

# Evaluating Passenger Delays in the US Domestic Air Transportation System

by

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Submitted to the Department of Civil and Environmental Engineering

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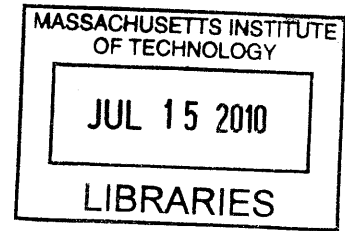
Master of Science in Transportation

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## ABSTRACT

A fundamental component of any National Airspace System (NAS) performance evaluation is the cost impact of air traffic delays, and more generally capacity limitations, on the travelling passengers. In previous research it has been conclusively shown that flight delay data and flight-centric metrics fail to accurately represent the passenger travel experience and passenger trip delays accurately. This is because they do not capture the effect of passenger itinerary disruptions such as flight cancellations and misconnections. There are several complexities and subtleties underlying the conversion of flight delay data to passenger trip delay data, because of which delay cost to passengers is typically not measured accurately nor understood well. The primary aim of this thesis is to use the passenger-based metric, passenger delay, to capture the effect of itinerary disruptions, and evaluate the performance of the air transportation system from the passenger's perspective. A new methodology to improve current estimates of passenger delays relying solely on publically available data sources is reviewed. Later, the methodology is applied to estimate the magnitude of passenger delays in the US domestic air transportation system for the year 2007. The passenger trip data generated using this methodology is also used to carry out a comprehensive disaggregate analysis of air traffic delays in the US domestic air transportation system for the same timeframe.

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# Chapter 1

## Introduction

Passenger trip time is one of the most critical performance indicators of the Quality of Service (QOS) provided by any air transportation system. Passenger trip time informs passenger choices of flights, airlines, and airports, and has been found to be positively correlated with customer satisfaction, airfare elasticity and brand loyalty that drives airline profits. Regulatory consumer information available to airline passengers provides measures of trip performance using only flight data, and not passenger trip data. Previously, researchers, using a small set of proprietary airline data, demonstrated that trip delays experienced by passengers due to missed connections, and cancelled flights are far from negligible, and in fact add very significantly to the delays associated directly with delayed flights. Further it has been shown that airline on-time based metrics and other flight-centric measures of air transportation system performance fail to reflect accurately the passenger experience, as they tend to greatly underestimate the magnitude of delays experienced by passengers disrupted due to cancellations and misconnections. Thus, flight-based metrics fail to represent the true passenger travel experience accurately and may not be a good proxy for passenger trip delays [32]. It is the objective of this thesis to use the passenger-based metric, passenger delay, to capture the effect of itinerary disruptions such as flight cancellations and misconnections, and evaluate the performance of the air transportation system from the passenger's perspective.

### 1.1 Flight Delays

According to the Bureau of Transportation Statistics (BTS), from 1990 to 2006, the number of flights operated by commercial airlines in the United States grew from 6.6 million in 1989 to 8.0 million in 2006, a 21% increase. Aggregate airport capacity gains during the same period were more modest. This unbalanced increase in flight operations relative to total airport capacity caused severe system congestion, and numerous flight delays as well as cancellations, adversely affecting the traveling public. In addition, as more and more flights were scheduled at congested airports, ground congestion became a major hindrance to efficient operations.

The major airlines in the U.S, defined as airlines generating at least one percent of total domestic scheduled-service passenger revenues annually, are mandated by federal law to provide flight operation information, including actual departure time, arrival time, cancellation and diversion, for each domestic U.S. flight serviced by jet aircraft. Since 1987, flight delay statistics have been published in the Air Travel Consumer Report on a monthly basis and maintained in the Airline Service Quality Performance (ASQP) database, which is publically accessible [36]. In 2009, 19 carriers reported these numbers, including Pinnacle Airlines that reports its flight delay data voluntarily [2].

The metric currently employed by the DOT and airlines to estimate on-time performance is the 15 minutes on-time performance (15-OTP), also referred to as the airline dependability statistic. According to this metric, a flight is counted as "on time" if it operated less than 15 minutes later the scheduled time shown in the carriers' Computerized Reservations Systems (CRS). Arrival performance is based on arrival at the gate, while departure performance is based on departure from the gate. Moreover, a canceled flight is classified as a delayed flight. Based on the Air Travel Consumer Report for May 2009, the industry achieved an average 80.5% on-time arrival rate for all US airports reported, and 79.5 % at the 31 major U.S. airports that account for at least one percent of the nation's total domestic scheduled-service passenger enplanements. Hawaiian Airlines reported the best performance with 90.3% on-time arrivals, while Atlantic Southeast Airlines reported the worst performance with 65.7% on-time arrivals. In terms of airports, New York LaGuardia (LGA) experienced the worst on-time arrival performance of 60.5% and Salt Lake City (SLC) achieved the best performance of 91.0%. Table 1.1 lists the percentage of flight operations arriving on time by carrier. Table 1.2 displays the ranking of major airports' on-time arrival performance.

AT ALL REPORTABLE AIRPORTS		
CARRIER A/	NUMBER OF AIRPORTS REPORTED	PERCENT OF ARRIVALS ON TIME
HAWAIIAN AIRLINES S/	15	90.3
SKYWEST AIRLINES S/	138	86.8
PINNACLE AIRLINES S/V	115	86.8
ALASKA AIRLINES S/	46	85.7
SOUTHWEST AIRLINES S/	65	83.7
CONTINENTAL AIRLINES S/	56	83.5
NORTHWEST AIRLINES S/	77	82.9
FRONTIER AIRLINES S/	40	81.8
EXPRESSJET AIRLINES S/	94	81.6
MESA AIRLINE S/	112	81.6
UNITED AIRLINES S/	74	80.1
US AIRWAYS S/	77	79.2
AMERICAN AIRLINES S/	73	77.9
DELTA AIR LINES S/	85	77.4
JETBLUE AIRWAYS S/	44	77.2
AMERICAN EAGLE S/	112	76.8
AIRTRAN AIRWAYS S/	57	75.6
ATLANTIC SOUTHEAST AIRLINES S/	106	70.8
COMAIR S/	62	65.7
<b>TOTAL</b>		<b>80.5</b>

Table 1.1: Percentage of flight operations arriving on time by carrier in May 2009

Source: Air Travel Consumer Report [2]

<b>Rank</b>	<b>Airport</b>	<b>% on time arrival</b>
1	SLC	91.0
2	IAH	89.3
3	LAX	86.4
4	LAS	86.3
5	PHX	86.3
6	DTW	86.0
7	MSP	85.4
8	SAN	85.3
9	MDW	85.0
10	DEN	84.2
11	CVG	83.9
12	BWI	83.4
13	ORD	83.0
14	STL	82.6
15	SEA	82.0
16	DCA	81.9
17	PDX	81.6
18	TPA	80.1
19	IAD	79.6
20	MCO	79.5
21	BOS	78.6
22	DFW	78.6
23	CLT	76.5
24	FLL	74.9
25	MIA	71.2
26	ATL	69.8
27	PHL	69.7
28	SFO	68.6
29	JFK	68.4
30	EWR	64.8
31	LGA	60.5
	Total	79.5

Table 1.2: Ranking of major airport on-time arrival performance in May 2009

Source: BTS, Airline On-Time Data [2]

Since June 2003, the airlines that report on-time data have also been reporting the causes of delays and cancellations to the Bureau of Transportation Statistics. The causes of delay are reported by the airlines in five broad categories that were created by the Air Carrier On-Time Reporting Advisory Committee. These categories are Air Carrier, National Aviation System, Extreme Weather, Late-Arriving Aircraft and Security Delay. The causes of cancellation are the same, except there is no late-arriving aircraft category. The categories have been defined as follows [8]:

- Air Carrier Delay: The cause of the cancellation or delay was due to circumstances within the airline's control (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc.).
- Extreme Weather Delay: Significant meteorological conditions (actual or forecasted) that, in the judgment of the carrier, delays or prevents the operation of a flight such as tornado, blizzard or hurricane.
- National Aviation System (NAS) Delay: Delays and cancellations attributable to the national aviation system that refer to a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control.
- Late-arriving aircraft: A previous flight with same aircraft arrived late, causing the present flight to depart late.
- Security Delays: Delays or cancellations caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas .

Figure 1.1 depicts the distribution of the overall causes of flight delays for May, 2009. We observe that NAS delay contributes the greatest level of delay among all carriers. It is interesting to note that Late Arriving Aircraft Delay representing delay propagating to downstream flights contributes a significant proportion (5.84%) of the total delay. In other words, while a total of 12.57% (4.56% + 7.36% + 0.62% + 0.03%) of flights are delayed due to extreme weather, NAS, security or delay of air carrier, 5.84% of flights have their delay propagated to the next flight in the trajectory. This suggests that in almost half of the cases, on average, in which an aircraft is delayed due to one of these four causes, the delay is long enough to propagate to the next flight.

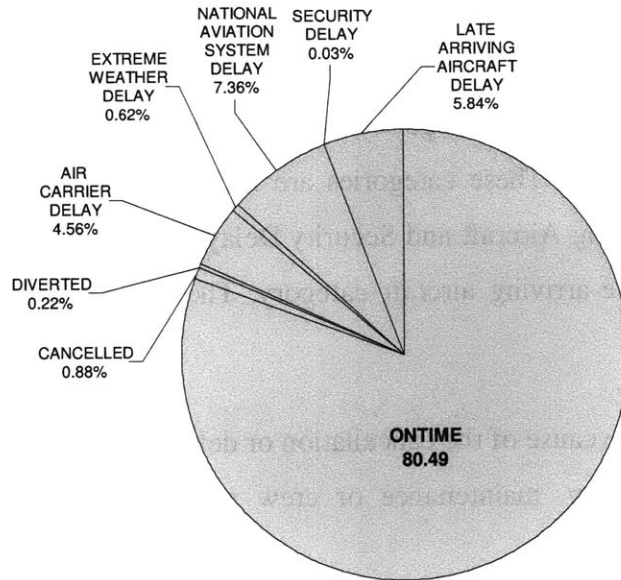


Figure 1.1: Overall causes of flight delay for May, 2009 [2]

While flight schedules and ticket prices are the main drivers of airline profitability, studies show that customer satisfaction and loyalty drive long-term profitability of any airline [23]. Because the airline industry is a highly competitive business, high service reliability can be a major advantage in attracting and retaining passengers. In particular, this is true for business passengers, who tend to be more time sensitive and are especially valuable to airline profitability. To provide consumers information on the quality of services provided by the airlines, the US Department of Transportation (DOT) currently uses the following six types of information to evaluate airline service reliability: (1) flight delays, (2) mishandled baggage, (3) over-sales, (4) consumer complaints (5) loss or injury of animals during air transportation, and (6) customer service reports. While (1), (2), and (3) are reported by the BTS; (4) and (5) are reported by the DOT Aviation Consumer Protection Division based on complaints submitted by customers; and (6) is generated from information submitted to the Transportation Security Administration related to airline and airport security. As illustrated in Figure 1.2, the most common complaints are related to flight problems, defined by the DOT [36] as “flight delays, cancellations, misconnections, or any other deviations from schedule, whether planned or unplanned”.

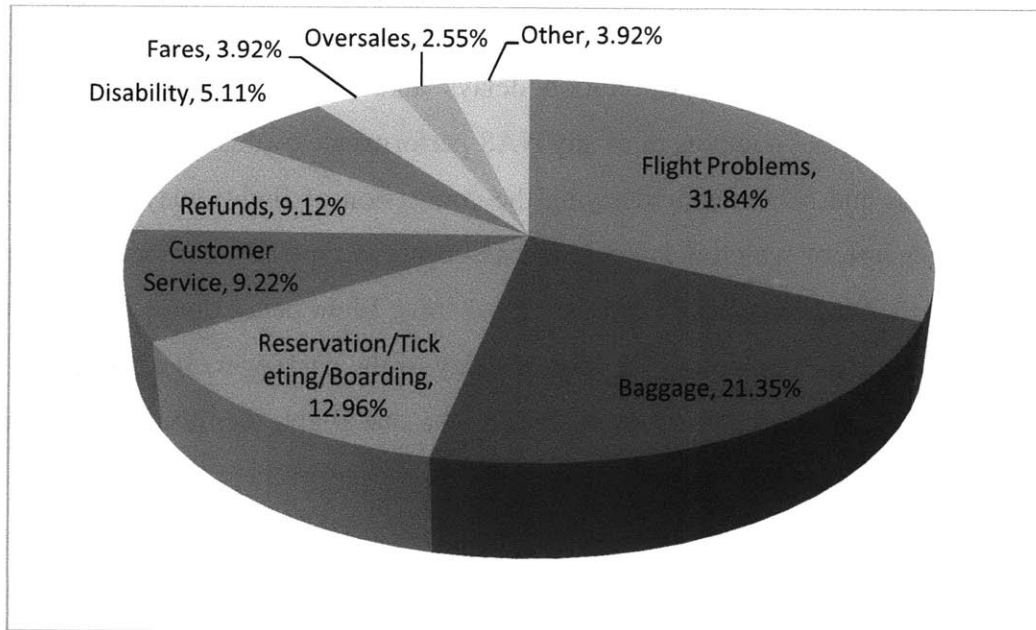


Figure 1.2: Distribution of passenger complaints in May, 2009 [2]

In research done by Bratu and Barnhart (2005), passenger complaints and negative reports for the period 1995 to 2000 were compared with flight-based performance metrics. From this comparison, the researchers inferred that the flight based metrics could not explain the sharp increase of complaints and negative reports in 2000 [31]. In other research projects, including those of Wang and Sherry (2006) and Ball, Lovell, Mukherjee and Subramanian (2005), similar results have been derived. Thus, it may be concluded that while flight delay has been one of the key indicators of system performance, and will continue to be an important indicator, more sophisticated delay metrics are needed to provide a complete picture of the performance of the air transportation system from the viewpoint of the passenger. Our proposed passenger-centric metric of the performance of the air transportation system is '*passenger delay*'.

## 1.2 Estimation of Passenger Delays from Flight Delays

The cost to passengers of air transportation delays and, more generally of NAS capacity limitations is a fundamental component of any NAS performance evaluation. However, there are several complexities and subtleties underlying the conversion of flight delay data to passenger trip delay data, because of which delay cost to passengers is typically not measured accurately nor understood well. Studies typically estimate an average flight delay figure and implicitly use this figure as the basis for computing the cost of delay to the passenger. If a passenger books a direct flight to his or her destination and is able to take that flight, then the delay of that flight does indeed correspond to the delay of the passenger. However, average flight delay statistics do not capture the delays associated with *disrupted passengers*. The two most typical cases for trip disruptions are:

- when a passenger arrives at the airport and subsequently the booked flight is canceled; and
- when a passenger misses a connection on a multi-leg trip.

Previously researchers have shown that flight-based metrics do not include the trip delays accrued by passengers who were re-booked due to cancelled flights or missed connections. Moreover, flight-based metrics do not quantify the magnitude, but only the likelihood of delay. It has been shown conclusively that, when the effects of disruptions are considered, the average passenger delay can be substantially higher than the average flight delay. Thus flight data and flight based metrics fail to provide the consumer with a complete assessment of the impact of a delay. One of the major hindrances to developing passenger-centric metrics is the unavailability of relevant airline data, which are considered proprietary and are also protected by anti-trust collusion concerns and civil liberty privacy restrictions [30].

While there are readily available statistics that allow direct compilation of total flight delays, it is more difficult to compute (or estimate) total passenger delays. Bratu and Barnhart's (2005) research on passenger on-time performance was the first to validate and measure the discrepancy between the vehicle performance and passenger service with actual airline data [6, 7]. The

analysis was performed using proprietary airline data to study passenger trip times of a major U.S. airline. The study clearly showed that flight-based metrics are poor surrogates for passenger delays for hub-and-spoke airlines as they do not capture the effect of missed connections and flight cancellations. However, the limitation of this research approach is that it must rely on proprietary airline data. Later, Professor Michael Ball at the University of Maryland expanded MIT's research on passenger trip delay estimation. Unlike Bratu and Barnhart's research, Ball et al [4] developed an analytical passenger delay model that focused on the estimation of disruption probability rather than the estimation of passenger trip delay. This research tried to expand the passenger trip delay estimation to the system level. However, a major limitation of it is that it assumes an average passenger trip delay of 420 minutes for all the disrupted passengers, regardless of other factors. Because passenger trip delay is not homogeneous in the system, but differs in terms of route, airport, time of day and carrier, the validity of results that rely heavily on this assumption is questionable.

According to a report prepared for the Senate Joint Economic Committee (JEC (2008) [29]), “the economic costs of air traffic delays are large and far-reaching”. As per JEC estimates, the total cost to airlines, passengers, and the rest of the economy, is estimated by this report to be as high as \$41 billion in 2007, including \$31 billion in direct costs and \$10 billion in spillovers. The Air Transport Association, using a different methodology, estimates costs (for the year ending September 2008) to be \$14.5 billion, excluding spillovers (ATA (2008) [1]). This is just about half the JEC estimate. The disparity in these estimates reflects differences in the way delay is measured, and particularly how flight delay is converted to passenger delay. Since the methodologies used to generate the JEC and ATA estimates are only intended to give reasonable estimates, it is understandable that they overlook many issues. Specifically, on the passenger side, they oversimplify the rather complex relationship between delays to individual flights and delays to passengers aboard those flights. The aviation community has generally accepted these limitations. Nonetheless, it would be interesting to know just how different the results would be if a more sophisticated and comprehensive analysis were performed. In the methodology developed by the research team at MIT discussed in this thesis, we use an algorithm to convert flight data into passenger trip data relying solely on publically available databases, but validated

with propriety airline data. More importantly, the methodology overcomes the primary challenge faced in earlier research work of extending the analysis to the system wide level.

### **1.3 Data for the Assessment of Airline Operational Performance**

The major data sources for assessing airline operational performance in this thesis comes from the U.S. Bureau of Transportation Statistics (BTS), which maintains a number of publically available datasets related to airline travel. The description of each data file used in our analysis is as follows:

**T-100 Domestic Segment (U.S. Carriers)** contains domestic non-stop segment data reported by U.S. air carriers by month. Information includes carrier, origin, destination, available capacity, number of scheduled departures, number of performed departures, number of passengers on each flight segment, and load factor when both origin and destination airports are located within the boundaries of the United States and its territories. The number of passengers in this data file is aggregated on a monthly basis over each flight segment (BTS (2006) [13]).

**DB1B** is a 10% sample of airline tickets from reporting carriers collected by the Office of Airline Information of the BTS. It consists of 3 parts: DB1B Coupon, DB1B Market, and DB1B Tickets, described as follows.

**DB1B Coupon** provides coupon-specific information for each domestic itinerary of the Origin and Destination Survey, such as the operating carrier, origin and destination airports, number of passengers, fare class, coupon type, trip break indicator, and distance. The number of passengers reported in this data file is aggregated on a quarterly basis over each domestic itinerary and the itineraries do not contain flight schedules (BTS (2006) [10]).

**DB1B Market** contains directional market characteristics of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination

airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators (BTS 2006 [11]).

**DB1B Ticket** contains summary characteristics of each domestic itinerary on the Origin and Destination Survey, including the reporting carrier, itinerary fare, number of passengers, originating airport, roundtrip indicator, and miles flown. The number of passengers in this data file is aggregated on a quarterly basis over each domestic itinerary and the itineraries do not contain flight schedules (BTS 2006 [12]).

**Flight On-Time Performance (ASQP)** contains on-time arrival data for non-stop domestic flights by major air carriers, and provides such additional items as departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance. (BTS 2006 [9]).

**Enhanced Traffic Management System (ETMS)** maintained by the Federal Aviation Administration (FAA) includes schedule information for all flights tracked by air traffic control. This database is not publicly available, due to the presence of sensitive military flight information, but a filtered version was made accessible for the purposes of our research.

**Schedule B-43 Aircraft Inventory Data** provides annual lists of aircraft in inventory for most airlines.

**Continental Proprietary Booking Data** for the 4<sup>th</sup> quarter of 2007. This data is used for training our passenger flow estimation model and also for validating our results. The flights in the proprietary booking data are matched against the ASQP data using an Oracle database.

## 1.4 Definitions

To facilitate the description of our analysis, we introduce the following notation and definitions. A non-stop flight  $f$ , also referred to as a flight leg, is associated with a flight number, an origin airport, a destination airport, a Planned Departure Time,  $PDT(f)$ , and a Planned Arrival Time,  $PAT(f)$ . In actual operations,  $AAT(f)$  represents the Actual Arrival Time of flight  $f$  at the gate and  $ADT(f)$  to the Actual Departure Time from the gate. The Flight Arrival Delay of flight  $f$ , denoted by  $FAD(f)$ , equals  $\max(AAT(f) - PAT(f); 0)$  and the Flight Departure Delay, denoted by  $FDD(f)$ , equals  $\max(ADT(f) - PDT(f); 0)$ . A Scheduled Itinerary, (SI) is a sequence of scheduled flight legs serving a group of passengers.

Two other useful definitions are concerned with connection times at transfer airports. The Minimum Connecting Time (MCT) is the minimum time required to disembark an aircraft and walk between the arrival and departure gates of two connecting flights. For the purposes of our analysis, we have also defined the Maximum Layover Time (MLT) as the maximum allowable waiting time at a connecting airport between the passenger's incoming flight's arrival and his/her outgoing flight's departure (please see Chapter 3 for more details).

A passenger is said to be disrupted if:

- One or more of the flights in his/her scheduled itinerary is canceled; or
- The time between consecutive flights in his/her scheduled itinerary is less than the MCT; In this case, the passenger misses his/her connection.

By DOT definition, a "cancelled" flight refers to "a flight that was not operated, but was in the carrier's computer reservation system within seven days of the scheduled departure." A "diverted" flight refers to "a flight which is operated from the scheduled origin point to a point other than the scheduled destination point in the carrier's published schedule."

Additionally, in our future discussion, we adopt the conventional definition of segment (a pair of points served or scheduled to be served by a single stage of at least one flight leg at any given

time), and route (the sequence of one or more flight legs serving an origin/destination airport pair).

## **1.5 Thesis Contributions**

The primary goal of this thesis is to evaluate passenger delays and study the distribution of delays across the various segments of the US domestic air transportation system for the year 2007. We use the passenger-based metric, passenger delay, to capture the effect of itinerary disruptions such as flight cancellations and misconnections, and evaluate the performance of the air transportation system from the perspective of passengers. In earlier research, the primary challenge in estimating passenger delays has been that publically available data sources do not contain passenger itinerary flows. For example, on a given day, there is no way to determine from publically available data sources how many passengers planned to take the 9:05 am American Airlines flight from Boston (BOS) to Chicago (ORD) followed by the 1:15 pm flight from Chicago (ORD) to Los Angeles (LAX), or even the number of non-stop passengers on each of these flights. The new methodology developed by the research team at MIT addresses this limitation. The algorithm converts flight data to passenger trip data, based on a number of publically available datasets related to airline travel. The proposed methodology uses a statistical model of passenger itinerary choice trained on a small set of proprietary passenger booking data to simulate passenger itinerary flows for all airlines. Subsequently, the Passenger Delay Calculator developed in earlier research work by Barnhart and Bratu (2005) is used to estimate the magnitude of U.S. domestic passenger delays for 2007 based on these simulated passenger itinerary flows.

The passenger trip data generated using the algorithm described above was also used for the first time to carry out a comprehensive disaggregate analysis of air traffic delays in the US domestic air transportation system. We study the variation and distribution of passenger delays and flight delays across different airports and airlines. More importantly, we try to understand the important factors that affect passenger delays such as flight cancellation rates, percentage of connecting passengers, percentage of misconnections and connection times for individual carriers. Further, we try to identify any patterns in the variation of the delay multiplier ratios,

defined as the ratio of average passenger delay and average flight delay, over time as well as across different carriers. We also try to identify carriers with the highest level of disruptions in the form of cancellations and misconnections, and identify airports which are associated with the highest levels of passenger delays as well as those most prone to misconnections.

## **1.6 Thesis Outline**

The remainder of the thesis is structured as follows: Chapter 2 provides a review of previous studies related to the investigation of the cost impact of delays on airlines, passengers and the spillovers to the rest of the US economy. The estimation of delays to passengers is the subject of Chapter 3, which presents an approximate estimate of passenger delays in the US domestic air transportation system for the year 2007, as well as a new methodology for improving current estimates of passenger delays by relying solely on publically available data sources. We carry out a detailed disaggregate analysis of the distribution of passenger and flight delays across different segments of the air transportation system such as airports and carriers in Chapter 4. Chapter 5 provides conclusions and recommendations for future work.

## **Chapter 2**

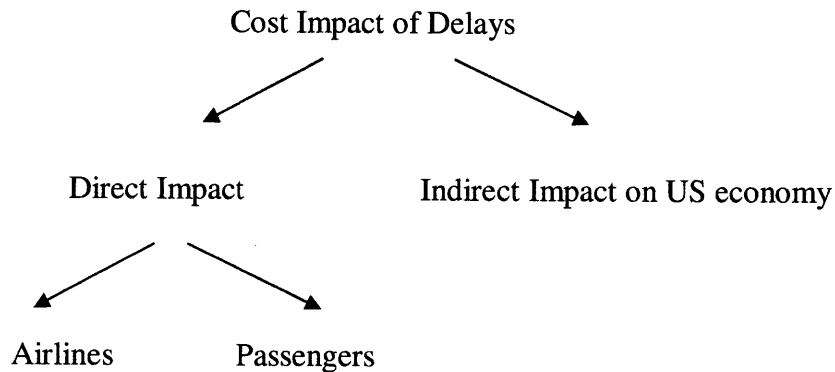
### **Literature Review and a Perspective on Passenger Delays**

This chapter discusses some of the ideas outlined in the interim report of the Total Delay Impact Study (2009) [28] being performed by NEXTOR, designed to be one of the most comprehensive and scientific treatments of the subject of air traffic delay performed to date. In particular, the chapter amplifies on the ideas and tries to explain clearly some of the subtle points involved in the analysis of air traffic delays presented in the combined TDI document prepared by Professor Michael Ball of the University of Maryland (UMD). The chapter uses the same structure and notation as in Professor Ball's document. In Section 2.1 we begin by introducing a few notations and definitions, and break down our discussion of cost impact of delays into three cost categories – airlines, passengers and the indirect impact on the US economy. Section 2.2 discusses the cost impact of delays on the providers of air transportation service, the airlines, in the form of added expense and lost revenue, and further discusses three different methodologies to estimate the cost of delays to airlines. In section 2.3, we discuss the cost impact of delays to passengers and provide a qualitative discussion on how flight delays differ from passenger delays. Moreover, we discuss other forms of delay costs resulting from particular types of passenger response to delays — rescheduling trips to allow time for delays in reaching the destination, and schedule delay to passengers caused by airport capacity limitations. We then provide an estimate for the total delay cost to passengers, and also briefly discuss the potential interactions between the different delay cost components of passengers. Finally in section 2.4, we look at how passengers are affected by and respond to air traffic delays.

#### **2.1 Delays: Definition and Impact**

One of the most pressing problems of The National Airspace System (NAS) of the United States is flight delay. Delay creates high cost to airlines, complaints from passengers, and difficulties for airport operations. As demand on the system increases, the delay problem becomes more and

more prominent. For this reason, it is essential to understand the causes of delay and to find ways to reduce delay (Kathryn et al., 2006). Figure 2.1 illustrates a schematic representation of the cost break down of congestion and resulting flight delays in the air transportation system.

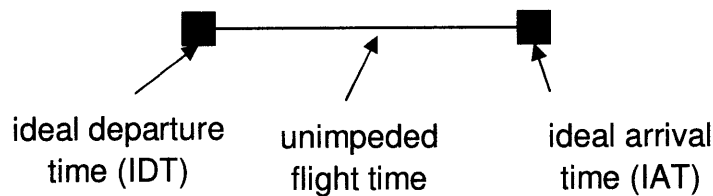


**Figure 2.1 Schematic representation of cost breakdown of flight congestion and delay**

Thus, as shown, the cost of congestion and delays is broken down into the following two broad categories – (1) Direct Cost and (2) Indirect Cost. The direct costs of congestion and flight delay include costs to airlines in the form of added expense and lost revenue, and to passengers in the form of decreased convenience and additional misery and stress, which may further lead to additional expenses for food and lodging. The consequences of flight delays are of course not confined to airlines and their passengers, but also any other industry that depends on air travel. The added costs and reduced efficiency in other industry segments dependent on air travel e.g., manufacturing, retail, etc, and the resulting impact on their customers, creates a third cost category which is a form of indirect cost of delays.

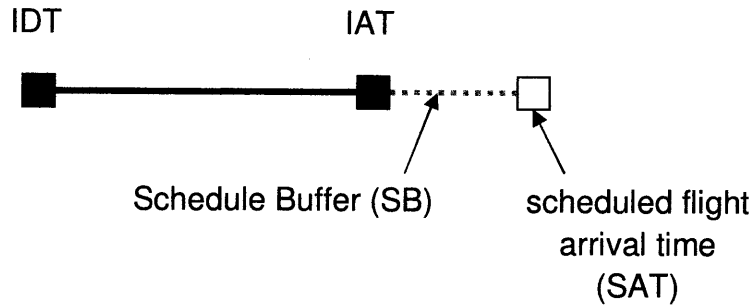
To understand and estimate the impact of congestion and delays on airlines, passengers and the rest of the economy, we start by introducing a few notations and definitions. To begin with, we consider an ideal air transportation system with no congestion and delays at all. In such a system, let us assume that the airline initiates the process of scheduling a flight with an *ideal flight departure time (IDT)*. The airline would then choose the most appropriate aircraft type from their

fleet for the flight. Using the characteristics of the chosen aircraft, the time required to fly the optimal, unimpeded origin-to-destination trajectory, may be estimated as the *unimpeded flight time*. Using IDT and the unimpeded flight time, the *ideal arrival time (IAT)* can then be computed. This is shown schematically in Figure 2.2.



**Figure 2.2:** Ideal Flight in absence of congestion and delays

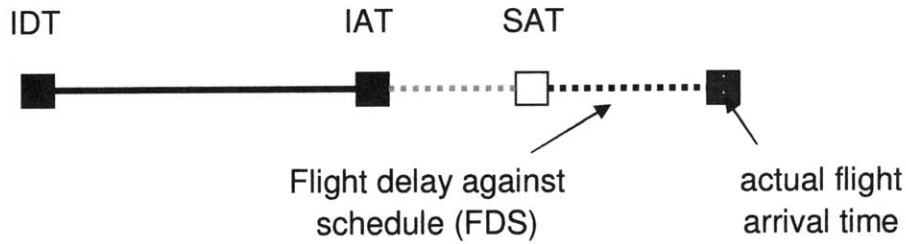
In the real world with congestion and delays in the air transportation system, the airlines typically increase scheduled flight times over unimpeded ones in order to account for delays resulting from flight restrictions imposed to organize traffic, congestion, and a variety of other factors. We call this added time the *schedule buffer (SB)*. This is illustrated in Figure 2.3. We may define SB as the time difference between the scheduled flight time and the 5<sup>th</sup> percentile of all observed travel times, for a given segment and study period. Choosing the 5<sup>th</sup> percentile rather than minimum travel time makes sense, because it makes the calculation more robust to measurement error, and reduces the influence of unusually favorable conditions, such as strong tailwinds. Thus, once an unimpeded flight time has been determined, the schedule buffer can be computed from historical data.



**Figure 2.3:** Schedule Buffer (SB)

In addition to the buffer inserted in the flight block time, buffer times are also placed on the ground times for aircraft turnaround operations, because airlines have more control, power and flexibility over the turnaround processes on the ground. Moreover, the cost of delay per unit time on the ground is much less than the unit cost of delay to aircraft delays in airspace. Thus, the scheduled ground times for turnarounds are seen as a tactical and effective means to stabilize aircraft rotations and to prevent further knock-on delays, also called reactionary delays or delay propagation, down the rotation lines of the whole fleet. Given the exchange of passengers and other resources among flights, disruptions to some resources and activities may cause delay propagation in the network via aircraft rotation, unless delays are effectively absorbed by the buffer times built into the schedule or contained by other tactical measures [14]. Thus, although the ground buffer time is another component of delay cost to both the airline and passengers, one can realize the crucial role it plays in maintaining efficient and effective aircraft turnaround operations in daily airline operations control.

In practice, the type of delay that passengers are most typically concerned about is late flight arrival relative to schedule. We define this time difference between the scheduled arrival time and actual arrival time as the flight delay against schedule (FDS). This is illustrated in Figure 2.4. Both SB and the FDS represent excess travel times that would not exist in a system with ample capacity that was free of congestion. However, while SB is known in advance and anticipated by the passenger, FDS is highly stochastic and varies unpredictably from day to day and flight to flight. FDS can even be negative because the SB may exceed the delays incurred for a particular flight. This gives FDS a very different character when compared to SB.



**Figure 2.4:** Flight Delay against Schedule (FDS)

In the subsequent sections, we study the impact of delays on airlines and passengers, in terms of the two measurable quantities defined above: schedule buffer (SB) and flight delay against schedule (FDS).

## 2.2 Cost Impact of delays on Airlines

Airlines, the suppliers of air transportation service, experience flight delays through increased operating cost, due to extra fuel, crew time, aircraft maintenance, and other resources that are consumed by flight delays. To mitigate delays, schedule padding has now become common practice in airline operations, causing airlines additional expenses in order to output the same amount of service. Unfortunately schedule padding has not received much attention in research so far. The quantification of the schedule padding effect on total cost is largely ignored except for two studies (ITA, 2000 [24], U.S. Senate JEC, 2008 [29]). While airlines no-doubt realize that schedule padding is expensive, they must weigh this cost against the substantive and marketing advantages of maintaining a good on-time performance record. To illustrate the impact of SB on airline costs, we note that the typical pilot contract specifies that pilots are paid based on the maximum of scheduled block time and actual block time. Thus, the SB directly increases pilot (and airline) costs. Further, airlines create their fleet plans based on the scheduled flight arrival and departure times so that increasing SB leads to changes in schedules and eventually to poorer aircraft utilization and larger fleets. The high degree of uncertainty associated with FDS gives it a very different character. Because airline fleet and crew schedules

are based largely on the scheduled times, excessive or even moderate amounts of flight delays can be highly disruptive causing extra crew costs, various costs associated with accommodating disrupted passengers and even aircraft repositioning.

### **2.2.1 Methods for estimation of delay costs to airlines**

Broadly speaking, there are three established methods for estimating the cost of delays to airlines. One method is cost factor based, a second approaches the question from the total cost perspective, while the third uses a formulation built upon economic production theory to investigate the statistical relationship between airline cost and its various influencing factors, including delay.

The cost factor approach assumes a unit cost for delay, often differentiated by category, and calculates the total cost by multiplication with the total amount of delay minutes, similarly differentiated. The use of this method is intuitive, and consequently, has been adopted by the majority of existing cost-of-delay studies (ITA, 2000 [24], Cook et al., 2004 [17], Wingrove et al., 2005 [35], ATA, 2008 [1]). Categorization schemes vary across studies. For a single flight, this could be done according to where delay occurs, such as en-route, at-gate, and taxi (Cook et al. 2004 [17]), or based on whether the delay is triggered during this flight or propagated from operations of the aircraft on earlier legs (ITA, 2000 [24]), or delays to other flights that may be carrying connecting passengers or crews for the flight in question. This can be especially important in a hub-and-spoke network. The choice of delay classification largely depends on the data that are available to the researcher. This is a critical issue in employing the cost factor approach. Another issue associated with the cost factor based approach is determining the costs of factors themselves. A given type of delay often involves several cost components. Such components include cost from fuel, crew, maintenance, handling equipment, rentals, etc. The cost factor is the sum of the components, measured by \$/unit time. The question arises as to which components should be considered for a specific type of delay, and how the value for each cost component is determined. Very few efforts have been made so far to address these two issues. A typical way of estimating cost factors is to interview personnel from airlines, airports, handling agents, and research and administrative institutions (Cook et al. 2004 [17]). The

accuracy of results from this method is questionable since interviewees tend omit cost impacts that are not directly visible to them, thus usually underestimating the total cost. The difficulty of determining cost factor values is demonstrated by the wide range of unit cost factors appearing in the literature. Moreover, cost factors may vary across carriers and aircraft type. It would cause serious bias if only one single cost factor is assigned to all aircraft and airlines, for a specific type of delay, without detailed and hard to obtain fleet and cost information. Unfortunately, in many cost-of-delay studies this is just the case.

The second approach looks at the effect of delay on airlines' operating cost in a holistic manner. Compared to the previous method, it avoids the underestimation issue, because all elements are implicitly accounted for. In the U.S. Senate JEC study (2008), for example, both cost factor and total cost based approaches were adopted. It was found that the latter estimate is constantly higher than the former. However, in using the total cost approach the study inappropriately applied the share of operating time loss due to delay to total operating expenses. In effect, the cost structure of different flight operating phases can vary substantially. As noted by U.S. Senate JEC (2008), this simple calculation method can lead to an overestimation of total cost, because cost elements such as landing fees and advertising, are much less affected by delays.

The third, a more rigorous approach based on economic production theory, involves deriving a cost function such that each airline minimizes its cost of producing a certain output given an input vector. It enables the establishment of a direct empirical basis for translating delay and other aspects of punctuality performance into monetary terms, which, unlike the cost factor approach, involves a minimum of assumptions about the delay–cost interaction mechanisms. Limited efforts to incorporate delay into airline cost models have met with some success (Hansen et al., 2000 [21], Hansen et al., 2001 [22]). These studies recognize that the quantity of delay is only one of the multiplicity of operational performance metrics that may affect operating cost. Other dimensions of airline operational performance, for instance, delay variability and schedule disruption, may play significant roles as well.

## 2.3 Cost Impact of delays on Passengers

### 2.3.1 Passenger Delays against Schedule (PDS)

It is frequently assumed that flight delay statistics provide an accurate depiction of passenger delay. However, the quantity analogous to FDS, *passenger delay against schedule* (PDS), can be dramatically different from FDS. If a passenger books a direct flight to his or her destination and is able to take that flight, then the delay of that flight corresponds to the delay of the passenger. However, average flight delay statistics do not capture the delays associated with *disrupted passengers*. A passenger's trip is disrupted if that passenger is not able to take one or more of his or her booked flights. The two most typical cases for trip disruptions are:

- when a passenger arrives at the airport and subsequently the booked flight is canceled and
- when a passenger misses a connection on a multi-leg trip.

Researchers, using a small set of proprietary airline data, have already demonstrated that trip delays experienced by disrupted passengers are on average, much larger than the corresponding flight delays. Thus, flight delay data cannot be used as a proxy for passenger trip delays. Further, we note that in the event of disruption, such as a flight cancellation or a missed connection, the passengers need to be re-accommodated on flights for which they were not originally ticketed. Doing this requires available space on the flights in question. As load factors become higher, such space is harder to find, which leads to slower recovery and increasing delays for disrupted passengers. It is also interesting to note the rather complex relationship between the delay on the first leg of a two-leg trip and the passenger's final delay. If the passenger makes his or her connection then the final delay depends only on the delay on the second flight leg. Thus, small delays on the first flight leg have no impact on the final delay. On the other hand, larger delays on the first leg can have the very dramatic effect of causing a missed connection and subsequently, sometimes extreme delays.

The above examples illustrate the fact that average PDS depends not only on the distribution of flight delays and the average FDS, but also on other metrics that represent the effect of disruptions, such as flight cancellation rates and load factors. To see the differences and understand passenger costs, let us take a simple view of how a passenger approaches air travel in an ideal environment. A passenger might start with a *preferred arrival time (PAT)*, and based on

the travel times offered by a chosen airline convert it into a *preferred departure time (PDT)*. We note that this time is a bit different from the unimpeded flight time described earlier. First, it could be that the scheduled itinerary time involves multiple flights. Of course, a passenger in most cases would prefer a single nonstop flight. However, multi-flight-leg itineraries are a way in which the airlines provide cost effective service to passengers. Thus, while the extra time associated with such itineraries might be viewed as a type of delay, it is not caused by congestion or deficiencies in air traffic management but rather by mechanisms used by airlines to provide cost effective service. On the other hand, the schedule buffer included within each constituent flight is a result of congestion as discussed previously and certainly represents extra passenger travel time and thus a cost to passengers. Thus, to summarize the above discussion, passenger delay costs can be related to a combination of SB and PDS. While statistics on SB can be readily derived from historical data, PDS statistics must be estimated based on sophisticated models that depend on flight delays, cancellation rates and load factors.

### **2.3.2 Voluntary Departure Time Adjustment (VDA)**

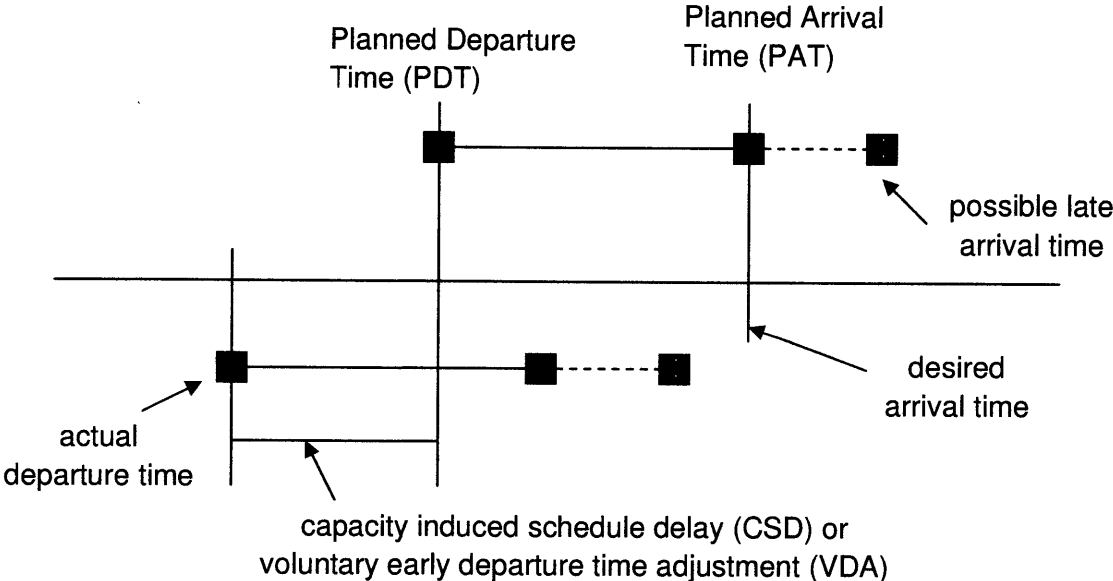
Passengers, especially business travelers often plan their departure times taking into account the possibility of arrival delays. For example, if a passenger absolutely needs to be at a destination by 10:00 AM, he or she typically would not take a flight scheduled to arrive at 10:00 AM, but rather would take a flight scheduled to arrive earlier to ensure arrival by 10:00 AM even in the case of significant flight delays. In fact, it is not uncommon for a business traveler to fly in the night before, only to ensure timely arrival at a morning meeting. This phenomenon, resulting in an associated adjustment in departure time, is called the *voluntary departure time adjustment (VDA)*.

### **2.3.3 Capacity Induced Schedule Delays (CSD)**

The time penalty suffered by a passenger owing to unavailability of any flights at his preferred departure time or the exact time at which he wishes to fly is referred to as the *schedule delay* of the passenger. For example, if a passenger wishes to arrive at a destination at 9:00 AM via a one hour flight, he would ideally book an 8:00 AM flight. However, if the only flight offered before

9:00 AM is a 7:00 AM flight, the passenger would be “forced” to take the 7:00 AM flight. We say that, in this case, the passenger suffered one hour of schedule delay. Generally, schedule delay is the result of airline scheduling practices and not owing to NAS capacity constraints. However, at highly constrained airports, the schedule delay could be a result of the flattening of schedules by airlines, thereby forcing them to offer flights at inconvenient times, when otherwise they would seek to provide better service to their passengers. We call this phenomenon and the associated added time as *capacity induced schedule delay (CSD)*.

Figure 2.5 illustrates the phenomena of *capacity induced schedule delay CSD* as well as Voluntary Departure Adjustment (VA) discussed earlier.



**Figure 2.5:** Illustration of delays related to difference between actual and desired departure time.

### **2.3.4 Estimation of total delay costs to passengers**

Based on our discussion, the total delay costs to passengers are combined via a simple addition, as shown.

$$\text{Total Passenger Cost} = \text{TC [SB]} + \text{TC [PDS]} + \text{TC [CSD]} + \text{TC [VSA]}.$$

Here, the notation TC [ ] refers to the total cost of the respective component over all domestic passengers during the time period under consideration. It may be noted that while in some cases, we can simply estimate the average or total values and multiply by a standard cost per unit time, in other cases it becomes important to investigate other approaches that recognize the non-linear nature of some of the cost functions. For example, it could be that the cost of a 3-hour passenger delay is much greater than 6 times the cost of a ½ hour delay. We should also point out that the cost functions associated with each of the four cases described above can potentially be quite different from one another because each of these types of delays or time adjustments are also different. Moreover, it also makes intuitive sense to have different cost functions for the same kind of delay in different situations. For example, if a business traveler leaves the night before to attend an early morning meeting to account for possible arrival delays (voluntary adjustment departure delays), then the arrival delay suffered by him on this night flight should not have the same cost per unit time as the unit delay cost he would have incurred because of arrival delays on an early morning flight, because by booking early he has already paid some price for possible arrival delays.

### **2.3.5 Potential interactions between different delay components**

In this section we seek to discuss the potential interactions between the different components of delay costs to passengers, as discussed in the preceding sections. Clearly, these delays and schedule adjustments are inter-related but when one considers a particular passenger trip they are largely independent phenomena. SB is an expansion of the passenger's scheduled (and actual) flight time, and is known in advance for a particular flight. PDS on the other hand, is highly unpredictable and therefore extremely disruptive. VSA and CSD represent adjustments to the passenger's chosen departure time due to generally independent mechanisms. For argument's

sake, if a passenger chooses to leave the night before to insure getting to a morning meeting on time, then the passenger has already adjusted for, and paid the price for, possible arrival delays (PDS). Thus, one might argue that there is a degree of “double counting” in this approach. However, such a passenger may plan to have a leisurely dinner and/or get to bed at a convenient time. If that passenger arrives 3 hours late, then these planned activities would be disrupted and further costs would be incurred. Thus, although the cost per unit time of arrival delays suffered by this passenger should be lower than the cost per unit time of arrival delays if he had taken the morning flight (as discussed in the previous section), the SB and PDS costs are still real and can be added to any costs related to the adjusted departure time.

## **2.4 Passenger responses to air travel delays**

Researchers studying travel behavior have previously established that the various components of travel time differ in their associated disutility. The two distinct dimensions of disutility relevant to assessment of the burden of travel have been identified as ‘*time of day*’ and ‘*travel setting*’. Trips that occur when a traveler would otherwise be sleeping are more burdensome than trips of comparable length that can be completed during the day. Some of the recent research work even provides estimates of business traveler value of time by time of day (Mehndiratta, Shomik Raj, 1996). Similarly, there is a considerable difference between the experience of working quietly during an un-crowded midday flight, and jostling late at night at an airport ticket counter with dozens of stranded, angry passengers trying simultaneously to rebook their canceled flights. In the Total Delay Impact Study, one of the major insights that emerged from the assessment of qualitative air passenger responses to delay is that the burden of delay depends strongly on the setting in which the delayed traveler finds himself and the activities in which he is engaged during that period.

This setting-specific disutility can be referred to as the intrinsic disutility of travel time. The amount of delay a traveler experiences can alter the intrinsic disutility of the traveler experience in broadly two ways. First, with increase in delay, the total trip travel time increases and, thus there is a greater likelihood that a traveler will be in transit in the early morning or late night

hours. Second, delay can also increase the amount of time travelers spend in unpleasant and/or unproductive settings. For example, a traveler whose flight has been canceled may have to spend large amounts of time waiting in line and negotiating with ticket agents over rebooking arrangements, or a traveler experiencing a long ground hold will be unable to access his laptop.

Over and above the quantity of potentially productive time lost to delay, the intrinsic disutility has other macroeconomic implications. Many companies and business travelers believe that travel is a fundamental element of their business model, and although alternatives to business travel do exist, and in fact continually improve in quality, they are generally regarded as less effective than face-to-face interaction. Thus, the fundamental tradeoff in decisions regarding business travel has always been between the value of being there in person and the cost of getting there. The qualitative research carried out as part of the TDI project indicates that there is growing concern on the part of employers about the toll that business travel takes on their employees. This is out of the fear of losing their employees, typically to jobs that don't require travel, or to employers who do offer compensation for the time and aggravation of business travel.

Typically, factors contributing to the increasingly negative experience of travelers include flight delays, increased security measures, and the degradation of airline service standards. Confounding the problem even further is the unpredictability of air travel. Delays and unpredictability are widely perceived as significant problems, which increase the time, cost and aggravation of air travel. In response business travelers have adopted a variety of coping strategies. The growing time, uncertainty and overall unpleasantness of air travel is stimulating a growing interest in and acceptance of alternatives to air travel. For example, to avoid air travel delays and minimize the uncertainty in total travel time, business travelers are driving and taking trains, buses and private jets in lieu of commercial airlines. In order better to inform their expectations, travelers are also advised to arm themselves with as much information as possible. When they must travel, employees attempt to minimize the uncertainty and avoid delays as much as possible by selecting alternative flights, modes of transport and airlines.

It has also been found that passengers' choices are influenced more by information about the average delay experienced on a given route, regardless of whether or how delay varies across the day. The analysis performed as part of the TDI project suggests that business passengers form

their expectations of delay not on the basis of hour-to-hour changes or daily patterns, but rather on the basis of patterns of delay that existed across all hours for a given quarter some time in the past (*e.g.*, one year previously), or across multiple years of travel experience – or some combination of the two. This suggests that reliable real-time data on delay are either not sufficiently accessible to be used by business passengers planning a trip, or that business passengers lack the capacity to process such data effectively. An intuitive finding of this study suggests that passengers react more strongly to extreme delays than to moderate delays. This finding implies that the shape of the delay distribution matters, and that passengers may be better able to adapt to a system in which they experience frequent but small delays, than to a system in which they have a significant chance of being massively delayed.

While electronic communication has become a substitute for air travel, it has also enabled business travelers to work productively in situations where this would not previously have been possible. In this way it has helped to reduce the burden of air travel. Thus to summarize, all the above findings suggest that more widespread and timely dissemination of information about aspects of delay relevant to travel choices of passengers, could be very beneficial. As the time required to complete business trips increases, it is stimulating more concerted efforts to use travel time as productively as possible, or at minimum, as enjoyably as the situation permits.

## Chapter 3

### Passenger Delay Estimation

This chapter summarizes research performed by a team at MIT consisting of Amedeo Odoni, Cynthia Barnhart, Douglas Fearing, Vikrant Vaze and Nitish Umang. We present a new methodology for the computation of passenger delays, which converts flight data to passenger trip data relying solely on publically available data sources. The primary challenge addressed in this work is estimating disaggregate passenger itinerary flows from publicly available aggregate demand data using a small set of proprietary booking data. In earlier research, Ying and Barnhart (2009) presented an algorithm that used an allocation approach based on linear programming. The author of this thesis implemented the complete Ying's algorithm with some modifications in JAVA programming language. However, the one major limitation in using JAVA is its inability to efficiently process highly aggregated data such as BTS data. In the new methodology presented in this chapter, we first join passenger and flight data from multiple sources into a large Oracle database. We process the data to establish the necessary inputs for passenger allocation, such as potential itineraries and flight seating capacities. We then use a statistical model of passenger itinerary choice trained on a small set of proprietary passenger booking data to simulate passenger itinerary flows for all airlines. Subsequently, the Passenger Delay Calculator of Barnhart and Bratu (2005) is used to estimate the magnitude of U.S. domestic passenger delays for 2007 based on these simulated passenger itinerary flows. A more complete account of this work will appear in a forthcoming report prepared by the full team.

Barnhart and Bratu (2005) developed the Passenger Delay Calculator (PDC) to investigate the impact of delayed flights, cancelled flights and missed connections on passenger trip time. The analysis was performed using one month of proprietary passenger booking data of a major U.S. airline that makes extensive use of hub operations. From the analysis, it was estimated that while the average delay of passengers not disrupted by missed connections or cancelled flights was roughly equivalent to the average flight delay, disrupted passengers experienced an average delay that was about 20 times greater than the average flight delay in that same period. The

research done by Bratu and Barnhart quantified the gap between passenger delays and flight delays with real data, as well as demonstrated that flight-based metrics alone are a poor proxy for passenger delays in hub-and-spoke airlines. The major limitation of this research is that results required the use of proprietary airline data. This limitation restricts the applicability of the approach. The primary challenge in estimating passenger delays has been that publically available data sources do not contain passenger itinerary flows. For example, on a given day, there is no way to determine from publically available data sources how many passengers planned to take the 9:05 AM American Airlines flight from Boston (BOS) to Chicago (ORD) followed by the 1:15 pm flight from Chicago (ORD) to Los Angeles (LAX), or even the number of non-stop passengers on each of these flights. The new methodology presented in this chapter addresses precisely this limitation. The algorithm converts flight data to passenger trip data, relying solely on publically available datasets related to airline travel. At the end of the chapter, we also present an approximate estimate of passenger delays in the US domestic air transportation system for the year 2007.

### **3.1. Passenger Trip Delay Metrics**

Passenger Trip Delay is defined as the difference between the actual time of arrival of the passenger and the scheduled time of arrival on the ticket purchased by the passenger:

Passenger Trip Delay = Actual Passenger Time of Arrival – Scheduled Time of Arrival on Ticket.

Passenger Trip Delay can occur as a result of one or more of the following scenarios:

1. Passenger arrives late when the ticketed flight is delayed.
2. Passenger arrives late when the ticketed flight is diverted.
3. Passenger arrives late after being re-booked on a later flight when the ticketed flight is cancelled.
4. Passenger arrives late, when the passenger is denied boarding as a result of overbooking on the ticketed flight and is re-booked on a later flight.

5. Passenger on connecting itineraries arrives at the connecting airport late, misses the next leg in his/ her itinerary, and is re-booked on a later flight.

The trip delays experienced by passengers on late flights and on diverted flights are proportional to the magnitude of the delay of these flights. The trip delays experienced by passengers disrupted due to flight cancellations and missed connections, or those denied boarding because of overbooking, are also a function of the frequency and load factors, i.e. availability of seats on other flights to the desired destination. As the frequency of the flights diminishes and/or the load factor of candidate re-booked flights increases, the trip delay experienced by these passengers increases non-linearly, possibly at an exponential rate.

### **3.2 Methodology for estimation of passenger delays**

In this section we present the new methodology to estimate passenger delays using publically available data sources. The data sources and the algorithm used in the computation of delays are described in the following subsections.

#### **3.2.1 Data Sources**

The following description of data sources is drawn largely from the draft paper prepared by Fearing et al. (2010). The U.S. Bureau of Transportation Statistics (BTS) maintains a number of publically available datasets related to airline travel. The Airline Service Quality Performance (ASQP) database provides planned and realized flight schedules for many airlines. Reporting is mandatory for all airlines that carry at least 1% of U.S. domestic passengers. For calendar year 2007, the database contains information for 20 airlines, ranging from Aloha Airlines with 46,360 flights to Southwest Airlines with 1,168,871 flights. BTS also maintains the Schedule B-43 Aircraft Inventory that provides annual lists of aircraft in inventory for most airlines. The Federal Aviation Administration (FAA) maintains the Enhanced Traffic Management System (ETMS) database, which includes schedule information for all flights tracked by air traffic control. This database is not publically available, due to the presence of sensitive military flight information, but a filtered version was made accessible for the purposes of this research. The benefit of this database over ASQP is that, in addition to the planned and realized flight

schedules, it contains the International Civil Aviation Organization (ICAO) aircraft equipment code for each flight.

There are two BTS datasets that we depend on for passenger demand information. The first is the T-100 Domestic Segment (T-100) database, which contains passenger and seat counts for each carrier, segment and equipment type aggregated monthly. The second is the Airline Origin and Destination Survey (DB1B Coupon), which provides a 10% sample of domestic passenger tickets from reporting carriers, including all of the carriers in ASQP, aggregated quarterly by removing information on flight times. We use this data, adjusted according to T-100, to determine the approximate number of monthly passengers travelling on each non-stop or one stop *carrier-route* (which we define as the combination of the carrier, origin and destination for non-stop itineraries or the combination of first carrier, second carrier, origin, connection and destination for one-stop itineraries). The last data set we use contains proprietary booking data from a large legacy carrier for the 4<sup>th</sup> quarter of 2007. This data is used for training our passenger flow estimation model and also for validating our results. The flights in the proprietary booking data are matched against the ASQP data using an Oracle database.

**Estimating flight seating capacities:** Flight seating capacities are an important input in the algorithm for the computation of passenger delays. The Schedule B-43 provides the seating capacity for each aircraft, matching approximately 75% of the flights in ASQP by tail number. For the remaining 25% of the flights, we determine the equipment codes using the International Civil Aviation Organization (ICAO) aircraft equipment codes listed in the ETMS database. In the case of aircraft for which an airline maintains only one configuration (or multiple configurations with similar seating capacities), we use this information to subsequently determine the flight seating capacity. T-100 is a particularly useful database in that it contains information on both passenger demand and aircraft types. If the variation in seating capacity is sufficiently low<sup>1</sup> for a *carrier-segment* (which we define as the combination of the operating carrier, origin and destination of a flight segment), we estimate the seating capacity of each flight by dividing the number of seats available by the number of departures performed. By combining

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<sup>1</sup> We say that the variation in seating capacity is sufficiently low if the coefficient of variation (the standard deviation divided by the mean) is less than 2.5%.

T-100 with the data from Schedule B-43 and ETMS described above, we are then able to estimate accurate seating capacities for approximately 98.5% of the ASQP flights. For the remaining 1.5% of ASQP flights, since the variation in seating capacity is high, we use the T-100 data to estimate a seating capacity that is slightly higher than average<sup>2</sup>.

### 3.2.2 Overview of Algorithm

The algorithm for the computation of passenger delays involves three core steps: generating potential itineraries based on planned ASQP flights, allocation of passengers to generated itineraries, and computation of total delays to passengers on each itinerary. These steps are described in detail in the following subsections:

#### 3.2.2.1 Generation of Itineraries

The first step in the algorithm involves generation of potential itineraries for the year based on the flights in ASQP and the *carrier* routes represented in DB1B Coupon. Because itineraries with more than one stop account for only 2.5% of the one-way trips in DB1B, we only include non-stop and one-stop itineraries in our analysis. For each carrier route identified in DB1B, we construct the corresponding sequence of flight legs, or itineraries, from ASQP. A non-stop itinerary is generated for each flight in ASQP. One-stop itineraries are generated for all valid flight pairs as determined by the following rules:

- 1) The *carrier-route* represented by the flight pair exists within DB1B. This filters out nonsensical routes, such as BOS – IAH – PVD (Boston to Houston to Providence). Moreover, since DB1B contains multi-carrier routes we do not explicitly consider code shares.
- 2) We use discriminators such as Minimum Connecting Time (MCT) and Maximum Layover Time (MLT) to determine whether a particular itinerary should be selected or not. For each one stop itinerary O-T-D, the time between the arrival of the first flight leg and the departure of the second flight leg in the itinerary must be no less than MCT

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<sup>2</sup> For these flights, the seating capacity we use equals the average seating capacity across the matching T-100 rows plus one standard deviation to account for variation across aircraft types.

(Minimum Connecting Time); and the time between the arrival of the first flight leg and the departure of the second flight leg in the itinerary must be no greater than MLT (Maximum Layover Time). Thus if flight  $i$  serves as the first leg and flight  $j$  serves as the second leg, we have the following two feasibility conditions:

$$PAT_i + MCT \leq PDT_j$$

$$PAT_i + MLT \geq PDT_j$$

where  $PAT_i$  is the planned arrival time of flight  $i$ , and  $PDT_j$  is the planned departure time of flight  $j$ . In our analysis, we have used a minimum connection time (MCT) of 30 minutes and maximum layover time (MLT) of 300 minutes.

- 3) To ensure that passengers are not assigned to longer connections when multiple shorter connection times are available, we generate at most 2 connections for a given first flight and matching *carrier-route*. Passenger utility associated with connection time is also explicitly considered within our passenger flow estimation model.

Using the 2007 ASQP and DB1B data sets, this procedure leads to 273,473,424 itineraries, of which 7,455,428 are non-stop. These itineraries are stored in a large Oracle database for ease of querying during passenger flow estimation.

**Data Processing:** Prior to estimating the number of passengers to be allocated to matching itineraries using the discrete choice allocation model (described in the next section), the number of passengers travelling each month on each *carrier-route* are estimated as follows.

1. First, for each *carrier-segment*,  $s$ , we calculate a monthly scaling factor,  $\alpha_s$ , as determined by the ratio between the monthly *carrier-segment* demands specified by T-100 and the quarterly *carrier-segment* demands calculated from DB1B. Since, DB1B samples only domestic itineraries and there are no guarantees that the sampling is exactly 10% for each *carrier-segment*, we find that the calculated ratio varies around a mean of approximately 4.1, instead of the expected 3.33 for all *carrier-segments* (the inverse of the product of the sampling rate, 10%, and the number of months per quarter, 3).
2. For each one-stop *carrier-route* represented in DB1B, we estimate the monthly passenger demand by first scaling the quarterly DB1B passenger counts by the minimum  $\alpha_s$  across

the corresponding sequence of monthly *carrier-segments*. To ensure that the percentage of one stop passengers is consistent with DB1B and resolve the undercounting of one-stop passengers, we subsequently apply a uniform scaling to all *carrier-route* demands.

3. For each non-stop *carrier-route* represented in DB1B, we calculate the monthly passenger demand by starting with the *carrier-segment* demands from T-100 and subtracting the passengers allocated on all matching *carrier-routes* based on the estimated demands in step 2. We wait to calculate the non-stop *carrier-route* demands until after allocating one-stop passengers. This ensures that, when aggregated by *carrier-segment*, our estimated *carrier-route* demands match the original T-100 data set.

In the next section, we describe the discrete choice allocation model we use for allocating the monthly *carrier-route* passengers to the generated itineraries.

### **3.2.2.2 Estimation of passenger flows**

This section describes the discrete choice allocation model developed by Douglas Fearing and Vikrant Vaze, and is drawn largely from the draft paper prepared by Fearing et al. (2010). As described in the previous section, for each month and *carrier-route*, we generate a set of potential itineraries. The next step in the algorithm is to allocate passenger flows to these itineraries. In the past, researchers have tried different approaches to tackle this problem. Ying and Barnhart (2009) developed a linear integer programming formulation to solve this problem. In this approach, a linear program assigns passengers to itineraries to minimize deviation from aggregate demand statistics subject to a set of flow constraints and a flight seating capacity constraint. The major advantage of the optimization-based approach is that it can handle quantitative constraints associated with highly aggregated data, such as BTS data. However, the basic problems with the optimization approach are the extreme point nature of linear programming optimal solutions, and the difficulty to incorporate secondary factors such as connection time. Another way to allocate passengers is to apply discrete choice models and quantify passengers' travel preferences, referred to as itinerary choice methods. The limitations of the optimization-based approach have led us to use instead the discrete choice modeling approach. Coldren, Koppelman and others have applied discrete choice models to estimate

airline itinerary shares in Coldren et al. (2003) and Coldren et al. (2005) from booking data. In the problem of estimating airline itinerary shares, the goal is to predict the share of passenger demand for an origin-destination market that will utilize each of a set of available itinerary choices offered by all airlines. Thus, the itinerary shares problem is more complex in that all *carrier-routes* for a market are considered simultaneously. In our problem, we are only interested in the estimated choice probabilities for a single *carrier-route*, because the DB1B data effectively splits the market demand among *carrier-routes*. Nonetheless, the success of the Coldren, Koppelman, et al. models suggests that a discrete choice model is reasonable in this context.

The passenger flow estimation process used in our model can be described as follows. Given the month of travel and the *carrier-route* for a non-stop or one-stop passenger, we sample a matching itinerary for this passenger using a probability distribution estimated from proprietary booking data. Based on features such as local time of departure, day of week, and connection time, we assign a passenger utility,  $u(x_i)$ , for each of these itineraries. Then, for each passenger, we sample an itinerary allocation according to the proportions,  $P(i)$ , described by the discrete choice multinomial logit function in Equation 3.1.

$$P(i) = \frac{e^{u(x_i)}}{\sum_j e^{u(x_j)}} \quad (\text{Equation 3.1})$$

The utility function,  $u(\cdot)$  in our discrete choice model includes parameters for the combination of the local time of departure and day of week, as well as parameters for a piecewise linear function of connection time (to model the disutility associated with short and long connection times) as well as parameters for flight cancellations and seating capacities. Departure time is split into six 4-hour blocks: 1:01 – 5:00am, 5:01 – 9:00am, 9:01am – 1:00pm, .., and 9:01pm – 1:00am; and each day of week is represented distinctly. We fix the utility associated with departures between 5:01am and 9:00am on Monday to 0 to enable identifiability of the model. The piecewise linear utility that we use for connection time has three parts, corresponding to a mildly increasing utility up to a connection time of 45 minutes, a more dramatically increasing utility up to 60 minutes, and then a mildly decreasing utility beyond 60 minutes. To describe the utility function, we first define the following notation:

- $x_i^{\text{day}}$  = the day of week for itinerary  $i$  with Sunday = 1 and Saturday = 7;
- $x_i^{\text{time}}$  = the local time of departure for itinerary  $i$ ;
- $x_i^{\text{connect}}$  = the connection time for itinerary  $i$  with  $x_{ic} = 0$  for non-stop itineraries;
- $x_i^{\text{cancel}}$  = 1 if any flight in itinerary  $i$  is marked as cancelled in ASQP, 0 otherwise;
- $x_i^{\text{seats}}$  = the minimum seating capacity for the flights in itinerary  $i$ ;
- $T_n$  = the  $n^{\text{th}}$  four-hour daily block of departures, with  $T_1 = 1:01 - 5:00\text{am}$  and  $T_6 = 9:01\text{pm} - 1:00\text{am}$  the following day;
- $c_m$  = the  $m^{\text{th}}$  threshold for the piecewise linear utility for connection time in minutes with  $c_0 = 0$ ,  $c_1 = 45$ ,  $c_2 = 60$ ,  $c_3 = \infty$  ; and
- $I(\cdot)$  = the indicator function for the expression argument.

$$\begin{aligned}
u(x_i) = & \sum_{d=1}^7 \sum_{n=1}^6 \beta_{dn}^{\text{day-time}} I(x_i^{\text{day}} = d) I(x_i^{\text{time}} \in T_n) + \\
& \sum_{m=1}^3 \beta_m^{\text{connect}} \left( \min\{x_i^{\text{connect}}, c_m\} - c_{m-1} \right)^+ + \beta^{\text{cancel}} x_i^{\text{cancel}} + \beta^{\text{seats}} x_i^{\text{seats}} .
\end{aligned}
\tag{Equation 3.2}$$

The discrete choice model represented by Equation 3.2. is trained with BIOGEME (Bierlaire , 2003) using the proprietary booking data, mentioned earlier, from a single legacy carrier for the 4<sup>th</sup> Quarter of 2007, extended to include unselected itineraries from our set of generated itineraries. When extending the booking data, we consider only the generated itineraries with connection times of one hour or longer to eliminate choice set issues due to airport-specific minimum connection times. Additionally, this ensures that the distribution of connection times in our allocation aligns with the distribution of connection times in the booking data. To limit computational effort and still maintain a high level of accuracy, the size of the choice set is limited to 10 for each observation through sampling of alternatives, where each passenger in the booking data represents a single observation. The estimated parameter values and statistics from this model are listed in Table 3.1.

Description <sup>3</sup>	Parameter	Estimate	t-test	p-value
Sunday, 1:01am – 5:00am	$\beta_{1,1}$	-0.2320	-15.42	0
Sunday, 5:01am – 9:00am	$\beta_{1,2}$	-0.4090	-5.53	0
Sunday, 9:01am – 1:00pm	$\beta_{1,3}$	-0.1430	-19.55	0
Sunday, 1:01pm – 5:00pm	$\beta_{1,4}$	0.0735	9.99	0
Sunday, 5:01pm – 9:00pm	$\beta_{1,5}$	0.1270	17.17	0
Sunday, 9:01pm – 1:00am *	$\beta_{1,6}$	0.1330	15.34	0
Monday, 1:01am – 5:00am	$\beta_{2,1}$	-0.4190	-26.93	0
Monday, 5:01am – 9:00am	$\beta_{2,2}$	-0.4790	-7.17	0
Monday, 9:01am – 1:00pm	$\beta_{2,3}$	0.0000	fixed	
Monday, 1:01pm – 5:00pm	$\beta_{2,4}$	0.0344	4.8	0
Monday, 5:01pm – 9:00pm	$\beta_{2,5}$	-0.0845	-10.91	0
Monday, 9:01pm – 1:00am *	$\beta_{2,6}$	-0.2200	-22.21	0
Tuesday, 1:01am – 5:00am	$\beta_{3,1}$	-0.4100	-25.98	0
Tuesday, 5:01am – 9:00am	$\beta_{3,2}$	-0.5820	-7.56	0
Tuesday, 9:01am – 1:00pm	$\beta_{3,3}$	-0.2540	-35.16	0
Tuesday, 1:01pm – 5:00pm	$\beta_{3,4}$	-0.1180	-15.32	0
Tuesday, 5:01pm – 9:00pm	$\beta_{3,5}$	-0.1440	-17.89	0
Tuesday, 9:01pm – 1:00am *	$\beta_{3,6}$	-0.1520	-15.8	0
Wednesday, 1:01am – 5:00am	$\beta_{4,1}$	-0.3750	-24.94	0
Wednesday, 5:01am – 9:00am	$\beta_{4,2}$	-0.4940	-7.13	0
Wednesday, 9:01am – 1:00pm	$\beta_{4,3}$	-0.1970	-28.11	0
Wednesday, 1:01pm – 5:00pm	$\beta_{4,4}$	-0.0694	-9.15	0
Wednesday, 5:01pm – 9:00pm	$\beta_{4,5}$	-0.0828	-10.62	0

<sup>3</sup> The starred time intervals start at 9:01pm on the specified day and include all flights departing up until 1:00am on the following day.

Description <sup>3</sup>	Parameter	Estimate	t-test	p-value
Wednesday, 9:01pm – 1:00am *	$\beta_{4,6}$	-0.0767	-8.34	0
Thursday, 1:01am – 5:00am	$\beta_{5,1}$	-0.2590	-18.15	0
Thursday, 5:01am – 9:00am	$\beta_{5,2}$	-0.4530	-7.05	0
Thursday, 9:01am – 1:00pm	$\beta_{5,3}$	-0.1340	-19.76	0
Thursday, 1:01pm – 5:00pm	$\beta_{5,4}$	-0.0251	-3.34	0
Thursday, 5:01pm – 9:00pm	$\beta_{5,5}$	-0.0318	-4.11	0
Thursday, 9:01pm – 1:00am *	$\beta_{5,6}$	0.1020	11.56	0
Friday, 1:01am – 5:00am	$\beta_{6,1}$	-0.2800	-18.07	0
Friday, 5:01am – 9:00am	$\beta_{6,2}$	-0.4610	-6.94	0
Friday, 9:01am – 1:00pm	$\beta_{6,3}$	-0.1190	-17.55	0
Friday, 1:01pm – 5:00pm	$\beta_{6,4}$	0.0396	5.37	0
Friday, 5:01pm – 9:00pm	$\beta_{6,5}$	0.0477	6.39	0
Friday, 9:01pm – 1:00am *	$\beta_{6,6}$	0.0567	6.45	0
Saturday, 1:01am – 5:00am	$\beta_{7,1}$	-0.3130	-17.52	0
Saturday, 5:01am – 9:00am	$\beta_{7,2}$	-0.5010	-7.13	0
Saturday, 9:01am – 1:00pm	$\beta_{7,3}$	-0.1540	-20.36	0
Saturday, 1:01pm – 5:00pm	$\beta_{7,4}$	0.0120	1.45	0.15
Saturday, 5:01pm – 9:00pm	$\beta_{7,5}$	-0.1590	-17.08	0
Saturday, 9:01pm – 1:00am *	$\beta_{7,6}$	-0.2690	-19.5	0
Connection time (minutes) $\leq 45$	$\alpha_1$	-0.0018	-75.92	0
Connection time (minutes) $> 45$ and $\leq 60$	$\alpha_2$	0.0029	28.6	0
Connection time (minutes) $> 60$	$\alpha_3$	0.0092	21.74	0

Table 3.1: Estimated itinerary choice utility function parameters and statistics

Using the estimated parameters of this model, we calculate the utility associated with each of the generated itineraries and then sample passenger itinerary allocations based on the proportions calculated using Equation 3.1.

### **Validating Passenger Itinerary Flows**

When viewed on a *carrier-segment* basis, DB1B significantly undercounts T-100 demand, since T-100 includes all passengers traveling on a domestic segment, including passengers with international origins or destinations. A validation effort using a direct comparison between the allocation described above and the proprietary data would thus lead to results that are heavily biased by this discrepancy. Instead, we perform a validation allocation where we scale the DB1B (as described in Section 3.2.2.1) by the monthly *carrier-segment* passenger counts from the booking data (instead of T-100). Using this approach, the total number of validation passengers allocated is approximately equal to the number of passengers represented in the booking data.

Since we have no way of determining the exact itinerary for each passenger, we instead focus on ensuring that our allocation is reasonable in an aggregate sense. We do so by comparing aggregate distributions of our validation allocation against the aggregate distributions of the proprietary booking data. The distributions we consider are distribution of flight load factors, distribution of percentage of connecting passengers, and distribution of connection times for one-stop passengers. For each of these distributions, we compare our validation allocation to the booking data and to a randomized allocation (in which we assume all itinerary utilities,  $u(x_i)$ , are equal). The randomized allocation allows us to test the sensitivity of our approach to the individual parameter values of our discrete choice model. From these distributions we were able to observe the following:

- With regard to load factors, the discrete choice allocation performs similarly to the randomized allocation. Although there are a few discrepancies, each of these approaches appears to perform quite well, especially when compared to the linear programming allocation.

- With regard to distribution of connecting passengers, both the randomized allocation and the discrete choice allocation match the booking data very well.
- With regard to distribution of connection times for one-stop passengers, we are able to very accurately match the discrete choice allocation with the distribution that exists in the proprietary booking data. The randomized allocation exhibits no preference towards connection times, so all variation is due to availability of connections.

Thus, from these observations it is safe to conclude that the aggregate distributions of our validation allocation correspond very well with the aggregate distributions of the proprietary booking data. A more comprehensive account of the validation work including the validation plots will appear in Fearing et al (2010).

### **3.2.2.3 Calculation of passenger delays**

So far we have described a model for estimating passenger flows across different itineraries over the network of flights. The next and final step in the algorithm involves computation of delays to each passenger including the disrupted passengers. The method we use for calculating passenger delays is an extension of the passenger delay calculator (PDC), originally developed by Bratu and Barnhart (2005). The core of PDC is to distinguish between disrupted and non-disrupted passengers, as well as to recover the disrupted passengers. As defined earlier, a passenger is disrupted if:

- One or more of the flights in his/her scheduled itinerary is canceled; or
- The passenger misses one or more of his/ her connections.

Non-disrupted passengers have the same scheduled and actual itineraries, while disrupted passengers must be re-accommodated on alternative itineraries. For non-disrupted passengers, the passenger delay is simply equal to the flight delay associated with the last flight in the itinerary. Note that for passengers on one-stop itineraries this means that delays on the first leg are absorbed into the planned connection time unless the connection is missed. If an itinerary is disrupted, either through a flight cancellation or missed connection, each of the passengers on the itinerary must be re-accommodated from the point of disruption to the final destination of

itinerary. The passenger delay for such a passenger is then the time he/ she reaches the final destination minus the planned arrival time. In cases where the passenger reaches his/her destination before or at the planned arrival time, we define the delay as being equal to zero. Note that this may even be the case for a disrupted passenger on a one-stop itinerary, whose first flight is cancelled and is subsequently re-accommodated on a direct flight to his or her final destination. Further note that in our analysis, we treat diversions in the same way as cancellations. This is not due to any limitations of the algorithm, but to the fact that we have no information on the destination of the diversions in ASQP. The number of diversions is equal to about 10% of the number of cancellations (or far less than 1% of total flights), so we do not expect this method of handling diversions to impact the final results significantly, as long as they are not ignored entirely.

**PDC Assumptions:** PDC provides only approximate delay estimates. Taken collectively, the assumptions underlying the PDC are more likely to lead to underestimates than to overestimates of actual passenger delays. We present them in the following:

a. Perfect information: We assume in PDC that the airline has perfect knowledge of the number of seats available for each flight. In reality, airlines do not have this information, as some passengers might not show-up for their flights, especially business passengers who sometimes have fully refundable tickets.

b. Instantaneous information: we assume that a disrupted passenger is instantaneously rebooked on the best feasible recovery itinerary, that is, the one which arrives earliest at the disrupted passenger's destination, has an available seat, and has at least the minimum connect time between the passenger disruption time and the departure of the first flight in the recovery itinerary.

Regarding service priorities, based on current industry practices and available information, we have made the following assumptions:

c. Booking priority: Consistent with industry practice, non-disrupted passengers have priority over disrupted passengers. Therefore, non-disrupted passengers are not reassigned to an itinerary different from their scheduled itinerary.

d. No bumped passengers: We assume all non-disrupted passengers fly their booked itineraries, with passenger bumping not allowed.

e. Time passengers are informed about flight schedule disruptions: We do not have information pertaining to the time at which passengers are informed that their schedules are disrupted. We have, therefore, assumed that passengers disrupted by a canceled flight are notified when the flight is scheduled to depart.

f. Rebooking order: Various service policies are possible in the ordering of disrupted passengers, including: (1) re-accommodating passengers in the order in which they are disrupted, called First-Disrupted-First-Recovered (FDFR); (2) re-accommodating passengers in the order of decreasing fare class value; or (3) re-accommodating passengers in the order of decreasing frequent flyer status. In our analysis, disrupted passengers are re-accommodated under a First-Disrupted-First-Recovered (FDFR) policy, i.e., in an order based on the itinerary's time of disruption, because detailed information on fare class value or frequent flyer status is not available.

g. No Luggage Disruption: Although checked-in luggage is another important dimension of passenger service, we do not consider luggage disruption in our analysis.

**PDC Algorithm:** In order to calculate the passenger delays associated with the estimated passenger flows, we use the realized flight schedules in ASQP database. Details of the steps of PDC are as follows:

**STEP 1:** Identifying disrupted and non-disrupted itineraries.

If a passenger itinerary is disrupted through a flight cancellation or a missed connection, we search for a recovery itinerary to re-accommodate the disrupted passengers. A recovery itinerary is defined as a sequence of flights with at least one seat available on each flight to re-accommodate a disrupted passenger to his/her desired destination. Given the partitioning of passengers into the disrupted passenger subset  $D$  and the non disrupted passenger subset  $ND$ , the algorithm reserves seats first for each non-disrupted passenger, as it is industry practice to give them priority over disrupted passengers (as discussed in the service priority assumptions). Then,

delay statistics for non-disrupted passengers are recorded and available seat inventories are reduced to reflect their assignments.

#### STEP 2: Ordering the disrupted passengers.

The second step of PDC is to build the queue of disrupted passengers. In this analysis, we sort the disrupted passengers according to the First-Disrupted-First-Recovered (FDFR) (as discussed previously in re-booking assumptions). When two different passengers are disrupted at the same time, we randomly select whom to re-accommodate first.

#### STEP 3: Re-accommodating disrupted passengers.

The final step of the passenger delay calculator is the re-accommodation of passengers whose itineraries have been disrupted. For re-accommodation purposes, the passenger delay calculator uses all generated itineraries as potential recovery alternatives. In order to be conservative in our estimates, and since ASQP does not include all possible flight options (e.g. non-reporting carriers), we cap the amount of expected delay for each disrupted passenger based on the time of disruption. For passengers disrupted between 5:00am and 5:00pm, we cap the expected delay at 8 hours. For passengers disrupted during the evening and night (i.e., between 5:00pm and 5:00am), we cap the expected delay at 16 hours to allow for re-accommodation the following day. Then, in order to re-accommodate each passenger, we check if there are any recovery itineraries departing from the point of disruption at least 45 minutes after the time of disruption (to allow time for rebooking and transfer) and planned to arrive at the passenger's final destination before the delay cap (based on the planned arrival time). A disrupted passenger is instantaneously rebooked on the best feasible recovery itinerary (as described in the assumptions section above). In the selection of alternative itineraries to re-accommodate disrupted passengers, we first search for itineraries that use airlines matching the original itinerary (e.g., the two carriers on a multi-carrier or code-share itinerary), along with any sub-contracted or parent airlines. For example, when a Continental itinerary is disrupted, we look first for recovery itineraries on Continental or ExpressJet (or a combination of the two). If we are unable to find a matching itinerary using these airlines, we attempt to re-accommodate the passenger using any

matching itinerary (ignoring the operating airlines). If we are unable to find an alternative at this point, we assign the passenger a delay equal to the cap, assuming that he or she will be re-accommodated in some other fashion. It may also be noted that we allow disruption chaining in our passenger delay calculator, but maintain the original delay cap throughout. Thus, while there is no maximum to the number of times a passenger can be disrupted, the passengers are often defaulted to the cap after the second disruption. This ensures that our disruption chains do not become overly long, since in many cases airlines have knowledge of future disruptions at the time of re-accommodation (e.g. a severe weather event that is projected to last throughout the day).

### 3.3 Results for 2007

This section provides estimates of Passenger Trip Delay for January – December 2007. According to our estimates, in 2007, passengers experienced a total of close to 15 billion minutes of delay due to flight delays (50% of the total), flight cancellations (34% of the total), and missed connections (16% of the total). In the following tables (Table 3.2, Table 3.3, Table 3.4, Table 3.5 and Table 3.6), we list the annual and monthly passenger delay estimates based on the methodology described in the previous section.

	<b>2007</b>
Number of flight operations	7,455,428
Number of onboard passengers	487,197,841
Percentage of delayed flights	26.58%
Percentage of cancelled flights	2.16%
Average delay of operated flights	14.96
Average delay of all passengers	30.81
Number of disrupted passengers	16,396,693
Percentage of passengers disrupted	3.37%
- Due to cancellations	69.78%
- Due to missed connections	30.22%
Average delay of non-disrupted passengers	15.95
Average delay of disrupted passengers	457.39
- Due to cancellations	68.57%
- Due to missed connections	31.43%

Table 3.2: Passenger delay estimates for calendar year 2007

	<b>January</b>	<b>February</b>	<b>March</b>
Number of flight operations	621,557	565,603	639,209
Number of passengers	36,352,036	43,924,926	39,088,143
Percentage of delayed flights	26.89%	31.93%	19.97%
Percentage of cancelled flights	2.54%	3.05%	0.98%
Average delay of operated flights(minutes)	14.06	19.65	10.89
Average Delay of all Passengers	28.38	43.10	18.60
Number of disrupted passengers	1,316,327	1,932,281	748,294
Percentage of passengers disrupted	3.62%	4.40%	1.91%
- Due to cancellations	72.61%	70.98%	60.96%
- Due to misconnections	27.39%	29.02%	39.04%
Average delay for non disrupted passengers	14.29	21.66	11.41
Average delay of disrupted passengers	403.46	509.18	386.92
- Due to cancellations	70.89%	70.35%	55.77%
- Due to misconnections	29.11%	29.65%	44.23%

Table 3.3: Monthly passenger delay estimates for the 1<sup>st</sup> calendar quarter of 2007

	<b>April</b>	<b>May</b>	<b>June</b>
Number of flight operations	614,648	631,609	629,280
Number of passengers	34,397,063	41,407,785	42,679,350
Percentage of delayed flights	32.74%	24.29%	22.10%
Percentage of cancelled flights	4.14%	1.76%	1.09%
Average delay of operated flights(minutes)	17.16	13.51	12.30
Average Delay of all Passengers	43.01	27.31	22.64
Number of disrupted passengers	1,944,508	1,199,778	946,246
Percentage of passengers disrupted	5.65%	2.90%	2.22%
- Due to cancellations	79.24%	69.31%	62.45%
- Due to misconnections	20.76%	30.69%	37.55%
Average delay for non disrupted passengers	18.01	14.57	13.16
Average delay of disrupted passengers	460.18	454.14	440.63
- Due to cancellations	79.61%	68.28%	59.45%
- Due to misconnections	20.39%	31.72%	40.55%

Table 3.4: Monthly passenger delay estimates for the 2<sup>nd</sup> calendar quarter of 2007

	<b>July</b>	<b>August</b>	<b>September</b>
Number of flight operations	648,542	653,276	600,186
Number of passengers	44,915,327	42,640,299	45,614,020
Percentage of delayed flights	28.36%	26.73%	30.22%
Percentage of cancelled flights	1.90%	2.58%	2.25%
Average delay of operated flights(minutes)	16.84	14.85	18.13
Average Delay of all Passengers	33.56	34.59	37.09
Number of disrupted passengers	1,497,394	1,672,360	1,663,621
Percentage of passengers disrupted	3.33%	3.92%	3.65%
- Due to cancellations	66.06%	74.88%	67.33%
- Due to misconnections	33.94%	25.12%	32.67%
Average delay for non disrupted passengers	18.26	15.80	19.82
Average delay of disrupted passengers	477.27	494.92	493.46
- Due to cancellations	64.56%	75.95%	65.65%
- Due to misconnections	35.44%	24.05%	34.35%

Table 3.5: Monthly passenger delay estimates for the 3<sup>rd</sup> calendar quarter of 2007

	<b>October</b>	<b>November</b>	<b>December</b>
Number of flight operations	629,990	605,148	616,380
Number of passengers	37,400,260	40,784,454	37,994,178
Percentage of delayed flights	18.30%	21.79%	35.66%
Percentage of cancelled flights	1.03%	3.56%	1.19%
Average delay of operated flights(minutes)	10.09	12.00	19.75
Average Delay of all Passengers	18.50	21.11	40.90
Number of disrupted passengers	775,022	868,179	1,832,683
Percentage of passengers disrupted	2.07%	2.13%	4.82%
- Due to cancellations	63.48%	60.53%	71.83%
- Due to misconnections	36.52%	39.47%	28.17%
Average delay for non disrupted passengers	10.60	12.81	20.25
Average delay of disrupted passengers	391.68	402.85	448.48
- Due to cancellations	57.14%	55.01%	71.21%
- Due to misconnections	42.86%	44.99%	28.79%

Table 3.6: Monthly passenger delay estimates for the 4<sup>th</sup> calendar quarter of 2007



## **Chapter 4**

### **Results and Analysis**

#### **4.1 Introduction**

In this chapter we carry out a disaggregate analysis of the distribution of passenger delays across different segments of the air transportation system such as airports and carriers, and try to identify any recognizable patterns of flight and passenger trip delays. In Section 4.2, we begin with a statistical comparison of flight delay and passenger trip delay distributions and look at the variation in passenger trip delays across different days of the week and the seasonal variation across different months over the year 2007. In Section 4.3 we look at the daily and seasonal variation and distribution of delay multipliers, defined as the ratio of the average passenger delay and average flight delay for a particular set of carriers and given time frame. We also try to determine the strength of correlation between the delay multipliers and other factors that take into account the effect of disruptions, using a non-parametric statistical test also described in the same section. Finally, we also look at the variation of the delay multipliers across different carriers and try to identify any patterns across the three broad categories of carriers - regional, low cost and legacy carriers. In Section 4.4, we introduce some new metrics to evaluate the performance of the US air transportation system in terms of passenger travel experience and passenger trip delays, and further try to quantify the strength of correlation between airline rankings based on flight delay based metrics and passenger trip delay based metrics, using the same statistical test as mentioned before. In Section 4.5, we look at the distributions of passenger trip delays and flight delays across different carriers. In Section 4.6 we study and analyze the variation in the level of disruptions across different carriers, and try to identify any patterns across the three broad categories of carriers. In the last two sections of the chapter, we try to identify the most delayed airports in the US in year 2007. While, in Sections 4.7 we identify the airports with the highest total and average passenger delays, in section 4.8, we identify airports with the highest percentage of misconnections, and the highest total and average misconnection delays.

## 4.2. Delay Variation and Distribution

### 4.2.1 Statistical comparison of flight delays and passenger trip delays

Figure 4.1 shows the distributions of flight delays and estimated passenger trip delays for year 2007.

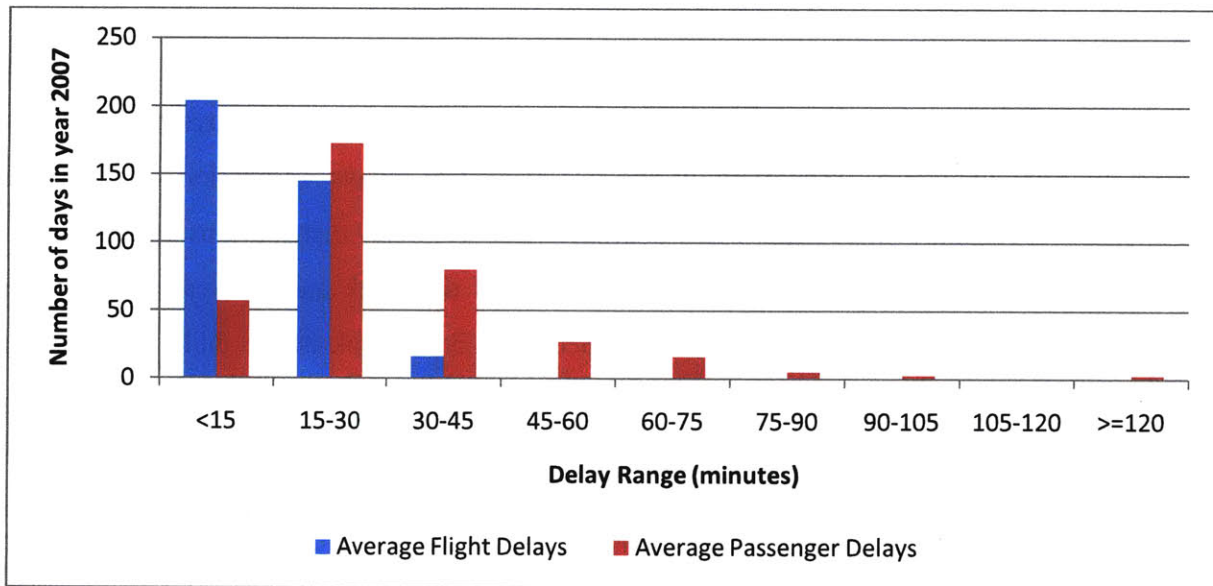


Figure 4.1: Passenger and flight delay distributions for year 2007

The underlying relationship between flight delays and passenger trip delays is suggested by the right-tail of the passenger delay distribution. Since passenger trip delays include the delays experienced by passengers due to delayed flights, plus the delays accrued by waiting to be re-booked on a later flight when a flight is cancelled or the passenger misses a connecting flight, the distribution for passenger trip delays exhibits a longer right-tail.

From the distributions it is seen that the most frequent level of flight delay is in the range of less than 15 minutes. The frequency declines steadily as we move to higher range values. The highest frequency of average passenger delays, on the other hand is observed in the range 15-30 minutes. Also, the highest average flight delay on any day over the year was 39.3 minutes, while the highest average passenger delay was estimated at 167.4 minutes. Further the mean average flight delay for the year was found to be 15.2 minutes with a standard deviation of 6.8 minutes,

while the mean daily average passenger delay for the year was 30.4 minutes with a standard deviation of 20.2 minutes.

**On-Time Percentage:** We define a passenger or flight as being on-time if the arrival delay beyond the scheduled arrival time is less than 15 minutes. From the distribution of flight delays we observe that for the year 2007, the flight on-time percentage expressed as the percentage of days with average arrival delays of less than 15 minutes was 56 %, while the passenger on-time performance expressed as the percentage of days with average passenger delay less than 15 minutes was only 16 %.

**Delayed Flights and Passengers:** Similarly, we define a flight or passenger as delayed if the arrival delay is equal to or in excess of 15 minutes beyond the planned arrival time. Thus from the distributions, we observe that on 44% of the days, the average flight (flight with delay equal to the average flight delay on that particular day) was delayed, with a mean daily average flight delay of 21.2 minutes. While on 84 % of the days, the average passenger (passenger with delay equal to the average passenger delay on that particular day) was delayed, with a mean daily average passenger delay of 33.7 minutes.

#### **4.2.2 Day of the week variation in passenger delays**

Figure 4.2 illustrates the variation in passenger delays across different days of the week in year 2007. We observe that the passenger traffic volume as well as the average passenger delay is highest on Friday, while the lowest traffic volume and lowest average passenger delays are observed on Saturday. It is interesting to note that the variation in delays is very similar to the variation in the total volume of passenger traffic, with high values of passenger delays on days with higher numbers of travelling passengers. This is intuitive because on days with higher passenger traffic volumes and more congestion, the utilization of the airport capacity as well as the load factors on flights are higher, and thus one would also expect higher levels of disruptions such as misconnections and cancellations, as well as slower recovery of disrupted passengers, which ultimately leads to higher average delays to passengers.

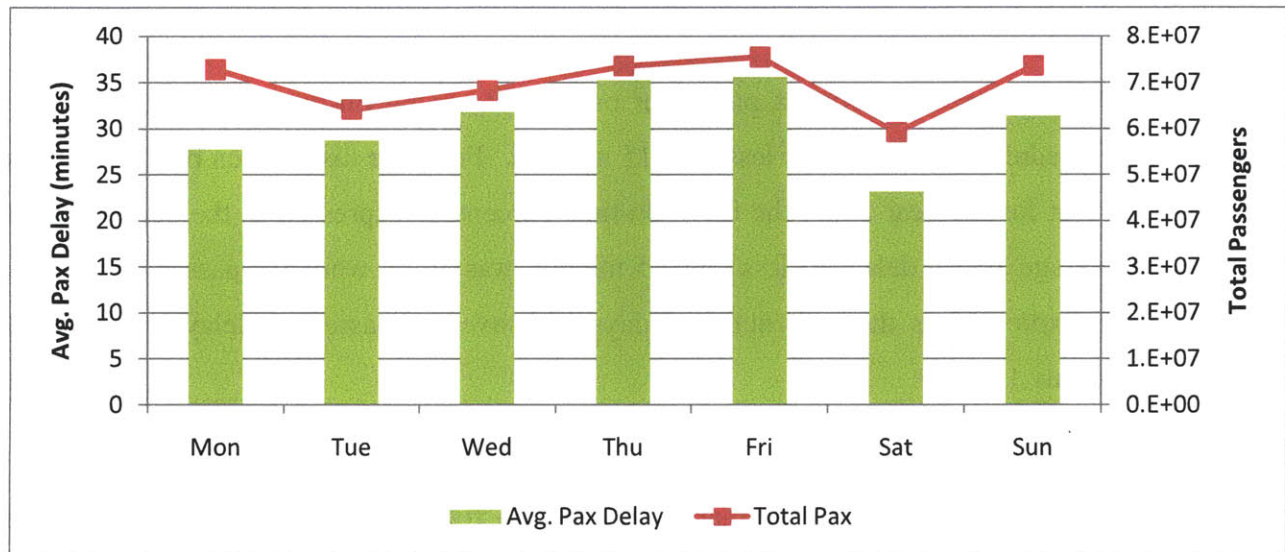


Figure 4.2: Day of the week variation in average passenger delays

#### 4.2.3 Variation in passenger delays across different months over the year

Figure 4.3 shows the variation in average passenger delays across different months over the year 2007. We can see that the average passenger delay was highest in the month of June and lowest in September. However, it is interesting to note that, unlike the variation in delays across days of the week as shown previously, the variation in average delays across different months is not very similar to the variation in the total passenger volume. This is because among the various causes of air flight delay, weather is a dominant factor, since during adverse weather, the airport capacity is reduced due to the increased aircraft separations. Since the prevailing weather conditions vary greatly across different months over the year, variation in average delays does not follow the same trend as the passenger traffic volume.

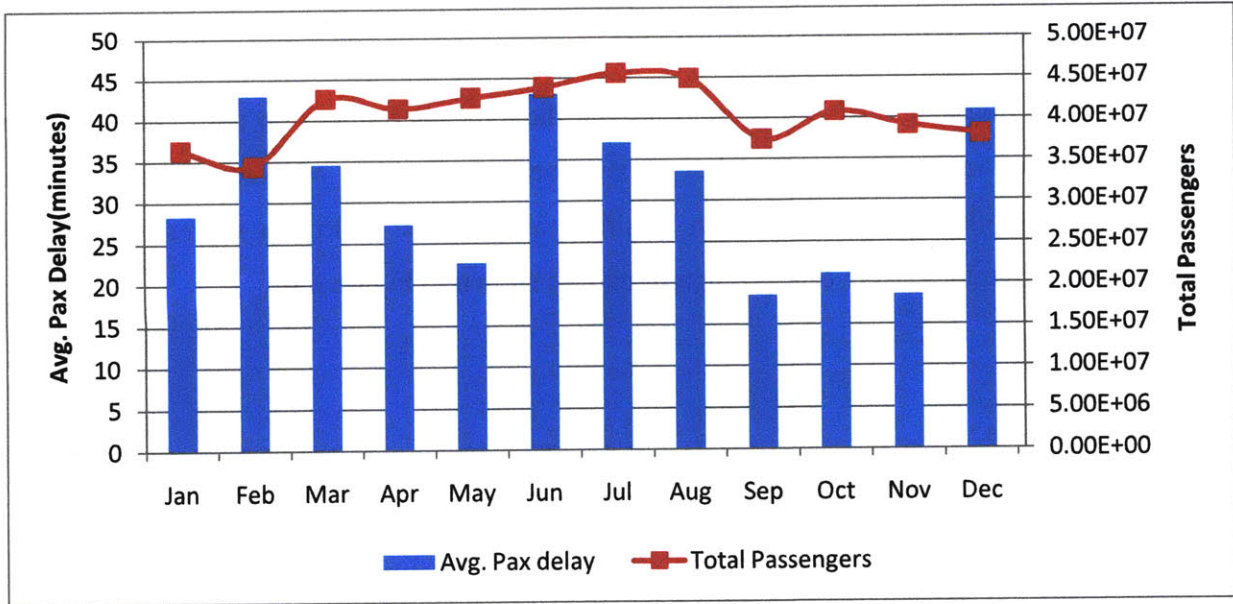


Figure 4.3: Month of the year variation in average passenger delays

### 4.3. Multipliers

The average flight delay for all flights, excluding cancelled flights for year 2007 was 15.29 minutes. The average passenger delay for the year, taking into account the effect of disruptions like cancellations and misconnections, was estimated at 30.81 minutes. We define this ratio between the average passenger delay and average flight delay for a particular carrier or set of carriers and a given time frame, as the *delay multiplier* or simply *multiplier*. Thus, the delay multiplier for 2007 was estimated at 2.015. These findings are summarized in Table 4.1.

Average Flight delay in year 2007	15.29 minutes
Average Passenger Delay in year 2007	30.81 minutes
Multiplier for year 2007	2.015

Table 4.1: Delay Multiplier for year 2007

### 4.3.1 Variation and Distribution of multipliers

We perform the following analysis to establish that the multiplier values do not remain constant over the year, but vary over time, as they depend on cancellations, misconnections and other forms of passenger disruptions. We begin by simply plotting the multiplier values for each day of 2007, arranged in increasing order of magnitude, as shown in Figure 4.4.

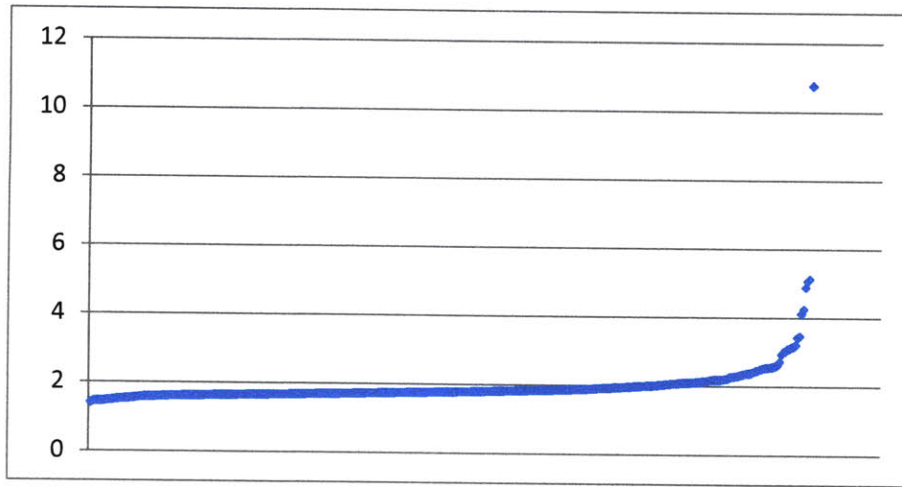


Figure 4.4: Multiplier values for 2007 (arranged in increasing order of magnitude).

It is seen that the multiplier values vary over a wide range from 1.40 to as large as 10.76 over the course of the year, though for most of the year, the value is quite close to 2. Figure 4.5 illustrates the distribution of the multiplier values for 2007 across different ranges of multiplier values.

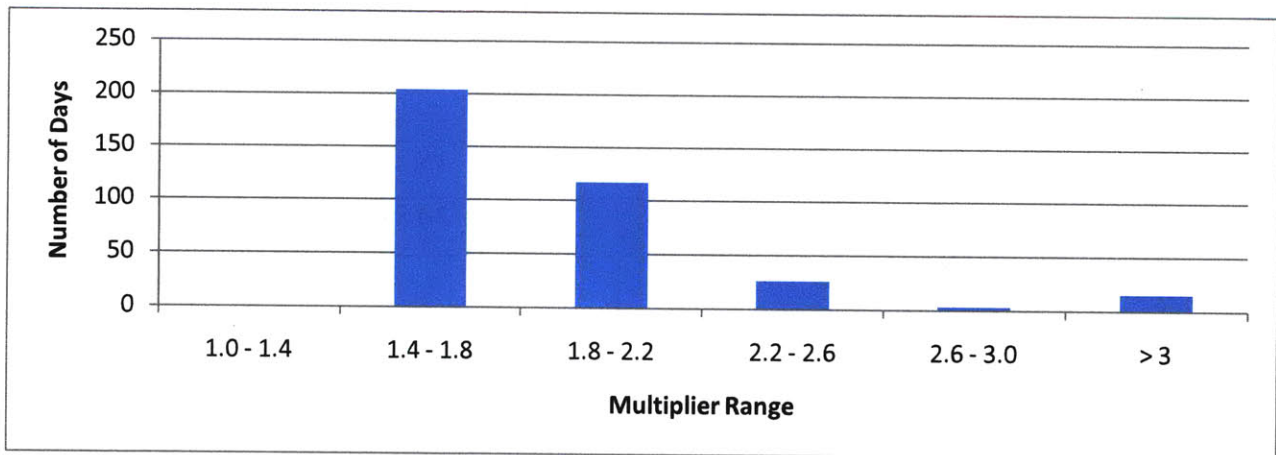


Figure 4.5: Distribution of multipliers

From the plot we observe that the multipliers lie in the range 1.4-1.8 for the highest number of days, and on only 4% of the days (15 out of the 365 days), the multiplier value was greater than 3. This could be a result of high levels of passenger disruptions on those days. Another interesting analysis is to look at the seasonal variation in the values of multipliers over the course of the year. This is illustrated in Figure 4.6.

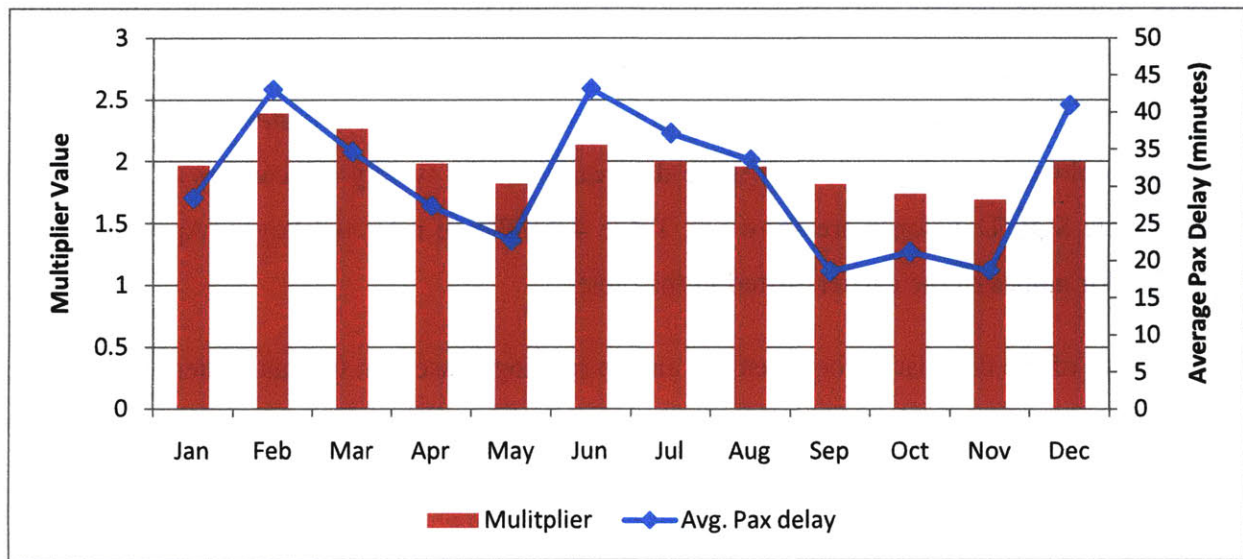


Figure 4.6: Seasonal variation in multiplier values

We note that the multipliers vary in a similar fashion as the average passenger delays for different months. Thus, the multipliers are high for high delay seasons and low for low delay seasons. It is important to take note of the fact that a high passenger delay value does not necessarily imply a high multiplier, since the multiplier is only the ratio of the average passenger delay and average flight delay for a given time period. Thus, the similarity in variation could be explained by reasoning that during periods of high delay, resulting from high congestion of passengers, bad prevailing weather conditions or any other factors, there is a higher level of passenger disruptions like flight cancellations and misconnections. Moreover, if the delays are large owing to high passenger throughput, the re-accommodation of passengers on alternative itineraries in the event of a disruption on the original itinerary of the passenger would be much slower because of the high load factors. This in turn leads to a higher multiplier value for that time period.

### 4.3.2 Correlation testing of multipliers with other variables

Intuitively, we can expect the multiplier ratio for a particular carrier or set of carriers to be directly correlated with the level of disruptions experienced by the passengers on those carriers. In this section, we try to determine the strength of correlation between airline rankings based on the multiplier values and other variables. To take into account the effect of cancellations on multipliers, we choose our test variable as the *percentage of flight cancellations* on individual carriers. Similarly, to take into account the effect of misconnections on multipliers, we choose our test variables as *percentage of connecting passengers*, *percentage of passengers misconnected*, and the *connection times averaged over the number of connecting passengers* of the individual carriers. The values of these data variables for twenty US carriers as determined using Oracle SQL Developer are shown in Table 4.2. (Please refer the key in Appendix A on page 103, for names of the carriers listed in the table).

The strength of the correlation between the airline rankings based on the multipliers and the test variables was determined using a statistical test called the Spearman Rank Correlation Coefficient Test. This test is as described in the following section.

<b>Carrier</b>	<b>Multiplier</b>	<b>% Flights Cancelled</b>	<b>% of connecting passengers misconnected</b>	<b>% connecting passengers</b>	<b>Average Connection Times (minutes)</b>
9E	2.15206	3.07%	4.82%	56.20%	86.30
AA	2.031931	2.83%	3.72%	33.48%	87.76
AQ	1.668647	0.84%	1.47%	9.43%	83.70
AS	1.532186	1.60%	4.32%	10.67%	92.49
B6	1.71144	1.94%	4.80%	9.09%	91.65
CO	1.553153	0.91%	3.27%	26.12%	85.85
DL	1.950377	1.37%	2.87%	45.48%	87.59
EV	2.088727	3.12%	5.14%	73.28%	94.43
F9	1.58211	0.41%	2.47%	30.24%	78.50
FL	1.959453	0.99%	2.84%	33.88%	84.64
HA	2.112449	0.42%	2.21%	20.86%	86.42
MQ	2.384793	4.22%	4.45%	57.45%	91.53
NW	2.034381	1.89%	3.78%	40.86%	85.79
OH	2.613552	3.78%	4.92%	39.82%	75.14
OO	2.156473	2.37%	3.64%	56.50%	87.18
UA	1.893136	2.43%	4.45%	34.48%	86.70
US	1.953984	1.84%	3.96%	32.75%	78.35
WN	1.520157	0.85%	1.92%	16.06%	90.39
XE	2.143607	2.48%	5.03%	31.05%	83.10
YV	2.09624	3.83%	4.80%	51.00%	80.62

Table 4.2: Statistics for different carriers in year 2007

## Spearman Rank Correlation Test

In statistics, **Spearman's rank correlation coefficient** or **Spearman's rho**, denoted by the Greek letter  $\rho$  (rho) or as  $r_s$ , is a non-parametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function. If there are no repeated data values, a perfect Spearman correlation of +1 or -1 occurs when each of the variables is a perfect monotone function of the other. Unlike, most other correlation tests, such as the Pearson's correlation coefficient which require samples to be normal, the Spearman's rank correlation coefficient test doesn't require sample normality. It is the non-parametric alternative to correlation, and it is used when the data do not meet the assumptions about normality, homoscedasticity and linearity. The other advantage of this test is that it is less affected by the outliers (independently of the outlier size, its impact on correlation coefficient is bounded from above), which makes it valuable when processing noisy data [3].

The Spearman correlation coefficient is often thought of as being the Pearson correlation coefficient between the ranked variables. In practice, however, a simpler procedure is normally used to calculate  $\rho$ . The  $n$  raw scores  $X_i, Y_i$  are converted to ranks  $x_i, y_i$ , and the differences  $d_i = x_i - y_i$  between the ranks of each observation on the two variables are calculated.

If there are no tied ranks, then  $\rho$  is given by:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}.$$

If tied ranks exist, Pearson's correlation coefficient between ranks should be used for the calculation :

$$\rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}.$$

One has to assign the same rank to each of the equal values. It is an average of their positions in the ascending order of the values [34].

Once the correlation coefficient is calculated for the two columns of ranks, the significance of the coefficient is tested in the same way as the correlation coefficient for a regular correlation. The null hypothesis for the significance testing is that the ranks of one variable do not co-vary with the ranks of the other variable; in other words, as the ranks of one variable increase, the ranks of the other variable are not more likely to increase (or decrease) [20].

Using the above test, the Spearman Rank Correlation coefficients between the airline rankings based on the multiplier and the test variables were determined and are summarized in Table 4.3.

<b>Variable</b>	<b>Spearman Rank Correlation Coefficient</b>
% flights cancelled	0.687218045
% passengers misconnected	0.511278195
% connecting passengers	0.693233083
connection times	-0.12481203

Table 4.3: Spearman Rank Correlation coefficients to test correlation between multipliers and other variables

Now, for each test variable, we start with the null hypothesis that there is no significant relationship between the multipliers and the test variable values. Using the tables of critical values for correlation coefficients, for a confidence interval of 95% and  $(N-2 = 20-2 =) 18$  degrees of freedom, the critical value of the correlation coefficient is 0.444 [26].

From the above table, we see that the correlation coefficients between the multipliers and the test variables are greater than this critical value for percentage flights cancelled, percentage of connecting passengers and percentage of connecting passengers misconnected. Thus, we deduce that our null hypothesis is incorrect in these cases and all the three variables are significantly positively correlated with the multipliers.

The correlation coefficient for connection times is found to be negative, with absolute value less than the critical value of 0.444. The negative correlation is intuitive since with a longer connection time, one would expect a smaller probability of missing the connection and thus a smaller multiplier. However, from the significance test we deduce that our null hypothesis is correct and that the multipliers and connection times are not significantly correlated. One possible explanation for this could be that in our estimated data, the variation in connection times across different carriers is small, with no recognizable patterns across regional, low cost and legacy carriers, as shown in Figure 4.10 in Section 4.3.3. Thus, the correlation between the airline rankings based on the multiplier values and connection times is found to be very weak.

### 4.3.3 Variation in multipliers across carriers

Figure 4.7 illustrates the variation in multiplier values across different carriers. To study any recognizable patterns across the three broad categories of carriers i.e. regional, low cost and legacy carriers, the carriers belonging to these three different categories are plotted in different colors. Thus, all the regional carriers have been shown in blue, all the legacy carriers in red and all the low cost carriers in green.

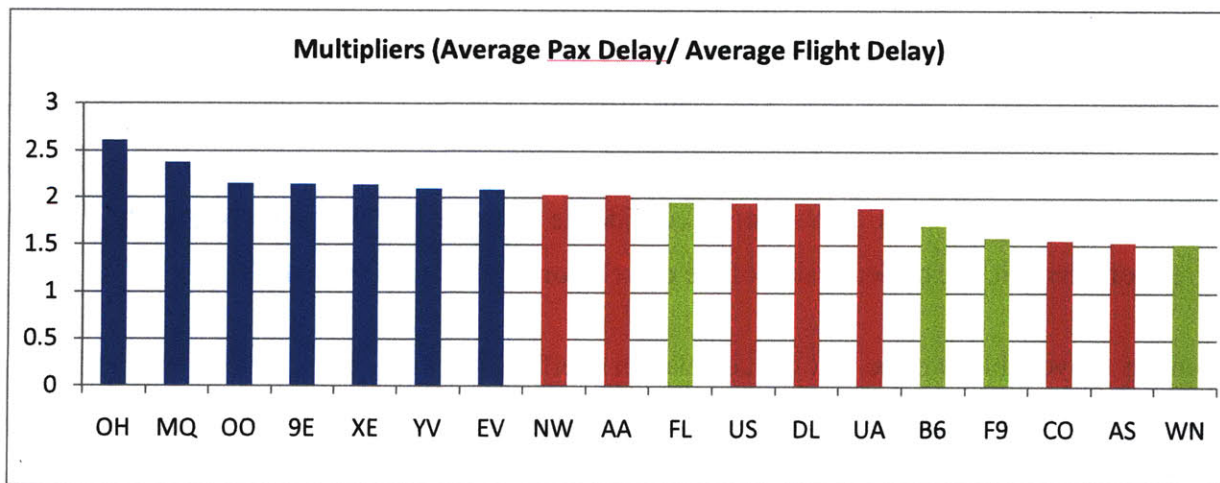


Figure 4.7: Variation in multipliers across different carriers

We observe that among all carriers, the regional carriers such as Comair (OH), American Eagle (MQ), SkyWest (OO) etc. have the highest multiplier values. Moreover, all regional carriers

have multiplier values greater than two, implying the average passenger delay for all regional carriers was more than twice the observed average flight delay for 2007. The high multiplier values for the regional carriers can be explained as resulting from the higher flight cancellation rates as well as the higher percentage of connecting passengers on these carriers. Figure 4.8 shows the variation in the percentage of flights cancelled, while Figure 4.9 shows the variation in the percentage of connecting passengers across the three broad categories of carriers. Also, as mentioned before, the computed average connection times for different carriers do not show much variation or any identifiable patterns across the three broad categories of carriers as shown in Figure 4.10.

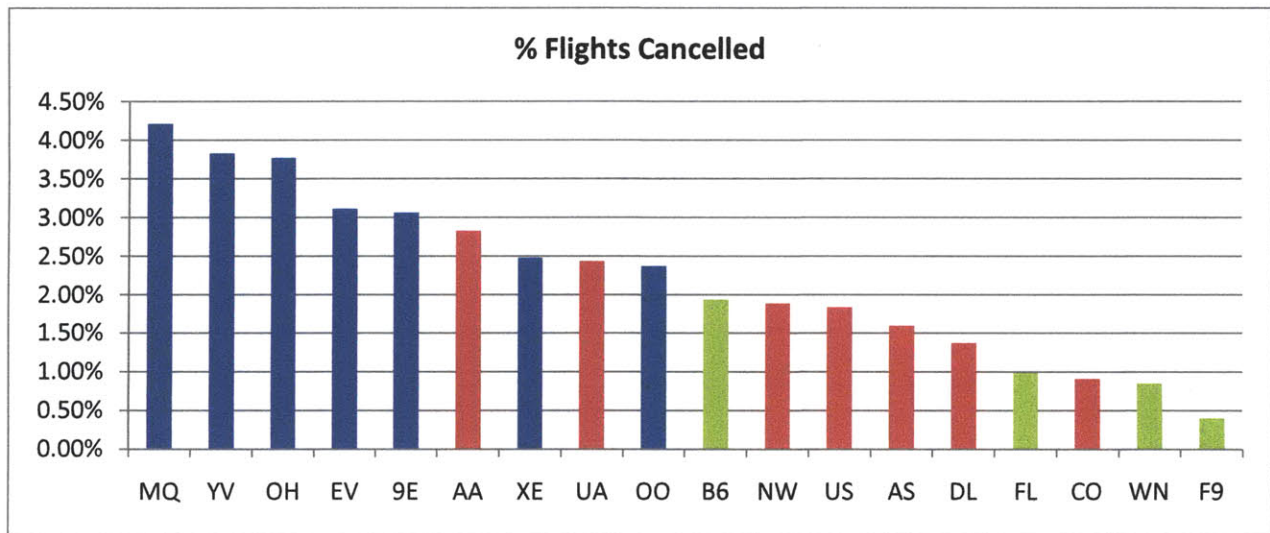


Figure 4.8: Variation in percentage flights cancelled across different carriers

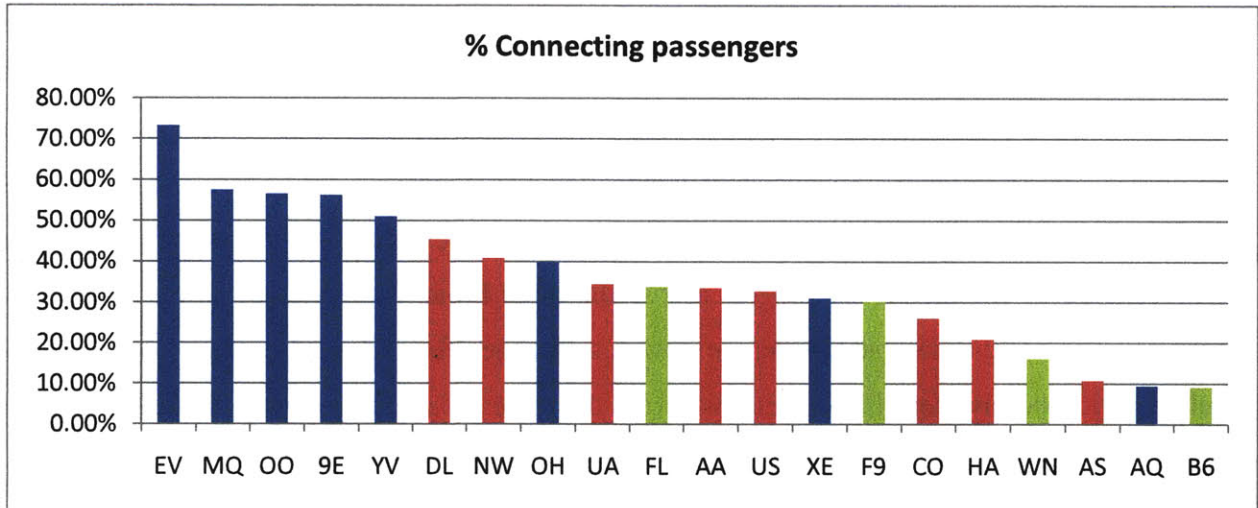


Figure 4.9: Variation in percentage connecting passengers across different carriers

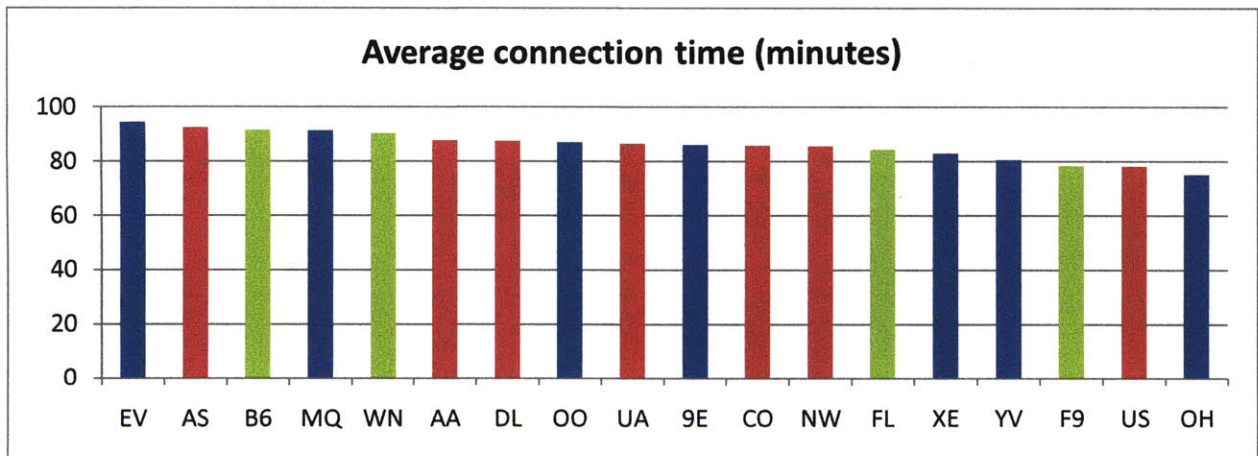


Figure 4.10: Variation in average connection times across different carriers

Thus, as visible in Figure 4.8, passengers on regional carriers typically experience higher levels of disruptions in the form of cancellations, and also have a higher percentage of connecting passengers as shown in Figure 4.9. Since the multipliers are significantly positively correlated with both cancellation rates as well as percentage of connecting passengers, as shown previously in section 4.3.2, the regional carriers typically have higher multipliers than legacy and low cost carriers.

#### **4.4. Correlation between airline rankings based on flight and passenger delays**

In this section we evaluate the existing airline performance metrics, propose some new performance metrics and also try to investigate potential problems caused by inappropriate performance metrics. Furthermore, we try to study and determine the strength of correlation between flight on time performance and passenger on time performance.

The commonly used flight-based metrics of delay do not provide a complete picture of the performance of the air transportation system. For example, the popularly used 15 On-Time Performance (OTP) metric which measures the percentage of flights with delays less than 15 minutes, does not reflect the size of delay suffered by flights experiencing delays in excess of 15 minutes [31]. Most importantly, simple flight-based statistics tend to underestimate passenger delays, since on average, disrupted passengers experience much longer delays than flights.

To facilitate the description of our analysis, we introduce a new metric to evaluate the performance of the air transportation system in terms of passenger on-time performance and call it simply the *Passenger On Time Performance* or *POTP metric*. This has a definition similar to the OTP metric, where 15 POTP measures the percentage of passengers with arrival delays less than 15 minutes, 30 POTP measures the percentage of passengers with delays less than 30 minutes and so on. Also, for the sake of analysis, similar to flights, we define a passenger as *delayed* if his/ her arrival delay at the final destination, is more than or equal to 15 minutes beyond the scheduled arrival time.

In Figures 4.11 - 4.15 the carriers are plotted in order of decreasing airline on-time performance for 15, 30, 45, 60 and 90 OTP metrics. The corresponding passenger on time performance metric, POTP is plotted alongside, to permit observation of how well the airline rankings based on these two metrics correspond with each other.

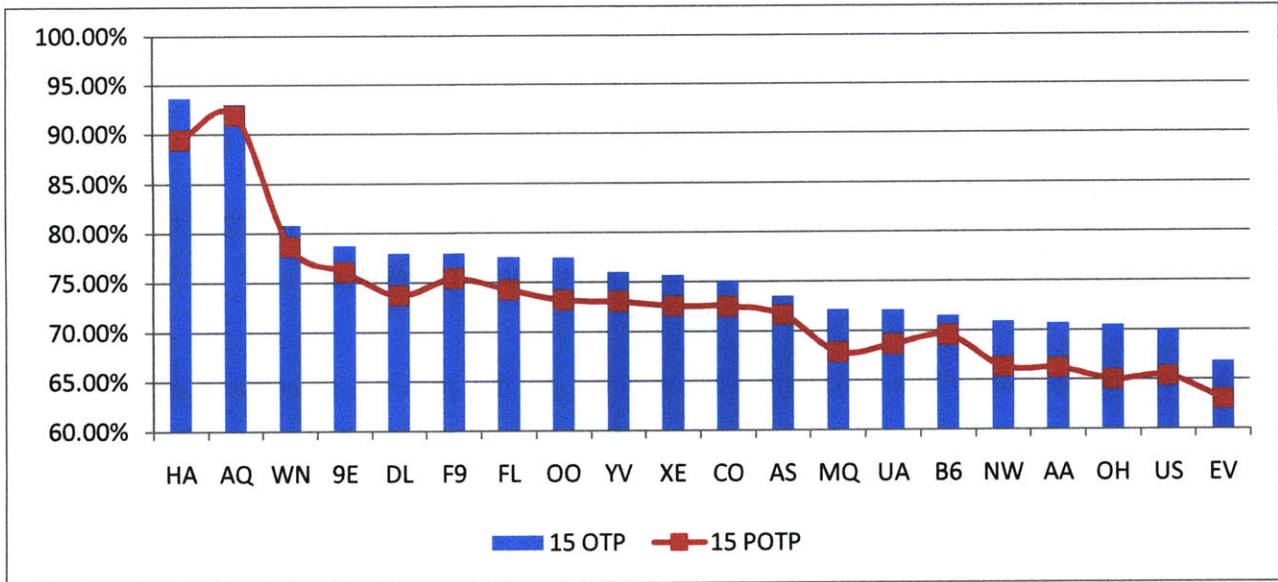


Figure 4.11: Airline rankings for 15 OTP and 15 POTP

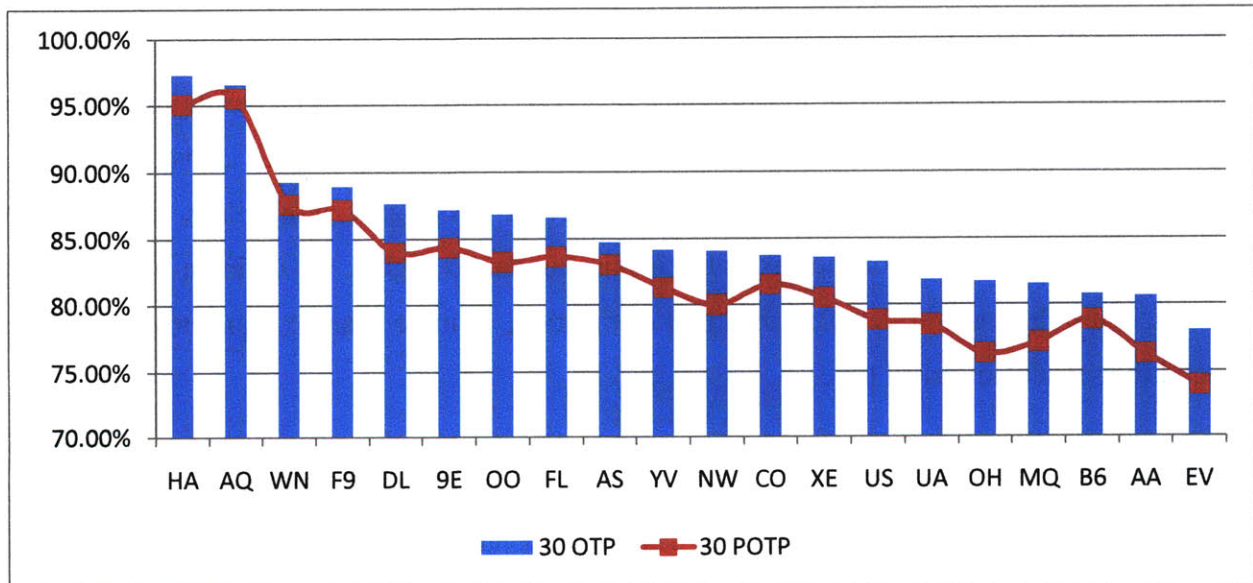


Figure 4.12: Airline rankings for 30 OTP and 30 POTP

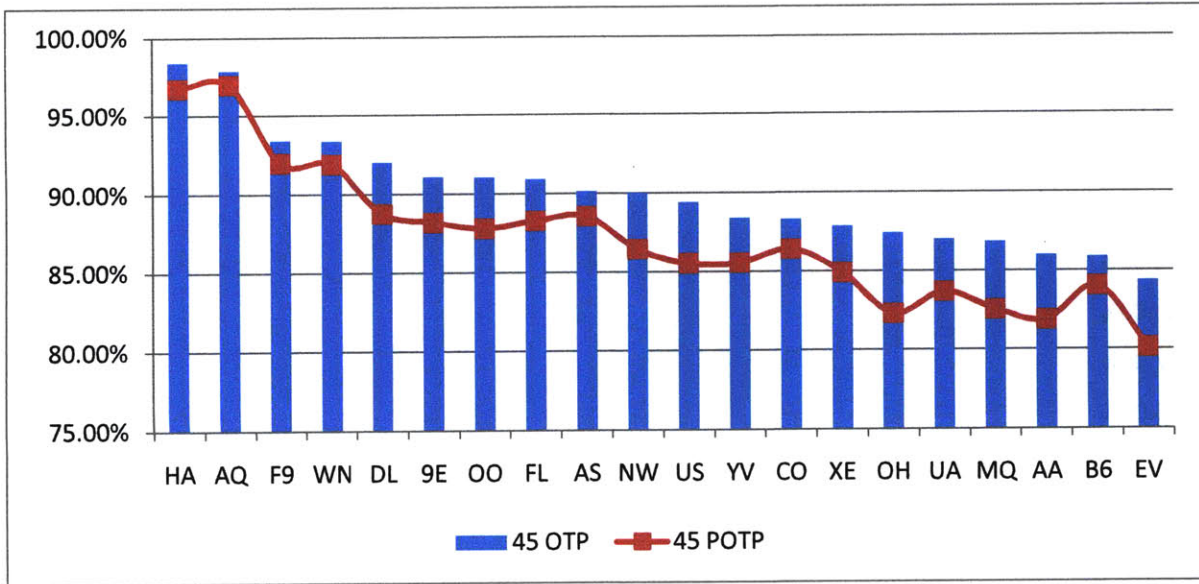


Figure 4.13: Airline rankings for 45 OTP and 45 POTP

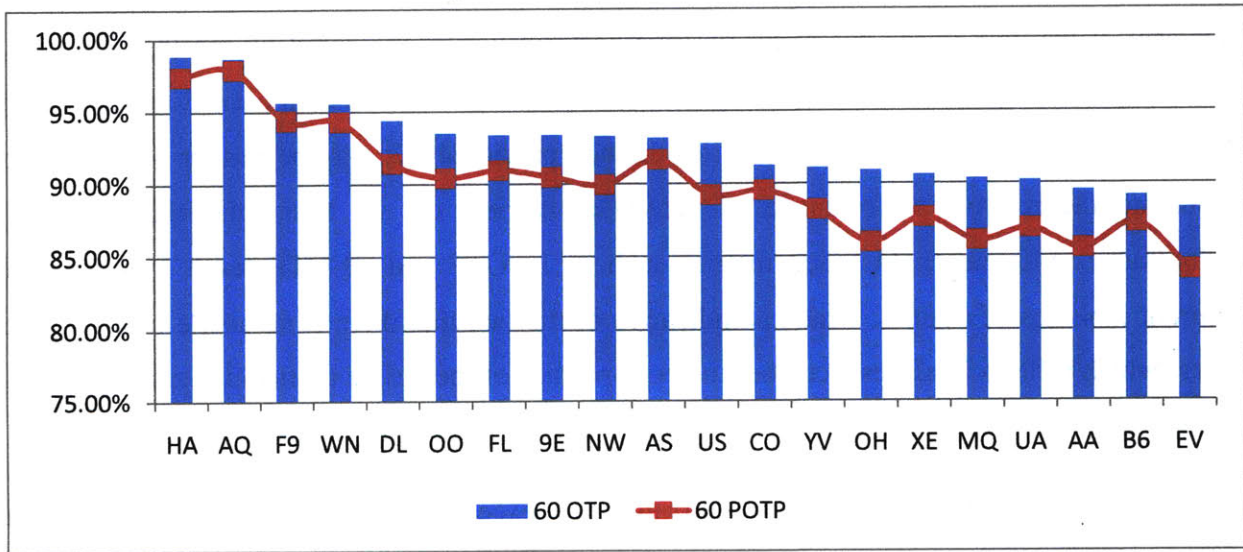


Figure 4.14: Airline rankings for 60 OTP and 60 POTP

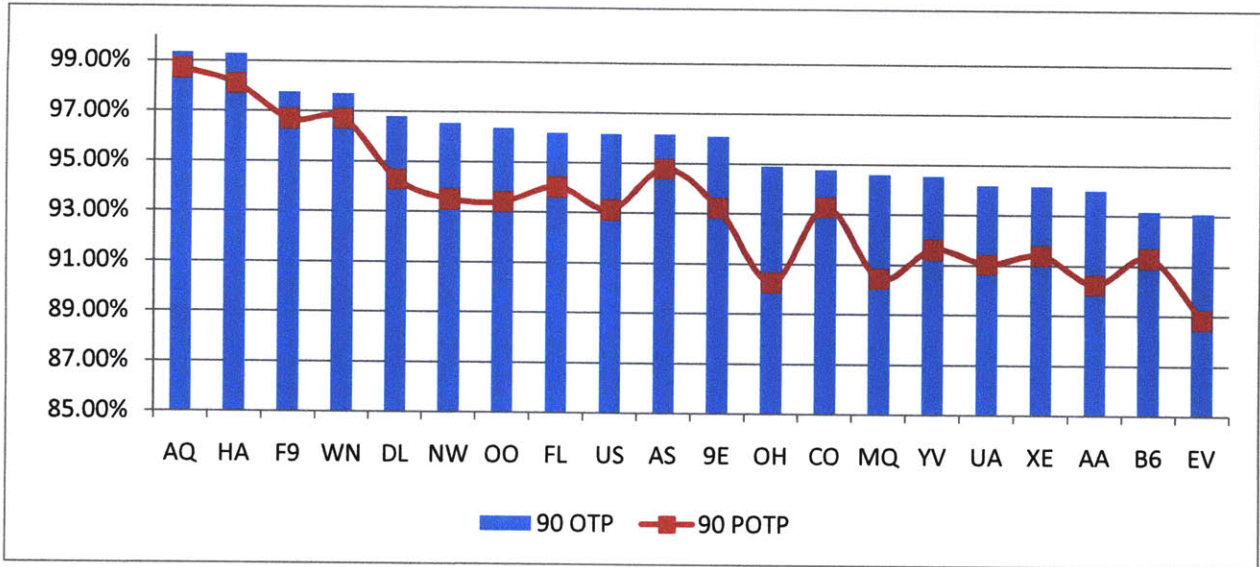


Figure 4.15: Airline rankings for 90 OTP and 90 POTP

We observe that Hawaii Airlines (HA) has the best airline on time performance, while Atlantic Southeast (EV) has the worst as per the 15 OTP, 30 OTP, 45 OTP and 60 OTP metrics. Similarly, if we look at the passenger on time performance as measured by the POTP metric, Aloha Airlines (AQ) has the best passenger on time performance, while Atlantic Southeast (EV) has the worst for all the five POTP metrics defined previously. It may be further noted that in evaluating the relative performance of individual carriers on the basis of airline on time performance, different flight based metrics such as 15 OTP and 60 OTP result in somewhat different rankings of airlines, which is indicative of the fact that there is no single best on-time metric which reflects in all respects the true performance of the airline carriers in terms of delays to flights.

From the plots, we further observe, that barring a few exceptions, the airline rankings based on airline on-time performance as measured by the OTP metric correspond quite well with the rankings based on passenger on time performance metric as determined by the POTP metric. In order to quantify the strength of correlation in rankings, we use the Spearman Rank Correlation Coefficient Test described in Section 4.3.2. The results from the test have been summarized in Table 4.4.

<b>Variable 1</b>	<b>Variable 2</b>	<b>Spearman Rank Correlation Coefficient</b>
15 OTP	15 POTP	0.986466165
30 OTP	30 POTP	0.971428571
45 OTP	45 POTP	0.959398496
60 OTP	60 POTP	0.942857143
90 OTP	90 POTP	0.902255639

Table 4.4: Spearman Rank Correlation coefficients for OTP and POTP metrics

From the above results, we see that the airline rankings based on OTP and POTP metrics have a very strong correlation, which implies that carriers which have a high flight on time performance also have a high passenger on time performance, and vice versa. However, one interesting deduction from the above analysis is that the strength of correlation weakens as we move from 15 OTP-POTP to 90 OTP-POTP. This can be explained as resulting from the added effect of passenger disruptions like cancellations and misconnections in the POTP metric, which increases as we move to higher POTP metrics. In other words, the number of passengers arriving within 90 minutes of the scheduled arrival time (arrival delay less than 90 minutes) a much higher percentage of disrupted passengers, than passengers with arrival delays of less than 15 minutes. Thus, while for passengers with delays of less than 15 minutes, as determined by the 15 POTP metric, we can expect the delays as largely resulting from only flight arrival delays, the passengers with arrival delays of less than 90 minutes, as determined by the 90 POTP metric, will have a much higher percentage of passengers disrupted due to cancellations and misconnections. Thus, there is a poorer correlation between 90 OTP and 90 POTP metrics. This further illustrates why for large delays, flight-based metrics might not accurately reflect the passenger travel experience, and thus might not be a good proxy for passenger trip delays.

We next test the correlation in airline rankings between average flight delays and average passenger delays across carriers, as shown in Figure 4.16, and between average flight delays and average passenger delays for only delayed flights and delayed passengers respectively, as shown in Figure 4.17.

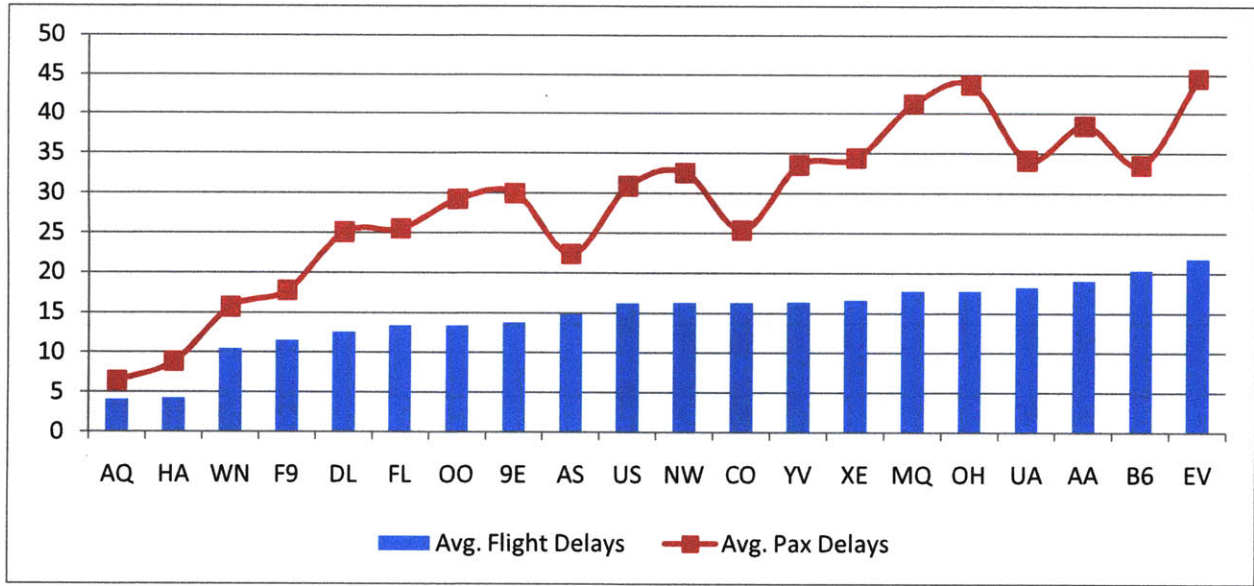


Figure 4.16: Airline rankings for average flight delays and average passenger delays

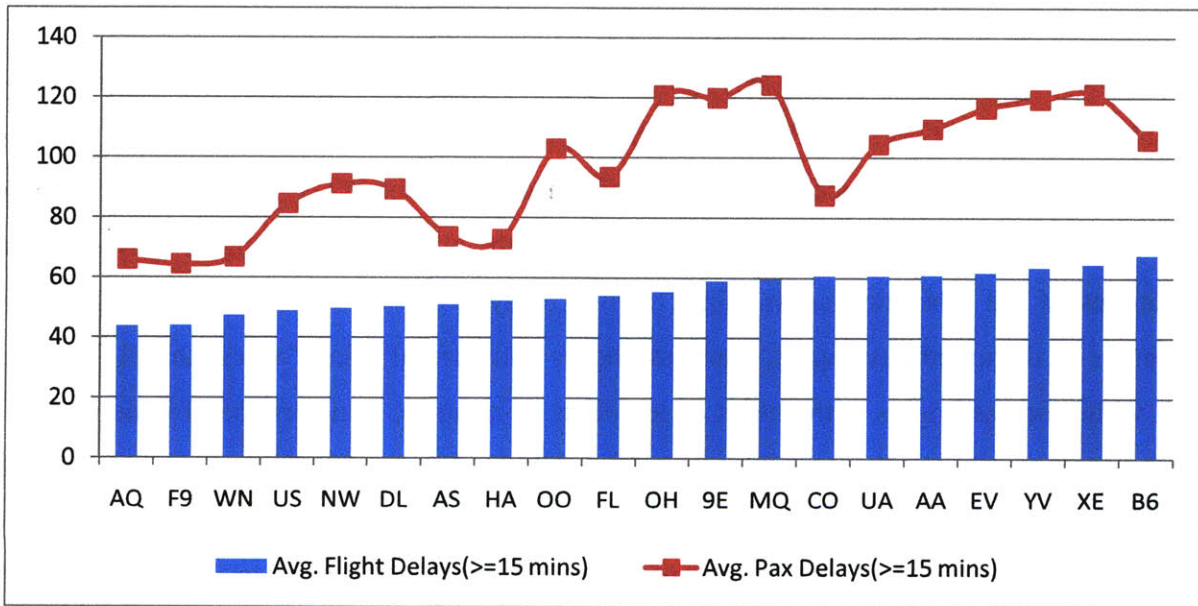


Figure 4.17: Airline rankings for average delays of delayed flights (delay  $\geq 15$  minutes) and average delays of delayed passengers (delay  $\geq 15$  minutes)

We observe that the airline rankings based on average passenger delays have a high correlation with rankings based on average flight delays, except for some glaring exceptions resulting from the relatively high multipliers for regional carriers such as OH, MQ, EV, etc., as discussed previously in section 4.3.3, and the low multipliers for hub carriers like CO and AS (due to low

cancellation rates and small percentages of connecting passengers on these carriers, as shown in Figures 4.8 and 4.9 respectively). To quantify the above analysis, we again use the Spearman Rank Correlation Coefficient Test and obtain results summarized in Table 4.5.

<b>Variable</b>	<b>Spearman Rank Correlation Coefficient</b>
Avg. Passenger Delay	0.909774436
Avg. Passenger delay (>=15 minutes)	0.780451128

Table 4.5: Spearman Rank Correlation coefficients for airline rankings based on average passenger delays and average flight delays

We again observe that while average flight delays for all flights correspond very well with average passenger delays for all passengers, the correlation weakens when we consider only delayed flights and delayed passengers. This is because delayed passengers have a much higher percentage of passengers disrupted due to cancellations and misconnections, and thus the airline rankings are dependent on the multipliers of individual carriers to a larger degree.

Thus, the above discussion clearly points to the fact that for large delays, flight on-time and other airline performance based metrics might not be good surrogates for passenger travel experience and passenger trip delays, primarily because they do not capture the effect of disruptions, such as cancellations and misconnections. Thus, there is a need for metrics designed to ensure more consistency in assessing and monitoring system performance from the viewpoint of the passenger.

#### 4.5. Passenger Delay Distributions across major carriers

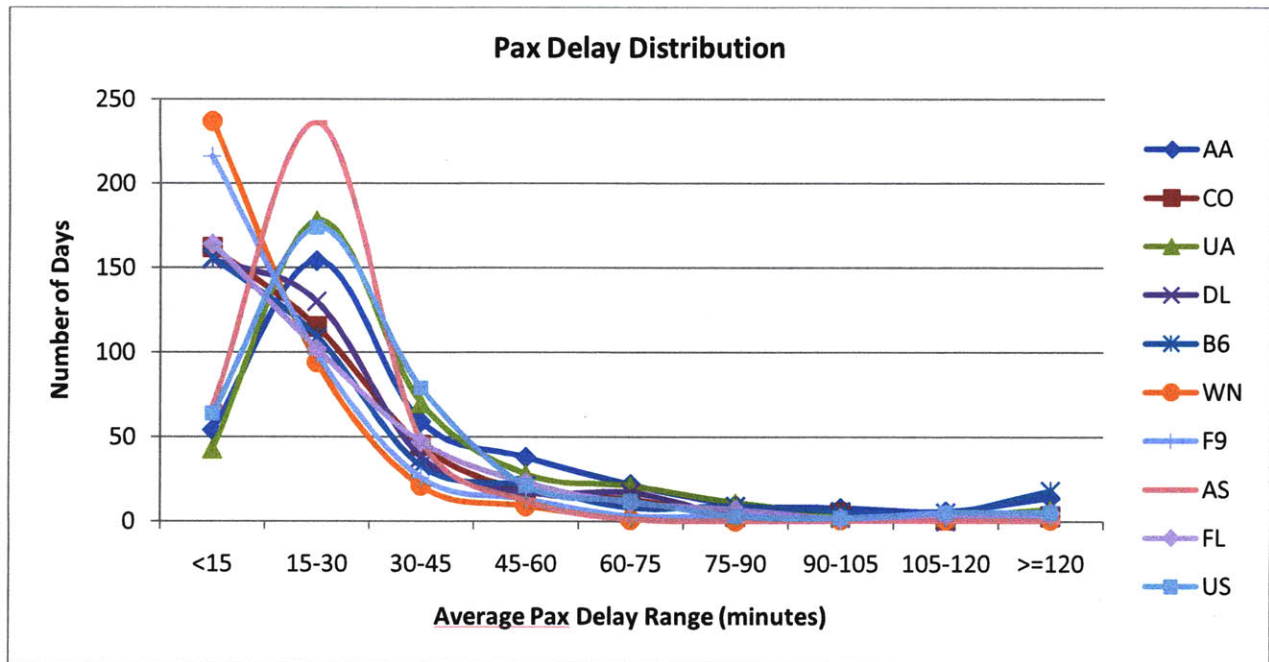


Figure 4.18: Passenger Delay Distributions of major US carriers in year 2007

Figure 4.18 shows the distribution of average passenger delays across the major US legacy and low cost carriers. It is observed that all low cost carriers including JetBlue (B6), Southwest (WN), Air Tran (FL) and Frontier (F9) had delays that most frequently fell in the delay range of less than 15 minutes. Most major legacy carriers, on the other hand, such as American (AA), United (UA), US airways (US) and Alaska (AS) most frequently had delays in the range of 15-30 minutes for year 2007, while Continental (CO) and Delta(DL) were the only two legacy carriers with the highest frequency of average daily passenger delays in the range of less than 15 minutes.

If we look at the flight delay distributions for these carriers as illustrated in Figure 4.19, we observe that average flight delays for all carriers are most frequent for the delay range of less than 15 minutes, with generally higher peaks in the case of low cost carriers. Another plausible explanation for the observed distribution of passenger delays could be that the legacy carriers have higher flight cancellation rates (as shown in Figure 4.8), and that they revolve around a

hub-and spoke network with relatively higher percentage of connecting passengers than the mostly point-to-point low cost carriers (as also shown in Figure 4.9). Thus, broadly speaking the multipliers for the legacy carriers are higher than the low cost carriers, resulting in peak delays in the higher delay range of 15-30 minutes.

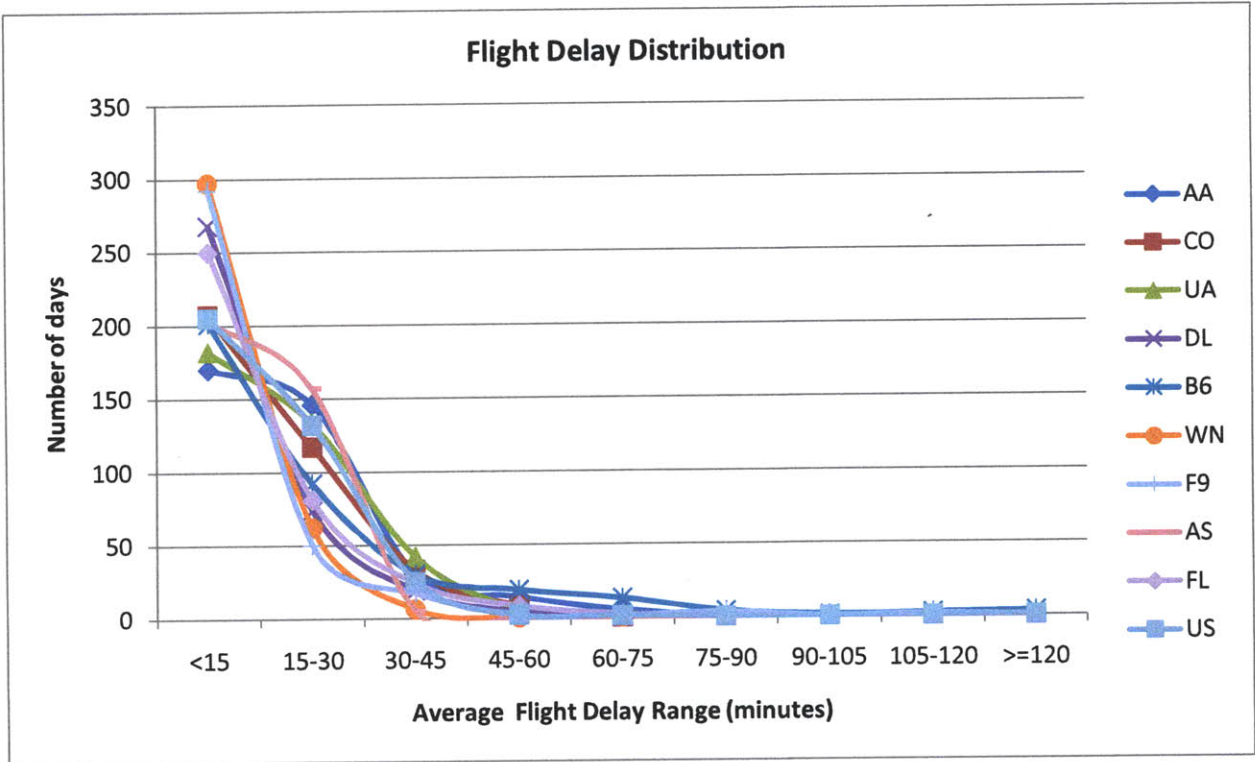


Figure 4.19: Flight Delay Distributions of major US legacy and low cost carriers in year 2007

#### 4.6. Passenger Disruptions across airlines

Figure 4.20 illustrates the variation in the percentage of passengers disrupted due to flight cancellations across the three broad categories of carriers - legacy, low cost and regional carriers. We notice that the highest percentages of passengers disrupted due to cancellations are observed for the regional carriers such as American Eagle (MQ), Comair (OH) and Atlantic Southeast (EV). The low cost carriers such as Frontier (F9), Southwest (WN) and Air Tran (FL) have some of the lowest percentages. It is also reasonable to expect a strong relationship between the

percentage of passengers disrupted due to cancellations and the percentage of flights cancelled as shown previously in Figure 4.8. We quantify the degree of correlation using the Spearman Rank Correlation Coefficient Test discussed previously, and find an almost perfect correlation of 0.985 between the two variables.

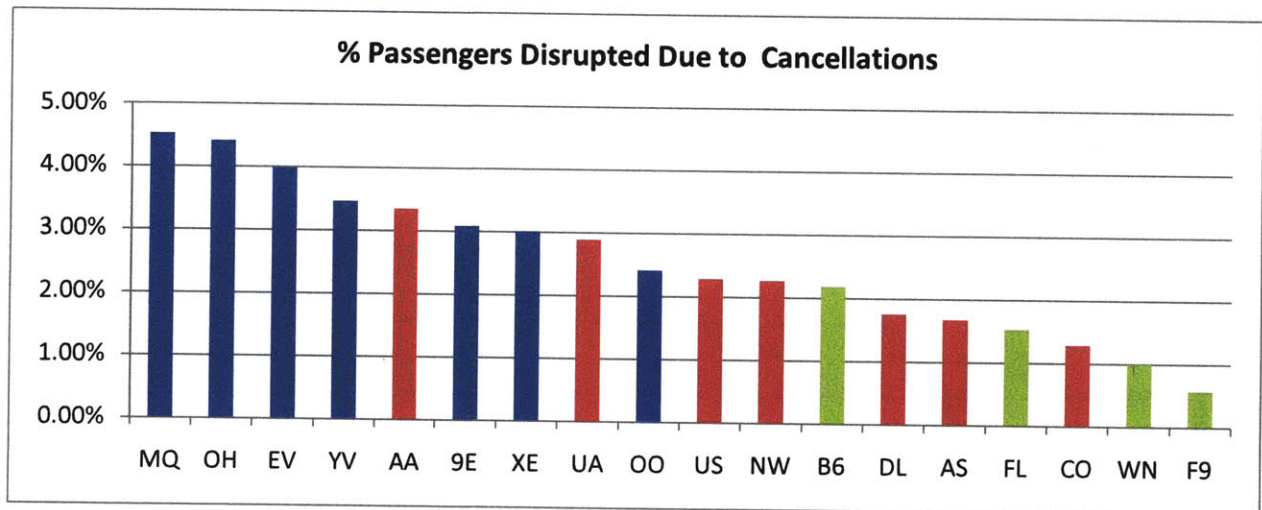


Figure 4.20: Variation in percentage passengers disrupted due to cancellations across carriers

Figure 4.21 shows the variation in the percentage of connecting passengers disrupted due to misconnections for all one-stop single carrier itineraries across carriers. Here too, we observe that the regional carriers have the highest percentage of passengers disrupted due to misconnections among all carriers. As a first guess, we would expect the percentage of misconnected passengers to be strongly correlated with the average connection times of the individual carriers. However, as per our computed estimates of the average connection times for different carriers, the variation in connection times across carriers is very small with no identifiable patterns. Thus, we could infer the high percentage of misconnections of connecting passengers on regional carriers to be resulting from high average flight arrival delay of the first flight in one-stop itineraries. It might also be because of the difference between airlines in the percentage of connecting passengers who stay with the same plane versus who have to switch planes.

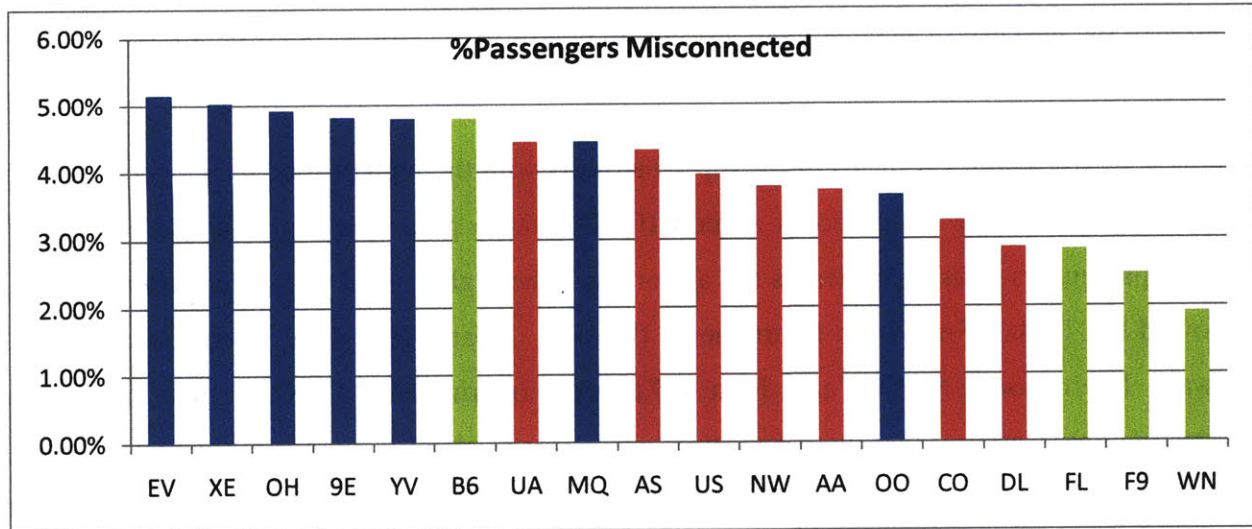


Figure 4.21: Variation in percentage of connecting passengers disrupted due to misconnections across carriers

#### 4.7. Delay Distribution across airports

In this section we identify the airports with the highest total and average passenger delays in 2007. It may be noted that in the allocation of delays to individual airports in the passenger itinerary, we do not consider delays at any intermediate stops, but only the arrival delay at the final destination of the passenger itinerary. The allocation is carried out taking into consideration the relative levels of congestion of airports, as determined by the estimated average flight delays at the airports. In other words, each airport in the itinerary is charged with delay in proportion to its average delay per flight, determined simply by taking the product of the total arrival delay at the final destination with the ratio of the average flight delay at the respective airport divided by the sum of average flight delays of all airports in the passenger itinerary. For example, consider the case where a passenger is 30 minutes late on a nonstop JFK - ATL trip. According to our estimates, JFK has an average arrival delay per flight of about 12 minutes in 2007, while ATL has an average arrival delay per flight of about 8 minutes. Thus, we allocate the 30 minute delay to the two airports in proportion to their average delay per flight, i.e., JFK would be charged with 18 minutes of delay (three fifths of the 30 minutes) and ATL with 12 minutes (two fifths of the

delay). In the absence of detailed data attributing delays to specific airports or segments of the airspace, this seems to be a reasonable first-order approximation.

Figure 4.22 shows our estimates of the top 25 airports with the highest total passenger delays in 2007. Chicago O'Hare International Airport (ORD) with a passenger throughput of over 46.7 million passengers was identified as the airport with the highest total passenger delay minutes, followed by Dallas Fort Worth International (DFW), Atlanta Hartsfield International (ATL), Newark International (EWR) and John F. Kennedy International (JFK) in that order. An interesting observation is that these 5 most delayed airports alone account for around 48.50 % of the total passenger delays, whereas the top 25 most delayed airports shown in the plot, account for 92.80 % of the total passenger delay minutes at all 309 US airports in 2007.

The airport rankings, based on total delay minutes of all passengers, correspond reasonably well with the total passenger throughput at these airports. For year 2007, the airport with the highest passenger throughput was Atlanta Hartsfield International (ATL) with over 51.5 million passengers, followed by Chicago O'Hare (ORD) and Los Angeles International (LAX). On comparing the airport rankings based on the highest total passenger delay minutes with rankings based on our allocations of total flight delay minutes as shown in Figure 4.23, we notice that the correlation is strong, though not perfect. This is indicative of the fact that the severity of disruptions in the form of cancellations and misconnections is also different at different airports, which we can expect to be a function of several factors such as the passenger throughput, functionality of the airport and weather conditions in the geographical area where the airport is located.

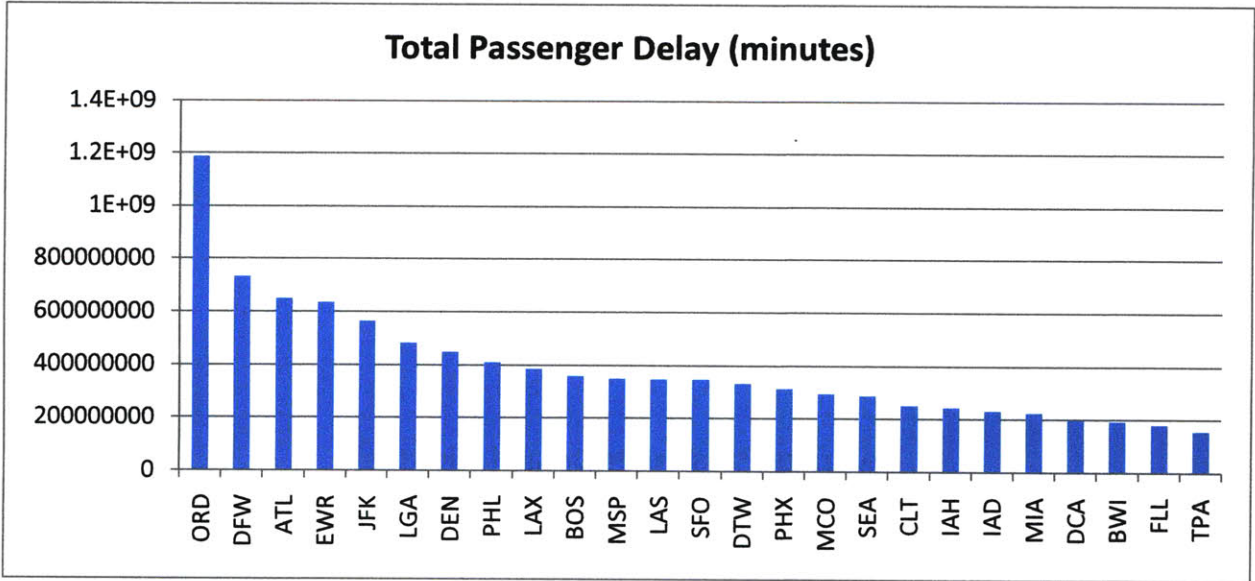


Figure 4.22: US airports with the highest total passenger delay in year 2007

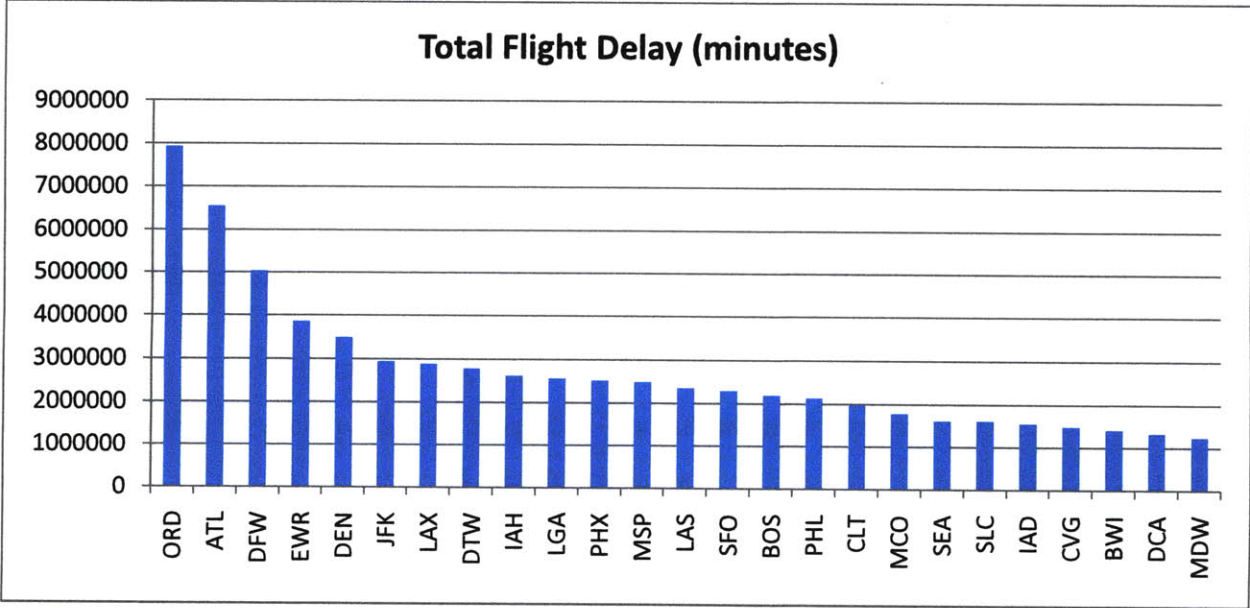


Figure 4.23: US airports with the highest total flight delay in year 2007

In the analysis that follows, we identify the airports with the highest average passenger delays. Here, we only consider airports with more than 1% of the total domestic passenger throughput of all US airports. Out of the total 309 airports, 58 airports were found to satisfy this criterion. Out of these 58 airports, the top ten airports with the highest average passenger delays are shown in Figure 4.24.

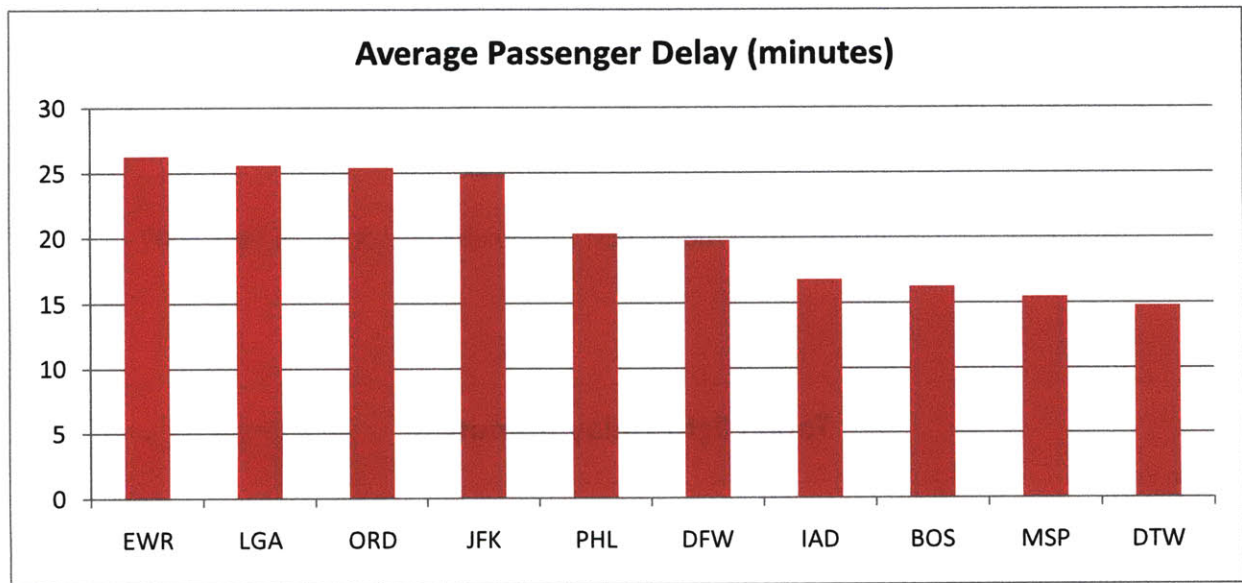


Figure 4.24: US airports with the highest average passenger delay in year 2007

As seen in the plot, Newark International (EWR), New York La Guardia (LGA) and Chicago O'Hare (ORD) are the airports with the highest average passenger delays in year 2007. It is interesting to note that Chicago O'Hare is a major hub and LaGuardia a focus city of American Airlines as shown in Figure 4.25, while Chicago O'Hare is also the primary hub for United airlines as shown in Figure 4.26, and Newark International (EWR) is one of the primary hubs of Continental Airlines as shown in Figure 4.27. In fact the high average passenger delays at these airports could be one explanation for the high average passenger delays for American, United and Continental Airlines, which rank highest in terms of average passenger delays amongst all the major legacy carriers in 2007, as also shown previously in Figure 4.16.

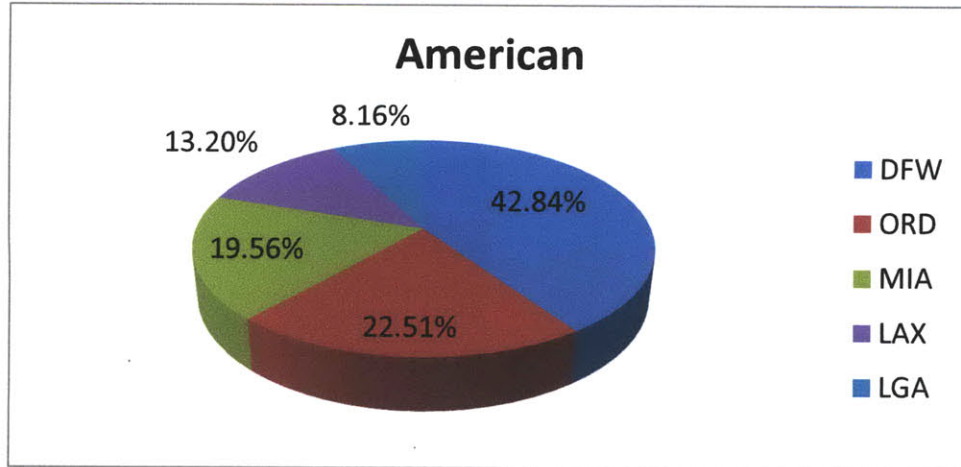


Figure 4.25: Top 5 destinations of American Airlines in terms of passenger throughput

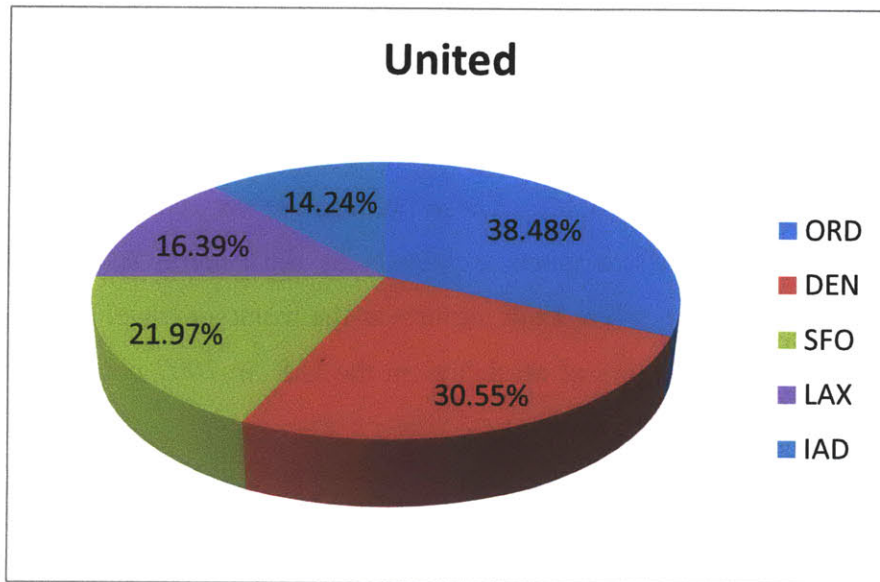


Figure 4.26: Top 5 destinations of United Airlines in terms of passenger throughput

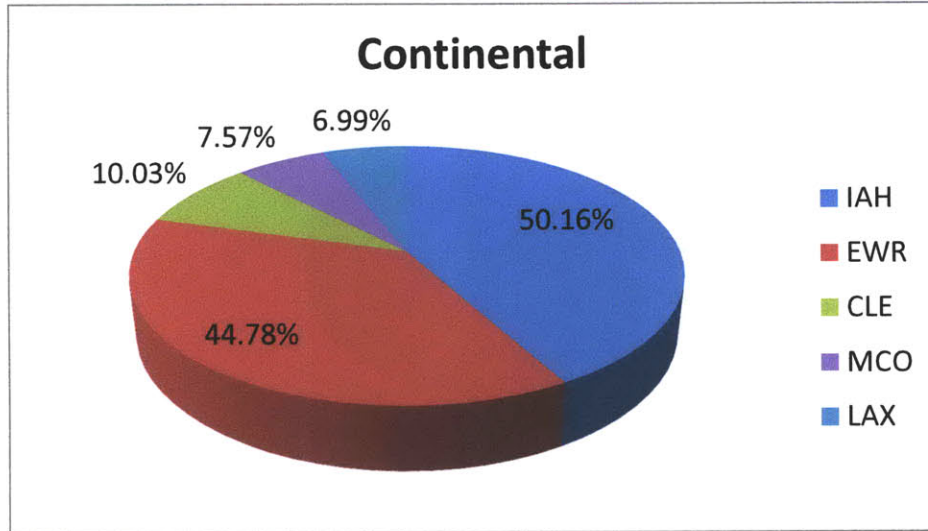


Figure 4.27: Top 5 destinations of Continental Airlines in terms of passenger throughput

Another interesting observation is that all three major airports of New York - Newark (EWR), La Guardia (LGA) and John F. Kennedy International (JFK) – rank among the top 5 US airports with the highest average passenger delays. These findings are very consistent with the growing concern about congestion at these airports, especially by the Federal Aviation Administration (FAA) which identified the three New York airports as the worst air travel bottleneck in the US, and stated that nearly three-quarters of all delays in the U.S. in 2007 could be traced to some problem in New York [27].

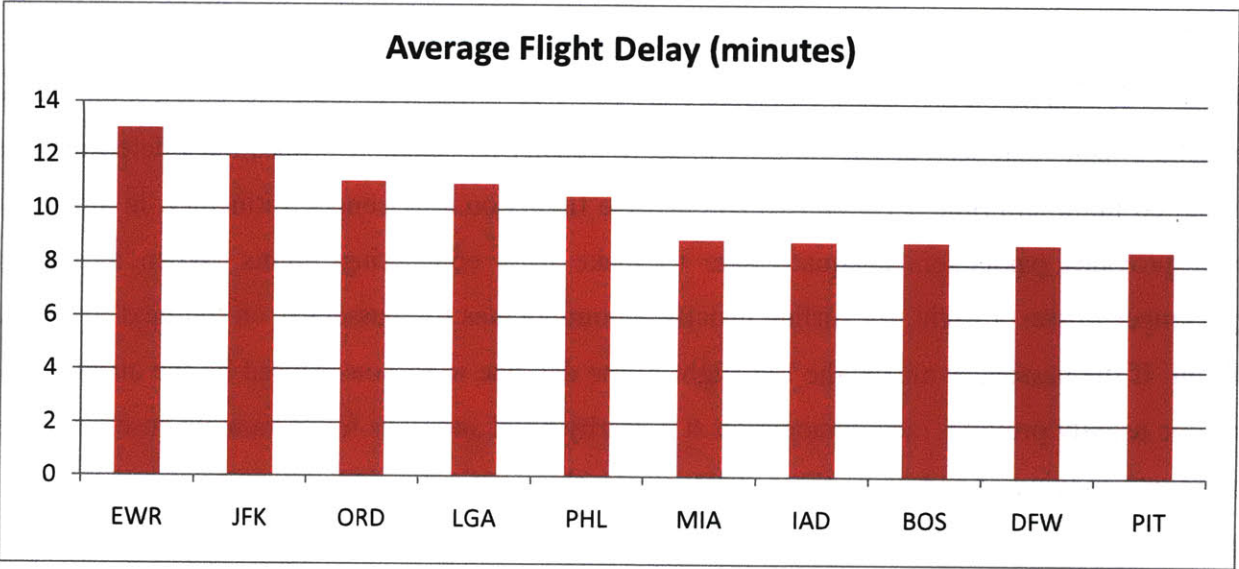


Figure 4.28: US airports with the highest average flight delay in year 2007

Further, it may be noted the airport rankings based on average passenger delays do not correspond very well with rankings based on average flight delays as shown in Figure 4.28 (only airports with more than 1% of the total domestic flights in the US), which again might be attributed to the difference in disruption levels at different airports. In terms of average flight delays, Newark International (EWR) ranks the highest, followed by John F. Kennedy (JFK) which is the main base of JetBlue Airways and also a major hub of Delta Airlines, and Chicago O’ Hare (ORD) is in the third position.

## 4.8. Misconnection Analysis

With most major airlines operating a hub-and-spoke system and partnering with other airlines to offer code-shared flights, many passengers are required to make at least one connection before reaching their final destination. In order to serve transfer passengers, airlines must determine the required minimum time between two consecutive flights on a passenger's itinerary, in a manner that provides passengers adequate time to make their connecting flights. When a transfer passenger misses a flight, the airline usually accommodates the passenger on the next available flight. If the passenger misses the last flight of the day due to reasons caused by the airlines, the airline usually provides accommodation at a nearby hotel and pays for certain expenses, such as food and lodging. Apart from these direct costs, there are other indirect costs associated with passenger misconnections, such as loss of goodwill [19].

According to our estimates, 16% of the total passenger delay in 2007 was due to misconnections alone. Thus, most certainly misconnections account for a significant proportion of the total delay costs in the US air transportation system. In this section we identify the US airports with the highest percentage of misconnected itineraries, the airports with the highest percentage of misconnected passengers, and finally airports with the highest total and average misconnection delay.

Out of the 173 airports with reported misconnections, the 24 airports with more than 1 million connecting passengers in 2007 were considered, and the top 10 US airports with the highest percentage of misconnected itineraries identified, as shown in Figure 4.29. We see that Newark International (EWR), one of the principal hubs of Continental Airlines, had the highest percentage of misconnections among all airports at 7.42% followed by Washington Dulles International (IAD) at 6.14% and John F. Kennedy International (JFK) at 5.64%.

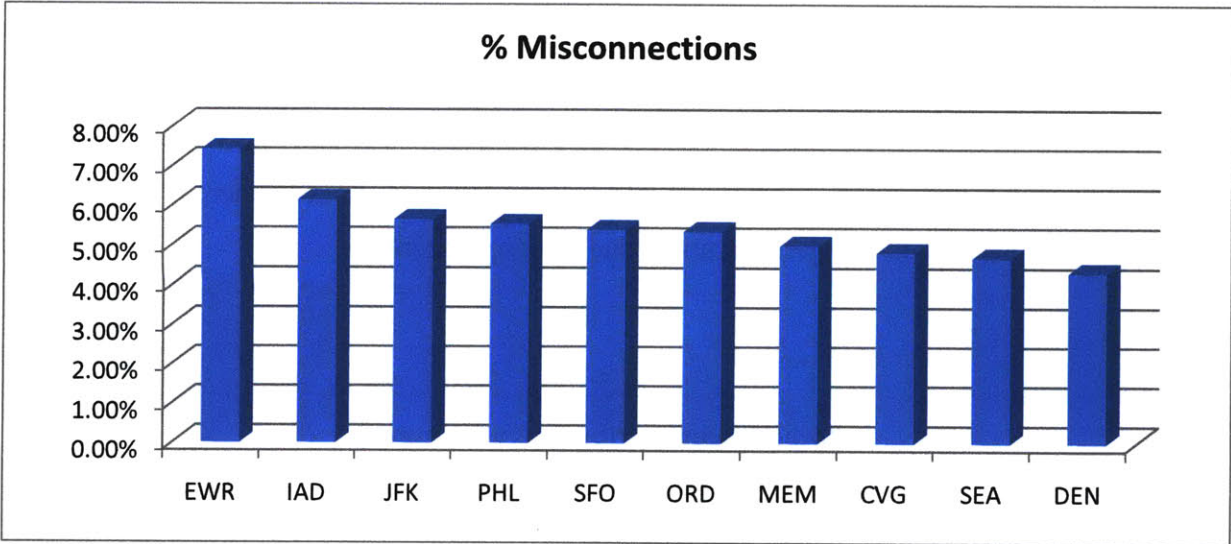


Figure 4.29: US airports with the highest percentage of misconnections in year 2007

In terms of percentage of connecting passengers who misconnect, which is a better indicator of the service performance of an airport to transfer passengers, Newark International (EWR) still ranks the highest at 7.17%, followed by Washington Dulles International (IAD) at 5.86% , while Philadelphia International (PHL) ranks third at 5.34% . This is shown in Figure 4.30.

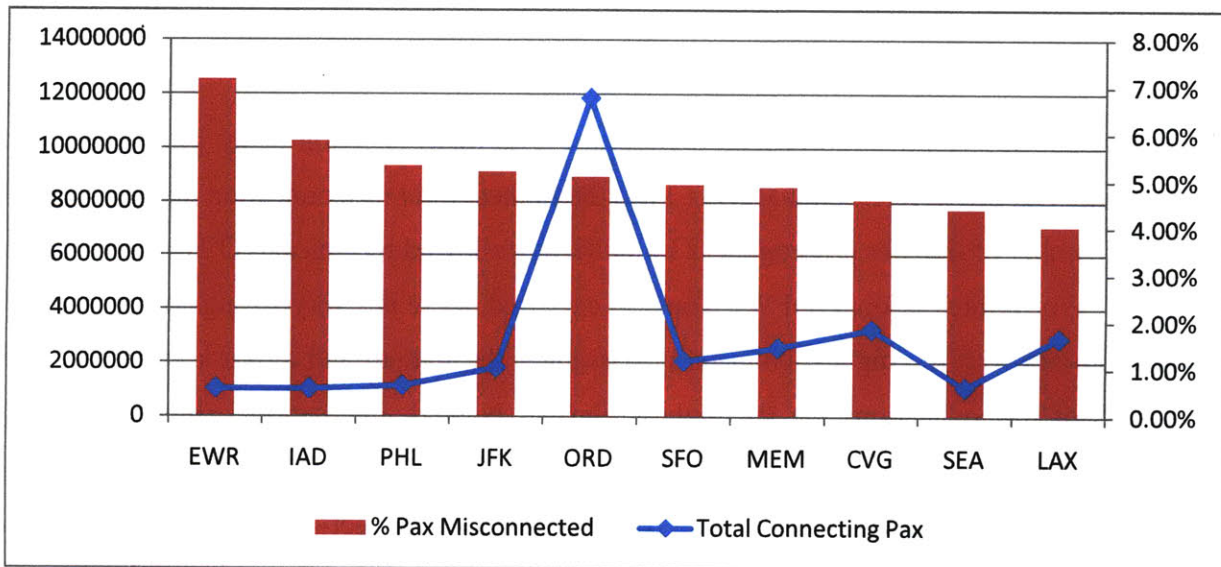


Figure 4.30: US airports with the highest percentage of passengers misconnected in 2007

Chicago O Hare International airport (ORD), with over 11.8 million connecting passengers in 2007, ranks third in terms of total throughput of connecting passengers after Atlanta Hartsfield International (ATL) with 23.6 million and Dallas Fort Worth International (DFW) with 14.3 million connecting passengers, and ranks 5th among all airports considered, in terms of percentage of connecting passengers disrupted due to misconnections.

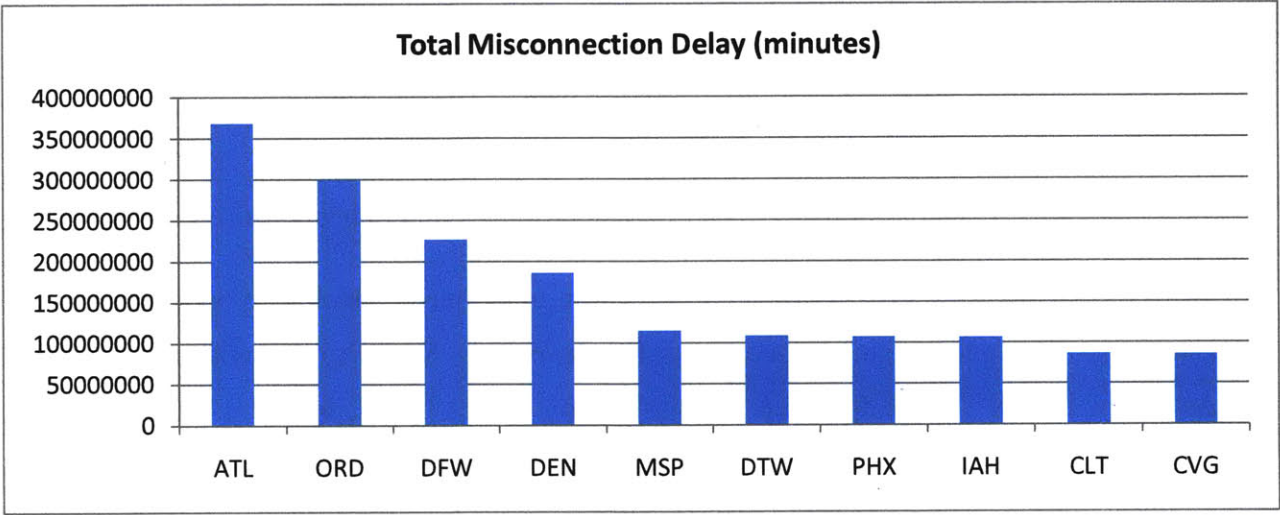


Figure 4.31: US airports with the highest total misconnection delay of passengers in year 2007

Figure 4.31 shows the US airports with the highest total misconnection delay of passengers in 2007. Atlanta Hartsfield International (ATL) has the highest total misconnection delay due to the enormous number of transfer passengers (23.6 million), followed by Chicago O’Hare (ORD) and Dallas Fort Worth International (DFW). Thus, as expected, there is a very strong correspondence between airports with the highest connecting passenger throughput and airports where the total delay costs of misconnections are the highest. Further Newark International (EWR), with the highest percentage of misconnections and percentage of passengers disrupted due to misconnections, ranks much lower (17<sup>th</sup>) in terms of total misconnection delays, because of the relatively low number of transfer passengers, which is just over one million.

In the analysis of airport rankings based on highest average misconnection delays per passenger disrupted due to misconnection, we again consider only the 24 US airports with more than 1 million transfer passengers in 2007. In terms of average misconnection delays, Memphis International (MEM) was identified as the airport with the highest average misconnection delay in year 2007, followed by Cincinnati-Northern Kentucky (CVG) and Philadelphia International (PHL), while Newark International (EWR) with the highest percentage misconnections ranks fourth. This is illustrated in Figure 4.32, which shows the top ten US airports with the highest average misconnection delays in 2007. It is also interesting to note that the top three airports in terms of throughput of connecting passengers, Atlanta Hartsfield International (ATL), Dallas Fort Worth International (DFW) and Chicago O Hare International airport (ORD) rank much lower in terms of average misconnection delays, which may be due to higher frequency of alternative services at these airports.

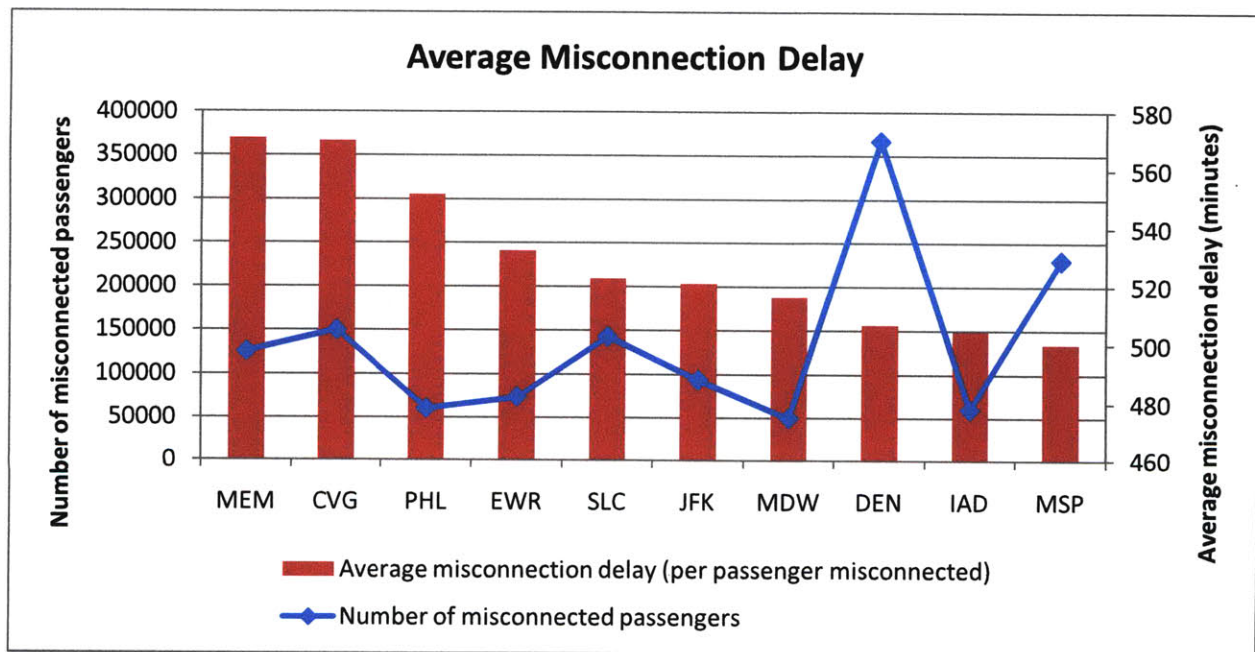


Figure 4.32: US airports with the highest percentage of average misconnection delay per passenger misconnected in year 2007



## **Chapter 5**

### **Conclusions**

This thesis focuses on capturing the effects of itinerary disruptions, such as flight cancellations and misconnections, on air passenger delays, and on evaluating the performance of the air transportation system from passengers' perspectives. A new methodology is presented to improve current estimates of passenger delays by relying solely on publically available data sources. The methodology is used to estimate the magnitude of passenger delays in the US domestic air transportation system for the year 2007. The passenger trip data generated using this methodology is also used to carry out a comprehensive disaggregate analysis of air traffic delays in the US domestic air transportation system. This chapter is divided into two sections. The first section summarizes the major findings and research contributions of the thesis. The second focuses on directions for future research.

#### **5.1 Major findings and research contributions**

The major findings and research contributions of this thesis are summarized as follows:

In Chapter 2, we provide a review of previous studies related to the investigation of the cost impact of delays on airlines, passengers and the spillovers to the rest of the US economy. We discuss the cost impact of delays on airlines, in the form of added expense and lost revenue, and provide an overview of three different methodologies to estimate the cost of delays to airlines. We also provide a qualitative discussion on how flight delays differ from passenger delays, and further discuss other forms of delays as resulting from airline scheduling practices due to airport capacity limitations. Focusing on the business traveler, we provide a qualitative overview of (1) how delay intrudes on the lives of those experiencing it, and (2) delays that result from one

particular response mechanism of passengers—rescheduling trips to allow time for delays in reaching their destination.

The work presented in Chapter 3 is based on joint research with Douglas Fearing, Vikrant Vaze and Professor Cynthia Barnhart. In that chapter, we describe a new methodology which converts flight data to passenger trip data relying solely on publically available datasets related to airline travel. The primary challenge addressed in this work is estimating disaggregate passenger itinerary flows from publically available aggregate demand data using a small set of proprietary booking data. Due to the limitations in the optimization-based approach used in earlier research, such as the extreme point nature of linear programming solutions and the inability to incorporate secondary factors such as connection time, the discrete choice modeling approach is instead used to estimate passenger flows on generated itineraries.

The algorithm for the computation of passenger delays involves the following three core steps:

1. Generation of potential itineraries based on planned ASQP flights, and processing DB1B data to estimate the number of passengers travelling each month on each *carrier-route*.
2. Allocation of the monthly *carrier-route* passengers to generated itineraries using a discrete choice allocation approach.
3. Computation of total delays to passengers on each itinerary, using an extension of the passenger delay calculator (PDC) originally developed by Barnhart and Bratu (2005).

We also present our estimates of the total passenger delays in the US domestic air transportation system for the year 2007, using the methodology described above. According to our estimates, in year 2007 passengers experienced a total of close to 15 billion minutes of delay due to flight delays (50% of the total), flight cancellations (34% of the total), and missed connections (16% of the total). Interestingly, the average passenger delay for all passengers in year 2007, estimated at 30.81 minutes, is more than twice the average delay of all operated flights during the same period estimated at 14.96 minutes.

In Chapter 4, we use the passenger trip data generated by the algorithm described in Chapter 3 to carry out for the first time a comprehensive disaggregate analysis of air traffic delays in the US domestic air transportation system for the year 2007. Our main findings from the analysis are summarized as follows:

- From the statistical comparison of flight delays and passenger trip delays, it was found that the mean daily average flight delay in 2007 was 15.2 minutes with a standard deviation of 6.8 minutes, while the mean daily average passenger delay for the year was 30.4 minutes with a standard deviation of 20.2 minutes. We observe that on 44% of the days, the average flight (flight with delay equal to the average flight delay on that particular day) was delayed, with a mean daily average flight delay of 21.2 minutes. While on 84 % of the days, the average passenger (passenger with delay equal to the average passenger delay on that particular day) was delayed, with a mean daily average passenger delay of 33.7 minutes.
- The multiplier ratios (average passenger delay divided by average flight delay) do not remain constant over the year, but vary over time. For year 2007, the multiplier values on a given day were found to vary over a wide range from 1.40 to as large as 10.76 over the course of the year.
- Using a non-parametric statistical test called the Spearman Rank Correlation Coefficient Test, the multiplier values were found to be significantly positively correlated to *flight cancellation rates*, *percentage of connecting passengers* and *percentage of passenger misconnections* across carriers.
- It was observed that all regional carriers such as Comair (OH), American Eagle (MQ), SkyWest (OO), etc., have higher multiplier values than legacy and low-cost carriers. This is attributed to the higher rates of flight cancellations as well as the much higher percentage of connecting passengers on regional carriers.

- Using the Spearman Rank Correlation Coefficient Test, we also study and determine the strength of correlation between flight on-time performance and passenger on-time performance. From this analysis, it is inferred that there is no single best on-time metric which reflects in all respects the true performance of the airline carriers in terms of delays to flights. More importantly, we are able to show that, for large delays, flight-based metrics may not be a good proxy for passenger trip delays.
- From the passenger delay distributions of major legacy and low cost carriers, it is observed that all low cost carriers had average passenger delays that most frequently fall in the delay range of less than 15 minutes. On the other hand, most major legacy carriers, such as American (AA), United (UA), US airways (US) and Alaska (AS), most frequently had average delays in the range of 15-30 minutes for year 2007. This can be attributed to the higher flight cancellation rates and the hub-and-spoke system of operation of legacy carriers.
- For the year 2007, Chicago O'Hare International Airport (ORD) was identified as the airport with the highest total passenger delay minutes, followed by Dallas Fort Worth International (DFW) and Atlanta Hartsfield International (ATL). Further, it was determined that the 5 most delayed airports alone accounted for around 48.50 % of the total passenger delays, whereas the top 25 most delayed airports accounted for 92.80 % of the total passenger delay minutes at all 309 US airports in 2007. In terms of average passenger delays (only considered airports with more than 1% of the total domestic passenger throughput of all US airports.), Newark International (EWR), New York La Guardia (LGA) and Chicago O'Hare (ORD) were found to rank the highest among all airports for year 2007.
- Newark International (EWR) followed by Washington Dulles International (IAD) were identified as the airports with the highest percentage of misconnects both on an itinerary basis as well as in terms of passengers (only considered airports with more than 1 million transfer passengers in year 2007). In terms of total misconnection delay, Atlanta Hartsfield International (ATL), followed by Chicago O'Hare (ORD) and Dallas Fort

Worth International (DFW) were identified as the top 3 US airports. In terms of average misconnection delay (only considered airports with more than 1 million transfer passengers in year 2007), Memphis International (MEM) was found to rank the highest among all airports considered.

## **5.2 Directions for future research**

This section outlines a couple of the unexplored research topics and future directions for research work.

- In the validation of passenger itinerary flows, both the discrete choice allocation and the randomized allocations were found to under-estimate or over-estimate the load factors when compared to proprietary booking data. This may be attributed to the impacts of revenue management. By incorporating price as a dependent feature in the discrete choice allocation model, it should be possible to more accurately match the distribution of load factors in the proprietary booking data.
- Developing a more sophisticated model to understand the factors affecting the conversion of flight delays to passenger delays would be another natural extension of the current work. The model should incorporate factors that take into account not only the effect of itinerary disruptions, such as cancellations and misconnections, but also factors affecting the recovery of disrupted passengers, such as load factors and frequency of service of other flights to the desired destination. It would be particularly interesting to see how the trip delay experienced by disrupted passengers changes in response to changes in frequency of other flights or the load factor of the disrupted passenger's re-booked flights.



## APPENDIX A

### CARRIER CODES

<b>Carrier</b>	<b>Airline</b>
MQ	American Eagle Airlines Inc.
YV	Mesa Airlines Inc.
OH	Comair Inc.
EV	Atlantic Southeast Airlines
9E	Pinnacle Airlines Inc.
AA	American Airlines Inc.
XE	Expressjet Airlines Inc.
UA	United Air Lines Inc.
OO	Skywest Airlines Inc.
B6	JetBlue Airways
NW	Northwest Airlines Inc.
US	US Airways Inc.
AS	Alaska Airlines Inc.
DL	Delta Air Lines Inc.
FL	AirTran Airways Corporation
CO	Continental Air Lines Inc.
WN	Southwest Airlines Co.
AQ	Aloha Air Cargo
HA	Hawaiian Airlines Inc.
F9	Frontier Airlines Inc.

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