Purchase discounts on federal 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. 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 1.8% 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. 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, Thanks-

[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.

[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 "shopping holidays" such as Black Friday, Christmas Eve, and New Year's Eve because many public and private sector employees request these days off from work.

giving 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 collusive 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 1.8% cheaper on average. Allowing for heterogeneity in discounts across holidays, we find that the holiday booking discount ranges from 0.9% on Cyber Monday to 5.9% on Christmas Eve and 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), supporting the conjecture that airlines discount fares on federal holidays because price inelastic business travelers are unlikely to purchase on these dates. However, 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 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 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]

[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.

[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.

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.

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

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

[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.

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.

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 route, fares 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

[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 (2021), among others.

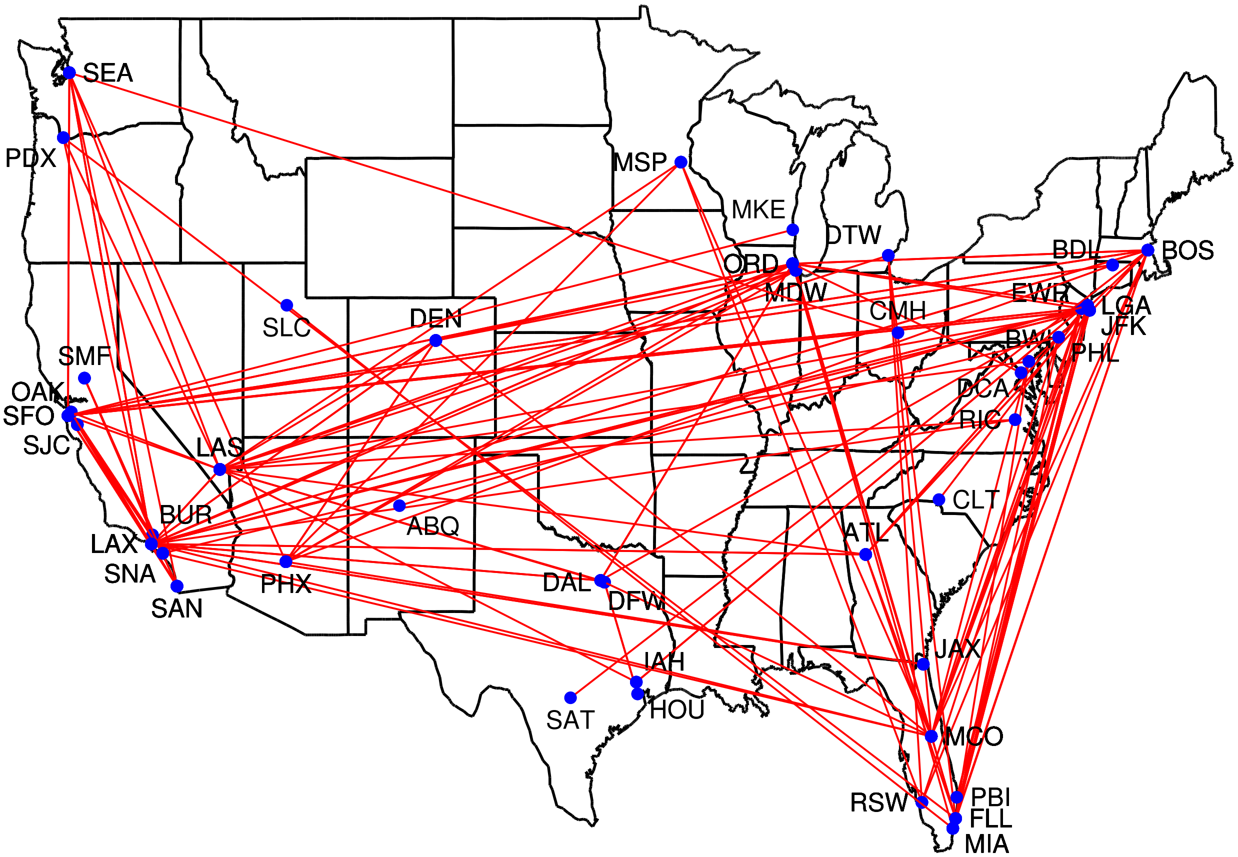
[11]A market in our analysis is defined as a directional pair of origin and destination airports. Therefore, Los Angeles (LAX)-New York (JFK) and New York (JFK)-Los Angeles (LAX) are treated as separate markets.

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

[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).

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



period prior to departure.[15] We 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 largest full-service 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 full-service carriers (FSCs) 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 FSCs, 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 other words, FSCs 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

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

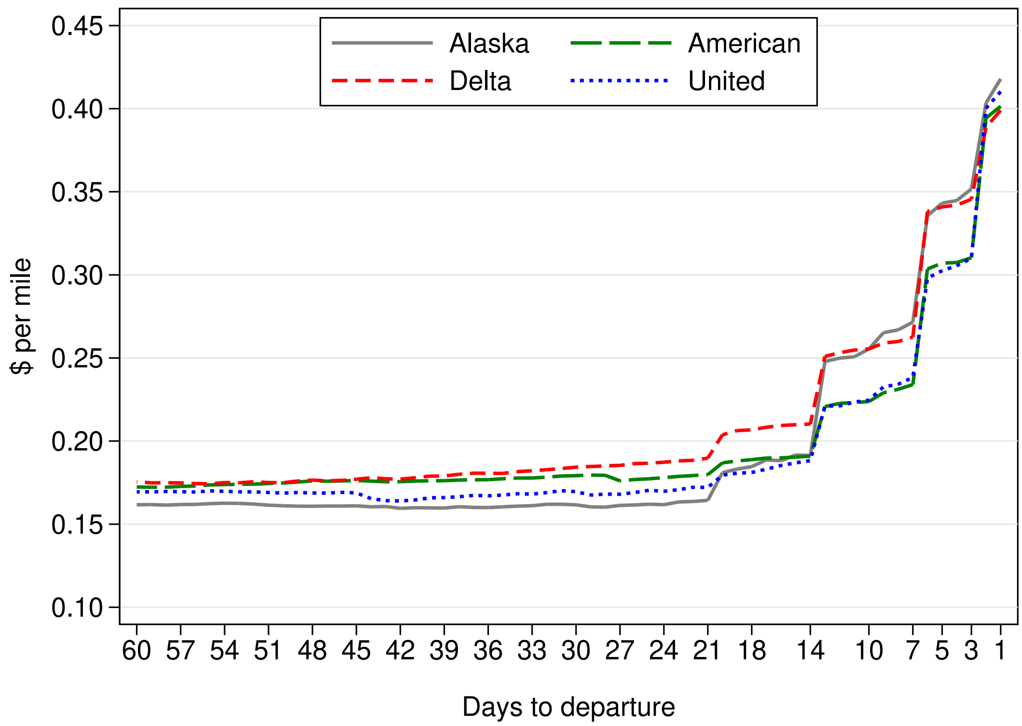
[16]In his analysis of intertemporal price discrimination in monopoly airline markets, Lazarev (2013) employs a six-week data collection window.

[17]Fare quotes for Southwest Airlines are not available on travel aggregator websites such as Expedia, Google Flights, and Kayak.

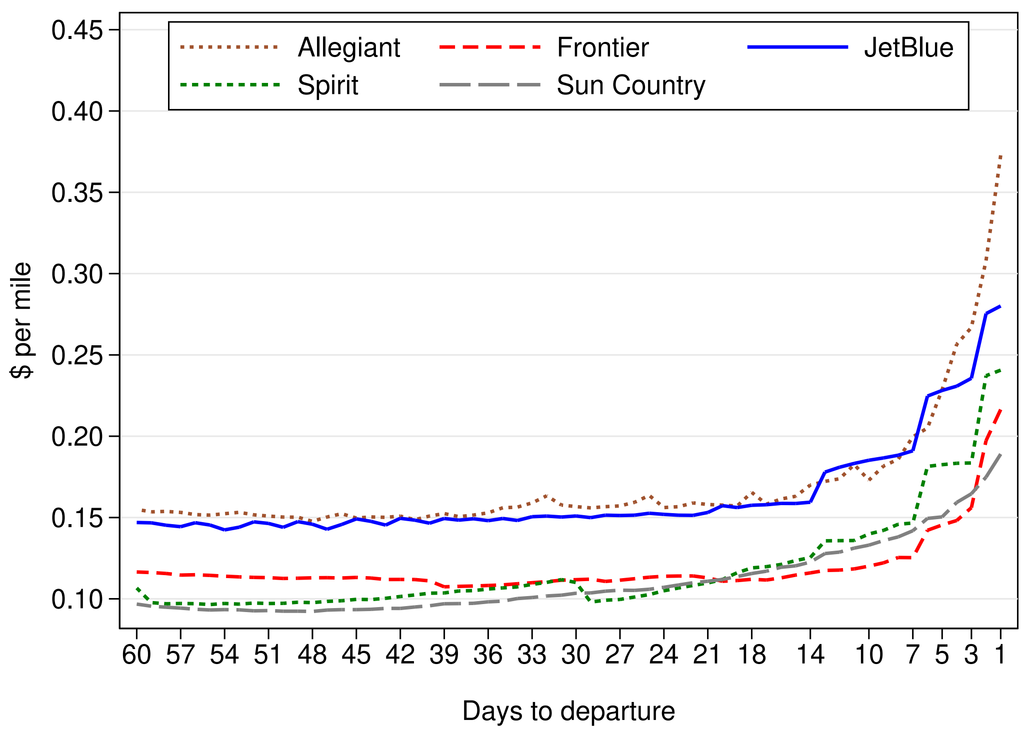
[18]Only nonstop flights were used to generate Figure 2. Of the 21,829,963 observations in our sample, 69.2% (15,106,864) are for nonstop travel.

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

(a) Full-service carriers



(b) Low-cost carriers



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.

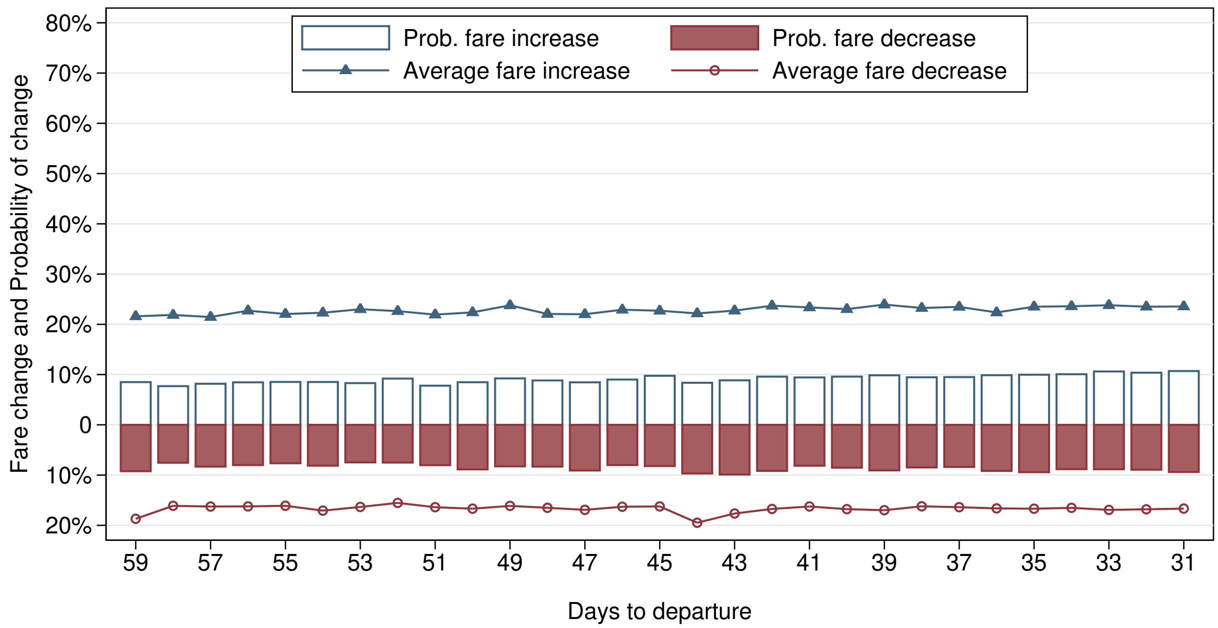
Consistent with their status as a LCC, Allegiant, Frontier, JetBlue, Spirit, and Sun Country all have a lower average fare per mile than the four FSCs (see bottom panel of Figure 2). Allegiant and JetBlue fares are also consistently higher than Frontier, Spirit, and Sun Country fares across the entire sixty-day booking period. Nevertheless, both FSCs 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%.

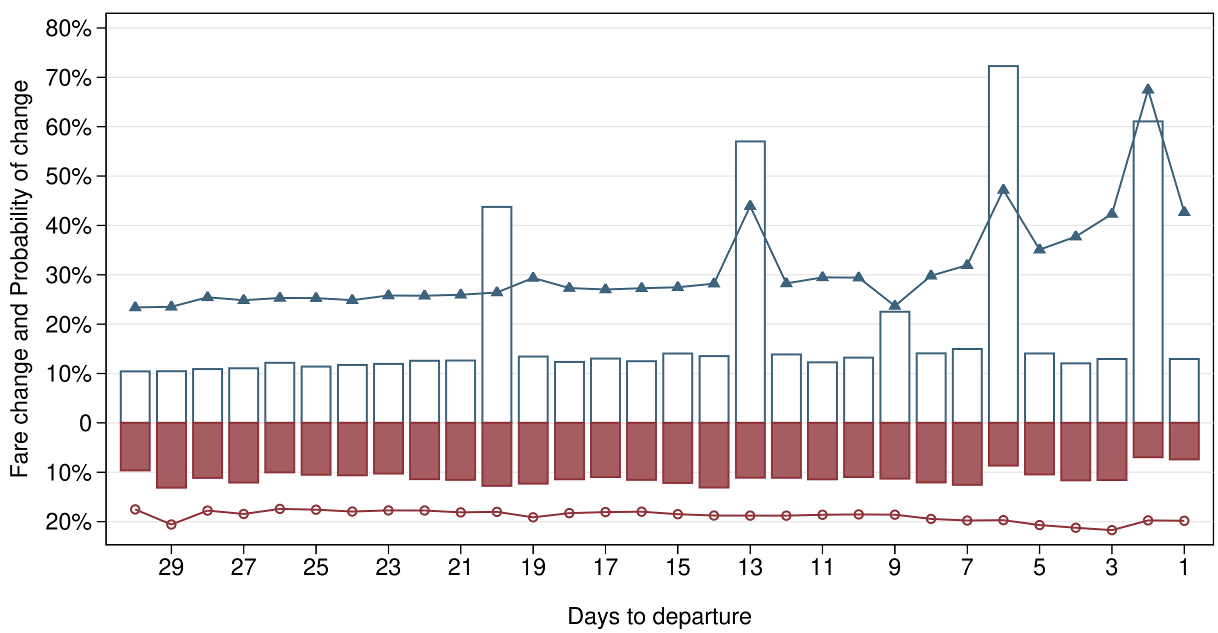
As depicted in the top panel of Figure 3, fares are relatively stable during the early booking period, with the probability of a fare increase hovering around 10% and the probability of a fare decrease at 8% on average. The magnitude of fare increases and decreases are also stable

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



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 twelve 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 fare effects attributable to the airline's frequent flyer program, cost structure, and average

[19]These five days to departure categories correspond to the fare increases observed in Figures 2 and 3. Results are qualitatively similar if we replace the $DaysToDeparture$ dummies with a single variable that indicates the number of days to departure.

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	Holiday Type	Date	Day of Week
Labor Day	National	September 2, 2019	Monday
Columbus Day	Federal/State	October 14, 2019	Monday
Veteran's Day	Federal/State	November 11, 2019	Monday
Thanksgiving Day	National	November 28, 2019	Thursday
Black Friday	Shopping	November 29, 2019	Friday
Cyber Monday	Shopping	December 2, 2019	Monday
Christmas Eve	Shopping	December 24, 2019	Tuesday
Christmas Day	National	December 25, 2019	Wednesday
New Year's Eve	Shopping	December 31, 2019	Tuesday
New Year's Day	National	January 1, 2020	Wednesday
Martin Luther King Day	Federal/State	January 20, 2020	Monday
President's Day	Federal/State	February 17, 2020	Monday

Notes: National holidays are days most government and private sector employees receive off from work. Federal/State 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 decide to take off (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 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 twelve federal or shopping holidays that occur during our sample period. To further explore heterogeneity in holiday booking discounts, additional specifications examine how these discounts are affected by market structure, itinerary type (e.g., nonstop vs. connecting flights), the number of days to departure,

[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.

and carrier type.

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, the presence of 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 Tables 3-5 that follow) are provided in Appendix C. 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 128.2%, 76.8%, 35.5%, and 10.7% more expensive, respectively.[21]

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),

[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.

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 or shopping holiday are 1.8% 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 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 12.9% 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 6.0%, 1.0%, and 1.3% cheaper, respectively.

It is not surprising to find that the holiday booking discount is largest for flights booked 1-2 or 3-6 days prior to departure. Because passengers shopping on a holiday are more likely to be price elastic, high fares typically reserved for late arriving business travelers must be heavily discounted to stimulate purchases from these price elastic customers.

Table 2: Baseline holiday booking effects

	(1)	(2)	(3)	(4)	(5)
DaysToDeparture 1-2	0.825***	0.825***	0.834***	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		-0.018***	-0.013***		
HolidayBook × DaysToDeparture 1-2			-0.125***		
HolidayBook × DaysToDeparture 3-6			-0.049***		
HolidayBook × DaysToDeparture 7-13			0.020***		
HolidayBook × DaysToDeparture 14-20			0.003		
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				-0.016***	-0.016***
Book on Black Friday				-0.023***	-0.025***
Book on Cyber Monday				-0.009***	-0.007***
Book on Christmas Eve				-0.061***	-0.058***
Book on Christmas Day				-0.061***	-0.059***
Book on New Year's Eve				-0.048***	-0.043***
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 Cyber Monday					-0.008
LCC × Book on Christmas Eve					-0.016**
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 C1. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

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 twelve federal and shopping holidays that occur during our sample period. We find substantial heterogeneity in holiday discounts ranging from 0.9% for fares booked on Cyber Monday to 5.9% for fares booked on Christmas Eve or Christmas Day. Although we estimate fare premiums ranging from 0.9% to 5.0% for flights booked on Martin Luther King Day, President's Day, Columbus Day, and Veteran's Day, not all private sector or state government employers observe these federal holidays.[22] Therefore, it is not surprising to find that holiday booking discounts do not extend to these four holidays.

The last column of Table 2 presents results when the holiday booking effects are allowed to vary between FSCs (Alaska, American, Delta, and United) and LCCs (Allegiant, Frontier, JetBlue, Spirit, and Sun Country). Consistent with column (4), the positive 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, Cyber Monday, and Christmas Day interaction terms suggests that FSCs 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%, 0.7% and 5.7% cheaper on Labor Day, Thanksgiving Day, Black Friday, Cyber Monday, 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 FSCs on these three holidays. On Christmas Eve, fares for LCCs are 7.1% cheaper compared to 5.6% cheaper for FSCs. On New Year's Eve and New Year's day, LCC fares are 6.7% and 5.8% cheaper compared to 4.2% and 3.5% cheaper for FSCs.

[22]For example, employees of The MITRE Corporation (the current employer for one of the author's of this study) currently do not receive 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`).

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 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.

Although both explanations likely contribute to holiday discounts, our second explanation may explain the majority of the observed effects in Table 2. Foremost, we find that the largest discounts are offered on Christmas and New Year's, holidays where many consumers are away on vacation visiting family or celebrating the new year. Second, other 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) show no statistically significant holiday discounts. Finally, because weekends are another period when the mix of purchasing passengers is expected to make demand more elastic (since business travelers are less likely to purchase from home) the lack of a statistically significant weekend purchase discount suggests that lower than average airline demand can most likely explain the majority of our observed holiday purchase discounts.

6.2 Holiday Booking Discounts and Southwest Presence

There may be a concern that the results in Table 2 are biased due to our lack of available fare data from Southwest.[23] To examine this possibility, Table 3 presents results when the

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

advance-purchase and holiday booking effects are allowed to vary across two types of markets: markets where Southwest is present (i.e., airport-pairs where Southwest provides nonstop service) and markets where Southwest is not present (i.e., airport-pairs that Southwest does not serve nonstop).

Column (1) of Table 3 presents results when the specification in column (1) of Table 2 is augmented to include interactions between the $DaysToDeparture$ dummies and the Southwest presence indicator.[24] The statistically insignificant coefficients on the 7-13 and 14-20 interactions indicates that the presence of Southwest does not affect average fare hikes for flights purchased 7-20 days before departure. However, the negative and statistically significant coefficients on the 1-2 and 3-6 interaction terms indicates that the presence of Southwest dampens average fare premiums for flights within one-week of departure. Compared to flights purchased 21-60 days before departure, flights purchased 1-2 days before departure are 137.0% more expensive in markets without Southwest compared to 116.4% more expensive in markets where Southwest is present. Similarly, flights purchased 3-6 days before departure are 83.7% more expensive in markets without Southwest compared to 67.2% more expensive in markets where Southwest is present.

Column (2) of Table 3 presents results when $WeekendBook$, $HolidayBook$, and the interaction between $HolidayBook$ and $Southwest$ are added to the specification in column (1). The small and statistically insignificant coefficient on $HolidayBook \times Southwest$ indicates that average holiday booking discounts do not differ across markets where Southwest is present and markets where Southwest is not present. Similar to the results in column (2) of Table 2, fares published on a federal or shopping holiday are 1.8% cheaper in both types of markets.

In Table 2, holiday booking discounts were found to differ with how far in advance airfare is purchased, with the largest discounts reserved for flights within one-week of departure. To determine if the presence of Southwest affects these holiday booking discounts,

[24]The Southwest presence indicator itself is not separately identified from the flight-route fixed effects.

Table 3: Holiday booking effects and the presence of Southwest

	(1)	(2)	(3)
DaysToDeparture 1-2	0.863***	0.863***	0.871***
DaysToDeparture 3-6	0.608***	0.608***	0.612***
DaysToDeparture 7-13	0.314***	0.314***	0.312***
DaysToDeparture 14-20	0.101***	0.101***	0.101***
DaysToDeparture 1-2 × Southwest	-0.091**	-0.091**	-0.090**
DaysToDeparture 3-6 × Southwest	-0.094*	-0.094*	-0.095*
DaysToDeparture 7-13 × Southwest	-0.024	-0.024	-0.024
DaysToDeparture 14-20 × Southwest	0.004	0.004	0.004
WeekendBook		0.001	0.001
HolidayBook		-0.018***	-0.013***
HolidayBook × Southwest		0.0003	0.001
HolidayBook × DaysToDeparture 1-2			-0.122***
HolidayBook × DaysToDeparture 3-6			-0.051***
HolidayBook × DaysToDeparture 7-13			0.023***
HolidayBook × DaysToDeparture 14-20			0.001
HolidayBook × DaysToDeparture 1-2 × Southwest			-0.008
HolidayBook × DaysToDeparture 3-6 × Southwest			0.007
HolidayBook × DaysToDeparture 7-13 × Southwest			-0.007
HolidayBook × DaysToDeparture 14-20 × Southwest			0.003
R^2	0.422	0.422	0.422
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 C2. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

column (3) of Table 3 presents results when the $HolidayBook \times DaysToDeparture$ interaction terms are interacted with the Southwest presence indicator. In this specification, the $HolidayBook \times Southwest$ and $HolidayBook \times DaysToDeparture \times Southwest$ interactions are all statistically insignificant, providing further evidence that the presence of Southwest does not affect average holiday booking discounts.

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 4 presents results when the advance-purchase and holiday booking effects are allowed to vary across nonstop and connecting trips.

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 connecting trip indicator.[25] 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 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 4 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 or shopping holiday are 2.0% cheaper for nonstop trips and 1.6% cheaper for connecting trips.

In Table 2, holiday booking discounts differed with how far in advance airfare is pur-

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

Table 4: Holiday booking effects and connecting flights

	(1)	(2)	(3)
DaysToDeparture 1-2	0.893***	0.893***	0.902***
DaysToDeparture 3-6	0.614***	0.614***	0.619***
DaysToDeparture 7-13	0.319***	0.319***	0.317***
DaysToDeparture 14-20	0.104***	0.104***	0.104***
DaysToDeparture 1-2 × Connect	-0.264***	-0.264***	-0.265***
DaysToDeparture 3-6 × Connect	-0.184***	-0.184***	-0.187***
DaysToDeparture 7-13 × Connect	-0.072***	-0.072***	-0.072***
DaysToDeparture 14-20 × Connect	-0.015	-0.015	-0.015
WeekendBook		0.001	0.001
HolidayBook		-0.020***	-0.013***
HolidayBook × Connect		0.004**	0.001
HolidayBook × DaysToDeparture 1-2			-0.130***
HolidayBook × DaysToDeparture 3-6			-0.061***
HolidayBook × DaysToDeparture 7-13			0.020***
HolidayBook × DaysToDeparture 14-20			0.002
HolidayBook × DaysToDeparture 1-2 × Connect			0.015
HolidayBook × DaysToDeparture 3-6 × Connect			0.034***
HolidayBook × DaysToDeparture 7-13 × Connect			0.002
HolidayBook × DaysToDeparture 14-20 × Connect			0.003
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. 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 C3. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

chased, 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 4 presents results when the $HolidayBook \times DaysToDeparture$ interaction terms are interacted with the connecting trip indicator. In this specification, the $HolidayBook \times Connect$ and $HolidayBook \times DaysToDeparture \times Connect$ 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

$HolidayBook \times DaysToDeparture$ 3-6$\times Connect$ 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 are 7.4% cheaper for nonstop trips and 3.9% cheaper for connecting trips.

6.4 Holiday Booking Discounts and Market Structure

The results in Tables 2, 3, and 4 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 5 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 ($NCarriers$).[26]

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 5, the coefficient on $NCarriers \times HolidayBook$ is small and statistically insignificant, suggesting that the level of competition does not impact the magnitude of the holiday booking discount. However, $NCarriers \times HolidayBook$ 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 $NCarriers \times HolidayBook$.

To correct for the potential endogeneity of $NCarriers \times HolidayBook$, we employ an instrumental variables (IV) strategy consistent with the one used in Chandra and Lederman (2018).[27] This IV approach is based on a route-entry decision model that assumes that air-

[26]The $NCarriers$ variable itself is not separately identified from the flight-route fixed effects.

[27]We thank an anonymous referee for suggesting this IV strategy.

lines 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 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.

Table 5: Holiday booking effects and market structure

	(1)	(2)	(3)
Dependent variable:	$ln(fare)$	NCarriers × HolidayBook	$ln(fare)$
Estimator:	OLS	OLS (First-Stage)	2SLS
DaysToDeparture 1-2	0.825***	-0.0002	0.825***
DaysToDeparture 3-6	0.570***	-0.0004	0.570***
DaysToDeparture 7-13	0.304***	-0.0002	0.304***
DaysToDeparture 14-20	0.102***	-0.001***	0.102***
WeekendBook	0.001	-0.00004	0.001
HolidayBook	-0.017***	0.008	-0.018***
NCarriers × HolidayBook	-0.0003		-0.0001
$\widehat{\text{NCarriers}}$ × HolidayBook		1.023***	
Kleibergen-Paap rk LM statistic			40.58***
Kleibergen-Paap rk Wald F statistic			2694***
R^2	0.420	0.985	0.420
Observations	21,829,963	21,704,815	21,704,815

Notes: The dependent variable in columns (1) and (3) is the natural logarithm of fare while the interaction between $NCarriers$ (potential endogenous variable) and $HolidayBook$ is the dependent variable in column (2). Column (3) presents two-stage least squares (2SLS) estimates of column (1) using $\widehat{NCarriers} \times HolidayBook$ as an instrument for $NCarriers \times HolidayBook$. Column (2) presents first-stage estimates for the 2SLS estimates in column (3). In columns (1) and (3), 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 C4. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

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 6 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).[28]

Column (3) of Table 5 presents 2SLS estimates using the interaction between the predicted number of carriers and $HolidayBook$ ($\widehat{NCarriers} \times HolidayBook$) as an instrument for $NCarriers \times HolidayBook$ while column (2) presents first-stage results. The statistically significant coefficient on $\widehat{NCarriers} \times HolidayBook$ in column (2) and the statistically significant Kleibergen-Paap rk Wald F statistic in column (3) indicates that our instrument is both strong and relevant. After correcting for potential endogeneity, the coefficient on $NCarriers \times HolidayBook$ while decreasing in absolute value to -0.0001, remains statistically insignificant. Accordingly, the use of holiday discounts by U.S. airlines does not appear to vary with the level of route competition.

Table 6: Predicted number of carriers by the actual number of carriers

	$\widehat{\text{NCarriers}}$			
NCarriers	Mean	Std. Dev.	Min	Max
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.

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

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. 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 1.8% 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 (5.9% 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 fares are not discounted on weekends (when demand is expected to be more elastic), 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

As outlined in Section 6.4, we employ an instrumental variables (IV) strategy to correct for the potential endogeneity of $NCarriers \times HolidayBook$. 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.[29]

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.[30] 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 ($N\widehat{Carriers}$).

4. Finally, we interacted $N\widehat{Carriers}$ with $HolidayBook$ to generate $N\widehat{Carriers} \times HolidayBook$. $N\widehat{Carriers} \times HolidayBook$ is then used as an instrument for $NCarriers \times HolidayBook$ in a two-stage least squares regression.

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

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

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 $\times$ 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.

Appendix C: Standard errors for coefficient estimates in Tables 2-5

Table C1: 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			(0.006)		
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 Cyber Monday				(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 Cyber Monday					(0.006)
LCC × Book on Christmas Eve					(0.006)
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 C2: Standard errors for coefficient estimates in Table 3

	(1)	(2)	(3)
DaysToDeparture 1-2	(0.027)	(0.027)	(0.027)
DaysToDeparture 3-6	(0.037)	(0.037)	(0.038)
DaysToDeparture 7-13	(0.028)	(0.028)	(0.028)
DaysToDeparture 14-20	(0.009)	(0.009)	(0.009)
DaysToDeparture 1-2 × Southwest	(0.044)	(0.044)	(0.044)
DaysToDeparture 3-6 × Southwest	(0.048)	(0.048)	(0.048)
DaysToDeparture 7-13 × Southwest	(0.037)	(0.037)	(0.036)
DaysToDeparture 14-20 × Southwest	(0.013)	(0.013)	(0.013)
WeekendBook		(0.000)	(0.000)
HolidayBook		(0.001)	(0.002)
HolidayBook × Southwest		(0.002)	(0.002)
HolidayBook × DaysToDeparture 1-2			(0.010)
HolidayBook × DaysToDeparture 3-6			(0.009)
HolidayBook × DaysToDeparture 7-13			(0.005)
HolidayBook × DaysToDeparture 14-20			(0.004)
HolidayBook × DaysToDeparture 1-2 × Southwest			(0.015)
HolidayBook × DaysToDeparture 3-6 × Southwest			(0.012)
HolidayBook × DaysToDeparture 7-13 × Southwest			(0.007)
HolidayBook × DaysToDeparture 14-20 × Southwest			(0.005)

Table C3: Standard errors for coefficient estimates in Table 4

	(1)	(2)	(3)
DaysToDeparture 1-2	(0.023)	(0.023)	(0.023)
DaysToDeparture 3-6	(0.031)	(0.031)	(0.031)
DaysToDeparture 7-13	(0.024)	(0.024)	(0.024)
DaysToDeparture 14-20	(0.008)	(0.008)	(0.008)
DaysToDeparture 1-2 × Connect	(0.035)	(0.035)	(0.035)
DaysToDeparture 3-6 × Connect	(0.038)	(0.038)	(0.038)
DaysToDeparture 7-13 × Connect	(0.028)	(0.028)	(0.027)
DaysToDeparture 14-20 × Connect	(0.010)	(0.010)	(0.010)
WeekendBook		(0.000)	(0.000)
HolidayBook		(0.001)	(0.001)
HolidayBook × Connect		(0.002)	(0.003)
HolidayBook × DaysToDeparture 1-2			(0.009)
HolidayBook × DaysToDeparture 3-6			(0.008)
HolidayBook × DaysToDeparture 7-13			(0.005)
HolidayBook × DaysToDeparture 14-20			(0.003)
HolidayBook × DaysToDeparture 1-2 × Connect			(0.013)
HolidayBook × DaysToDeparture 3-6 × Connect			(0.010)
HolidayBook × DaysToDeparture 7-13 × Connect			(0.006)
HolidayBook × DaysToDeparture 14-20 × Connect			(0.004)

Table C4: Standard errors for coefficient estimates in Table 5

	(1)	(2)	(3)
DaysToDeparture 1-2	(0.022)	(0.000)	(0.022)
DaysToDeparture 3-6	(0.026)	(0.000)	(0.026)
DaysToDeparture 7-13	(0.019)	(0.000)	(0.019)
DaysToDeparture 14-20	(0.007)	(0.000)	(0.007)
WeekendBook	(0.000)	(0.000)	(0.000)
HolidayBook	(0.003)	(0.050)	(0.003)
NCarriers × HolidayBook	(0.001)		(0.001)
$\widehat{\text{NCarriers}}$ × HolidayBook		(0.020)	