair (for connecting itineraries) f, directional airport-pair j, and number of days to departure $t \in [1, 60]$, level. $DaysToDeparture$ are a set of dummy variables that indicate if the fare is collected 1-2, 3-6, 7-13, or 14-20 days before departure. The earliest days to departure group (21-60 days) serves as the base category, so that the coefficients on the included $DaysToDeparture$ dummies indicate the change in fare relative to the early booking period.[19]

$WeekendBook$ is a dummy indicating whether the fare is collected on a Saturday or Sunday. α is the regression intercept while ε is an error term. Standard errors are clustered at the airport-pair level.

ρ_{fj} is a flight-route fixed effect that controls for time-invariant flight, carrier, and airport-pair-specific characteristics that may affect fares (i.e., unobservable factors that may impact the log price level and the general level of the demand elasticity). For example, flight-specific characteristics include the size and type of aircraft used, the scheduled departure and arrival times, and the date of departure. Carrier-specific characteristics include any

[19] These five days to departure categories correspond to the fare increases observed in Figures 2 and 3. These days to departure groupings are also consistent with the analyses in Gaggero and Luttmann (2023a,b). Results are qualitatively similar if we replace the $DaysToDeparture$ dummies with a single variable that indicates the number of days to departure.

fare effects attributable to the airline's frequent flyer program, cost structure, and average quality of service. Airport-pair-specific characteristics include the level of competition on the route, whether low-cost carriers are present on the route, distance between the origin and destination airports, and the level of airport dominance at the origin and destination airports.[20]

Table 1: Holidays during our sample period

Holiday Name	Holiday Type	Holiday Date	Day of Week	Percentage of workers with day off: Civilian	Private	Government
Labor Day	National	Sep. 2, 2019	Mon	91%	91%	96%
Columbus Day	Federal	Oct. 14, 2019	Mon	*	*	*
Veteran's Day	Federal	Nov. 11, 2019	Mon	19%	11%	70%
Thanksgiving Day	National	Nov. 28, 2019	Thu	97%	97%	99%
Black Friday	Shopping	Nov. 29, 2019	Fri	43%	39%	69%
Christmas Eve	Shopping	Dec. 24, 2019	Tue	28%	26%	45%
Christmas Day	National	Dec. 25, 2019	Wed	97%	97%	93%
New Year's Eve	Shopping	Dec. 31, 2019	Tue	15%	14%	20%
New Year's Day	National	Jan. 1, 2020	Wed	90%	90%	90%
M. L. King Day	Federal	Jan. 20, 2020	Mon	32%	24%	86%
President's Day	Federal	Feb. 17, 2020	Mon	24%	19%	58%

Notes: National holidays are days most government and private sector employees receive off from work. Federal holidays are days most federal/state government employees receive off from work that private sector employees may or may not receive. Finally, shopping holidays are dates adjacent to a national holiday that are typically associated with high volumes of retail sales. These shopping holidays are also dates that many private and public sector employees either receive or request off from work (i.e., use some of their allotted vacation time). Because our data collection begins in August 2019 and ends in February 2020, Memorial Day and Independence Day are not observed in our sample. The statistics reported in the last three columns are obtained from the National Compensation Survey conducted by the U.S. Bureau of Labor Statistics in 2018 (see `https://www.bls.gov/ebs/factsheets/holiday-profiles.htm`). *The percentage of workers with Columbus Day off was not reported in the 2018 National Compensation Survey.

The variables of interest in equation (1) are the set of $HolidayBook$ dummies that indicate if the fare is published on a holiday. We allow for heterogeneity in fare effects across holidays by including a separate dummy for each of the eleven federal or shopping holidays that occur

[20]Note that the ρ_{fj} fixed effect controls for any fare effects attributable to the route's market concentration (typically measured by the Herfindahl-Hirschman Index or a variable counting the number of competitors) in addition to any hub premium that affects fares for all flights operating from the origin and destination airports.

during our sample period. To further explore heterogeneity in holiday booking discounts, additional specifications examine how these discounts are affected by carrier type, the number of days to departure, itinerary type, and market structure.

6 Results

We begin by presenting our baseline holiday booking discount results (Section 6.1). These results are followed by additional specifications that examine how holiday booking discounts are affected by advance-purchase requirements, carrier type, competition from Southwest (Section 6.2), itinerary type (Section 6.3), and market structure (Section 6.4).

6.1 Baseline Holiday Booking Discounts

Table 2 presents regression results from the model described by equation (1). Due to space constraints and to improve readability, standard errors for the coefficient estimates in Table 2 (and Table 4 that follows) are provided in Appendix D. All specifications include flight-route fixed effects to control for unobservable time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares and the general level of the demand elasticity. To provide a baseline for the magnitude of advance-purchase discounts, the first column of Table 2 reports results when only the $DaysToDeparture$ dummies and flight-route fixed effects are included. Consistent with Figure 2 and Figure 3, the positive coefficients on the $DaysToDeparture$ dummies provide clear evidence of advance-purchase discounts (i.e., intertemporal price discrimination). Compared to flights purchased 21-60 days before departure, flights purchased 1-2, 3-6, 7-13, and 14-20 days before departure are 128.1%, 76.8%, 35.5%, and 10.7% more expensive, respectively.[21]

[21] Because the dependent variable is in natural log form and the $DaysToDeparture$ variables are dummies, marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. These results are consistent with Alderighi et al. (2015), Gaggero and Piga (2010), Gillen and Mantin (2009), Luttmann (2019a), and Mantin and Koo (2009) who find that fares begin to substantially increase three weeks prior to departure.

Table 2: Baseline holiday booking effects

	(1)	(2)	(3)	(4)	(5)
DaysToDeparture 1-2	0.825***	0.825***	0.835***	0.825***	0.825***
DaysToDeparture 3-6	0.570***	0.570***	0.574***	0.570***	0.570***
DaysToDeparture 7-13	0.304***	0.304***	0.303***	0.304***	0.304***
DaysToDeparture 14-20	0.102***	0.102***	0.102***	0.102***	0.102***
WeekendBook		0.001	0.001	0.001	0.001
HolidayBook		-0.019***	-0.013***		
HolidayBook × DaysToDeparture 1-2			-0.152***		
HolidayBook × DaysToDeparture 3-6			-0.061***		
HolidayBook × DaysToDeparture 7-13			0.021***		
HolidayBook × DaysToDeparture 14-20			0.008***		
Book on Labor Day				-0.015***	-0.017***
Book on Columbus Day				0.025***	0.021***
Book on Veteran's Day				0.009***	0.007**
Book on Thanksgiving				-0.015***	-0.016***
Book on Black Friday				-0.023***	-0.025***
Book on Christmas Eve				-0.060***	-0.058***
Book on Christmas Day				-0.061***	-0.059***
Book on New Year's Eve				-0.048***	-0.042***
Book on New Year's Day				-0.041***	-0.036***
Book on M.L. King Day				0.049***	0.047***
Book on President's Day				0.009	0.009
LCC × Book on Labor Day					0.008
LCC × Book on Columbus Day					0.018***
LCC × Book on Veteran's Day					0.012***
LCC × Book on Thanksgiving					0.002
LCC × Book on Black Friday					0.007
LCC × Book on Christmas Eve					-0.015**
LCC × Book on Christmas Day					-0.007
LCC × Book on New Year's Eve					-0.026***
LCC × Book on New Year's Day					-0.024***
LCC × Book on M.L. King Day					0.013**
LCC × Book on President's Day					-0.002
R^2	0.420	0.420	0.421	0.421	0.421
Observations	21,829,963	21,829,963	21,829,963	21,829,963	21,829,963

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Standard errors are clustered at the airport-pair level. Due to space constraints, the regression constant is not reported and standard errors are provided in Appendix Table D1. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

The second column of Table 2 adds the $WeekendBook$ and $HolidayBook$ indicators to the specification presented in column (1). Contrary to the results in Puller and Taylor (2012), but consistent with Mantin and Koo (2010), we find that economy fares published (i.e., "purchased" or "booked") on a weekend (Saturday-Sunday) are not statistically different from fares published during the workweek (Monday-Friday). The analysis in Puller and Taylor (2012) relied on detailed transacted fare data from the fourth quarter of 2004, a timeframe prior to the mergers between US Airways and America West, Delta and Northwest, United and Continental, Southwest and AirTran, American and US Airways, and Alaska and Virgin America. While uncertainty exists whether fares in our sample were purchased at the published rates, our results suggest that the weekend purchase discount may no longer hold in the newly consolidated U.S. airline industry.

The negative and statistically significant coefficient on $HolidayBook$ in column (2) of Table 2 indicates that fares published on a federal holiday or an adjacent shopping holiday are 1.9% cheaper than fares published on non-holiday dates, supporting the conjecture that airlines price discriminate when the mix of purchasing passengers makes demand more elastic. To determine if the holiday booking discount differs with how far in advance airfare is booked, column (3) presents results when $HolidayBook$ is interacted with the $DaysToDeparture$ dummies. We find substantial heterogeneity in the magnitude of the holiday booking discount, ranging from no discount for flights booked 7-13 days in advance to 15.2% for flights booked 1-2 days in advance. In addition, flights booked on a holiday with 3-6, 14-20, or 21-60 day advance-purchase requirements are 7.1%, 0.5%, and 1.3% cheaper, respectively.

To determine if holiday booking discounts differ across holidays, column (4) of Table 2 replaces the $HolidayBook$ indicator with separate indicators for each of the eleven federal and shopping holidays that occur during our sample period. We find substantial heterogeneity in holiday discounts ranging from 1.5% for fares booked on Labor Day and Thanksgiving to 5.9% for fares booked on Christmas Day. Although we estimate fare premiums ranging from 0.9% to 5.0% for flights booked on Columbus Day, Martin Luther King Day, President's Day, and Veteran's Day, not all civilian, private sector, or state government employers observe these federal holidays (e.g., see Table 1).[22] Therefore, it is not surprising to find that holiday booking discounts do not extend to these four holidays.[23]

The last column of Table 2 presents results when the holiday booking effects are allowed to vary between legacy (Alaska, American, Delta, and United) and LCCs (Allegiant, Frontier, JetBlue, Spirit, and Sun Country). Consistent with column (4), the positive or statistically insignificant coefficients on the Martin Luther King, President's, Columbus, and Veteran's Day variables indicate that both carrier types do not discount fares on these four federal holidays. Furthermore, the statistically insignificant coefficients on the Labor Day, Thanksgiving Day, Black Friday, and Christmas Day interaction terms suggest that legacy and LCCs do not differ in average discounts offered on these five holidays. Similar to the column (4) results, published fares are 1.7%, 1.6%, 2.5%, and 5.7% cheaper on Labor Day, Thanksgiving Day, Black Friday, and Christmas Day, respectively.

However, the negative and statistically significant coefficients on the Christmas Eve, New Year's Eve, and New Year's Day interactions in column (5) of Table 2 indicate that LCCs offer larger discounts than legacy carriers on these three holidays. On Christmas Eve, fares for LCCs are 7.0% cheaper compared to 5.6% cheaper for legacy carriers. On New Year's Eve and New Year's day, LCC fares are 6.6% and 5.8% cheaper compared to 4.1% and 3.5% cheaper for legacy carriers.

[22]For example, employees of The MITRE Corporation (the current employer for one of the author's of this study) currently do not receive Veteran's Day, President's Day, or Columbus Day off from work. Many state government employees (e.g., California, Oregon, South Carolina, Texas, and Washington, among others) do not receive Columbus Day off. According to the Bureau of Labor Statistics, full-time private-sector employees receive an average of 7.6 paid federal holidays (`https://www.bls.gov/news.release/ebs.t05.htm`).

[23]In Appendix C, we explore whether airlines discount fares on state holidays (e.g., Confederate Heroes Day in Texas, Rosa Parks Day in California, and Lincoln's Birthday in New York) using a difference-in-differences approach where flights departing from states not observing the holiday serve as the control group. Except for flights booked on Lincoln's Birthday from New York airports, we find that airlines generally do not discount fares on state holidays. Consistent with the lack of holiday purchase discounts estimated for Columbus Day, Martin Luther King Day, President's Day, and Veteran's Day, our state holiday findings are sensible considering that most federal government and private sector employees do not receive state holidays off from work.

6.1.1 More Elastic Demand or Lower Than Average Demand?

In Section 1, we offered two potential explanations for why airlines may discount fares on federal holidays. Our first explanation is that demand is more elastic on holidays because price inelastic business travelers are less likely to purchase tickets when offices are closed. Our finding that the largest holiday discounts are reserved for flights within one-week of departure (flights typically purchased by business travelers) is consistent with this first explanation. Our second explanation is that federal holidays coincide with periods of lower than average airline demand because people who are already away from home (e.g., visiting family over Thanksgiving and Christmas) may not be ready to plan yet another vacation after having just incurred significant travel expenses. Our finding that large discounts are offered on Christmas Eve and Christmas Day when many consumers are away visiting family is consistent with this second explanation.

Although we do not have access to data on ticket sales to investigate the lower than average demand hypothesis, we are able to explore the more elastic demand hypothesis by examining if holiday purchase discounts are larger on routes that typically have more business travel. For example, if demand is more elastic on federal holidays because business travelers are less likely to purchase on these dates, then holiday purchase discounts should be larger on routes with high shares of business travel and lower on routes with high shares of leisure travel. To determine if holiday purchase discounts differ across business and leisure routes, column (1) of Table 3 presents results when the specification in column (2) of Table 2 is augmented to include the interaction between HolidayBook and an indicator identifying a tourist destination.[24] The coefficient on $HolidayBook \times TouristDestination$ while positive is statistically insignificant, suggesting that more elastic demand may not be driving the holiday purchase discount.

As an alternative approach to identify routes with more business travel, column (2) of

[24] Consistent with Berry and Jia (2010), Las Vegas (LAS) and all airports in Florida (i.e., FLL, MIA, PBI, RSW, and JAX) are identified as tourist destinations in our analysis sample. The tourist destination indicator itself is not separately identified from the flight-route fixed effects.

Table 3: Holiday booking effects and the more elastic demand hypothesis

	(1)	(2)	(3)
DaysToDeparture 1-2	0.825***	0.825***	0.825***
	(0.022)	(0.022)	(0.022)
DaysToDeparture 3-6	0.570***	0.570***	0.570***
	(0.026)	(0.026)	(0.026)
DaysToDeparture 7-13	0.304***	0.304***	0.304***
	(0.019)	(0.019)	(0.019)
DaysToDeparture 14-20	0.102***	0.102***	0.102***
	(0.007)	(0.007)	(0.007)
WeekendBook	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)
HolidayBook	-0.020***	-0.019**	-0.019**
	(0.002)	(0.007)	(0.008)
HolidayBook × TouristDestination	0.002		0.001
	(0.002)		(0.002)
HolidayBook × OriginIncome		0.001	0.001
		(0.001)	(0.001)
HolidayBook × DestinationIncome		-0.001	-0.001
		(0.001)	(0.001)
R^2	0.420	0.420	0.420
Observations	21,829,963	21,829,963	21,829,963

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Constant is included but not reported. Standard errors are clustered at the airport-pair level and provided in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3 presents results when the specification in column (2) of Table 2 is augmented to include the interaction between $HolidayBook$ and the per capita incomes (in \$10,000s) of the origin and destination cities.[25] The implicit assumption is that routes to or from high income cities are likely to have more business travel. However, the coefficients on $HolidayBook \times OriginIncome$ and $HolidayBook \times DestinationIncome$ are also statistically insignificant, providing additional evidence that more elastic demand is likely not driving the holiday purchase discount.

[25] Per capita income data for each metropolitan statistical area are taken from the Bureau of Economic Analysis. Origin Income and Destination Income are not separately identified from the flight-route fixed effects.

Finally, column (3) of Table 3 includes the Tourist Destination, Origin Income, and Destination Income interactions in the same specification. Consistent with the results from the first two columns, the coefficients on $HolidayBook \times TouristDestination$, $HolidayBook \times OriginIncome$, and $HolidayBook \times DestinationIncome$ remain statistically insignificant. Accordingly, the results in Table 3 suggest that lower than average demand rather than more elastic demand is the more likely driver behind the holiday purchase discounts we observe.

6.2 Holiday Booking Discounts and Competition from Southwest

There may be a concern that the results in Table 2 are biased due to our lack of available fare data from Southwest.[26] To examine this possibility, Table 4 presents results when the advance-purchase and holiday booking effects are allowed to vary across three types of markets: markets where Southwest is a nonstop competitor (i.e., airport-pairs that Southwest serves nonstop), markets where Southwest is a potential competitor (i.e., airport-pairs that Southwest does not serve nonstop, but serves at least one destination from both endpoint airports), and markets where Southwest is not present as a nonstop or potential competitor.[27]

Column (1) of Table 4 presents results when the specification in column (1) of Table 2 is augmented to include interactions between the $DaysToDeparture$ dummies and the Southwest Nonstop ($SWNonstop$) and Southwest Potential ($SWPotential$) competition indicators.[28] The statistically insignificant coefficients on the $SWNonstop$ 1-2, 3-6, and 7-13 interactions indicates that nonstop competition from Southwest does not affect average fare hikes for flights purchased 1-13 days before departure. Similarly, the statistically insignificant coefficient on the $SWPotential$ 3-6 interaction indicates that the presence of potential

[26] For example, both nonstop and potential competition from Southwest have been shown to have large negative fare effects (Brueckner et al., 2013; Goolsbee and Syverson, 2008; Morrison, 2001; Kwoka et al., 2016).

[27] For example, Southwest is a potential competitor in the BOS-DCA market because while Southwest does not serve BOS-DCA directly, it does serve other markets from BOS (e.g., BOS-ORL) and DCA (e.g., DCA-ORL).

[28] The Southwest Nonstop and Southwest Potential competition indicators are not separately identified from the flight-route fixed effects.

competition from Southwest does not affect average fare hikes for flights purchased 3-6 days before departure.

However, the negative and marginally significant coefficient on the $SWPotential$ 1-2 interaction suggests that potential competition from Southwest decreases average fare premiums for flights purchased 1-2 days before departure.[29] In contrast, the positive and marginally significant coefficient on the $SWNonstop$ 14-20 interaction suggests that average fare premiums increase for flights purchased 14-20 days before departure in markets where Southwest is a nonstop competitor.[30] Additionally, the positive and statistically significant coefficients on the $SWPotential$ 7-13 and 14-20 interactions indicate that average fare hikes for flights purchased 7-20 days before departure are larger in markets where Southwest is a potential competitor.[31]

Column (2) of Table 4 presents results when $WeekendBook$, $HolidayBook$, and the interactions between $HolidayBook$ and the $SWNonstop$ and $SWPotential$ competition indicators are added to the specification in column (1). The small and statistically insignificant coefficients on $HolidayBook \times SWNonstop$ and $HolidayBook \times SWPotential$ indicate that average holiday booking discounts do not differ across markets where Southwest is a nonstop competitor, markets where Southwest is a potential competitor, and markets where Southwest is not present as a nonstop or potential competitor. Similar to the results in column (2) of Table 2, fares published on a federal holiday or an adjacent shopping holiday are 1.8%-2.1% cheaper on average across these three types of markets.

In Table 2, holiday booking discounts were found to differ with how far in advance airfare

[29] Compared to flights purchased 21-60 days before departure, flights purchased 1-2 days before departure are 136.6% more expensive in markets where Southwest is not present as a nonstop or potential competitor compared to 114.9% more expensive in markets where Southwest is a potential competitor.

[30] Compared to flights purchased 21-60 days before departure, flights purchased 7-13 days before departure are 26.4% more expensive in markets where Southwest is not present as a nonstop or potential competitor compared to 51.1% more expensive in markets where Southwest is a potential competitor.

[31] Compared to flights purchased 21-60 days before departure, flights purchased 14-20 days before departure are 7.7% more expensive in markets where Southwest is not present as a nonstop or potential competitor compared to 11.0% more expensive in markets where Southwest is a nonstop competitor and 14.9% more expensive in markets where Southwest is a potential competitor.

Table 4: Holiday booking effects and competition from Southwest (SW)

	(1)	(2)	(3)
DaysToDeparture 1-2	0.861***	0.861***	0.871***
DaysToDeparture 3-6	0.542***	0.542***	0.546***
DaysToDeparture 7-13	0.234***	0.234***	0.233***
DaysToDeparture 14-20	0.074***	0.074***	0.073***
SW Nonstop × DaysToDeparture 1-2	-0.008	-0.008	-0.009
SW Nonstop × DaysToDeparture 3-6	-0.014	-0.014	-0.014
SW Nonstop × DaysToDeparture 7-13	0.053	0.053	0.053
SW Nonstop × DaysToDeparture 14-20	0.030*	0.030*	0.030*
SW Potential × DaysToDeparture 1-2	-0.096*	-0.096*	-0.096*
SW Potential × DaysToDeparture 3-6	0.107	0.107	0.107
SW Potential × DaysToDeparture 7-13	0.179***	0.179***	0.177***
SW Potential × DaysToDeparture 14-20	0.065***	0.065***	0.066***
WeekendBook		0.001	0.001
HolidayBook		-0.021***	-0.014***
HolidayBook × SW Nonstop		0.002	0.002
HolidayBook × SW Potential		0.003	0.002
HolidayBook × DaysToDeparture 1-2			-0.155***
HolidayBook × DaysToDeparture 3-6			-0.056***
HolidayBook × DaysToDeparture 7-13			0.016**
HolidayBook × DaysToDeparture 14-20			0.008**
HolidayBook × SW Nonstop × DaysToDep. 1-2			0.011
HolidayBook × SW Nonstop × DaysToDep. 3-6			0.002
HolidayBook × SW Nonstop × DaysToDep. 7-13			-0.008
HolidayBook × SW Nonstop × DaysToDep. 14-20			0.004
HolidayBook × SW Potential × DaysToDep. 1-2			-0.008
HolidayBook × SW Potential × DaysToDep. 3-6			-0.012
HolidayBook × SW Potential × DaysToDep. 7-13			0.025***
HolidayBook × SW Potential × DaysToDep. 14-20			-0.006
R^2	0.428	0.428	0.429
Observations	21,829,963	21,829,963	21,829,963

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Standard errors are clustered at the airport-pair level. Due to space constraints, the regression constant is not reported and standard errors are provided in Appendix Table D2. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

is purchased, with the largest discounts reserved for flights within one-week of departure. To determine if nonstop and potential competition from Southwest affects these holiday booking discounts, column (3) of Table 4 presents results when the $HolidayBook \times DaysToDeparture$ interaction terms are interacted with the Southwest Nonstop and Southwest Potential competition indicators. In this specification, the $HolidayBook \times SWNonstop$, $HolidayBook \times SWPotential$, $HolidayBook \times SWNonstop \times DaysToDeparture$, and $HolidayBook \times SWPotential \times DaysToDeparture$ interactions are generally statistically insignificant, providing further evidence that the presence of nonstop or potential competition from Southwest does not affect average holiday booking discounts.[32]

6.3 Holiday Booking Discounts and Itinerary Type

Our baseline results in Table 2 constrain the advance-purchase and holiday booking effects to be constant across nonstop and connecting trips. However, because the quality of nonstop and connecting trips differ, it is possible that the advance-purchase and holiday booking effects differ between these two types of trips (Luttmann, 2019a). To examine this possibility, Table 5 presents results when the advance-purchase and holiday booking effects are allowed to vary across nonstop and connecting trips.

Column (1) of Table 5 presents results when the specification in column (1) of Table 2 is augmented to include interactions between the $DaysToDeparture$ dummies and the connecting trip indicator.[33] The statistically insignificant coefficient on the 14-20 interaction term indicates that trip type does not affect average fare hikes for flights purchased 14-20 days before departure. However, the negative and statistically significant coefficients on the 1-2, 3-6, and 7-13 interactions indicates that fare hikes for flights purchased within two weeks of departure are larger for nonstop trips. Compared to flights purchased 21-60 days before departure, flights purchased 1-2 days before departure are 144.2% more expensive for

[32]The coefficient on $HolidayBook \times SWPotential \times DaysToDeparture$ 7-13 is positive, statistically significant, and larger in absolute value than the coefficient on $HolidayBook$, indicating that holiday booking discounts do not extend to flights purchased 7-13 days before departure in markets where Southwest is a potential competitor. This finding is consistent with the results in column (3) of Table 2 where no holiday booking discount was estimated for flights purchased 7-13 days before departure.

[33]The connecting trip indicator itself is not separately identified from the flight-route fixed effects.

nonstop trips and 87.6% more expensive for connecting trips. Similarly, flights purchased 3-6 days before departure are 84.8% more expensive for nonstop trips and 53.7% more expensive for connecting trips. Finally, flights purchased 7-13 days before departure are 37.6% more expensive for nonstop trips and 28.0% more expensive for connecting trips.

Column (2) of Table 5 presents results when $WeekendBook$, $HolidayBook$, and the interaction between $HolidayBook$ and the connecting trip indicator are added to the specification in column (1). The positive and statistically significant coefficient on $HolidayBook \times Connect$ indicates that holiday booking discounts are larger for nonstop trips. Compared to fares published on non-holiday dates, fares published on a federal holiday or an adjacent shopping holiday are 2.1% cheaper for nonstop trips and 1.5% cheaper for connecting trips.

In Table 2, holiday booking discounts differed with how far in advance airfare is purchased, with the largest discounts reserved for flights within one-week of departure. To determine if these holiday booking discounts differ across nonstop and connecting trips, column (3) of Table 5 presents results when the $HolidayBook \times DaysToDeparture$ interaction terms are interacted with the connecting trip indicator. In this specification, the $HolidayBook \times Connect$ and $HolidayBook \times Connect \times DaysToDeparture$ interactions attached to the 1-2, 7-13, and 14-20 advance-purchase requirements are all statistically insignificant, implying that average holiday booking discounts do not differ across nonstop and connecting trips for flights purchased 1-2 or 7-60 days before departure. However, the $HolidayBook \times Connect \times DaysToDeparture$ 3-6 coefficient is positive and statistically significant, indicating that holiday booking discounts are larger for nonstop trips purchased 3-6 days before departure. Compared to flights purchased 21-60 days before departure, flights purchased 3-6 days before departure on a federal holiday or an adjacent shopping holiday are 8.2% cheaper for nonstop trips and 4.8% cheaper for connecting trips.

Table 5: Holiday booking effects and connecting flights

	(1)	(2)	(3)
DaysToDeparture 1-2	0.893***	0.893***	0.903***
	(0.023)	(0.023)	(0.023)
DaysToDeparture 3-6	0.614***	0.614***	0.619***
	(0.031)	(0.031)	(0.031)
DaysToDeparture 7-13	0.319***	0.319***	0.317***
	(0.024)	(0.024)	(0.024)
DaysToDeparture 14-20	0.104***	0.104***	0.104***
	(0.008)	(0.008)	(0.008)
Connect × DaysToDeparture 1-2	-0.264***	-0.264***	-0.265***
	(0.035)	(0.035)	(0.035)
Connect × DaysToDeparture 3-6	-0.184***	-0.184***	-0.187***
	(0.038)	(0.038)	(0.038)
Connect × DaysToDeparture 7-13	-0.072***	-0.072***	-0.072***
	(0.028)	(0.028)	(0.027)
Connect × DaysToDeparture 14-20	-0.015	-0.015	-0.015
	(0.010)	(0.010)	(0.010)
WeekendBook		0.001	0.001
		(0.000)	(0.000)
HolidayBook		-0.021***	-0.014***
		(0.002)	(0.002)
HolidayBook × Connect		0.006***	0.003
		(0.002)	(0.003)
HolidayBook × DaysToDeparture 1-2			-0.157***
			(0.010)
HolidayBook × DaysToDeparture 3-6			-0.072***
			(0.009)
HolidayBook × DaysToDeparture 7-13			0.021***
			(0.005)
HolidayBook × DaysToDeparture 14-20			0.007**
			(0.003)
HolidayBook × Connect × DaysToDep. 1-2			0.012
			(0.013)
HolidayBook × Connect × DaysToDep. 3-6			0.034***
			(0.011)
HolidayBook × Connect × DaysToDep. 7-13			0.001
			(0.006)
HolidayBook × Connect × DaysToDep. 14-20			0.001
			(0.004)
R^2	0.428	0.428	0.428
Observations	21,829,963	21,829,963	21,829,963

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Constant is included but not reported. Standard errors are clustered at the airport-pair level and provided in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

6.4 Holiday Booking Discounts and Market Structure

The results in Tables 2, 3, 4, and 5 provide evidence consistent with airlines discounting fares on several major holidays. To determine how holiday booking discounts are affected by the level of competition, Table 6 presents results when the specification in column (2) of Table 2 is augmented to include the interaction between $HolidayBook$ and the number of nonstop carriers serving the route on the observed departure date ($NCarriers$).[34] To be consistent with previous literature on competition and price discrimination in the airline industry (Borenstein and Rose, 1994; Dai et al., 2014; Gaggero and Piga, 2011; Gerardi and Shapiro, 2009; Siegert and Ulbricht, 2020), we restrict the analysis in Table 6 to the subsample of nonstop flights.[35]

Although classical economic theory predicts that the extent of price discrimination should decrease with competition because incumbent firms find it more difficult to maintain markups over marginal cost as new competitors enter, the predicted effect in oligopolistic markets is ambiguous (Borenstein, 1985; Chandra and Lederman, 2018; Holmes, 1989; Stole, 2007). In column (1) of Table 6, the coefficient on $HolidayBook \times NCarriers$ is small and statistically insignificant, suggesting that the level of competition does not impact the magnitude of the holiday booking discount. However, $HolidayBook \times NCarriers$ is potentially endogenous. For example, there may be an unobserved factor that is correlated with both the number of carriers and the use of holiday discounts. If such an unobserved factor exists, then the bias that results from this factor may be attenuating the coefficient on $HolidayBook \times NCarriers$.

To correct for the potential endogeneity of $HolidayBook \times NCarriers$, we employ an instrumental variables (IV) strategy consistent with the one used in Chandra and Lederman (2018). This IV approach is based on a route-entry decision model that assumes that airlines choose which routes to enter, and in what order, based on their expected profitability. Following Chandra and Lederman (2018), we first estimate a logit regression to predict the

[34] Southwest is included in the count of nonstop carriers. The $NCarriers$ variable itself is not separately identified from the flight-route fixed effects.

[35] Results are qualitatively similar if connecting trips are included.

likelihood that each U.S. airline serves a given route on a particular day using the following variables: the population of the endpoint cities, the distance and distance squared of the route, the distance of the route from the airline's headquarters (i.e., the largest hub for legacy carriers), the airline's age, and an interaction between the distance of the route from the airline's headquarters and the airline's age. Coefficient estimates from this logit regression and additional details on the assumptions underlying this IV approach are provided in Appendix B.

After predicting each airline's likelihood of serving a given route on a given day, we use the predictions to calculate the predicted number of carriers on each route and day in our analysis sample. The predicted number of carriers are then used as an instrument for the actual number of carriers in a two-stage least squares (2SLS) regression. Table 7 summarizes the predicted number of carriers by the actual number of carriers. While we slightly overpredict the number of carriers on monopoly and duopoly routes and underpredict on routes with three or more carriers, the logit model produces reasonable overall predictions (the Pseudo-R^2 of our logit model is 0.30).[36]

[36]See Appendix Table B1 for coefficient estimates from this first-stage logit model.

Table 6: Holiday booking effects and market structure

Estimator	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
DaysToDeparture 1-2	0.893***	0.893***	0.893***	0.893***	0.893***	0.893***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
DaysToDeparture 3-6	0.614***	0.614***	0.614***	0.614***	0.615***	0.615***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
DaysToDeparture 7-13	0.319***	0.319***	0.319***	0.319***	0.319***	0.319***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
DaysToDeparture 14-20	0.104***	0.104***	0.104***	0.104***	0.104***	0.104***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
WeekendBook	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
HolidayBook	-0.019***	-0.021***	-0.019***	-0.021***	-0.022***	-0.022***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)	(0.003)
HolidayBook × NCarriers	-0.0004	-0.00002				
	(0.002)	(0.002)				
HolidayBook × NLegacy			-0.0005	-0.0004		
			(0.002)	(0.002)		
HolidayBook × NLCCs			-0.0002	0.0005		
			(0.002)	(0.002)		
HolidayBook × HHI					0.004	0.005
					(0.005)	(0.010)
Kleibergen-Paap rk LM statistic		20.542***		30.398***		44.384***
Kleibergen-Paap rk Wald F stat.		405.034***		67.325***		116.145***
R^2	0.439	0.439	0.439	0.439	0.439	0.439
Observations	15,106,864	15,106,827	15,106,864	15,106,827	15,096,815	15,088,229

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta}-1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Constant is included but not reported. Standard errors are clustered at the airport-pair level and provided in parentheses. First-stage estimates for columns (2), (4), and (6) are provided in Appendix Table B2. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: Predicted number of carriers by the actual number of carriers

	$\widehat{\text{NCarriers}}$			
NCarriers	Mean	Std. Dev.	Min	Max
0	0.033	0.057	0.000	0.497
1	1.069	0.334	0.466	2.575
2	2.155	0.411	1.015	3.841
3	2.949	0.493	1.201	4.073
4	3.877	0.233	2.497	4.832
5	4.699	0.513	3.118	5.530
6	5.729	0.453	3.516	6.122
7	6.097	0.027	6.046	6.134

Notes: Coefficient estimates from the logit model used to generate the predicted number of carriers are provided in Appendix Table B1.

Column (2) of Table 6 presents 2SLS estimates using the interaction between the predicted number of carriers and $HolidayBook$ ($HolidayBook \times \widehat{NCarriers}$) as an instrument for $HolidayBook \times NCarriers$ (first-stage results are provided in Appendix Table B2). The statistically significant coefficient on $HolidayBook \times \widehat{NCarriers}$ in column (1) of Appendix Table B2 and the statistically significant Kleibergen-Paap rk Wald F statistic in column (2) of Table 6 indicates that our instrument is both strong and relevant. After correcting for potential endogeneity, the coefficient on $HolidayBook \times NCarriers$ while decreasing in absolute value, remains statistically insignificant. Accordingly, the use of holiday discounts by U.S. airlines does not appear to vary with the level of route competition.

Brueckner et al. (2013) found that competition from legacy carriers has minimal impacts on fares while competition from LCCs leads to large fare reductions. As a robustness check, we split the $NCarriers$ variable into two separate variables that count the number of legacy carriers ($NLegacy$) and the number of LCCs ($NLCCs$) providing nonstop service. Column (3) of Table 6 presents ordinary least squares (OLS) results when the interactions between $HolidayBook$ and $NLegacy$ and $HolidayBook$ and $NLCCs$ are added to the specification while column (4) presents 2SLS results using the same IV strategy described in Appendix B.[37]

[37]The predicted number of legacy carriers and the predicted number of LCCs serving a given route on a

In both columns, the coefficients on $HolidayBook \times NLegacy$ and $HolidayBook \times NLCCs$ are statistically insignificant, indicating that average holiday purchase discounts do not vary with the number of legacy carriers or the number of LCCs providing nonstop service.

The market structure analysis in the first four columns of Table 6 relies on a count of competitors. As an additional robustness check, column (5) presents OLS results when the interaction between $HolidayBook$ and the Herfindahl-Hirschman Index of the route on the observed departure date (HHI) is added to the specification in column (2) of Table 2.[38] The coefficient on $HolidayBook \times HHI$ is also statistically insignificant, indicating that the level of competition does not affect the magnitude of the holiday purchase discount. However, similar to $NCarriers$, HHI is potentially endogenous.

To correct for the potential endogeneity of HHI, we follow the approach used by Evans et al. (1993), Whalen (2007), and Greenfield (2014) and instrument for HHI using its one-year lag.[39] Results from this 2SLS approach are provided in column (6) of Table 6. The coefficient on $HolidayBook \times HHI$ remains statistically insignificant, providing additional evidence that the level of competition does not affect the magnitude of the holiday purchase discount.

7 Conclusion

Sales during Thanksgiving, Christmas, and other holiday periods are common in a variety of retail markets. In this article, we examined whether holiday discounts also occur in the airline industry. In contrast to retail markets where purchased goods are immediately consumed (e.g., groceries), the purchase date typically differs from the consumption date in airline markets due to advance purchases. As a result, the holiday occurs prior to the actual date

given day are used as instruments for NLegacy and NLCCs, respectively.

[38] HHI is computed using daily capacity. Similar results are obtained if monthly enplaned passengers from the T-100 Domestic Segment database are used to construct HHI.

[39] Although unobserved demand and supply shocks may persist over time, these shocks are less likely to be correlated with previous year market structure than with current year market structure.

of travel in our setting.

We offer two potential explanations for why airlines may discount fares on federal holidays. Foremost, demand may be more elastic on holidays because business travelers are unlikely to purchase tickets when offices are closed. Second, holidays may coincide with lower than average airline demand because people who are already away from home (e.g., visiting family over Christmas) may not be ready to plan yet another vacation after having just incurred significant travel expenses. Both explanations imply that federal holidays provide airlines with an opportunity to practice third-degree price discrimination by offering discounts to passengers who purchase on these dates.

Exploiting a unique panel of almost 22 million fares collected over a seven-month period, we find that fares published on a federal holiday for flights in the sixty-day period following the holiday are 1.9% cheaper, supporting the conjecture that airlines price discriminate on federal holidays. Further decomposing our results, we find that the largest holiday discounts are offered for flights that are within one-week of departure and for flights booked during the Christmas (5.8%-5.9% cheaper) and New Year's (4.0%-4.7% cheaper) holidays.

For three reasons, we believe lower than average airline demand explains the majority of holiday purchase discounts observed in our sample. Foremost, the largest discounts occur on Christmas and New Year's when many consumers are away from home. Second, we find no statistically significant purchase discounts on holidays that do not coincide with large volumes of vacation travel (e.g., Columbus Day, Veteran's Day, Martin Luther King Jr. Day, and President's Day). Finally, we find that the holiday purchase discount does not differ across business and leisure routes, providing additional evidence that airlines discount fares on federal holidays due to lower than average airline demand as opposed to more elastic demand. Nevertheless, finding that the largest discounts are reserved for flights within one-week of departure (flights typically purchased by business travelers) suggests that more elastic demand may also contribute to the use of holiday discounts.

We also offer new evidence on the relationship between market structure and price discrimination. In oligopolistic markets, competition may either increase or decrease the extent of price discrimination when consumers differ both in their underlying willingness-to-pay and their degree of brand loyalty (as exists in the U.S. airline industry). We find that the level of route competition has no statistically measurable impact on the magnitude of the holiday purchase discount.

The analysis presented in this article offer some interesting avenues for further research. Future studies could extend the present analysis to other oligopolistic markets such as the cruise line, hotel, passenger railway, retail gasoline, and shipping markets. Although the analysis in this article focused on the U.S. airline industry, similar analyses could also be performed for the African, Asian, Australian, Canadian, European, and South American airline markets.

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Appendix A: List of markets included in our analysis

Table A1: List of directional airport-pairs included in our analysis

ABQ-LGA	DFW-LAS	JFK-MIA	MKE-SFO	RIC-LAX
ATL-BOS	DFW-LAX	JFK-PBI	MSP-LAS	SAN-OAK
ATL-FLL	DFW-LGA	JFK-SFO	MSP-MCO	SAN-SFO
ATL-LAS	DFW-MCO	LAS-LAX	MSP-PHX	SAN-SJC
ATL-LAX	DFW-ORD	LAX-ATL	MSP-RSW	SAN-SMF
ATL-LGA	DTW-FLL	LAX-BOS	OAK-BUR	SAT-BOS
ATL-MCO	DTW-LAS	LAX-DEN	OAK-LAS	SEA-LAS
BDL-PHX	DTW-MCO	LAX-DFW	OAK-LAX	SEA-LAX
BDL-SFO	DTW-RSW	LAX-EWR	OAK-SAN	SEA-PHX
BOS-ATL	EWR-FLL	LAX-JAX	OAK-SNA	SEA-SAN
BOS-DCA	EWR-IAH	LAX-JFK	ORD-BOS	SEA-SFO
BOS-FLL	EWR-LAX	LAX-LAS	ORD-DCA	SFO-BDL
BOS-LAX	EWR-MCO	LAX-MCO	ORD-DEN	SFO-BOS
BOS-MCO	EWR-MIA	LAX-OAK	ORD-DFW	SFO-EWR
BOS-MIA	EWR-ORD	LAX-ORD	ORD-FLL	SFO-JFK
BOS-ORD	EWR-PBI	LAX-SEA	ORD-LAS	SFO-LAS
BOS-RSW	EWR-RSW	LAX-SFO	ORD-LAX	SFO-LAX
BOS-SFO	EWR-SFO	LGA-ATL	ORD-LGA	SFO-ORD
BUR-OAK	FLL-EWR	LGA-FLL	ORD-MCO	SFO-SAN
BWI-FLL	FLL-JFK	LGA-MCO	ORD-MIA	SFO-SEA
BWI-LAS	FLL-LGA	LGA-MIA	ORD-PHX	SJC-SAN
BWI-MCO	HOU-DAL	LGA-ORD	ORD-SFO	SJC-SNA
CLT-LGA	IAH-EWR	MCO-EWR	PDX-FLL	SLC-MIA
CMH-SEA	IAH-LAS	MDW-DEN	PDX-LAS	SMF-BUR
DAL-HOU	JAX-LAX	MDW-FLL	PDX-LAX	SMF-SAN
DAL-LAS	JAX-PHX	MDW-LAS	PHL-FLL	SMF-SNA
DEN-LAS	JFK-FLL	MDW-LAX	PHL-MCO	SNA-MCO
DEN-LAX	JFK-LAS	MDW-MCO	PHL-SNA	SNA-SJC
DEN-MCO	JFK-LAX	MDW-PHX	PHX-DEN	
DEN-PHX	JFK-MCO	MIA-LGA	RIC-LAS	

Appendix B: Instrumental variables strategy and first-stage estimates

As outlined in Section 6.4, we employ an instrumental variables (IV) strategy to correct for the potential endogeneity of $HolidayBook \times NCarriers$ (in addition to $HolidayBook \times NLegacy$ and $HolidayBook \times NLCC$). This IV strategy hinges on a route-entry decision model that assumes that airlines choose which routes to enter, and in what order, based on their expected profitability. Following Chandra and Lederman (2018), two types of instruments are used: variables that impact the expected cost to a particular airline of entering a given route and variables that impact the suitability of a given route for a particular airline's fleet. The variables we use are the population of the endpoint cities of the route, the distance and distance squared of the route, the distance of the route from the airline's headquarters (i.e., the largest airline hub for legacy carriers), the airline's age, and the interaction between the distance of the route from the airline's headquarters and the airline's age.

The rationale for including these variables is straightforward. The population and distance variables help capture the suitability of a route to a given airline's fleet type, size, and range. The distance of the route from the airline's headquarters reflects that the cost of entry likely increases the further the airline is from its headquarters. The age variable reflects that airlines may enter less profitable routes over time.

As discussed in Chandra and Lederman (2018), this IV strategy requires two key assumptions. First, the airlines' business models (e.g., decision of which aircraft types to operate) are exogenous. Second, an airline's decision of where to locate their headquarters must not be driven by time-varying unobservable characteristics of the routes close to their headquarters. This assumption ensures that the distance from an airline's headquarters meets the exclusion restriction for use as a valid instrument. This assumption seems reasonable given the geographic distribution of U.S. airline headquarters. For example, Alaska (Seattle), Allegiant (Las Vegas), American (Fort Worth), Delta (Atlanta), Frontier (Denver), JetBlue (New

York City), Southwest (Dallas), Spirit (Fort Lauderdale), Sun Country (Minneapolis), and United (Chicago) have all chosen different cities for the location of their headquarters (with the exception that the American and Southwest headquarters are nearby).

To implement our IV strategy, we proceeded with the following steps.

1. We constructed a daily airline-route dataset from January 1st, 2018 to February 29th, 2020 that captures all nonstop routes in the continental U.S. market.[40]

2. Then, we estimated the probability that each U.S. airline serves a given route on a particular day using a logit model where the dependent variable is an indicator equal to one if the airline serves the route on the observed day and zero otherwise. The explanatory variables are: the population of the endpoint cities of the route, the distance and distance squared of the route, the distance of the route from the airline's headquarters, the airline's age, and an interaction between the distance of the route from the airline's headquarters and the airline's age. To capture differences in business models (and to be consistent with the Chandra and Lederman (2018) approach), we allowed each of these variables to have a different effect for each airline by interacting these variables with a dummy for each airline. Day-of-week, month-of-year, and route fixed effects were also included to improve predictive power.[41] Coefficient estimates from this logit regression are provided in Table B1.

3. Using the coefficient estimates from this logit regression, we predicted each airline's likelihood of serving each route on each day during our sample period. For each route-day pair, the predictions across all carriers were summed to calculate the predicted number of carriers serving the route ($\widehat{NCarriers}$) in addition to the predicted number of legacy carriers ($\widehat{NLegacy}$) and the predicted number of low-cost carriers ($\widehat{NLCCs}$).

[40]This dataset is constructed using information from the "Marketing Carrier On-Time Performance" data provided by the Bureau of Transportation Statistics.

[41]We are able to include route fixed effects because our explanatory variables vary at the airline-route or airline-route-day level.

4. Finally, we interacted $HolidayBook$ with $N\widehat{Carriers}$ to generate $HolidayBook \times N\widehat{Carriers}$. $HolidayBook \times N\widehat{Carriers}$ is then used as an instrument for $HolidayBook \times NCarriers$ in a two-stage least squares regression. Similarly, $HolidayBook \times N\widehat{Legacy}$ and $HolidayBook \times \widehat{NLCC}s$ were also used as instruments for $HolidayBook \times NLegacy$ and $HolidayBook \times NLCCs$ in a separate two-stage least squares regression.

Table B1: Logit regression estimates for predicted service by carrier

	Alaska	Allegiant	American	Delta	Frontier	JetBlue	Southwest	Spirit	United
Origin population (100,000s)	0.007	-0.046***	0.009	0.004	-0.011	0.010	0.001	0.004	0.008
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Destination population (100,000s)	0.007	-0.045***	0.009	0.004	-0.011	0.010	0.001	0.004	0.009
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Route distance (100s of miles)	-0.299	0.852	-0.377	-0.234	0.501	-0.042	0.046	0.197	-0.211
	(1.807)	(1.808)	(1.805)	(1.806)	(1.806)	(1.807)	(1.806)	(1.806)	(1.807)
Route distance^2 (100s of miles)	-0.047	-0.099	-0.048	-0.053	-0.078	-0.056	-0.062	-0.067	-0.053
	(0.135)	(0.135)	(0.134)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)
Min. distance to HQ (100s of miles)	3.244***	-0.142***	1.075***	0.070	-0.706***	-0.221***	0.557***	0.220**	-0.577***
	(1.104)	(0.039)	(0.234)	(0.114)	(0.155)	(0.065)	(0.118)	(0.098)	(0.215)
Age (100s of days)	0.070***	-0.011**	0.045***	0.008***	-0.011	-0.015**	0.020***	0.064***	0.001
	(0.018)	(0.005)	(0.006)	(0.003)	(0.012)	(0.006)	(0.005)	(0.009)	(0.004)
Age × min. distance to HQ	-0.012***	0.002***	-0.004***	-0.000	0.007***	0.001	-0.004***	-0.003***	0.002**
	(0.003)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Carrier intercepts	-6.415	9.952***	-11.159	11.473***	10.466***	11.621***	9.448***	4.386*	13.020***
	(6.150)	(2.106)	(8.059)	(2.179)	(2.325)	(2.140)	(2.145)	(2.246)	(2.471)

Notes: Coefficients are from a single logit regression where the identity of each airline is interacted with the corresponding variable in the first column. The dependent variable is an indicator equal to one if the airline serves the route on the given day and zero otherwise. The regression includes day-of-week, month-of-year, and route fixed effects. Standard errors are provided in parentheses and clustered at the route level. The sample period is January 1st, 2018 to February 29th, 2020. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Observations = 45,546,660; Pseudo-R^2 = 0.297.

Table B2: First-stage estimates for Table 6

	(1)	(2)	(3)	(4)
Dependent variable	HolidayBook×NCarriers	HolidayBook×NLegacy	HolidayBook×NLCCs	HolidayBook×HHI
DaysToDeparture 1-2	-0.0003	0.0005	-0.0008	0.0007**
	(0.0005)	(0.0003)	(0.0005)	(0.0003)
DaysToDeparture 3-6	-0.0003	-0.0001	-0.0002	0.0004*
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
DaysToDeparture 7-13	0.00002	0.00005	-0.00006	0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
DaysToDeparture 14-20	-0.0003*	-0.0002	-0.0002	0.0002
	(0.0002)	(0.0001)	(0.0001)	(0.0002)
WeekendBook	-0.0001***	-0.00006**	-0.00005	0.00003***
	(0.00004)	(0.00003)	(0.00004)	(0.00001)
HolidayBook	0.118	0.476***	-0.347*	0.126***
	(0.166)	(0.163)	(0.191)	(0.0128)
HolidayBook × $\widehat{\text{NCarriers}}$	0.999***			
	(0.050)			
HolidayBook × $\widehat{\text{NLegacy}}$		1.285***	-0.254***	
		(0.064)	(0.066)	
HolidayBook × $\widehat{\text{NLCCs}}$		-0.734***	1.675***	
		(0.122)	(0.144)	
HolidayBook × HHI_{t-1}				0.441***
				(0.041)
R^2	0.987	0.944	0.863	0.611
Observations	15,106,864	15,106,864	15,106,864	15,106,864

Notes: All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. The regression constant is included but not reported. Standard errors are clustered at the airport-pair level and provided in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix C: Holiday booking effects on state holidays

Table C1 presents results from a difference-in-differences analysis to determine if holiday purchase discounts also occur on state holidays. There are nine relevant state holidays that occur during our sample period: Rosa Parks Day (observed in Ohio on December 1, 2019 and in California on February 4, 2020), Confederate Heroes Day (observed in Texas on January 19, 2020), Lincoln's Birthday (observed in Connecticut, Illinois, and New York on February 12, 2020), Georgia State Holiday (observed in Georgia on November 29, 2019), Lee-Jackson Day (observed in Virginia on January 17, 2020), and Nevada Day (observed in Nevada on October 20, 2019).

The difference-in-differences specification is an augmented version of equation (1) and is described by equation (2) below:

$$ln(fare)_{fjt} = \alpha + \sum_{i=1}^{4} \delta_i \cdot DaysToDeparture_{ft} + \gamma \cdot WeekendBook_{ft} + \beta \cdot HolidayBook_{ft} + \sum_{i=1}^{7} \sigma_i \cdot BookOnStateHoliday_t + \sum_{i=1}^{9} \mu_i \cdot StateDeparture_f \times BookOnStateHoliday_t + \rho_{fj} + \varepsilon_{fjt} \quad (2)$$

where $BookOnStateHoliday$ is a series of indicators that equal one if the fare is published on the state holiday (one indicator for each of the seven different state holiday dates mentioned above) and $StateDeparture$ is a series of indicators that equal one if the departure airport for flight f on directional airport-pair j is in the state observing the holiday (one indicator for each of the nine states mentioned above). In this specification, flights from states not observing the state holiday serve as the control group, so that the nine estimated μ's are the difference-in-differences estimates of the state holiday booking effects.[42]

Eight of the nine difference-in-differences coefficients are either positive or statistically

[42]The $StateDeparture$ variables are not separately identified from the flight-route fixed effects (i.e., ρ_{fj}).

insignificant in Table C1, indicating that holiday purchase discounts generally do not extend to state holidays. This finding is sensible considering that most federal government and private sector employees do not receive state holidays off from work. This finding is also consistent with the lack of holiday purchase discounts estimated for Martin Luther King Day, President's Day, and Veteran's Day in Table 2, federal holidays that the majority of private sector employees also do not receive off from work (e.g., see Table 1).

The only difference-in-differences estimate that is negative and statistically significant is the estimate for Lincoln's Birthday in New York ($NY\,Departure \times Book\ on\ Lincoln's\ Birthday$). This difference-in-differences estimate indicates that published fares for flights that originate at New York airports are 7.5% cheaper on Lincoln's Birthday (February 12^{th}) relative to other non-holiday dates.

Table C1: Holiday booking effects on state holidays

	(1)
DaysToDeparture 1-2	0.825***
	(0.022)
DaysToDeparture 3-6	0.570***
	(0.026)
DaysToDeparture 7-13	0.304***
	(0.019)
DaysToDeparture 14-20	0.102***
	(0.007)
WeekendBook	0.001
	(0.000)
HolidayBook	-0.018***
	(0.001)
Book on Rosa Parks Day (Feb. 4^{th})	0.028***
	(0.007)
Book on Confederate Heroes Day	0.055***
	(0.004)
Book on Lincoln's Birthday	-0.031***
	(0.009)
Book on Rosa Parks Day (Dec. 1^{st})	-0.002
	(0.003)
Book on Georgia State Holiday	-0.005
	(0.003)
Book on Lee-Jackson Day	0.052***
	(0.003)
Book on Nevada Day	0.024***
	(0.003)
CADeparture × Book on Rosa Parks Day (Feb. 4^{th})	0.038**
	(0.019)
TXDeparture × Book on Confederate Heroes Day	-0.016
	(0.018)
NYDeparture × Book on Lincoln's Birthday	-0.078**
	(0.033)
ILDeparture × Book on Lincoln's Birthday	-0.016
	(0.046)
OHDeparture × Book on Rosa Parks Day (Dec. 1^{st})	-0.001
	(0.002)
GADeparture × Book on Georgia State Holiday	0.004
	(0.007)
VADeparture × Book on Lee-Jackson Day	-0.009
	(0.006)
CTDeparture × Book on Lincoln's Birthday	-0.025
	(0.025)
NVDeparture × Book on Nevada Day	0.005**
	(0.003)
R^2	0.421
Observations	21,829,963

Notes: The dependent variable is the natural logarithm of fare. Marginal effects are interpreted as the $100(\exp^{\beta} - 1)\%$ change in fare. All specifications include flight-route fixed effects that control for time-invariant flight, carrier, and airport-pair-specific characteristics that affect fares. Constant is included but not reported. Standard errors are clustered at the airport-pair level and provided in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix D: Standard errors for coefficient estimates in Tables 2 and 4

Table D1: Standard errors for coefficient estimates in Table 2

	(1)	(2)	(3)	(4)	(5)
DaysToDeparture 1-2	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
DaysToDeparture 3-6	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
DaysToDeparture 7-13	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DaysToDeparture 14-20	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
WeekendBook		(0.000)	(0.000)	(0.000)	(0.000)
HolidayBook		(0.001)	(0.001)		
HolidayBook × DaysToDeparture 1-2			(0.007)		
HolidayBook × DaysToDeparture 3-6			(0.007)		
HolidayBook × DaysToDeparture 7-13			(0.004)		
HolidayBook × DaysToDeparture 14-20			(0.003)		
Book on Labor Day				(0.004)	(0.004)
Book on Columbus Day				(0.003)	(0.003)
Book on Veteran's Day				(0.003)	(0.003)
Book on Thanksgiving				(0.003)	(0.003)
Book on Black Friday				(0.003)	(0.003)
Book on Christmas Eve				(0.004)	(0.004)
Book on Christmas Day				(0.004)	(0.004)
Book on New Year's Eve				(0.003)	(0.003)
Book on New Year's Day				(0.003)	(0.003)
Book on M.L. King Day				(0.004)	(0.004)
Book on President's Day				(0.007)	(0.008)
LCC × Book on Labor Day					(0.009)
LCC × Book on Columbus Day					(0.005)
LCC × Book on Veteran's Day					(0.004)
LCC × Book on Thanksgiving					(0.005)
LCC × Book on Black Friday					(0.006)
LCC × Book on Christmas Eve					(0.007)
LCC × Book on Christmas Day					(0.007)
LCC × Book on New Year's Eve					(0.005)
LCC × Book on New Year's Day					(0.005)
LCC × Book on M.L. King Day					(0.006)
LCC × Book on President's Day					(0.021)

Table D2: Standard errors for coefficient estimates in Table 4

	(1)	(2)	(3)
DaysToDeparture 1-2	(0.031)	(0.031)	(0.031)
DaysToDeparture 3-6	(0.042)	(0.042)	(0.043)
DaysToDeparture 7-13	(0.025)	(0.025)	(0.025)
DaysToDeparture 14-20	(0.009)	(0.009)	(0.009)
SW Nonstop × DaysToDeparture 1-2	(0.048)	(0.048)	(0.048)
SW Nonstop × DaysToDeparture 3-6	(0.056)	(0.056)	(0.057)
SW Nonstop × DaysToDeparture 7-13	(0.039)	(0.039)	(0.039)
SW Nonstop × DaysToDeparture 14-20	(0.016)	(0.016)	(0.016)
SW Potential × DaysToDeparture 1-2	(0.057)	(0.057)	(0.057)
SW Potential × DaysToDeparture 3-6	(0.066)	(0.066)	(0.066)
SW Potential × DaysToDeparture 7-13	(0.045)	(0.045)	(0.045)
SW Potential × DaysToDeparture 14-20	(0.014)	(0.014)	(0.014)
WeekendBook		(0.000)	(0.000)
HolidayBook		(0.002)	(0.002)
HolidayBook × SW Nonstop		(0.003)	(0.003)
HolidayBook × SW Potential		(0.003)	(0.003)
HolidayBook × DaysToDeparture 1-2			(0.012)
HolidayBook × DaysToDeparture 3-6			(0.012)
HolidayBook × DaysToDeparture 7-13			(0.006)
HolidayBook × DaysToDeparture 14-20			(0.004)
HolidayBook × SW Nonstop × DaysToDep. 1-2			(0.019)
HolidayBook × SW Nonstop × DaysToDep. 3-6			(0.016)
HolidayBook × SW Nonstop × DaysToDep. 7-13			(0.009)
HolidayBook × SW Nonstop × DaysToDep. 14-20			(0.005)
HolidayBook × SW Potential × DaysToDep. 1-2			(0.018)
HolidayBook × SW Potential × DaysToDep. 3-6			(0.016)
HolidayBook × SW Potential × DaysToDep. 7-13			(0.008)
HolidayBook × SW Potential × DaysToDep. 14-20			(0.007)