1-1-2013

Essays In the Airline Industry

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Submitted in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy in

Business Administration

Darla Moore School of Business

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2013

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Dedication

To my parents, Valentin and Zoia Nicolae.

Acknowledgments

I would like to express my sincerest gratitude to my advisor, Dr. Mark Ferguson. I could not have completed this dissertation without his constant support, guidance and encouragement. I would also like to thank Dr. Carolyn Queenan, Dr. Pelin Pekgün and Dr. Orgül Öztürk for their encouragement, mentoring and helpful insights throughout the dissertation process. Additionally, I would like to thank Dr. Vinayak Deshpande, Dr. Mazhar Arıkan and Dr. Laurie Garrow for their collaboration and guidance. Finally, I would like to thank Resource Systems Group, Inc. for making data available for the analysis in the second essay.

Abstract

In 2008, most U.S. airlines implemented checked baggage fee policies to generate additional revenue to help with their financial distress caused by abnormally high fuel prices. Since this time, the fees have provided a steady revenue stream and often are the difference between a profit and a loss. Recently, some literature in the operations management field has postulated that altering consumer behavior in a manner that is beneficial to both the firm and customers is an additional purpose of these fees. In Essay 1, we empirically investigate the airline perspective of this hypothesis by considering the operational impact of airline baggage fees as measured by the airlines' departure delays. We do so by using primarily data collected by the Bureau of Transportation Statistics for the time periods immediately before and after fees for one and two checked bags were imposed by most U.S. airlines in 2008, and using a Tobit regression model to assess the impact of the fees on departure time performance. According to the 2013 North America Airline Satisfaction Study by J.D. Power & Associates, the baggage fees are still a source of passenger dissatisfaction. In Essay 2, we empirically investigate the customer perspective of the above hypothesis by considering the benefits provided by the service of checking bags. Thus, we examine airline service attributes that affect customer choice itinerary, and how checking or not checking bags influence these relationships, by employing discrete choice models estimated on stated-preference survey data.

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Chapter 1

Introduction

In the early 2008 the U.S. airlines were struggling with severe financial pressure due especially to record fuel prices. For competitive reasons, they had not been able to raise ticket prices enough to offset that increasing expense. Consequently, the airlines were trying to both reduce costs and add new revenues such as charging for products and services that once were complimentary, moving customers to “a la carte” pricing. United Airlines’ move of imposing a fee on the second bag checked by its passengers led to an industry shift as the competitors mimicked it. Soon after, checking two 50-pound suitcases free of charge was not the industry standard anymore. The financial implications were immediate, with U.S. airlines collecting in 2008 more than $1 billion in baggage fees, which represents a 148% increase from 2007.

Even though fuel prices receded, baggage fees have remained to boost the airline industry’s usually poor finances. As recently as 2012, the baggage fees amounted to $3.5 billion, or 3.8% increase compared to 2011, when the baggage fees generated approximately one-half of the industry’s profit of $7 billion [BTS, 2013]. Given that in 2012 only 0.8% more total system passengers were carried by U.S. airlines than in 2011 [BTS Press Release, March 2013], we can conclude the growing acceptance of baggage fees by travelers.

However, a significant increase in the amount of carry-on baggage as a direct result of passengers avoiding the checked baggage fees has also been documented [U.S. Government Accountability Office, 2010]. Dinkar [2010] reports the concerns of flight attendants over the more and heavier carry-on baggage brought into the cabin, which leads to an increase in the amount of bags checked at the gate when there is no room for them in the cabin, and subsequent delays that occur from the process. In 2007[1] flight delays were estimated to have raised the operating costs of U.S. airlines by $19 billion [Joint Economic Committee, 2008], being thus a big burden to airlines' profits [Bishop, Rupp, and Zheng, 2011]. If the checked baggage fees are seen as an additional cause of flight delays due to excessive carry-on baggage, they should provide the necessary impetus for airlines to reconsider them.

Thus, in Essay 1 we examine the operational impact of airline baggage fees as measured by departure delays, by using primarily data collected by the Bureau of Transportation Statistics. More specifically, we use data on 1,929,733 domestic flights flown by Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, US Airways, American Airlines, AirTran Airways, JetBlue Airways and Southwest Airlines, starting with 35 days prior to the date when the fees for one checked bag were implemented and continuing until 35 days after the implementation of two checked bags fees. We supplement this data with data published by the Federal Aviation Administration and the National Climatic Data Center of the National Oceanic and Atmospheric Administration, and use regression analyses to examine the impact of implementing checked baggage fees on departure delay performance.

While recognizing the main purpose of the baggage fees, the literature (e.g. Allon, Bassamboo, and Lariviere [2011]) has postulated that:

> *"[B]aggage fees are not just about revenue. They serve to alter consumer behavior in a manner that is beneficial to both the firm and customers. The firm enjoys lower costs (...)"*

[1] The fees for one, respectively two checked bags were gradually implemented by most U.S. airlines in 2008, starting May 5th.

That is, because offering the service of checking bags adds additional costs to the airlines, one approach taken by airlines in order to lower their costs has been to discourage travelers from checking bags by implementing checked baggage fees, which some have argued would also benefit travelers. Yet, the recent 2013 North America Airline Satisfaction Study by J.D. Power & Associates has revealed that "[b]aggage fees continue to be a source of passenger dissatisfaction and to lead to lower satisfaction levels" [J.D. Power & Associates Press Release, May 2013]. Consequently, it remains to be shown what benefits the service of checking bags provides, beyond the increase in revenues from the fees, as previously mentioned.

Thus, in Essay 2 we explore a potential new way of segmenting travelers based on their sensitivities to itinerary attributes. More specifically, we investigate whether travelers who check bags and travelers who do not check bags have different sensitivities to the historical on-time performance, total travel time, airfare and number of connections when choosing an itinerary. This is particularly relevant as most major airlines are evaluating operational changes that may make the process of checking bags even more inconvenient than it currently is. In this essay, we use data from an Internet-based stated-preference survey conducted by Resource Systems Group, Inc. in the Spring of 2012, who surveyed 878 U.S. domestic travelers who had flown a domestic flight within the last six months, and employ discrete choice modeling.

Through empirically evaluating these two issues using secondary and primary data sources, this dissertation will help explicate the airlines' perspective of the impact of the checked baggage fees implemented by most U.S. airlines in 2008, and travelers' perspective with regard to itinerary-choice, given that they check bags or not.

Chapter 2

Do Bags Fly Free? An Empirical Analysis of the Operational Implications of Airline Baggage Fees

2.1 Introduction

The once industry standard of two 50-pound free checked bags is now virtually extinct in the domestic U.S. airline market. Today, most U.S. airlines charge fees for checking a bag. On February 10^{th} 2007 Spirit Airlines, an ultra low-cost carrier, became the first airline to charge for one checked bag (i.e. the second checked bag fee), a policy that was extended to two checked bags (i.e., by adding the first checked bag fee) on June 19^{th}, 2007. United Airlines was the first major U.S. carrier that announced a fee for one checked bag[1], which was estimated to generate cost savings and additional revenue of more than $100 million annually [Carey, 2008]. Citing high fuel prices, large carriers such as Continental Airlines, Delta Air Lines, Northwest Airlines, and US Airways quickly matched United's decision and all began charging their passengers for one checked bag (i.e. the second checked bag fee) starting May 5^{th}, 2008. A week later, American Airlines matched the other airlines' baggage policy and, on June 15^{th}, started charging its passengers for two checked bags (i.e. by adding the first checked bag fee), hoping to get more than $350 million in additional revenues [McCartney,

[1]Unless the travelers had elite status in its Mileage Plus frequent-flyer program.

2008b]. By the end of 2008, all major U.S. carriers except Alaska Airlines, JetBlue Airways, and Southwest Airlines[2] had instituted fees for the first two checked bags.

The financial implications were immediate, with U.S. airlines collecting more than one billion dollars in baggage fees for overweight, oversized and/or extra bags in 2008, which represents a 148% increase from 2007 [BTS, 2012]. Expressed as a percentage of operating revenues, baggage fees increased from 0.27% in 2007 to 0.62% in 2008 for U.S. airlines (reaching 1.94% in 2010), generating a sustainable source of revenues. In the first half of 2012, the industry set a new record by collecting $1.7 billion in baggage fees [Mayerowitz, 2012]. Ignoring these potential financial gains, the no-fee policy was used as part of its marketing strategy by Southwest Airlines which saw an opportunity to distinguish itself from the competition by launching its “Fees Don’t Fly With Us” campaign. This marketing campaign has been viewed as successful by Southwest, as they continue to be the only major U.S. airline that does not charge a fee for the first two checked bags. This policy indicates that they view the marginal increase in revenue from the increased volume of passengers generated by the campaign as being larger than the loss in potential revenue from charging the fees and any associated cost increases. Their decision has not gone unquestioned, however, as stock analysts have repeatedly suggested that they begin charging for checked bags in order to raise additional revenues.

While the baggage fee policies are now generally agreed upon as a successful way of improving revenues for both the airlines that started charging for checked bags, as well as those that did not (Southwest), the question still remains about the impact the policies have had on airlines’ operations such as on-time departure performance. At the aggregate level (i.e. all U.S. airlines and airports), the percentage of delayed departures remained constant over the 2007-2008 period, according to

[2] Alaska Airlines instituted the first two checked bags fees policy on July 7th, 2009; JetBlue Airways has only charged for one checked bag as of 2012, i.e. starting June 1st, 2008; Southwest Airlines has not charged for the first two checked bags as of 2012.

the U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics (BTS). Aggregate statistics, however, may disguise the impact at the individual airline level. Thus, it is worthwhile to evaluate whether a marketing strategy decision such as charging or not charging fees for one or two checked bags has had implications on an airline's operational performance.

As pointed out in the popular press [Johnsson and Hilkevitch, 2011], Southwest had to cope with a surge in checked baggage, a byproduct of its "Bags Fly Free" marketing campaign. Transferring bags between flights under an extreme time crunch is perhaps the most challenging aspect of running an airport hub and a common cause of delays. Departure delays at Midway airport for Southwest Airlines were reported to increase after the checked baggage fee implementation by other airlines. Ryanair, an Irish low-cost airline, claims that baggage fees are a necessity in order to keep costs down, and it has been popularly hypothesized that if Southwest is going to welcome free checked bags, they have to expect higher costs [Lariviere, 2011]. On the other hand, to avoid baggage fees, passengers have continued to bulk up their carry-on bags, turning the allotment of one bag and a purse or briefcase into a two-suitcase load. Some game the system by fully intending to check a bag – they volunteer at the gate instead of the counter, and thus avoid the airline fee [McCartney, 2012a]. Baggage fees have made the overhead bin a precious commodity and the accompanying boarding stampede can increase departure delays. Thus, whether baggage fees lead to increased departure delays for the carrier that charges fees, or does not charge fees, is an empirical question that we seek to answer.

That a firm will perform better if it links its operations strategy to the competitive strategy to achieve the so-called *external fit*, is well established in the operations strategy literature [Smith and Reece, 1999]. Moreover, the alignment between operations and marketing strategies should exist to benefit organizational performance [Roth and Van Der Velde, 1991, Rhee and Mehra, 2006]. In a special issue on this topic, Malhotra and Sharma [2002, p. 210] note that "managing the interface between the marketing and operations functions is a challenging task since these two functional areas may often have conflicting objectives and plans of action. Yet co-ordination between them is critical for firm success". Thus, the implementation of checked bag fees (a marketing decision) provides an ideal setting to study how an industry changed, or coordinated, their operations to respond to this marketing strategy change.

To empirically address the impact of baggage fees in the airline industry, we primarily use data collected by the BTS for the time periods immediately before and after fees for one and two checked bags were imposed by the majority of the U.S. airlines. We supplement this data with data published by the Federal Aviation Administration (FAA) and the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA) and use regression analyses to examine the impact of implementing checked baggage fees on departure delay performance. We collected data on 1,929,733 domestic flights flown by Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, US Airways, American Airlines, AirTran Airways, JetBlue Airways and Southwest Airlines, starting with 35 days prior to the date when the fees for one checked bag were implemented and continuing until 35 days after the implementation of two checked bags fees. Since Southwest Airlines is the only major U.S. airline that does not charge for two checked bags, it resembles a control variable of operational performance in a quasi-experiment[3] when compared against competing airlines (that did begin charging for checked bags) that operated in the same airports.

[3] In a true experimental study, the treatment group receives the intervention, while the control group receives the usual conditions, meaning they only receive interventions that they would have gotten if they had not participated in the study. As Southwest Airlines might have gotten new customers who used to fly the now-baggage fee charging airlines, we do not have a true experiment, and consequently we do not employ a traditional difference-in-difference approach [Card and Krueger, 1994] in our analysis.

Our focus is on the operational impact of airline baggage fees instituted by most U.S. airlines in 2008. More specifically, we seek to answer the following questions: Do baggage fees impact airline operations as measured by departure delays? Is there a differential impact of one checked bag fee and two checked bags fees policies? Did airlines increase or decrease scheduled block-times in anticipation/response to the impact of baggage fees?

We show that, at the aggregate level, the airlines that began charging for one checked bag saw a significant relative improvement in their on-time departure performance in the 35-day period afterwards, compared to the airlines that were not charging for a checked bag during the same time period. When grouped into 'low-cost' versus 'legacy' carriers, however, we find opposite effects: the departure performance of the low-cost airlines became worse while it improved for the legacy carriers. When the airlines began charging for two checked bags, we find no significant change in departure performance of legacy carriers, but a degradation of departure performance of low-cost carriers. These findings indicate that the baggage fees did influence customer behavior, but in the case of charging for both checked bags, not in the direction the airlines had hoped for. The degradation of departure performance appears to be especially bad for the low-cost carriers, as it appears that their more price sensitive passengers may have begun carrying on more baggage to avoid the checked bag fees. Thus, our findings also support the notion that Southwest's marketing strategy of being the only major U.S. airline not charging for the first two checked bags is in line with their historical operations oriented strategy.

The remainder of this study is organized as follows. In Section 2 we briefly review the related literature on on-time performance and baggage fees. Section 3 describes the hypotheses of this study. Section 4 explains the data, variables and empirical specifications. Section 5 presents and discusses the results, and Section 6 concludes this study.

2.2 Literature Review

This paper relates to two streams of research in economics and operations management: (1) research that uses data provided by the DOT to investigate the impact of various factors on the quality dimension of airline's operational performance, as measured by on-time departures, on-time arrivals, and flight cancellations, and the impact of service quality dimensions on financial performance, and (2) research that examines the consequences of implementing baggage fees.

Within the first stream, economics researchers have looked at the impact of competition on airline service quality. Prince and Simon [2009] use BTS data on 10 major airlines in the 1995-2001 period on Fridays on the 1,000 busiest routes, and find that multimarket contact has a positive effect on arrival delays, causing delays on the ground, more in the form of gate departure delays rather than time spent on the runway. Using over 800,000 individual flights scheduled between 50 major U.S. airports in January, April, and July of 2000, Mazzeo [2003] finds that the prevalence and duration of arrival delays are significantly greater on routes where only one airline provides direct service, and that weather, congestion, and scheduling decisions have a significant contribution to arrival delays.

Using over 27,000 monthly route observations between 1997 to 2000, Rupp, Owens, and Plumly [2006] find that less competitive routes are characterized by lower service quality, in terms of both more frequent and longer flight delays. Further, Rupp [2009] examines the effect of competitive, economic, logistical, and weather measures on flight delays, by using 505,127 domestic flights between January 1995 and December 2004. He finds that airlines do not internalize passenger delay costs as departure and arrival delays are more likely at highly concentrated airports, and that the local market competition improves on-time performance, delays being more prevalent on monopoly routes. Rupp and Holmes [2006] examine the effect of the same measures on flight cancellations, by using 1,447,096 domestic flights in the

U.S. between January 1995 and August 2001. Their findings indicate that route competition improves service quality as measured by cancellation rates, and that flight cancellations are independent of airport concentration. They also identify a hub airline effect for both origin and destination airports that lowers the frequency of cancelled flights. Further, Rupp and Sayanak [2008] use 1,065,953 domestic flights of twenty-one U.S. carriers in 2006, and find that low-cost carriers have slightly shorter arrival delays (about one minute) than their competitors. In our study we also differentiate between legacy and low-cost carriers, and control for weather and logistical aspects. However, to control for the propagation of flight delays, unlike Rupp and colleagues who use a measure of scheduled departure time, we use a spillover-adjusted measure of departure delay in addition to our measure of scheduled departure time (i.e., departure block time). Unlike this previous literature, we use a Tobit regression model, which is more appropriate for measuring departure delay as a left-censored dependent variable. Thus, our study adds a robustness check to the earlier results. Finally, other economics researchers (e.g., Mayer and Sinai [2003], Forbes and Lederman [2010], Ater and Orlov [2011]) have investigated the impact of factors such as hub origin, vertical integration with regional partners to operate flights, and Internet access on departure delays, but these factors are not relevant for our objective.

In the operations management literature, Ramdas, Williams, Li, and Lipson [2012] examine the relationship between performance along several dimensions of service quality, including on-time performance, long delays, and cancellations, and stock market performance, by using monthly data for eleven major U.S. airlines over a 20-year period. They find that unexpected changes in service quality have a contemporaneous impact on stock returns, and that the cost of flight delays is convex in time. They also estimate a conservative marginal cost of a delay as being $150 per minute. Other researchers have used the DOT data to study the impact of operational aspects of running an airline on airline service quality. Li and Netessine [2011] consider that airline alliances provide higher service quality in the form of more options, smoother connections, shared alliance lounges, and flexibility regarding frequent flyer programs. Others equate higher quality with on-time performance. For example, Ramdas and Williams [2008] investigate the tradeoff between aircraft capacity utilization and on-time performance using flights flown within the continental U.S. in the years 1995-2005. They find that greater aircraft utilization results in higher delays, with this effect being worse for airlines that are close to their asset frontiers in terms of already being at high levels of aircraft utilization. Deshpande and Arıkan [2012] examine the impact of the airline flight schedules on on-time arrival performance. They use 20,681,160 flights covering 294 U.S. airports in the years 2005-2007 to provide a method for forecasting the scheduled on-time arrival probability for each individual scheduled domestic flight in the U.S. They find that revenue drivers, competitive measures, and operational characteristics such as the hub and spoke network structure have a significant effect on the scheduled on-time arrival probability. In addition, they find that, unlike low-cost airlines, full-service airlines assign a higher weight on the cost of late arrivals. Using the same dataset, Arıkan, Deshpande, and Sohoni [2012] develop stochastic models to analyze the propagation of delays through air-transportation networks. They find that the actual block times averages of all U.S. airlines exceed their average scheduled block times, potentially driven by the 15-minute buffer used by the DOT in reporting on-time arrival performance. They also construct a measure for "passenger" on-time arrival probability, in addition to the flight on-time arrival performance currently reported by the DOT. Our study contributes to this research stream by including a new possible factor that influences departure delays, i.e. charging for checked bags. More specifically, we study how a marketing strategy decision such as charging or not charging passengers for one, and respectively two checked bags, impacts airline service quality as measured by on-time departures.

Within the second research stream, Allon, Bassamboo, and Lariviere [2011] analytically examine whether airlines should bundle the main service (i.e. transporting a person) and an ancillary service such as transporting a checked bag, and if they should post a single price or unbundle them and price the ancillary service separately. Their modeling approach indicates that the way in which airlines have been implementing baggage fees has more direct impact on controlling customer behavior than segmenting customers. Our study is the first to show empirically that baggage fees do seem to have influenced customer behavior, and that the effect depends on the type of airline. Unlike Allon, Bassamboo, and Lariviere [2011] who posit that pricing the baggage separately induces customers to exert effort (i.e., to reduce the volume of checked baggage) and thus lowers the airline's costs, we find that this practice also induces customers to increase the volume of carry-on baggage, which does not lower the airline's costs. Using an event study methodology, Barone, Henrickson, and Voy [2012] explore the impact of the first checked bag fee announcements on airline stock prices. They find negative abnormal returns on the day of announcement for the announcing airline and other competing airlines, since perceived as an industry weakness. On the other hand, they find that subsequent announcements of fee increases for the first checked bag are correlated with positive abnormal returns, justified by investors learning the revenue implication of these baggage fees that have positively impacted the airline's financial performance. Using a spatial autoregressive model to account for airport substitutability, Henrickson and Scott [2012] consider the top 150 domestic routes from 2007 to 2009, and find that a one dollar increase in baggage fees reduces airline ticket prices on the fee charging airlines by \$0.24 and increases Southwest Airlines' ticket prices on routes in which they compete with baggage fee charging airlines by \$0.73. Thus, their results indicate very little difference between the change in total customer costs on the airlines that charge baggage fees versus Southwest. Our study also contributes to this research stream, by linking baggage fees directly to an airline's operational costs.

2.3 Hypothesis Development

Due to severe financial pressures in 2008, especially increased jet fuel prices, the majority of the U.S. airlines stripped out previously free services and began charging customers for anything more than basic transportation. While customers adapted to most of these changes, the implementation of checked bags fee tested the boundaries of what a basic airline service was. As United Airlines' Senior VP of Marketing explained in 2008, "the definition of basic airline service is evolving, and different airlines today have different answers of what comes standard with a ticket. "Unbundling" services means travelers will pay only for what they use. Currently, every customer pays for baggage service, whether used or not. We believe it has been too much of a one-size-fits-all model. (...) the baggage decision was difficult because changing customer expectations is obviously difficult" [McCartney, 2008a]. Indeed, the U.S. airlines saw competitive concerns as the deciding factor in implementing à-la-carte pricing regarding checked baggage. If they began charging for bags, a service that had been long built into the ticket price, they would start to lose business among the price-sensitive, non-elite frequent flyers. However, once Spirit Airlines, the "ultra-low cost airline", successfully experimented with fees for checked bags, most U.S. airlines followed it. The current theory does not clearly predict the effect of baggage fees on departure delays. We speculate that the imposition of baggage fees (of similar $ value for all airlines) caused passengers to change their behavior, and thus impacted departure delays, as follows:

Let x_1 and x_2 represent the percentage of passengers who travel by checking in one and two bags respectively[4]. When the airlines which previously had not charged their passengers for the first two pieces of checked baggage instituted a policy change by charging for one checked bag (see Table 2.2 for exact dates), the x_1 passengers were not affected. However, x_2 passengers' behavior was affected, and depending on their price sensitivity, they chose one of the following three options: (1) paying the fee for one checked bag while checking the other bag for free, (2) checking only one bag (instead of two) and thus not paying the fee, hence turning into the x_1 type of passengers, or (3) switching to a carrier which did not implement such a policy. Let y_1, y_2, and y_3 represent the percentage of x_2 passengers who chose the first, second and third option respectively. While y_1 and y_2 passengers did not switch to a carrier without such a baggage policy, overall they contributed to a decline in the checked baggage load of those airlines which implemented such a policy. That is, when faced with a fee for checked baggage, passengers checked 40 to 50 percent fewer bags on some carriers [U.S. Government Accountability Office, 2010]. Moreover, y_2 passengers may have brought on board a larger carry-on to make up for the "loss" of one bag. Indeed, checked baggage fees led to more and heavier bags brought as carry-on into the cabin [Dinkar, 2010]. The existing carry-on baggage limits were not always enforced. Related to the increase of carry-on baggage, a survey of the Association of Flight Attendants show an increase in tense boarding situations, the number of checked bags at the gate and pushback delays [U.S. Government Accountability Office, 2010]. Consequently, the implementation of checked baggage fees resulted in reduced

[4]We assume that these two categories describe the most typical passengers, and thus the most relevant for the purpose of our study. While passengers can travel with a carry-on bag only, we believe that they would also check in one or two bags as long as there are no additional fees imposed by the airline. The passengers can also check more than two bags, however these extra-bags have always incurred additional fees, thus our discussion reduces to their behavior regarding the first two checked bags. Also, the passengers who are insensitive to baggage fees (e.g. elite frequent flyers, business travelers, those who do not check in bags) are not affected by the fees instituted on one or two checked bags, and thus this customer segment is irrelevant for the purpose of our study.

likelihood of on-time departures as long as the carry-on baggage limits were loosely enforced. The popular press describes the real-estate crisis in the plane through as follows:

> *"For many travelers, the most odious aspect of the baggage fee is the anticipated battle for overhead-bin space. To make sure they can find room, some customers already push their way through boarding queues. Passengers struggle to stuff large bags into small bins, and flight attendants often find themselves taking bags off planes and checking them to their destinations once bins fill up. All this will likely get worse, though the airlines say that the new fee won't be collected in airplane cabins from customers who can't find space for their allowed carry-on bags. Bin battles can delay flights and leave customers frustrated."* [McCartney, 2008b]

In this vein, Spirit Airlines, the airline that initiated the checked bag fees in the U.S., started charging fees for carry-on baggage in 2010. They estimated that charging for carry-on baggage would eliminate the gate delay caused by gate-checking for carry-on bags that do not fit in the overhead bins. Spirit Airlines estimated savings of five minutes per flight[5] or 20 hours of airplane time per day, which was the equivalent of two extra planes which cost about $40 million each [McCartney, 2010a].

On the other hand, the switching behavior of the y_3 passengers caused those carriers which did not have the one checked bag fee in place, to experience higher checked baggage volume. This higher volume brought about additional challenges, as "[m]oving passenger baggage is an intensely manual operation, requiring lots of workers. On average, each bag gets touched by about 10 workers during its journey. Once bags are tagged, they are sorted and placed on carts, then driven planeside,

[5] According to Spirit Airlines' CEO, each flight has saved, on average, five to six minutes spent checking bags at gates [McCartney, 2012a].

where a crew loads them into the belly of a jet. The unloading process is more labor-intensive: Bags are sorted into luggage to be delivered to the carousel for passengers to collect and luggage that needs to be routed to connecting flights and has to be sorted and driven to lots of different planes" [McCartney, 2008d]. As the US Airways' VP of Customer Service Planning simply put it, "[t]he art, or science, of handling bags is really more complex than people realize" [McCartney, 2008d]. Moreover, the correlation between on-time dependability and amount of baggage checked has been pointed out by the American Airlines' VP of Airport Services [McCartney, 2008c]. Thus, reducing the volume of checked bags should increase the likelihood of on-time departure. Therefore, we hypothesize that an airline that charges its passengers for baggage may have a reduced volume of checked bags and thus reduced likelihood of departure delay. On the other hand, an airline that does not charge its passengers for baggage may have a high volume of checked bags and thus its flights are more likely to depart later than their scheduled departure times. Indeed, the distribution of x and y passengers (as described before) plays an important role in the operational impact of baggage fees. Because the theory does not provide a clear direction, we let the data dictate the correct hypothesis:

HYPOTHESIS 1A. *Better relative performance as measured by departure delays is achieved when charging for one checked bag versus not charging for a checked bag.*

HYPOTHESIS 1B. *Worse relative performance as measured by departure delays is achieved when charging for one checked bag versus not charging for a checked bag.*

Further, when the airlines which were charging their passengers for one checked bag instituted a policy change by charging the first two checked bags (see Table 2.2 for exact dates), both x_2 and x_1 passengers were affected, depending on their price sensitivity. Regarding x_2, their y_1 subset of passengers (previously defined) faced the following options: (1) paying the fees for the first two checked bags, (2) instead of two bags, checking only one bag (thus turning into x_1 passengers) and paying for it, and potentially having a bigger carry-on bag to make up for one bag, or (3) switching to a carrier which did not implement such a policy. The y_2 subset, as previously mentioned, identifies with x_1 passengers, who have the following options: (1) checking one bag and paying for it, (2) not checking the bag as it is a carry-on bag, or (3) switching to a carrier which did not implement such a policy.

Let z represent the percentage of x_1 passengers who switch to a carrier which did not institute the above mentioned policy. If z is large, then we hypothesize that the departure delays encountered by the airlines without fees for the first two checked bags exceed the departure delays of those airlines which have a one checked bag fee policy, which in turn are larger than the departure delays of the airlines which do charge fees for the first two checked bags. Let f and g represent the percentage of x_1 passengers who pay the fee for their one checked bag and those who do not pay the fee as their bag is a carry-on. If g is large, we expect the departure delays of the airlines charging fees for the first two checked bags to be larger than the departure delays of the airlines with a single checked bag fee policy, which in turn exceeds the departure delays of the airlines without fees for the first two checked bags. Regarding the larger carry-on bag that passengers might have considered to make up for the "loss" of a free checked bag (i.e. either the second or the first checked bag), we expect passengers to exhibit a more pronounced behavior change when facing a change in baggage policy from one checked bag fee to two checked bags fees, rather than from no checked bag fee to one checked bag fee. That is, we expect an incremental impact of implementing fees for the first two checked bags over implementing fees for only one checked bag.

Similar to the one checked bag fee policy, the theory does not offer a clear direction of the impact of the first two checked bags fees policy on departure delays, and hence we let the data dictate the correct hypothesis:

Hypothesis 2A. *Better relative performance as measured by departure delays is achieved when charging for the first two checked bags versus charging only for one checked bag.*

Hypothesis 2B. *Worse relative performance as measured by departure delays is achieved when charging for the first two checked bags versus charging only for one checked bag.*

It is understood that the new policies on checked baggage, motivated by poor financial performance, required strategic decisions at the carrier level, given the unknown impact it would have on passengers and on the entire industry. As "service factories" [Schmenner, 1986], the airlines were facing another challenge in providing their services as reliably and rapidly as possible. American Airlines declared: "[we] took extraordinary pains to prepare for the step. We did a lot of research on how our customers would be impacted. We did a lot of preparation with our airport people and our flight attendants" [Field, 2009]. United Airlines acknowledged a potential drawback, given the exemptions accompanying the policies: "determining passengers' mileage status and ticket types could require more interaction with airline agents" [McCartney, 2008d]. It seems obvious that a decision of such caliber required closer coordination and communication within airlines, especially between the marketing and operations functions. Given the expected disruptions in the boarding process, we expect airlines allocate more slack in their scheduled block times[6] to make up for departure delays and still arrive on-time, according to the DOT performance metrics. However, this practice of adding minutes to schedules[7] comes at a high cost to airlines: "Pilot-and flight-attendant costs increase since many are paid based on

[6]The scheduled block time is the difference between the scheduled arrival time and the scheduled departure time of a flight.

[7]Other reasons offered by airlines for this practice are increased congestion at the airports and in the sky, high fuel prices that force airlines to slow cruising speeds for savings, and lack of modern equipment for air-traffic controllers that prevents flights from taking the most direct routes [McCartney, 2007].

scheduled time. Maintenance costs rise since many functions are based on how many hours that engines and airplanes are in service. Inefficient schedules can even mean more planes are needed to fly the same schedule" [McCartney, 2007]. It also hurts passengers, who value the most realistic schedules. That is, while from the planning perspective the increased scheduled block time is viewed as a waste of resources, from the operational perspective it becomes an opportunity to absorb disruption and avoid its propagation. Hence, given the previously hypothesized departure performances (i.e. both worse and better) triggered by implementing checked bags fees policies, we let the data dictate the correct hypothesis for the impact of these policies on the scheduled block time:

Hypothesis 3A. *As the checked baggage fee policy gets implemented from zero to one to two bags, the scheduled block time increases.*

Hypothesis 3B. *As the checked baggage fee policy gets implemented from zero to one to two bags, the scheduled block time decreases.*

2.4 Methods

2.4.1 Data and Variables

The main data source is BTS' Airline On-Time Performance data, which includes flight information of all major U.S. airlines that have at least 1 percent of total domestic scheduled-service passenger revenues. The data cover nonstop scheduled-service flights between points within the U.S., and include detailed departure and arrival statistics by airport and airline, such as: scheduled and actual departure and arrival times, departure and arrival delays, origin and destination airports, flight numbers, flight date, one-hour time block based on the scheduled departure/arrival time (e.g. 6:00am-6:59am), cancelled or diverted flights, taxi-out and taxi-in times, air time, tail number of the aircraft that flew the flight etc. Thus, our unit of analysis is an individual flight from its origin airport to the destination airport operated by its carrier on a given day at a particular time.

An ideal setup for understanding how the implementation of checked bags fees affects departure performance would be an experiment where, for the same time period and at the same airports, some airlines charge their passengers for their baggage while others do not. Because we focus only on the airports used by Southwest Airlines, which did not impose fees on the first two checked bags (unless they exceeded the maximum weight limit), our research employs a quasi-experiment that approximates the ideal setting. For our comparison set, we included all U.S. airlines with greater than $2B in annual revenues in 2008, i.e. Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, US Airways, American Airlines, JetBlue Airways[8] and AirTran Airways. All but AirTran Airways and JetBlue Airways are considered "legacy" U.S. airlines (airlines that were operating before the deregulation of the industry in 1978). Notably, for our purposes, we use Southwest Airlines to approximate the ideal setup where some randomly selected flights encounter fees for two pieces of baggage whereas others do not and thus constitute the "control" group. In our study, Southwest flights act as a pseudo-control for trends and unobservable factors that can also affect flight delays in addition to baggage fees and other observable factors such as congestion. For a meaningful comparison, we restricted our analysis to the 57 origin airports used simultaneously by Southwest Airlines and one or more of the other airlines (see Table 2.1). These airports constitute a representative sample of Southwest's airports, i.e. 89% of the total number of airports used by Southwest in 2008.

[8]We performed analysis by first excluding, and later including, JetBlue Airways because the timing of their implementation of one checked bag fee overlaps with the timing of other airlines' implementation of two checked bags fees. Thus, we cannot isolate the impact of the one checked baggage fee for JetBlue Airways. Also, JetBlue Airways has not charged for two checked bags fees as of 2012.

Table 2.1 The 57 origin airports used by Southwest Airlines and the other airlines in our datasets

Airport Code	Airport Name	Airport Code	Airport Name
ABQ	Albuquerque International Sunport, Albuquerque, NM	MSY	Louis Armstrong New Orleans International, New Orleans, LA
ALB	Albany International, Albany, NY	OAK	Oakland International, Oakland, CA
AUS	Austin-Bergstrom International, Austin, TX	OKC	Will Rogers World, Oklahoma City, OK
BDL	Bradley International, Hartford, CT	OMA	Eppley, Omaha, NE
BHM	Birmingham International, Birmingham, AL	ONT	Ontario International, Ontario, CA
BNA	Nashville International, Nashville, TN	ORF	Norfolk International, Norfolk/Virginia Beach, VA
BOI	Boise, Boise, ID	PBI	Palm Beach International, West Palm Beach, FL
BUF	Buffalo Niagara International, Buffalo, NY	PDX	Portland International, Portland, OR
BUR	Bob Hope, Burbank, CA	PHL	Philadelphia International, Philadelphia, PA
BWI	Baltimore/Washington International, Baltimore, MD	PHX	Phoenix Sky Harbor International, Phoenix, AZ
CLE	Cleveland Hopkins International, Cleveland, OH	PIT	Pittsburgh International, Pittsburgh, PA
CMH	Port Columbus International, Columbus, OH	PVD	T. F. Green International, Providence, RI
DEN	Denver International, Denver, CO	RDU	Raleigh-Durham International, Raleigh/Durham, NC
DTW	Detroit Metropolitan Wayne County, Detroit, MI	RNO	Reno/Tahoe International, Reno, NV
ELP	El Paso International, El Paso, TX	RSW	Southwest Florida International, Ft. Myers, FL
FLL	Ft. Lauderdale-Hollywood International, Ft. Lauderdale, FL	SAN	San Diego International, San Diego, CA
GEG	Spokane International, Spokane, WA	SAT	San Antonio International, San Antonio, TX
HOU	William P. Hobby, Houston, TX	SDF	Louisville International, Louisville, KY
IAD	Washington Dulles International, Washington, DC	SEA	Seattle-Tacoma International, Seattle, WA
IND	Indianapolis International, Indianapolis, IN	SFO	San Francisco International, San Francisco, CA
JAN	Jackson International, Jackson, MS	SJC	Norman Y. Mineta San Jose International, San Jose, CA
JAX	Jacksonville International, Jacksonville, FL	SLC	Salt Lake City International, Salt Lake City, UT
LAS	McCarran International, Las Vegas, NV	SMF	Sacramento International, Sacramento, CA
LAX	Los Angeles International, Los Angeles, CA	SNA	John Wayne, Orange County, CA
LIT	Adams Field, Little Rock, AR	STL	Lambert-St. Louis International, St. Louis, MO
MCI	Kansas City International, Kansas City, MO	TPA	Tampa International, Tampa, FL
MCO	Orlando International, Orlando, FL	TUL	Tulsa International, Tulsa, OK
MDW	Midway International, Chicago, IL	TUS	Tucson International, Tucson, AZ
MHT	Manchester-Boston Regional, Manchester, NH		

To examine the impact of charging for one checked bag, we selected the flights in the 35-day period preceding and the 35-day period following the implementation of one checked bag fee by the specific airline. A 35-day window guarantees four occurrences of the same day of a week, and is large enough to provide an adequate sample size but small enough to isolate the impact of the baggage fee policies. Table 2.2 shows the dates when the airlines implemented their fees for one checked bag. For instance, Continental, as one of the first airlines that started charging for one checked bag, had its March 31 - June 8, 2008 flights included; AirTran, as the last among our airlines to charge for one checked bag, had its April 10 - June 18, 2008 flights included. However, Southwest, as the airline that did not charge for a checked bag (unless more than two checked bags or overweight), had March 31 - June 18, 2008 flights included. Using similar criteria as Deshpande and Arıkan [2012] and Arıkan, Deshpande, and Sohoni [2012], we eliminated some bad records, and the final number of observations in this first dataset after excluding cancelled flights was 513,907 flights.

Table 2.2 Dates of implementing fee policies on one checked bag and two checked bags

Airline	Date of implementing the fee policy on one checked bag	Date of implementing the fee policy on two checked bags
Continental Airlines	May 5th, 2008	October 7th, 2008
Delta Air Lines	May 5th, 2008	December 5th, 2008
Northwest Airlines	May 5th, 2008	August 28th, 2008
United Airlines	May 5th, 2008	June 13th, 2008
US Airways	May 5th, 2008	July 9th, 2008
American Airlines	May 12th, 2008	June 15th, 2008
AirTran Airways	May 15th, 2008	December 5th, 2008

To study the impact of two checked bags fees, we selected the flights of all the airlines in our study in the March 31, 2008 - January 8, 2009 period. According to Table 2.2, the boundaries of this period are given by the lower bound of the 35-day period preceding the earliest implementation of one checked bag fee policy, and the upper bound of the 35-day period following the last implementation of the two checked bags fees policy. After eliminating bad records similar to the first dataset, the final number of observations in this second dataset after excluding cancelled flights was 1,866,208 flights.

For our flight-level datasets, we used data from several sources such as the BTS[9], the FAA[10], and the NCDC[11] websites. Since most airports are weather reporting stations, for each origin and destination airports we collected data on daily precipitation level and average daily wind speed from the NCDC. Additional variables were computed as well (see Table 2.3). All the variables in our datasets are described next.

[9] http://www.transtats.bts.gov/databases.asp?Mode_ID=1&MODE_Desc=Aviation&Subject_ID2=0 (last accessed September 22, 2012).

[10] http://www.faa.gov/licenses_certificates/aircraft_certification/aircraft_registry/releaseable_aircraft_download/(last accessed September 22, 2012).

[11] http://www.ncdc.noaa.gov/cdo-web/search(last accessed September 22, 2012).

Table 2.3 Description of variables

Variable	Description
$Bag\text{-}Fee_i$	{0,1,2} variable indicating whether: a) no checked bag fee policy; or b) one checked bag fee policy; or c) two checked bags fees policy was implemented on the flight i date.
$SpAdj\text{-}Departure\text{-}Delay_i$	Difference between the actual departure time and the scheduled departure time of flight i, adjusted for the spillover from the previous flight in an aircraft rotation.
$Scheduled\text{-}Block\text{-}Time_i$	Difference between the scheduled arrival time and the scheduled departure time of flight i.
$Actual\text{-}TurnAround\text{-}Time_i$	Turn-around duration between the actual departure time of flight i and the actual arrival time of the previous flight in an aircraft rotation (not applicable to the first flight in an aircraft rotation).
$Route_i$	Origin-destination airports pair of flight i.
$Origin_i$	Origin airport of flight i.
$Carrier_i$	Airline that flew flight i.
$Month_i$	Month of flight i.
$Day\text{-}of\text{-}Week_i$	Day of week of flight i.
$Dep\text{-}Time\text{-}Block_i$	One-hour time block based on the scheduled departure time (e.g., 6:00am-6:59am) of flight i.
$Arr\text{-}Time\text{-}Block_i$	One-hour time block based on the scheduled arrival time of flight i.
$Dep\text{-}Congestion_i$	Number of flights scheduled to depart between 45 minutes before and 15 minutes after the scheduled departure time of flight i.
$Arr\text{-}Congestion_i$	Number of flights scheduled to arrive between 45 minutes before and 15 minutes after the scheduled arrival time of flight i.
$Aircraft\text{-}Age_i$	Age of the aircraft that flew flight i.
$Avg\text{-}Passengers_i$	Expected number of passengers on the aircraft that flew flight i.
$Origin\text{-}Prcp_i$	Precipitation level at the origin airport on the day of flight i (tenths of mm).
$Dest\text{-}Prcp_i$	Precipitation level at the destination airport on the day of flight i (tenths of mm).
$Origin\text{-}Awnd_i$	Average wind speed at the origin airport on the day of flight i (tenths of meters per second).
$Dest\text{-}Awnd_i$	Average wind speed at the destination airport on the day of flight i (tenths of meters) per second).

2.4.1.1 Explanatory Variable

Checked bag fee. The *Bag-Fee* ordinal variable indicates the status of each flight in our datasets with regard to the checked bag fee policy of the airline that flew the flight. Thus, $Bag\text{-}Fee$=1 indicates a flight with the one checked bag fee policy implemented by the specific airline on that specific date, whereas $Bag\text{-}Fee$=0 indicates the absence of such policy, i.e. no checked bag fee policy is implemented by the airline. Further, $Bag\text{-}Fee$=2 indicates a flight with the first two checked bags fees policy implemented by the airline on that specific date. Thus, the variable *Bag-Fee* has three levels, and we estimate two coefficients (for $Bag\text{-}Fee$=1 and $Bag\text{-}Fee$=2) in our regression.

2.4.1.2 Dependent Variables

Scheduled block time. For each flight i in our datasets, we computed the *Scheduled-Block-Time* (Q_i) as the difference between the scheduled arrival time and its scheduled departure time, as shown in the carrier's Computerized Reservations System (CRS).

Spillover-adjusted departure delay. According to BTS, the departure performance is based on departure from the gate. The departure delay is given by the difference between the actual departure time and CRS departure time. In case the actual departure occurs prior to the scheduled departure, the departure delay becomes zero as a negative departure delay does not represent a "true" delay. Also, a delay on one flight can potentially spill-over, or propagate, to the next flight since any given aircraft for an airline typically flies multiple flights over the course of a day. Therefore, our main dependent variable is spillover-adjusted departure delay (*SpAdj-Departure-Delay*), which we computed for each flight i in our datasets by subtracting any late aircraft delay from the previous flight $i-1$ in the aircraft's rotation, from the departure delay of flight i. This eliminates the serial correlation between observations in our dataset induced by consecutive flights using a common aircraft routing.

To calculate the spillover, we follow Arıkan, Deshpande, and Sohoni [2012]'s approach. Thus, we consider the sequence of flights operated by a particular tail number as an *aircraft rotation*. More specifically, an aircraft's rotation begins with the first revenue flight after a major maintenance, or a layover of more than five hours at an airport, and ends with the last flight operated before the aircraft returns for its next maintenance or remains on the ground for several hours.[12] Further, we refer to the *actual block time* of a flight as D_i^L, and compute it as the difference between

[12]As crew schedule information is not publicly available, we assume that airline crews remain with the aircraft.

the actual arrival time of the flight and its scheduled departure time. Unlike the traditional definition of actual block time, i.e. the difference between the actual arrival time of the flight and its actual departure time, our definition captures the impact of flight delays propagated through the system and departure delays associated with the observed flight. The actual block time is comprised of several components including taxi-out time, en route time, and taxi-in time, each one being subject to different causes of delay, and thus the total block time delay is the sum of all individual component delays.

The time duration between the next flight's scheduled departure time, on an aircraft rotation, and the earlier flight's scheduled arrival time is referred to as the *scheduled ground time* (G_i). In order to compute G_i, from the Airline On-time Performance dataset, we first sorted the data by airline, tail number and scheduled departure time so that all aircraft rotations are grouped together. Then, for each flight i, we computed G_i by subtracting the scheduled arrival time of flight $i-1$ from the scheduled departure time of flight i. A snapshot of one such aircraft rotation flown by Southwest Airlines' aircraft with tail number N208WN is shown in Table 2.4.

We computed the minimum time to turn an aircraft (T_i) by analyzing ground times at different airports for different types of aircraft for each airline. First, we grouped the actual ground-times for each flight flown in 2008 by airline, aircraft model, and departure airport. We then computed the 5^{th} percentile value (in minutes) across all actual ground-times for each airline, aircraft model, and departure airport combination. Additionally, we calculated the 5^{th} percentile value (in minutes) of actual ground-times for each airline-aircraft model and airline-departure airport combinations. The minimum turn-around time for the corresponding flight i was assumed to be this 5^{th} percentile. Further, the buffer time available on ground for flight i, B_i, is calculated by subtracting T_i from G_i for all flights except the first flight on the rotation. The B_i value of the first flight of any rotation is assumed to

Table 2.4 A snapshot of aircraft rotation: Southwest Airlines' aircraft with tail number N208WN

Position	Route	CRS Departure Time	Actual Departure Time	CRS Arrival Time	Actual Arrival Time
1	MHT–MDW	7:10 AM	7:12 AM	8:35 AM	8:55 AM
2	MDW–HOU	9:05 AM	9:27 AM	11:35 AM	11:55 AM
3	HOU–LAS	12:05 PM	12:27 PM	1:10 PM	1:32 PM
4	LAS–RNO	1:40 PM	2:00 PM	3:00 PM	3:09 PM
5	RNO–LAS	3:30 PM	3:42 PM	4:45 PM	4:56 PM
6	LAS–BUF	5:15 PM	5:31 PM	12:40 AM	12:45 AM
Scheduled Block Time (Q_i)	Actual Block Time (D_i^L)	Scheduled Ground Time (G_i)	Minimum Turn-Around Time (T_i)	Buffer Time (B_i)	Spillover (L_i)
145 min	165 min	-	-	-	-
150 min	170 min	30 min	25 min	5 min	15 min
185 min	207 min	30 min	20 min	10 min	10 min
80 min	89 min	30 min	22 min	8 min	14 min
75 min	86 min	30 min	18 min	12 min	0 min
265 min	270 min	30 min	22 min	8 min	3 min

be zero. Thus, the spillover, L_i, from flight $i-1$ to flight i is given by

$$L_i = [D_{i-1}^L - (Q_{i-1} + B_i)]^+.$$

Therefore, we computed the spillover-adjusted departure delay of a given flight by subtracting the spillover from the previous flight in the aircraft's rotation, from the departure delay:

$$\textit{SpAdj-Departure-Delay}_i = (\textit{Actual Departure Time}_i - \textit{CRS Departure Time}_i)^+ - L_i.$$

Actual turn-around time. The time duration between the next flight's actual departure time, on an aircraft rotation, and the earlier flight's actual arrival time is referred to as *Actual-TurnAround-Time*.

2.4.1.3 Controls

Typical factors that influence departure delays are seasonal (e.g. passenger load factor, weather, etc.), daily propagation related (e.g. late arriving crew, late arriving aircraft, connecting passengers from late incoming flights, air traffic congestion), and random (e.g. mechanical problems, baggage problems, security delays) [Tu, Ball, and Jank, 2008]. Since June 2003, the airlines that report on-time data to the BTS also report the causes of delays[13] for their flights. Figure 2.1 shows, for example, the flight delays by cause in the year 2008, across all U.S. airports. The weather shows up as the main source of delays, followed by air carrier delay (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc.), aircraft arriving late, National Aviation System (e.g. airport operations, heavy traffic volume, air traffic control, etc.), and lastly, security delay. However, a shortcoming of the Airline On-Time Performance data is that the source of delay cannot distinguish between origin and destination airports. By using individual flight level congestion and weather related control variables at the origin and destination airports, and spillover-adjusted departure delay as dependent variable, we do control for the main drivers of flight delays. Hence, our conclusions related to baggage fees and departure delays are robust, given that we used the following control variables:

Route. The *Route* variable captures all the fixed effects of an origin-destination pair for each flight.

Origin. The *Origin* variable controls for unobserved origin airport specific effects such as maintenance facilities, airport capacity, etc. that can potentially affect flight departure.

Carrier. The *Carrier* variable denotes the airline that flew the flight, and controls for airline specific effects.

Congestion at the origin/destination airport. Unlike prior literature which used an average congestion measure, we computed two congestion measures for each individual flight, i.e.: 1) departure congestion, *Dep-Congestion*, as the number of

[13] The causes of delays are reported in the following broad categories: air carrier, extreme weather, National Aviation System (NAS), late-arriving aircraft, and security. To obtain total weather-related delays, we combined the extreme weather delays and the NAS weather category, with the weather-related delays included in the "late-arriving aircraft" category (calculated as per the BTS methodology).

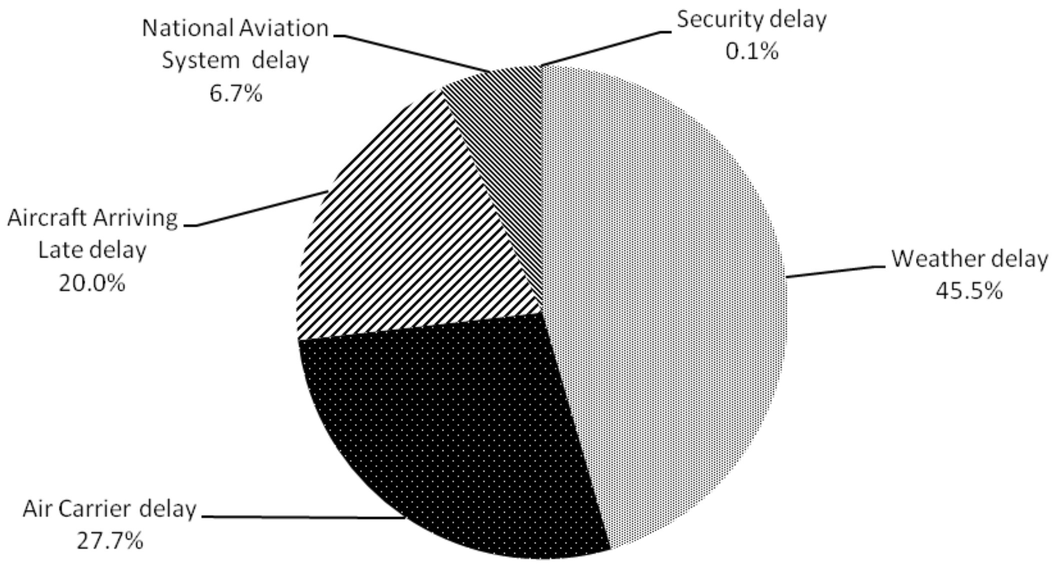

Figure 2.1 Flight delays by cause in January-December, 2008 (based on the BTS data on all carriers and airports)

flights scheduled to depart in an adjacent time block (i.e. between 45 minutes before and 15 minutes after the scheduled departure time of that flight) from the origin airport, that can potentially delay the flight, and 2) arrival congestion, *Arr-Congestion*, as the number of flights scheduled to arrive in an adjacent time block (between 45 minutes before and 15 minutes after the scheduled arrival of that flight) at the destination airport.

Month. The *Month* variable denotes the month of the flight which controls for the seasonal demand fluctuations.

Day of the week. The *Day-of-Week* variable indicates the day of the week of the flight, controlling thus for lighter versus heavier travel days.

Departure/arrival time block. Because delays are generally expected to worsen over the course of a day, we use *Dep-Time-Block/Arr-Time-Block* variables to control for the one-hour time block of the scheduled departure/arrival time (e.g., 6:00am-6:59am) of the flight.

Age of aircraft. As the tail number is an unique identifier for each aircraft, we used it to collect the aircraft's year of manufacturing from the Aircraft Registry Database hosted by FAA. Hence, we were able to compute the age of the aircraft as of the year of the flight.

Average number of passengers. The uniqueness of the tail number also offers information on the number of seats of each aircraft, as per the Aircraft Registry Database. We multiplied this seating capacity by the load factor we collected from BTS' *T*-100 Domestic Segment (U.S. Carriers). As the load factor is the monthly proportion of total seats that were actually filled for an airline on a specific route, we were able to compute the average number of passengers on each flight, thus controlling for the demand for air travel.

Weather related variables. Adverse weather conditions increase the likelihood of making adaptation decisions. Thus, the precipitation level (tenths of mm) on the day of the flight at the origin and destination airports are captured by *Origin-Prcp* and *Dest-Prcp* variables. Similarly, the average wind speed (tenth of meters per second) on the day of the flight at the origin and destination airports are captured by *Origin-Awnd* and *Dest-Awnd* variables.

A summary of descriptive statistics of the continuous variables used in our analysis is presented in Table 2.5.

2.4.2 Models

Previous studies have investigated the impact of various factors on departure delay by examining OLS and instrumental variables estimates. However, to evaluate the impact of charging for checked bags on departure delay, we employ the censored regression model Tobit, given the following:

Table 2.5 Descriptive statistics

Variable	First dataset			Second dataset		
	N	Mean	SD	N	Mean	SD
SpAdj-Departure-Delay	513,907	6.0995	22.8233	1,866,208	6.2358	23.6840
Scheduled-Block-Time	512,928	138.3611	71.9553	1,861,809	140.2325	72.5715
Actual-TurnAround-Time	365,087	47.4051	30.5309	1,316,591	49.3889	31.5419
Dep-Congestion	513,907	19.6835	14.3445	1,866,208	19.2749	14.3013
Arr-Congestion	513,907	24.3167	21.0789	1,866,208	24.5563	21.5455
Aircraft-Age	492,170	10.2811	8.5675	1,781,660	11.2789	8.0856
Avg-Passengers	492,233	107.9543	29.9775	1,791,887	105.9316	31.9048
Origin-Prcp	510,868	18.5503	67.9132	1,863,071	19.4913	72.9711
Dest-Prcp	511,290	20.6380	69.7319	1,863,394	21.4509	78.0365
Origin-Awnd	488,641	39.5498	16.6166	1,830,698	34.0933	16.0301
Dest-Awnd	491,503	41.2326	17.5546	1,834,650	35.9083	16.8022

Let y_i represent the time when a flight i is ready for take-off and let $CRSdeparture_i$ represent the scheduled departure time shown in the carrier's CRS. Then, departure delay is:

$$DepartureDelay_i = (y_i - CRSdeparture_i)^+.$$

However, y_i is a latent variable and $DepartureDelay_i$ is the observed variable. Hence, a Tobit regression model is appropriate here. Moreover, standard regression techniques (OLS) provide inconsistent parameter estimates when applied to a large number of observations in the sample equal to the lower bound for the dependent variable [Greene, 2008]. In the Tobit model, which uses the maximum likelihood estimation, the statistical significance of individual parameter estimates is evaluated by Wald Chi-square tests which replace the t-tests in OLS[14]

The estimation model of the impact of the checked bag fees on the spillover-adjusted departure delay is shown in Eq.2.1. We use the first dataset to differentiate between the effects of charging for one checked bag ($Bag\text{-}Fee$=1), respectively not charging for a checked bag ($Bag\text{-}Fee$=0), and label this model Tobit1. In addition, to concurrently disentangle the effects of charging for the first two checked bags

[14] All the analyses are conducted using SAS 9.3.

(Bag-Fee=2), only charging for one checked bag (Bag-Fee=1), and not charging for a checked bag (Bag-Fee=0), we use the second dataset and label the model Tobit2.

$$\begin{aligned}
\textit{SpAdj-Departure-Delay}_i \;=\;& \beta_0 + \beta_1 * (\textit{Bag-Fee}_i = 1) + \beta_2 * (\textit{Bag-Fee}_i = 2) + \\
& \beta_3 * \textit{Route}_i + \beta_4 * \textit{Origin}_i + \beta_5 * \textit{Carrier}_i + \\
& \beta_6 * \textit{Month}_i + \beta_7 * \textit{Day-of-Week}_i + \\
& \beta_8 * \textit{Dep-Time-Block}_i + \beta_9 * \textit{Arr-Time-Block}_i + \\
& \beta_{10} * \textit{Dep-Congestion}_i + \beta_{11} * \textit{Arr-Congestion}_i + \\
& \beta_{12} * \textit{Aircraft-Age}_i + \beta_{13} * \textit{Avg-Passengers}_i + \\
& \beta_{14} * \textit{Origin-Prcp}_i + \beta_{15} * \textit{Dest-Prcp}_i + \\
& \beta_{16} * \textit{Origin-Awnd}_i + \beta_{17} * \textit{Dest-Awnd}_i + \varepsilon_i. \qquad (2.1)
\end{aligned}$$

To analyze the impact of *Bag-Fee* on *Scheduled-Block-Time*, we use the second dataset to test the model in Eq.2.2, an OLS regression model (labeled OLS1) as *Scheduled-Block-Time* is not affected by censoring. Given that the scheduled block time is typically determined several months in advance based on the estimates of the time it takes to complete each flight [Deshpande and Arıkan, 2012], the model does not include weather related variables.

$$\begin{aligned}
\textit{Scheduled-Block-Time}_i \;=\;& \beta_0 + \beta_1 * (\textit{Bag-Fee} = 1) + \beta_2 * (\textit{Bag-Fee} = 2) + \\
& \beta_3 * \textit{Route}_i + \beta_4 * \textit{Origin}_i + \beta_5 * \textit{Carrier}_i + \\
& \beta_6 * \textit{Month}_i + \beta_7 * \textit{Day-of-Week}_i + \\
& \beta_8 * \textit{Dep-Time-Block}_i + \beta_9 * \textit{Arr-Time-Block}_i + \\
& \beta_{10} * \textit{Dep-Congestion}_i + \beta_{11} * \textit{Arr-Congestion}_i + \\
& \beta_{12} * \textit{Aircraft-Age}_i + \beta_{13} * \textit{Avg-Passengers}_i + \varepsilon_i. \qquad (2.2)
\end{aligned}$$

2.5 Results and Discussion

2.5.1 Spillover-Adjusted Departure Delay

The results of the estimation of our Tobit1 model are shown in Table 2.6[15]. The coefficient for the *Bag-Fee* indicator variable which indicates one checked bag fee as being implemented, is negative and statistically significant (-1.8701; $p<0.0001$). This indicates that when the flights encounter departure delays, the implementation of one checked bag fees reduces *SpAdj-Departure-Delay* by 1.8701 minutes versus no implementation of these fees. In other words, the airlines that implemented the fee for one checked bag saw their departure performance improve, whereas Southwest Airlines experienced a negative impact on its departure performance. We thus find support for Hypothesis 1A, and consequently reject Hypothesis 1B. The coefficients for the categorical variables for *Origin, Route, Carrier, Month, Day-of-Week, Dep-Time-Block,* and *Arr-Time-Block* are not reported to conserve space, although they are statistically significant. Table 2.6 also shows that the other control variables, except *Avg-Passengers*, are statistically significant.

Our study suggests that in the 35-day period following the date of implementing fees for one checked bag, the airlines that did implement these fees experienced improved relative performance in terms of their departure delays. We expect that the price-insensitive passengers or those passengers traveling with only one checked bag were indifferent to this policy change. The same policy may have caused a change in other passengers' behavior in the sense that fewer passengers may have checked a second bag while still flying their preferred airline. Another possible explanation is that price-sensitive customers of those airlines that charged for one checked bag started flying Southwest instead. While it is obvious that additional passengers generate additional revenues for an airline, it is less obvious that more

[15] The results were robust when controlling for *Scheduled-Block-Time* variable as well.

Table 2.6 Summary of Tobit1 regression

Dependent variable: SpAdj-Departure-Delay			
Variable	d.f.	Level	Parameter estimate
Intercept			-23.5479***
			(5.6745)
Bag-Fee	1	0	-
		1	-1.8701***
			(0.2712)
Origin	56		
Route	1600		
Carrier	7		
Month	3		
Day-of-Week	6		
Dep-Time-Block	18		
Arr-Time-Block	18		
Dep-Congestion	1		0.2132***
			(0.0112)
Arr-Congestion	1		0.0768***
			(0.0091)
Aircraft-Age	1		-0.0150
			(0.0131)
Avg-Passengers	1		0.0004
			(0.0031)
Origin-Prcp	1		0.0336***
			(0.0010)
Dest-Prcp	1		0.0409***
			(0.0010)
Origin-Awnd	1		0.0701***
			(0.0052)
Dest-Awnd	1		0.0965***
			(0.0050)
Log Likelihood	-1,018,613		
Number of observations used	448,659		

Note. Standard errors are shown in parantheses.
The number of observations used is different from the first dataset sample size due to missing values of Aircraft-Age, Avg-Passengers, Origin-Prcp, Dest-Prcp, Origin-Awnd, and Dest-Awnd variables.
***$p < 0.0001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$

passengers represent an increased likelihood of departure delays. One indication of this relationship comes from AirTran Airways' Senior VP who openly declared that it is sometimes better to delay a flight to wait for passengers or baggage [McCartney, 2010b]. Thus, the more passengers, the higher the probability of a delayed pushback.

Table 2.7 lists the Tobit2 estimation results[16]. The coefficient for the *Bag-Fee* variable which indicates the one checked bag fee as being implemented, is negative and marginally significant (-0.4443; p<0.1), whereas the coefficient for the *Bag-*

[16]The results were robust when controlling for *Scheduled-Block-Time* variable as well.

Fee variable corresponding to implementing two checked bag fees, is positive and statistically significant (0.6229; p<0.05).

Table 2.7 Summary of Tobit2 regression

Dependent variable: SpAdj-Departure-Delay			
Variable	d.f.	Level	Parameter estimate
Intercept			-21.8447***
			(3.2547)
Bag-Fee	2	0	-
		1	-0.4443^{+}
			(0.2485)
		2	0.6229*
			(0.2504)
Origin	56		
Route	1646		
Carrier	7		
Month	10		
Day-of-Week	6		
Dep-Time-Block	18		
Arr-Time-Block	18		
Dep-Congestion	1		0.2025***
			(0.0060)
Arr-Congestion	1		0.1139***
			(0.0048)
Aircraft-Age	1		0.0914***
			(0.0065)
Avg-Passengers	1		0.0474***
			(0.0019)
Origin-Prcp	1		0.0335***
			(0.0005)
Dest-Prcp	1		0.0399***
			(0.0005)
Origin-Awnd	1		0.0712***
			(0.0029)
Dest-Awnd	1		0.0535***
			(0.0028)
Log Likelihood	-3,760,650		
Number of observations used	1,718,598		

Note. Standard errors are shown in parantheses.
The number of observations used is different from the second dataset sample size due to missing values of Aircraft-Age, Avg-Passengers, Origin-Prcp, Dest-Prcp, Origin-Awnd, and Dest-Awnd variables.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

That is, when the flights encounter departure delays, the implementation of two checked bag fees has triggered an additional increase in *SpAdj-Departure-Delay* relative to the implementation of only one checked bag fees of 1.0672 minutes. We reject Hypothesis 2A as we find support for Hypothesis 2B. Similar to Table 2.6, the coefficients for the categorical variables for *Origin, Route, Carrier, Month, Day-of-*

Week, Dep-Time-Block, and *Arr-Time-Block* are not shown in the interest of space, although they are statistically significant. As seen in Table 2.7, the other control variables are also statistically significant.

Thus, when examining departure delays over a longer period of time covering the time periods around the implementation dates of one checked bag and two checked bags fees policies, the fee for one checked bag showed the same impact as previously described. Moreover, the implementation of two checked bags fees policy indicated worse departure performance relative to the implementation of only one checked bag fee, as well as relative to not charging for checked bags. Our finding can be explained by the fact that the passengers that had previously traveled with only one checked bag may have changed their behavior and began carrying on their baggage instead, increasing the likelihood of a delayed departure.

Because JetBlue Airways started charging their passengers for one checked bag on June 1st 2008, we did not include its flights in our first dataset. Its inclusion would have prevented us from identifying the effect of one checked bag fees implemented by the other airlines, as its 'after' 35-day time window overlaps with the period of charging for the first two checked bags by American Airlines, US Airways, and United Airlines. Yet, when including JetBlue Airways' flights in the second dataset (i.e. March 31, 2008 - January 8, 2009), the Tobit results in Table 2.8[17] show positive and statistically significant coefficients of *Bag-Fee* variable for both one checked bag fee (0.5453; $p<0.05$) and two checked bags fees (1.3410; $p<0.0001$) policies.

To better understand the change of sign for the coefficient for the one checked bag fee variable[18], we created two datasets, i.e. 'Legacy Carriers' dataset comprising American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, United

[17] The results were robust when controlling for *Scheduled-Block-Time* variable as well.

[18] We did not include interaction terms between the *Bag-Fee* indicator variables and *Carrier* dummy variable since they are complicated to interpret in nonlinear models such as Tobit [Ai and Norton, 2003].

Table 2.8 Summary of Tobit2 regression - JetBlue Airways included

Dependent variable: SpAdj-Departure-Delay			
Variable	d.f.	Level	Parameter estimate
Intercept			-21.5563***
			(3.3168)
Bag-Fee	2	0	-
		1	0.5453*
			(0.2377)
		2	1.3410***
			(0.2492)
Origin	56		
Route	1698		
Carrier	8		
Month	10		
Day-of-Week	6		
Dep-Time-Block	18		
Arr-Time-Block	18		
Dep-Congestion	1		0.2124***
			(0.0060)
Arr-Congestion	1		0.1258***
			(0.0049)
Aircraft-Age	1		0.0929***
			(0.0067)
Avg-Passengers	1		0.0496***
			(0.0019)
Origin-Prcp	1		0.0335***
			(0.0005)
Dest-Prcp	1		0.0422***
			(0.0005)
Origin-Awnd	1		0.0685***
			(0.0029)
Dest-Awnd	1		0.0582***
			(0.0028)
Log Likelihood	-3,897,351		
Number of observations used	1,779,002		

Note. Standard errors are shown in parantheses.
The number of observations used is different from the dataset sample size due to missing values of Aircraft-Age, Avg-Passengers, Origin-Prcp, Dest-Prcp, Origin-Awnd, and Dest-Awnd variables.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Airlines, US Airways, and Southwest Airlines, and 'Low-Cost Carriers' dataset comprising AirTran Airways, JetBlue Airways, and Southwest Airlines[19]. The Tobit results in Table 2.9[20] show positive and statistically significant coefficients of *Bag-Fee* variable for both one checked bag fee and two checked bags fees policies, for Low-Cost

[19] As Southwest Airlines is used as control in our experiments (being the only major airline that never charged a bag fee), we include it in both datasets.

[20] The results were robust when controlling for *Scheduled-Block-Time* variable as well.

Table 2.9 Summary of Tobit2 regression: Legacy Carriers vs. Low-Cost Carriers

	Dependent variable: SpAdj-Departure-Delay					
	Legacy Carriers			Low-Cost Carriers		
Variable	d.f.	Level	Parameter estimate	d.f.	Level	Parameter estimate
Intercept			-22.6933***			-29.3415***
			(3.2435)			(2.0576)
Bag-Fee	2	0	-	2	0	-
		1	-1.8724***		1	6.3123***
			(0.2598)			(0.3095)
		2	-0.1719		2	3.2532***
			(0.2557)			(0.5110)
Origin	56			36		
Route	1581			856		
Carrier	6			2		
Month	10			10		
Day-of-Week	6			6		
Dep-Time-Block	18			18		
Arr-Time-Block	18			18		
Dep-Congestion	1		0.1991***	1		0.1468***
			(0.0060)			(0.0067)
Arr-Congestion	1		0.1224***	1		0.1256***
			(0.0051)			(0.0062)
Aircraft-Age	1		0.0867***	1		0.1723***
			(0.0065)			(0.0072)
Avg-Passengers	1		0.0443***	1		0.1078***
			(0.0019)			(0.0036)
Origin-Prcp	1		0.0331***	1		0.0276***
			(0.0005)			(0.0005)
Dest-Prcp	1		0.0384***	1		0.0293***
			(0.0005)			(0.0005)
Origin-Awnd	1		0.0723***	1		0.048***
			(0.0029)			(0.0030)
Dest-Awnd	1		0.0543***	1		0.0276***
			(0.0028)			(0.0029)
Log Likelihood	-3,627,536			-1,945,625		
Number of observations used	1,642,925			816,985		

Note. The Legacy Carriers include American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, US Airways, and Southwest Airlines.
The Low-Cost Carriers include AirTran Airways, JetBlue Airways, and Southwest Airlines.
Standard errors are shown in parantheses.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Carriers. Thus, it appears that JetBlue and AirTran Airways passengers were more likely to carry their previously checked bags on board. This in turn increases the likelihood of a delayed departure, especially considering the loose enforcement of carry-on rules leading to traffic jams while boarding.

While citing Boeing's discovery that boarding times had doubled over the last two decades, Mouawad [2011] has recently argued that "[c]hecked-baggage fees have only added to the problem, because travelers now take more roll-ons onboard, blocking the isles as they try to cram their belongings into any available space". Moreover, this practice increases the likelihood of lack of overhead space, which in turn leads to "bags that need to be checked at the last minute - a common cause of delayed flights". On the other hand, Table 2.9 shows negative coefficients of the same variable, and thus indicates that American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, United Airlines, and US Airways passengers were less price sensitive and did not change their behavior to carry on more bags as the low-cost carriers customers appear to have.

2.5.2 Scheduled Block Time

The results of the OLS1 regression estimates for each airline's scheduled block times are shown in Table 2.10. The coefficient of *Bag-Fee* corresponding to one checked bag fee is not significant, whereas the coefficient of *Bag-Fee* corresponding to the first two checked bags fees is negative and statistically significant (-0.3796; $p<0.0001$), providing partial support for Hypothesis H3B. These results indicate that any anticipated change in departure performance due to one checked bag fee policy was not originally captured in airlines' scheduled block times. The airlines were not able to capture it as they typically schedule the block times about six months in advance [Deshpande and Arıkan, 2012]. On February 4$^{\text{th}}$, 2008 United Airlines was the first airline announcing its plan to implement the fee for the second piece of baggage in three months, namely starting May 5$^{\text{th}}$, whereas the other airlines were still contemplating a similar move[21].

[21] "American declined to comment on United's move. So did Delta Air Lines Inc., citing a policy of not discussing future fee changes. US Airways Group Inc., and Northwest Airlines Corp. said they are studying it. Discount king Southwest Airlines Co. last month started charging $25 for a third checked bag in place of letting customers bring three bags free of charge. But a spokesman said Southwest doesn't anticipate charging for the first two pieces, if they aren't overweight."[Carey, 2008]

Table 2.10 Summary of OLS1 regression

Dependent variable: Scheduled-Block-Time			
Variable	d.f.	Level	Parameter estimate
Intercept			56.3201***
			(0.3259)
Bag-Fee	2	0	-
		1	-0.0022
			(0.0217)
		2	-0.3796***
			(0.0229)
Origin	56		
Route	1712		
Carrier	8		
Month	10		
Day-of-Week	6		
Dep-Time-Block	18		
Arr-Time-Block	18		
Dep-Congestion	1		0.0924***
			(0.0006)
Arr-Congestion	1		0.0530***
			(0.0005)
Aircraft-Age	1		0.0248***
			(0.0006)
Avg-Passengers	1		-0.0120***
			(0.0002)
R-square	0.9947		
Number of observations used	1,839,718		

Note. Standard errors are shown in parantheses.
The number of observations used is different from the second dataset sample size due to missing values of Aircraft-Age and Avg-Passengers variables.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

It is well known that airlines pad their scheduled block times so that even late flights technically arrive on time and boost the "on-time" performance records released to the public. However, this action can frustrate passengers who have to wait on board since the planes often arrive well before gates are available. As American Airlines' VP of Operations Planning and Performance simply put it, "[e]ven if you arrive on time, the goodwill is blown, and people think we are idiots" [McCartney, 2012b]. Referring to the padded approach, US Airways' COO also recognized: "You can do all sort of things to make up for poor performance. But you sacrifice efficiency, the passenger experience, the employee experience and profits" [McCartney, 2012b]. Our results indicate that the airlines anticipated an improvement in their departure performance due to the checked bag fees policies. Given that inflated scheduled block times irritate passengers and are costly, the results indicate that airlines decreased the scheduled block times and, given the longer time span over which the first two checked bags fees policy was implemented, the effect is captured in our results. We thus have an indication that the operations managers of these airlines may have acted proactively to the marketing decision to impose fees for checked bags, but they did so in the wrong direction as their departure delay performance actually decreased.

2.5.3 Robustness Checks

To rule out the possibility that our results are driven by other factors within the airline's control, we used the second dataset to analyze the impact of *Bag-Fee* on *Actual-TurnAround-Time*, which is the time duration between the next flight's actual departure time and the preceding flight's actual arrival time on an aircraft rotation. We employ an OLS regression model (labeled OLS2), as follows:

$$
\begin{aligned}
\textit{Actual-TurnAround-Time}_i \;=\;& \beta_0 + \beta_1 * (\textit{Bag-Fee} = 1) + \beta_2 * (\textit{Bag-Fee} = 2) + \\
& \beta_3 * \textit{Route}_i + \beta_4 * \textit{Origin}_i + \beta_5 * \textit{Carrier}_i + \\
& \beta_6 * \textit{Month}_i + \beta_7 * \textit{Day-of-Week}_i + \\
& \beta_8 * \textit{Dep-Time-Block}_i + \beta_9 * \textit{Arr-Time-Block}_i + \\
& \beta_{10} * \textit{Dep-Congestion}_i + \beta_{11} * \textit{Aircraft-Age}_i + \\
& \beta_{12} * \textit{Avg-Passengers}_i + \beta_{13} * \textit{Origin-Awnd}_i + \\
& \beta_{14} * \textit{Origin-Prcp}_i + \varepsilon_i. \qquad (2.3)
\end{aligned}
$$

Table 2.11 shows the results according to Eq.2.3. The coefficient for the *Bag-Fee* variable corresponding to charging only for one checked bag, is negative (-0.1326) but not statistically significant. The coefficient for the *Bag-Fee* variable corresponding to the implementation of first two checked bag fees is positive and statistically significant (0.9624; $p<0.0001$), indicating that the two checked bags fees policy brings about

Table 2.11 Summary of OLS2 regression

Dependent variable: Actual-TurnAround-Time			
Variable	d.f.	Level	Parameter estimate
Intercept			42.5939***
			(1.5736)
Bag-Fee	2	0	-
		1	-0.1326
			(0.1277)
		2	0.9624***
			(0.1358)
Origin	56		
Route	1664		
Carrier	8		
Month	10		
Day-of-Week	6		
Dep-Time-Block	18		
Arr-Time-Block	18		
Dep-Congestion	1		0.1276***
			(0.0035)
Aircraft-Age	1		-0.0184***
			(0.0037)
Avg-Passengers	1		0.0745***
			(0.0012)
Origin-Prcp	1		0.0041***
			(0.0003)
Origin-Awnd	1		-0.0147***
			(0.0016)
R-square	0.3782		
Number of observations used	1,285,420		

Note. Standard errors are shown in parantheses.
The number of observations used is different from the second dataset sample size due to missing values of Actual-TurnAround-Time, Aircraft-Age and Avg-Passengers variables.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

an additional increase in *Actual-TurnAround-Time* relative to charging only for one checked bag of 1.095 minutes. This incremental effect is also consistent with the incremental effect caused by the two checked bags fees policy on *SpAdj-Departure-Delay*. Because our model includes a rich set of control variables, we are able to explain about 38% of the variation in *Actual-TurnAround-Time* variable.

As another robustness check, we conducted a paired t-test by comparing the delay differences experienced by the airlines that implemented the one checked bag fee against the delay differences encountered by Southwest Airlines within the same time windows at the corresponding airports. For each airport-airline combination, we calculated the departure delay averages in the 30-day period preceding (the Before period) and the 30-day period following (the After period) the implementation of the one checked bag fee policy by the specific airline. Thus, for each airport, we calculated the average difference in the departure delays, i.e. average delay in the After period minus average delay in the Before period. Further, for comparison purposes we paired the departure delay difference experienced by an airline at a particular airport with the departure delay difference experienced by Southwest at the same airport. We computed relative weighted averages for non-Southwest airlines group and Southwest, by deriving the relative market shares from the absolute market shares of airlines within each airport as calculated by the number of flights completed. To examine whether there is a difference in departure delays across the two groups, we performed a paired t-test, whose difference of -3.68 minutes was statistically significant with a p-value < 0.05. Thus, Southwest Airlines experienced a greater difference in departure delays between the After and Before periods than the other airlines, at the 57 airports. That is, the airline that did not implement one checked bag fees encountered a greater relative average departure delay than the airlines that imposed fees on one checked bag. We did not conduct a similar test for the first two checked bags fees, as the airlines started charging these fees over a longer time horizon (see Table 2.2), which makes it difficult to isolate an unique effect of this policy using this technique. Nor did we include JetBlue in this test, for the same reasons we did not include it in the Tobit1 regression. However, this test adds support to our Tobit1 regression results.

2.6 Conclusions

While investigating whether the social planner would let bags fly free, Allon, Bassamboo, and Lariviere [2011] argue that "baggage fees are not just about revenue. They serve to alter consumer behavior in a manner that is beneficial to both the firm and customers. The firm enjoys lower costs and passes some of these savings on to customers". Our study provides empirical evidence that the checked baggage fee policies did alter passengers' behavior, yet in a different way than previously postulated. While the reduction in the number of checked bags may indeed have resulted in savings due to lower labor costs for handling checked bags, our findings suggest that the resulting increase in the quantity of bags carried-on may have had a detrimental effect on the airline's costs through a decrease in their on-time departure performance. As is the case with many incentives and penalties, finding the right amount for each that results in a positive change in customers' behavior is a complex task. Our findings highlight factors, such as the effect of carry-on bags, that need to be incorporated in designing incentive schemes.

Our research also sheds some light on the decisions made by a very operationally focused airline. When the other airlines started charging for one checked bag, Southwest Airlines' decision to not charge for bags went against their high operational service level strategy as their relative departure delay performance initially decreased. When the other airlines began charging for the first two checked bags, however, Southwest's decision appears to be in line with their strategy. While bags may not really "fly free" in an operational sense at Southwest, not charging passengers for checking bags does seem to help avoid the worst carry-on abuses seen at other airlines that have led to a degradation of on-time departure performance. This degradation seems to be especially pronounced for low cost airlines. Southwest is currently faced with this decision again as it has recently merged with AirTran Airways, an airline that currently charges for checked bags. Thus, for a company like Southwest Airlines, which has a long history of being one of the best in its industry for operational performance and customer satisfaction, the decision of not charging AirTran Airways' passengers for the first two checked bags appears to be in line with their operational strategy.

Ultimately, operations managers need to be involved in the discussions about marketing initiatives such as this one to evaluate the operational impact of marketing initiatives. We have an indication that this occurred at some level as our results support the argument that after initially observing little performance decline, the airlines felt the need to shorten their scheduled block times. In hindsight, however, this may not have been the right decision given the performance deterioration observed after they began charging for the two checked bags.

Increased boarding times as a result of baggage fees have financial implications as well. In 2005 Southwest estimated that, if its boarding times increased by 10 minutes per flight, it would need 40 more planes at a cost of $40 million each to fly the same number of flights [Lewis and Lieber, 2005]. When other airlines started charging for one bag, our analysis shows an impact of increased departure delays of 1.87 minutes per flight for Southwest, resulting in an estimated financial impact of approximately $40 million per year [22]. We speculate that Southwest now achieves savings of similar magnitude after other airlines implemented the first two checked bags fee policy. As Southwest completes its merger with AirTran Airways, they face a difficult decision of whether to keep the baggage fee policy in place at AirTran or convert them to their no baggage fee policy. Our research shows that this decision is more nuanced than it may first appear. As of this writing, Southwest has decided to keep the baggage fee policy at AirTran in place for the short term. Our research helps shed light on some of the tradeoffs involved in this decision.

[22] This estimation is based on a delay cost of $19.49 per minute for Southwest Airlines [Ferguson, Kara, Hoffman, and Sherry, 2012] which operates more than 3,000 flights a day (`http://swamedia.com/channels/Corporate-Fact-Sheet/pages/corporate-fact-sheet#history` last accessed March 7, 2013).

Chapter 3

Airline Customer Preferences in the Baggage Fees Era

3.1 Introduction

In the early 2008, record fuel prices were a source of severe financial pressure in the U.S. airline industry. For competitive reasons, the airlines had not been able to raise ticket prices enough to offset that increasing expense. Consequently, the airlines were looking for ways to both increase revenues and reduce costs. Moving customers to "a la carte" pricing has proved such a way, and bags checking has become a service that was once complimentary. Since instituted in 2008 by most U.S. airlines, the fees for checked bags have proven a steady revenue stream. As recently as 2012, the baggage fees amounted to $3.5 billion, or 3.8% increase compared to 2011, when the baggage fees generated approximately one-half of the industry's profit of $7 billion [BTS, 2013]. Given that in 2012 only 0.8% more total system passengers were carried by U.S. airlines than in 2011 [BTS Press Release, March 2013], we can conclude the growing acceptance of baggage fees by travelers, which in turn, has helped return the industry to profitability.

The previous literature (e.g., Allon, Bassamboo, and Lariviere [2011]) has postulated an additional purpose of the baggage fees, i.e. "to alter consumer behavior in a manner that is beneficial to both the firm and customers". That is, one approach taken by airlines in order to lower their costs has been to discourage travelers from checking bags by implementing checked baggage fees, which some have argued would also benefit travelers. Indeed, it has been documented that the number of checked bags declined since the airlines imposed checked baggage fees [U.S. Government Accountability Office, 2010]. Thus, customers who check baggage enjoy fewer opportunities for mishandled baggage. Yet, the recent 2013 North America Airline Satisfaction Study by J.D. Power & Associates has revealed that "[b]aggage fees continue (...) to lead to lower satisfaction levels" [J.D. Power & Associates Press Release, May 2013] as they still represent a source of dissatisfaction for customers who check bags.

While offering the service of checking bags adds additional costs to the airlines, it remains to be shown what benefits this service provides, beyond the obvious increase in revenues from the fees. In other words, airlines are interested in determining whether they should change their operations policies and spend more or less resources to make it easier or harder for customers to check bags. We seek to provide guidance for this decision by explaining a potential new way of segmenting travelers based on their sensitivities to itinerary attributes. More specifically, we investigate whether travelers who check bags and travelers who do not check bags have different sensitivities to the historical on-time performance, total travel time, airfare, and number of connections when choosing an itinerary. Addressing this issue is particularly important as most major airlines are evaluating operational changes that may make the process of checking bags even less convenient than it currently is. If these actions result in the loss of additional customers who prefer to check their bags, then it is important to understand the relative value of this customer segment.

To empirically examine these issues, we use data from an Internet-based stated-preference survey conducted by Resource Systems Group, Inc. in the Spring of 2012, who surveyed 878 U.S. domestic travelers who had flown a domestic flight within the last six months. We analyze this data using discrete choice modeling, to help understand why a customer makes a particular choice and how the customer makes trade-offs among the characteristics of the choices [Garrow, 2010]. Our results confirm previous studies that show the positive effect of on-time performance, and negative effects of total travel time, airfare, and number of connections on the probability that a traveler chooses a particular itinerary. In addition, we find evidence that travelers who check bags appear to be more valuable customers than customers who do not check bags are. Regarding the total travel time of an itinerary, we identify a less negative impact on the itinerary utility for travelers who check bags versus travelers who do not check bags. Next, we find the airfare as having a more negative impact on the itinerary utility for travelers who do not check bags relative to travelers who check bags and pay the associated baggage fees. Our results show a more negative impact of the airfare on the itinerary utility for travelers who check bags but do not pay the associated fees versus travelers who check bags and pay the associated fees. Finally, we identify a less negative impact of the number of connections for travelers who check bags versus those who do not check bags relative to those who check bags. Thus, travelers who check bags appear to be less sensitive to total travel time, airfare, and number of connections than those travelers who do not check bags. These findings have important implications for airlines that are considering making further cost savings in their baggage checking operations.

The remainder of this study is organized as follows. Section 2 reviews relevant literature on air travel choice behavior, then the hypotheses tested in this study are presented in Section 3. The description of the data used in the analysis is shown in Section 4, along with the econometric framework of discrete choice models. Section 5 presents the estimation results of model specifications, while Section 6 concludes the paper.

3.2 Literature Review

Earlier studies of air travel choice behavior examined a single-dimension choice or only a few dimensions of choice such as origin and destination airports in regions with multiple airports, airline, desired departure and arrival times, airfare, aircraft type, access mode, etc. However, as travelers select a multi-dimension choice set, researchers shifted their focus towards the choice between itineraries as defined by multi-dimension choices. As such, a large body of research has been developed based on the online stated-preference survey of U.S. domestic air travelers conducted periodically by Resource Systems Group, Inc. since 2000, which has been supported by various airlines and government agencies [Garrow, 2010].

Warburg, Bhat, and Adler [2006] use the 2001 survey to model demographic and unobserved heterogeneity in *business* air travelers' sensitivity to service attributes in itinerary choice. They find that women, individuals traveling in a group, and high income earners are less sensitive to airfares than men, individuals traveling alone, and low income earners. They also find that frequent travelers and travelers who check bags are more time-tolerant, less likely to be influenced by on-time performance, and more patient to connections than occasional travelers and travelers who do not check bags.

Using the 2003 survey, Adler, Falzarano, and Spitz [2005] model the effects of airline, airport, aircraft type, airfare, access time, flight time, scheduled arrival time, and on-time performance on itinerary choices. Their results indicate the importance of factoring in traveler preference heterogeneity by using segmentation by trip purpose (i.e. business vs. non-business). Also, the service attributes included in their model have significant values to travelers, being impacted by the travelers' frequent flyer status. Although the on-time performance was not reported in a real-situation itinerary in 2003, the survey identifies it as an important selection criterion for travelers. Hess, Adler, and Polak [2007] further segment the same dataset into business, holiday, visiting friends and relatives (VFR) segments, and find for all of these segments a negative sensitivity to access time, airfare, flight time, and the number of connections, along with a positive sensitivity to improvements in on-time performance and top-ranked airports. Hess, Adler, and Polak [2007] also identify a higher sensitivity to airfare on longer flights for holiday and VFR segments, with no such significant sensitivity to airfare in case of business travelers. Unlike business and VFR travelers, holiday travelers were found to be more sensitive to on-time performance on longer flights. Finally, the results show negative effects of late arrival times for the case of business travelers, and early arrival times for the case of VFR travelers.

Using the 2005 survey, Hess [2007] conducts a posterior analysis of random taste coefficients in air travel behavior modeling, while Hess [2008] examines the treatment of reference alternatives in stated choice surveys for air travel choice behavior. Both studies show the expected impacts of all the attributes considered as affecting the utility of an itinerary, i.e. access time, airfare, flight time, on-time performance, number of connections, frequent flyer membership, and airport proximity. Further, Theis, Adler, Clarke, and Ben-Akiva [2006] use the same dataset to investigate the risk aversion to short connections in airline itinerary choice. Although these researchers speculate that travelers might incur lower utilities from shorter connecting time versus longer connecting time based on the potential discomfort of a rapid connection and the associated misconnection risk, they do not find support for their premise.

Finally, Hess and Adler [2011] analyze trends in air travel behavior by using four related stated-preference surveys (in 2000, 2001, 2002, and 2005) to examine how much the basic choice processes that travelers use to select flight alternatives have changed over this time period. They find changes in the type of air trips (fewer short trips due to time-consuming security checks), ticket booking (more online flight searches and self-ticketing) and preferences among individual airlines and airports (due to changed conditions and services).

Other researchers have also contributed to the air travel choice literature based on stated-preference survey methodology. For instance, Proussaloglou and Koppelman [1999] use a telephone survey to obtain stated preferences of travelers in the Chicago-Denver and Dallas-Denver markets, for whom reported choices of actual trips have been already collected. Their analysis shows negative effects of airfare, especially for leisure travelers, and schedule delay, and positive effects of frequent flyer membership, increased market presence of the carrier, and quality of service.

Using stated-preference data collected from international air travelers who have flown Taipei-Tokyo and Taipei-Hong Kong routes, Wen and Lai [2010] confirm the importance of service attributes such as airfare, schedule time difference, flight frequency, on-time performance, check-in service, in-flight seat space, and cabin crew service, when making airline choice. Similarly, based on stated-preference surveys of travelers in a Portuguese air corridor, Pereira, Almeida, de Menezes, and Vieira [2007] find the airfare, penalty for changes in the ticket, food, comfort, frequency, and reliability (as punctuality warranties) have the expected effect on itinerary choice.

Collins, Rose, and Hess [2012] use both traditional and interactive stated-choice surveys to elicit individuals' responses on air travel behavior regarding return travel from Sydney, Australia to either London or Paris. They find negative effects of the airfare, carbon tax, charge of flight change, flight time, number of connections, and arrival times. No aircraft effects have been retrieved, while positive effects have been found for the frequent flyer memberships.

A stated-preference experiment to analyze individuals' preferences for the main attributes defining the service offered by the airlines on the most important route connecting the Canary Islands archipelago with the Iberian Peninsula (i.e. Gran Canaria - Madrid) was conducted and used by Espino, Martín, and Román [2008] and Martín, Román, and Espino [2008]. Their analyses show the expected negative effects of airfare and penalty for changes in the ticket, and positive effects of free food on board, comfort (as leg room), frequency, and reliability (as compensation in case of delay). Also, Brey and Walker [2011] use an Internet-based stated preference survey conducted by the Boeing Company in the Fall of 2004 targeted to individuals searching for round trips within the continental U.S., and find negative effects of airfare and flight time.

To conclude, the previously mentioned studies model air travel choices by relying on stated preference experiments that compare customer choices between either a revealed preference alternative against one or more stated preference alternatives, or two or more stated preference alternatives. Our study, based on the Resource Systems Group survey data, is most similar to Adler, Falzarano, and Spitz [2005], Warburg, Bhat, and Adler [2006], Hess, Adler, and Polak [2007], and Hess and Adler [2011], who consider attributes such as airfare, flight time, on-time performance, number of connections, aircraft type, and carrier, that potentially affect itinerary choice.

Our study adds to the literature on air travel choice behavior by modeling airline service trade-offs in air itinerary choices as recently as 2012. Recognizing that airlines are facing domestic changes in their business environment and in customer behavior, Teichert, Shehu, and von Wartburg [2008] assert that class flown and trip purpose (i.e. business vs. leisure) have become obsolete, failing to accurately discriminate heterogeneous customer segments. Adler, Falzarano, and Spitz [2005] emphasize the importance of “explicitly accounting for traveler preference heterogeneities by using segmentation, interaction effects, and random parameter specifications”. We take these aspects into consideration when seeking a better understanding of the impact the checked bags policies have had on customer choice. More specifically, we explore whether the fact that customers check bags or not identifies customers into a distinct segment, similar to how trip purpose has been explored in previous studies (see business vs. non-business in Adler, Falzarano, and Spitz [2005]; business, holiday and VFR in Hess, Adler, and Polak [2007]).

Whether the travelers check bags or not is also among the trip related characteristics considered by Warburg, Bhat, and Adler [2006]. However, their analysis is based on the Spring 2001 survey of business travelers, when no U.S. airlines were charging their passengers for the first two checked bags. The U.S. domestic air industry has changed dramatically since the Spring of 2001. The range of options available to air travelers has increased in many markets, and most airlines implemented fee policies on the first two checked bags in 2008. As such, further examination of the attributes valued by travelers is warranted four years after most U.S. airlines implemented fee policies on the first two checked bags. Moreover, although on-time performance estimates were available, most online reservation services have not provided these data until recently. Thus, by using a 2012 survey data, our study is a more recent reflection of the purchasing behavior of airline customers.

3.3 Hypothesis Development

As any other organizations, airlines are interested in the satisfaction level of their customers. One aspect that delights air customers is the on-time performance, often used as a proxy for service quality, and one of the key performance indicators in the airline industry. Although both departure performance and arrival performance theoretically define the on-time performance of a flight, it is the arrival times that can boost on-time rankings charted by the DOT. In ranking flight delays among airlines, the DOT uses the percentage of flights with delayed arrivals. This measure is widely reported by the media as the official metric of on-time performance of a flight. Although the duration of delay is not factored in the on-time performance rankings, the numbers can have a real influence on public perception. Suzuki [2000] suggests that travelers' choice of airlines may be affected by the on-time arrival experience of travelers. According to Mazzeo [2003, p. 277], the expected on-time performance is a "key non-pecuniary component of an air traveler's utility function. Such a consumer would compare prices and expected on-time performance of the competing carriers on the route for which he or she was buying a ticket. To the extent that consumers' expectation of future delays are based on a carrier's past on-time performance on that route, one potential cost of flight delays for airlines is reduction in future demand." In this sense, Adler, Falzarano, and Spitz [2005] identify on-time performance as an important selection criterion for travelers based on a stated-preference survey conducted in 2003, when travelers did not have convenient access to this information when booking a flight. In the recent years, the on-time performance of flights has been used to influence customer bookings through its availability on airlines' and travel agencies' websites.

Based on a 2001 survey of business travelers, Warburg, Bhat, and Adler [2006] find that business travelers who check bags are less time-sensitive and subsequently less impacted by on-time performance than business travelers who do not check bags. We also expect this relationship to hold for leisure travelers (our respondents include both business and leisure travelers). Thus, we suggest the following hypotheses:

HYPOTHESIS 1A. *The historical on-time performance of an itinerary has a positive impact on the utility of that itinerary.*

HYPOTHESIS 1B. *The historical on-time performance of an itinerary has a less positive impact on the utility of that itinerary for customers who check bags versus customers who do not check bags.*

Airlines frequently pad their scheduled block times so that even late flights technically arrive on time and boost the "on-time" performance records released to the public [McCartney, 2007, 2010c]. However, this practice can frustrate passengers who have to wait on board since the planes often arrive well before gates are available. Thus, from the customer standpoint, the most realistic schedule is the most desirable [McCartney, 2010c]. In addition to realistic schedules, customers prefer short-duration flights over long-duration flights on the same route.

As previously mentioned, Warburg, Bhat, and Adler [2006] find that business travelers who check bags are less time-sensitive than business travelers who do not check bags. They explain their finding through the additional time those business travelers are willing to spend at the origin airport checking bags and then retrieving them at the destination airport. We expect this finding to be true for leisure travelers as well. Thus, the following hypotheses are suggested:

HYPOTHESIS 2A. *The total travel time of an itinerary has a negative impact on the utility of that itinerary.*

HYPOTHESIS 2B. *The total travel time of an itinerary has a less negative impact on the utility of that itinerary for customers who check bags versus customers who do not check bags.*

Estimating customer price sensitivity from transaction data is problematic, as customers may sometimes purchase a more expensive airfare only when the less expensive airfares have been sold out [Hess, Adler, and Polak, 2007]. However, this difficulty in retrieving significant effects for the airfare can be overcome by stated-preference data which allows explicit specification of available alternatives. Works such as Proussaloglou and Koppelman [1999], Adler, Falzarano, and Spitz [2005], Theis, Adler, Clarke, and Ben-Akiva [2006], Warburg, Bhat, and Adler [2006], Hess [2007], Pereira, Almeida, de Menezes, and Vieira [2007], Hess, Adler, and Polak [2007], Hess [2008], Hess [2010], Wen and Lai [2010], and Collins, Rose, and Hess [2012], have identified the negative impact of the airfare on the utility of an alternative for all customers as well as different segments (business travelers, holiday travelers, 'visiting friends and relatives' travelers).

It is generally understood that higher priced items trigger a higher price sensitivity than lower priced items. Given that checked baggage fees increase the total cost of travel, price sensitivity increases with the total cost. Thus, we expect those who check bags to be more price sensitive to airfares than those who do not check bags, given the higher total cost of travel. Travelers who do not personally pay for their travel, including baggage fees (i.e. business travelers or flying using redeemed frequent flyer points), may be less affected by the checked baggage fees than those who pay for their travel and check bags. Moreover, given that an airline knows about a potential customer whether or not she has historically checked bags, we expect travelers who check bags but do not pay the corresponding fees and travelers who do not check bags to share the same price sensitivity. Overall, however, we expect the airfare to have a more negative impact on the choice of customers who check bags than customers who do not check bags. Thus, we propose the following hypotheses:

HYPOTHESIS 3A. *The airfare of an itinerary has a negative impact on the utility of that itinerary.*

HYPOTHESIS 3B. *The airfare of an itinerary has a more negative impact on the utility of that itinerary for customers who check bags and pay the associated fees versus customers who do not check bags.*

HYPOTHESIS 3C. *The airfare of an itinerary has a similar negative impact on the utility of that itinerary for customers who check bags but do not pay the associated fees versus customers who do not check bags.*

HYPOTHESIS 3D. *The airfare of an itinerary has a more negative impact on the utility of that itinerary for customers who check bags and pay the associated fees versus customers who check bags but do not pay the associated fees.*

The number of connections is another aspect considered by customers when booking a trip. One commonly held belief among airline executives is that travelers prefer to avoid connections [Koppelman, Coldren, and Parker, 2008]. Graham, Garrow, and Leonard [2010] find evidence consistent with the belief that business travelers are more risk-adverse and/or time-sensitive on the outbound portion of their trip, and thus are less willing to choose connection(s) due to increased travel time and the additional risk that checked baggage may be delayed or lost. As Adler, Falzarano, and Spitz [2005] point out, more connections increase travel time and can negatively affect the on-time performance of the itinerary. In addition, connections bring along risk and/or inconvenience. More specifically, if travelers check bags, we expect them to show a higher sensitivity to the number of connections than those who do not check bags due to the additional risk of mishandled baggage. In this sense, an itinerary with connections may be more acceptable to travelers who do not check bags than to those who check bags. On the other hand, given the benefit from checking bags instead of inconveniently carrying them while disembarking, waiting for a connection, and reboarding, we expect travelers who check bags to have a lower sensitivity to the number of connections than those who do not check bags. Thus, an itinerary with connections may be more acceptable to travelers who check bags than to those who do not check bags.

The two opposite effects are not strong enough to support one hypothesis over another, hence no direction can be offered on how travelers who check bags differ from those who do not check bags with regard to the utility of the itinerary as influenced by the number of connections. Thus, we suggest the following hypotheses:

HYPOTHESIS 4A. *The number of connections of an itinerary has a negative impact on the utility of that itinerary.*

HYPOTHESIS 4B. *The number of connections of an itinerary has a different impact on the utility of that itinerary for customers who check bags versus customers who do not check bags.*

An illustration of the hypotheses tested in this study is given in Figure 3.1.

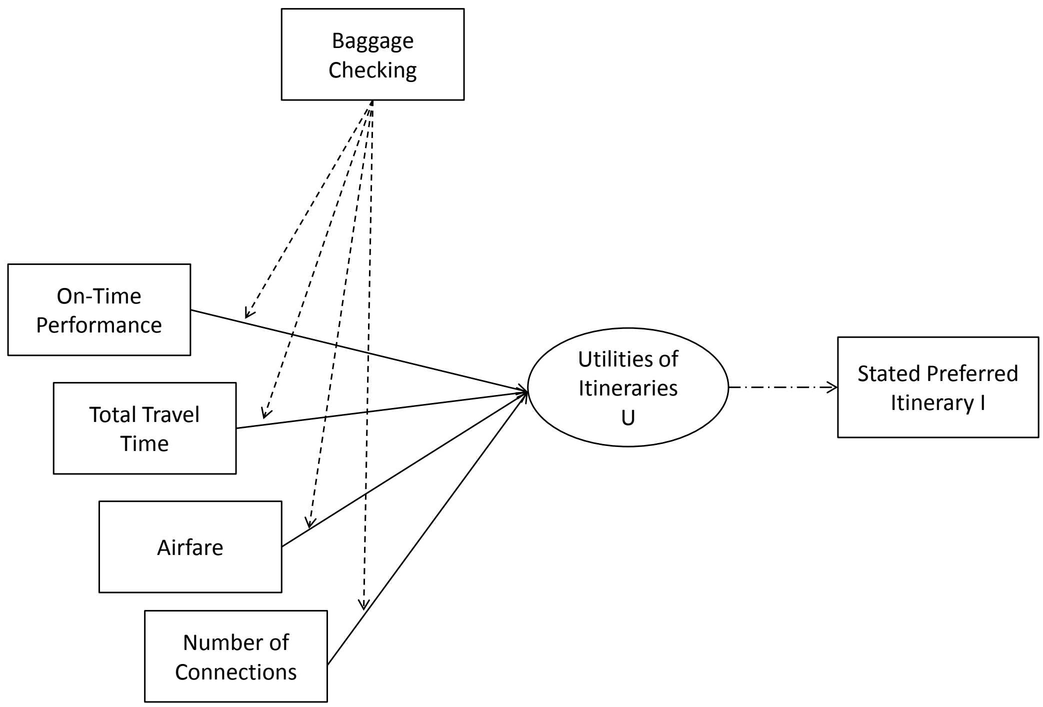

Figure 3.1 Conceptual model

3.4 Methods

3.4.1 Data

The data was generated by an Internet-based survey conducted by Resource Systems Group, Inc. in Spring 2012. An overview of the survey is provided in Figure 3.2. A total of 878 U.S. domestic travelers were surveyed on their most recent air travel experience. The qualified respondents have made a paid air trip within the last six months. The survey probed the respondents regarding their ticket purchasing attitude and experience, including the purchasing time relative to the trip date, level of satisfaction during the purchasing experience, and amount paid for the ticket.

Further, flight related information was collected, such as: the origin and destination airports, trip purpose, number of party members, trip length, number of checked and carry-on bags, baggage fees cost, on-time arrival performance, airline that flew the flight, aircraft type, number of connections, total travel time, flight quality, level of satisfaction regarding the flight, etc.

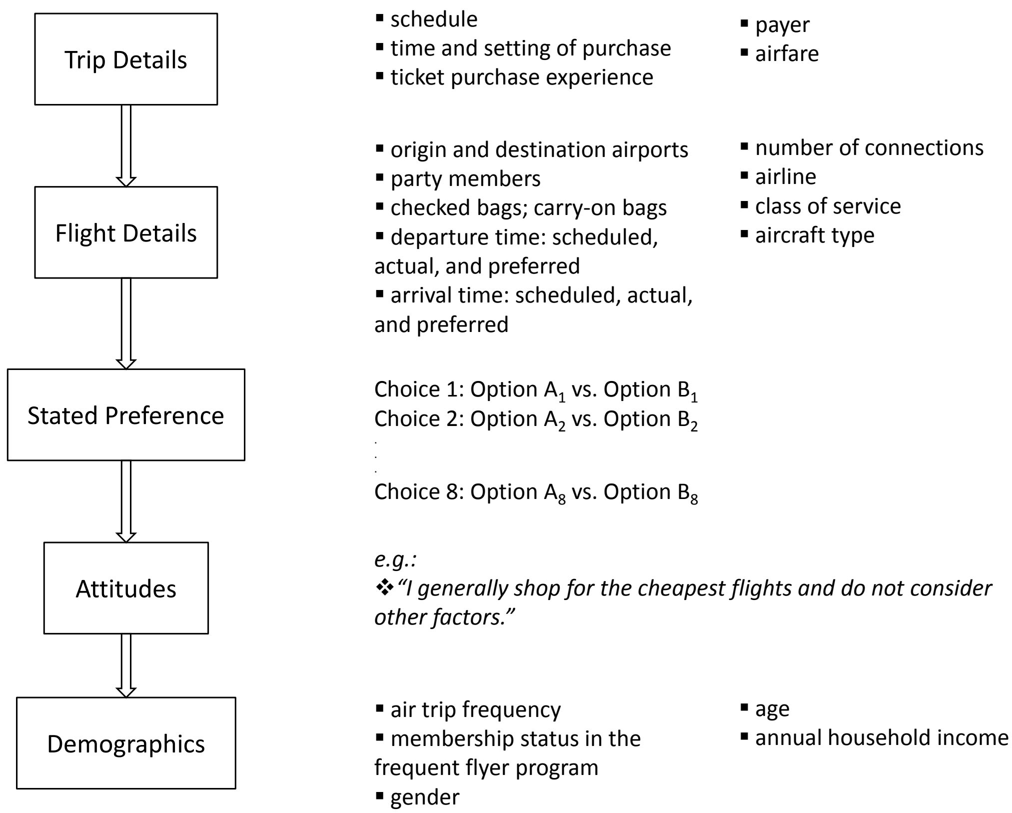

Figure 3.2 Overview of RSG survey

Thus, the survey used the actual flight information to provide a reference trip, i.e. the revealed preference trip. Next, discrete choice scenarios were built based on the outbound portion of the revealed preference trip, to capture responses to choice situations or so-called stated preferences. The scenarios were designed to trade off alternative flight options on the airline, aircraft type, flight departure and arrival times, number of connections, flight time (including connection times), on-time

Which of these two alternatives would you have preferred on your trip from the General Lawrence Logan International Airport (BOS) to the Los Angeles International Airport (LAX)?

Note: Flight information may change from screen to screen.

	Option A	Option B
Airline	Delta Air Lines	United Airlines
Aircraft Type	Standard Jet	Widebody Jet
Flight Departure Time	9:15 AM Eastern Time	7:20 AM Eastern Time
Number of Connections	Direct flight	1 connection
Total Travel Time	8 hours and 15 minutes	9 hours and 10 minutes
Flight Arrival Time	2:30 PM Pacific Time	1:30 PM Pacific Time
On-Time Performance	60% of these flights are on time	70% of these flights are on time
One-Way Fare	$180	$315
Select one:	○	○

(Question 6 of 8)

Figure 3.3 Stated-preference survey: screen-shot example

performance, and airfare. Each respondent was asked to make a choice in each of eight binomial choice sets. A choice-set example is illustrated in Figure 3.3.

As respondents had previously indicated their three preferred airlines and their least preferred airline from a list of 24 airlines (under the assumption of equal fares), the scenarios included airlines from this set of four. Four different types of aircraft (propeller, regional jet, etc.) were included in the scenarios. Table 3.1 shows the attributes and levels of the stated preference experiment.

In total, 7,024 choice sets were collected. Unlike previous studies, neither choice coincided with the revealed preference trip, avoiding non-trading and excessive point formation issues [Hess, 2008, Hess, Rose, and Polak, 2010]. As some respondents did not provide their frequent flyer membership status with specific airlines, the sample size was reduced to 6,996 choices between two itineraries resulting in 13,992

Table 3.1 Attributes and levels characterizing the itinerary in the stated preference experiment

Attribute	Definition and Level
Airline	Based on previously collected preferences (1st, 2nd, 3rd, least preferred airline)
Aircraft type	Propeller, regional jet, standard jet, widebody jet
Departure time	Departure time of itinerary
Arrival time	Arrival time of itinerary
Number of connections	Nonstop (0), one stop, two stops
Flight time	Total departure to arrival gate time (realistic values which varied based on design)
On-time performance	Percentage of times the flight itinerary is on time (60%, 70%, 80%, 90%)
Airfare	Based on airfare of revelead preference trip (-40%, -20%, +20%, +40%)

observations (half chosen and half not chosen). Further, the final sample size was reduced to 12,216 observations corresponding only to respondents who flied economy class (i.e. only 1,776 of 13,992 observations correspond to respondents who flied business class) on their revealed-preference trip.

In addition to the stated-preference experiment, the respondents were asked to rate 5-point Likert scale (from "strongly disagree" to "strongly agree") statements such as "I generally shop for the cheapest flights and do not consider other factors", etc. Finally, the survey collected demographics information such as the respondents' frequent flyer status, gender, age, income, and employment. Table 3.2 provides a breakdown of the sample. Thus, 35% of the respondents were aged under 34, 44% were aged between 35 and 54, and the remaining respondents were over 55 years old. The majority (77%) of respondents were working, either full-time (60%), part-time (7%), or self-employed (10%). With regard to the annual household income, 27% of respondents had under \$50,000 annual income, while 41% of the respondents had annual income between \$50,000 and \$100,000, and 32% had annual income over \$100,000.

Table 3.2 Demographics of respondents

	Percentage
Age	
34 or under	35
Between 35-54	44
55 or above	21
Employment status	
Full-time	60
Part-time	7
Self-employed	10
Unemployed	3
Others	20
Annual household income	
$49,999 or less	27
Between $50,000-$99,999	41
$100,000 or more	32
Gender	
Female	59
Male	41

A breakdown of the sample by the airline indicated by the respondents in the revealed-preference trip is provided in Table 3.3. This profile is representative of the overall U.S. air travel market in 2012, as described by the following market shares based on the percentage of airline customers on U.S. carriers: 15% - American Airlines; Delta Air Lines - 22%; Southwest Airlines - 18%; United Airlines & Continental Airlines - 19%; US Airways - 9%; all others - 17% [CNN Money, 2013].

Table 3.3 The revealed-preference trips by airline

Airline	Percentage	Airline	Percentage
AirTran Airways	3.42	JetBlue Airways	7.52
Air Canada	0.23	Pinnacle Airlines	0.11
Alaska Airlines	1.71	Southwest Airlines	21.98
Allegiant Air	0.46	Spirit Airlines	0.46
American Airlines	13.44	Sun Country Airlines	0.46
American Eagle	1.03	United Airlines	10.25
Continental Airlines	6.04	United Express	0.68
Delta Air Lines	19.48	US Airways	6.15
Delta Connection	1.25	US Airways Express	0.34
Frontier Airlines	2.62	Virgin America	0.91
Hawaiian Airlines	1.03	Others	0.46

3.4.2 Model

The most common research on air travel choice behavior relies on discrete choice models that are based on random utility theory [Train, 2003, Greene, 2008]. Utility can be defined as the 'value' placed by an individual on different attributes, thus capturing how trade-offs are made among different attributes. Random utility theory is based on the hypothesis that every individual is a rational decision-maker, maximizing utility relative to his/her choices. The utility assigned by the decision-maker to an alternative is not known with certainty by the analyst, and consequently must be represented by a random variable. The statistical model is driven by the probability that the individual chooses the alternative with the maximum utility among the j choices, which is the essence of one of the most common discrete choice models, i.e. multinomial logit (MNL) model [McFadden, 1974].

Thus, we employ a MNL model and test a standard specification for the base model, with parameters entering the utility function in a linear fashion. Although the stated choice experiments offer the advantage of exact information on all attributes presented to the respondent, it is still possible that the respondent's choice is also influenced by factors not presented during the experiments [Hess, 2010]. Thus, two dummy variables accounting for the effects of frequent flyer (FF) membership, i.e. basic membership and elite membership, are included in the model (*no membership* is the base level and thus excluded). Given the negative impact of schedule delay, i.e. the difference between desired and offered departure times [Proussaloglou and Koppelman, 1995, 1999, Algers and Beser, 2001, Parker and Walker, 2005], we capture this effect by introducing two schedule delay variables in the utility function, i.e. *Early-departure* (if the alternative flight departs earlier than the revealed preference flight) and *Late-departure* (if the alternative flight departs later than the revealed preference flight). Our base model is as follows:

$$
\begin{aligned}
U_j = &\beta_{A-w} * \delta_{\textit{Aircraft-widebody},j} + \beta_{A-r-j} * \delta_{\textit{Aircraft-regional-jet},j} + \beta_{A-p} * \delta_{\textit{Aircraft-propeller},j} + \\
&\beta_{A-r1} * \delta_{\textit{Airline-rank1},j} + \beta_{A-r2-r3} * \delta_{\textit{Airline-rank2-rank3},j} + \beta_{FF-b} * \delta_{\textit{FF-basic},j} + \\
&\beta_{FF-e} * \delta_{\textit{FF-elite},j} + \beta_{E-d} * \delta_{\textit{Early-departure},j} + \beta_{L-d} * \delta_{\textit{Late-departure},j} + \\
&\beta_{OT-P} * \textit{OnTime-Perf}_j + \beta_{T-T} * \textit{Travel-Time}_j + \beta_A * \textit{Airfare}_j + \\
&\beta_{N-of-C} * \textit{No-of-Connections}_j
\end{aligned}
\tag{3.1}
$$

where j=1,2.

Parameters β_{T-T} and β_A are marginal utility coefficients that capture the utility associated with an increase by 1 hour in travel time, respectively \$100 in airfare[1]. β_{OT-P} relates to the on-time performance (in four levels percentage points) of an itinerary, while β_{N-of-C} refers to the number of connections of the itinerary. The aircraft type is defined by $\delta_{Aircraft-widebody}$, $\delta_{Aircraft-regional-jet}$, $\delta_{Aircraft-standard-jet}$, and $\delta_{Aircraft-propeller}$ dummy variables, where $\delta_{Aircraft-standard-jet}$ is the base level, and thus not included in the model. Finally, the three most preferred airlines are defined by $\delta_{Airline-rank1}$ and $\delta_{Airline-rank2-rank3}$ dummy variables, whereas $\delta_{Airline-rank4}$ dummy variable has been left out of the model as it defines the least preferred airline as the reference.

While there may be some collinearity among the *OnTime-Performance*, *Travel-Time*, *Airfare* and *No-of-Connections* variables, we evaluate whether the inclusion of each one is statistically validated and results in a better model fit. In this sense we conduct several nested likelihood ratio tests[2] [Garrow, 2010]. These tests are used to compare two models, where one model can be written as a restricted version of a

[1]When shown to the respondents in the stated-preference experiments, the *Travel-Time* and *Airfare* variables were expressed in minutes, respectively \$. However, for an easier interpretation of the results, we rescaled them in our analyses, i.e. the *Travel-Time* is expressed in hours, while the *Airfare* is expressed in \$'00.

[2]All the analyses in this study are conducted using Stata 12.

different model. Thus, in a restricted model some parameters are set to zero and/or one or more parameters are set equal to each other. The null hypothesis of a nested likelihood ratio test is:

$$H_0 : \text{Model1 } (\textit{restricted}) = \text{Model2 } (\textit{unrestricted})$$

and the decision rule that rejects the null hypothesis is:

$$-2 * [LL_R - LL_U)] > \text{critical value from } \chi^2_{NR,\alpha} \text{ distribution}$$

where:

LL_R = the log likelihood of the restricted model

LL_U = the log likelihood of the unrestricted model

NR = the number of restrictions

α = the statistical significance level

If the nested likelihood ratio tests rejects the null hypothesis, it is an indication that the restrictions are not valid, and the unrestricted model is preferred.

Table 3.4 reports the results of four nested likelihood ratio tests (based on MNL models). The first two tests evaluate whether the improvement in the log likelihood of a joint model with *Travel-Time* and *No-of-Connections* as main variables outperforms the single *Travel-Time* and *No-of-Connections* models. Given the previously mentioned decision rule of the nested likelihood ratio test, Table 3.4 shows that the inclusion of both *Travel-Time* and *No-of-Connections* in the joint model results in a better model fit (p=0.05) than both *Travel-Time* model and *No-of-Connections* model. Thus, although the travel time and number of connections may be correlated (i.e. more connections increase travel time), their presence in the same model still results in significant t-statistics and improves the model fit such that it is statistically recommended to include both, not one, in the model.

The next two tests in Table 3.4 evaluate whether the improvement in the log likelihood of a joint model with *No-of-Connections* and *OnTime-Performance* as

Table 3.4 Nested Likelihood Ratio tests (1)

Variable	No-of-Connections & Travel-Time			No-of-Connections & On-Time Performance		
	No-of-Connections Model: Parameter estimate	*Travel-Time* Model: Parameter estimate	*Joint* Model: Parameter estimate	*No-of-Connections* Model: Parameter estimate	*OnTime-Perf* Model: Parameter estimate	*Joint* Model: Parameter estimate
Aircraft type (Reference = standard jet)						
Widebody	-0.4360***	-0.4350***	-0.4351***	-0.4360***	-0.4532***	-0.4347***
Regional jet	0.3191***	0.3191***	0.3243***	0.3191***	0.2923***	0.3271***
Propeller	0.6329***	0.6469***	0.6458***	0.6329***	0.5687***	0.6473***
Airline preference (Reference = least preferred)						
Airline-rank 1	0.8112***	0.7997***	0.8176***	0.8112***	0.7007***	0.8022***
Airline-rank 2 or 3	0.7798***	0.7695***	0.7873***	0.7798***	0.6913***	0.7801***
FF (Reference = no membership)						
Basic	0.1338**	0.1325**	0.1312**	0.1338**	0.1580***	0.1373**
Elite	0.3702***	0.3441***	0.3536***	0.3702***	0.3944***	0.3761***
Schedule delay						
Early departure	-0.0008***	-0.0004	-0.0003	-0.0008***	-0.0039***	-0.0008***
Late departure	0.0002	0.0004*	0.0003	0.0002	-0.0004*	0.0002
OnTime-Perf					0.0133***	0.0143***
Travel-Time		-0.5162***	-0.2026***			
Airfare						
No-of-Connections	-0.8668***		-0.6181***	-0.8668***		-0.8743***
Likelihood Ratio χ^2(d.f.)	1235.16(10)	1148.86(10)	1265.83(11)	1235.16(10)	687.57(10)	1301.98(11)
Pseudo *R-square*	0.1459	0.1357	0.1495	0.1459	0.0812	0.1538
Log Likelihood (LL)	-3616.16	-3659.31	-3600.83	-3616.16	-3889.96	-3582.75
Number of Restrictions (NR)	1	1		1	1	
$-2*(LL_{Joint} - LL_{Single})$	30.67	116.98		66.82	614.41	
$\chi^2_{NR,0.05}$	3.84	3.84		3.84	3.84	

Note: Number of observations = 12,216
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

main variables is superior to the single *No-of-Connections* and *OnTime-Performance* models. The results indicate that the inclusion of both *No-of-Connections* and *OnTime-Performance* in the joint model results in a better model fit (p=0.05) than both *No-of-Connections* model and *No-of-Connections* model. Thus, although the number of connections and on-time performance may be correlated (i.e. more connections can negatively affect the on-time performance of the itinerary), their inclusion in the same model is statistically warranted.

Similar to Table 3.4, Tables 3.5 and 3.6 report the results of additional nested likelihood ratio tests (based on MNL models). First, we find that the joint model with *No-of-Connections* and *Airfare* as main variables results in a better model fit (p=0.05) than both the *No-of-Connections* model and the *Airfare* model. Thus, although the number of connections of an itinerary and the airfare of that itinerary may be correlated, i.e. a direct flight is more expensive than an one-connection flight, both *No-of-Connections* and *Airfare* can be simultaneously included in the model. Then we find statistical support (p=0.05) for the concurrent presence of *Travel-Time* and *OnTime-Performance* in the model, in spite of the fact that these variables may be correlated (i.e. a longer travel time of the itinerary can deteriorate its on-time performance).

Next, Table 3.6 shows that the inclusion of both *Travel-Time* and *Airfare* in the joint model results in an improved model fit (p=0.05) than both *Travel-Time* model and *Airfare* model. That is, although the travel time and airfare of an itinerary may be correlated, their simultaneous inclusion in the model is statistically justified. Finally, we find that the joint model with *OnTime-Performance* and *Airfare* as main variables results in a better model fit (p=0.05) than both the *OnTime-Performance* model and the *Airfare* model. Thus, although correlation may exist between the airfare and on-time performance as an expensive airfare on an itinerary can be justified through a high service level measured by superior on-time performance, our nested

Table 3.5 Nested Likelihood Ratio tests (2)

	No-of-Connections & Airfare			Travel-Time & OnTime-Performance		
Variable	*No-of-Connections* Model: Parameter estimate	*Airfare* Model: Parameter estimate	*Joint* Model: Parameter estimate	*Travel-Time* Model: Parameter estimate	*OnTime-Perf* Model: Parameter estimate	*Joint* Model: Parameter estimate
Aircraft type (Reference = standard jet)						
Widebody	-0.4360***	-0.5340***	-0.5315***	-0.4350***	-0.4532***	-0.4344***
Regional jet	0.3191***	0.3152***	0.3001***	0.3191***	0.2923***	0.3271***
Propeller	0.6329***	0.6152***	0.5264***	0.6469***	0.5687***	0.6582***
Airline preference (Reference = least preferred)						
Airline-rank 1	0.8112***	0.7818***	0.9480***	0.7997***	0.7007***	0.7932***
Airline-rank 2 or 3	0.7798***	0.7537***	0.8685***	0.7695***	0.6913***	0.7766***
FF (Reference = no membership)						
Basic	0.1338**	0.1846***	0.1650***	0.1325**	0.1580***	0.1357**
Elite	0.3702***	0.4355***	0.4202***	0.3441***	0.3944***	0.3520***
Schedule delay						
Early departure	-0.0008***	-0.0049***	-0.0015***	-0.0004	-0.0039***	-0.0004
Late departure	0.0002	-0.0007***	-0.0002	0.0004*	-0.0004*	0.0004*
OnTime-Perf					0.0133***	0.0147***
Travel-Time				-0.5162***		-0.5243***
Airfare		-0.6657***	-0.7300***			
No-of-Connections	-0.8668***		-0.9932***			
Likelihood Ratio χ^2(d.f.)	1235.16(10)	1602.48(10)	2269.70(11)	1148.86(10)	687.57(10)	1219.32(11)
Pseudo *R-square*	0.1459	0.1893	0.2680	0.1357	0.0812	0.1440
Log Likelihood (LL)	-3616.16	-3432.50	-3098.89	-3659.31	-3889.96	-3624.08
Number of Restrictions (NR)	1	1		1	1	
$-2*(LL_{Joint} - LL_{Single})$	1034.54	667.21		70.47	531.75	
$\chi^2_{NR,0.05}$	3.84	3.84		3.84	3.84	

Note: Number of observations = 12,216
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$

Table 3.6 Nested Likelihood Ratio tests (3)

	Travel-Time & Airfare			OnTime-Performance & Airfare		
Variable	*Travel-Time* Model: Parameter estimate	*Airfare* Model: Parameter estimate	*Joint* Model: Parameter estimate	*OnTime-Perf* Model: Parameter estimate	*Airfare* Model: Parameter estimate	*Joint* Model: Parameter estimate
Aircraft type (Reference = standard jet)						
Widebody	-0.4350***	-0.5340***	-0.5334***	-0.4532***	-0.5340***	-0.5325***
Regional jet	0.3191***	0.3152***	0.3067***	0.2923***	0.3152***	0.3213***
Propeller	0.6469***	0.6152***	0.5818***	0.5687***	0.6152***	0.6222***
Airline preference (Reference = least preferred)						
Airline-rank 1	0.7997***	0.7818***	0.9179***	0.7007***	0.7818***	0.7796***
Airline-rank 2 or 3	0.7695***	0.7537***	0.8503***	0.6913***	0.7537***	0.7579***
FF (Reference = no membership)						
Basic	0.1325**	0.1846***	0.1730***	0.1580***	0.1846***	0.1873***
Elite	0.3441***	0.4355***	0.3848***	0.3944***	0.4355***	0.4401***
Schedule delay						
Early departure	-0.0004	-0.0049***	-0.0008***	-0.0039***	-0.0049***	-0.0050***
Late departure	0.0004*	-0.0007***	0.0001***	-0.0004*	-0.0007***	-0.0007***
OnTime-Perf				0.0133***		0.0150***
Travel-Time	-0.5162***		-0.6091***			
Airfare		-0.6657***	-0.7265***		-0.6657***	-0.6710***
No-of-Connections						
Likelihood Ratio χ^2(d.f.)	1148.86(10)	1602.48(10)	2183.61(11)	687.57(10)	1602.48(10)	1670.48(11)
Pseudo *R-square*	0.1357	0.1893	0.2579	0.0812	0.1893	0.1973
Log Likelihood (LL)	-3659.31	-3432.50	-3141.94	-3889.96	-3432.50	-3398.50
Number of Restrictions (NR)	1	1		1	1	
$-2*(LL_{Joint} - LL_{Single})$	1034.75	581.12		982.91	68.00	
$\chi^2_{NR,0.05}$	3.84	3.84		3.84	3.84	

Note: Number of observations = 12,216
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

likelihood ratio tests indicate that it is statistically recommended to include both *OnTime-Performance* and *Airfare* in the model.

To distinguish between travelers who check bags and those who do not check bags, we allow for separate coefficients in the same model[3]. More specifically, we create interactions between the *OnTime-Performance*, *Travel-Time*, *Airfare*, *No-of-Connections* variables and whether the traveler checks bags or not. Thus, the heterogeneous[4] *OnTime-Perf* model is as follows:

$$
\begin{aligned}
U_j =& \beta_{A-w} * \delta_{\textit{Aircraft-widebody,j}} + \beta_{A-r-j} * \delta_{\textit{Aircraft-regional-jet,j}} + \beta_{A-p} * \delta_{\textit{Aircraft-propeller,j}} + \\
& \beta_{A-r1} * \delta_{\textit{Airline-rank1,j}} + \beta_{A-r2-r3} * \delta_{\textit{Airline-rank2-rank3,j}} + \beta_{FF-b} * \delta_{\textit{FF-basic,j}} + \\
& \beta_{FF-e} * \delta_{\textit{FF-elite,j}} + \beta_{E-d} * \delta_{\textit{Early-departure,j}} + \beta_{L-d} * \delta_{\textit{Late-departure,j}} + \\
& \beta_{T-T} * \textit{Travel-Time}_j + \beta_{A} * \textit{Airfare}_j + \beta_{N-of-C} * \textit{No-of-Connections}_j + \\
& \beta_{OT-P*C} * (\textit{OnTime-Perf}_j * \textit{Check}) + \beta_{OT-P*NC} * (\textit{OnTime-Perf}_j * \textit{NoCheck})
\end{aligned}
\tag{3.2}
$$

where j=1,2.

Similarly, we employ heterogeneous *Travel-Time*, *No-of-Connections*, and *Airfare* models. In the heterogeneous *Airfare* model we also factor in whether travelers who check bags, pay the associated checked baggage fees or not. This becomes an important distinction when measuring the total travel cost. Finally, the heterogeneous pooled model includes all the interaction terms, as follows:

$$
\begin{aligned}
U_j =& \beta_{A-w} * \delta_{\textit{Aircraft-widebody,j}} + \beta_{A-r-j} * \delta_{\textit{Aircraft-regional-jet,j}} + \beta_{A-p} * \delta_{\textit{Aircraft-propeller,j}} + \\
& \beta_{A-r1} * \delta_{\textit{Airline-rank1,j}} + \beta_{A-r2-r3} * \delta_{\textit{Airline-rank2-rank3,j}} + \beta_{FF-b} * \delta_{\textit{FF-basic,j}} +
\end{aligned}
$$

[3]We also ran the base model using two datasets, i.e. comprising travelers who check bags and travelers who do not check bags. However, the absolute magnitude of parameter estimates cannot be compared across different datasets [Garrow, 2010], and therefore we assess the support or lack of support of the corresponding hypotheses based on heterogeneous single and pooled models, as mentioned next.

[4]We use this terminology to account for the distinction between travelers who check bags and travelers who do not check bags included in the model.

$$\beta_{FF-e} * \delta_{FF\text{-}elite,j} + \beta_{E-d} * \delta_{Early\text{-}departure,j} + \beta_{L-d} * \delta_{Late\text{-}departure,j} +$$
$$\beta_{OT-P*C} * (OnTime\text{-}Perf_j * Check) + \beta_{OT-P*NC} * (OnTime\text{-}Perf_j * NoCheck) +$$
$$\beta_{T-T*C} * (Travel\text{-}Time_j * Check) + \beta_{T-T*NC} * (Travel\text{-}Time_j * NoCheck) +$$
$$\beta_{A*C\&NPF} * (Airfare_j * Check\&NoPaidFees) +$$
$$\beta_{A*C\&PF} * (Airfare_j * Check\&PaidFees) +$$
$$\beta_{A*NC} * (Airfare_j * NoCheck) + \beta_{N-of-C*C} * (No\text{-}of\text{-}Connections_j * Check) +$$
$$\beta_{N-of-C*NC} * (No\text{-}of\text{-}Connections_j * NoCheck) \tag{3.3}$$

where j=1,2.

3.5 Results and Discussion

3.5.1 Confirming Previous Results

The results[5] of our base model in Eq.3.1 are shown in Table 3.7. The model shows the expected positive effect of *OnTime-Perf* on the choice probability of an itinerary (e.g., Wen and Lai [2010], Hess [2010], Teichert, Shehu, and von Wartburg [2008]), which confirms hypothesis H1A. That is, an increase in the value of *OnTime-Perf* will increase the utility of that flight option (and thus the probability of being chosen), all else being equal. More specifically, if the *OnTime-Perf* increases by 1%, the odds of choosing that flight option are multiplied by 1.0175. Next, we find the expected negative effects of *Travel-Time* (e.g., Collins, Rose, and Hess [2012], Hess [2008]), *Airfare* (e.g., Wen and Lai [2010], Teichert, Shehu, and von Wartburg [2008], Pereira, Almeida, de Menezes, and Vieira [2007], Proussaloglou and Koppelman [1999]), and *No-of-Connections* (e.g., Collins, Rose, and Hess [2012], Hess [2010]) on the choice probability of an itinerary, which confirm hypotheses H2A, H3A, and H4A. A negative

[5]Given the assumption of constant tastes across choices for the same respondent, the standard errors reported in this study account for the correlations among the stated-preference experiments through clustering at the respondent level.

Table 3.7 MNL: Base model results

Variable	Parameter Estimate	Standard Error	Odds Ratio
Aircraft type (Reference = standard jet)			
Widebody	-0.5452***	0.1041	0.5797
Regional jet	0.3048***	0.0554	1.3564
Propeller	0.5399***	0.0890	1.7159
Airline preference (Reference = least preferred)			
Airline-rank 1	0.9418***	0.0820	2.5646
Airline-rank 2 or 3	0.8785***	0.0653	2.4072
FF (Reference = no membership)			
Basic	0.1719**	0.0670	1.1876
Elite	0.4103***	0.1535	1.5073
Schedule delay			
Early departure	-0.0010***	0.0003	0.9990
Late departure	-0.0000	0.0003	1.0000
OnTime-Perf	0.0173***	0.0021	1.0175
Travel-Time	-0.2430***	0.0431	0.7843
Airfare	-0.7411***	0.0793	0.4766
No-of-Connections	-0.7136***	0.0698	0.4899
Likelihood Ratio χ^2(d.f.)	2382.87(13)		
Pseudo *R-square*	0.2814		
Log Likelihood (LL)	-3042.31		

Note: Number of observations = 12,216
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

coefficient indicates that an increase in the value of that variable will decrease the utility of that flight option, all else being equal. More specifically, our results indicate that if the *Travel-Time* increases by 1 hour, then a traveler is 0.7843 times less likely to choose that flight option. Or if the *Airfare* increases by $100, then a traveler is 0.4766 times less likely to choose that flight option. As regards the *No-of-Connections*, the results indicate that an additional connection decreases the odds of choosing that flight option by 51%.

With regard to the airline preference, Table 3.7 reports that travelers prefer mostly itineraries associated with their first-ranked airline, followed by those associated with their second- and third-ranked preferences, relative to itineraries with least preferred airlines. This finding is consistent with Warburg, Bhat, and Adler [2006] who only examine the choice behavior of business travelers. Similarly, the finding that travelers prefer itineraries that include airlines with which they are frequent flyers (where the loyalty effect is higher for the elite members than for the basic members) confirms previous studies (e.g. Warburg, Bhat, and Adler [2006], Theis, Adler, Clarke, and Ben-Akiva [2006], Hess [2008]). Finally, the negative and significant coefficient of the schedule delay variable *Early-departure* indicates travelers' reluctance to deviate from the departure time of their reference flight. This finding is in line with Proussaloglou and Koppelman [1999] who find a greater sensitivity associated with early departure than with late departure flights, whereby their measure of schedule delay reflects the inconvenience of traveling at a time other than the preferred departure time.

The results of the heterogeneous models based on Eq.3.2 are shown in Tables 3.8 and 3.9, while Table 3.10 reports the results of the heterogeneous pooled model based on Eq.3.3. In these models, the aircraft type, airline preference, frequent flyer status, and schedule delay variables exhibit similar results as previously discussed. In addition, the parameter estimates of *OnTime-Perf*, *Travel-Time*, *Airfare*, and *No-of-Connections* variables show the expected effects, and thus provide additional support for hypotheses H1A, H2A, H3A, and H4A.

3.5.2 Are Travelers Who Check Bags Different Than Those Who Do Not Check Bags?

As Table 3.8 shows, the heterogeneous *OnTime-Perf* model reports a positive and statistically significant *OnTime-Perf* coefficient for travelers who check bags (0.0179; $p<0.01$), which exceeds the *OnTime-Perf* coefficient for travelers who do not check bags (0.0162; $p<0.01$). However, the nested log likelihood test indicates that the heterogeneous *OnTime-Perf* model fit does not improve over that of the base model. Thus, we cannot distinguish between travelers who check bags and travelers who do not check bags based on their sensitivity to on-time performance, and so we do not find support for hypothesis H1B.

Table 3.8 MNL: Heterogeneous models results (1)

	Model: On-Time Performance			Model: Travel Time		
Variable	Parameter Estimate	Standard Error	Odds Ratio	Parameter Estimate	Standard Error	Odds Ratio
Aircraft type (Reference = standard jet)						
Widebody	-0.5452***	0.1041	0.5798	-0.5450***	0.1043	0.5798
Regional jet	0.3049***	0.0554	1.3565	0.3068***	0.0554	1.3590
Propeller	0.5401***	0.0890	1.7161	0.5408***	0.0889	1.7174
Airline preference (Reference = least preferred)						
Airline-rank 1	0.9417***	0.0820	2.5643	0.9419***	0.0820	2.5649
Airline-rank 2 or 3	0.8784***	0.0653	2.4071	0.8799***	0.0654	2.4108
FF (Reference = no membership)						
Basic	0.1718**	0.0671	1.1875	0.1722**	0.0672	1.1879
Elite	0.4101***	0.1534	1.5069	0.4108***	0.1532	1.5079
Schedule delay						
Early departure	-0.0010***	0.0003	0.9990	-0.0010***	0.0003	0.9990
Late departure	-0.0000	0.0003	1.0000	-0.0001	0.0003	0.9999
OnTime-Perf				0.0173***	0.0021	1.0174
Travel-Time	-0.2431***	0.0431	0.7842			
Airfare	-0.7412***	0.0793	0.4766	-0.7398***	0.0792	0.4772
No-of-Connections	-0.7139***	0.0698	0.4898	-0.7095***	0.0697	0.4919
OnTime-Perf * Check	0.0179***	0.0026	1.0180			
OnTime-Perf * NoCheck	0.0162***	0.0031	1.0163			
Travel-Time * Check				-0.2113***	0.0478	0.8096
Travel-Time * NoCheck				-0.3269***	0.0580	0.7212
Likelihood Ratio χ^2(d.f.)		2383.04(14)			2387.77(14)	
Pseudo *R-square*		0.2814			0.2820	
Log Likelihood (LL)		-3042.22			-3039.86	
Number of Restrictions (NR)		1			1	
$-2 * (LL_{Base-model} - LL)$		0.16			4.90	
$\chi^2_{NR,0.05}$		3.84			3.84	

Note: Number of observations = 12,216.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

The heterogeneous *Travel-Time* model in Table 3.8 shows negative and statistically significant ($p<0.01$) coefficients of interaction terms, i.e. -0.2113 *Travel-Time* coefficient for travelers who check bags, and -0.3269 *Travel-Time* coefficient for travelers who do not check bags. The nested log likelihood test indicates that the heterogeneous *Travel-Time* model fit improves over that of the base model. All else being equal, the odds that a customer who checks bags will choose the itinerary with a 60-minute longer total travel time are reduced by approximately 19%, as compared to a reduction of approximately 28% for a customer who does not check bags. Thus, customers who check bags appear to be significantly less sensitive to the total travel time of an itinerary than customers who do not check bags. Our study finds support for hypothesis H2B, and hence extends the work of Warburg, Bhat, and Adler [2006] who find the same relationship for business travelers only. Therefore, an airline with most of its customers checking bags should be less concerned about inflated flight schedules and could schedule longer connecting times. Moreover, investments in flying additional flights and shortening the connecting times would be less effective for an airline with most of its customers checking bags.

The coefficients of interaction terms in the heterogeneous *Airfare* model (Table 3.9) are negative and statistically significant ($p<0.01$). More specifically, we find that travelers who check bags but do not pay the associated baggage fees (as a benefit of the frequent flyer status or because they do not exist in case of Southwest Airlines and JetBlue Airways) are the most sensitive to the airfare (-1.1158), followed by the travelers who do not check bags (-0.8860), while the travelers who check bags and pay the associated baggage fees are the least sensitive to the airfare (-0.5543). The nested log likelihood test indicates that the heterogeneous *Airfare* model fit improves over that of the base model. However, we do not find support for hypothesis H3B since the airfare has a more negative impact on the itinerary utility for travelers who do not check bags relative to travelers who check bags and pay the associated fees. That is,

Table 3.9 MNL: Heterogeneous models results (2)

	Model: Airfare			Model: Number of Connections		
Variable	Parameter Estimate	Standard Error	Odds Ratio	Parameter Estimate	Standard Error	Odds Ratio
Aircraft type (Reference = standard jet)						
Widebody	-0.5464***	0.1057	0.5790	-0.5453***	0.1043	0.5796
Regional jet	0.3083***	0.0568	1.3611	0.3061***	0.0554	1.3581
Propeller	0.5464***	0.0905	1.7271	0.5434***	0.0888	1.7219
Airline preference (Reference = least preferred)						
Airline-rank 1	0.9514***	0.0828	2.5893	0.9427***	0.0819	2.5668
Airline-rank 2 or 3	0.8866***	0.0665	2.4268	0.8800***	0.0653	2.4110
FF (Reference = no membership)						
Basic	0.1668**	0.0678	1.1815	0.1721**	0.0671	1.1878
Elite	0.4492***	0.1583	1.5670	0.4068***	0.1541	1.5020
Schedule delay						
Early departure	-0.0010***	0.0003	0.9990	-0.0010***	0.0003	0.9990
Late departure	-0.0000	0.0003	1.0000	-0.0001	0.0003	0.9999
OnTime-Perf	0.0177***	0.0021	1.0179	0.0173***	0.0021	1.0174
Travel-Time	-0.2464***	0.0439	0.7816	-0.2406***	0.0431	0.7861
Airfare				-0.7398***	0.0792	0.4772
No-of-Connections	-0.7233***	0.0700	0.4851			
Airfare * Check & NoPaidFees	-1.1158***	0.1052	0.3277			
Airfare * Check & PaidFees	-0.5543***	0.1003	0.5745			
Airfare * NoCheck	-0.8860***	0.1251	0.4123			
No-of-Connections * Check				-0.6637***	0.0732	0.5149
No-of-Connections * NoCheck				-0.8443***	0.1025	0.4298
Likelihood Ratio χ^2(d.f.)		2455.29(15)			2387.60(14)	
Pseudo *R-square*		0.2900			0.2820	
Log Likelihood (LL)		-3006.10			-3039.94	
Number of Restrictions (NR)		2			1	
$-2 * (LL_{Base-model} - LL)$		72.42			4.73	
$\chi^2_{NR,0.05}$		5.99			3.84	

Note: Number of observations = 12,216.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

the odds that a customer who checks bags and pay the corresponding fees will choose the itinerary with a \$100 more expensive airfare are reduced by approximately 43%, compared to 59% for customers who do not check bags, all else being equal.

We also find that travelers who check bags but do not pay the corresponding fees are more sensitive to the airfare than those who do not check bags, which indicates lack of support for hypothesis H3C. All else being equal, the odds that a customer who checks bags and does not pay the corresponding fees will choose the itinerary with a \$100 more expensive airfare are reduced by approximately 67% in comparison with 59% for customers who do not check bags. Similarly, the results indicate that the odds that a customer who checks bags and pay the corresponding fees will choose the itinerary with a \$100 more expensive airfare are reduced by approximately 43%, compared to 67% for customers who check bags but do not pay the corresponding fees, all else being equal. That is, we do not find support for hypothesis H3D as we find a more negative impact of the airfare on the itinerary utility for travelers who check bags but do not pay the associated fees versus travelers who check bags and pay the associated fees. Thus, our results indicate that travelers who check bags and pay the associated fees are the least price sensitive, and hence, more valuable customers. Given this, the airlines should seek to increase the size of this segment of customers, by offering perks or rewards (e.g., higher ranking on priority list for upgrades, offering discount when the traveler pre-pays for checked baggage when checking-in online, etc.). On the other hand, if the airlines make checking bags more of a hassle, they could be driving away their more profitable customers.

The heterogeneous *No-of-Connections* in Table 3.9 reports a negative and statistically significant *No-of-Connections* coefficient for travelers who check bags (-0.6637; $p<0.01$), which exceeds the *No-of-Connections* coefficient for travelers who do not check bags (-0.8443; $p<0.01$). All else being equal, the odds that a customer who checks bags will choose the itinerary with an additional connection are reduced

Table 3.10 MNL: Heterogeneous pooled model results

	Model: Pooled		
Variable	Parameter Estimate	Standard Error	Odds Ratio
Aircraft type (Reference = standard jet)			
Widebody	-0.5470***	0.1061	0.5787
Regional jet	0.309***	0.0568	1.3621
Propeller	0.5461***	0.0903	1.7265
Airline preference (Reference = least preferred)			
Airline-rank 1	0.9522***	0.0828	2.5913
Airline-rank 2 or 3	0.8884***	0.0666	2.4312
FF (Reference = no membership)			
Basic	0.1667**	0.0679	1.1813
Elite	0.4460***	0.1588	1.5621
Schedule delay			
Early departure	-0.001***	0.0003	0.9990
Late departure	0.0000	0.0003	1.0000
OnTime-Perf	0.0177***	0.0021	1.0178
Travel-Time * Check	-0.2219***	0.0513	0.8010
Travel-Time * NoCheck	-0.3093***	0.0809	0.7340
Airfare * Check & NoPaidFees	-1.0967***	0.1036	0.3340
Airfare * Check & PaidFees	-0.5455***	0.0990	0.5795
Airfare * NoCheck	-0.9231***	0.1350	0.3973
No-of-Connections * Check	-0.6872***	0.0799	0.5030
No-of-Connections * NoCheck	-0.8102***	0.1406	0.4448
Likelihood Ratio χ^2(d.f.)	2463.55(17)		
Pseudo *R-square*	0.2909		
Log Likelihood (LL)	-3001.97		
Number of Restrictions (NR)	4		
$-2 * (LL_{Base-model} - LL)$	80.68		
$\chi^2_{NR,0.05}$	9.49		

Note: Number of observations = 12,216.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$

by approximately 49%. This compares to a reduction in the odds for a customer who does not check bags of approximately 57%. The nested log likelihood test indicates that the heterogeneous *No-of-Connections* model fit improves over that of the base model. Thus, we find support for hypothesis H4B as the number of connections has a different impact on the itinerary utility for travelers who check bags versus those who do not. It appears that travelers who do not check bags have a stronger preference for fewer connections, while those who check bags may not be as concerned about the increased risk of mishandled baggage associated with a higher number of connections. The fact that in 2012 U.S. airlines reported the lowest mishandled baggage rate in 18 years [BTS Press Release, February 2013] supports this view of a decreased risk of mishandled baggage. Similar to total travel time, an airline who has a larger percentage of customers who check bags will gain less from reducing the number of connections or offering more direct flights than an airline with fewer customers who check bags.

Finally, the nested log likelihood test indicates that the heterogeneous pooled model fit improves over that of the base model. Thus, the heterogeneous pooled model (Table 3.10)[6] confirms the previously found support for hypotheses H2B and H4B, and rejects hypotheses H3B, H3C, and H3D. A summary of our findings is provided in Table 3.11.

Table 3.11 Hypotheses results

Hypothesis		Result
H1:	*On-Time Performance*	
	A: positive impact	supported
	B: checking bags vs. no checking bags	not supported
H2:	*Travel Time*	
	A: negative impact	supported
	B: checking bags vs. no checking bags	supported
H3:	*Airfare*	
	A: negative impact	supported
	B: checking bags & paying fees vs. no checking bags	opposite supported
	C: checking bags & not paying fees vs. no checking bags	opposite supported
	D: checking bags & paying fees vs. checking bags & not paying fees	opposite supported
H4:	*Number of Connections*	
	A: negative impact	supported
	B: checking bags vs. no checking bags	supported

3.6 Conclusions

This paper portrays a clear picture of the key factors that influence itinerary choice, by using stated-preference data collected in the U.S. in the Spring of 2012. In support

[6]Since we previously found that we cannot distinguish between travelers who check bags and travelers who do not check bags based on their sensitivity to on-time performance, we included the main effect *OnTime-Perf*.

of many previous studies, our analyses confirm the important role played by attributes such as historical on-time performance (with its positive effect) and total travel time, airfare, and number of connections (with their negative effects) on itinerary-choice behavior. Our models were estimated on all 12,216 observations, as opposed to using a segmentation along a socio-demographic dimension such as trip purpose, which it has traditionally been done in the air travel research. We contribute to extant literature by exploring a new dimension for segmenting airline travelers. Since airlines are interested in determining whether they should change their operations policies and spend more or less resources to make it easier or harder for customers to check bags, we provide a tool for this decision by explaining a potential new way of segmenting travelers based on their sensitivities to itinerary attributes.

An important avenue for air travel research comes in the use of a combination of revealed-preference and stated-preference data [Algers and Beser, 2001]. As such, we use interactions between an attribute disclosed in the revealed-preference data and the sensitivity to travel attributes from stated-preference data. By distinguishing between customer segments, we show that, as compared to travelers who do not check bags, travelers who check bags are more valuable as they are less price sensitive *and* less likely to choose an itinerary flown by a different airline because of a shorter total travel time or because of fewer connections. This finding clearly indicates that airlines, in their pursuit to reduce costs, cannot afford hurting the experience of customers who check bags by cutting corners on such a complex operational process as handling bags: “Moving passenger baggage is an intensely manual operation, requiring lots of workers. On average, each bag gets touched by about 10 workers during its journey. Once bags are tagged, they are sorted and placed on carts, then driven planeside, where a crew loads them into the belly of a jet. The unloading process is more labor-intensive: Bags are sorted into luggage to be delivered to the carousel for passengers to collect and luggage that needs to be routed to connecting flights and has to be sorted and driven to lots of different planes" [McCartney, 2008d].

One implication of this finding is that airlines should actively engage in the acquisition and retention of customers who check bags in general, and especially customers who check bags and pay the associated fees. This contradicts one of airlines' widely held beliefs about the relative importance of customers who check bags. Specifically, our discussion with a major airline revealed that they believe that travelers who check bags and pay the associated fees are the airline's least valuable customers. Checking bags and paying the corresponding fees equates to not enjoying the elite frequent flyer status. Thus, the airlines attach a lower trip frequency to these travelers, hence a high price sensitivity.

In this study, only multinomial logit structures are used. We estimate our models using a clustered sandwich estimator to allow for intra-respondent correlation, and thus take into account the repeated choice nature of the stated-preference data. In addition to service attributes, it is likely that individual characteristics and trip context affect itinerary choices. It is also reasonable to assume that some preference heterogeneity exists within the sample, and recovering this heterogeneity remains an area for future work. A mixture model such as mixed logit relaxes the assumption that all individuals in a given segment have identical preferences, which is assumed in the widely used multinomial logit models. However, the use of mixed logit model that identifies and accounts for variations in individual and context preferences across the sample is warranted as long as it shows additional gain in model fit.

Latent class modeling accounts for preference heterogeneity across individuals as well. However, as opposed to the assumption of continuous random variations in taste parameters used by the mixed logit model, the latent class model uses a discrete distribution [Greene and Hensher, 2003]. Future research using a post-segmentation method based on latent class model with travelers' demographic and trip characteristics in the segment membership can improve our understanding of air travelers' preferences. By recognizing segments' characteristics and differential sensitivity to service attributes, airlines can establish effective marketing strategy and resources allocation for each customer segment.

Chapter 4

Conclusions

The studies within this dissertation were conducted to provide new empirical evidence related to the baggage fees policies implemented by most U.S. airlines in 2008, and to the itinerary-choice behavior of travelers who check or do not check bags. More specifically, in Essay 1 we investigate the operational impact of the baggage fee policies, while in Essay 2 we explore the additional benefits that the service of checking bags provides to the airlines aside from the obvious revenue increase from the fees.

In Essay 1 we find that at the aggregate level, the airlines that began charging for one checked bag saw a significant relative improvement in their on-time departure performance in the 35-day period afterwards, compared to the airlines that were not charging for a checked bag during the same time period. When grouped into 'low-cost' versus 'legacy' carriers, however, we find opposite effects: the departure performance of the low-cost airlines became worse while it improved for the legacy carriers. When the airlines began charging for two checked bags, we find no significant change in departure performance of legacy carriers, but a degradation of departure performance of low-cost carriers. These findings indicate that the baggage fees did influence customer behavior, but in the case of charging for both checked bags, not in the direction the airlines had hoped for. The degradation of departure performance appears to be especially bad for the low-cost carriers, as it appears that their more price sensitive passengers may have begun carrying on more baggage to avoid the checked bag fees. Thus, our findings also support the notion that Southwest Airlines' marketing strategy of being the only major U.S. airline not charging for the first two checked bags is in line with their historical operations oriented strategy.

In Essay 2 we find additional support for the impact of key factors such as the on-time performance, travel time, airfare, and number of connections on the choice probability of an itinerary. However, although our study supports the premise that monitoring and improving on-time performance is among the strategies adopted by air carriers to increase product differentiation and obtain market advantage, the results indicate that travelers who check bags do not appear to value on-time performance any more or less than those who do not check bags. Regarding the total travel time, we identify the higher likelihood of travelers who check bags versus those who do not check bags to choose an itinerary with a higher travel time. For the airlines with more customers who check bags than customers who do not check bags, this finding translates to less concern about the impact of padded flight schedules on customers' satisfaction.

Next, we find a more negative impact of the airfare on the itinerary utility for travelers who do not check bags relative to travelers who check bags and pay the associated fees. Our results also indicate that travelers who check bags but do not pay the corresponding fees are more sensitive to the airfare than those who do not check bags. We also find a more negative impact of the airfare on the itinerary utility for travelers who check bags but do not pay the associated fees versus travelers who check bags and pay the associated fees. Thus, it appears that travelers who check bags and pay the associated fees are more valuable customers due to their lowest sensitivity to price. As such, instead of making checking bags more of a hassle that could be driving away these valuable customers, the airlines could offer them perks or rewards, such as higher ranking on priority list for upgrades, offering discount when the traveler pre-pays for checked baggage when checking-in online, etc. Finally, we find that travelers who check bags are less sensitive to the number of connections of their itinerary, which are more acceptable due to the convenience factor of having bags checked. Thus, it appears that travelers who do not check bags have a stronger preference for fewer connections.

To conclude, this dissertation contributes to three streams of research, as follows: (1) research that uses data provided by the DOT to investigate the impact of various factors on the quality dimension of airline's operational performance, as measured by on-time departures, on-time arrivals, flight cancellations, and the impact of service quality dimensions on financial performance, (2) research that examines the consequences of implementing baggage fees, and (3) research on air travel choice behavior that models airline service trade-offs in air itinerary choices using stated-preference survey methodology. Our results in Essay 1 emphasize the impact of checked baggage fees policies on departure performance, while the results in Essay 2 lead to the conclusion that travelers who check bags are more valuable to the airlines than travelers who do not check bags. Future research could examine whether the implementation of checked baggage fees reduced the probability of mishandling baggage, and if so, led to better service for travelers who continue to check bags.

Bibliography

Adler, T., C.S. Falzarano, G. Spitz. 2005. Modeling service trade-offs in air itinerary choices. *Transportation Research Record: Journal of the Transportation Research Board*, **1915**:20–26.

Ai, C., E.C. Norton. 2003. Interaction terms in logit and probit models. *Economics Letters*, **80**(1):123–129.

Algers, S., M. Beser. 2001. Modelling choice of flight and booking class - a study using stated preference and revealed preference data. *International Journal of Services Technology and Management*, **2**(1/2):28–45.

Allon, G., A. Bassamboo, M.A. Lariviere. 2011. Would the social planner let bags fly free? Working paper.

Arıkan, M., V. Deshpande, M. Sohoni. 2012. Building reliable air-travel infrastructure using empirical data and stochastic models of airline networks. Working paper.

Ater, I., E. Orlov. 2011. The effect of the Internet on product quality. Working paper.

Barone, G.J., K.E. Henrickson, A. Voy. 2012. Baggage fees and airline performance: A case study of initial investor misperception. *Journal of the Transportation Research Forum*, **51**(1):5–18.

Bishop, J.A., N.G. Rupp, B. Zheng. 2011. Flight delays and passenger preferences: An axiomatic approach. *Southern Economic Journal*, **77**(3):543–556.

Brey, R., J.L. Walker. 2011. Latent temporal preferences: An application to airline travel. *Transportation Research Part A: Policy and Practice*, **45**:880–895.

Bureau of Transportation Statistics. 2012. Schedule p-12. `http://www.bts.gov/programs/airline_information/baggage_fees/`

Bureau of Transportation Statistics. 2013. Press Release, February. http://www.rita.dot.gov/bts/press_releases/dot015_13

Bureau of Transportation Statistics. 2013. Press Release, March. http://www.rita.dot.gov/bts/press_releases/bts013_13

Bureau of Transportation Statistics. 2013. Schedule p-12. http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/subject_areas/airline_information/baggage_fees/html/2012.html

Card, D., A.B. Krueger. 1994. Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. *American Economic Review*, **84**(4):774–775.

Carey, S. 2008. Another reason not to overpack. *Wall Street Journal* (February 5) D1–D3.

CNN Money. 2013. American-US Air deal would cut passenger choices. http://money.cnn.com/2013/02/08/news/companies/american-us-airways/index.html. February 8, 2013.

Collins, A.T., J.M. Rose, S. Hess. 2012. Interactive stated choice surveys: a study of air travel behaviour. *Transportation*, **39**(1):55–79.

Deshpande, V., M. Arıkan. 2012. The impact of airline flight schedules on flight delays. *Manufacturing & Service Operations Management*, **14**(3):423–440.

Dinkar, M. 2010. www.EndCarryOnCrunch.org: Campaign to restore cabin safety, security. *FlightLog*, **47**(1).

Espino, R., J.C. Martín, C. Román. 2008. Analyzing the effect of preference heterogeneity on willingness to pay for improving service quality in an airline choice context. *Transportation Research Part E: Logistics And Transportation Review*, **44**:593–606.

Ferguson, J., A.Q. Kara, K. Hoffman, L. Sherry. 2012. Estimating domestic US airline cost of delay based on European model. *Transportation Research Part C: Emerging Technologies*. Forthcoming.

Field, D. 2009. Emotional baggage. *Airline Business*, **25**(1):42–43.

Forbes, S.J., M. Lederman. 2010. Does vertical integration affect firm performance? Evidence from the airline industry. *RAND Journal of Economics*, **41**(4):765–790.

Garrow, L. 2010. Discrete choice modeling and air travel demand: Theory and applications. Ashgate Publishing.

Graham, J.R., L.A. Garrow, J.D. Leonard. 2010. Business travelers' ticketing, refund, and exchange behavior. *Journal of Air Transport Management*, **16**(4):196–201.

Greene, W.H. 2008. Econometric analysis, 6th edition. Prentice-Hall. Upper Saddle River, NJ.

Greene, W.H., Hensher, D.A. 2003. A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, **37**:681–698.

Henrickson, K.E., J. Scott. 2012. Baggage fees and changes in airline ticket prices. In J. Peoples (Ed.), Advances in Airline Economics, **3**. Pricing Behaviour and Non-Price Characteristics in the Airline Industry (pp. 177-192). Bradford, UK: Emerald Group Publishing Limited.

Hess, S. 2007. Posterior analysis of random taste coefficients in air travel behavior modeling. *Journal of Air Transport Management*, **13**:203–212.

Hess, S., T. Adler, J.W. Polak. 2007. Modeling airport and airline choice behavior with the use of stated preference survey data. *Transportation Research Part E: Logistics And Transportation Review*, **43**:221–233.

Hess, S. 2008. Treatment of reference alternatives in stated choice surveys for air travel choice behavior. *Journal of Air Transport Management*, **14**:275–279.

Hess, S. 2010. Evidence of passenger preferences for specific types of airports. *Journal of Air Transport Management*, **16**:191–195.

Hess, S., J.M. Rose, J.W. Polak. 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. *Transportation Research Part D: Transport and Environment*, **15**(7):405–417.

Hess, S., T. Adler. 2011. An analysis of trends in air travel behavior using four related SP datasets collected between 2000 and 2005. *Journal of Air Transport Management*, **17**:244–248.

J.D. Power & Associates. 2013. Press Release, May. `http://www.jdpower.com/content/press-release/5sYQtpZ/2013-north-america-airline-satisfaction-study.htm`

Johnsson, J., J. Hilkevitch. 2011. As Southwest Airlines tries to cope with its success, problems at Midway will get team's attention. *Chicago Tribune*, March 3.

Joint Economic Committee. 2008. Your flight has been delayed again – `http://www.jec.senate.gov/public/?a=Files.Serve&File_id=47e8d8a7-661d-4e6b-ae72-0f1831dd1207`. Release date: May 22, 2008.

Koppelman, F.S., G.M. Coldren, R.A. Parker. 2008. Schedule delay impacts on air-travel itinerary demand. *Transportation Research Part B: Methodological*, **42**(3):263–273.

Lariviere, M. 2011. Southwest Airlines: Do free bags create problems? `http://pomsblog.wordpress.com/category/martin-lariviere/`, March 9.

Lewis, C.N., R. Lieber. 2005. Testing the latest boarding procedures. *Wall Street Journal* (November 2) D1–D5.

Li, J., S. Netessine. 2011. Partnering with competitors - An empirical analysis of airline alliances and multimarket competition. Working paper, INSEAD, France.

Malhotra, M.K., S. Sharma. 2002. Spanning the continuum between marketing and operations. *Journal of Operations Management*, **20**(3):209–219.

Martín, J.C., C. Román, R. Espino. 2008. Willingness to pay for airline service quality. *Transport Reviews*, **28**(2):199–217.

Mayer, C., T. Sinai. 2003. Network effects, congestion externalities, and air traffic delays: Or why not all delays are evil. *American Economic Review*, **93**(4):1194–1215.

Mayerowitz, S. 2012. Airlines set bag fee record in first half of year. `http://www.businessweek.com/ap/2012-09-25/airlines-collect-a-record-amount-of-bag-fees/`.

Mazzeo, M.J. 2003. Competition and service quality in the U.S. airline industry. *Review of Industrial Organization*, **22**(4):275–296.

McCartney, S. 2007. Why flights are getting longer. *Wall Street Journal* (May 29) D1–D5.

McCartney, S. 2008a. Baggage becomes a big-ticket item. *Wall Street Journal* (March 11) D1–D2.

McCartney, S. 2008b. Space race: A battle looms for the overhead bins. *Wall Street Journal* (June 17) D1–D2.

McCartney, S. 2008c. Why your bags aren't better off on a big airline. *Wall Street Journal* (September 2) D1–D3.

McCartney, S. 2008d. What it costs an airline to fly your luggage. *Wall Street Journal* (November 25) D1–D8.

McCartney, S. 2010a. What's behind new baggage fees. *Wall Street Journal* (April 29) D1–D4.

McCartney, S. 2010b. An airline report card: Fewer delays, hassles last year, but bumpy times may be ahead. *Wall Street Journal* (January 7) D1–D3.

McCartney, S. 2010. Why a six-hour flight now takes seven. *Wall Street Journal* (February 4) D1–D2.

McCartney, S. 2012a. The tough tactics to avoid luggage check-in fees. *Wall Street Journal* (February 2) D1–D3.

McCartney, S. 2012b. Reality check: Why airlines are shrinking flight times. *Wall Street Journal* (June 14) D1–D2.

McFadden, D. 1974. Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed.), Frontiers of Econometrics. Academic Press, New York, pp. 05Ű-142.

Mouawad, J. 2011. Most annoying airline delays might just be in the boarding. *The New York Times* (October 31).

Parker, R.A., J. Walker. 2005. Estimating the utility of time-of-day demand for airline schedules. Presented at the 2006 Annual Meeting of the Transportation Research Board, Washington, DC.

Pereira, P.T., A. Almeida, A.G. de Menezes, J.C. Vieira. 2007. How do consumers value airline services attributes? A stated preferences discrete choice model approach. *Management*, **12**(2):25–40.

Prince, J.T., D.H. Simon. 2009. Multimarket contact and service quality: Evidence from on-time performance in the U.S. airline industry. *Academy of Management Journal*, **52**(2):336–354.

Proussaloglou, K., F.S. Koppelman. 1995. Air carrier demand: An analysis of market share determinants. *Transportation*, **22**(4):371–388.

Proussaloglou, K., F.S. Koppelman. 1999. The choice of air carrier, flight, and fare class. *Journal of Air Transport Management*, **5**:193–201.

Ramdas, K., J. Williams. 2008. An empirical investigation into the tradeoffs that impact on-time performance in the airline industry. Working paper, London Business School, London.

Ramdas, K., J. Williams, W. Li, M. Lipson. 2012. Can financial markets inform operational improvement efforts? Evidence from the airline industry. Working paper.

Rhee, M., S. Mehra. 2006. Aligning operations, marketing, and competitive strategies to enhance performance: An empirical test in the retail banking industry. *Omega*, **34**(5):505–515.

Roth, A.V., M. Van Der Velde. 1991. Operations as marketing: A competitive service strategy. *Journal of Operations Management*, **10**(3):303–328.

Rupp, N.G., D.H. Owens, L. Plumly. 2006. Does competition influence airline on-time performance? In D. Lee (Ed.), Advances in Airline Economics, **1**. Competition Policy and Antitrust (pp. 251-272). Amsterdam and San Diego.

Rupp, N.G. 2009. Do carriers internalize congestion costs? Empirical evidence on the internalization question. *Journal of Urban Economics*, **65**(1):24–37.

Rupp, N.G., G.M. Holmes. 2006. An investigation into the determinants of flight cancellations. *Economica*, **73**(292):749–783.

Rupp, N.G., T. Sayanak. 2008. Do low cost carriers provide low quality service? *Revista de Análisis Económico*, **23**(1):3–20.

Schmenner, R. 1986. How can service businesses survive and prosper? *Sloan Management Review*, **27**, 21.

Smith, T., J. Reece. 1999. The relationship of strategy, fit, productivity, and business performance in a services setting. *Journal of Operations Management*, **17**:145–161.

Suzuki, Y., 2000. The relationship between on-time performance and airline market share: a new approach. *Transportation Research Part E: Logistics and Transportation Review*, **36**(9):139–154.

Teichert, T., E. Shehu, I. von Wartburg. 2008. Customer segmentation revisited: The case of the airline industry. *Transportation Research Part A: Policy and Practice*, **42**:227–242.

Theis, G., T. Adler, J.P. Clarke, M. Ben-Akiva. 2006. Risk aversion to short connections in airline itinerary choice. *Transportation Research Record: Journal of the Transportation Research Board*, **1951**:28–36.

Train, K. 2003. Discrete choice models using simulation. Cambridge University Press, Cambridge.

Tu, Y., M.O. Ball, W.S., Jank. 2008. Estimating flight departure delay distributions. A statistical approach with long-term trend and short-term pattern. *Journal of the American Statistical Association*, **103**(481):112–125.

U.S. Government Accountability Office. 2010. Commercial Aviation: Consumers could benefit from better information about airline-imposed fees. July 14, 2010; `http://www.gao.gov/products/GAO-10-785`.

Warburg, V., C. Bhat, T. Adler. 2006. Modeling demographic and unobserved heterogeneity in air passengers' sensitivity to service attributes in itinerary choice. *Transportation Research Record: Journal of the Transportation Research Board*, **1951**:7–16.

Wen, C., S. Lai. 2010. Latent class models of international air carrier choice. *Transportation Research Part E: Logistics And Transportation Review*, **46**(2):211–221.