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

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In 2008, the majority of U.S. airlines began charging first for one, and then, two checked bags. One of the often cited reasons for this action by the airlines' executives was that this would influence customers to travel with less baggage and thus improve cost and operational performance. A notable exception to the charging for checked bags trend was Southwest Airlines, who turned their resistance to this practice into a "Bags Fly Free" marketing campaign. Using a publicly available database of the airlines' departure performance, we investigate whether the implementation of checked bag fees really did result in better operational performance metrics. At the aggregate level we find that 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. However, charging a fee for both checked bags results in a worse on-time departure performance compared to charging for one checked bag. We also identify the differential impact of baggage fees on 'low-cost' versus 'legacy' carriers: the departure performance of the low-cost airlines became worse while it improved for the legacy carriers when charging for one checked bag. 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. Thus, our study provides empirical evidence on the influence of checked baggage fee policies on airlines' operational performance.

Key words: baggage fees; departure delays; on-time performance; airlines
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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 10th 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 19th, 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 5th, 2008. A week later, American Airlines matched the other airlines' baggage policy and, on June 15th, 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 2008a). 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

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

[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.

(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 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.

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?

[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.

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 the paper 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 the paper.

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 et al. (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 delays as a 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 et al. (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. Lapre and Tsikriktsis (2006) use airline data to examine organizational learning curves in the airline industry. Diwas and Venkataraman (2012) perform an event study analysis, a methodology related to our paper, to examine the impact of the passage of health care laws requiring universal coverage on patient behavior. 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 flier 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 et al. (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 et al. (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 et al. (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 et al. (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.

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 2008c). 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 fliers. 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

[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

checked bag (see Table 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 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:

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.

> *"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 2008a)

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, 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

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

connecting flights and has to be sorted and driven to lots of different planes." 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." 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 2008b). 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, y, and z 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 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 2008c). 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

[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).

airlines: "Pilot-and flight-attendant costs increase since many are paid based on 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.*

4. Methods

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 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 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 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 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. Similar to the methodology in Deshpande and Arıkan (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 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, 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 3). All the variables in our datasets are described next.

4.1.1. Explanatory Variable

Checked bag fee. The *Bag-Fee* ordinal variable indicates the status of each flight in our datasets with regards to the checked bag fee policy of the airline that flew the flight. Thus,

[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 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).

$Bag\text{-}Fee$=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.

4.1.2. Dependent Variables

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 et al. (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 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*

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

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 4.

Table 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

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. For the minimum time to turn an aircraft (T_i), we used one of these 5^{th} percentile values instead of the original one in case the original turn-time variable was obtained from very few flights (i.e., less than 20 observations) or was very high (i.e., more than 90 minutes). 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 be zero. Thus, the spillover, L_i, from flight $i-1$ to flight i is given by

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

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:

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

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).

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*.

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 et al. 2008). Since June 2003, the airlines that report on-time data to the BTS also report the causes of delays[13] for their

[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).

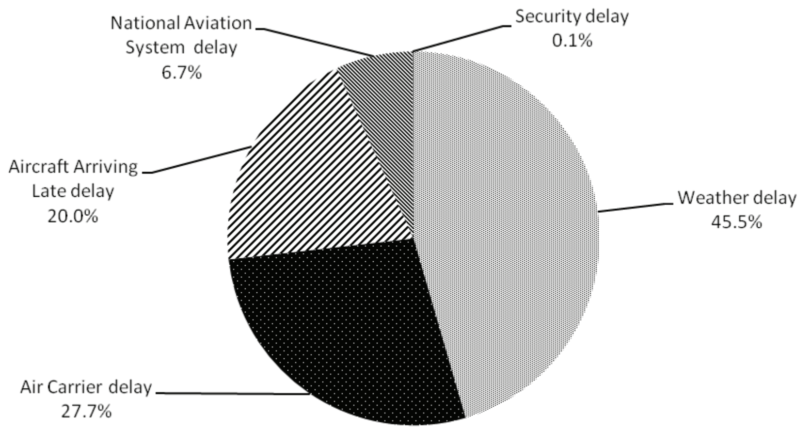

Figure 1 **Flight delays by cause in January-December, 2008 (based on the BTS data on all carriers and airports)**

flights. Figure 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 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 year 2008.

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 5.

Table 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

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:

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 2007). 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.

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

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

To analyze the impact of *Bag-Fee* on *Scheduled-Block-Time*, we use the second dataset to test Model 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.

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

5. Results and Discussion

5.1. Spillover-Adjusted Departure Delay

The results of the estimation of our Tobit1 model are shown in Table 6[14]. 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 (when a delay occurs) 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 6 also shows that the other control variables, except *Avg-Passengers*, are statistically significant.

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

Table 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.
***$p < 0.0001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$

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 determined 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 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 7 lists the Tobit2 estimation results[15]. 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-Fee* variable corresponding to implementing two checked bag fees, is positive and statistically significant (0.6229; $p<0.05$). 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 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 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

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

Table 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.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

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 8[16] 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[17], we created two datasets, i.e. 'Legacy Carriers' dataset comprising American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, US Airways, and Southwest Airlines, and 'Low-Cost Carriers' dataset comprising AirTran Airways, JetBlue Airways, and Southwest Airlines[18]. The Tobit results in Table 9[19] 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 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

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

[17] 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).

[18] 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.

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

Table 8 Summary of Tobit2 regression - JetBlue Airways included

Dependent variable: SpAdj-DepDelay			
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.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

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 9 shows negative coefficients of the same variable, and thus indicates that American Airlines, Continental Airlines, Delta Airlines, 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.

Table 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 Airlines, 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.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

5.2. Scheduled Block Time

The results of the OLS1 regression estimates for each airline's scheduled block times are shown in Table 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^{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[20].

Table 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

[20] "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)

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.

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:

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

$$\beta_{12} * \textit{Avg-Passengers}_i + \beta_{13} * \textit{Origin-Awnd}_i +$$
$$\beta_{14} * \textit{Origin-Prcp}_i + \varepsilon_i. \tag{3}$$

Table 11 shows the results according to (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 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

Table 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.
$^{***}p < 0.0001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

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 Tabel 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.

6. Conclusions

While investigating whether the social planner would let bags fly free, Allon et al. (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 [21]. We speculate that Southwest now achieves savings of similar magnitude after other airlines

[21] This estimation is based on a delay cost of $19.49 per minute for Southwest Airlines (Ferguson et al. 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).

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.

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