THE IMPACT OF AIRPORT SIZE ON SERVICE CONTINUITY AND OPERATIONAL PERFORMANCE

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ABSTRACT

This dissertation looks at the relationship between airport size (e.g. small, medium, large) and air service continuity and operational performance. It consists of three studies, each written in journal format. The first study analyzes the markets served pre- and post-recession while focusing on the operational strategies adopted by the top Major Carriers and Low-Cost Carriers (LCCs) in the United States. Findings show that LCCs have outpaced major carriers in terms of expanding their network and the number of markets served. During the same time, major carriers have gained a greater flight share in the markets they already serve. Post-recession, LCCs have shown preference to competing with major carriers over other LCCs. The second study investigates the declining service levels at small airports compared to large-hub airports, which continue to benefit from higher levels of service and increased airline presence. Using a fixed-effects conditional logistic regression, this study looked at factors contributing to service loss in region-to-region markets serving small communities between 2007 and 2013. Results show that 1) markets affected by a merger are indeed at a higher risk of losing service; 2) markets that are operated by a fuel-intensive, small-aircraft fleet have a higher chance to be discontinued and 3) an increased number of competitors greatly reduces potential market service loss. The third and final study proposes a new methodology to calculate original delay and propagated delays using combined aviation operational datasets that provide detailed flight information and causal factors behind delays. In addition to calculating original and propagated delay for the month of July of 2018, this study

differentiated between original delays that occur during the turnaround phase, taxiing phase and en-route and incorporates causal factor information to identify the true source behind propagated delay. Two fixed-effects linear regression models were introduced that predict Total Propagated Delay and the share of propagated delay given an airport's ability to absorb upstream delay during the turnaround phase. Results show that most delay propagation chains originate at large-hub airports and are mostly concentrated at airports within the same geographical area. However, delays originating at large-hub airports were found to be the quickest to recover (i.e. least number of downstream flight legs affected) and large-hub airports have a higher ability to absorb delay at the turnaround phase compared to smaller airports given the significantly higher schedule buffer time airlines plan at large-hub airports.

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GENERAL AUDIENCE ABSTRACT

The changing nature of the air service industry is dependent on several key factors, including but not limited to the major and low-cost airlines, the frequency of service at different sized-airports and the operational performance of the airports in the system. Each airport can be classified by size based on the annual number of enplanements. This dissertation looks at the relationship between airport size (e.g. small, medium, large), service continuity and operational performance. It consists of three studies, each written in journal format. Over the past two decades, the U.S. air transportation network witnessed several economic downturns forcing airlines to shift their operational strategies, cease service or merge with an airline counterpart. The first study analyzes routes served before and after the recession by exploring the presence of major and low-cost carriers in these markets to understand how several economic downturns have influenced the operating strategy of airlines in the US. While Low-cost carriers focused on expanding their network and offering service in an increased number of new routes, major carriers increased their presence in the markets in which they already serve. Furthermore, after the recession, low-cost carriers chose to increasingly compete with major carriers over their low-cost counterparts. The second study explored the factors that can potentially contribute to the loss of service in routes serving small communities. While airlines continue to compete on the most profitable routes, small airports recently suffered from reduced service levels and in some instance service discontinuity. Results show that 1) routes that were once served by two airlines that merged are at a higher risk of losing service; 2) routes that are operated by a fuel-intensive small aircraft fleet have a higher

chance to be discontinued and 3) an increased presence of airlines competing in a route greatly reduces potential service loss. In addition to evaluating service continuity, the third and final study looks at flight delays across the US and dives into the effect of airport size on propagated delay. Delays on a flight can be caused by inefficiencies and capacity restrictions at airports and may also be the result of delay that happen earlier in the day and that propagates to multiple flights downstream that share the same resources. That is, a delay can affect multiple flights whenever these flights are all operated by the same aircraft equipment. Costing the air transportation network billions of dollars annually, the third study examines the original and propagated delays at US airports by collecting data from multiple sources to incorporate the original source and cause of delay. Results show that most delay originates at large-hub airports and are mostly concentrated at airports within the same geographical area. However, delays originating at large-hub airports were found to be the quickest to recover and large-hub airports have a higher ability to absorb delay at the turn compared to smaller airports as airlines allocate additional minutes of schedule padding at large-hub airports.

DEDICATION

In memory of my father, Pierre Atallah, for always believing in me and teaching me life's most important values – I hope I've made you proud.

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TABLE OF CONTENTS

List of Figures

List of Tables

LIST OF ABBREVIATIONS

ARTCC	Air Route Traffic Control Center
ASQP	Airline Service Quality Performance
ASPM	Aviation System Performance Metrics
BTS	Bureau of Transportation Statistics
CONUS	Continental United States
DB1B	Origin and Destination Data Bank
EAS	Essential Air Service Program
FAA	Federal Aviation Administration
GAO	Government Accountability Office
KPI	Key Performance Indicator
LCC	Low-Cost Carrier
OAG	Official Airline Guide
OD	Origin-Destination
OPSNET	Operations Network
SCASDP	Small Community Air Service Development Program
TPD	Total Propagated Delay

CHAPTER 1

Introduction

1.1 Background and Motivation

Small airports constitute approximately 88% of commercial airports in the US according to the latest passenger boarding data published by the Federal Aviation Administration (FAA) (FAA, 2017). The Federal Aviation Administration (FAA) classifies airports in the US by size based on the percentage of annual passenger boardings at each airport and label an airport as either large, medium, small, non-hub, or non-primary[1]. The latest passenger boarding data published by the FAA for the 2017 calendar year reports a total of 30 large hubs, 31 medium hubs, 70 small hubs, 255 non-hubs and 125 non-primary commercial service airports.

In recent years, small airports experienced lower growth rates in total passenger enplanements while large and medium hubs continued to benefit from significantly higher passenger activity. More specifically, between 1979 and 2014, while the annual average growth in total passengers was 4.37% across 306 U.S. airports, small-hub airports reported an average annual growth of 3.15% and non-hub reported an annual growth of only 1.3% (Hammond and Czaban, 2016). Furthermore, Cheung et al. (2020) analyzed global airport connectivity for 3,500 airports worldwide and found that between 2006 and 2016, large airports experienced a compound passenger-capacity growth of 5.54% year on year as compared to only 1.55% from smaller airports. In addition, small airports continue to observe traffic leakage to large-hub airports in multiple airport regions (Gao, 2020).

[1] FAA defines a primary airport as commercial service airports with more than 10,000 passenger boardings each year. Primary airports are classified as large, medium, small or non-hub. Large hub airports have 1% or more of annual passenger boardings. Medium hub have at least 0.25% of annual passenger boardings. Small hub have at least 0.05% of annual passenger boarding and non-hub have more than 10,000 annual passenger boardings. Non-Hub nonprimary airports have at least 2,500 annual passengers boardings (FAA, 2014).

Given the uniqueness of small airports in terms of demand, throughput and capacity, the purpose of this dissertation is to see how they differ in terms of service continuity and operational performance. Specifically, this dissertation contains three studies, each written in journal format. The first study looks at the changes in airline operational strategies across markets serving different airport sizes pre- and post- recession. The second study examines factors that may have contributed to a small community's loss of air service. Lastly, the third study proposes a fixed-effects model that compares between small and large-hub airports' contribution to delay propagation using on-time performance metrics.

1.2 Airport Size and Service Continuity

Understanding the major historical milestones in the Air Transportation System is important for analyzing the shifting dynamics and major changes in this industry in the areas of service continuity and airline competition. More specifically, this section looks at major historical events that led to the contrast in service growth and airline presence across airports of various size in the U.S.

In 1978, the deregulation of the airline industry in the United States marked the growth of Low-Cost Carriers (LCCs) among known legacy carriers. While major carriers were known for their higher service quality and ability to sustain long-haul flights while operating on larger networks, low-cost carriers provided cheap flights and introduced new operational strategies.

Despite the cost savings generated by the operation of hub-spoke networks (Brueckner and Spiller, 1994), the airline industry faced several challenges caused by a limited capacity at airports and a growing passenger demand, creating delays and congestion problems specifically at hubs (Pels, 2008). In an effort to mitigate congestion at the nation's largest hubs, LCCs sought operating mainly from secondary airports while benefiting from lower airport fees charged by these secondary airports.

The "low-cost airline revolution," enabled new carriers to enter existing markets and existing carriers to explore new markets. Although many of these low-cost carriers failed to succeed, some proved to be very successful and profitable such as Southwest Airlines. Following the 2001 downturn, low-cost carriers generated most of its profit by winning over legacy clients through offering reduced-fare flights and creating new demands that were not satisfied by the existing airline service (Franke and John, 2011).

In 2008, the great economic recession impacted airline market structures over the years that followed. The series of major economic events marked by a surge in fuel prices resulted in an increase in the airlines' incurred costs while travel demand plummeted. As a result, airlines reduced the number of domestic scheduled passenger flights by 13.9% between June 2007 and June 2012 and most of these flights were cut between 2008 and 2009 without being restored (USDOT, 2012). While many major carriers filed for bankruptcy protection, other airlines filed for bankruptcy and ended their operations (Mumbower, 2013).

In recent years, the airline industry witnessed many changes particularly in competition structures and the number of markets served within the US. In 2014, the U.S. Government Accountability Office (GAO) reported that the top four American carriers dominated 85% of the market following a series of mergers and acquisitions. Merger activity occurred between the nation's largest airlines and several airlines witnessed a shift in their strategy of operations as they now seek operation in profitable markets while cutting down on their operating costs. Although recent changes in the airline service impacted the entire industry, smaller communities were the most affected. As noted in ACRP Project 03-29, "Airports serving smaller communities have been particularly affected by the changes, resulting in reduced service levels, less airline competition, and poorer service quality." In fact, Hammond and Czaban (2016) reported that of the 67 airports that experienced a net loss in total passenger enplanements from 1979 to 2014, all were identified as non-hub airports.

According to a recent MIT study published by Wittman and Swelbar (2013), the economic recession along with rising fuel costs and the "capacity discipline" strategies employed by airlines prioritizing higher load factors have led to a consolidation of service in the largest airports of the US and a loss of service in smaller airports. Moreover, airports located next to large hub airports were more likely to lose service as passengers prefer to drive to these airports and benefit from better services and a higher service frequency.

Therefore, it is important to analyze the shift in operational strategies for major airline competitors across various size airports and evaluate the factors that may contribute to a small community's loss to air service. The latter can help the industry's key players, such as airport managers and airlines, understand the dynamics governing the air transportation industry today.

1.3 Airport Size and Operational Performance

Similar to the air service levels that vary across large and small-hub airports, the size and the number of operations at an airport plays a large role in its on-time performance. Several studies have looked at the relationship between airline competitiveness on a route and flight delays. While Mayer and Sinai (2003) found that increased competition is correlated with worse on-time performance, Deshpande and Arıkan (2012) indicated that increased market share reduced the scheduled on-time arrival probability leading to greater delays on less competitive routes. With more airlines shifting their operations from the smaller airports to the large-hub airports, airlines compete by offering greater flight frequency at the larger airports to meet the needs of passengers.

As a result, airlines are expected to operate tighter schedules which results in an airport operating near capacity and eventually contributes to its overall on-time performance.

Different sized airports vary in capacity, number of flight connections and hourly throughput. As a result, many factors may contribute to the resilience of the airport to overcome service disruptions and schedule recovery. Flight delays, calculated using a flight's scheduled times, can occur on the ground or while the aircraft is airborne (i.e. enroute) due to adverse weather conditions or due to other factors. As different flights share common resources such as the aircraft, crew members, connecting passengers, etc., these interdependencies may lead to delay propagation throughout the National Airspace System (Wang et al., 2003). Therefore, many flights are late due to delay propagated from upstream flights using the same airplane.

According to the Bureau of Transportation Statistics (2019), the number one cause for delays reported by carriers since 2004 is a delayed aircraft arrival on a previous flight leg causing the next flight to depart late. As flights continue to experience delays daily, an assessment of key performance indicators and the on-time performance of flights across airports can indicate how each airport size may contribute to or absorb delay propagation in the NAS. What is most interesting is the significant growing percentage of flights delayed because of an "Aircraft Arriving Late" between years 2009 and 2014.

1.4 Major Contributions

The main contribution of this dissertation is the analysis of airport size contribution to service continuity and operational performance while overcoming current limitations in the literature. Of the three studies in this dissertation, the first one looks at LCCs and major carriers' operational strategies and changes in markets' competition structure pre- and post-recession. The contribution of this study is that it is market-based (i.e. which origin-destination pair markets are served) whereas most previous studies in the literature are predominately airport-based (i.e. focus on the origin and destination airports served). This market-based approach helps capture the changes in airlines' competitive presence and market share while incorporating the characteristics of both departure and arrival airport (i.e., size) as opposed to an aggregated analysis at the airport-level.

The second study's contribution is the ability to quantify the influence of different regional and market characteristics on service continuity in small communities. This was done through building a fixed-effects conditional logit model and focusing on region-to-region markets departing from regions that only have access to a small or a non-hub airport between 2007 and 2013. The findings of this research will help airport managers and stakeholders better understand the impact of market competition structure and other market and region-specific factors on service continuity in small airports and address on-going challenges faced by the air transportation system as well as small communities in today's industry.

The third study's contribution is that it offers a new methodology to assess propagated delay while building a unique dataset that merges data from different sources: Aviation System Performance Metrics (ASPM), Airline Service Quality Performance (ASQP), Operational Network (OPSNET) and Cancellations. In other words, to date, there have been no studies to the author's knowledge that combine information from these four data sources to calculate propagated delay while taking into account the causal factors for delay, cancelled flights and diversions. This study not only presents a new way for calculating propagated delay and defining Key Performance Indicators (KPIs), but also provides an analysis comparing the contribution of different sized-airports, measured by enplanements, to delay propagation by developing two models using fixed-effects linear regression.

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CHAPTER 2

The Evolution of Low-Cost Carrier Operational Strategies Pre- and Post-Recession

Atallah, S., Hotle, S. L., & Mumbower, S. (2018). The evolution of low-cost Carrier operational strategies pre-and post-recession. *Journal of Air Transport Management*, *73*, 87-94.

2.1 Abstract

This study presents an analysis of low-cost carrier (LCC) competition strategies for Continental US (CONUS) domestic markets. Using OAG schedule data from 2005-2015, pre- and post-recession trends in LCC flight offerings were analyzed and compared with their major carrier counterparts in terms of number of markets served, flight frequency, and competition structures of served markets. Results show that LCCs are increasing the number of markets served to/from large airports and are entering highly competitive markets. The results further suggest that LCCs and major carrier strategies evolved differently during the study period, where LCCs outpaced major carriers in terms of markets entered while major carriers have gained a greater flight frequency share in the markets they already serve. Results clearly indicate that overall LCCs are still growing in terms of O-D markets served and increasing competition with major carriers. However, evidence suggests that each of the top four LCCs adopted different operating strategies as part of their business model during the study period.

Keywords: Market Share, Competition Structures, Low-Cost Carriers, CONUS-Domestic Markets

2.2 Introduction

In the past two decades, LCCs have become an increasingly popular alternative to air travel consumers by providing a cost-effective option to price-sensitive customers. According to the Bureau of Transportation Statistics (2016), the share of passengers carried by network carriers declined from 62.0% to 50.2% between 2003 and 2015 whereas the share of LCCs' passengers has been increasing. This shift in demand to LCCs has been seen even in Europe where low-cost flights increased by 61% from 2007 to 2016 while traditional carriers' flights declined by 10% during the same time period (Eurocontrol, 2017).

In the United States, much of the initial growth in popularity of LCCs was generated after the 2001 downturn, with LCCs winning over major carrier customers through offering reduced fares and creating new demand that was not satisfied by the existing airline service (Franke and John, 2011). Specifically, LCCs were able to generate new demand from infrequent price-sensitive fliers by offering them no-frills reduced fare flights (Maidenberg, 2017) as well as attract passengers who were willing to drive to nearby airports served by LCCs to benefit from their services (Spitz et al., 2015). As LCCs increasingly competed on overlapping markets with network carriers, the latter were forced to respond by implementing new business strategies (Pearson et al., 2015; Babicé and Kalicé, 2018). One strategy included network carriers establishing low-cost carrier offshoots or what is also known as the "no frills" divisions within the airline such as Song by Delta in 2003 and Ted by United in 2004. However, major carriers were unsuccessful in their attempts to respond to rising competition from LCCs through these offshoots as they were unable to reduce their unit costs to Southwest levels (Morrell, 2005). Consequently, airline divisions Song and Ted ceased operations by 2006 and 2009, respectively (Pearson and Merkert, 2014).

Much has been hypothesized about the operational future of LCCs and how they compete with major carriers in recent literature. For example, Abda et al. (2012) predicted the unconstrained growth of LCCs in the top 200 US airports was approaching an end by stating, “The well-known impacts of LCCs on air travel markets of lower average fares and higher passenger volumes are evident over the entire period of our study from 1990 to 2008. However, several more specific trends suggest that the unbridled growth of LCCs in US domestic markets may be ending.” Similarly, de Wit and Zuidberg (2012) predicted a slowdown to LCC growth in the upcoming years in face of route density problems and continental market saturation. They hypothesized that for future growth, LCCs will need to adopt new business strategies such as shifting operations to primary airports and creating new alliances. This was further discussed in Dobruszkes et al. (2017), which found that LCCs are increasingly competing from major airports while continually growing and expanding. Hence, “the largest cities' traditional airports will not be sanctuaries for traditional airlines anymore” as direct competition between low-cost carriers and major carriers is increasing.

The purpose of this study is to analyze the evolution in LCC operations and competitive strategies as they have gained popularity compared with their major carrier counterparts. This study contributes to literature as it is market-based (i.e. which origin-destination pair markets are served) and current literature is predominately airport-based (i.e. focuses on the origin and destination airports served). Specifically, the research questions to be addressed in this paper include 1) have LCCs altered operational strategies with regard to the markets and airports they serve and 2) have LCCs changed the competitive dynamics in which they compete (i.e. how they interact with major carriers) pre- and post- recession[2]. The rest of this paper is structured as follows: Section 2 describes the data and methodology used to study the operational evolution of LCCs over the years. Section 3 presents the analysis results for LCC competition strategies over

2 The great recession began in December 2007 and ended in June 2009, lasting 18 months (BLS, 2012). During the first three quarters of 2008, the U.S. passenger airline industry lost $4.3 billion mainly caused by the increase in fuel prices (GAO-09-393).

the study period. Specifically, results are presented in three different subsections: 1) service and competition structures, 2) flight share frequency and 3) LCC presence by market size. Finally, Section 4 highlights the conclusions of this study and provides recommendations regarding the future research direction.

2.3 Data and Methodology

To evaluate the competitive strategies of LCCs over time in comparison to their major carrier counterparts, this study utilized OAG flight schedules data, which provides carrier, flight number, origin, destination, aircraft equipment, and scheduled departure/arrival times for scheduled flights. This study uses service information indicated in the OAG schedules from 2005-2015 for nonstop continental US (CONUS) directional origin-destination (OD) airport markets. For example, in this study ATL-LAX and LAX-ATL were considered as two different markets. Directional OD airport markets were considered to capture markets with different market competition structure in each route direction. For example, in 2007, Southwest was the only significant operating carrier in the market departing from LAS and arriving at BUR. However, for flights departing from BUR and headed to LAS, both US Airways and Southwest Airlines competed on this route. Only non-stop service was considered as air passengers value a non-stop itinerary "up to 8 times more than a connecting itinerary" (Emrich and Harris, 2008) as well as to stay consistent with previous literature that only considered non-stop flights (e.g. de Wit and Zuidberg, 2012; Reynolds-Feighan, 2001; Spitz et al., 2015; Zhang et al., 2018). This analysis uses the third week of July for each year, which is a notably high-demand time of year, to reduce any impacts of seasonality on market offerings.

Table 1 shows the LCC and major carriers included in the analysis, which were categorized as either major or low-cost, consistent with the classification using existing literature (Abda et al., 2012; Spitz et al., 2015; USDOT, 2012). Select studies classify carriers that are not major or LCC as "Other" (Abda et al., 2012), but these carriers were outside the scope of this study as the objective is to determine how major carriers and LCCs have interacted over time[3].

Table 2.1: Airline classification by type.

Major Carriers	Low-Cost Carriers
Alaska Airlines	Airtran Airway
American Airlines	Allegiant Air
Continental Airlines	America West Airlines
Delta Air Lines	Ata Airlines, Inc.
Northwest Airlines	Frontier Airlines Inc.
United Airlines	Independence Air
US Airways	JetBlue Airways Corporation
	Midwest Airlines Op By Republic A/L
	Southwest Airlines
	Spirit Airlines
	Sun Country Airlines
	USA 3000 Airlines
	Virgin America

In this study, an airline was considered a significant operating competitor (i.e. a probable customer choice) on a market if it operated at least 7 non-stop flights during the third week of July (i.e. an average of one a day), with an average of at least 20 seats per flight. An OD pair market

[3] Upon conducting a sensitivity analysis, it was found that the number of markets with significant service from a regional carrier, as defined earlier in the methodology section, is very minimal. The number of markets with significant presence by a regional carrier (at least 7 non-stop flights during the third week of July and operating flights with a seating capacity greater than 20 seats/flight) include: Great Lakes Aviation (14 markets in 2006, 2009, 2012; 6 markets in 2015), Republic Airlines (1 market in 2006), Mesaba Airlines (2 markets in 2009), Shuttle America (1 market in 2009, 2012), Penair (6 markets in 2012, 2015) and ViaAir (2 markets in 2015). Therefore, this study excludes regional carriers and only considers major and low-cost carriers in the analysis.

was said to be served if it had at least one significant operating competitor from Table 1. It is important to note that competitors in this study were operating carriers and did not include codeshares.

In addition to using OAG Schedules, which provided market competition structures and flight frequency, airport size was incorporated into the study through the annual FAA Airport Classification (FAA, 2014)[4]. These classifications are based on the number of annual passenger boardings and label an airport as either large, medium, small, non-hub, or non-primary. This study classifies both primary non-hub and non-primary non-hub airports as “non-hub” and therefore any airport with less than 10,000 passenger boardings per year or less than 0.05% of annual passenger boardings fall in the same classification. The airport classification was used for each year, therefore an airport could be labeled small one year and medium the next if annual passengers increased.

2.4 Results

The following sections present different dimensions to LCC competition strategies in comparison to major carriers during the study period. The results include the analyses and sections in the following order: 1) market service and competition structures, 2) flight frequency, and 3) OD airport sizes.

2.4.1 Market Service and Competition Structures

As a result of the recession, airlines implemented several cost-cutting strategies which included increasing load factors (Garrow et al., 2012), but they also decreased the total number of OD pair

[4] FAA defines a primary airport as commercial service airports with more than 10,000 passenger boardings each year. Primary airports are classified as large, medium, small or non-hub. Large hub airports have 1% or more of annual passenger boardings. Medium hub have at least 0.25% of annual passenger boardings. Small hub have at least 0.05% of annual passenger boarding and non-hub have more than 10,000 annual passenger boardings. Non-Hub nonprimary airports have at least 2,500 annual passengers boardings (FAA, 2014).

markets served within the U.S. As shown in Table 2, in 2005 there were 4,656 non-stop, CONUS-domestic markets served by at least one of the airlines listed in Table 1. By 2015, the total of number of non-stop markets had decreased to 4,199 (a 9.82% decrease). This decrease in markets served was not uniformly seen across all market competition structures. This is seen in Table 2, which presents the number of markets served and the year-over-year percent change in market offerings for three competition structures: 1) markets with major carrier competitors only, 2) markets with LCC competitors only, and 3) markets with both LCC and major competitors. Taking a look at the markets served only by LCC competitors shows that there were 782 markets in 2005. By 2015, the number of markets served only by LCCs grew to 976 markets, indicating a 24.8% increase. Additionally, markets with both LCC and major carrier presence (i.e. at least one LCC and at least one major carrier competitor) increased by 102 markets (corresponding to a 16.1% market increase) during the same time period.

On the other hand, markets served only by major carrier competitors decreased by 753 markets (23.2% market decrease) during that time period. It is interesting that during post-recession years, markets with only major carriers competing decreased steadily while markets with an LCC presence increased. That is, the number of markets served by major carriers only remained in somewhat steady decline between years 2010 and 2014 (decreasing by around 2-3% annually) and then decreased by 6.4% between 2014 and 2015. During that same time period (2010-2015), markets with an LCC and major carrier presence increased by 25.8% and markets with only LCCs increased by 11.4%. These post-recession findings suggest that the LCC business strategies of catering to the increasing price-sensitive market segment during the recession made LCC service more resilient to national economic trends.

Table 2.2: OD pair CONUS markets served by year.

Year	Total Number of Markets	Percentage of Markets			Year-over-Year Change		
		Major Carrier Only Markets	LCC Only Markets	Major Carrier & LCC Markets	Major Carrier Only Markets	LCC Only Markets	Major Carrier & LCC Markets
2005	4,656	69.6%	16.8%	13.6%	-	-	-
2006	4,588	69.9%	16.9%	13.3%	-1.0%	-1.0%	-4.1%
2007	4,726	70.0%	15.5%	14.5%	3.2%	-5.4%	12.7%
2008	4,734	69.2%	16.6%	14.2%	-1.0%	7.7%	-2.2%
2009	4,436	68.0%	18.0%	13.9%	-7.9%	1.5%	-7.8%
2010	4,404	66.8%	20.0%	13.3%	-2.6%	9.9%	-5.3%
2011	4,410	64.9%	21.0%	14.1%	-2.7%	5.1%	6.7%
2012	4,304	64.7%	21.1%	14.3%	-2.7%	-1.9%	-1.6%
2013	4,269	64.0%	20.9%	15.1%	-1.8%	-1.5%	4.9%
2014	4,193	63.4%	21.1%	15.5%	-2.8%	-0.9%	1.2%
2015	4,199	59.2%	23.2%	17.5%	-6.4%	10.4%	12.9%
Total percent change 2015 vs 2005					**-23.2%**	**24.8%**	**16.1%**

Figure 1 provides a more disaggregate view of these evolving operational strategies, showing the market offerings of the four top LCCs that served the most markets in 2015 (i.e. Southwest, Frontier, JetBlue, and Spirit) compared with the four top major carriers (i.e. Delta, United, American, and US Airways)[5]. As can be seen, each of the four top LCCs individually increased the number of markets served, where the overall LCC growth has been driven predominately by Southwest's expansion. It is important to note that much of Southwest's growth in markets between 2012-2015 was due to its merger with AirTran. Of 178 markets served by AirTran in 2012 with no Southwest presence, 116 markets (65.17%) were still in service by Southwest in 2015. Another point to consider is that Southwest was already competing in nearly 23.9% of the markets in which AirTran competed back in 2012. The large overlap in markets between these two LCCs prior to its merger is not observed in the case of mergers between major

[5] Carriers such as AirTran Airways, Northwest Airlines and Continental Airlines are not illustrated in Figure 1 as the top four carriers were selected based on the number of markets served in year 2015, therefore requiring the carriers to operate during that year.

carriers. In fact, when the merger between Delta and Northwest was announced in 2008, Delta was only serving 2.8% of the markets that were already being served by Northwest. Similarly, when the merger between United and Continental was announced in 2010, United was only serving 4.9% of the markets that were already being served by Continental.

Three years after its merger with Northwest, Delta entered 566 markets out of the 704 markets (80.4%) that were previously served by Northwest in 2008 with no Delta presence. Furthermore, United Airlines added 382 new markets by 2013, three years after its merger with Continental was announced, adding up to 89.7% of the markets that were previously served by Continental back in 2010. This effect can be seen in Figure 1, where there is an increase in the markets served by the remaining carrier of a merger or acquisition (i.e. Delta-Northwest in 2008 and United-Continental in 2010).

However, 2015 results show the long-term impacts of consolidation that have taken effect. That is, for each merger between major carriers, the initial increase in markets is followed by a service discontinuity to a portion of the newly acquired markets. In 2015, Delta discontinued service to 172 markets of the 566 markets that were added in 2011 and therefore only 56% of the markets that used to benefit from Northwest service in 2008 were served by Delta in 2015. This finding is validated by Memphis (MEM) airport where concerns were raised as flights were continuously reduced after the Delta-Northwest merger followed by Delta's "de-hubbing" of MEM in 2013 (Mutzabaugh, 2013). Additionally, United Airlines discontinued service to 67 markets of the 382 markets that were added to its network in 2013 and therefore only 73.9% of markets previously served by Continental Airlines in 2010 were served by United in 2015.

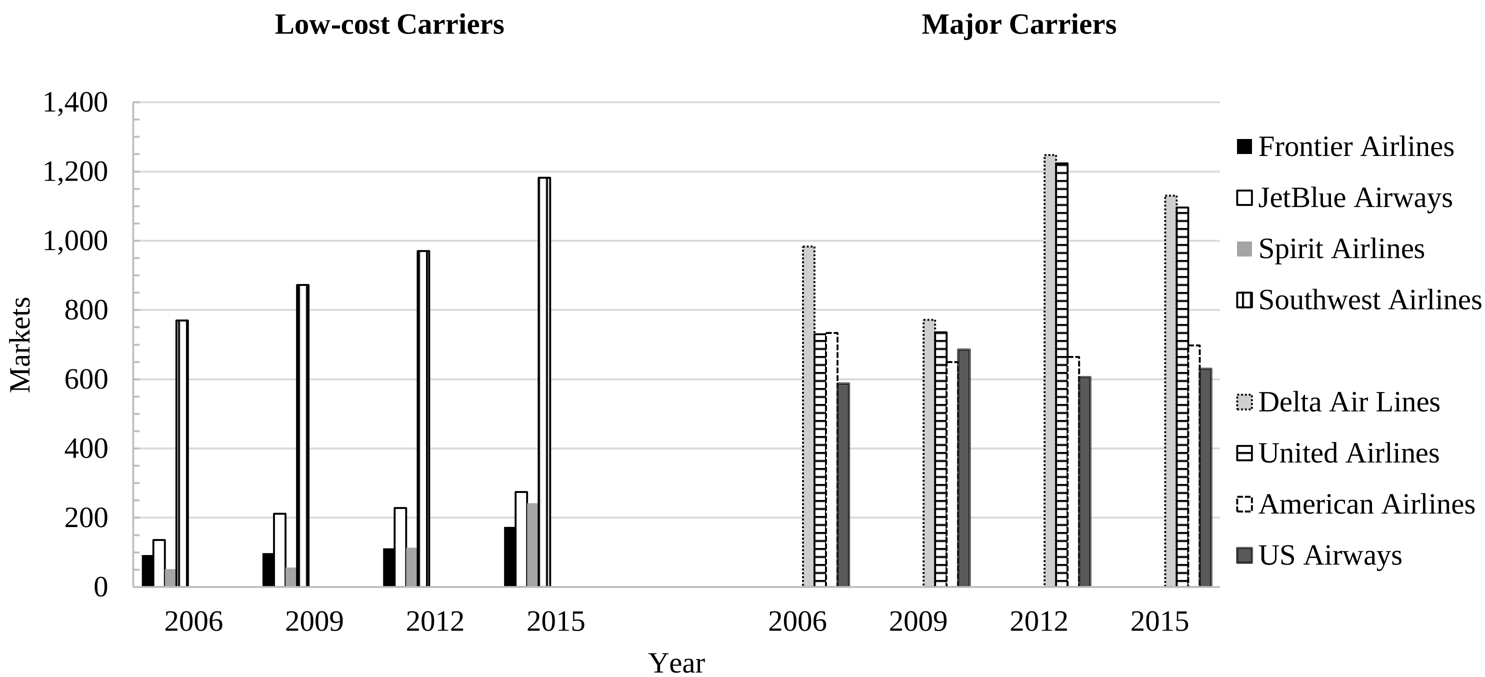

Figure 2.1: Markets served by the top four LCCs and major carriers.

Not only have LCCs expanded the number of OD pairs served, but the competition structures of the markets that LCCs compete in have shifted over the years as shown in a further analysis of the markets served by at least one LCC. Figure 2 shows the distribution of markets served with at least one LCC (i.e. LCC presence) competing across different market competition structures. As shown in Figure 2 (percentages for each year add to 100%), 48.2% of the non-stop markets with an LCC presence in 2006 were LCC monopolies and by 2012 LCC monopolies had increased to 54.7% of the total non-stop markets with an LCC presence. This indicates that pre-recession, LCCs were focused on developing new, previously unserved markets, therefore leading to an increase in LCC monopolies. This trend reached its peak near the end of the recession in 2012, and by 2015 LCC monopolies had decreased slightly to 53.2% of the total non-stop markets with an LCC presence.

Although one may hypothesize the growth in LCC monopolies is simply the result of major carriers exiting markets where they compete with an LCC, further analysis of changes in market structure suggests otherwise. In 2006, the total number of markets with 1 major carrier and LCC presence was 516 markets. By 2012, all carriers dropped from 102 of these markets whereas the remaining 414 markets were still being served by 1 major carrier and at least 1 LCC. Similarly, out of the 832 monopoly markets served by 1 LCC in 2012, 224 of these markets were not served by any carrier in 2006. The remaining 608 markets that were in service between 2006 and 2012 did not change competition structures and continued to be an LCC monopoly. Consequently, it can be said that the increase in LCC monopolies is not the direct effect of major carriers leaving the competition, but rather the result of LCCs expanding their networks.

Post-recession, however, the growth of LCCs has led to more overlap with major carrier networks as seen in Figure 2. Between 2012 and 2015, the majority of the LCC shift in competition structures did not occur in OD pairs with just one other competitor (i.e., 1 major carrier + LCC presence, or 2 LCCs), but rather markets with several airlines already competing. That is, LCCs relied less on markets with few competitors and instead shifted towards competing in markets with multiple competitors over the years. For example, out of all the markets with an LCC presence in 2006, only 0.4% of these markets were served by 3 major carriers and at least 1 LCC. By 2015, LCC increased their presence in markets also served by 3 major carriers, making up 2.6% of all markets with LCC presence. This is consistent with existing literature, which states that one of the most important factors in determining low-cost entry to a market is pre-entry passenger demand (Ito and Lee 2003). These markets would be correlated with high-demand markets.

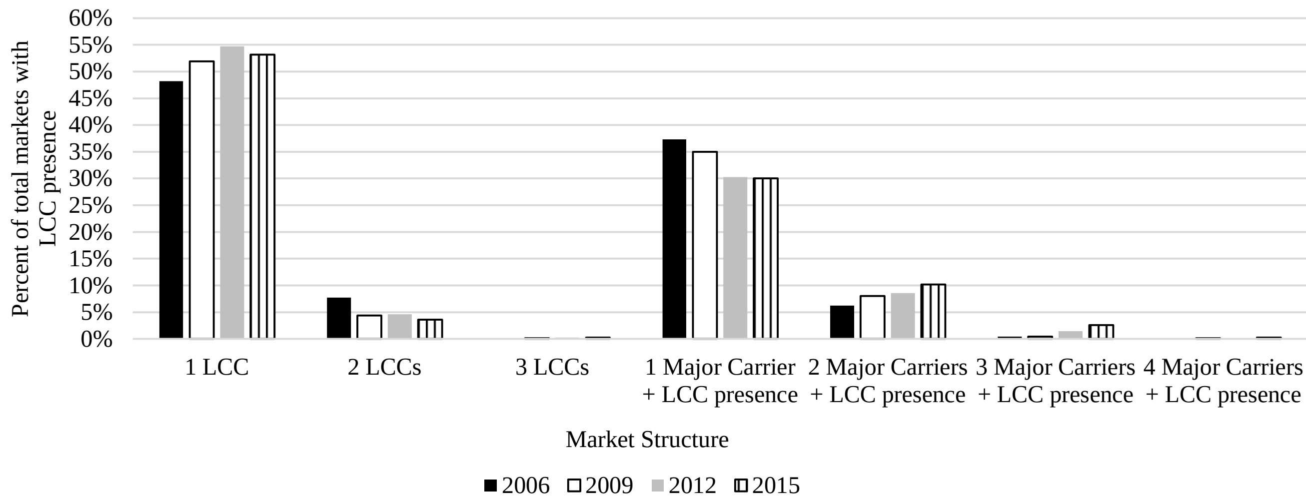

Figure 2.2: Market competition structure with LCC presence

Among the top four LCCs, competition structures across markets served were not uniform as the operating strategies differed both pre- and post-recession. Figure 3 shows the percentage of each airline's total number of markets in each of three market competition structures: 1) monopoly markets, 2) markets with a major carrier presence, and 3) markets with another LCC present. A single market with both a major carrier competitor and another LCC competitor present shows up in both of the two last categories. For this figure, percentages do not add up to a 100% each year as, for example, a market with 1 major carrier and 2 LCCs will be featured in both "markets with major carrier presence" and "markets with another LCC present" categories.

As can be seen in Figure 3, Southwest Airlines depends more heavily on monopoly markets than the other three top LCCs, where it is the only competitor in 60% of its markets. Further analysis shows that some of Southwest's increase in monopoly markets can be attributed to other LCCs exiting markets in which they compete with Southwest Airlines. For example, in 2006 there were 97 markets served by 2 LCCs. By 2009, 34 of those markets became monopolies only served by Southwest Airlines indicating the other competing LCCs dropped out. However, post-recession Southwest has increased direct competition with major carriers as the percent of markets with major carrier presence increased from 29.9% in 2012 to 33.3% in 2015 out of the total number of markets where Southwest competes.

In contrast, the distribution of Frontier Airlines is especially unique compared to the other three carriers in that Frontier Airlines' markets are extremely competitive. Its percentages show that in 2015, 55.2% of total markets served by Frontier were also served by at least one other LCC and 81.6% were also served by at least one major carrier. Overall, trends show that post-recession, Southwest and Spirit are increasing dependence on markets with major carrier competition, while JetBlue is competing more with other LCCs. For example, the percent of JetBlue markets with major carriers' presence dropped from 58.8% to 52.6% between 2006 and 2015 while the percent of markets with other LCC presence increased from 11.8% to 24.1%. It is also worth mentioning trends show that Spirit is competing more with both major carriers and LCCs.

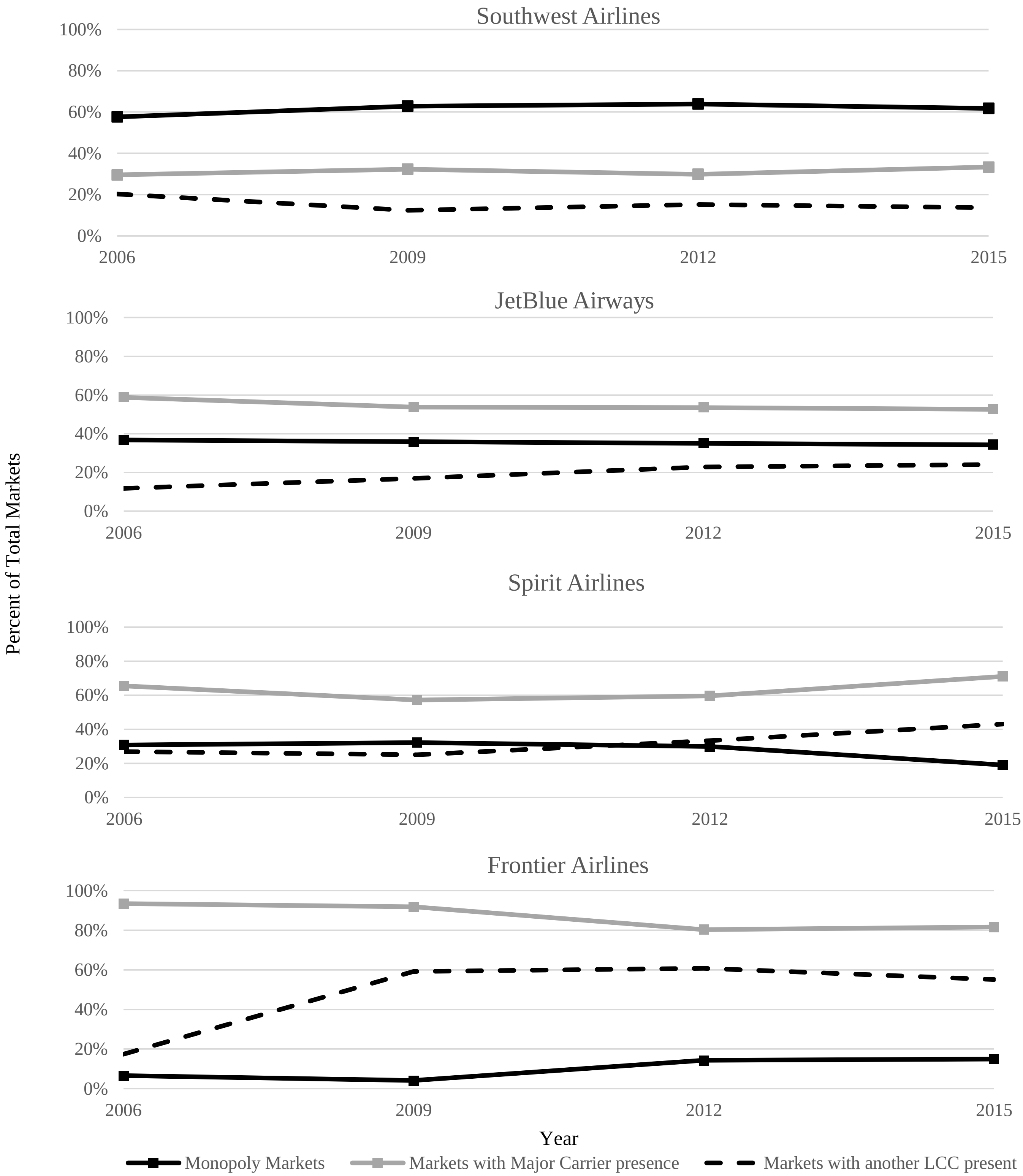

Figure 2.3: Market competition structures for the top four LCCs

2.4.2 Flight Frequency

This section looks at the frequency of LCC operations in CONUS domestic markets as compared to major carriers. Figure 4 shows the percent of flights on average served by an LCC for each competition structure, where only competition structures containing at least 10 markets are shown for comparison. For example, in 2006 when a single LCC competed with one major carrier, the LCC on average served 42.21% of the flights on the market (and major carriers served the remaining 57.79% of flights). The threshold line at 50% shows market structures in which the flight market share, or the average number of operations, by LCCs exceeds the flight market share of major carriers. It is important to note that in 2009, a single LCC did not serve markets in which 3 major carriers competed, which explains the 0% flight market share.

It can be concluded that on average LCCs offer less frequent flight service than major carriers and the flight frequency shares for LCCs have been declining over time[6]. Therefore, while LCCs are gaining in terms of the number of markets served in recent years, major carriers are gaining flight share in the markets in which they already compete. It can be interpreted that LCCs are actively seeking to explore new markets while reallocating resources by decreasing market share in terms of the frequency of their flight offerings. One possible reason that may have hindered the ability of LCCs to match the flight frequency share of their rivals is the on-going slot control and gate constraints imposed by major carriers at the nation's busiest and largest airports (Stellin, 2010).

[6] A similar analysis was performed using LCCs seating capacity instead of flight frequency. Results show similar trends as the one found using LCCs flight frequency share.

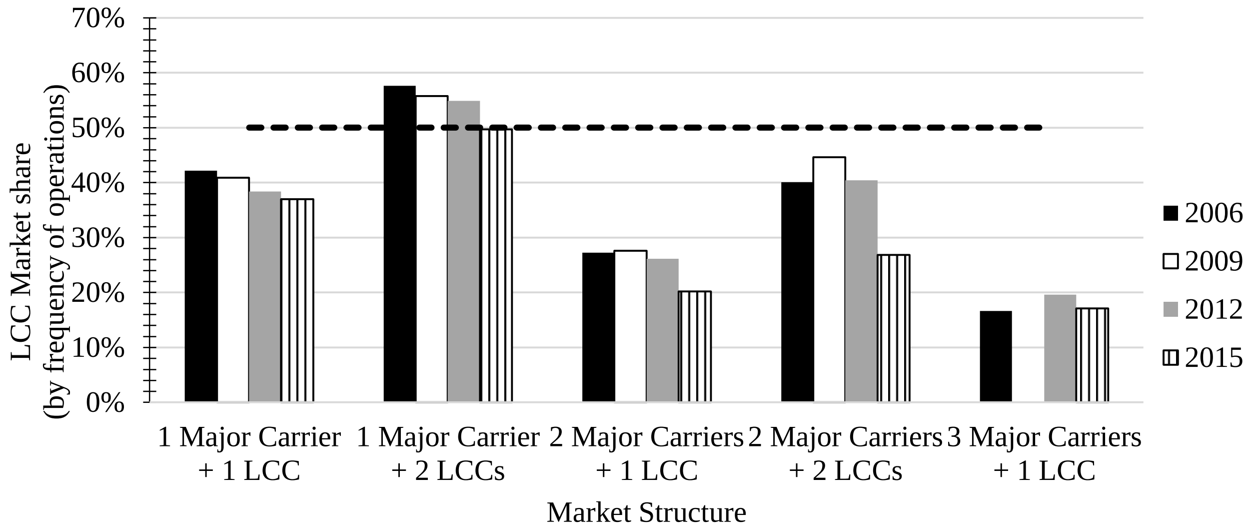

Figure 2.4: LCC market flight share by market structure

2.4.3 OD Airport Sizes

In addition to LCC competitive strategies changing post-recession, the size of OD airports served has also evolved. As shown in Figure 5, most market offerings focus on large and medium airports (FAA, 2015) as LCCs have mainly served Large-Large (L-L) and Large-Medium (L-M) markets pre- and post-recession. For example, 632 out of the 1,712 markets (37%) served by at least 1 LCC in 2015 were between a medium and a large hub airport. The increase in service to large airports is not only due to LCCs entering highly competitive markets as discussed in the previous section, but also due to increased service to/from secondary airports in multi-airport cities. For each of the years, about 50 (12%) of the Large-Large markets with an LCC presence were monopolies, typically connecting the secondary airports of two multi-airport cities. Counts for small markets are not shown (i.e. Small-Small, Small-Nonhub, Nonhub-Nonhub) as they were minimal.

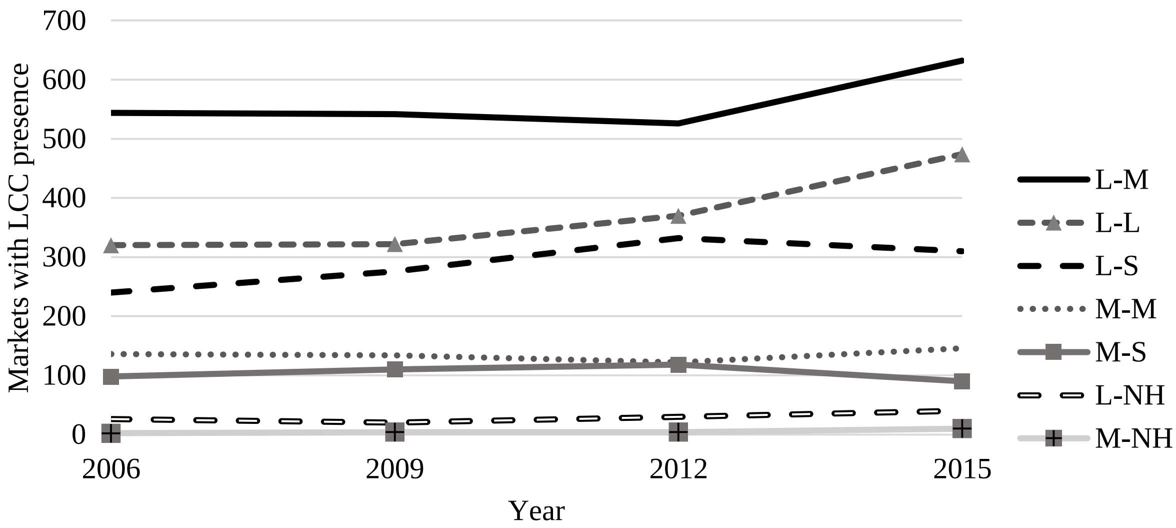

Figure 2.5: Markets with an LCC presence by OD airport sizes

Notes:

1. Airport Size: L = Large Hub, M = Medium Hub, S = Small Hub, NH = Non-Hub (FAA, 2015)

When comparing the strategies of the top four LCCs, Southwest has a lower percentage of Large-Large markets than others, but serves more Large-Large markets in count due to the high number of markets in general that it serves. Figure 6 illustrates the distribution of markets served by the top four LCCs in terms of market size. For example, 48.6% of markets served by Southwest Airlines in 2006 are between a large and a medium hub airport. The overall trends shown in Figure 5 apply to the majority of the four top LCCs, where post-recession Southwest, Spirit and Frontier have increased their percent of service to large airports to the detriment of smaller communities. This is due to both the loss of these small markets as well as market additions to large airports. For example, in Southwest's case, 92 of the 770 total markets served were between non-hub, small, and medium airports (i.e. M-NH, M-S, S-S, S-NH) in 2006 whereas 82 of the 1,182 total markets served were between these airport sizes in 2015. The only improvement in accessibility for small airport communities between 2006 and 2015 was the percent increase in Large-Small airports served by Southwest and JetBlue.

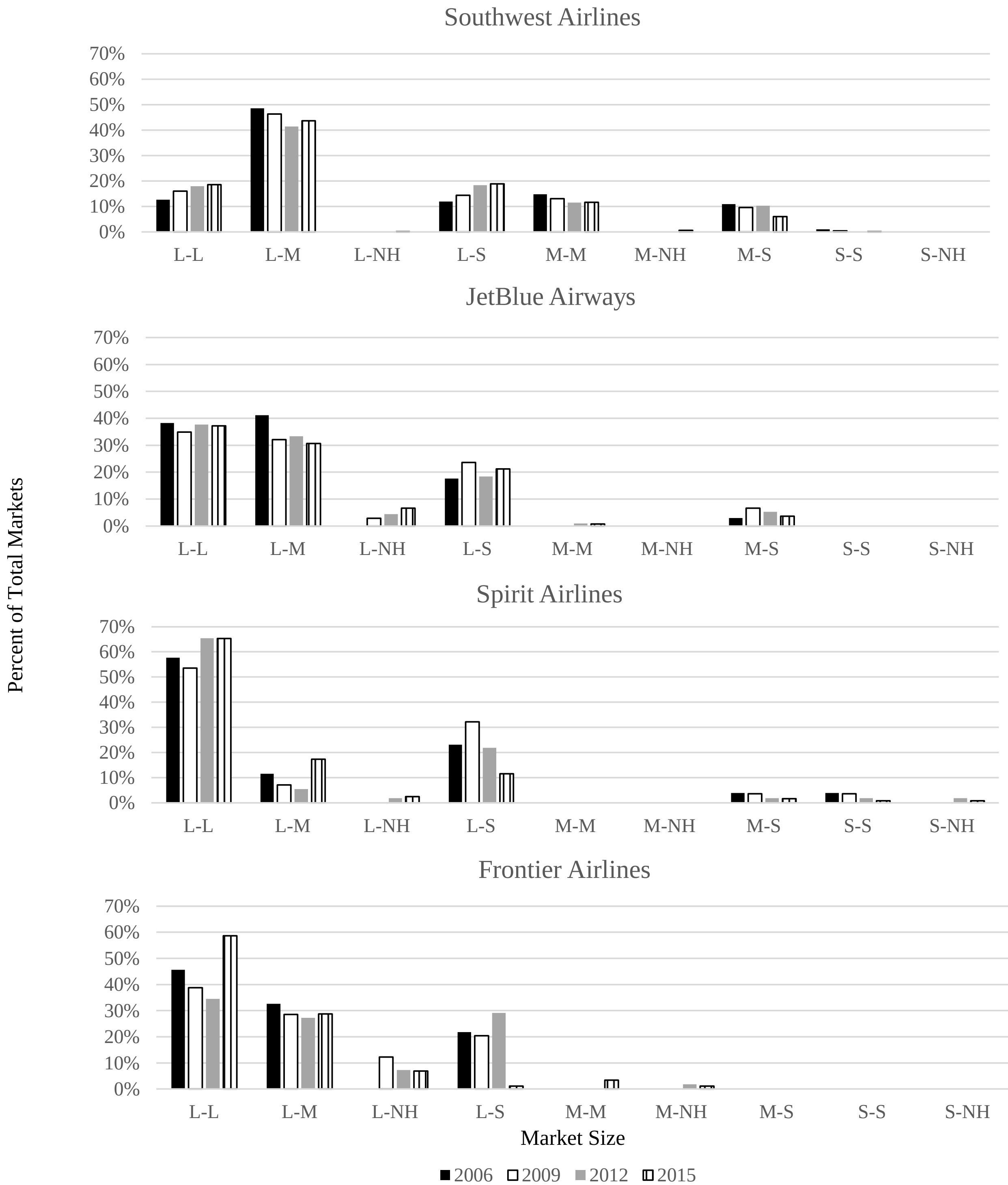

Figure 2.6: Market OD airport size for top four LCC markets

Notes:

1. Airport Size: L = Large Hub, M = Medium Hub, S = Small Hub, NH = Non-Hub (FAA, 2015)

2.5 Conclusions and Future Research Direction

This study provides an in-depth analysis of the evolving LCC operational strategies compared to their major carrier counterparts between 2005 and 2015. During the third week of July in these 11 years, we see contrasting strategies between LCCs and majors, where LCCs have outpaced major carriers in terms of markets entered while major carriers have gained a greater flight share in the markets they serve. In general, LCCs have gravitated more towards serving large markets (i.e. Large-Large and Large-Medium), including entering markets that already have 2 or 3 competitors present. Post-recession, LCCs have shown preference to competing with major carriers over other LCC airlines.

LCCs' expansion into the nation's largest airports is possible through changes in the LCC business model. For future research, it would be interesting to look into how business models have evolved for LCCs that have been successful at gradually shifting operations from secondary to primary large airports. Another research question to be addressed is how fares have been impacted in light of the trends found in this study. That is, literature has acknowledged that LCC-presence decreases average market fares, as demonstrated through the "Southwest Effect" (Vowles, 2001). Given LCCs show a decreasing average flight share over time in this study, knowledge of the minimum flight frequency or flight market share needed to retain this effect would be beneficial for future consumer welfare studies.

Another interesting research direction would be to quantify the amount of new demand that LCCs stimulate when they enter into a market, as well as their passenger market share growth over the years. For instance, Windle and Dresner (1995) looked at a time series between 1991 and 1994 and found that when Southwest entered a route, the average passenger traffic increased by 300% in the fourth quarter following entry compared to a 182% increase for the other carriers. Lastly, it would be interesting to use an airport-based approach (in contrast to our market-based approach) to analyze LCC growth in the nation's airports in more recent years, possibly in terms of number of LCCs, flight frequency, and seating capacity share. For example, Abda et al. (2012) uses an airport-based approach using Origin and Destination Traffic Survey (DB1B) data for years between 1990 and 2008 and finds that as growth opportunities at the largest airports (top 50 airports) dwindled, LCCs started to shift to second, third and fourth tier airports. Abda et al. (2012) also projected that the unconstrained growth of LCCs at the top 200 U.S. airports may soon be ending. It would be interesting to update this study to take a look at airport trends in more recent years.

2.6 Acknowledgements

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CHAPTER 3

An Assessment of Contributing Factors to Air Service Loss in Small Communities

Atallah, S., & Hotle, S. L. (2019). Assessment of Contributing Factors to Air Service Loss in Small Communities. *Transportation Research Record*, 0361198119840618.

3.1 Abstract

As indicated by current literature, service at small community airports was negatively affected by the Great Recession from 2007-2009 and recent changes in competition structure. Existing studies have looked at the recession's lingering impact on the small community airports (e.g. hub premiums, airport dominance, connectivity) and markets (e.g. market competition structure). However, to date it has been difficult to determine which factors contribute to a market's potential future loss of service that serves a small community. In this study, we identify characteristics that can potentially contribute to a market's loss or gain of service by incorporating different regional- and market-specific characteristics that have evolved over the years. This study uses a fixed-effects conditional logistic regression and focuses on region-to-region markets serving small communities that were in service at least once between 2007 and 2013. In total, the panel data included 1,367 markets departing from a small region and arriving at a small-, medium-, or large-sized region with 453 markets adding or losing service during that time. Fixed-effects were used to identify the impact of within-market variation on service loss over the years. Results show that, first, markets affected by a merger are indeed at a higher risk of losing service. Second, markets that are operated by a fuel-intensive, small-aircraft fleet have a higher chance to be discontinued. Third, an increased number of competitors greatly reduces potential market service loss.

3.2 Introduction and Literature Review

During the Great Recession that occurred between December 2007 and June 2009 *(1)*, the airline industry experienced decreased air travel demand due to a significant drop in consumer purchasing power *(2)* coupled with increased service costs through a surge in fuel prices from $69 per barrel in January 2007 to $130 per barrel in January 2013 *(3)*. As a result, U.S. airlines were placed in a difficult financial position resulting in the inability to generate a profit. Between 2000 and 2009, major carriers incurred a total of $62.8 billion in financial losses *(2)* and five of the nine largest U.S. airlines reported a total loss of $4 billion in 2009 alone *(4)*. In 2008, 13 U.S. carriers filed for bankruptcy with 7 other U.S. airlines filing for bankruptcy between years 2011 and 2012*(2)*. In an effort to overcome the challenging financial strain, airlines implemented several cost-cutting strategies including increased load factors, an introduction of new ancillary fees, reduction in capacity, flight frequency, and markets served as well as the replacement of fuel-intensive aircraft with a more fuel-efficient fleet containing larger aircraft types *(2,4,5)*.

While these policies financially helped carriers during this time, air service for small communities was particularly affected by these actions. That is, “Small communities may become cost-cutting targets because they are often a carrier’s least profitable operation” *(6)*. Prior studies in the literature have identified small communities as primary targets for service loss. Hammond and Czaban *(7)* analyzed trends in airport growth by looking at passenger enplanements for a sample of 306 US airports during the post-deregulation period from years 1979-2014. One of the major findings outlined by this study is the difference in growth observed between airports of various sizes. Although large and medium hub airports, defined by FAA airport size classification *(8)*, only account for approximately 20% of all U.S. primary airports, they in fact experienced the largest growth in total passenger enplanements with an average annual growth rate of 4.82% and 4.97%, respectively, during the study years. A significant difference exists, however, when comparing this same growth rate to small hub airports where the average annual growth is 3.15% during the 1979-2014 time period. A more significant difference is observed in non-hub airports with an average annual growth of 1.3%. Hammond and Czaban reported that all airports that have experienced a net loss in total passenger boardings during the entire study period (1979-2014) were in fact non-hub airports. It is important to note that in recent years, some large hubs such as Memphis, Cincinnati and St. Louis saw a significant loss in passenger boardings as a result of merger and consolidation activity *(9)*.

There are many factors driving this loss in service to small communities. First, small aircraft types that used to serve these markets tend to have increased operating costs per passenger. As noted by the U.S. DOT in 2012 *(2),* the number of scheduled domestic flights operated with 30- to 70-seat regional jets declined by 20.4% from June 2007 to June 2012 as airlines shifted their fleet to larger-sized aircraft. Additionally, airline management was able to renegotiate scope clauses with the pilot unions, increasing the maximum aircraft size that can be used for flights subcontracted from major to regional carriers and amending the original size restriction from 50 to 70 and 76 seats *(10,11)*. As airlines sought higher load factors while operating larger regional jets, smaller cities saw a reduction in service given the greater seat availability per flight *(12).* Network carriers that continued to serve small-hub airports reduced the number of flights to their connecting hubs and were substituting flights operated by regional jets with a 37 to 50 seating capacity with fewer flights operated by 50-76 seat regional jets *(13).* Airlines have recognized the inefficiency and unsustainability of using small regional jets, where major carriers such as Delta and American are continuously reducing the number of 50-seater jets from their fleet and replacing them with larger Embraer and Bombardier aircraft. United, on the other hand, limited by pilot scope clauses that cap the number of large regional jets possible in their fleet, have no choice but to continue to operate and increase their 50-seater fleet. However, the carrier intends to push for a scope relief in the upcoming pilot's contract negotiation in January 2019 to be able to acquire larger regional jets *(11).*

A second factor leading to service loss in small communities can be attributed to the reduced air travel demand for these airport-airport markets. Not only do small airport communities serve smaller populations, but also the rise of LCCs offering reduced-fare flights at the larger airports have prompted residents of small communities to drive to these larger airports to benefit from cheaper flights *(6,13).* This dynamic was coupled with a decreasing flight service level at small and non-hub airports, where the flight frequency and number of seats available at small airports serving small communities has declined since 2007 *(14).* The average number of daily flights offered at small- and non-hub airports dropped approximately by 18% and 20%, respectively, between 2007 and 2013 *(13).* Most flight reductions occurred in the short-haul markets, as passengers are more sensitive to price changes for short-haul flights as compared to long-haul flights *(15).* Furthermore, short-haul passenger traffic declined post 9/11 and following the TSA's implementation of severe airport security measures as passengers were more likely to make ground trips than to take a short-haul flight *(16)*.

A third factor has been the changing competition structure due to mergers and acquisitions, increased operating costs, and reduced travel demand. Hammond and Czaban *(7)* reported that fewer carriers compete at small community airports. According to the Office of Inspector General *(2)*, between June 2007 and June 2012, "61 out of the Nation's 457 airports receiving scheduled air service lost one half or more of the air carriers serving their community." The Government Accountability Office *(17)* investigated changes in competition in the airline industry and found that the smallest-sized markets, based on the number of passengers served, had an average number of competitors of 3 in 2012 compared to 3.3 competitors on average in 2007.

Reduced service levels at small airports have been extensively researched. For example, Wittman and Swelbar *(18)* developed a taxonomy analysis to help small airports identify whether they are at risk of losing total network carrier service. The authors identified the following characteristics of airports that are "at risk" of losing service: "1) lack of local demand, 2) proximity to nearby hub and 3) presence of ultra-low-cost carriers (ULCCs)" such as Allegiant Air and Spirit Airlines. This was based on 24 airports that have lost network carrier service from 2007-2012. More recently, Spitz et al. *(13)* provided a self-assessment tool that helps evaluate the performance of each airport in five different categories: "1) local economic performance, 2) existing air service profile, 3) recent change in air service performance, 4) airline and community incentive programs and 5) level of community engagement." This tool aims at helping airport managers and communities with only small and non-hub airports customize their air service development (ASD) strategies based on their specific needs to attract and maintain service at these airports.

The government has established several programs over the years to support small community air service. One of the most well-known strategies implemented was the Essential Air Service Program (EAS), established by Congress to provide subsidies for airlines serving these airports. In addition, the Small Community Air Service Development Program (SCASDP) supplied small communities with competitive grants to support its service *(13,14).* Between 2003 and 2010, there was a 19% increase in the number of communities that have received subsidized service. In 2008, several EAS carriers discontinued their operations leaving some communities without essential air service *(15)*. Furthermore, recent legislation such as the FAA Modernization and Reform Act of 2012 along with program restrictions and limited availability of funding hindered the ability of these programs to guarantee future service to these communities as eligibility requirements for EAS funds have become more demanding over time *(2,13)*.

Given the impact of the last decade on small-airport service, it is important for airport managers to develop contingency plans for dealing with service loss or preventing service reduction affecting small communities in particular. This study is intended to develop insights into how factors contribute to service loss. To date, it has been difficult to determine which markets are at risk of potential future service loss, specifically in markets serving a small community.

Therefore, the purpose of this study is to understand the dynamics behind markets that are likely to lose or maintain service by identifying how different regional and market characteristics may have contributed to service continuity. This research uses a fixed-effects conditional logit model to evaluate how changes in the market operations and airport community demographics can contribute to a market's loss of service between 2008 and 2013. Specifically, this study focuses on region-to-region market service, where the market origin is a community that only has access to small or non-hub airports during those years.

3.3 Data

Data for this study comes predominantly from OAG commercial service data. OAG provides schedule information for all commercial flights flown, along with the corresponding marketing carriers. This includes information on flight frequency, seat capacity and aircraft fleet operated in each airport-pair market. Flight data in this study was obtained for the month of October for every year between 2007 and 2013. Consistent with ACRP report 142 *(13),* the month of October was selected since it represents a "shoulder" month, i.e. a period between peak and off-peak airline traffic seasons.

The scope of the study is to assess service on a region-basis instead of an airport-basis, as a small airport may be located near a large airport and, therefore, the community would still have access to higher levels of air service. For instance, residents with access to Hagerstown Regional Airport (HGR) classified as a non-hub non-primary airport, also have access to three large-hub airports (BWI, IAD, DCA) whereas residents near Roanoke Regional Airport (ROA) do not have access to a large airport in the vicinity of the region. Therefore, it was important to conduct a regional analysis to better capture residents' access to the air transportation network. Airports were aggregated by regions defined as Primary Statistical Areas (PSAs). There are three types of PSAs: 1) Micropolitan Statistical Areas have populations between 10,000-50,000 people, such as Aberdeen, SD and Garden City, KS; 2) Metropolitan Statistical Areas have populations greater than 50,000 people, such as Abilene, TX and Roanoke, VA; and 3) Combined Statistical areas contain multiple micropolitan and metropolitan areas, such as Washington-Baltimore-Arlington. If the largest airport in a region was a small airport (i.e. had less than 0.25% of the annual U.S. passenger boardings), it was considered a small airport community in this study *(8)*.

To evaluate service over time, a carrier was considered a significant marketing carrier if it marketed as least 3 non-stop domestic flights per week in at least one of the airport-pairs within the region-pair market with an average of at least 10 seats per flight. Table 1 shows the list of variables used in this study's model for determining factors that increase or decrease the likelihood of continuing service. Consistent with previous literature *(2,13,19)*, carriers were then classified into four main categories: Major, Low-cost, Regional or Other. Other carriers include any carrier that does not classify into the other three categories in addition to any foreign carrier in the study. Furthermore, connectivity data was collected from Wittman *(20)* Air Service Accessibility Indices (ASAIs), which quantifies air service accessibility for each region based on daily scheduled flights, non-stop destinations, number of online/codeshare connecting regions, destination quality and preference to non-stop service.

An indicator variable for Allegiant Air market presence was included due to its unique business model. A preliminary analysis from OAG data demonstrated that Allegiant drops and enters new markets every year at a high rate. In 2009, Allegiant discontinued service to 33.3% of the markets departing from a small community that it previously served in 2008. Similarly, in 2013, Allegiant eliminated service to 30.7% of markets departing from a small region that it served back in 2012. Additionally, recent case studies also considered the presence of Allegiant in their analysis *(13)* as Allegiant Air is known for its "seasonal suspension" of markets whenever the seasonal demand is not as high as in other seasons of the year *(21).*

Table 3.1: Variable Definitions and Descriptions.

Dependent variable	
Service	Region-pair market departing from a small community had service from at least one significant marketing carrier for that year (0=No, 1=Yes)
Independent variables	
Frequency	Number of non-stop flights departing from a small region to another region during the month of October, retrieved from OAG operating schedules
Fuel Consumption	Frequency-weighted average fuel consumption in each market depending on the aircraft types operated in the market. Fuel consumption for different aircraft types was retrieved from the Bureau of Transportation Statistics schedules P-5.1 and P-5.2 *(22)* and calculated in gallons per seat-hour
Allegiant	Allegiant is the sole marketing carrier in the market (0=No, 1=Yes)
Major	Number of marketing major carriers providing non-stop service in the market. Major carriers include: American, Continental, Delta, Hawaiian, Northwest, United and US Airways *(2, 13, 19)*
LCC_Other	Total number of marketing low-cost and other carriers providing non-stop service in the market. Low-cost carriers include: AirTran, Allegiant, Frontier, JetBlue, Midwest, Southwest, Spirit and Sun Country while examples of the other carriers include: Air Canada, Alaska, Aloha Airlines, Chautauqua, Kenmore Air, etc. *(2, 13, 19)*
ASAI_Dest	Air Service Accessibility Index of the destination region. A higher index means greater regional accessibility measured by the quantity and quality of service available from the PSA region *(20)*

PopDest	Population of the destination region as reported by the U.S. Census Bureau expressed in hundred-thousands *(23)*
Merger	Market is at risk of being discontinued due to one of the three mergers between Delta and Northwest, United and Continental, or Southwest and AirTran (0=No, 1=Yes). This variable is further described in Table 2
Year	Year of service under analysis. 2008 is the reference year in the fixed effects model

When it comes to a merger announcement, airport managers may be concerned if a market is currently served by the acquired airline (Northwest, Continental, AirTran) but not the parent airline (Delta, United, Southwest). This is incorporated into the model through the Merger variable, which is 1 when the market is served by the acquired airline and not the parent airline at the time of the merger announcement and is 0 when this is not the case. To better understand how the merger interaction variable is calculated, an example is shown in Table 2. A trigger event for the merger variable is when the merger has been announced and the acquired airline is present in a market, but the parent airline is not (e.g. NW = 1, DL=0, Merger Announced =1). When and if this event occurs in a market, the merger interaction term is set to 1 for the years that follow even if Delta enters the market once Northwest is acquired. If the parent airline starts serving this market once the merger is complete, it can take a while to see the full effects of the merger on small airport regions. A period of four years' post-merger announcement was considered as a check to evaluate if a market is no longer at risk of having its service impacted by the merger and that the carrier is likely to continue its service to the region-pair market in the future.

Table 3:2: Defining Merger Indicator.

Year	NW Service	DL Service	Merger Announced	Merger Interaction	Interpretation of Row
2007	1	1	0	0	Low risk- Merger not announced
2008	1	1	1	0	Low risk- Parent Airline already present
2009	1	0	1	1	High risk- Parent Airline not serving the market and merger announced
2010	0	1	1	1	High risk-Parent airline could still leave the market and merger announced
2011	0	1	1	1	High risk-Parent airline could still leave the market
2012	0	1	1	0	Low risk- Greater than four years post-merger announcement

Notes:
1. The example corresponds to the market departing from Palm Bay-Melbourne-Titusville, FL and arriving at Atlanta—Athens-Clarke County—Sandy Springs, GA.

The final dataset contains 1,367 distinct region-pair markets departing from 253 different small communities at least once between 2007 and 2013. For the purposes of this study's model, the origin has to be a small-community region and the destination region can be either a small-, medium- or large-sized region. Figure 1 illustrates the number of region-to-region markets serving small communities each year during the study period. Consistent with the existing literature, it is evident that losses in air service have been experienced in these communities as the number of total markets served decreased by 22% between 2007 and 2013.

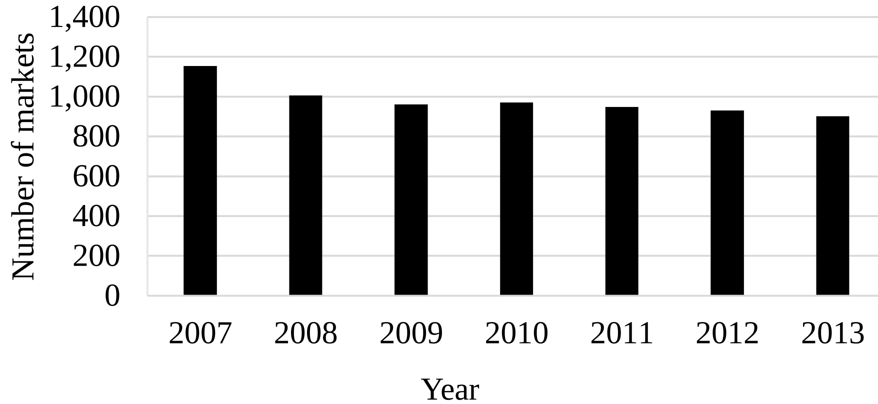

Figure 3.1: Number of markets involving small communities

Further data analysis confirms the shift to larger and more fuel-efficient aircraft. Figure 2 illustrates the change in the average number of seats offered per flight during the month of October in each year as well as the changes in the average fuel consumption expressed in gallons per seat-hr. Consistent with previous studies, air carriers are operating fewer flights from small communities with a larger fuel-efficient fleet. That is, while the average number of flights departing from a small community decreased by 2.9% between 2007 and 2013, the average seat capacity increased by 5.2%. Between 2007 and 2013, the average seats per flight increased by 11.9% while the average fuel consumption per seat-hr decreased by 0.9%. The latter indicates recent changes in fleet mix in markets departing from small communities. This shift in fleet mix prioritizing larger and newer aircraft, driven by the volatility in fuel prices, will continue to have an impact on service availability to the nation's smallest airports *(13).*

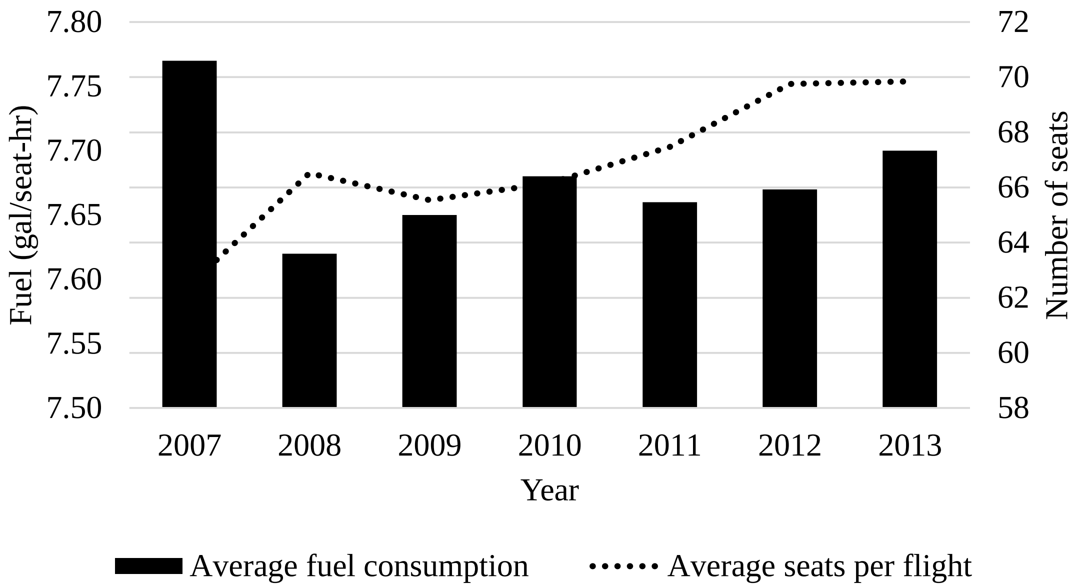

Figure 1.2: Shifts in fleet capacity and fuel consumption over time

3.4 Methodology

The focus of this study is to evaluate how different market- and region-specific characteristics can contribute to service loss. Using a panel data of 1,367 markets measured for service availability at seven points in time (2007-2013), markets are used as their own controls using a conditional fixed-effects logit model. In general, a logistic regression associates a binary outcome to a series of explanatory predictors. Conditional logistic regression for matched-case control groups, also referred to as fixed-effects logit, is a special type of logistic regression that matches subjects satisfying a particular condition to control subjects that do not fulfill this condition. That is, a conditional logistic regression is used to investigate the relationship between a market having service or not given a set of independent variables. Therefore, the probability of having service in a market is conditional on the number of service occurrences within this market over time *(24,25,26)*. The model will estimate the coefficient for each independent variable based on within-variability in each market. Only the effect of time-varying variables are considered in the model since constant characteristics of a market cannot explain variability in service *(27)*. The regression coefficients are estimated based on markets that have lost or gained service at some point in time between 2008 and 2013. Markets that always have service during the study period cannot be included in the model. Therefore, 453 of the original 1,367 markets could be used for the fixed-effects conditional logit model. Note that the structure of the model results in the elimination of two thirds of the original market sample for the time period examined. Testing a different period would keep different markets in the dataset.

Lagged independent variables were used in predicting the dependent variable. The number of flights operated, the number of major carriers present, the population base in the market and other predictors in 2007, were considered to predict the availability of service in 2008. Therefore, the market and region information for years 2007-2012 were used to predict service between years 2008-2013. The panel data was limited by this timeframe due to the unavailability of some datasets beyond this period of time, but it does cover the recession period and its aftermath. It is important to note that lagged variables were used to ensure the model converges and to avoid perfect correlation. In fact, of all variables, the highest correlation with the dependent variable is the monthly frequency of operations with a Pearson's correlation coefficient of 0.46 indicating the strength of the linear relationship between the two variables and is significant at the 99% level. Although fixed-effects logit models can help identify how a market's service will respond to a change in the number of non-stop flights, number of competitors, merger activity, etc., future predictions are not possible. The model is a "two-way" model with both group-specific and time-specific fixed effects. However, the conditional logistic regression does not estimate the group specific intercepts that are essential to estimate the unconditional probabilities of events. Therefore, the model cannot make specific point predictions about the probability of any given community losing or retaining service but it is able to make inferences about the impacts of other explanatory variables on the likelihood of losing or retaining service.

3.5 Estimation Results and Discussion

As described in the previous section, 453 out of the 1,367 markets initially present in the panel data remained in the model. The 453 region-pair markets that remained in the model had at some time during the 6-year period switched from having service to service being discontinued or switched from not having service to being in service. Table 3 reports the summary statistics for the significant predictors of these 453 markets while Table 4 presents the estimation results from the logistic regression.

Table 3.3: Descriptive Statistics of Data.

	Min	Mean	Median	Max	Std. Dev.
Flight Frequency	0.00	27.31	0.00	248.00	35.72
Fuel Consumption	3.76	7.63	7.44	12.05	1.65
Allegiant	0.00	0.03	0.00	1.00	0.16
Major	0.00	0.41	0.00	3.00	0.65
LCC_Other	0.00	0.32	0.00	6.00	0.58
ASAI_Dest	0.04	330.60	289.08	954.38	231.74
PopDest	0.16	43.60	28.98	233.99	42.22
Merger	0.00	0.04	0.00	1.00	0.20

Notes:

1. Included observations: 2,718 (453 markets, 6 years each).

As shown in Table 4, the model was built based on significant variables that contribute to a good fit of the model. Significant predictors were assessed at the 99%, 95% and 90% level of significance and the goodness of fit was evaluated using the adjusted McFadden's pseudo R-square, which was 0.238 for the final model. According to Louviere et al. *(28)*, McFadden suggested values between 0.2-0.4 represent a model with a very good fit.

The coefficient estimates generated by the fitted model show the expected positive or negative sign. For instance, the coefficient estimate of the "Merger" variable has a negative sign;

it is expected that a merger in a market will have a negative impact on service. However, these estimates are not enough to interpret results in logistic regressions. Therefore, it is helpful to look at the odds ratios (OR) shown in Table 4. The results show that the OR for operational frequency is 1.022. This means that each additional non-stop flight departing from a small region increases the odds of having service the following year by 2.2%. If the aircraft fleet operated in a market has a high fuel consumption (typically the 30-50 seater aircraft), the odds of having service the following year is reduced by 15.1% for every additional gal/seat-hr. According to Morrison et al. *(15)*, airlines relied increasingly on larger fuel-efficient aircraft and reduced flights flown on smaller aircraft such as regional jets. Since fuel prices carry a large influence on airlines' operations *(2)*, service reduction to small and non-hub airports can be associated with the change in fleet size. In fact, increased fuel cost drove the shift from small regional aircraft to newer fuel-efficient aircraft and long-haul capacity, leading to reduced service availability at small airports *(13).*

According to the model, the presence of Allegiant Air as the only marketing carrier reduces the chances of having service the following year in a market by 52.6%. The business model adopted by Allegiant Air is based on operating flights only when travelers want to seasonally fly in order to keep their airfares low for the passengers *(21).* This may have contributed to this high volatility in service as the airline suspends service in a market whenever the demand is not high enough. However, it is important to recognize that although markets with Allegiant as the sole providing carrier have an increased chance of discontinued service in the future, without Allegiant these markets would otherwise not have service in the first place. Model results also show that having an additional major carrier competing in a market increases the odds of having service the following year by 40.5% while having either an additional LCC or other carrier marketing flights in the region-pair market increases the chances of having service the following year by 47.6%. This means that the greater the number of marketing carriers serving a market, the greater the chances of maintaining service. This is consistent with literature, as a lower airport-level concentration was found to be strongly correlated with reduced airfares. As suggested by Bilotkach and Lakew *(29)*, "In smaller airports, however, a new entry will bring average fares down regardless of whether the new carrier comes in with new services, or competing with the incumbents." Therefore, an increase in travel demand may be driven by an increased ability to purchase.

Since the model suggests that increasing the number of marketing carriers is an important contributing factor to continued service, airport managers should focus on retaining air carriers and attracting new airlines into marketing routes from their airports. Investments spent on airports' air service development should consider strategies that may help in increasing airline competition by offering incentives to airlines to operate on cost-effective routes. EAS helps by providing subsidies to certificated air carriers to guarantee service to small communities, where the Department of Transportation defines the minimum level of service by the number of roundtrips and seats that need to be offered to a national hub *(30)*.

Results also show the destination region's population base and ASAI were good predicators of service at the 1% level of significance. An increase in the population of the destination region by 100,000 raise the chances of having service from a small community the following year by 78.5%. However, population can be considered a fixed variable that is impossible to control. Furthermore, an increase in the air accessibility index by 1 increases the odds of having service the following year by 1%. When creating the model shown in Table 4, none of the variables about the departure (small airport) region were significant, such as the population, per capita personal income or the ASAI index. It is possible that the insignificance at the 90% level was due to the low variability of these variables. Also, other variables such as average seats per flight, number of airport-pair routes between the regions, seat capacity, number of regional carriers, and Available Seat Miles (ASMs) were tested in the model. However, given the design of the study, including the choice of the dataset, timeframe and statistical tests for the conditional logistic model, this study did not find these particular factors to be significant.

Additionally, if a market is served by a carrier that is being acquired and the parent airline is not present in the market, then the market has an increased risk of losing service. This is due to the parent airline may either not enter the market or it may enter and then drop the market in order to realign its service to more profitable routes. Following a merger, the odds of retaining air service are reduced by 39%. As described in previous studies, recent consolidation activity may cause small communities consumer welfare losses *(29).* Lastly, the fixed-effects coefficients are all negative in comparison to the reference year of 2008. This means that markets departing from small communities were more likely to lose service in later years, consistent with what is found in the literature in response to reduced travel demand following the 2007-2009 recession *(13).*

Table 3.4: Regression Estimates.

Lagged Independent Variable	Coefficient	Standard Error	z	P>|z|	Odds Ratio
Flight Frequency	0.022***	0.003	7.06	0.000	1.022
Fuel Consumption	-0.164**	0.080	-2.05	0.041	0.849
Allegiant	-0.745*	0.438	-1.7	0.089	0.475
Major	0.340**	0.138	2.46	0.014	1.405
LCC_Other	0.390***	0.139	2.79	0.005	1.476
ASAI_Dest	0.010***	0.003	3.32	0.001	1.010
PopDest	0.579***	0.065	8.90	0.000	1.785
Merger	-0.494*	0.269	-1.84	0.066	0.610
Year					
2009	-0.426	0.154	-2.77	0.006	0.653
2010	-0.125	0.185	-0.68	0.498	0.882
2011	-0.590	0.199	-2.96	0.003	0.554
2012	-0.963	0.219	-4.40	0.000	0.382
2013	-1.439	0.248	-5.80	0.000	0.237

Notes:

1. McFadden's Pseudo R^2: 0.252; Adjusted McFadden's R^2: 0.238
2. Included observations: 2718; 453 markets over a 6-year period.
3. Significance: *0.1; **0.05; ***0.01.

3.6 Conclusion and Future Research

Understanding the factors that may play a role in a market's service loss is important because it will enable airport managers as well as the communities in small airport regions to better recognize the dynamics behind their potential loss of direct service to another region. This study identified significant factors that contribute to a market's loss or gain of service. While many studies in the literature recognized small communities as the main target to service cuts and reduced service quality, the model built in this research emphasizes the loss in service over the years. Results demonstrate that markets served only by Allegiant have a greater chance of losing service. Although Allegiant's operating strategies can lead to increased chances of service loss to a market, it is important to note that markets with Allegiant as the sole providing carrier would otherwise not have service in the first place. Furthermore, this study identified merger activity and usage of equipment types (e.g. small regional jets) with high fuel consumption as factors contributing to service loss.

While having an additional non-stop flight may slightly increase the chances of having service in a market, an important finding reiterates the importance of having multiple marketing carriers offering service in the region-pair market. Perhaps the most important finding is that, in this particular study, none of the variables related to the departure (small airport) region were significant. Increases in the population base, per capita personal income or air service accessibility of small regions may have not been large enough to drive an increase in the odds of having service in these markets. Another possible explanation for this result is the closely fitted distribution and low variation among each of these variables over the years.

3.7 Policy Implications

In this study, it was found that airport managers in small airport communities have little or no control as most of the factors that determine whether a market will continue to have service is determined by the characteristics of the market or the destination community (i.e. the small-, medium-, or large-airport community). Also, this study indicates that air service for small-airport communities will continue to be an issue as the high operating costs of the small equipment types operating the markets serving these communities increases the chances of market service loss. From a practical perspective, these findings suggest that if service is to be maintained in many of these small communities, then additional incentives would be needed, similar to the EAS program. These incentives could encourage carriers to provide service to small communities and to airports affected by a merger. Therefore, it is important for the government to intervene with programs that promote small airport community access to the air transportation system through allocating funds and grants in order to retain service.

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CHAPTER 4

Modeling Flight Delay Propagation in the United States and the Effect of Airport Size

4.1 Introduction

The National Airspace System (NAS) continues to experience flight delays that cost the economy billions of dollars annually (Ball et al., 2010). Increased delays are directly correlated with increase in costs as airlines incur additional costs driven by the need for additional gates, fuel and crew and by passengers increasing their travel time thus losing their productivity. Peterson et al. (2013) found that only a 10% reduction in flight delays would increase the net US welfare by $17.6 billion. Furthermore, in 2018, the Federal Aviation Administration (FAA) reported a total annual delay cost of $28 billion as a result of direct and indirect costs to airlines and air travelers (Airlines for America, 2019).

To assess the performance of the Air Traffic Management (ATM) system, the International Civil Aviation Organization (ICAO) identified 19 Key Performance Indicators (KPIs), including on-time performance, additional travel time and capacity utilization (ICAO, 2020). There are two KPIs used to measure on-time performance, specifically:

1) Gate departure punctuality (KPI01) is a metric that measures the actual gate departure (Gate-Out) against the scheduled gate departure time.

2) Gate arrival punctuality (KPI14) is a metric that measures the actual gate arrival (Gate-In) against the scheduled gate arrival time.

The departure punctuality (KPI01) and arrival punctuality (KPI14) are expressed in percentage of scheduled flights that are on-time. More specifically, a flight is on-time if it departs or arrives less than 15 minutes late compared to schedule. The utility of these KPI is to provide an overall indication of the service quality experienced by the travelers and to quantify the ability of carriers to operate their planned schedules on-time.

While the FAA publishes yearly metrics for arrival punctuality at the main airports in the US, it is important to understand that by strictly looking at the on-time performance of an airport, one cannot fully assess the true performance of that airport. In fact, as mentioned in the FAA and EUROCONTROL's report on the comparison of ATM-related operational performance between the U.S. and Europe, the on-time performance of a flight is the "end product" of complex interactions involving many entities and facilities (Eurocontrol and FAA, 2016).

While flight delays can originate at an airport for several reasons (e.g. crew scheduling, aircraft maintenance, weather, ground delay programs, etc.), it is important to differentiate between original and propagated delay. For a given flight leg, original delay is defined as delay that occurs at any point during the flight time window (ground turnaround, taxiing, en-route) and that is caused by existing conditions at the departure, arrival or en-route facility. In contrast, propagated delay is the result of flights sharing the same resources such as aircraft, crew or passengers. That is, an upstream flight delay can propagate to multiple flights throughout the day that are expected to use the same aircraft fleet. As illustrated in Figure 4.1 below, if a delay was initiated either in the turnaround phase or the block phase of flight leg_{i-1}, delay can propagate to the immediate downstream flight leg_i since both flights are operated by the same aircraft. Delay propagation can also occur on flights that are serviced by the same delayed crew or flights waiting on connecting passengers.

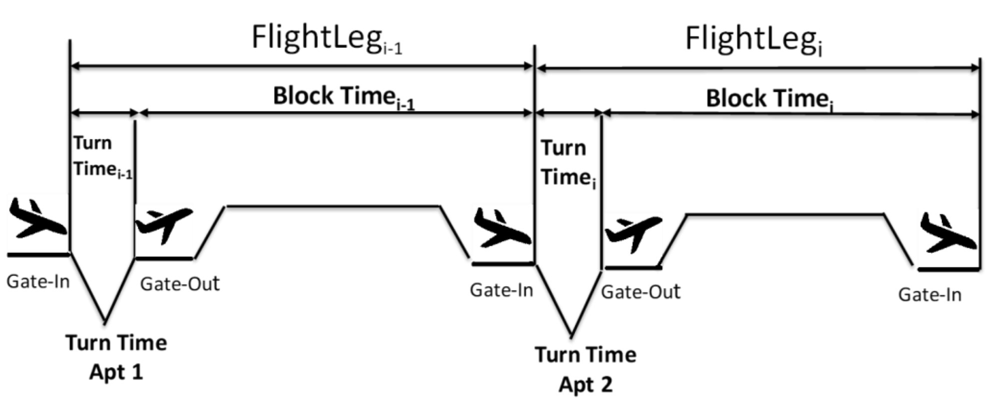

Figure 4.1: Typical flight leg sequence

As mentioned earlier, the on-time performance of an airport does not take into account the causal factors behind late departures or arrivals at an airport. For instance, while a flight may be late to depart from an airport due to a Ground Delay Program (GDP) charged to the destination airport, the current KPI definition measures the airport's departure punctuality by incorporating all delayed flights, regardless of the charged facility. Therefore, it is important not to make infrastructure investment decisions on the on-time performance KPIs alone.

4.2 Literature Review

Given the significant impact of flight delays on the economy and the need to incorporate the effects of propagated delay in performance analysis, literature contains several studies on delay propagation spanning different methodologies and approaches. These studies are outlined in Tables 4.1a and 4.1b, including their results and limitations. In 1999, Beatty et al. looked at delay propagation using over 500 delay trees that tracked propagated delay on American Airlines flights by either tail number or crew. Baden et al. (2006) investigated delays in the NAS using a backtracking algorithm based on historical data and the Airline Service Quality Performance (ASQP) actual and scheduled departure and arrival times in 2000 and 2004. The authors then tracked delay propagated for each aircraft across different airports and carriers. The research did not, however, look into the causes of delay propagation.

Pyrgiotis et al. (2013) developed an approach to model the effect of congestion and delay in major airports while accounting for stochastic demand and capacity. The authors proposed an analytical queuing and decomposition model known as "The Approximate Network Delays (AND)" model that employs a numeral queuing model or a "Queuing Engine (QE)" to study flight interactions in a network of nodes defined by 34 of the busiest airports in the U.S. The model calculates delay at each individual airport and tracks the propagation of delay throughout the network while updating flight schedules and demand shifts. Past literature has also focused on comparing the performance of the US and European flight performance. Campanelli et al. (2016) simulated delay propagation in a network using two agent-based models to compare flight prioritization management protocol. While the U.S. adopts a first-come first-served protocol (FCFS), an Air Traffic Flow Management (ATFM) slot system is used in Europe. Results showed that the former flight management protocol generates larger total delays.

Most studies in literature focused on assessing delay propagation by calculating a delay propagation multiplier. A delay propagation multiplier represents a number by which an initial delay is multiplied to calculate the total propagated delay on all downstream flights that are affected by this initial delay. For example, using the definition proposed by Welman et al. (2010), an airport with a multiplier of 1.5 means that, on average, each minute of original delay at the airport will result in a total of 0.5 minute of propagated arrival delay downstream.

In this context, Welman et al. (2010), developed a study for calculating delay propagation multipliers that can be used as a tool for airport cost benefit analysis. The authors used scheduled airline service and delay provided from ASQP data for year 2008 and calculated multipliers based on propagated arrival delay for the top 50 U.S. airports. Original delays were defined as delays at an airport that are more likely to be impacted by an investment at that airport such as taxi-out and local airspace delays. The methodology proposed in the study links any delay that is propagated to downstream airports to an upstream original delay. If at any point the aircraft gains time back, the reduction in delay was considered in proportion to the size of the original delay. For example, if a flight departs 50 minutes late with 30 minutes of propagated delay and 20 minutes of original delay at the turnaround phase, any time gain en-route is reduced from propagated and original delay in proportion to their contribution to the 50 minutes' delay at the departure.

Kondo (2010) examined city-pair flight sequences from ASQP data for year 2007 and considered a delay as propagated if the following three conditions were met: 1) A flight arrives late, 2) The subsequent flight leg departs late, and 3) The flight arrives late to its next destination. In addition to the delay propagation multiplier, Kondo defined a leap count indicator that indicates how far a delay propagation chain continues, measured in terms of the number of flight legs affected by the propagated delay. This approach does not however consider new operational delays that might form downstream such as Ground Delay Program (GDP) delays.

While many studies developed an approach to assess delay propagation in the NAS, other studies investigated factors that caused flight delays. Allan et al. (2001) examined causal factors for delays at Newark International airport and found that 41% of the total arrival delay that occurred between 1998 and 2001 took place on days with convective weather within or at a significant distance from New York Terminal Area. Furthermore, the most dominant type of delays arising from distant convective weather were in fact taxi-out delays.

Most recently, Shao and Xu (2018) studied the effect of uncertain factors such as those related to weather and Air Traffic Control (ATC) on flight delays and delay propagation. The authors simulated a network of 13 airports in China using colored-time Petri nets to predict flight delays caused by uncertain factors. As a result, the model offers a method to adjust flight schedules to improve flight delay recovery. In the same context, Wong and Tsai (2012) investigated contributing factors for departure and arrival delays using Cox regression analysis and found that "the key contributing factors of departure delays include 'turnaround buffer time', 'aircraft type', 'cargo and mail handling', 'technical and aircraft equipment', 'passenger and baggage handling', and 'weather', whilst the key contributing factors of arrival delays include 'block buffer time' and 'weather'".

One of the most relevant tools for mitigating delay propagation is flight and ground buffers. Buffers consist of increasing the scheduled airborne and ground turn time to allow delayed flights to recover without impacting downstream flights that use the same resources. This mitigation strategy does however come at the price of limiting aircraft and crew utilization and increasing capital costs (Kafle and Zou, 2016). Therefore, it is important to adequately assign flight and ground buffers to maximize the efficiency of airlines' flight schedules. Fleurquin et al. (2013) developed a model that reproduced delay propagation patterns in the air transportation network using the Bureau of Transportation Statistics (BTS) Airline on-time performance data for year 2010. One major limitation to their study is that the authors did not account for flight buffers and assumed that delays at the departure are equal to the delays at the arrival.

Arikan et al. (2013) reported that airlines do not allocate enough block time in their schedules. The authors proposed a stochastic model that identifies the airports that cause the highest delay propagation in the U.S. and provided guidelines to increase the robustness of airlines' schedules by considering trade-offs for allocating flight and ground buffers. Most recently, Kafle and Zou (2016) looked into ground and flight buffers and how it can absorb newly formed and propagated delays by developing an analytical model with three different scenarios for quantifying propagated delay. The model was applied to the US air network using domestic flight data for the first quarter of 2007 covering 168 US airports and from eight major carriers.

While most existing literature studies modeled delay propagation by focusing on the major and large-hub airports in the US (Pyrgiotis et al., 2013; Welman et al., 2010; Kafle and Zou, 2016), it is interesting to study to effect that an airport size can have on newly formed and propagated delay. More specifically, each airport is classified by size based on its annual enplanements and can be defined by how its hourly capacity compares to its scheduled arrival throughput. While large-hub airports tend to maximize their throughput by scheduling flights close to its maximum capacity, this may not be the case at smaller airports where throughput may not be as close to the capacity. To fill in this gap, the present study contributes to existing literature by assessing the on-time performance and delay propagation at different airport sizes. Specifically, it assesses schedule recovery and resilience to service disruptions at large-hub airports compared to small-hub airports in the US.

Table 4.1a: Delay Propagation studies in the literature

Title	Author (Year)	Study Overview	Results	Limitation
Preliminary evaluation of flight delay propagation through an airline schedule	Beatty, Hsu, Berry, Rome (1999)	Examined 500 delay trees to track propagated delay on American Airlines flights using either tail number or crew connectivity	The delay multiplier for a large carrier operator with long turn times and few crew and aircraft branching would be much smaller compared to a high-frequency, short turn-times airline	Excludes flight and ground buffers
Analysis of delay causality at Newark International Airport	Allan, Beesley, Evans, Gaddy (2001)	Analyzed causal factors for delays at Newark International airport	Most dominant type of delays arising from distant convective weather were taxi-out delays	Does not differentiate between Newly formed and Propagated Delay Data restricted to a single airport
Assessing schedule delay propagation in the national airspace system	Baden, DeArmon, Kee, Smith (2006)	Investigated delays in the National Airspace System (NAS) using historical data and the Airline Service Quality Performance (ASQP)	One third of the arrival delay experienced in 2004 and 2000 can be attributed to propagated delay Bad weather results in double the amount of propagated delay compared to the delay experienced on very good weather days	Excludes delay causality
Delay propagation and multiplier	Kondo (2010)	Examined city-pair flight sequences from ASQP data for year 2007	Generated delay propagation multipliers, leap count that indicates how far a delay propagates and a delay propagation accelerator	Does not account for new operational delays that might form downstream Excludes delay causality
Calculating delay propagation multipliers for cost-benefit analysis	Welman, Williams, Hechtman (2010)	Identified new and propagated delay by tracking the source of each minute of propagated delay in the context of cost-benefit analysis	Published delay multipliers for 51 US airports to evaluate the benefit of reducing delay propagation in the context of airport investment decisions	Excludes ground and flight buffer Excludes delay causality
A survival model for flight delay propagation	Wong, Tsai (2012)	Investigated contributing factors for departure and arrival delays using Cox regression analysis	Key contributing factors for departure delays are turnaround buffer time, aircraft type, cargo and mail handling, technical and aircraft equipment, passenger and baggage handling, and weather Key contributing factors for arrival delays include block buffer time and weather	Excludes airport size effect Data from a single Taiwanese domestic airline

Table 4.1b: Delay Propagation studies in the literature

Title	Author (Year)	Study Overview	Results	Limitation
Building reliable air-travel infrastructure using empirical data and stochastic models of airline networks	Arikan, Deshpande, Sohoni (2013)	Proposed a stochastic model to identify airports that cause the highest delay propagation in the U.S.	Airlines do not allocate enough block time in their schedules	Excludes flight buffer Exclude simultaneous use of flight and ground buffers in absorbing both propagated and newly formed delays
Systemic delay propagation in the US airport network	Fleurquin, Ramasco, Eguiluz (2013)	Developed a model that reproduces delay propagation patterns in the air transportation network using BTS Airline on-time performance data for year 2010	The most relevant factors contributing to delay propagation are passenger and crew connectivity	Excludes flight buffer Assumed that delays at the departure are equal to the delays at the arrival
Modelling delay propagation within an airport network	Pyrgiotis, Malone, Odoni (2013)	Proposed an analytical queuing and decomposition model known that employs a numeral queuing model to study flight interactions in a network of nodes in the U.S	Delay propagation tends to ‘‘smoothen’’ daily airport demand profiles and allocate more demand into late evening hours of the operational day	Data for 34 major U.S. Airports Excludes airport size effect
Comparing the modeling of delay propagation in the US and European air traffic networks	Campanelli, Fleurquin, Arranz, Etxebarria, Ciruelos, Eguíluz, Ramasco (2016)	Used two agent-based models to compare flight prioritization management protocol between US and Europe by simulating flight delay propagation	The first-come first-served protocol (FCFS) flight management protocol generates larger delays than the Air Traffic Flow Management (ATFM) slot system used in Europe	Excludes ground and flight buffer
Modeling flight delay propagation: A new analytical-econometric approach	Kafle, Zou (2016)	Developed 3 different scenarios for quantifying propagated delay Incorporated ground and flight buffers that can absorb newly formed and propagated delay	A strong spatial and temporal heterogeneity exists between newly formed and propagated delay	Excludes airport size effect Data from 8 major U.S. Carriers
Air transportation delay propagation analysis with uncertainty in coloured–timed Petri nets	Shao, Xu (2018)	Simulated a network in China using colored-time Petri nets to predict flight delays caused by uncertain factors	Flight delays caused by factors of uncertainty other than weather and ATC are quickly absorbed by buffer time Arrival delays tend to be longer than departure delays as there are more uncertainties that can occur on air routes	Exclude simultaneous use of flight and ground buffers in absorbing both propagated and newly formed delays Sample of 13 airports in China

While delay propagation has been widely researched for its economic relevance, the purpose of this paper is to use data from the Airline Service Quality Performance (ASQP), Aviation System Performance Metrics (ASPM) and Operational Network (OPSNET) to 1) develop delay propagation performance metrics and identify the facility that is the true source of the original delay, 2) better understand factors that affect schedule recovery after the original delay occurred and 3) compare the contribution of airports, classified by size, to the delay propagation phenomenon.

The contribution of this paper is two-fold. First, this study adds to existing literature by first looking at a new methodology for assessing delay propagation by accounting for schedule padding and introducing new Key Performance Indicators (KPI) for measuring delay propagation at different sized airports throughout the US. Second, this study looks at causal reasons for delays reported by carriers (ASQP) and the Operations Network (OPSNET) data while differentiating between delays that occur during the turn phase, taxiing phase or airtime and incorporating cancelled and diverted flight information. Therefore, the purpose of this study is to overcome the limitations listed in Table 4.1a and Table 4.1b of existing studies in the literature.

4.3 Data

To evaluate the relationship between delay propagation and causal factors, this study combines flight information from different FAA data sources. This section introduces the datasets merged to identify the source of delay and trace each source of propagated delay to its true origin airport while understanding its causal factors. Figure 4.2 below summarizes the key variables obtained from each dataset.

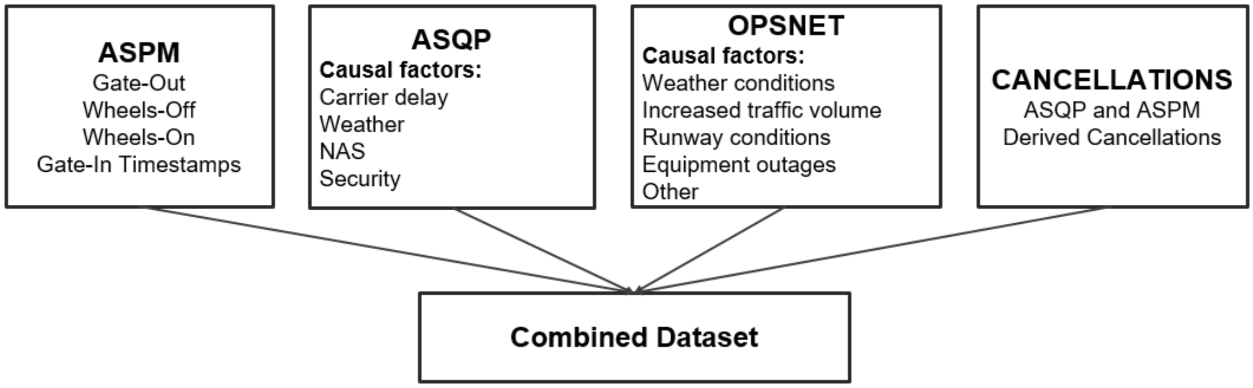

Figure 4.2: Key variables in combined dataset

4.3.1 Aviation System Performance Metrics (ASPM)

The Aviation System Performance Metrics (ASPM) provides the scheduled and actual times for flights to and from ASPM airports and all flights operated by ASPM carriers. Each flight is identified by an aircraft tail number and covers domestic flights as well as flights departing or arriving at an international destination and operated by an ASPM carrier. Using detailed flight activity information for flights scheduled during the month of July of 2018, delays at the departure and arrival gate can be calculated.

While ASPM includes flights operated by all ASPM carriers, this study focuses on the 21 ASPM carriers featured in Table 4.2 below. Data filtering is needed to process the data and eliminate inaccurate flight records, such as: a) negative scheduled turn time showing that a flight's departure time was scheduled earlier than the scheduled arrival time on the immediate upstream flight leg; and b) flight records missing the aircraft's tail number information causing a "teleportation event" where a flight leaves an airport it never arrived at.

To analyze propagated delay, ASPM flight records are processed into unique flight sequences. A sequence is defined as a series of flight legs that are operated by the same aircraft, identified by a tail number. It is important to define the aircraft operational day during which delays can propagate from one flight leg to another. That is, a period during which flight legs are dependent to one another. Two flight legs are considered independent if each occur on a different operational day. Due to results from a sensitivity analysis on scheduled turn times on narrow-body and wide-body aircraft, this analysis defined the aircraft-operational day as the period of time during which an aircraft does not have any scheduled turn times exceeding 180 minutes. Therefore, when an aircraft takes more than 180 minutes during its turn time phase, it can be assumed that the aircraft is grounded overnight, and the flight sequence ends while a new flight itinerary begins. This definition prevents any delays on the first flight of a day being attributed to the delayed arrival of the last flight the night before.

The final dataset consisted of 704,422 flight observations that cover domestic and international flights that departed from or arrived to 351 domestic US airports. Table 4.2 summarizes the number of flights and flight sequences by airline considered in this study.

Table 4.2: Number of flights operated by ASPM Airlines in July 2018

ICAO	Carrier Name	Total Number of Flights	Total Number of Flight Sequences
AAL	American Airlines	91,267	24,849
ASA	Alaska Airlines	25,028	5,705
ASH	Mesa Airlines	20,396	4,271
ASQ	Atlantic Southeast Air	17,509	4,473
AWI	Air Wisconsin	8,154	1,878
CPZ	Compass Air	8,795	1,619
DAL	Delta Airlines	97,574	24,670
EDV	Endeavor Air	21,771	5,012
ENY	Envoy Air	26,688	5,448
FFT	Frontier Airlines	9,238	1,471
GJS	GoJet Airlines	7,470	1,613
JBU	JetBlue Airways	31,222	6,361
JIA	PSA Airlines	23,327	3,955
LOF	Trans State Airlines	6,353	1,459
NKS	Spirit Airlines	16,789	2,704
PDT	Piedmont Air	7,829	1,614
QXE	Horizon Air	11,137	1,847
RPA	Republic Airlines	27,514	5,663
SKW	Skywest Air	65,542	13,465
SWA	Southwest	114,854	21,054
UAL	United Airlines	65,965	18,505

4.3.2 Operations Network (OPSNET)

Causal factors behind ground and airborne delays for delayed flights can be identified by merging OPSNET data records with the master dataset. The Operations Network (OPSNET) is the official source for the National Airspace System air traffic operations and delay data. The dataset reports delays to instrument flight rules (IFR) flights that are at least 15 minutes and caused by one of the following factors: 1) Weather conditions, 2) Increased traffic volume, 3) Runway conditions, 4) Equipment outages or 5) Other causes. The Operations Network dataset reported a total of 30,120 delay records in July 2018. The distribution of these delay records by delay type is as follows: 4,362 Airborne Holding, 1,211 Departure delays and 24,547 Traffic Management Initiatives (TMI).

While most delay records have a known origin and destination, an existing limitation to this dataset are MULT delays, representing delay records with multiple flights, each having an unknown destination. These MULTs are the result of a delay originating at a specific airport and affecting multiple flights at the same time, making it hard for Air Traffic Controllers to keep track of each flight's destination. As a result, all MULT records are either a departure or a Traffic Management Initiative (TMI) delay and the flights affected are combined in a single delay record that notes the total number of flights affected and the average minutes of delay per delayed flight. The challenge in merging these MULT OPSNET delays arise in assigning the delay causal factor to the corresponding flight affected while missing important information such as the destination airport, the flight number and the operating carrier.

To overcome this data limitation, several data observations and assumptions were made to match the appropriate MULT delay to the flight affected by that delay, such as: 1) ASPM flight should occur within the time window of the OPSNET reported delay program by considering the scheduled gate-out and actual wheels-off time of the flight; 2) original delay that happens during the turnaround or taxi-out phase and that overlaps with the MULT delay program should be at least 15 minutes and 3) the total number of flights matched to a MULT delay cannot exceed the total number of flights affected by the MULT delay program as reported in OPSNET. In total, 83.7% of the OPSNET delay records for the month of July of 2018 were matched to an ASPM flight to identify the causal facility and factor behind the delay.

4.3.3 Airline Service Quality Performance System (ASQP)

Every month, reporting carriers as defined in the Airline Service Quality Performance System (ASQP) are required to report the on-time performance of their flights as well as any delay causes associated with it. The types of delays reported in ASQP are defined as one of the following: 1) Carrier delay, 2) Late aircraft delay, 3) NAS delay, 4) Security delay or 5) Weather delay. What is most interesting about ASQP data is the flight diversion information that are included within the data in addition to cancelled flights. That is, if a flight was diverted for a specific cause, ASQP merged with ASPM information will provide the entire path of the flight along with the diversion airport as well as the minutes and causes for delay encountered on the ground and in the air.

In some instances, the accumulated delay propagates to a series of downstream flights leaving no room for schedule recovery. In this case, the airline may decide to cancel the next flight. As a result, it was important to incorporate ASQP cancellations data to be able to trace down flights that were canceled as a result of a built-up propagated delay in a flight sequence. The total number of cancelled flights with a reported aircraft tail number included in the study accounts for 1.4% of the flight records reported in the dataset while 0.2% of the total number of observations correspond to a diverted flight.

Figure 4.3 below shows an example of a flight departing from San Diego International airport (SAN) and scheduled to arrive at Newark Liberty International Airport (EWR). The ASPM flight records shows that the flight departed the gate on-time but reached its scheduled destination 169 minutes post its scheduled arrival time. By looking at the information provided strictly from ASPM, it is not possible to explain why 172 minutes of delay occurred during the flight block time. However, when merged with its corresponding flight record reported in ASQP, it becomes evident that the flight was actually diverted to Baltimore/Washington International Thurgood Marshall Airport (BWI) possibly for refueling purposes after encountering airborne holding due to adverse weather while in the air, as reported in OPSNET.

ASPM| TailNo=NXXXXX | July 3, 2018

Flight Leg	Airport		UTC Time				Turn Time		Block Time		Gate Arrival Delay
	Dep	Arr	Sched Out	Act Out	Sched In	Act In	Delay	Padding	Delay	Padding	
0	SJC	SAN	14:10	14:12	15:30	15:23	0	-	0	-9	-7
1	SAN	EWR	16:20	16:17	21:45	00:34	0	-3	**172**	0	169
2	EWR	DEN	22:35	01:31	03:10	05:24	7	0	0	-42	134

ASQP| TailNo=NXXXXX | July 3, 2018

Flight Leg	Airport		Causal Factor					Arrival Delay	Diverted	Diversion Airport	Diversion Delay
	Dep	Arr	Carrier	Weather	NAS	Security	Late Aircraft				
0	SJC	SAN	-	-	-	-	-	-7	0		
1	SAN	EWR	-	-	-	-	-	-	**1**	**BWI**	169
2	EWR	DEN	7	0	0	0	127	134	0		

OPSNET| Dep = SAN| Arr = EWR| July 3, 2018

Delay Start	Delay End	CAT	Airborne Holding	Dep Delay	TMI	Delays	Avg Min	Max Min	Causal Factor	Secondary Cause
21:00	21:36	AC	**1**	0	0	1	36	36	WX	Weather

Figure 4.3: Example of combined dataset flight information

4.4 Methodology

The next section goes over the methodology for calculating propagated and original delay and determining the causal facility responsible for the delay. The proposed methodology for calculating propagated delay builds off of several studies (Kafle and Zou, 2016; Kondo, 2010 and Welman et al.,2010) and adds to existing literature by proposing a new methodology that looks into the true cause for original and propagated delay and the facility to which that delay should be charged to.

4.4.1 Original Delay and Causal Facility

Each flight leg is defined using a Gate-In to Gate-In approach as illustrated in Figure 4.4 below. The turn time is defined as the time elapsed between the moment the aircraft reaches the gate till the aircraft leaves the gate again to taxi out and depart to its next destination, measured from Gate-In$_{(i-1)}$ to Gate-Out$_{(i)}$. Block Time is defined as the time elapsed between an aircraft pushing back from the gate of departure and reaching the gate at its arrival to the next destination, measured from Gate-Out$_{(i)}$ to Gate-In$_{(i)}$. Block time accounts for taxiing out at the departure airport, the time the aircraft spends while airborne and taxiing in at the destination airport.

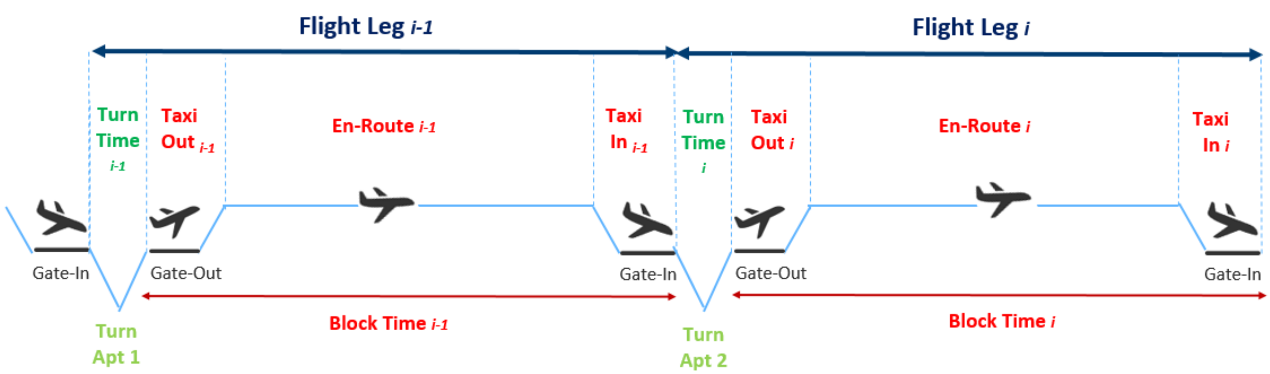

Figure 4.4: Illustration of a detailed flight leg sequence

In this study, original delay refers to any minute of delay measured against the scheduled or nominal time which can occur during any of the following four stages: 1) Turnaround, 2) Taxi-out, 3) En-route and 4) Taxi-In. Contrary to existing literature, this study does not simply measure delay as gate departure or gate arrival delay but traces the original delay to the timeframe at which it occurred to identify the causal facility behind the delay. For example, if a flight departed on-time from the departure gate but arrived 20 minutes late at the arrival gate, it is important to understand whether this delay occurred while the aircraft was taxiing-out due to high traffic volume or was it in fact caused by a delay charged to the arrival airport. Consequently, through incorporating causal factors from OPSNET and ASQP delay records, original delay is defined as the minutes of delay that can be counted towards the airport that bears the originating cause of the delay.

Once original delay is calculated during each of the four stages of a flight, the information retrieved from OPSNET can help identify the causal facility behind the delay. Traffic Management Initiative (TMI) delays report the facility that should be charged for the delay that can be either an airport, a terminal radar approach control, or an en-route center. Furthermore, delays can be further classified as Ground Delay Program (GDP), Ground Stop (GS) and Airspace Flow Program (AFP). It is important to allocate the minutes of original delay towards the facility responsible for the delay regardless of where that delay occurred. For example, if a flight departed 30 minutes late from Dallas/Fort Worth International Airport (DFW) and arrived 30 minutes late at John F. Kennedy International Airport (JFK) and OPSNET reported a ground delay program charged to JFK, then the original delay of 30 minutes should be charged towards JFK even if the delay was taken at DFW.

Furthermore, Departure delays reported in OPSNET are counted towards the departure airport while airborne holding delays are counted towards the destination airport since airborne holding typically occurs when an aircraft is unable to land for several reasons such as extreme weather conditions or runway unavailability at the arrival airport.

After determining the causal facility behind each delay, original delay at the departure airport can be calculated as delay encountered during the turnaround phase and the taxi-out phase unless there was a GDP, GS or AFP program in effect. Consequently, original delay at the destination can be calculated as delay encountered en-route or while taxiing-in in addition to any delay that was taken at the departure airport but that was charged to the arrival facility. It is important to note that if a flight was diverted, the arrival airport cannot be held accountable for long delays that happen en-route unless the reported conditions at the airport itself is the reason why the flight was diverted.

4.4.2 Schedule Padding and Propagated Delay

Delay can propagate from one flight to another when common resources are employed to operate both flights such as crew, aircraft or connecting passengers. In this study, propagated delay is calculated by tracking an aircraft identified by its tail number throughout its scheduled itinerary. After determining the causal facility charged for original delay, the net delay measured as gate departure delay and gate arrival delay on flight $\text{leg}_{(i-1)}$ can propagate to the downstream flight $\text{leg}_{(i)}$ within the same aircraft-operational day if it is not absorbed by padding either during the turnaround phase or during the block phase. Airlines tend to allocate additional buffer within their scheduled turn time and block time to help absorb possible and unforeseen delays. Net Turn and Block Time defined in equations *(5)* and *(6)* below may result in negative or positive values. While positive values are treated as Turn Delay and Block Delay, negative values represent Schedule Padding during which upstream delay may be absorbed.

$$\textit{Actual Turn}_{(i)} = \textit{Actual Gate-Out}_{(i)} - \textit{Actual Gate-In}_{(i-1)} \quad (1)$$

$$\textit{Scheduled Turn}_{(i)} = \textit{Scheduled Gate-Out}_{(i)} - \textit{Scheduled Gate-In}_{(i-1)} \quad (2)$$

$$\textit{Actual Block}_{(i)} = \textit{Actual Gate-In}_{(i)} - \textit{Actual Gate-Out}_{(i)} \quad (3)$$

$$\textit{Scheduled Block}_{(i)} = \textit{Scheduled Gate-In}_{(i)} - \textit{Scheduled Gate-Out}_{(i)} \quad (4)$$

$$\textit{Net Turn Time}_{(i)} = \textit{Actual Turn}_{(i)} - \textit{Scheduled Turn}_{(i)} \quad (5)$$

$$\textit{Net Block Time}_{(i)} = \textit{Actual Block}_{(i)} - \textit{Scheduled Block}_{(i)} \quad (6)$$

Delays encountered at the departure gate are the result of original delay in addition to propagated delay from upstream sources. For flight $\text{leg}_{(i)}$, propagated departure delay is the gate arrival delay from flight $\text{leg}_{(i-1)}$ that is not absorbed during the turnaround phase of flight $\text{leg}_{(i)}$. Equation *(7)* below calculates propagated delay at the departure gate. Specifically, if there is schedule padding during the turnaround phase and turn padding exists, some or all of the upstream delay will be absorbed. Gate Departure delay defined in equation *(8)* considers original delay at the turn, if any, and propagated delay that affects departure punctuality also referred to as KPI01.

$$Propagated\ Delay\ Dep_{(i)} = Maximum\ (0,\ Gate\ Arrival\ Delay_{(i-1)} + Turn\ Padding_{(i)}) \quad (7)$$

$$Gate\ Departure\ Delay_{(i)} = Propagated\ Delay\ Dep_{(i)} + Turn\ Delay_{(i)} \quad (8)$$

For arrival delay experienced on flight $leg_{(i)}$, the propagated delay is the gate arrival delay from flight $leg_{(i-1)}$ that is not absorbed during the turnaround phase and/or the block phase of flight $leg_{(i)}$. Equations *(9a,9b,9c)* below calculate propagated delay at the arrival gate while considering propagated delay that affects departure punctuality. Table 4.3 shows the different scenarios that can occur depending on whether there is padding during the block phase on flight $leg_{(i)}$. This means that flight buffer at the block phase can simultaneously absorb original delay at the turn phase and propagated delay in proportion to the share of each delay type. The proposed methodology simultaneously proportions the gain in schedule during the flight block phase to delay encountered at the turn (original delay) and propagated delay from the upstream flight leg. This proportioning of schedule recovery is consistent with the methodologies presented in Welman et al. (2010) and Kafle and Zou (2016).

The equations provided in Table 4.3 calculate propagated arrival delay based on three different scenarios. For Scenario 1, there is no Block Time Padding and therefore all the propagated delay that affected departure punctuality will in fact affect arrival punctuality. For the scenario where block padding exists, there are two possible scenarios depending on whether turnaround delay exists or not. If there is no turn delay (Scenario 2), the time gained back through padding is simply added to propagated delay that affected departure punctuality on that same flight leg. If turnaround delay exists (Scenario 3), the time gained during the block phase is proportioned back to propagated delay as well as original delay during the turn phase. Propagated Arrival Delay calculated using equation (9c) is conditional on the presence of turn delay (or gate departure delay).

Table 4.3: Scenarios for calculating delay propagated to the arrival gate

Scenario 1	No Block Padding	*(9)a*	$\text{Propagated Delay Arr(i)} = \text{Propagated Delay Dep(i)}$
Scenario 2	Block Padding No Turn Delay	*(9)b*	$\text{Propagated Delay Arr(i)} = Max(0, \text{Propagated Delay Dep(i)} + \ Block\ Padding(i))$
Scenario 3	Block Padding Turn Delay	*(9)c*	$\text{Propagated Delay Arr(i)} = Max(0, \text{Propagated Delay Dep(i)} + Block\ Padding(i) * \frac{\text{Propagated Delay Dep(i)}}{Gate\ Departure\ Delay(i)})$

If propagated delay exists, Gate Arrival Delay on flight $\text{leg}_{(i)}$ can be defined in terms of the share of delay that is propagated, using equations *(10a, 10b)* to calculate arrival punctuality or KPI14.

If there is schedule padding at the block phase:

$$Gate\ Arrival\ Delay_{(i)} = Propagated\ Delay\ Arr_{(i)} + Turn\ Delay_{(i)} + Block\ Padding_{(i)} * \frac{\text{TurnTimeDelay(i)}}{\text{GateDepDelay(i)}} \quad (10a)$$

If there is original delay at the block phase:

$$Gate\ Arrival\ Delay_{(i)} = Propagated\ Delay\ Arr_{(i)} + Turn\ Delay_{(i)} + Block\ Delay_{(i)} \quad (10b)$$

Figures 4.5 and 4.6 illustrate a decision tree that summarizes the step-by-step methodology for calculating propagated and gate delay.

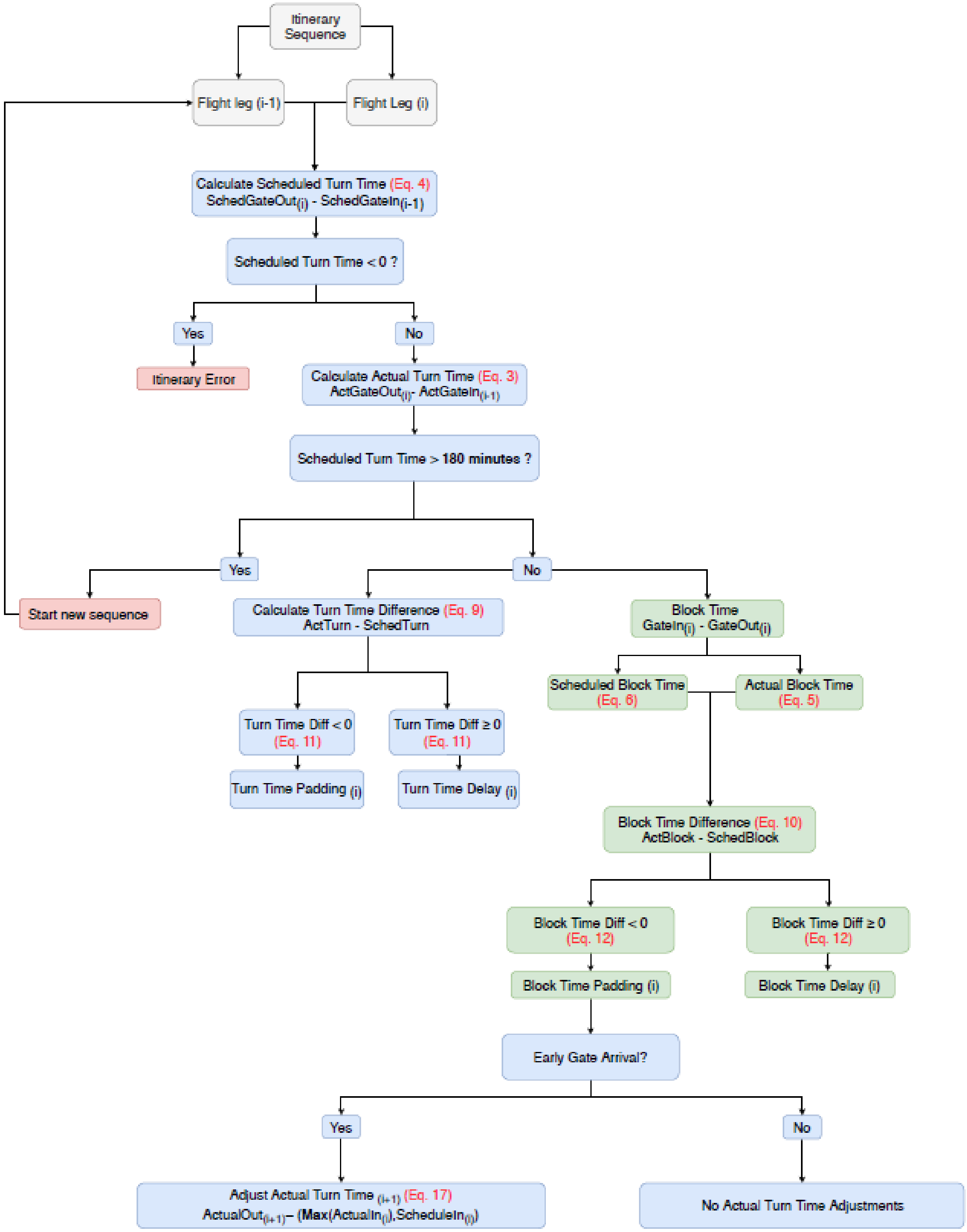

Figure 4.5: Defining Flight Itinerary flowchart

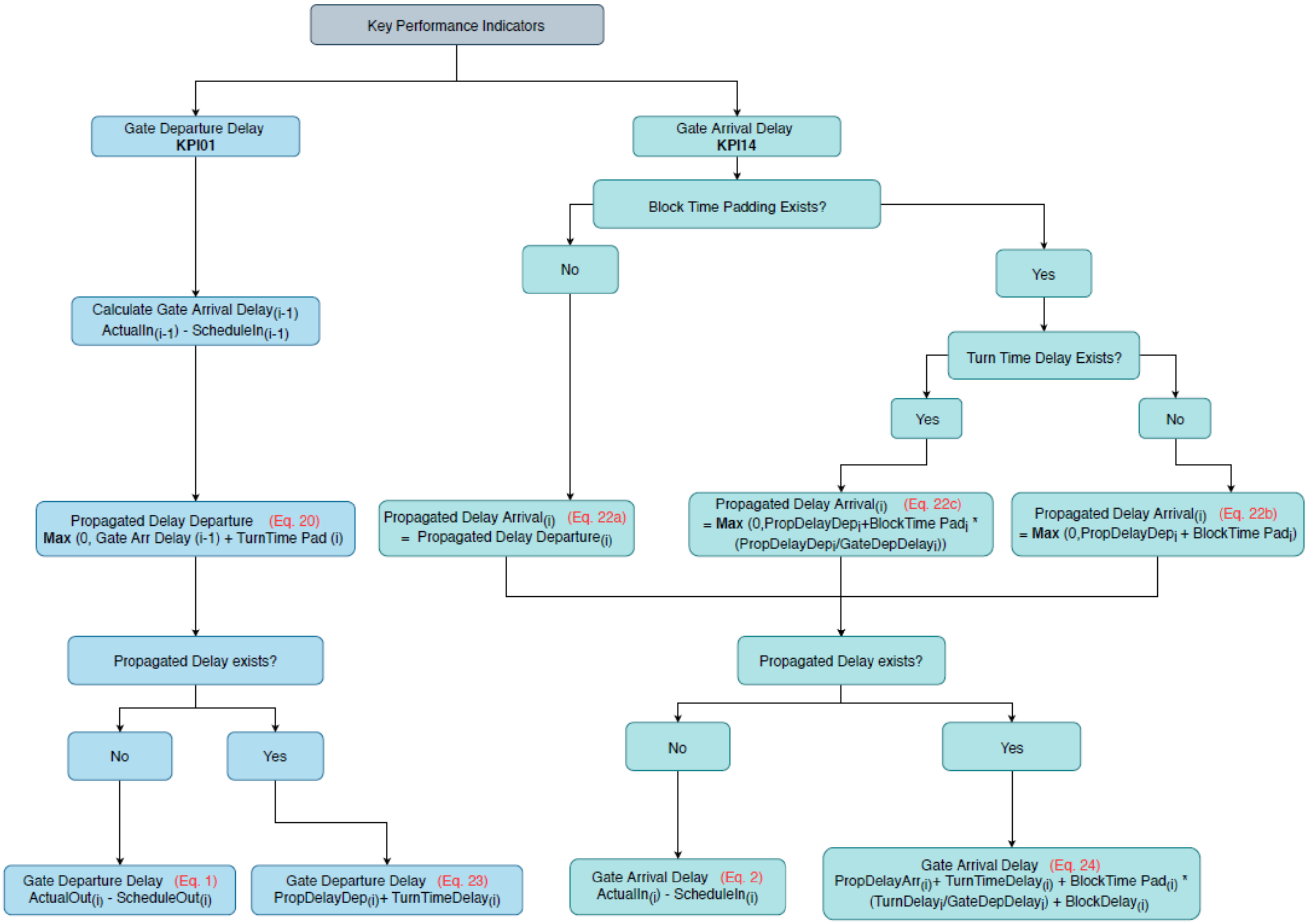

Figure 4.6: Delay Propagation and Key Performance Indicators flowchart

4.4.3 Fixed-Effects Linear Regression

Fixed effects is a regression model that examines the relationship between dependent and predictor variables within an entity. Each entity can have individual characteristics that may or may not influence the predictor variables. For example, flights operated by Southwest Airlines could have some effect on turnaround scheduling; or the weather region in which an airport is located may influence its original delays. Using fixed-effects controls for the individual characteristics within each entity that may cause a bias in the predictor or outcome variables. That is, fixed-effects controls for the average differences across entities in observable and unobservable predictors. Assuming predictor variables and each entity's error term are correlated, by incorporating fixed-effects, the effect of the omitted time-invariant characteristics is controlled for to assess the net effect of the predictors on the dependent variable (Torres-Reyna, 2007). The fixed-effects model for entities ($i=1,2,\ldots,n$) can be defined as follows:

$$Y_i = \beta_1 X_i + \beta_2 X_i + \cdots + \beta_k X_i + \alpha_i + \varepsilon_i$$

Where:

Y_i is the dependent variable with $i=1,2,\ldots,n$ entities

β_k is the coefficient for the k^{th} independent variable

α_i is the n entity-specific intercept

ε_i is the error term

The overall coefficient for each predictor variable β represents the average effect of that independent variable, i.e., the common slope averaged across all entities. The importance of fixed-effects models comes from the inability to control for all unobservable factors that are correlated with the regression variables, resulting in omitted bias. Furthermore, it is important to validate the assumption behind the use of fixed-effects model through the Durbin-Wu-Hausman test. The latter validates the assumption behind fixed-effects that the unique entities' error term is correlated with the predictors in the model (Chmelarova, 2007). Therefore, if there is a correlation between the individual-specific effects and the predictors, the Hausman test rejects the null hypothesis of no correlation and fixed effects are valid.

4.5 Results

This section first presents descriptive statistics obtained from modeling original and propagated delay at each airport while factoring in the size of the airport. In section 4.5.1, the KPI metrics are estimated for July 2018 data. Section 4.5.2 looks at the share of propagated delay across various-size airports. In section 4.5.3, the causal facilities behind late arrivals are examined followed by an analysis of the different propagation chains that originate at each airport in section 4.5.4. Finally, section 4.5.5 links between the KPI metrics previously defined and total propagated delay.

4.5.1 Key Performance Indicators: KPI01 and KPI14

Gate departure punctuality (KPI01) is a metric that measures the actual gate departure (Gate-Out) against the scheduled gate departure time, while gate arrival delay (KPI14) measures the actual gate arrival (Gate-In) against the scheduled gate arrival time. Figure 4.7 summarizes these KPI metrics for U.S. airports grouped by size category. The annual FAA airport classification[7] (FAA, 2018) classifies airport by size based on the number of annual passengers boarding and label an airport as either large-, medium-, small- hub, non-hub, or non-primary airport. Similarly, Figure 4.8 summarizes the arrival punctuality (KP14) and gate arrival delay for flights arriving at U.S. airports grouped by size. Note that the 15 airports featured in each size category correspond to the top 15

[7] FAA defines a primary airport as commercial service airports with more than 10,000 passenger boardings each year. Primary airports are classified as large, medium, small or non-hub. Large hub airports have 1% or more of annual passenger boardings. Medium hub have at least 0.25% of annual passenger boardings. Small hub have at least 0.05% of annual passenger boarding and non-hub have more than 10,000 annual passenger boardings. Non-Hub nonprimary airports have at least 2,500 annual passengers boardings (FAA, 2018). This study classifies both primary non-hub and non-primary non-hub airports as "non-hub" and therefore any airport with less than 10,000 passenger boardings per year or less than 0.05% of annual passenger boardings fall in the same classification.

airports ranked by total number of departures in Figure 4.7 and total number of arrivals in Figure 4.8 during the month of July of 2018.

According to Figures 4.7 and 4.8, the worst on-time departure and arrival performance of large-hub airports correspond to airports located in the New York metropolitan area. In fact, 74.2% of flights departing from JFK in July 2018 were on time which means that 25.8% of the flights departed at least 15 minutes late. In addition, the average delay for all flights departing from JFK was 17 minutes. When considering arrival punctuality, Newark Liberty International Airport (EWR) reported the worst on-time arrival performance among the top 15 large-hub airports with only 67.5% of the flights arriving on-time and an average arrival delay of 22.2 minutes.

Looking at the on-time departure performance of medium-hub airports, William P. Hobby Airport (HOU) and Dallas Love Field Airport (DAL) experienced the worst on-time performance among the top 15 medium-hub airports with a reported departure punctuality of 68.2% and 69% respectively. Furthermore, the average gate departure delay for flights departing from HOU was 16.1 minutes and 15.8 minutes for DAL. What is most interesting is that both airports are within the same geographical area and evidently within the same south weather region. As results show that airports within the same geographic face similar delays, a possible explanation could be the adverse weather conditions affecting their on-time performance.

Figures 4.7 and 4.8 also show the median on-time performance across all airports in each size category for departure and arrival punctuality, respectively. Results show that small-hub airports achieve a better departure on-time performance compared to larger airports. In fact, the median departure punctuality (KPI01) for small-hub airports is 82.6% compared to 81.1% for medium-hubs and 78.3% for large-hub airports. However, there is no significant difference in arrival punctuality across the different airport size categories. In fact, small-hub airports have a median arrival punctuality of 78.2% compared to 78.3% for medium-hubs and 78.8% for large-hub airports.

The Key Performance Indicators KPI01 and KPI14, measuring departure and arrival punctuality respectively, assesses the on-time performance at each airport by looking at delays experienced at the departure or arrival gate without differentiating between original and propagated delay. While an airport may experience poor on-time performance, it is important to identify whether this airport is truly responsible for the increased delay or whether this delay is the result of upstream delay propagating to the facility and affecting its on-time performance. Hence, the need to incorporate propagated delay in measuring the performance of airports.

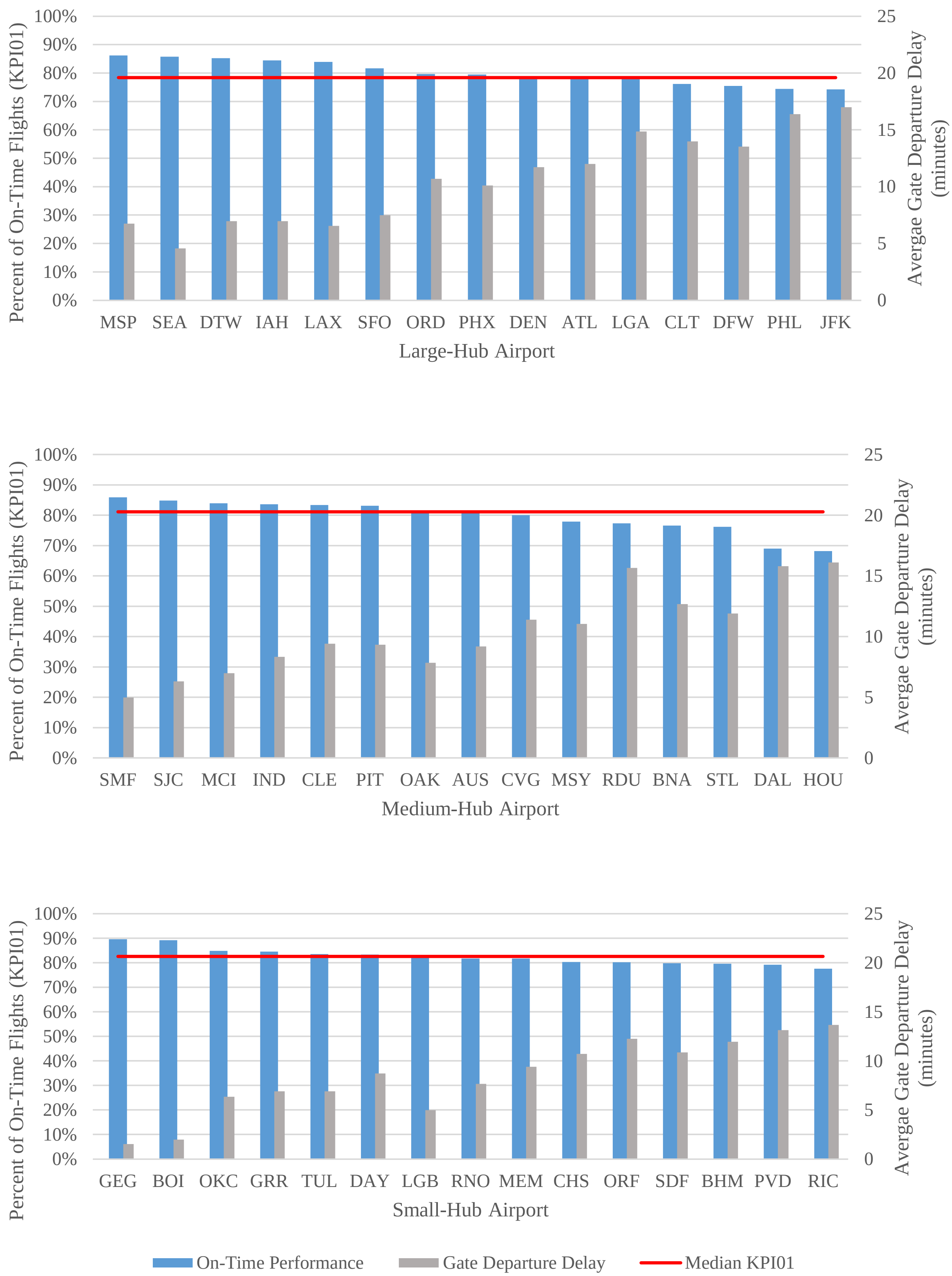

Figure 4.7: Departure punctuality (KPI01) and average gate departure delay

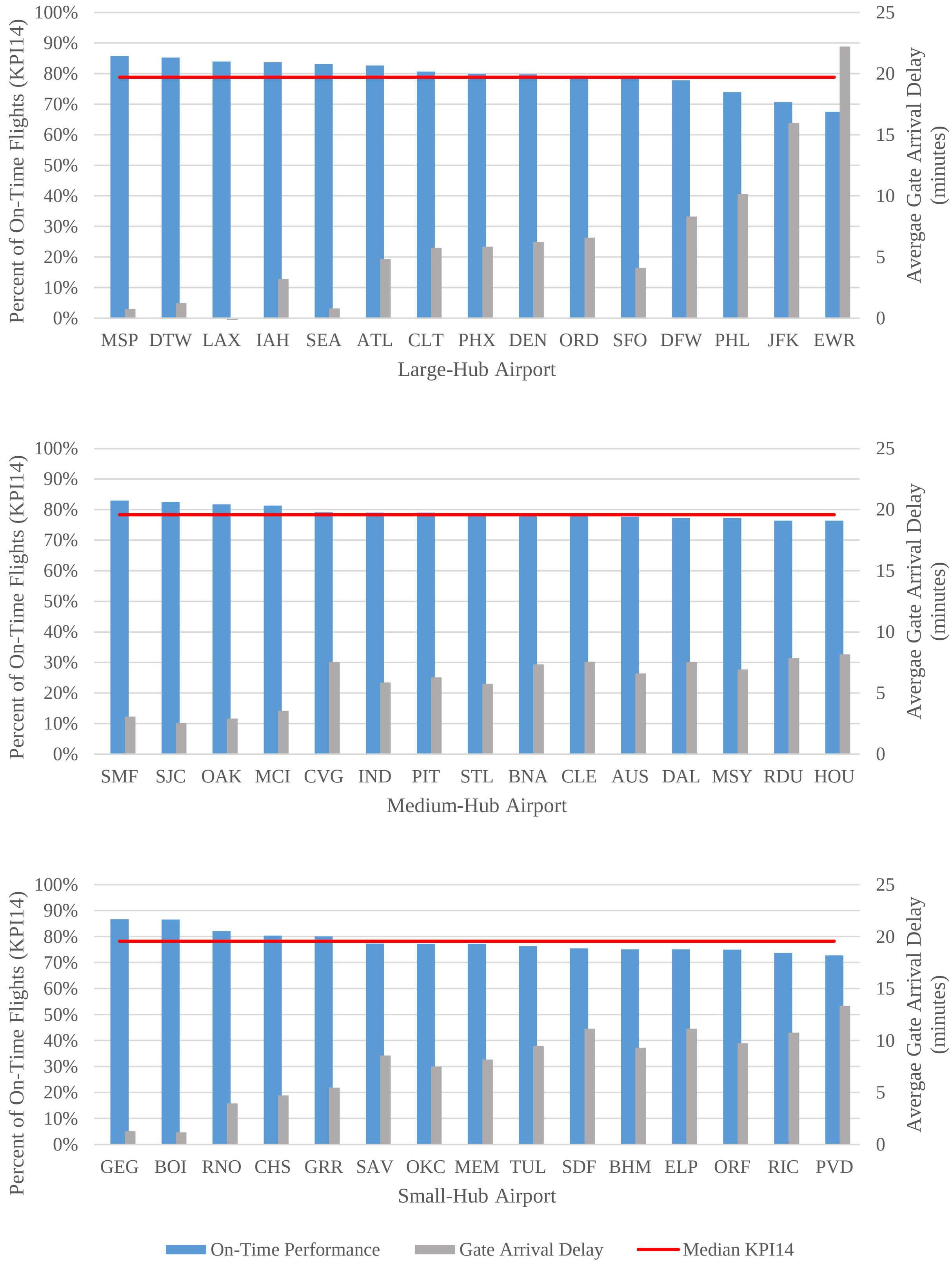

Figure 4.8: Arrival punctuality (KPI14) and average gate arrival delay

4.5.2 Original and propagated delay

This section looks at late flights that are at least 15 minutes late to depart or arrive at an airport. More specifically, Figure 4.9 looks at the average delay on late departing flights and the share of delay that is attributed to propagated delay. That is, given an airport, the average share of the delay minutes that correspond to propagated delay from upstream flight legs. Note that the airports featured in each size category correspond to the top 15 airports ranked by highest number of late departures during the month of July of 2018. For example, on average, a flight that departed late from EWR experienced 78.8 minutes of delay at the departure gate. Furthermore, the share of propagated delay on flight departing late from EWR was 62.5%. This means that on average, 62.5% of the total gate departure delay was caused by propagated delay from upstream flights and only 37.5% was caused by original delay.

The higher the share of propagated delay, the greater the contribution from propagated delay to gate departure delay and the smaller the contribution from original delay. Among large-hub airports, EWR had the highest share of its gate departure delay caused by propagated delay while Miami International Airport (MIA) had the lowest share of its departure delay attributed to propagated delay. In fact, while flights departing late from MIA experienced 68.8 minutes of delay on average, only 41.7% of its departure delay minutes is caused by propagated delay. The latter indicates that MIA airport is a significant source for original delays causing late departures.

What is most interesting is the share of propagated delay for departures from small-hub airports. The share of propagated delay is greater at small-hub airports indicating that the dominant cause for flights departing late is propagated delay instead of original delay. The overall share of propagated delay for late departures is illustrated in Figure 4.9 by the dashed line. On average, for a flight departing late from a large-hub airport, 52.4% of that delay is caused by propagated delay compared to 58.2% if it was departing from a medium-hub airport and 64.4% if it was departing from a small-hub airport. Interestingly, this suggests that larger airports may experience greater original delay at the departure compared to smaller-sized airports.

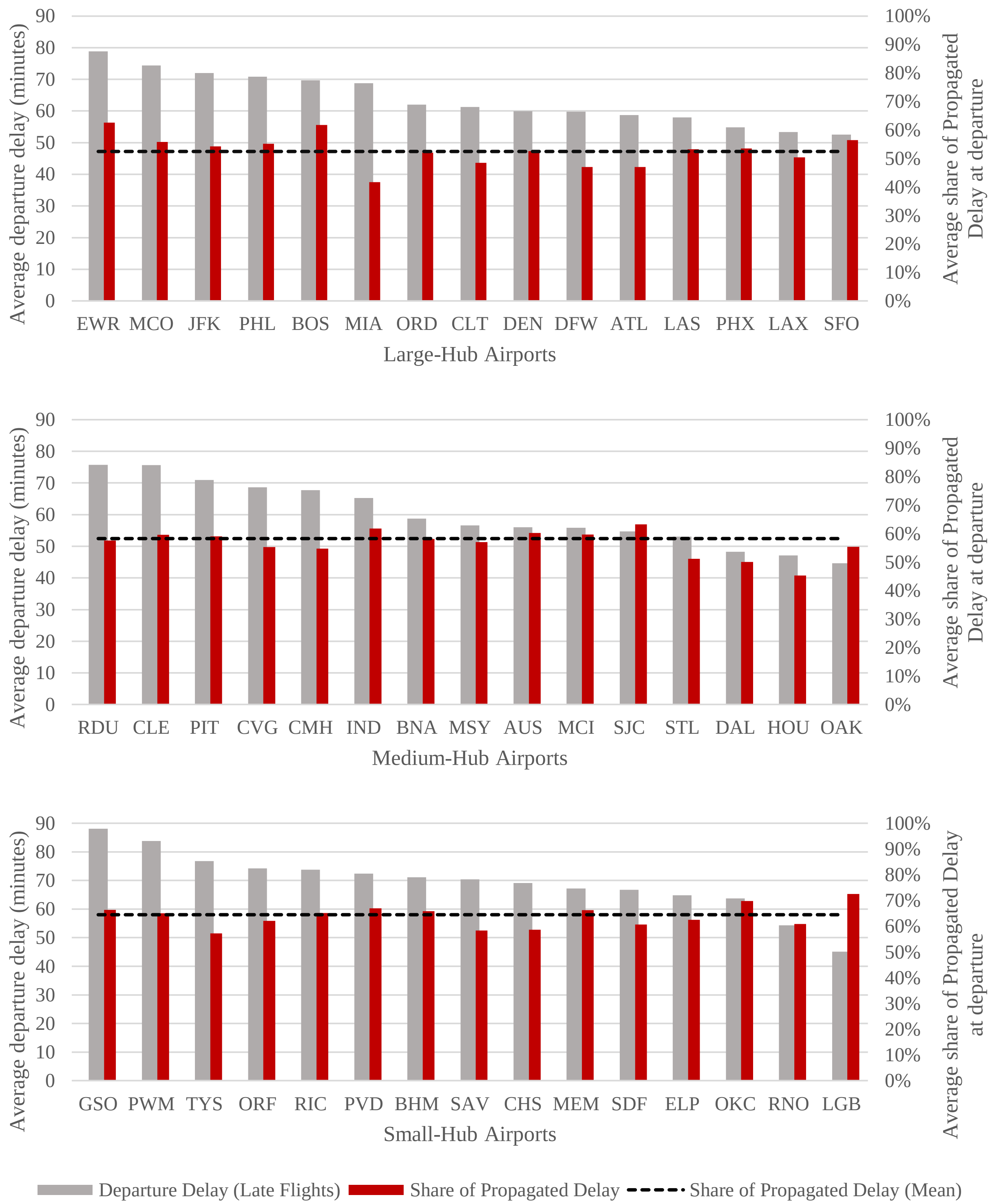

Figure 4.9: Average departure delay and share of propagated delay for late flights

Figure 4.10 illustrates the average delay encountered on late flights arriving at each of the top 15 airports ranked by total number of late arrivals. It also appears that the top 3 airports experiencing the highest average arrival delay are all located within New York Metropolitan area (JFK, LGA and EWR) with 86.5 minutes of arrival delay on average for flights arriving late to EWR. Interestingly, the share of delay that propagated from upstream flights is only 32.6% indicating that 67.4% of the arrival delay is caused by original delay. This validates the finding in section 4.5.1 that suggests that airports located within the same geographical area may experience similar on-time performance. In fact, weather delay may be the leading cause behind original delay encountered by aircraft arriving at one of the 3 airports in New York.

Looking at the overall share of propagated delay at airports grouped by size; On average, for a flight arriving late at a large-hub airport, 43.6% of that delay is caused by propagated delay compared to 46.7% if it was arriving at a medium-hub airport and 42.3% if it was arriving at a small-hub airport. Therefore, it appears that there is no substantial difference between large and small-hub airports when it comes to share of propagated delay at late arrivals. This means that the dominant cause for a late arrival is original formed delay that is developed after the aircraft pushed back from the departure gate. The original delay contributing to arrival delay may develop during the taxi-out phase, en-route or during the taxi-in phase. Results are consistent with the findings of Churchill et al. (2010) that suggested that propagated arrival delay constitute 20-30% of total reported flight delays.

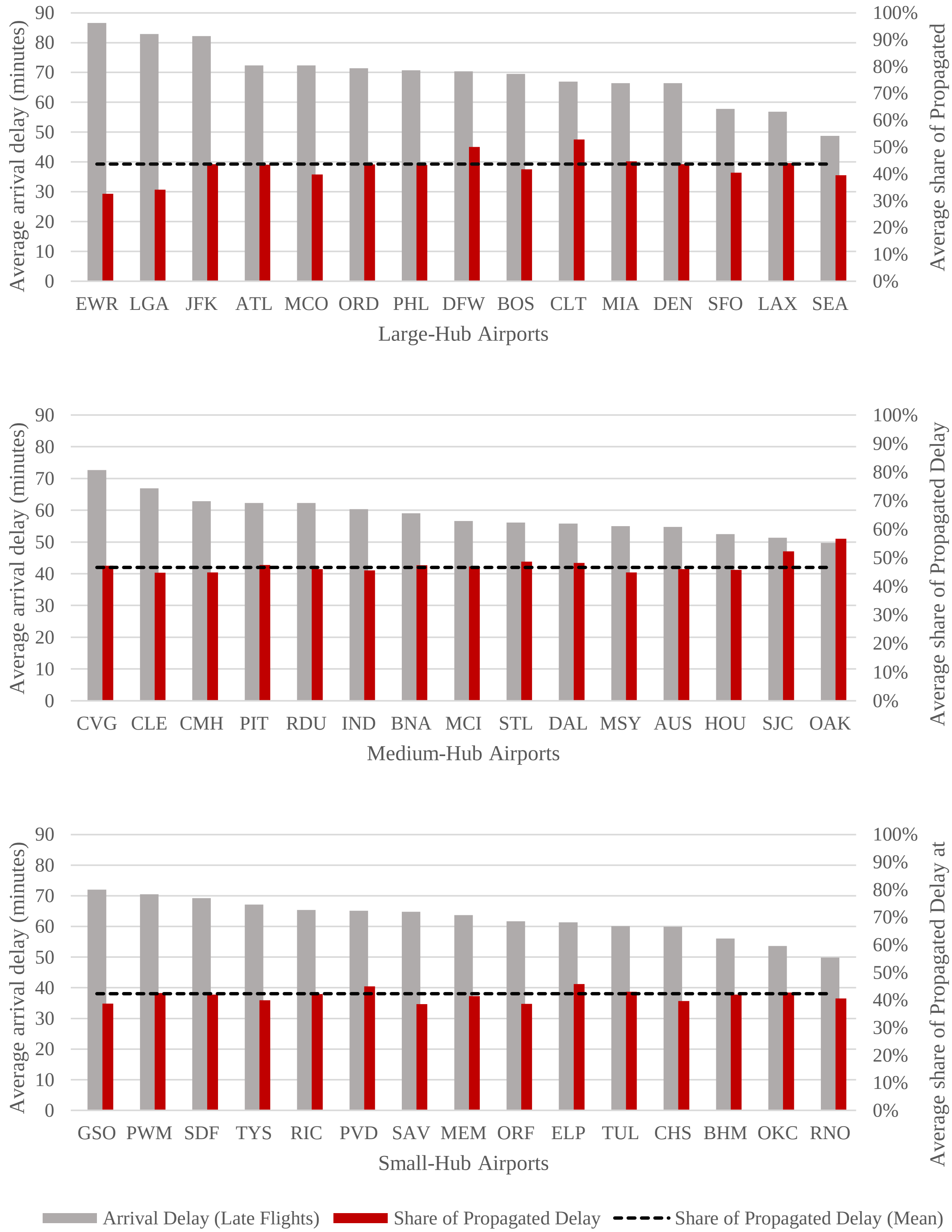

Figure 4.10: Average arrival delay and share of propagated delay for late flights

4.5.3 Causal facility

By identifying the causal facility from the data sources introduced earlier and calculating original delay, it is possible to investigate the source for arrivals delays at each facility. Figure 4.11 looks at the causal facility for flights arriving at least 15 minutes late at the top 10 U.S. Airports grouped by size and ranked by the highest number of late arrivals. The causal facility illustrated can be: 1) The arrival facility itself if the flight is late predominantly due to original delay charged to the airport; 2) Propagated delay if the delay that propagated from upstream flights is the dominant cause behind the late arrival; and 3) Air Route Traffic Control Center (ARTCC) as identified by OPSNET delay records.

It is important to note that the causal facility can be the departure airport if the dominant cause for late arrival is original delay occurring during the taxi-out or turnaround phase. Furthermore, a flight can have more than one source of delay, typically caused by both departure and arrival airports. Figure 4.11 shows that late flights arriving to a large-hub airport are typically charged to the arrival facility itself. That is, the arrival airport is the causal facility for the delay. In fact, 66.9% of the flights arriving late to Chicago O'Hare International Airport (ORD) are charged to ORD as the causal facility behind the delay while 27.3% of the flights arriving late to ORD are delayed due to propagated delay from upstream flights and 2.6% of the flights arriving late to ORD are charged to an ARTCC. The remaining late flights report a different facility/departure airport as the charged facility.

One of the main contributions of this study is to examine the on-time performance of airports through identifying delays that are truly caused by the airport. For example, out of all the flights arriving late to HOU, only 40.3% of these flights are late because of delays that can be charged to HOU. Furthermore, what is most interesting is the number of late flights arriving to a small-hub airport that are charged to an ARTCC. For example, 15.2% of the flights arriving late to Richmond International Airport (RIC) are charged to an ARTCC.

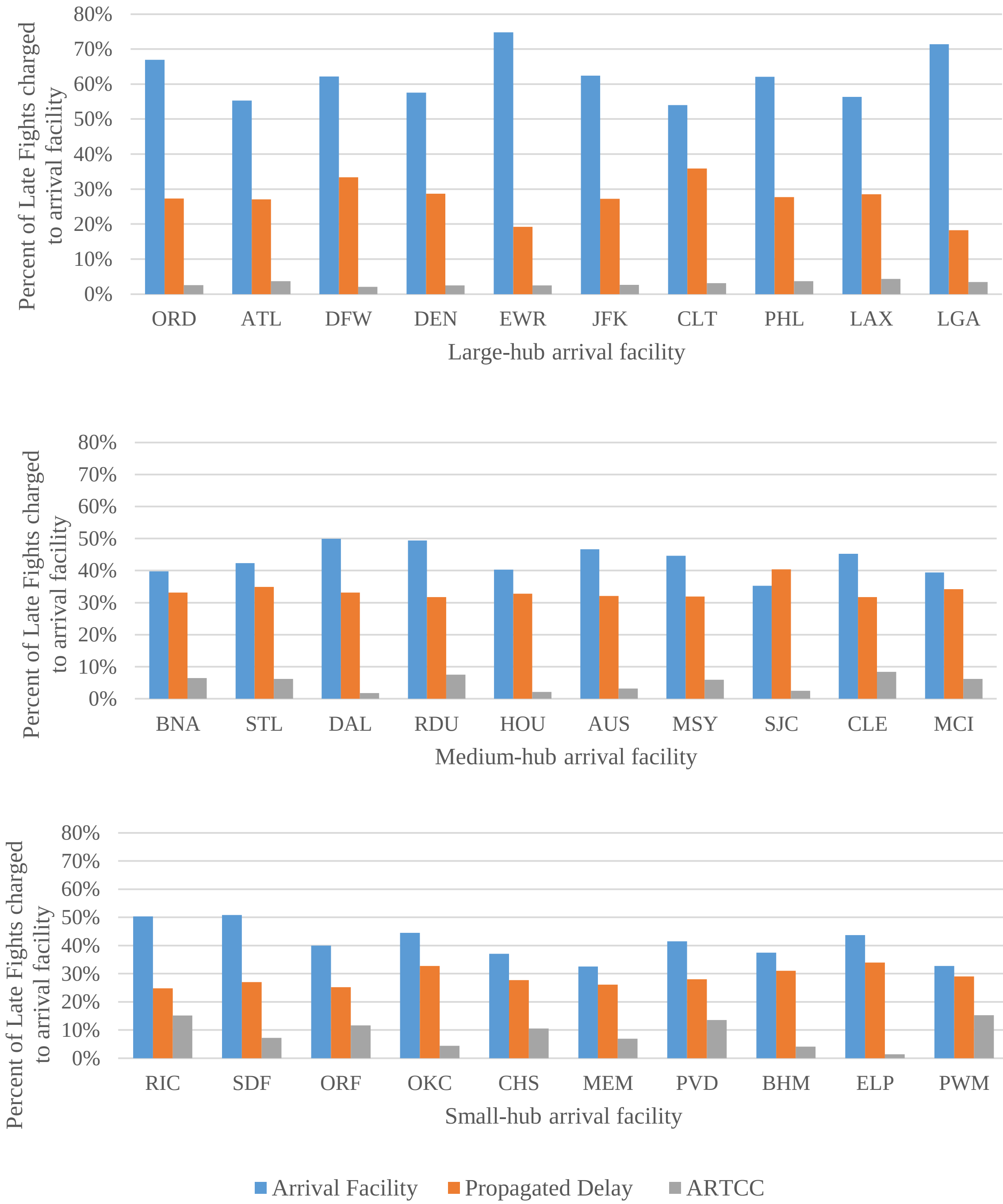

Figure 4.11: Causal Facility for late arrivals

4.5.4 Delay origin and propagation chains

This section examines the different propagation chains that initiated at a U.S. Airport and propagated to downstream flights within the same aircraft-operational day. Figure 4.12 illustrates the total number of propagation chains that originated at each airport during the month of July of 2018. It is important to note that an airport is considered as the originating facility for a propagated chain, if it is the true source for original delay that propagate to at least one flight downstream. The airports with the greatest number of propagation chains originating at their facility are: DFW, ORD, ATL, CLT and DEN. Evidently, all these airports correspond to a large-hub airport. The latter supports the early findings that suggest that large-hub airports are the main source for original delay. For example, there were 3,482 propagation chains that originated at DFW.

As for medium-hub airports, the airports with the highest number of propagation chains originating at the facility are DAL and HOU. Both airports are located within the same geographic area as large-hub airports DFW and IAH suggesting that the dominant weather region and conditions may be the leading cause for original delay that results in increased propagated delay in the system. In contrast, the number of propagation chains originating at a small- or non-hub airport is significantly lower compared to large-hub airports. While the number of small airports dispersed throughout the US is relatively high, the number of propagation chains that originate at these airports does not exceed 100 propagation chains, with the exception of small-hub airports SDF, RNO and CHS.

Once the number of propagation chains originating at each airport is identified, it is interesting to determine the number of recovery stages associated with each propagation chain, meaning the total number of downstream flight legs that are affected by propagated delay. The latter indicates how many flights were affected downstream before the system was able to recover. This can help identify whether there was not enough schedule padding to absorb propagated delay.

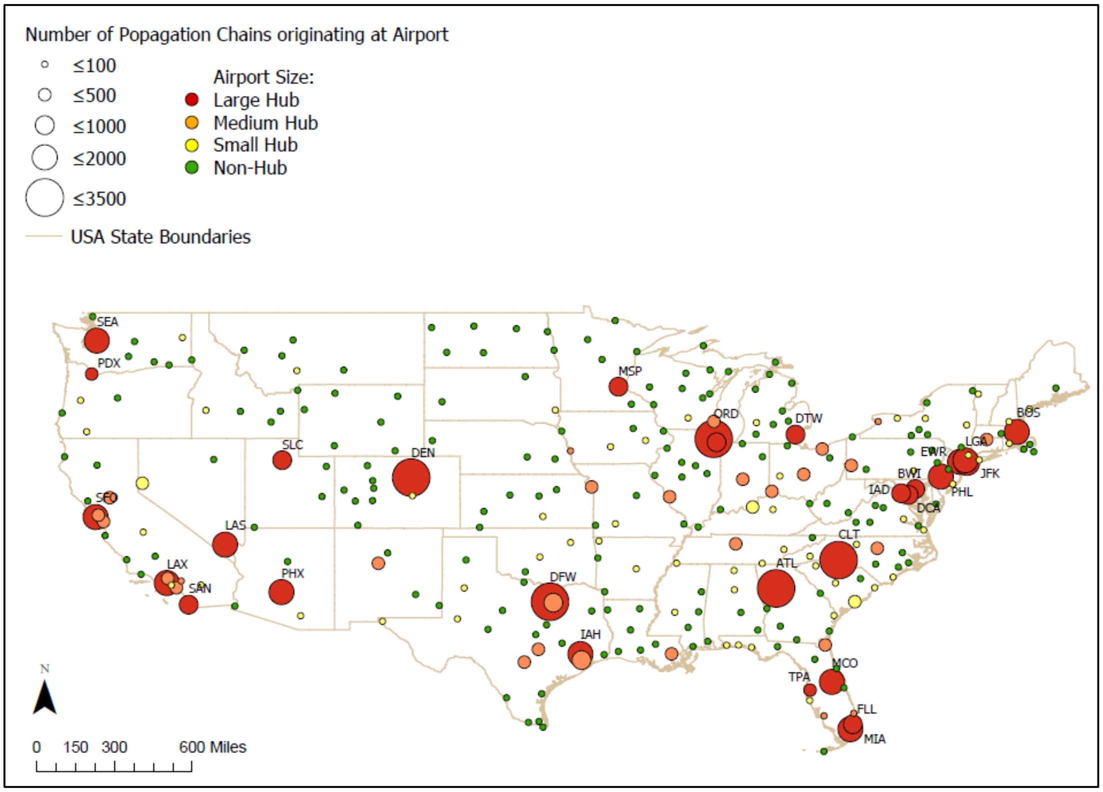

Figure 4.12: Propagated delay chains originating at each airport

Figure 4.13 shows the overall distribution of recovery stages for delay propagation chains that originate at different sized airports, where bars of the same color add up to 100%. For example, 53.3% of the delay propagation chains that originated at large-hub airports propagated to one flight downstream while 12.1% of originating delays at large-hub airports propagate to 3 flights downstream. Note that most of the propagation chains originating at large-hub airports affect a single flight downstream while delays originating at smaller airports (small- and non-hub airports) take longer to recover. Therefore, it can be suggested that although large-hub airports can be charged for most of the propagated delay in the system, those propagation chains dissipate quicker than those that originate at small airports.

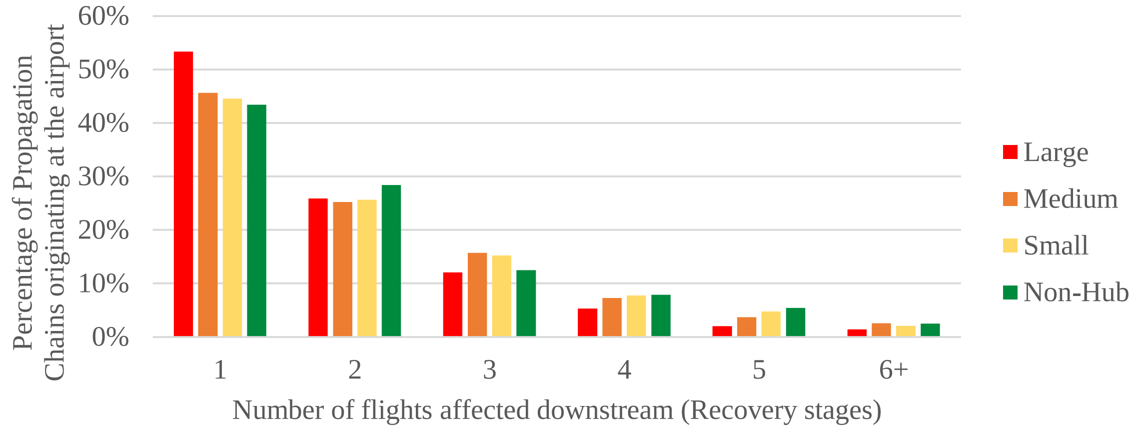

Figure 4.13: Overall recovery stages, by airport size

Each propagation delay chain in the system is initiated by an original delay that was not absorbed by either ground or flight buffer on that flight. The magnitude of total propagated arrival delay in relation to the original delay can indicate whether downstream propagated delay is absorbed by schedule buffer. The smaller the magnitude of total propagated delay in comparison to original delay, the greater the schedule padding that absorbs original delays and helps bring flights back on schedule.

It is important to note that in this study, each propagation chain is charged to the airport that initiated the delay as it can be assumed that original delay on downstream flights within the same propagation chain are caused by the initial delay. For example, if 30 minutes of original delay at ORD propagated downstream, a flight downstream may experience in addition to the 30 minutes of propagated delay, 10 minutes of delay during the taxi-in phase at STL due to gate unavailability. While STL will be counted as a new source of delay within the propagation chain, original delay at ORD will be the main causal facility behind propagated delay. The logic behind this is that had the flight have landed on-time at STL, it may have been able to taxi-in smoothly to its assigned gate without incurring any extra delay. Figures 4.14 to 4.16 illustrate the total original minutes of delay at each airport in addition to the total sum of propagated arrival delay on downstream flights for all the propagation chains that were initiated at that airport.

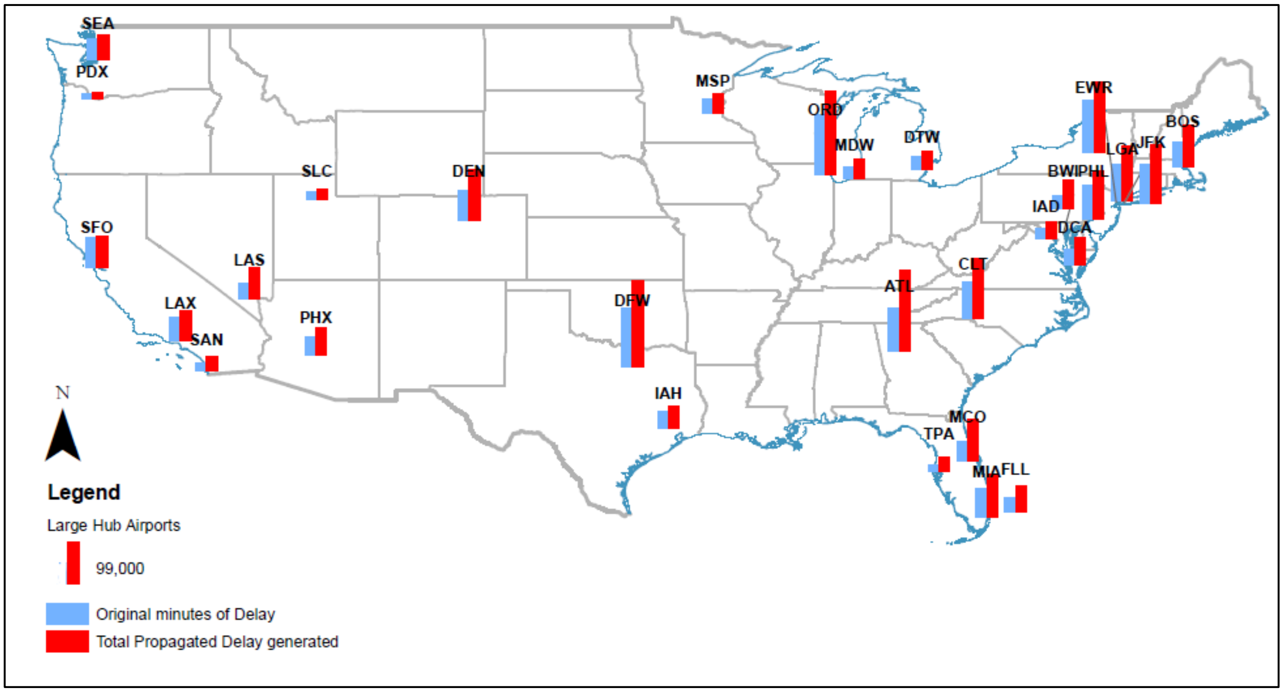

Figure 4.14: Original and Total Propagated Delay at large-hub airports

Figure 4.14 shows that while large-hub airports experience the greatest total original delays, the magnitude of total propagated delay in relation to the original delay is not as significant as that observed at smaller airports. As it was discussed earlier, propagation chains initiated at large-hub airports are mostly recovered within the first flight downstream and it is more likely that propagated delay will be partly or fully absorbed. Furthermore, Figure 4.16 shows significant propagated delay generated at some small airports such as Memphis International Airport (MEM) and Louisville International Airport (SDF). It is hypothesized that while cargo flights are not included in the analysis, delays experienced on commercial flights can be further exacerbated given the high volume of cargo operations operated at these airports. In addition, smaller regional jets are typically operated at small airports. Therefore, while original delays may start early in the day, the numerous short-haul flights operated throughout the day may contribute to larger propagated delay especially when these flights are operated in the Northeast area and subjected to convective weather, such as the case of Westchester County Airport (HPN).

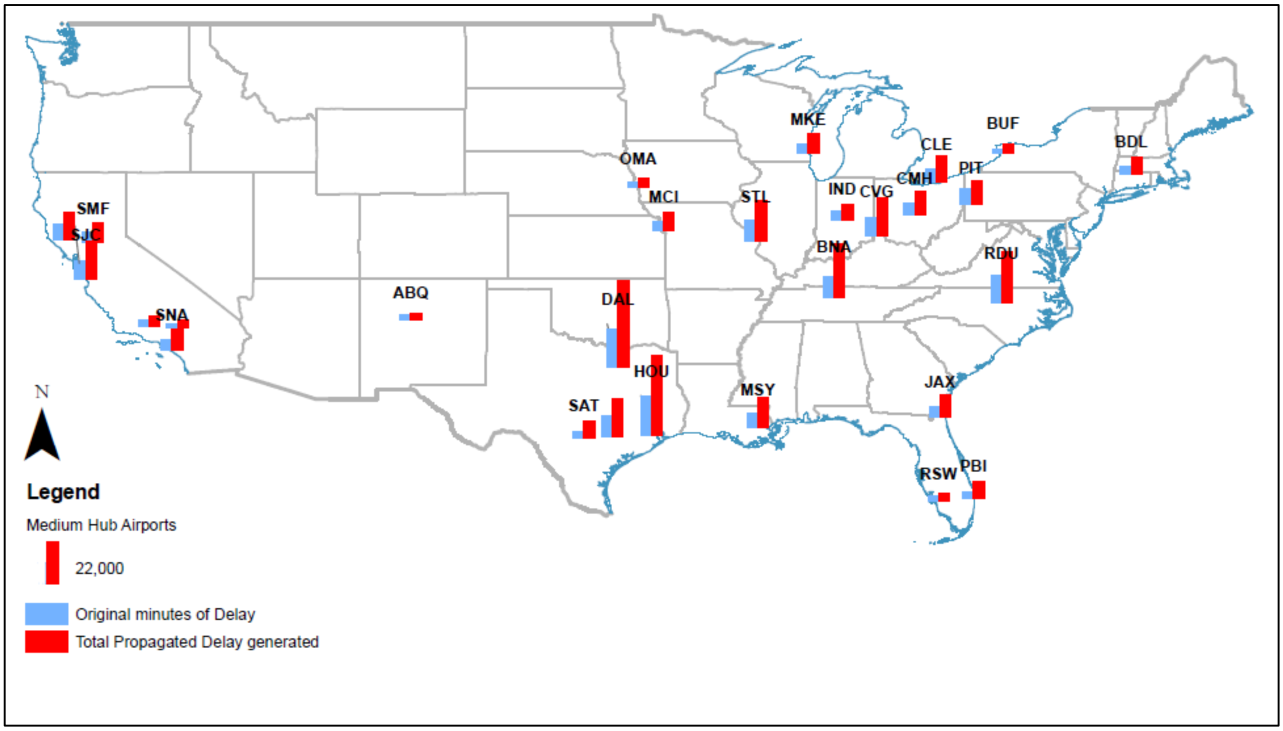

Figure 4.15: Original and Total Propagated Delay at medium-hub airports

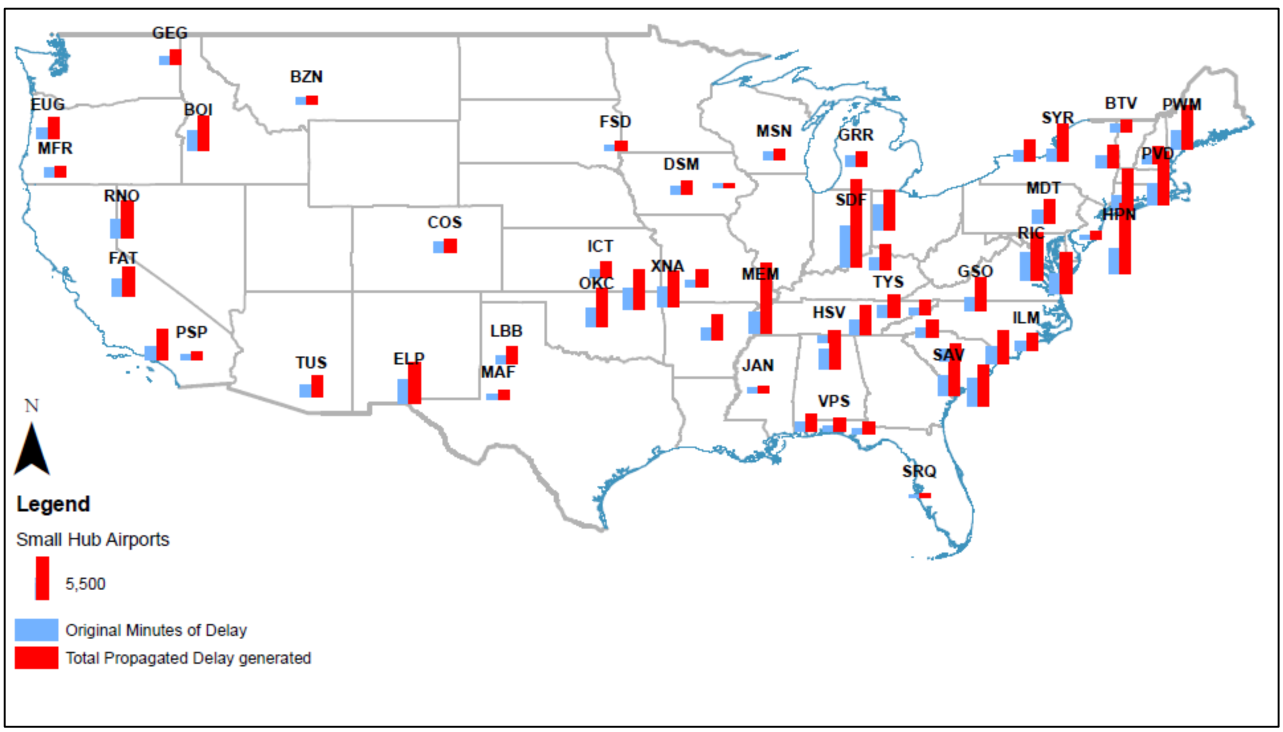

Figure 4.16: Original and Total Propagated Delay at small-hub airports

4.5.5 KPI and Total Propagated Delay

As it was mentioned in earlier sections, current practices for evaluating airports' operational performance, uses gate punctuality as the basis for on-time performance. This section extends the previously estimated measures of departure punctuality by looking into airport-specific progression of total propagated delay that originate at each airport. Figure 4.17 shows that simply assessing an airport's performance by its gate punctuality does not always reflect the true dynamics behind delays experienced at that airport.

Furthermore, measuring gate punctuality does not account for delay causality. For instance, the average flight departing from MIA and MCO experienced 21.2 minutes and 22.1 minutes of delay respectively. While these two airports report the highest average gate departure delay per flight among large-hub airports, the airports do not generate a large total propagated delay downstream compared to airports with better on-time departure performance. For example, DFW and ATL which report a much better departure delay per flight, 13.5 minutes and 12 minutes respectively, are in fact the cause behind much larger total propagated delay downstream. In fact, the total minutes of downstream propagated delay that originated at DFW is 198,537 minutes.

Similarly, evaluating Total Propagated Delay that can be counted towards each airport can drive well informed high-level decisions and management policies. For instance, if system-wide programs are looking to make performance-based investments at medium-hub airports, PBI might be considered a priority since the airport reports the worst on-time performance with an average departure delay of 20.4 minutes per flight. However, factoring in the total propagation delay that can be charged to the airport, it becomes evident that PBI is one of the best performing medium-hub airports in terms of propagated delay. Therefore, stakeholders need to also consider directing their investments towards facilities that are in fact the highest source behind propagated delay in the system. In addition, this approach can be mostly used in the context of a cost-benefit analysis in which investments at different airports are evaluated.

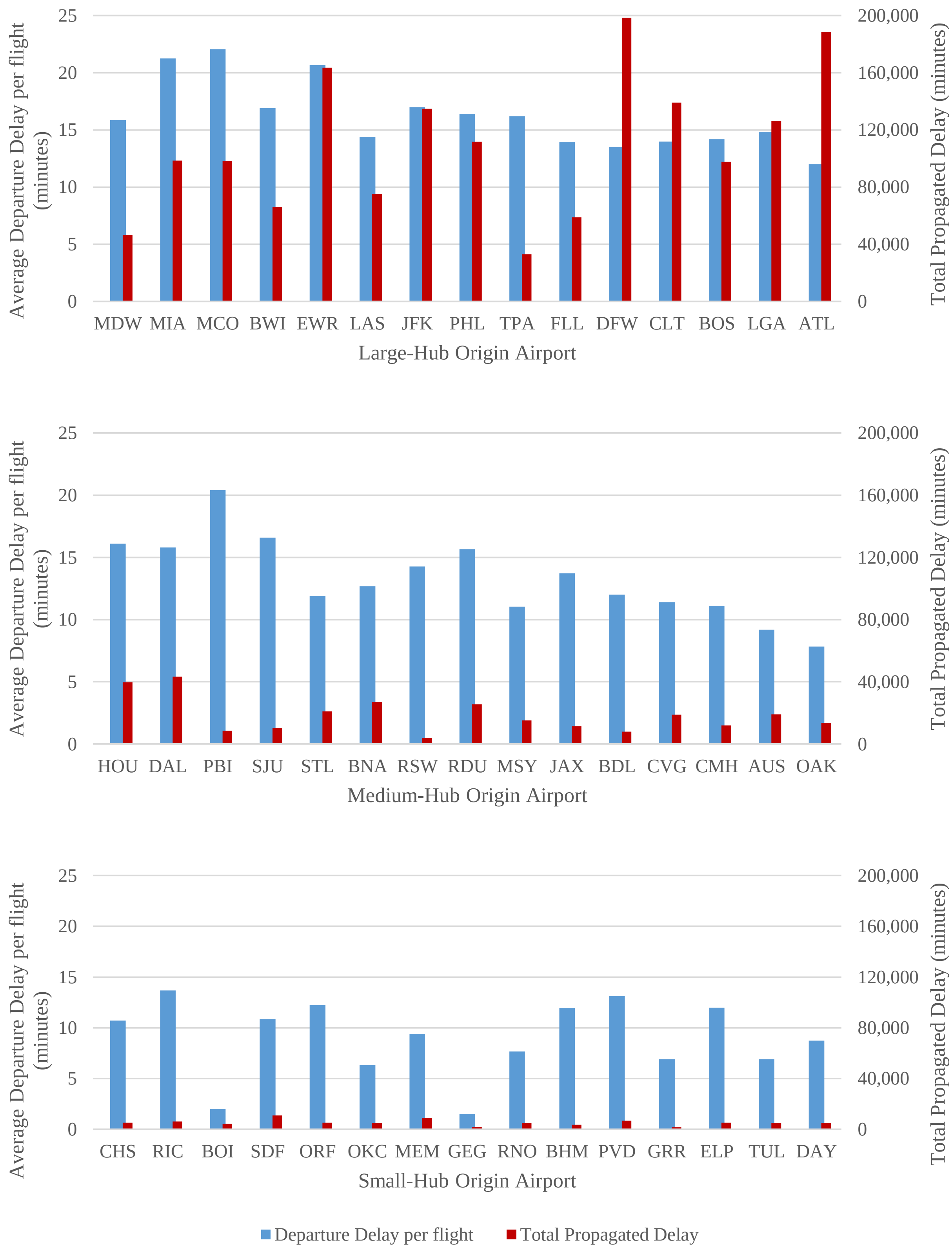

Figure 4.17: Departure Punctuality Vs Total Propagated Delay

4.6 Model Specification

This section describes the fixed effects linear regression models that predict 1) Total propagated delay and 2) Share of propagated delay, as well as the variables used in this analysis. Besides calculating original and propagated delay, the question remains how total propagated delay is absorbed downstream and what factors influence the progression of propagated delay downstream. This section introduces two fixed-effects linear regression models. The first model estimates the effect of different factors on Total Propagated Delay while the second model quantifies the effect of several variables on the ability of ground turnaround buffer to absorb propagated delay.

4.6.1 Modeling Total Propagated Delay (TPD)

The focus of this study is to evaluate how different delay characteristics can contribute to progression of delay propagation. Using a panel data of 47,260 propagation chains, each propagation chain is grouped by the weather region in which it originated. Using the classification of U.S. climate region, published by the National Oceanic and Atmospheric Administration (NOAA), airports can be grouped into 10 different weather regions depending on their geographic location (Karl and Koss, 1984). Note that airports located in Alaska and Hawaii are each grouped into their own weather region group.

Table 4.4 below summarizes the total number of propagation chains that originated in each weather region during the month of July, 2018. Using fixed-effects, each propagation chain is grouped into the weather region where it originated, i.e. each group consists of all propagation chain that initiated in a specific weather region. This grouping will help control for endogenous factors such as the effects of geographical location and weather conditions on propagated delay by using the within-group variability to determine the effect of each predictor on total propagated delay using the fixed-effects model. Specifically, the model will estimate the coefficient for each independent variable based on within-variability in each weather region while controlling for unobserved factors (omitted variables) that are correlated with the variables include in the regression and eliminate omitted variable bias (Hsiao, 2003; Wooldridge, 2013). Only the effect of time-varying variables is considered in the model since constant characteristics cannot explain in-group variability in total propagated delay (Allison, 2009).

Table 4.4: Total number of propagations chains, grouped by climate region

Weather Region	**Number of Propagation Chains**	**Percent**
Alaska	79	0.17%
Central	5,985	12.66%
East North Central	1,803	3.82%
Hawaii	112	0.24%
Northeast	8,160	17.27%
Northwest	2,199	4.65%
U.S. Territories	159	0.34%
South	6,847	14.49%
Southeast	11,208	23.72%
Southwest	3,961	8.38%
West	6,430	13.61%
West North Central	317	0.67%

Total propagated delay in each delay propagation chain is calculated as the sum of propagated arrival delay on downstream flights affected by the propagation of delay. Prior to processing the panel data, the average Total Propagated Delay was 62.1 minutes. However, some total propagated delays are too large, with a reported maximum of 1,532 minutes, which may be caused by unexpected aircraft maintenance or measurement errors. To reduce the influence of such outliers, and similar to the study conducted by Kafle and Zou (2016), observations with total propagated delay larger than the 75th percentile value plus 1.5 times the inter-quantile range are dropped from the dataset (9.6% of observations) resulting in an average total propagated delay of 36 minutes and a maximum of 174.3 minutes.

Table 4.5 shows the variables tested out in the model to estimate Total Propagated Delay. Note that the size of the airport refers to the size of the airport where the propagation delay originated. In fact, 78.8% of the 47,260 propagation delays included in the panel data originated at a large-hub airport while 13.3% originated at a medium-hub and 5.2% originated at small-hub airport. Only 2.7% of the propagation chains originated at a non-hub airport. As it was discussed in section 4.5.4, while a propagation chain can start from a single source of original delay, it is possible that throughout the propagation of the delay, facilities experience original delays that can contribute to the propagated delay. More specifically, the variable "Total sources" refers to the total number of sources of original delay within a propagation chain. As the number of recovery stages increase, there can be more sources for newly formed delay and vice versa.

The overall delay propagation multiplier follows the definition proposed by Kondo (2010) and can be calculated using equation *(11)* below. That is, the overall multiplier is the ratio of Gate Arrival Delay of the originating delayed flight to the Gate Arrival Delay of the last flight impacted by the propagated delay. For example, for 10 minutes of original delay at the arrival gate and a delay propagation multiplier of 2, the last flight affected by the propagation of this delay will arrive 20 minutes late at the arrival gate. The delay propagation multiplier helps capture the additional benefits that emerge from the reduction of original delays that initiate a ripple effect of propagated delay in the system. For a propagation chain starting at flight $\text{leg}_{(i=0)}$ and propagating to flight $\text{leg}_{(i=1,2,3,\ldots n)}$ downstream:

$$\textit{Overall Delay Propagation Multiplier} = \textit{Gate Arrival Delay}_{(i=0)} / \textit{Gate Arrival Delay}_{(i=n)} \qquad (11)$$

Table 4.5: Modeling total propagated delay - Variable definitions and descriptions

Dependent variable	
Total Propagated delay	Total sum of propagated arrival delay in each delay propagation chain, measured in minutes of total delay.
Independent variables	
Stages	Represents the number of recovery stages. i.e. the number of flights downstream affected by propagated delay
Original Delay	Newly formed delay charged to the airport that started the propagation chain, measured in minutes
Size	Size of the airport that started the propagation chain (Large-, Medium-, Small and Non-Hub). Large-hub is the reference size in the fixed-effects model
Delay Propagation Multiplier	Overall Delay Propagation Multiplier as defined by Kondo (2010)
Total Sources	Total number of sources of newly formed delay within a propagation chain
Ground Turn Buffer	Average minutes of buffer at the turnaround phase on downstream flight
Flight Buffer	Average minutes of buffer at the block phase on downstream flight
Weather Delay	Indicates whether the reported cause for the original delay is Weather related (0=No, 1=Yes)
NAS Delay	Indicates whether the reported cause for the original delay is NAS related (0=No, 1=Yes)

The correlation between the predictors was calculated using Pearson's correlation to identify the strength and significance of the linear relationship between two variables. The Durbin-Wu-Hausman test was used to identify whether the null hypothesis holds true and random effects model is appropriate by calculating the systematic difference in coefficients between a fixed-effects and a random-effects model. The test reported a p-value of 0, and a chi-square of 225.5. Therefore, the null hypothesis can be rejected indicating that the fixed-effects model is appropriate, and the individual-specific effects are correlated with the independent variables.

As described earlier, 47,260 propagation chains were grouped into 12 U.S. climate regions. 23 propagation chains dropped out because of missing information leaving 47,237 propagation chains present in the panel data remained in the model. Table 4.6 presents the estimation results from the fixed-effects linear regression. Note that the reference alternative for all the airport sizes shown below is the large-hub size and the reference alternative for 'Weather' and 'NAS' dummy variables is that the reported cause for original delay is not weather or NAS related, respectively.

Table 4.6: Modeling total propagated delay - Regression estimates

Independent Variable	Coefficient	Standard Error	t	P>|t|	95% Confidence Interval	
Stages	18.71362***	0.225	83.12	0.000	18.27233	19.1549
Original Delay	0.70918***	0.005	139.25	0.000	0.69919	0.71916
Delay Propagation Multiplier	0.18455***	0.008	22.22	0.000	0.16826	0.20083
Total Sources	2.55877***	0.159	16.06	0.000	2.24654	2.871
Ground Turn Buffer	-0.29813***	0.013	-22.34	0.000	-0.32428	-0.27198
Flight Buffer	-0.3759***	0.020	-18.94	0.000	-0.4148	-0.337
Weather Delay	11.60678***	0.468	24.79	0.000	10.68918	12.52439
NAS Delay	4.78989***	0.345	13.88	0.000	4.11326	5.46651
Constant	-24.598***	0.351	-70.10	0.000	-25.28572	-23.91015
Size						
Medium	-0.85857**	0.416	-2.06	0.039	-1.16745	-0.04262
Small	0.99236*	0.596	1.67	0.096	-0.17562	2.16033
Non-Hub	-0.76643	0.845	-0.91	0.365	-2.42354	0.89068

Notes:

1. Within R^2: 0.518; Overall R^2: 0.523
2. Included observations: 47,237; 12 weather region groups
3. Prob > F = 0.00; ρ = 0.013
4. Significance: *0.1; **0.05; ***0.01

As shown in Table 4.6, the model was built based on significant variables that contribute to a good fit of the model. Significant predictors were assessed at the 99%, 95% and 90% level of significance and the coefficient estimates generated by the fitted model show the expected positive or negative sign. For instance, the coefficient estimates of the “Ground Turn Buffer” and “Flight Buffer” variables have a negative sign since it is expected that schedule buffer will help absorb propagated delay. In fact, each minute of buffer during the turnaround phase will decrease total propagated delay by 0.3 minutes while each minute of buffer during the block phase results in total propagated delay dropping by 0.38 minutes.

The results show that the greater the number of recovery stages, the greater the minutes of total propagated delay in a propagation chain. In fact, each additional flight affected by downstream delay adds 18.7 minutes on average to the Total Propagated Arrival Delay. The model shows that the greater the original delay, the greater the total propagated delay. In fact, each additional minute of original delay results in an increase of 0.7 minutes in total propagated delay and each additional source of original delay within the propagation chain results in an additional 2.55 minutes of total propagated delay. This is consistent with the results found in Kafle and Zou (2016), the effect of original delay is greater than the effect of ground and flight buffer.

The results also look at the causal factors behind original delay. Specifically, the regression coefficients show that if the weather was the original cause for the original delay that propagated downstream, total propagated delays increase by 11.6 minutes as compared to non-weather delays. In contrast, if the National Airspace System (NAS) was the original cause for the original delay that propagated downstream, total propagated delays increase by 4.8 minutes as compared to delays not caused by the NAS. Note that other causal factors were tested out in the model but were not statistically significant.

Lastly, the regression coefficients for each airport size are made in reference to large-hub airports. Results show that a propagation chain originating at a medium-hub airport will result in 0.85 minutes less in total propagated delay compared to propagation chains originating at large-hub airports. However, total propagated delay is expected to increase by 0.99 minutes if it originated at a small-hub airport compared to a large-hub airport. This is consistent with the results shown earlier that demonstrated that propagation chains initiated at large-hub airports are mostly recovered within the first flight downstream and it is more likely that propagated delay will be partly or fully absorbed.

4.6.2 Modeling share of propagated delay

To better understand how different sized airports contribute to the progression of propagated delay, this next section proposes a model that examines the share of propagated delay on each downstream flight affected by the propagation phenomenon. The questions of interest are what factors help absorb propagated delay and how is this delay influenced by the turnaround time at different sized-airports. The independent variable in the model is defined as follows:

$$\textit{Share of Propagated Delay on flight leg } i = \frac{\textit{Propagated Delay at the Departure on flight leg } i}{\textit{Gate Arrival Delay of flight } (i\text{-}1)}$$

The share of propagated delay is calculated for each flight that is preceded by a late arrival. The purpose of this variable is to quantify the delay recovery at the turnaround phase by considering the amount of delay that propagates from an upstream late arrival to the departure of the next scheduled flight. It is important to note that all flights preceded by a late arrival are considered in this model regardless whether the delay propagated or was fully recovered. In other words, a flight may have a share of propagated delay equal to 0 if the arrival delay was fully recovered during the turnaround phase.

Since airlines tend to allocate additional buffer within their scheduled turnaround time to help absorb possible and unforeseen delays, this model uses a fixed-effects linear regression that groups flight by operating carrier. In fact, carriers employ different scheduling strategies and it is important to account for confounding factors that can influence the ability of an airport to absorb propagated delay. For instance, Southwest Airlines is known for actively reducing its turnaround time, placing the airline at a competitive advantage but at a higher risk of experiencing delays given the minimal ground buffer allocated within its schedule (Cao et al., 2019; Gilbertson, 2019; Kafle and Zou, 2016; Tierney and Kuby, 2008).

Table 4.7 shows the variables tested out in the model to estimate the share of propagated delay. Note that the size variable refers to the size of the airport where the ground turnaround is taking place. It is the size of the airport where the upstream flight arrived late and is scheduled to depart again to its next scheduled destination. The latter will show whether the size of the airport has any effect on the ability of an airport to absorb upstream delay during the turnaround phase. Similar to the first model, the “Total Sources” variable identifies the total number of sources of propagated delay on each flight. More specifically, this variable counts the total number of sources that have contributed to propagated delay on that flight leg.

The model also accounts for the causal factor behind the initial original delay that propagated downstream. The causal factors included in this model are introduced through dummy variables that test whether the original delay was due to: carrier, weather, volume, security or runway. It is important to know that other causal factors were tested out in the model but were omitted because they were not statistically significant. The number of seats available on a flight was also tested as a possible predictor in the model but after controlling for heteroscedasticity, the variable was not statistically significant.

Table 4.7: Modeling share of propagated delay - Variable definitions and descriptions

Dependent variable	
Propagated Delay share	Share of delay that propagates from an upstream late arrival to the departure of the next scheduled flight
Independent variables	
Size	Size of the airport where ground turnaround is taking place (Large-, Medium-, Small and Non-Hub). Large-hub is the reference size in the fixed-effects model
Total Sources	Total number of sources contributing to propagated delay
Weather Delay	Indicates whether the reported cause for the original delay is Weather related (0=No, 1=Yes)
Carrier Delay	Indicates whether the reported cause for the original delay is carrier related (0=No, 1=Yes)
Volume Delay	Indicates whether the reported cause for the original delay is volume related (0=No, 1=Yes)
Security Delay	Indicates whether the reported cause for the original delay is security related (0=No, 1=Yes)
Runway Delay	Indicates whether the reported cause for the original delay is runway related (0=No, 1=Yes)

It is important to note that the correlation between the predictors was calculated using Pearson's correlation to identify the strength and significance of the linear relationship between two variables. Furthermore, using Durbin-Wu-Hausman test, it can be tested whether the null hypothesis holds true and random effects model is appropriate by calculating the systematic difference in coefficients between a fixed-effects and a random-effects model. The test reported a p-value of 0, and a chi-square of 38.37. Therefore, the null hypothesis can be rejected indicating that the fixed-effects model is appropriate, and the individual-specific effects are correlated with the independent variables.

In total, 176,298 flights with upstream arrival delay were grouped into 21 groups based on the ASPM carrier operating the flight. Table 4.8 below presents the estimation results from the fixed-effects linear regression.

Table 4.8: Modeling propagated delay share - Regression estimates

Independent Variable	Coefficient	Standard Error	t	P>|t|	95% Confidence Interval	
Carrier Delay	0.13937***	0.002	57.7	0.000	0.13463	0.14410
Weather Delay	0.16656***	0.003	65.22	0.000	0.16156	0.17157
Volume Delay	0.02442***	0.008	3.1	0.002	0.00896	0.03988
Security Delay	0.03716***	0.012	2.99	0.003	0.01278	0.06154
Runway Delay	-0.05754***	0.021	-2.79	0.005	-0.09789	-0.01719
Total Sources	0.1102***	0.000	224.11	0.000	0.10924	0.11117
Constant	0.35664***	0.001	279.02	0.000	0.35414	0.35915
Size						
Medium	0.05493***	0.002	23.23	0.000	0.05029	0.05956
Small	0.10798***	0.003	36.87	0.000	0.10224	0.11371
Non-Hub	0.11009***	0.004	28.98	0.000	0.10264	0.11753

Notes:

1. Within R^2: 0.288; Overall R^2: 0.304
2. Included observations: 176,298; 21 ASPM Carrier groups
3. Prob > F = 0.00; ρ = 0.056
4. Significance: *0.1; **0.05; ***0.01

As shown in Table 4.8, the model was built based on significant variables assessed at the 99%, 95% and 90% level of significance and the coefficient estimates generated by the fitted model show the expected positive or negative sign. For instance, the greater the number of contributing sources to propagated delay, the higher the share of delay that will propagate and the lesser the ability to absorb delay. Delays that are caused by adverse weather conditions are the least to be absorbed. In fact, if the original delay reports weather as its causal factor, the share of delay that will propagate is increased by 16.7% compared to non-weather delays. The latter suggest that delay is more likely to propagate when conditions are outside the control of the airport and the airline. The lower the share of propagated delay, the greater the absorption of propagated delay during the ground turnaround phase. Carrier-related delays also increase the share of propagated delay by 13.9%. The latter could be explained by the utilization of multiple common resources on successive scheduled flights (crew, connecting passengers, etc.).

Contrary to delay that may have a system-wide effect, reportable delays caused by runway, volume or security typically affect a specific facility and not a system-wide area (unlike weather or carrier delays) which makes it easier to absorb on downstream flight. In fact, delays reporting runway as the cause for original delay result in a drop in the share of propagated delay by 0.05 (5%). Runway delays correspond to reductions in facility capacity caused by runway or taxiway closure or changes in the airport configuration.

Lastly, the regression coefficients for each airport size are made in reference to large-hub airports. Results show that large-hub airports are better able to absorb delay at the turnaround phase than small airports. The percent of delay that is likely to propagate from flight leg_i to flight $leg_{(i+1)}$ during the turnaround phase is 10.9% higher at small-hub airports compared to large-hub airports. Given the model output, the question of interest is whether airlines intentionally add more buffer at the turnaround phase at large-hub airports because they expect higher original delays which results in large-hub airports being able to absorb more delay compared to smaller airports in the system. To answer this question, the turnaround time scheduled by each carrier is calculated for different aircraft types while factoring in the size of the airport where the turnaround occurs. That is, for the same aircraft type, do carriers schedule longer turnaround at large-hub airports compared to smaller airports?

Table 4.9 reports the scheduled turnaround time for the aircraft that are mostly utilized by each of the following carriers: American, Delta, United, Southwest and Frontier. The scheduled turnaround time statistics reported are the minimum turnaround time represented by the 25th percentile, the median or 50th percentile, the 75th percentile and the overall average scheduled turnaround time for each aircraft type, operated at each airport size. Note that the results shown in

Table 4.9 below exclude flights with a scheduled ground turnaround greater than 180 minutes since these records typically correspond to aircraft parked overnight. The results tabulated below validate the hypothesis that airlines intentionally add more buffer at the turnaround phase at large-hub airports. The average scheduled ground turnaround allocated for the same aircraft is approximately between 10-20 minutes more at large-hub compared to small-hub airports. American Airlines schedule 50.8 minutes on average for their B738 fleet when turning at a small-hub airport. That same aircraft is allocated 69 minutes at the turn when operating at large-hub airport. It is important to note that for the same aircraft type (B738) Southwest Airlines scheduled significantly shorter turnaround time at large-hub airports compared to major carriers such as American and United.

Given that airlines allocate additional turnaround time at larger airports, Table 4.10 shows the net turnaround time for aircraft arriving late at the gate on the preceding flight leg. The statistics below summarize the net turnaround time for flights calculated using equation *(5)* defined in section 4.4.2. From a practical perspective, these flights have more incentive to make a quick turnaround to absorb upstream arrival delay. Negative values indicate that aircraft was able to make the turn in less time than scheduled, resulting in ground buffer, while positive values indicate that the aircraft experience additional delays at the turn.

Table 4.9: Scheduled ground turnaround statistics

Carrier	Aircraft Type	Airport Size	Scheduled Ground Turnaround (Minutes)			
			25th Percentile	50th Percentile	75th Percentile	Average
American Airlines	B738	Large	55	65	78	69.01
		Medium	46	50	58	54.37
		Small	46	50	57	50.79
		Non-Hub	50	51	53	50.86
American Airlines	A319	Large	50	60	72	64.57
		Medium	42	45	51	50.20
		Small	40	43	47	45.84
		Non-Hub	40	45	50	47.45
Delta Airlines	B712	Large	40	46	57	52.72
		Medium	35	36	43	42.48
		Small	35	35	38	36.56
		Non-Hub	35	36	40	35.73
Delta Airlines	MD88	Large	45	50	56	53.93
		Medium	40	41	43	42.07
		Small	40	40	42	41.31
		Non-Hub	40	40	42	37.10
United Airlines	B739	Large	61	68	85	76.23
		Medium	55	60	65	60.34
		Small	61	71	75	67.78
		Non-Hub	0	57	66	41.00
United Airlines	B738	Large	59	68	86	74.12
		Medium	51	57	75	65.50
		Small	55	62	75	66.91
		Non-Hub	51	51	66	49.86
Southwest Airlines	B738	Large	50	50	60	56.23
		Medium	50	50	55	53.86
		Small	45	50	50	50.55
		Non-Hub	45	45	45	44.32
Southwest Airlines	B737	Large	35	40	45	44.34
		Medium	35	35	45	40.41
		Small	30	30	35	34.22
		Non-Hub	30	30	35	32.61
Frontier Airlines	A320	Large	50	50	81	64.15
		Medium	48	50	50	53.36
		Small	45	50	50	52.79
		Non-Hub	45	45	45	44.67
Frontier Airlines	A321	Large	60	60	75	70.78
		Medium	60	60	100	75.31
		Small	59	60	60	58.71

Table 4.10: Net Turn Time statistics

Carrier	Aircraft Type	Airport Size	Net Ground Turnaround (Minutes) 25th Percentile	50th Percentile	75th Percentile	Average
American Airlines	B738	Large	-15	-6	5	-0.35
		Medium	-10	-4	1	1.00
		Small	-10	-5	0	1.26
		Non-Hub	-12	-9	-5	-8.00
American Airlines	A319	Large	-13	-5	5	0.31
		Medium	-11	-5	0	-0.81
		Small	-11	-5	1	-1.00
		Non-Hub	-10	-5	-1	17.14
Delta Airlines	B712	Large	-9	-2	6	1.72
		Medium	-6	0	7	6.45
		Small	-4	0	8	14.09
		Non-Hub	-6	-2	3	3.31
Delta Airlines	MD88	Large	-9	-2	8	-0.21
		Medium	-3	1	7	7.92
		Small	-4	0	6	7.96
		Non-Hub	-4	2	19	17.32
United Airlines	B739	Large	-17	-9	-3	-6.12
		Medium	-13	-6	0	-0.53
		Small	-15	-9	-4	-4.88
		Non-Hub	-10	-10	-10	-10.00
United Airlines	B738	Large	-17	-8	2	-2.36
		Medium	-12	-4	4	3.52
		Small	-15	-9.5	-3	-3.71
		Non-Hub	-10	-8	-2	-3.83
Southwest Airlines	B738	Large	-5	1	11	5.60
		Medium	-6	0	8	3.86
		Small	-9	-3	2	-1.76
		Non-Hub	-15	-11	0	-6.67
Southwest Airlines	B737	Large	-4	3	10	5.15
		Medium	-3	3	10	4.78
		Small	-1	4	10	6.17
		Non-Hub	-3	2	7	6.55
Frontier Airlines	A320	Large	-13	-4	7	-0.12
		Medium	-8	-1	10	4.33
		Small	-9	-3	5	2.14
		Non-Hub	1	7	14	10.89
Frontier Airlines	A321	Large	-14	-5	5	-1.90
		Medium	-15	-5	6	-1.82
		Small	-15.5	-8	-1.5	-7.44

4.7 Conclusions and Future Research Directions

Delays experienced on a flight may be caused by original delay or could be the result of a ripple effect created by upstream delays that happened earlier in the day. Delay propagation can lead to numerous costly delays downstream and impact the on-time performance of an entire flight itinerary. This study proposes a new methodology to identify original and propagated delays using combined datasets that provide detailed flight information and causal factors behind delays. In addition to calculating original and propagated delay, this study differentiates between original delays that occur during the turnaround phase, taxiing phase and en-route and incorporates causal factor information to identify the true source behind propagated delay.

In this study, two models were introduced that estimate total propagated delay and the share of propagated delay given airports' ability to absorb upstream delay at the turn. This study contributes to existing literature by providing some of the first empirical insights into how the size of an airport contributes to the progression of propagated and original delay. Results show that the majority of delay propagation chains originate at large-hub airports and are mostly concentrated at airports within the same geographical area, i.e., exposed to the same weather climate. However, delays originating at large-hub airports were found to be the quickest to recover from as most of the propagation chains originating at these larger airports are recovered within the first downstream flight.

These findings are further supported through analyzing whether larger airports can better absorb delay compared to smaller airports. By modeling the share of propagated delay, it was found that large-hub airports are more likely to absorb upstream delay at the turnaround. It is suggested that airlines tend to incorporate greater schedule buffer at the turnaround at large-hub airports which results in a more significant delay recovery at those airports compared to smaller airports. Furthermore, a larger share of upstream delay propagates to downstream flights when the original delay is caused by the operating carrier or by adverse weather conditions. Airport-related delays such as those reported as runway, volume or security are easier to be absorbed as they typically entail a single facility rather than a delay that can affect an entire system.

The models and descriptive statistics developed in this study may have significant implications for future decision making and planning. Results from this study can be used in the context of benefit-cost studies that drive investment decisions at US airports. In addition, airports that are the source of the highest total propagation minutes are identified which can potentially lead to improving critical flight scheduling through allocating necessary schedule buffers. Looking ahead, it will be interesting to understand the decisions that drive schedule buffer allocation and whether Low-Cost Carriers adopt different strategies for allocating schedule buffer compared to their major carrier counterparts.

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CHAPTER 5

Conclusions and Future Research

5.1 Major conclusions and directions for future research

This dissertation presented three separate studies. The first study analyzed air service offerings in markets served pre- and post-recession while focusing on the operational strategies adopted by the top four Low-Cost Carriers (LCCs) across various sized-airports in the United States. The second study investigated the declining service levels at small airports compared to large-hub airports that continue to benefit from higher levels of service and increased airline presence. The third and final study examined the ripple effect of delays that propagate throughout the system and can lead to numerous costly delays downstream. Each of these studies has its own conclusions and recommendations for future research, outlined in the following sections.

5.1.1 Air service analysis pre- and post-recession

This study provides an in-depth analysis of the evolving LCC operational strategies compared to their major carrier counterparts between 2005 and 2015. During the third week of July in these 11 years, contrasting strategies are evident between LCCs and majors, where LCCs have outpaced major carriers in terms of markets entered while major carriers have gained a greater flight share in the markets they serve. In general, LCCs have gravitated more towards serving large markets (i.e. Large-Large and Large-Medium), including entering markets that already have 2 or 3 competitors present. Post-recession, LCCs have shown preference to competing with major carriers over other LCC airlines.

LCCs' expansion into the nation's largest airports is possible through changes in the LCC business model. For future research, it would be interesting to look into how business models have evolved for LCCs that have been successful at gradually shifting operations from secondary to primary large airports. Another research question to be addressed is how fares have been impacted in light of the trends found in this study. Specifically, literature has acknowledged that LCC-presence decreases average market fares, as demonstrated through the "Southwest Effect" (Vowles, 2001). Given LCCs show a decreasing average flight share over time in this study, knowledge of the minimum flight frequency or flight market share needed to retain this effect would be beneficial for future consumer welfare studies.

Another interesting research direction would be to quantify the amount of new demand that LCCs stimulate when they enter into a market, as well as their passenger market share growth over the years. For instance, Windle and Dresner (1995) looked at a time series between 1991 and 1994 and found that when Southwest entered a route, the average passenger traffic increased by 300% in the fourth quarter following entry compared to a 182% increase for the other carriers. Lastly, it would be interesting to use an airport-based approach (in contrast to our market-based approach) to analyze LCC growth in the nation's airports in more recent years, possibly in terms of number of LCCs, flight frequency, and seating capacity share. For example, Abda et al. (2012) uses an airport-based approach using Origin and Destination Traffic Survey (DB1B) data for years between 1990 and 2008 and finds that as growth opportunities at the largest airports (top 50 airports) dwindled, LCCs started to shift to second, third and fourth tier airports. Abda et al. (2012) also projected that the unconstrained growth of LCCs at the top 200 U.S. airports may soon be ending. It would be interesting to update this study to take a look at airport trends in more recent years.

5.1.2 Air service loss at small communities

Understanding the factors that may play a role in a market's service loss is important because it will enable airport managers as well as the communities in small airport regions to better recognize the dynamics behind their potential loss of direct service to another region. This study identified significant factors that contribute to a market's loss or gain of service. While many studies in the literature recognized small communities as the main target to service cuts and reduced service quality, the model built in this research emphasizes the loss in service over the years. Results demonstrate that markets served only by Allegiant have a greater chance of losing service. Although

Allegiant's operating strategies can lead to increased chances of service loss to a market, it is important to note that markets with Allegiant as the sole providing carrier would otherwise not have service in the first place. Furthermore, this study identified merger activity and usage of equipment types (e.g. small regional jets) with high fuel consumption as factors contributing to service loss. While having an additional non-stop flight may slightly increase the chances of having service in a market, an important finding reiterates the importance of having multiple marketing carriers offering service in the region-pair market. Perhaps the most important finding is that, in this particular study, none of the variables related to the departure (small airport) region were significant. Increases in the population base, per capita personal income or air service accessibility of small regions may have not been large enough to drive an increase in the odds of having service in these markets. Another possible explanation for this result is the closely fitted distribution and low variation among each of these variables over the years.

In terms of policy implications for this study, it was found that airport managers in small airport communities have little or no control as most of the factors that determine whether a market will continue to have service is determined by the characteristics of the market or the destination community (i.e. the small-, medium-, or large-airport community). Also, this study indicates that air service for small-airport communities will continue to be an issue as the high operating costs of the small equipment types operating the markets serving these communities increases the chances of market service loss. From a practical perspective, these findings suggest that if service is to be maintained in many of these small communities, then additional incentives would be needed, similar to the EAS program. These incentives could encourage carriers to provide service to small communities and to airports affected by a merger. Therefore, it is important for the government to intervene with programs that promote small airport community access to the air transportation system through allocating funds and grants in order to retain service.

5.1.3 Modeling propagated delay and airport size contribution

Delays experienced on a flight may be caused by original delay or could be the result of a ripple effect created by upstream delays that happened earlier in the day. Delay propagation can lead to numerous costly delays downstream and impact the on-time performance of an entire flight itinerary. This study proposes a new methodology to identify original delay and propagated delays using combined datasets that provide detailed flight information and causal factors behind delays. In addition to calculating original and propagated delay, this study differentiates between original delays that occur during the turnaround phase, taxiing phase and en-route and incorporates causal factor information to identify the true source behind propagated delay.

In this study, two models were introduced that estimate total propagated delay and the share if propagated delay given airports' ability to absorb upstream delay at the turn. This study contributes to existing literature by providing some of the first empirical insights into how the size of an airport contributes to the progression of propagated and newly formed delay. Results show that the majority of delay propagation chains originate at large-hub airports and are mostly concentrated at airports within the same geographical area, i.e., exposed to the same weather climate. However, delays originating at large-hub airports were found to be the quickest to recover from as most of the propagation chains originating at these larger airports are recovered within the first downstream flight.

These findings are further supported through analyzing whether larger airports can better absorb delay compared to smaller airports. By modeling the share of propagated delay, it was found that large-hub airports are more likely to absorb upstream delay at the turnaround. It is suggested that airlines tend to incorporate greater schedule buffer at the turnaround at large-hub airports which results in a more significant delay recovery at those airports compared to smaller airports. Furthermore, a larger share of upstream delay propagates to downstream flights when the original delay is caused by the operating carrier or by adverse weather conditions. In contrast, airport-related delays such as those reported as runway, volume or security are easier to be absorbed as they typically entail a single facility rather than a delay that can affect an entire system.

The models and descriptive statistics developed in this study may have significant implications for future decision making and planning. Results from this study can be used in the context of benefit-cost studies that drive investment decisions at US airports. In addition, air airports with the highest source of propagation chains are identified which can potentially lead to improving critical flight scheduling through allocating necessary schedule buffers. Looking ahead, it will be interesting to understand the decisions that drive schedule buffer allocation and whether LCCs adopt different strategies for allocating schedule buffer compared to their major carrier counterparts.

5.2 Concluding thoughts

As the airline industry continues to evolve with fluctuating service levels and operational performance across airports in addition to changing dynamics among airlines, this dissertation takes advantage of available aviation datasets to draw conclusions surrounding the effect of airport size on the overall system's performance. The findings suggest that as more carriers shift their operations to the nation's largest airports, small airports will continue to experience significant service reductions. Furthermore, while large-hub airports are behind most original delays in the air transportation network, airlines are allocating higher buffers within their schedules at those airports to absorb propagated delay.

These studies overcome the data limitations of previous studies as they offer a more exhaustive understanding of the effect of airport size by looking at data from multiple sources during more recent time periods. In addition, this study refines existing performance measures that can potentially drive investment decisions and implementation of system-wide program as well as airport management policies. Furthermore, results suggest that airlines, including Low-Cost Carriers, may find beneficial to re-configure their network in a way that de-emphasizes highly congested airports that are behind high volume of downstream propagated delay.