



Investigating airline customers' premium coach seat purchases and implications for optimal pricing strategies



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ARTICLE INFO

Article history:

Received 22 May 2013

Received in revised form 31 October 2014

Accepted 22 December 2014

Keywords:

Airline revenue

Seat fees

Product debundling

ABSTRACT

We investigate factors that influence airline customers' purchases of premium coach seats using a database of online prices and seat map displays collected from JetBlue's website. Results show that multiple factors influence purchasing behavior; these factors include the amount of the seat fee, how far in advance the ticket is purchased, the number of passengers traveling together, and load factors (as revealed through seat map displays). We find that customers are between 2 and 3.3 times more likely to purchase premium coach seats (with extra legroom and early boarding privileges) when there are no regular coach window or aisle seats that can be reserved for free. In addition, we find that customers who purchase tickets closer to the departure date are less price-sensitive and are willing to pay higher seat fees. We use these model results to show that JetBlue's seat fees are currently underpriced in many markets; an optimal static fee would increase revenues by 8% whereas optimal time-dependent fees would increase revenues by 10.2%. In addition, if JetBlue were to leave their seat fees unchanged and instead reserve certain rows of seats for premier customers, they could potentially increase revenues by 12.8%.

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1. Introduction

Over the course of the last decade, airlines have experienced numerous financial challenges, including ballooning costs and intense competition. Many of these challenges came to a head around 2008, when oil prices soared to more than \$130/barrel (CNN, 2010) and the global economic crisis hit, dropping the Dow Jones market value by 33.8% (the third worst calendar year performance on record) and triggering a worldwide slowdown in economic activity, including air travel (Seeking Alpha, 2009). Many major airlines had already implemented significant cost-cutting strategies during the early 2000s as part of their bankruptcy restructuring and merger processes, limiting their ability to cut expenses, and the deep market penetration of the Internet, combined with low cost carrier competition, hindered the ability to raise fares. Consequently, "2009 proved to be the worst year on record for U.S. airlines, in terms of year-over-year revenue declines" (Southwest Airlines, 2009).

In response, many airlines sought to increase revenues without increasing fares by creating new ancillary revenue sources, such as fees for checked baggage, on-board food, and seat reservations and upgrades. These services were once bundled into the base price of a ticket, but airlines began to price them separately. In addition, airlines increased the cost of existing ancillary services, including fees for redeeming mileage award tickets, exchanging tickets, and checking pets. Moreover, rather than being a temporary solution to help get airlines through a rough year, these fees have become a permanent fixture

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of the air travel marketplace. According to the Bureau of Transportation Statistics, revenues from ancillary fees have rapidly increased in the past few years: for U.S. carriers with operating revenues over \$20M, reported ancillary revenues increased 172% over five years, from \$3.6B in 2007 to \$9.8B in 2011 (US DOT, 2012). Similar trends are observed worldwide. A recent report sponsored by Amadeus and IdeaWorks, that represents a broader set of airlines and more comprehensive set of ancillary fees, finds that both the number of carriers reporting ancillary revenues as well as the amount of ancillary revenues have increased. In 2007, 23 airlines posted ancillary revenues of \$2.45B and in 2011, 50 airlines reported revenues of \$22.64B (Sorensen and Lucas, 2012).

Ancillary revenue streams are important to airlines, sometimes turning a loss-making carrier into a profitable one. This was the case for JetBlue in 2011, that reported a net profit of \$86M and seat fee revenues of more than \$120M (JetBlue Airways, 2011). For some carriers, ancillary revenues can represent a major portion of overall revenues. In the U.S., Spirit Air is notorious for its extremely low base fares and “optional” fees for services such as booking online or by phone, printing a boarding pass at the airport, and carrying on luggage; in 2011, Spirit earned 33.2% of its revenue from these fees. Major carriers such as United/Continental (13.9%), Alaska (14.1%), and American (8.8%) earn a notable percentage of revenue from ancillary fees (Sorensen and Lucas, 2012). Given that the margins on the ancillary services are generally quite large, these fees in many cases represent most or all of the carrier’s operating profit.

Despite the prevalence and growing importance of ancillary fees, few studies have examined the direct impact these fees have had on customers’ purchasing behavior, let alone the secondary effects of these fees. For example, when airlines began charging for checked baggage, the amount of carry-on luggage increased. As a result, demand for overhead bin space often exceeded what was available. This ultimately led to higher demand for seats with early boarding privileges that give customers earlier access to overhead space. Thus, it appears that by introducing new fees for checked baggage, airlines were also able to begin charging more for seats with early boarding privileges. Similarly, as aircraft load factors increase, passengers realize the probability of having an empty seat next to them drops, and the value of a premium coach seat with extra personal space increases.

Airline operators continue to search for ways to increase ancillary revenues, without negatively impacting sales of basic tickets so much as to cancel out these revenue gains. A principle avenue for achieving such increases is through making fees for ancillary products more complex and differentiating them across customer groups (e.g., by reserving premium coach seats for preferred customers).

On the other hand, customers generally dislike added fees, and in particular dislike fees that appear to be hidden, arbitrary, or unfair. From the regulatory perspective, agencies want to ensure that fees are displayed in a way that is easy for consumers to understand. One issue that is of particular concern is whether the airline practice of reserving seats for preferred customers (i.e., showing certain seats as unavailable for non-preferred customers without elite status in an airline’s frequent flier program and/or showing certain seats as unavailable for those customers who do not purchase tickets for higher yield fare classes) effectively “tricks” some customers into thinking a plane is full when in fact it is not, leading customers to buy an upgraded premium coach seat. However, answering this question is difficult, not only for regulatory agencies but also for the airlines themselves, because the majority of airlines only keep records of the customers’ final seat assignment. Without more extensive data on the allocation of seat assignments across the entire booking horizon, it is difficult to recreate seat map displays shown to customers at the time of booking (i.e., it is difficult to know what seat choices the customer had at the time of booking). Airlines could certainly collect this information directly, but would need to make major investments in technology infrastructure to do so, and they are unlikely to make such an investment unless they have a high level of confidence that they will receive a decent return on their investment. Regulatory agencies also do not have access to proprietary carrier data, and would need to conduct independent investigations into this issue using publically available data or stated preference surveys.

Our study contributes to the literature on ancillary fees by providing some of the first insights into the role of load factors and seat map displays on customers’ premium coach seat purchases. We investigate airline customers’ seat purchasing behavior using a database of revealed preference data that includes online prices and seat maps from JetBlue’s website. This data is used to investigate the probabilities that customers will pay between \$15 and \$65 to reserve a premium coach seat that includes extra legroom and early boarding privileges. By tracking seat maps and prices across the booking horizon, the JetBlue data provides the ability to estimate binary logit models of seat choice, which can be used to understand how demand for its premium coach seat product varies across the booking horizon, across markets, and as a function of load factors (as revealed through seat map displays).

The rest of this paper is organized as follows: Section 2 provides additional background context on premium coach seat fees. Sections 3 and 4 provide an overview of the data and modeling methodology. Section 5 presents results and Section 6 uses model results to assess different pricing and seat display policies. The paper concludes with a discussion of major findings.

2. Premium coach seat fees

One of the more common types of ancillary fees is a premium coach seat fee, which is charged to customers wanting to reserve a “good” seat on the aircraft. As of 2013, all mainline carriers in the U.S. with annual operating revenues exceeding

\$1B charged seat fees,¹ with the exception of Alaska and Southwest. The implementation of these fees varies by carrier, and many of the airlines waive certain fees for elite customers and/or high yield tickets. Some airlines charge fees to reserve seats that do not provide extra legroom but instead allow customers to board early and gain early access to overhead bin space. With many airlines charging checked baggage fees even for the first bag, early access to overhead bin space is desirable. These priority boarding seats, often called “preferred” seats, include seats in popular locations on the plane that were once free to reserve, such as exit and bulkhead rows (which may offer a little extra legroom) and seats near the front of the aircraft, especially aisle and window seats near the front of the plane. Based on our assessment of fees charged on domestic U.S. flights, we determined that fees for preferred seats range from approximately \$4–\$45 for domestic flights (Mumbower, 2013, Table 4.1). This is less than fees charged for seats that include extra legroom along with early boarding privileges, often referred to as “premium” economy or “premium” coach seats, which range from approximately \$5–\$99 per leg for domestic flights.

2.1. The airline perspective

Due to the need to quickly create additional revenue streams during the crisis, there was little to no research done by airlines to determine customers' willingness to pay for premium and preferred coach seats prior to implementation of these fees. Further, technology constraints limited how airlines could charge fees. For example, many airlines did not have the ability to change seat upgrade fees across the booking horizon, that is, the same fee was charged to customers regardless of how far in advance of departure they booked. This limitation persists today for most airlines, although many are now in a position where they can make investments in revenue enhancing opportunities, including technology to get around these time-dependent pricing limitations. There are also other opportunities to create marginal improvements in premium coach seat fee revenues. For example, if airlines have a better understanding of customers' behavior and willingness to pay for certain amenities, they can make long-range plans to acquire and configure new airplanes appropriately to capture more value from future customers: Are enough customers willing to pay enough money for premium coach seats (with extra legroom) that it is worth sacrificing a row of regular coach seats from the plane? Should airlines invest in technology that will enable them to dynamically price ancillary fees over the booking horizon? If so, what are the optimal revenue-generating fees they should charge?

Although it has been several years since ancillary fees became a prominent part of the air travel landscape, few studies have examined customers' willingness to pay for such fees, including premium coach seat fees. One study based on stated preference data from Resource Systems Group, Inc. found that the average customer was willing to pay \$19 more for a window seat and \$18 more for an aisle seat without extra legroom (Weinstein and Keller, 2012). However, that study did not control for other factors that influence willingness to pay, such as plane load factors. There is a research need to investigate the role of seat map displays on customers' premium coach seat purchases, and to investigate revenue potential associated with varying seat fees across the booking horizon. Our study contributes to this debate by investigating these two research questions. This objective is consistent with prior studies published in *Transportation Research Part A* that have examined one or more aspects of air travel behavior (e.g., see Brey and Walker, 2011; Chen, 2008; Garrow et al., 2012; Lee et al., 2012; Lu and Peeta, 2009; Peeta et al., 2008; Tsamboulas and Nikoleris, 2008).

To our knowledge, only one major airline (United) currently collects data about seat displays across the booking horizon, and uses it to improve yields from its premium coach product. In the quarter after implementing the “Shares” yield management system, which allows for time-dependent pricing of Economy Plus seats, United reported a 25% increase in revenues associated with Economy Plus, with only about a third of that increase attributable to an expansion in the number of Economy Plus seats available in the fleet (Ranson, 2012). As one of the world's largest airlines, United is better positioned than many other airlines to absorb the large fixed cost entailed in developing a time-dependent pricing system for ancillary revenues. In contrast with a full rollout of a comprehensive integrated system, the data collection approach we employ in this paper represents a comparatively smaller investment, which can help an airline decide whether to undertake the larger investment to actually implement time-dependent ancillary fees.

2.2. The customer perspective

Seat fee and reservation policies have the potential to greatly impact customer satisfaction levels both positively and negatively. We are not aware of any empirical research that examines how characteristics of seat fee policies influence customer satisfaction levels. However, searching online through comments that airline customers have posted on various news articles, travel blogs, and travel websites reveals that customers have a wide range of concerns and opinions about seat policies. For example, CNN recently published a series of four articles on their website which discuss seat reservations and how customers feel about seat fees (Hume, 2012a, 2012b; Patterson, 2012a, 2012b). One of these articles had nearly 2000 comments posted by readers. Customer satisfaction with seat reservations seems to be impacted by many factors, including ease of reserving seats for a group traveling together and how seats are displayed on seat maps.

Seat policies that impose fees to reserve window and aisle seats decrease the number of contiguous seats available, which may make it more difficult for groups and families to sit together without paying those fees. Gate agents will generally try to

¹ These carriers include AirTran, Alaska, American, Delta, Frontier, JetBlue, Southwest, United and US Airways.

accommodate families as well as they can, but if there are not extra seats available, then they may not always be able to work out a way for families to sit together. Due to widespread media coverage about this issue, Senator Charles Schumer recently (May 27, 2012) requested that Transportation Secretary Ray LaHood issue rules preventing airlines from charging parents more to sit next to their children (Schumer, 2012). Senator Schumer also asked the industry's trade group, Airlines for America, to try to persuade carriers to voluntarily waive the fee for families. A few days later at a Senate panel, Secretary LaHood responded by saying that he has been urging airlines against charging more for popular seats (without extra legroom). However, he also said that he "can't tell airlines what fees they can charge" (Jansen, 2012). Although charging fees for aisle and window seats may decrease customer satisfaction levels of groups traveling together, it could also negatively impact other travelers. Many customers have noted that people are asking them to trade seats more often now than in the past, and have posted comments on blogs describing scenarios where they paid for a window or aisle seat and someone asked them to trade seats so that they could sit by a family member. On the other hand, policies that reserve and/or charge for window and aisle seats may increase customer satisfaction levels of certain types of travelers. Many business travelers choose to fly coach instead of business class. These travelers often book a flight a few days in advance of the departure date when many seats are full and end up purchasing a ticket that is priced much higher than tickets purchased by people who booked far in advance. Policies that allow these customers to reserve a better seat may increase their satisfaction with the airline. Reserving seats for frequent fliers would also seem to increase satisfaction.

Another major issue of concern that customers have raised is how seat availabilities are displayed on seat maps. Airlines often block certain seats and do not allow customers to reserve these seats in order to set aside a few seats for accommodating passengers with disabilities or special needs. Now, with some airlines adopting policies that also reserve seats for elite members and higher-yield fares only, this means that other customers may be shown that these seats are "unavailable" on seat maps. Several columnists, including Bill McGee, a contributing editor to *Consumer Reports* and former editor of *Consumer Reports Travel Letter*, have noted that this has led to confusion among passengers upon boarding. Some customers have complained that while booking a ticket, the seat map showed that very few regular seats were available, which caused them to consider purchasing an upgraded seat. However, upon boarding the plane, they noticed that many more seats were actually available (McCartney, 2011; McGee, 2012a, 2012b). Comments these columnists have received from customers indicate that many customers feel they have been misled by the information displayed on seat maps, but it could be that they do not completely understand the airlines' seat policies. For example, many of the airlines open up preferred seats (without extra legroom) that can be reserved (sometimes for free) during check-in by non-elite customers, but some people may not understand that or think about that when looking at a seat map. If customers feel that they have been tricked into purchasing upgraded seats, then this could greatly decrease customer satisfaction with an airline.

In summary, the main concerns issued by customers and government officials relate to decreasing the number of contiguous seats (that are free to reserve) for families to sit together, and misleading customers into purchasing premium coach seats through displaying seat maps that are difficult to understand and/or that give the impression a plane is near capacity through showing seats as being occupied/unavailable to reserve. Our research contributes to this discussion through quantifying how seat map displays influence the probability that customers will purchase premium coach seats. This is valuable to both airlines that seek to optimize seat fees and/or invest in technologies that will enable them to implement time-dependent seat fees as well as regulatory agencies that seek to understand how the common airline practice of blocking seats for premier customers influences non-premium customers' purchases of premium coach seats.

3. Data

This section describes the database that was compiled from online pricing and seat map information from JetBlue's website.

3.1. Overview

To analyze how customers purchase premium coach seats with extra legroom, automated web client robots (or webbots) were used to query JetBlue's website and obtain detailed itinerary, fare, and seat map information for nonstop flights on a daily basis. Our paper is one of many that have used airline webbot data to analyze pricing and/or demand trends (e.g., see Bilotkach, 2006; Bilotkach and Pejcinovska, 2012; Bilotkach et al., 2010; Button and Vega, 2006, 2007; Horner et al., 2006; McAfee and Vera, 2007; Mentzer, 2000; Mumbower and Garrow, 2010; Newman et al., 2013; Pels and Rietveld, 2004; Pitfield, 2008; Pope et al., 2009; Dobson and Piga, 2013; Escobari, 2014). The period of data collection ran from August 5, 2010 through October 1, 2010. During this time period, queries were run to collect airfares and seat maps for a rolling set of departure dates. For example, when the data collection began on August 5, information for flights departing on September 2, September 3, ..., to October 2 was obtained. For the next day of data collection, August 6, information for the same flight departure dates was obtained. Collecting data in this way provides information for each flight in a market for 31 departure dates (September 2 to October 2) and over a booking period from 1 to at least 28 days before flight departure.

After the online data was collected, seat maps for each day were used to compile daily booking (or demand) data for regular coach and premium coach seats. When a customer books a ticket with JetBlue, they have the option to purchase a premium coach seat for between \$15 and \$65, or they can reserve a regular coach seat for free. Premium coach seats (hereafter

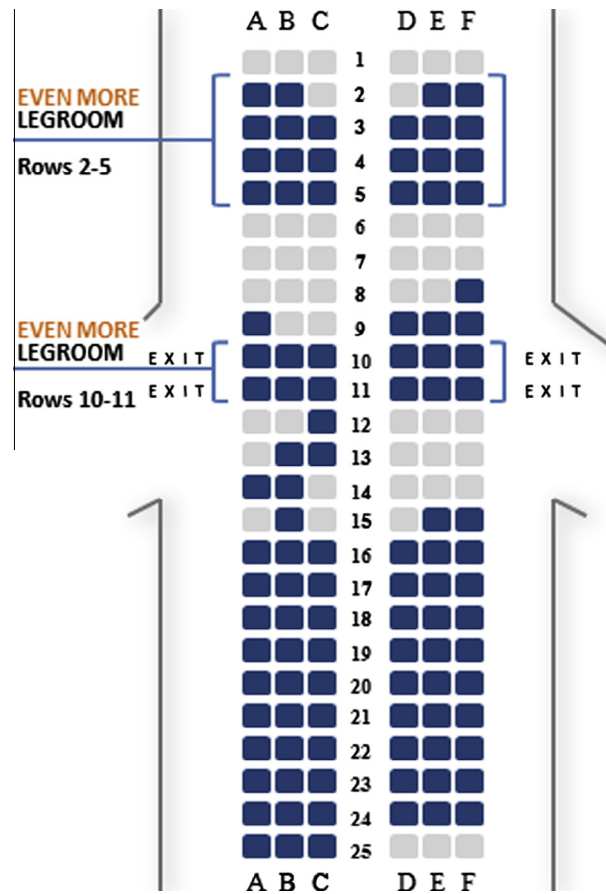


Fig. 1. Seat map display of a JetBlue plane.

referred to as Even More™ Space (EMS) seats,² which is the branding used by JetBlue) are priced by length of haul with higher prices for longer flights. EMS seat prices are the same for every flight in a particular market, for all EMS seats on the aircraft, and over the entire booking horizon. At the time of data collection, JetBlue's EMS seats provided 4–5 more inches of extra legroom over their regular coach seats,³ and also came with early boarding privileges.

We determined how many regular coach seats and EMS seats were sold on a particular day by determining when seats changed from being shown as “available” for one day but “reserved” for the next day. Fig. 1 shows a seat map of how JetBlue's Airbus A320 seats were configured at the time of data collection.⁴ Darker-colored seats are “available” and can be reserved, and lighter-colored seats have already been “reserved”. The plane has a total of 150 seats, which include 114 regular coach seats and 36 EMS seats. Note that of the 114 regular coach seats, seats 1A–F, 6B–E, and 25D–F are always “blocked” and are never available for customers to reserve online (blocked seats are typically set aside in order to provide advance seat assignments, as requested, to customers with disabilities). Rows 2–5 are EMS seats in the front of the plane; rows 6–9 are regular coach seats in front of the emergency exit rows; rows 10–11 are EMS seats in the emergency exit rows; and rows 12–25 are regular coach seats behind the emergency exit rows.

We assume that any customer who booked a ticket also selected a seat, as regular coach seat selections were free and the website prompts the customer to select a seat during the reservation process. We exclude customers who may have reserved a blocked seat from the analysis, as we have no way to distinguish between instances in which the blocked seat is occupied or is available (to disabled customers). We also exclude negative demand numbers from analysis, which occur when one or more customers cancel their reservations (and no new reservations occur on that booking date for that flight). In this sense, our demand estimates for regular coach and EMS seats can be viewed as lower bounds on demand, as they represent the

² At the time of data collection, JetBlue referred to these seats as Even More™ Legroom (EML) seats but subsequently rebranded these seats as Even More™ Space (EMS) seats. We use EMS terminology throughout the paper.

³ Note that JetBlue's regular coach seats have more legroom than other airlines' regular coach seats with a pitch of 32–34 in. as compared to an average pitch of 30–32 in. on most other carriers.

⁴ At the time of data collection, JetBlue operated two types of aircraft: Airbus A320 and Embraer ERJ-190. Because the Embraer aircraft only accounts for 29% of JetBlue's fleet and contains just four premium coach seats per flight (JetBlue Airways, 2011), only the Airbus A320 aircraft was used in the analysis.

minimum number of customers who reserved a seat for a given booking date and departure date. The actual demand may be slightly higher than what we can observe from the seat maps, as we cannot account for cases in which new bookings and cancellations occur for the same booking date and departure date combinations. Based on an assessment of the frequency of negative booking counts (which accounted for only 2.3% of the observations in the data), we conclude that the assumptions used to create demand estimates are reasonable.

The dataset includes 22 markets, across several different lengths of haul. [Table 1](#) provides a list of airport codes and airport names in our data. [Table 2](#) provides a list of the markets collected, along with market characteristics and seat fees, average fares, and number of bookings. A market is defined by an origin and destination airport pair. For example, the BOSDEN market includes passengers who travel from the Boston Logan International Airport to the Denver International Airport. The BOSDEN market includes local passengers (who board the plane in Boston and disembark in Denver), as well as connecting passengers (who start their itinerary on a flight before Boston and/or terminate their itinerary on a flight after Denver). The markets in our study were selected as they serve a large percentage of local nonstop passengers. With the exception of two markets in our dataset, 85% or more passengers are local nonstop passengers (the range of local nonstop passengers is 75.3–99.4% based on an analysis of ticketing data compiled by the Bureau of Transportation Statistics (BTS) for Q3 2010 as shown in [Table 2](#)) (US DOT, 2010). This is advantageous for two reasons. First, JetBlue uses one-way prices; this means that the online prices we see for each nonstop flight offered in a market are the prices that were offered to local customers traveling in the market. Second, the majority of individuals on the flight (on average, more than 91% of individuals) were local customers. From a modeling perspective, this enables us to model customers' willingness to pay for flight-level seat fees using flight-level nonstop prices.

A total of 59,242 flight-level bookings were observed (46,920 regular coach seat bookings and 12,322 EMS seat bookings). Thus, 20.8% of the observed bookings are for EMS seats.

3.2. Selection bias

Using JetBlue as the airline for our analysis enables us to control for potential sources of selection bias. Since JetBlue customers may reserve a regular coach seat for free (or a premium coach seat for a fee) at the time of booking, we expect the majority of customers to reserve seats at the time of booking. The majority of JetBlue customers make their bookings through JetBlue's website, which helps minimize potential bias due to channel differences ([JetBlue Airways, 2013](#)). Further, JetBlue does not overbook its flights, which means that all customers have the option to select a seat at the time of booking. Importantly, JetBlue is also the only airline in the U.S. that does not waive seat fees for certain customers, i.e., any individual who wants to sit in the premium coach section must pay to do so. Replicating this study on another airline would introduce selection bias, as customers who receive premium coach seat assignments for free or at a discount cannot be identified from the online data. In our data, however, this source of selection bias does not exist; all customers who reserve a premium coach seat must pay to do so.

The exact fee that customers pay to reserve a premium coach seat is known by the researcher and is charged on a per-flight basis. Thus, network-level effects are not relevant in the context of our problem, as connecting passengers would need to pay a separate premium coach seat fee for each flight on their itinerary. On the other hand, the exact one-way fare paid by the customer is not known, as JetBlue offered both non-refundable and refundable fares. At the time the data were collected, JetBlue's default website search option displayed one non-refundable fare for each flight. However, customers could search

Table 1
Airport codes and names.

Airport code	Name of Airport, City and State
AUS	Austin-Bergstrom International Airport, Austin, Texas
BOS	Logan International Airport, Boston, Massachusetts
BQN	Rafael Hernández Airport, Aguadilla, Puerto Rico
BUF	Buffalo Niagara International Airport, Buffalo, New York
DEN	Denver International Airport, Denver, Colorado
EWR	Newark Liberty International Airport, Newark, New Jersey
FLL	Fort Lauderdale Hollywood International Airport, Fort Lauderdale, Florida
IAD	Washington Dulles International Airport, Washington, DC
JFK	John F. Kennedy International, New York City, New York
LAS	McCarran International Airport, Las Vegas, Nevada
LAX	Los Angeles International Airport, Los Angeles, California
LGA	LaGuardia Airport, New York City, New York
MCO	Orlando International Airport, Orlando, Florida
OAK	Oakland International, Oakland, California
ORD	Chicago O'Hare International Airport, Chicago, Illinois
PBI	Palm Beach International Airport, West Palm Beach, Florida
PDX	Portland International Airport, Portland, Oregon
SFO	San Francisco International Airport, San Francisco, California
SYR	Syracuse Hancock International Airport, Syracuse, New York

Table 2

Market characteristics, observed fares and bookings, by market and type of haul.

Market	Market characteristics						Observed fares and bookings			
	Type haul ^a	Oneway distance	Avg. num flights	Oneway seat fee	Seat fee per mile	% Local nonstop pax	Avg. oneway fare paid ^b	Total bookings	Total EMS seats booked	Percent EMS bookings (%)
JFKBQN	E-PR	1576	2	\$30	\$0.019	95.1	\$147	2,133	112	5.3
MCQBQN	E-PR	1129	1	\$25	\$0.022	92.1	\$118	975	54	5.5
E-PR averages/totals		1437	2	\$28	\$0.020		\$138	3108	166	5.3
BOSIAD	E-E	500	7	\$15	\$0.030	92.1	\$92	6082	1086	17.9
BOSMCO	E-E	1121	5	\$30	\$0.027	96.8	\$130	2407	416	17.3
BUFMCO	E-E	1011	1	\$25	\$0.025	97.9	\$122	297	55	18.5
EWRMCO	E-E	937	4	\$19	\$0.020	96.4	\$125	2486	520	20.9
IADMCO	E-E	758	1	\$25	\$0.033	92.7	\$102	734	194	26.4
JFKFLL	E-E	1069	7	\$35	\$0.033	89.5	\$122	8998	1705	18.9
JFKPBI	E-E	1028	4	\$35	\$0.034	86.7	\$141	4843	1152	23.8
LGAFLI	E-E	1076	5	\$35	\$0.033	99.4	\$126	5543	1291	23.3
SYRMCO	E-E	1053	1	\$25	\$0.024	97.8	\$134	782	163	20.8
E-E averages/totals		943	5	\$29	\$0.031		\$120	32,172	6582	20.5
BOSDEN	E-MW	1754	2	\$40	\$0.023	92.3	\$183	1950	376	19.3
JFKORD	E-MW	740	3	\$30	\$0.041	85.8	\$119	2600	371	14.3
MCOAUS	E-MW	994	1	\$35	\$0.035	83.0	\$128	1049	150	14.3
E-MW averages/totals		1176	2	\$35	\$0.033		\$144	5599	897	16.0
BOSLAX	E-W	2600	2	\$50	\$0.019	94.9	\$184	2549	547	21.5
BOSSFO	E-W	2700	2	\$55	\$0.020	94.2	\$232	2071	609	29.4
FLLSFO	E-W	2580	1	\$50	\$0.019	91.1	\$152	999	150	15.0
JFKLAS	E-W	2240	5	\$50	\$0.022	88.0	\$252	3761	980	26.1
JFKLAX	E-W	2470	4	\$50	\$0.020	93.4	\$214	4907	1322	26.9
JFKOAK	E-W	2576	2	\$60	\$0.023	86.8	\$211	2109	562	26.6
JFKPDX	E-W	2454	1	\$50	\$0.020	75.3	\$257	944	160	16.9
JFKSFO	E-W	2580	2	\$60	\$0.023	88.7	\$285	1023	347	33.9
E-W averages/totals		2494	3	\$52	\$0.021		\$222	18,363	4677	25.5
Avg/totals all markets		1494	4	\$37	\$0.027		\$157	59,242	12,322	20.8

^a E-PR = East coast to Puerto Rico flights, E-E = East coast to east coast flights, E-MW = East coast to Midwest flights, E-W = East coast to west coast flights (JFKLAS is included due to length of haul).

^b Average fare is the average fare that was paid when tickets/seats were booked.

for refundable fares by changing the search options (and one refundable fare for each flight would be displayed). Still, the data does include the price of the non-refundable one-way leg-based fare for the flight, which represents a floor on the actual fare paid, and is strongly correlated with the actual ticket fare. Further, as we are studying price elasticity with respect to the seat upgrade fee and not the one-way fare, the noise in the fare data represents a loss of some information, but will not trigger a fundamental bias in our results.

Finally, it is important to note that we have not included passengers who choose to purchase a premium coach seat at the time of check-in. To do this, we would have needed to query JetBlue's website multiple times within the 24 h check-in period prior to flight departure. Moreover, some data would still be unobservable, as JetBlue does not sell tickets online in the final 90 min before departure, but they do sell seat upgrades at the airport during this time. The focus of our paper is on determining if seat map displays shown at the time of booking influence premium coach seat purchases and determining if airlines have an incentive to implement time-dependent seat fees. Both of these problems require knowledge about bookings that happen prior to the day of check-in. The underlying behavioral problem for day of check-in premium coach seat purchases is distinct from the problem that looks at premium coach seat purchases at the time of the initial booking. At the time of booking, the addition of a \$40 seat fee on top of a \$200 fare may seem large whereas at the time of check-in, faced with sitting in the back of a full plane, a \$40 fee may appear reasonable. The delay between the time of purchase and time of departure, in addition to more complete information on load factors at the time of check-in, may influence day-of-departure upgrades. A distinct modeling approach may be advisable to examine day-of-booking premium coach seat purchases vs. day-of-departure premium coach seat purchases. Examining day-of-departure premium coach seat purchases is beyond the scope of our study.

4. Methodology

A binary logit model was used to calculate the probability of purchasing an EMS seat, given that a ticket was purchased. In this model, a customer can choose between two options⁵:

⁵ Six observations (bookings) were removed from the data, as the customer did not have both regular coach seats and EMS seats to choose from.

$$\begin{cases} Y = 1 & \text{Buy a ticket and an EMS seat} \\ Y = 0 & \text{Buy a ticket only (and reserve a regular coach seat for free).} \end{cases}$$

Several variables were compiled from the online itinerary displays and seat maps, which are summarized in Table 3. For most of the variables, the definitions and descriptions are straight forward to interpret. Variables related to seat availabilities, prices and group bookings merit additional discussion.

4.1. Seat availability variables

Seat availability variables account for seat choices available to customers when booking a flight. These variables divide the plane into sections and provide information on whether a given section has window, aisle, and/or middle seats available. The “Row/Section Description” column in Table 4 shows how we grouped the rows into five main sections of the plane. Creating a set of variables to describe seat maps proved to be challenging due to two underlying factors: (1) planes fill up in a systematic way, i.e., customers prefer seats in the front of the plane; and, (2) when a section of a plane fills up, window and aisle seats always sell out before middle seats, i.e., customers prefer window and aisle seats.

In order to capture these two underlying factors, two seat availability variables are associated with each section of the plane. For example, when the *Regular Coach Front Seats Avail* dummy variable is 1 (indicating that seats are available in this section) and the *Regular Coach Front W/A Avail* dummy variable is 0 (indicating that no window or aisle seats are available in this section), this indicates that only middle seats are available in the Regular Coach Front of Plane section. When both of the indicator variables are 1, this indicates that at least one window or aisle seat in addition to at least one middle seat are available in that section. When both indicators are zero, this means no seats are available to reserve in that section. Note that not all dummy variables for each section of the plane are included in the model specification due to the systematic way in which planes fill up. First, there were only six observations in which all EMS seats were sold; these observations were excluded

Table 3
Variables and descriptions.

Variable	Definition
<i>Price variables</i>	
seatFeePerMile	Oneway EMS seat fee divided by the oneway market distance
lowestPrice	Value of one indicates booking was for the lowest priced flight available on itinerary screen
differenceOverLowestPrice	Price of booked flight minus lowest available priced flight on itinerary screen
<i>Seat availability variables</i>	
Reg Coach Front W/A Avail	Value of one indicates regular coach window/aisle seats available in front plane
EMS W/A Seats Avail	Value of one indicates EMS window/aisle seats available
Reg Coach Back1 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 1
Reg Coach Back2 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 2
Reg Coach Back3 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 3
Reg Coach Front Seats Avail	Value of one indicates regular coach seats available in front of plane
Reg Coach Back1 Seats Avail	Value of one indicates regular coach seats available in back plane section 1
Reg Coach Back2 Seats Avail	Value of one indicates regular coach seats available in back plane section 2
Reg Coach Back23 W/A Interaction	Value of one indicates regular coach window/aisle seats available in back plane sections 2 and 3
Reg Coach Back123 W/A Interaction	Value of one indicates regular coach window/aisle seats available in back plane sections 1, 2 and 3
<i>Group travel variables</i>	
NumberBookTogether1	Value of one indicates a booking made for an individual
NumberBookTogether2	Value of one indicates a booking made for a pair traveling together
NumberBookTogether3	Value of one indicates a booking made for three people traveling together
NumberBookTogether4	Value of one indicates a booking made for four people traveling together
NumberBookTogether5or6	Value of one indicates a booking made for 5 or 6 people traveling together
<i>Day of week variables</i>	
ddow1, ..., ddow7	Value of one indicates flight departs on a Sunday, Monday, ..., Saturday
bdow1, ..., bdow7	Value of one indicates flight was booked on a Sunday, Monday, ..., Saturday
<i>Number of days from flight departure dummy variables</i>	
dfd1, dfd2, ...	Value of one indicates a booking made 1, 2, ... days from flight departure
<i>Departure time of day variables</i>	
earlymorning	Value of one indicates flight departs 5am–7:59am
morning	Value of one indicates flight departs 8am–11:59am
afternoon	Value of one indicates flight departs Noon–4:59 pm
evening	Value of one indicates flight departs 5 pm–8:59 pm
lateevening	Value of one indicates flight departs 9 pm–11:59 pm
<i>Seat fee and DFD interaction variables</i>	
seatFeePerMile_DFD1–7	seatFeePerMile for bookings made 1–7 days from flight departure, zero otherwise
seatFeePerMile_DFD8–14	seatFeePerMile for bookings made 8–14 days from flight departure, zero otherwise
seatFeePerMile_DFD15–28	seatFeePerMile for bookings made 15–28 days from flight departure, zero otherwise
<i>Other variables</i>	
Market dummies	Dummy variable for each market

Table 4

Mean seat occupancies the day before flight departure.

Row number	Mean seat occupancies						Row/section description
	A window seats	B middle seats	C aisle seats	D aisle seats	E middle seats	F window seats	
1	Blocked	Blocked	Blocked	Blocked	Blocked	Blocked	Blocked row EMS seats
2	0.72	0.43	0.79	0.77	0.35	0.63	
3	0.56	0.30	0.72	0.68	0.27	0.50	
4	0.44	0.26	0.62	0.60	0.22	0.39	
5	0.39	0.21	0.55	0.55	0.19	0.35	
6	0.98	Blocked	Blocked	Blocked	Blocked	0.98	Regular Coach Front of Plane
7	0.99	0.92	0.98	0.99	0.91	0.97	
8	0.99	0.89	0.99	0.98	0.87	0.98	
9	0.95	0.78	0.98	0.98	0.77	0.93	
10	0.25	0.13	0.43	0.43	0.09	0.19	
11	0.26	0.10	0.44	0.43	0.09	0.24	EMS-Exit Row
12	0.97	0.81	0.98	0.98	0.79	0.96	Regular Coach Back of Plane Section 1
13	0.96	0.75	0.97	0.97	0.72	0.95	
14	0.96	0.75	0.96	0.97	0.72	0.95	
15	0.95	0.71	0.96	0.97	0.69	0.94	
16	0.94	0.69	0.95	0.95	0.68	0.94	
17	0.94	0.64	0.94	0.93	0.64	0.92	Regular Coach Back of Plane Section 2
18	0.92	0.63	0.92	0.92	0.61	0.90	
19	0.90	0.59	0.91	0.90	0.55	0.88	
20	0.86	0.56	0.87	0.88	0.53	0.85	
21	0.83	0.51	0.86	0.84	0.51	0.83	
22	0.81	0.46	0.82	0.82	0.45	0.80	Regular Coach Back of Plane Section 3
23	0.79	0.43	0.79	0.78	0.40	0.75	
24	0.75	0.36	0.75	0.75	0.35	0.69	
25	0.58	0.10	0.63	Blocked	Blocked	Blocked	

from the analysis, thus we do not include an indicator for the EMS middle seats. Also, there were no observations in which all middle seats in the back of the plane section 3 sold out, so we do not include an indicator for the middle seats of this section.

Table 4 shows mean seat occupancy rates calculated from seat maps observed the day before the flight departs. A value of 0.84 means that a seat was reserved before departing for 84% of the planes observed. Table 4 confirms that passengers prefer seats at the front of the plane and, in general, prefer window and aisle seats over middle seats, although middle seats toward the front of the plane have occupancy rates similar to window or aisle seats in the back of the plane. Middle seats in the EMS section have the lowest occupancy rates on the plane.

We do not account for cases in which all non-premium coach seats are booked and only premium coach seats are available. In this situation, passengers who purchased a ticket but did not purchase a premium coach seat would be assigned a seat during the check-in process. We conclude this was a reasonable assumption, as there are only six observations in which only premium coach seats were available.

4.2. Minimum flight price variables

A total of 10,699 itinerary screens (which provide a list of available flight choices and fares to customers) are observed in this dataset. Over all of the observed itinerary screens, tickets were booked for flights with fares ranging between \$39 and \$654 (with mean \$157 and median \$129). Out of these screens, 57% of the screens offer customers the same price for every flight, and 43% of the screens have at least one flight with a different price. *LowestPrice* is a dummy variable that indicates whether the booking was for the lowest priced flight(s) available on the itinerary screen.

For the screens that offer customers flights with different prices, the fare difference between the highest and lowest priced flights offered on the screen ranges from a difference of \$4 to a difference of \$417 (with mean difference of \$40 and median difference of \$15). *DifferenceOverLowestPrice* provides information on how much more expensive the booked flight was relative to the lowest priced flight available to purchase. For itinerary screens with varied flight prices, 59% of the observed bookings were made for the lowest priced flights.

As an example, consider the BOSLAX market. JetBlue operates an average of two daily flights in this market. Assume that the first flight has a price of \$175 and the second flight has a price of \$200. For the first price, the *lowestPrice* indicator would be set to 1 and the *differenceOverLowestPrice* would be set to 0. For the second flight, the *lowestPrice* indicator would be set to 0 and the *differenceOverLowestPrice* would be set to \$200 minus \$175, or \$25. Note that in a discrete choice modeling framework, a model that includes the *differenceOverLowestPrice* variable (or \$0 and \$25 for flights one and two, respectively) is identical to a model that includes flight price (or \$175 and \$200 for flights one and two, respectively). This is because only the difference in price is uniquely identified. The *lowestPrice* indicator provides additional information and can be interpreted

as a nonlinear effect, above and beyond any price difference across flights, for customers to select a flight with the lowest offered fare.

Together these two variables provide information as to whether the customer purchased a ticket for a nonstop flight that had the lowest fare, and if not, how much extra they paid over the lowest priced flight available to them (on the same search date and departure date). *A priori*, we expect that customers who purchase tickets on higher priced flights are less price-sensitive and may be more likely to purchase an EMS seat.

Our price variables reflect offered prices and may differ from the prices actually paid by consumers. We cannot identify leisure customers who used miles to pay for tickets or business customers who were reimbursed by their companies.

4.3. Group variables

Dummy variables (*NumberBookTogether1*, *NumberBookTogether2*, ..., *NumberBookTogether5or6*) were created to represent groups of people booking flights together. To do this, a few assumptions had to be made. If only one seat in a row was booked, then the booking is assumed to be made by an individual. If two seats were booked together in a row, then the booking is assumed to be a pair traveling together. The same logic is used to determine whether three, four, five, or six people booked together. We also assume that people traveling together do not book seats in different rows. Since there are six seats in a row, any groups larger than 6 would not be counted as the same group.⁶

An estimated 53% of the bookings are for individuals traveling alone, 32% of the bookings are made for two people traveling together, 9% of the bookings are made for three people together, 4% are for four people together, and the remaining 2% of bookings are made for groups of five or six people.

4.4. Seat fee per mile

As part of our model estimations, we compared models that included various transformations of flight time and flight distance. This is because, from a behavioral perspective, we expect that passengers will be more likely to pay for premium coach seats on longer flights. However, some long-haul markets (such as those to Puerto Rico) typically serve a large percentage of leisure travelers and those visiting family and friends. Customer behavior in these long-haul leisure markets differed from customer behavior in long-haul business markets. Therefore, instead of using flight time and/or flight distance, we included a set of market dummy variables and *seatFeePerMile* in the utility function. *SeatFeePerMile* captures the nonlinear effect of seat fees on choice behavior, i.e., customers are more likely to spend \$50 for a premium coach seat on a 2000 mile flight than a 500 mile flight. The market dummy variables control for unobserved factors, such as the prevalence of price-sensitive leisure customers, that can influence premium coach seat purchases.

5. Model results

Model coefficients, shown in Table 5 are intuitive and indicate that EMS seat purchases are influenced by seat fees and seat displays, along with flight and passenger characteristics.

5.1. Seat availabilities

The coefficients associated with the seat availability dummy variables show that premium coach seat purchases are influenced by seat displays. To visualize the influence of seat availabilities on premium coach seat purchases, we identified 13 representative seat map displays or “scenarios” from the data. Because customers tend to make free seat reservations systematically (closer to the front of the plane is preferred over further back, and window and aisle seats are preferred over middle seats), these 13 scenarios represent 86% of the seat map displays viewed by customers at the time of booking.

Descriptive statistics for these 13 seat map displays are shown in Table 6, along with the partial utilities calculated from the seat availability variables from the binary logit results. One interesting finding of note is that the utility associated with purchasing an EMS seat varies quite little among the first six scenarios, when there are still plenty of window and aisle seats available in the front and back of the plane (especially back sections 1 and 2). On the other hand, the utility of the upgrade increases dramatically after there are no window and aisle seats left (Scenarios 10–13), and large increases are observed with every block of middle seats that fills. Customers who book 1–3 days from departure (DFD) are two times more likely to purchase an EMS seat when faced with a nearly full plane (Scenario 13) vs. a nearly empty plane (Scenario 1) (i.e., 37.9% of bookings made 1–3 days from departure include an EMS seat for Scenario 13 vs. 18.7% for Scenario 1). Comparing seat availabilities scenarios for each DFD category indicates that customers are between 2 and 3.3 times more likely to purchase EMS seats when faced with reserving a seat on a nearly full plane vs. a nearly empty plane. These results suggest that the ability of JetBlue to collect seat reservation fees is strongly tied to seat map displays and corresponding load factors.

⁶ Although these assumptions are not perfect, they are necessary because no customer information could be collected.

Table 5

Binary logit model results.

	Coefficient	z	P > z ^a
<i>Price and travel time</i>			
seatFeePerMile/DFD 1–7 Interaction	–32.5201	–10.24	0.000
seatFeePerMile/DFD 8–14 Interaction	–38.0552	–12.37	0.000
seatFeePerMile/DFD 15–28 Interaction	–44.7677	–11.25	0.000
lowestPrice	–0.3471	–5.45	0.000
differenceOverLowestPrice	0.0011	1.91	0.056
<i>Seat availability variables</i>			
Reg Coach Front W/A Avail	0.0972	2.30	0.021
EMS W/A SeatsAvail	0.3045	3.16	0.002
Reg Coach Back1 W/A Avail	0.2493	3.57	0.000
Reg Coach Back2 W/A Avail	0.1304	1.06	0.290
Reg Coach Back3 W/A Avail	–0.4214	–6.03	0.000
Reg Coach Front SeatsAvail	–0.0609	–2.04	0.042
Reg Coach Back1 SeatsAvail	–0.1694	–3.04	0.002
Reg Coach Back2 SeatsAvail	–0.2027	–2.03	0.042
Reg Coach Back23 W/A Interaction	–0.4153	–3.30	0.001
Reg Coach Back123 W/A Interaction	–0.3001	–3.39	0.001
<i>Group travel variables (reference variable is NumberBookTogether5+)</i>			
NumberBookTogether1 (Individual)	0.6736	2.43	0.015
NumberBookTogether2 (Pair)	0.9388	3.57	0.000
NumberBookTogether3	0.7990	3.00	0.003
NumberBookTogether4	0.6083	1.98	0.048
<i>Departure day of week variables (reference variable is ddow7-Saturday Departure)</i>			
ddow1 (Sunday Departure)	0.2619	3.16	0.002
ddow2 (Monday Departure)	0.0806	1.86	0.063
ddow3 (Tues Departure)	0.1902	2.74	0.006
ddow4 (Wed Departure)	0.2095	2.65	0.008
ddow5 (Thurs Departure)	0.2750	4.29	0.000
ddow6 (Friday Departure)	0.2043	2.76	0.006
<i>Booking/search day of week variables</i>			
sdow1 (Book on Sunday)	–0.1094	–2.01	0.045
<i>Number of days from flight departure dummies (reference variable is dfd19+)</i>			
dfd1	0.7607	6.19	0.000
dfd2	0.3998	2.16	0.031
dfd3	0.5096	3.56	0.000
dfd4	0.4883	3.05	0.002
dfd5	0.5387	3.64	0.000
dfd6	0.2216	1.59	0.112
dfd7	0.3108	2.05	0.041
dfd8	0.4461	2.96	0.003
dfd9	0.3991	2.59	0.010
dfd10	0.1677	1.14	0.253
dfd11	0.1640	1.15	0.249
dfd12	0.3175	2.25	0.025
<i>Departure time of day (reference variable is evening-depart 5 pm–8:59 pm)</i>			
earlymorning (depart 5am–7:59am)	–0.1370	–1.01	0.311
morning (depart 8am–11:59am)	0.2027	3.22	0.001
afternoon (depart Noon–4:59 pm)	0.2132	3.64	0.000
lateevening (depart 9 pm–11:59 pm)	–0.3478	–3.47	0.001

Note: Variables not reported include dfd13–18, market dummies & constant term.

LL = –27,779, Pseudo R-squared = 0.083.

^a Reported z-statistics and p-values are based on clustering standard errors by market.

5.2. Premium seat fees

Table 6 also allows us to investigate price sensitivities of bookings made closer to departure while also controlling for load factors at the time of booking. For example, those customers who book a flight on a nearly empty plane (Scenario 1) between 1 and 3 DFD are 1.7 times more likely to purchase an EMS seat than those customers who book further in advance (DFD 22–28) on a nearly empty plane (18.7% vs. 10.8% of observed bookings include an EMS purchase).⁷ Comparing bookings made

⁷ This provides empirical evidence for theoretical models that seek to explain why airline prices increase over time. These theories, which include those proposed by Dana, Gale and Holmes (Dana, 1998, 1999a, 1999b; Gale and Holmes, 1992, 1993) rely on the assumption that there are multiple consumer types with different arrival processes. In the context of the airline industry, this assumption means that price-sensitive leisure consumers tend to search and purchase fares further in advance of flight departure than price-insensitive business travelers.

Table 6

Percent of EMS bookings by seat availability scenarios and days from flight departure (DFD).

Scenario number	Are window and/or aisle seats available?					Are middle ^a seats available?			Percent EMS bookings by DFD						Partial utility	
	EMS	Regular coach sections				DFD 1–3	DFD 4–7	DFD 8–14	DFD 15–21	DFD 22–28	Over all DFD					
		Front	Back1	Back2	Back3							Front	Back1	Back2		
Scenario with regular coach window and/or aisle seats available in Front, Back 1, Back 2, Back 3																
1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	18.7%	16.8%	13.2%	13.1%	10.8%	12.7%	–0.788	
Scenarios with regular coach window and/or aisle seats available only in Back 1, Back 2, Back 3																
2	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	21.7%	18.7%	13.6%	12.0%	11.9%	13.7%	–0.886	
3	Yes	No	Yes	Yes	Yes	No	Yes	Yes	18.5%	19.0%	16.3%	12.3%	14.7%	15.1%	–0.825	
Scenarios with regular coach window and/or aisle seats available only in Back 2, Back 3																
4	Yes	No	No	Yes	Yes	Yes	Yes	Yes	23.2%	19.3%	15.7%	14.9%	12.6%	16.4%	–0.835	
5	Yes	No	No	Yes	Yes	No	Yes	Yes	24.9%	17.5%	16.6%	15.8%	11.5%	16.7%	–0.774	
6	Yes	No	No	Yes	Yes	No	No	Yes	30.1%	22.3%	18.9%	18.6%	22.3%	21.1%	–0.604	
Scenarios with regular coach window and/or aisle seats available only in Back 3																
7	Yes	No	No	No	Yes	Yes	Yes	Yes	29.8%	26.4%	21.9%	20.8%	17.6%	23.5%	–0.550	
8	Yes	No	No	No	Yes	No	Yes	Yes	29.3%	24.2%	24.7%	20.0%	20.1%	24.3%	–0.489	
9	Yes	No	No	No	Yes	No	No	Yes	37.3%	35.0%	22.3%	32.4%	20.0%	31.1%	–0.320	
Scenarios with no regular coach window and/or aisle seats available in any section of the plane																
10	Yes	No	No	No	No	Yes	Yes	Yes	38.2%	41.5%	40.7%	30.9%	31.3%	38.4%	–0.129	
11	Yes	No	No	No	No	No	Yes	Yes	40.3%	34.0%	35.0%	26.8%	32.1%	35.1%	–0.068	
12	Yes	No	No	No	No	No	No	Yes	40.8%	44.1%	34.0%	32.6%	36.5%	38.9%	0.102	
13	Yes	No	No	No	No	No	No	No	37.9%	47.7%	42.3%	43.3%	26.3%	42.2%	0.304	

Note: EMS = Even More™ Space. See Table 4 for details about the row numbers that correspond to each section.

^a Middle seat availabilities for EMS and regular coach back section 3 are excluded because there are no observations in the data without available middle seats in these sections.

closer to departure (DFD 1–3) to bookings made further in advance (DFD 22–28) for each scenario indicates that customers are between 1.1 and 2.1 times more likely to purchase EMS seats when they book closer to departure. This is reflected in the coefficients associated with the premium coach seat fees, i.e., the *seatFeePerMile* for purchases made 15–28 days from departure is more negative (–44.77) than the coefficients associated with purchases made 8–14 days from departure (–38.06) and 1–7 days from departure (–32.5). The coefficients associated with the three interaction variables between *seatFeePerMile* and *DFD* show that customers who purchase closer to flight departure are less price-sensitive. This suggests that airlines may be able to charge different seat fees across the booking horizon, i.e., charge higher seat fees closer to the departure date.

5.3. Nonstop flight characteristics

EMS seat purchases are influenced by many itinerary characteristics including the minimum price that must have been paid for the flight, departure day of week and time of day, and market effects. The model coefficients for *lowestPrice* and *differenceOverLowestPrice* show that customers who purchased a ticket on a flight with a higher fare (when a lower fare was available on a flight departing at a different time of the day) are more likely to purchase an EMS seat. Moreover, the higher the fare difference that customers paid over the lowest priced flight, the more likely they are to purchase a seat. This corroborates our intuition that customers who purchase a fare on a flight that does not have the lowest fare are less price-sensitive.

Flight day of week and time of day effects also impact EMS seat purchases. Customers are more likely to purchase EMS seats for Sunday and Thursday departures, which are days in which business customers are likely to travel. With respect to departure time, customers who book flights with departure times between 8:00 am and 4:59 pm are more likely to purchase EMS seats than other flight times.

Market level fixed effects (dummy variables) are included in the model and are significant, but are not included in the table for space purposes. Coefficients on the markets showed that two markets were especially different than the other markets. For the two markets with destinations in Puerto Rico, customers were much less likely to purchase EMS seats. Seat fees are already priced particularly low in these markets. Flights from JFK to Rafael Hernández Airport (BQN) in Aguadilla, Puerto Rico have an EMS seat fee of \$30, which is 1.9 cents per mile and is the lowest seat fee per mile out of all the markets collected. Flights from Orlando International Airport (MCO) in Florida to BQN have an EMS seat fee of \$25, which is 2.2 cents per mile and is the third lowest seat fee per mile out of all the markets collected. The low price of the seat fees in these markets, coupled with model results indicating that customers are far less likely to purchase EMS seats in these markets shows that customers flying to Puerto Rico are highly price-sensitive. The demographics of New York and Orlando also suggest that these flights have a larger percentage of customers who are visiting friends and family and neither traveling on business nor splurging on a vacation.

5.4. Passenger characteristics

EMS seat purchases are influenced by several passenger characteristics including group bookings, booking day of week, and how far in advance of departure the customer books a flight. The group booking variables indicate that two people traveling together are more likely to purchase EMS seats than individuals and larger groups. Also, a group of three people booking together are more likely to purchase EMS seats than individuals and larger groups. The results show that groups of four or more are the least likely to purchase EMS seats, which seems to reflect price sensitivity of families traveling together. A family of four who purchases EMS seats could expect to pay an extra \$60–\$260 one-way, or \$120–\$520 roundtrip, for the family to sit in an EMS section. These prices may be too high for many families who are already paying for multiple plane tickets.

With respect to the booking day of week, customers who book on Sunday (who are likely to be leisure passengers) are less likely to purchase EMS seats, and this is the only significant booking day of week variable.

5.5. Prediction accuracy

The results related to days from departure, price sensitivities, and seat map displays may be confounded in the sense that the least desirable seat maps occur closer to flight departure when we expect price-insensitive business travelers to book. This suggests that the estimated binary logit model could really be capturing different passenger mixes across the booking horizon, and not the effects of seat map displays. To test the robustness of results, we compared predicted EMS seat purchase percentages across the booking horizon to observed EMS seat purchase percentages, shown in Table 7. In general, the model performs well, particularly at the aggregate level over all days from departure and over all scenarios. For example, the predicted percentage of EMS seat purchases over all DFD for Scenario 1 has an error of 0.23. Table 6 showed that 12.7% of bookings were observed to include an EMS seat purchase. Thus, the model predicts that 12.93% of bookings include an EMS seat purchase.

6. Policy analysis

In this section, we investigate revenue potentials associated with optimizing the current static seat fee structure, implementing time-dependent seat fees, and by changing seat displays by showing seats as being unavailable to customers. The latter would occur if an airline decided to reserve additional seats for its premier customers.

Table 7

Prediction accuracy of EMS seat purchases for seat availability scenarios and days from flight departure (DFD).

Scenario number ^a	Difference between predicted and observed percent of EMS purchases (number of bookings) for each scenario and DFD					
	DFD 1–3	DFD 4–7	DFD 8–14	DFD 15–21	DFD 22–28	Over all DFD
1	1.54 (386)	0.15 (871)	1.15 (2457)	–1.02 (3614)	0.63 (4748)	0.23 (12,076)
2	–0.20 (503)	–1.63 (921)	0.66 (2309)	0.26 (2325)	0.05 (2372)	0.08 (8430)
3	–0.29 (173)	–1.76 (305)	–1.33 (882)	0.49 (927)	–2.59 (832)	–1.11 (3119)
4	–1.25 (715)	0.29 (1414)	0.84 (2757)	–0.01 (1967)	1.13 (1102)	0.39 (7955)
5	–3.39 (394)	0.91 (750)	0.55 (1637)	–0.46 (1009)	2.8 (513)	0.29 (4303)
6	–8.49 (73)	0.49 (148)	0.33 (254)	–0.66 (145)	–6.04 (94)	–1.58 (714)
7	–1.14 (449)	0.41 (656)	0.63 (1116)	0.33 (475)	0.79 (284)	0.28 (2980)
8	–0.83 (501)	1.59 (920)	–1.78 (965)	0.23 (444)	–1.47 (189)	–0.28 (3019)
9	–6.1 (212)	–6.77 (223)	4.11 (233)	–10.31 (68)	0.6 (20)	–3.35 (756)
10	1.76 (314)	–3.83 (489)	–8.12 (548)	–1.26 (262)	–5.8 (96)	–3.9 (1709)
11	1.17 (760)	3.28 (995)	–1.95 (882)	1.95 (306)	–7.56 (81)	0.8 (3024)
12	3.94 (610)	–0.87 (576)	2.38 (579)	1.32 (175)	–2.8 (63)	1.67 (2003)
13	10.85 (264)	–0.74 (241)	–0.53 (241)	–2.02 (67)	15.39 (19)	3.26 (832)
Over all Scenarios	0.00 (7118)	0.00 (10,414)	0.00 (17,316)	–0.17 (13,088)	0.20 (11,306)	0.30 (59,242)

^a See Table 6 for the seat availabilities of each scenario and observed probabilities.

6.1. Optimizing static seat fees

We can use the results from our binary logit model to determine optimal seat fees by calculating the expected revenue for each customer. This is found by multiplying the upgrade fee by the probability that a customer will actually purchase an upgrade. Although customers' price sensitivities are seen to vary as a function of days from departure, most airlines currently do not have the technological capability to charge different fees across the booking horizon. Thus, it is interesting to examine whether the static seat fees currently charged by JetBlue are optimal.

The optimal static seat fees derived from our model are shown in Table 8. With the exception of two markets (MCOAUS and JFKORD), JetBlue's seat fees are currently underpriced, particularly in the east-coast to west-coast markets. Charging optimal static fees would increase expected revenues by 8.0% (from \$476,245 to \$514,530) for the observed data.

To test the sensitivity of the seat fee optimization results, we generated a distribution for the revenue forecast by using the variance–covariance matrix of parameter estimates from the binary logit model. The estimated seat fee revenue that the optimal seat fees would generate at the 25th percentile of the distribution is \$509,740 and at the 75th percentile is \$519,145, which represents a 7.0% and 9.0% revenue increase, respectively.

6.2. Time-dependent seat fees

Since the binary logit model results indicate that customers who book tickets closer to the date of flight departure are less price sensitive, we examine a pricing strategy which sets fees by route and three DFD categories: 1–7 days, 8–14 days, and 15 or more days. Within each route and DFD category, prices are set to maximize expected revenue based on the actual observations in the data. The optimal seat fees for each market are shown in Table 8.

The time-dependent seat fees calculated using this approach appear reasonable. Optimal seat fees for 15 days from departure and up are similar to the current seat fees that JetBlue is charging in each market. However, our results show that there is potential to charge higher fees closer to departure. Implementing time-dependent seat fees would increase expected seat fee revenues by 10.2% (from \$476,245 to \$524,875) for the observed data. Compared to the baseline that optimizes static seat fees, this represents an additional 2.0% increase in expected seat fee revenues. A sensitivity analysis of these time-dependent fees shows that the estimated seat fee revenue that the optimal seat fees would generate at the 25th percentile of the distribution is \$518,510 and at the 75th percentile is \$531,075, which represents an 8.9% and 11.5% revenue increase, respectively. Compared to the baseline that optimizes static seat fees, this represents an additional 0.8–3.2% increase in expected seat fee revenues.

Our results suggest that future increases in seat fees are likely; however, the revenue gains associated with time-dependent seat fees are not at a level that will likely justify technological investments for an airline the size of JetBlue. The expected revenue gains from time-dependent seat fees are only on the order of about \$1–4M per year,⁸ set against a cost of upgrading reservations and data systems that may well exceed that. Larger airlines, on the other hand, whose seat fee revenues are several times larger than JetBlue's may find it profitable to follow United's lead in implementing time-dependent premium coach seat fees.

⁸ Calculated by multiplying JetBlue's reported \$120M in seat fee revenues in 2011 (JetBlue Airways, 2011) by our estimated 0.8–3.2% increase in expected seat fee revenues from time-dependent pricing.

Table 8

Optimal seat fees by market.

Market	Optimal time-dependent seat fees			Optimal static seat fee	Current seat fee	Type haul ^a
	DFD 1–7	DFD 8–14	DFD 15–28			
JFKBQN	\$52	\$44	\$36	\$44	\$30	E–PR
MCQBQN	\$37	\$31	\$26	\$33	\$25	E–PR
BOSIAD	\$20	\$16	\$13	\$17	\$15	E–E
BOSMCO	\$45	\$37	\$30	\$37	\$30	E–E
BUFMCO	\$39	\$32	\$26	\$34	\$25	E–E
EWRMCO	\$38	\$30	\$24	\$31	\$19	E–E
IADMCO	\$35	\$28	\$22	\$38	\$25	E–E
JFKFLL	\$44	\$35	\$28	\$38	\$35	E–E
JFKPBI	\$46	\$37	\$30	\$37	\$35	E–E
LGAFLL	\$47	\$37	\$30	\$40	\$35	E–E
SYRMCO	\$43	\$35	\$28	\$34	\$25	E–E
BOSDEN	\$69	\$57	\$45	\$57	\$40	E–MW
JFKORD	\$32	\$25	\$20	\$25	\$30	E–MW
MCOAUS	\$40	\$32	\$26	\$33	\$35	E–MW
BOSLAX	\$104	\$82	\$67	\$85	\$50	E–W
BOSSFO	\$116	\$95	\$76	\$96	\$55	E–W
FLLSFO	\$93	\$76	\$63	\$80	\$50	E–W
JFKLAS	\$94	\$76	\$62	\$79	\$50	E–W
JFKLAX	\$106	\$86	\$68	\$87	\$50	E–W
JFKOAK	\$110	\$90	\$71	\$89	\$60	E–W
JFKPDX	\$93	\$77	\$62	\$76	\$50	E–W
JFKSFO	\$116	\$92	\$76	\$99	\$60	E–W

^a E–PR = East coast to Puerto Rico flights, E–E = East coast to east coast flights, E–MW = East coast to Midwest flights, E–W = East coast to west coast flights (JFKLAS is included due to length of haul).

6.3. Seat map displays that block seats

We can also use our model to examine the revenue potential of strategically blocking certain regular coach seats from reservations during the booking process, effectively making the plane appear more fully reserved than it is at the time of booking. We apply the same simulation technique as described above for determining optimal static seat fees, but artificially close certain seating positions for all new reservations. When all regular coach seats in the front of the plane (rows 6–9) and back of the plane section 1 (rows 12–16) are indicated as “unavailable” for every traveler making a new reservation, using the actual fees offered by JetBlue, the model indicates that the interquartile range of expected revenue is \$523,250–\$550,290, with a mean of \$537,350 (which represents a 9.9–15.5% revenue increase, with a mean of 12.8%). In other words, if JetBlue were to leave their seat fees unchanged and instead block certain rows of seats for premier customers, they could potentially increase revenues by 9.9–15.5%.

Of course, implementing such a reservation system is a complex change, and the effects would reach far beyond the seat fee revenues. Once the rear sections of the plane filled, either regular coach seats in these sections (front of the plane and back of the plane section 1) would need to be released (improving free seat availability in the late DFD times when willingness to pay is higher) or JetBlue would need to abandon its policy of allowing all travelers to choose seats at the time of booking (altering an important branding feature and potentially negatively impacting other revenues). Moreover, if passengers learn to expect that those seats are vacant and/or will be filled before departure, some of them (especially frequent fliers, who may have a higher willingness to pay for upgrades but also a larger expectation of receiving access to otherwise blocked seats) may shop for EMS upgrades more strategically, with results that cannot be predicted using the current data and model. However, the results suggest that, with or without other pricing changes, by blocking some seats from the reservation process it may be possible to nudge some customers into purchasing EMS seats when they would not otherwise do so.

7. Conclusions

The results of this study are based on a subset of JetBlue markets and equipment types. This prevents us from extrapolating our results to different markets, different equipment types, and different airlines. However, this does not prevent us from quantifying the relative importance of two questions that are at the core of tensions among customers, regulatory agencies, and airlines: customers and regulatory agencies are focusing on the importance of fee transparency and fairness, but airlines want to add complexity to further differentiate fees across customer groups (e.g., by blocking premium coach seats for preferred customers) so as to capture more of the consumer surplus.

The results from our study suggest that in the future, we can expect to see further increases in premium coach seat fees as airlines begin to better understand customers' willingness to pay for seat products. However, changing an airline's technological infrastructure to facilitate time-dependent and/or dynamic pricing imposes relatively high fixed costs. These costs are probably reasonable and recoupable for the mega-carriers emerging from the past few years of airline mergers, but we do not anticipate seeing time-dependent or dynamic seat fees on existing smaller carriers in the near future.

Further, it is interesting to note that blocking seats (and leaving current seat fees unchanged) has as much revenue potential as optimizing current static fees. That is, by reducing the number of “good” seats that are available to reserve for free to all passengers, it is possible to increase seat fee revenues overall. Some airlines already implement some form of this system, such as British Airways, which limits seat reservations before check-in to premier and fee-paying customers. This underscores the importance of ensuring customers are not inadvertently misled into purchasing premium coach seats by seat map displays that block seats for premier customers.

At the industry level, our study provides some insights into potential strategic directions of airlines. As airlines make plans to acquire and configure new aircraft, they must make decisions about cabin layout and amenities, and ideally these decisions should seek to provide the best return on investment over the long term. Although there have been some limited stated preference studies into customer behavior (Weinstein and Keller, 2012), it is unclear what customers really value in a premium product.

There are several extensions of our work that could be addressed by using stated preference surveys. Currently, it is unclear what specific attributes of premium coach seats are valued by customers, and how these valuations may differ across customer segments. For example, do customers purchasing JetBlue's premium coach seats value extra legroom? Do they value the ability to board first and store luggage in overhead bins? Do they value the ability to deplane first and have more time to make connecting flights? Do they value having an empty middle seat next to them? Determining the value of each of these components will help airlines better design products and bundles that provide the most value for customers. It will also help airlines determine whether they should invest in adding sections in coach that offer extra legroom, or simply sell existing coach seats that provide early boarding and alighting privileges. This is a particularly important decision for carriers, as removing planes from service to remove row(s) of seats to add extra legroom is costly, particularly when planes are flying near record-high load factor levels. The revenues generated by selling extra legroom seats need to outweigh any revenues lost by removing seats from the aircraft. As suggested by our analysis, carriers should consider a range of load factors in any break-even analysis related to adding extra legroom seats to coach.

Another extension of our work is to jointly examine itinerary and premium coach seat decisions. This study focused on a conditional choice, i.e., conditional on knowing that a customer selected a JetBlue flight, what is the probability the customer paid to sit in the premium coach section? It would be interesting to see if the results of our study hold under a nested logit structure in which the higher-level decision focused on which itinerary (across multiple carriers) an individual selected and the lower-level decision focused on whether, conditional on knowing the individual selected a specific carrier, the individual decided to purchase a premium coach seat.

Acknowledgements

This research was supported in part by NSF CAREER Grant SES-0846758 and a NSF Graduate Research Fellowship. We would also like to thank Dr. Matt Higgins, Dr. Rick Zeni, and the comments of two anonymous reviewers for their helpful comments and suggestions.

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