LONG-DISTANCE AIRPORT CHOICES, AND THEIR IMPLICATIONS FOR AVIATION EMISSIONS AND PRICE-BASED ENVIRONMENTAL POLICIES

by

Kaleab Woldeyohannes Yirgu

B.Sc., Addis Ababa University, 2014
M.Sc., Addis Ababa University, 2017

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
in
THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Civil Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA
(Vancouver)
July 2023

© Kaleab Woldeyohannes Yirgu, 2023
The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

Long-Distance Airport Choices, and their Implications for Aviation Emissions and Price-Based Environmental Policies

submitted by  Kaleab Woldeyohannes Yirgu  in partial fulfillment of the requirements for

the degree of  Doctor of Philosophy

in  Civil Engineering

Examining Committee:

Amy M. Kim, Associate Professor, Department of Civil Engineering, UBC  
Supervisor

Alex Bigazzi, Associate Professor, Department of Civil Engineering, UBC  
Supervisory Committee Member

Omar Swei, Assistant Professor, Department of Civil Engineering, UBC  
Supervisory Committee Member

Tarek Sayed, Professor, Department of Civil Engineering, UBC  
University Examiner

Amanda Giang, Assistant Professor, Department of Mechanical Engineering, UBC  
University Examiner
Abstract

Airports are often assumed to have static predetermined catchment areas, based on administrative boundaries or geographic measures, from which they draw air passenger demands. This has been shown, over decades of study, to be an oversimplification, particularly across large geographic regions where long-distance air passenger “leakage” to larger hub airports is of concern to the smaller local airports losing these passengers. In order to broadly understand the drivers of these airport choices, and the resulting potential implications on emissions and price-based environmental policies, it is important to study air passengers and airports over large areas spanning multiple administrative boundaries, which has had little attention due to data limitations.

First, using a dataset of air ticket purchases made by domestic air passengers in a large section of the U.S Midwest, this thesis proposes a utility-based choice model framework to understand the transportation service-based factors observed to influence airport choice probabilities, and thus airport market shares. Spatial plots resulting from these probabilities reveal that market areas and shares increase as airport size (and thus, services) increases. The market areas of small airports diminish towards the direction of surrounding airports whereas those of large airports cross strongly into multiple jurisdictional boundaries in all directions.

Next, the environmental implications of passengers’ choices for different airports are assessed by estimating average and marginal emission factors on alternative routes using Modified Breguet Range equations, and determining the relationship between aviation emissions and price-based environmental policies through a supply-and-demand relationship analysis. Findings show emissions factors could be 18% up to 105% higher when passengers choose small or medium airports over large hubs to travel to the same destination. Additionally, emissions on routes from all the aforementioned airport types are inelastic to price.

This thesis provides further evidence for the need to coordinate both air and ground transportation planning across jurisdictions and with airport authorities, given the implications for airports, air services and air travel, and environmental considerations. It also shows that price-based environmental policies, although critical for supporting various environmental protection initiatives, have no measurable effectiveness on directly reducing emissions from flying.
Lay Summary

Different airports offer different flight options, and as a result are not equally preferred by travelers flying to different destinations. Often, air travelers bypass their nearest airport, driving up to hundreds of kilometers to larger airports with more attractive flight options. Based on the departure airport they choose for their journey, these travelers’ contributions to aviation emissions also vary.

To investigate the abovementioned airport preferences and resulting emissions implications, this work uses air tickets of passengers from a large section of the US Midwest containing several airports. Results show passengers prioritize cheaper airfares over flight schedules and nonstop flight options in choosing airports. Also, choosing small airports over large ones to travel to the same destination could double pollutants emitted at the passenger level. Finally, the effectiveness of environmental policies, which aim to reduce emissions through increased air ticket prices, are investigated and found to be negligible.
Preface

This thesis is an original work by Kaleab Woldeyohannes Yirgu under the academic supervision of Dr. Amy M. Kim. Some parts of this thesis work have been published and presented while others are under preparation for journal submission.

An earlier version of the work of Chapter 4 has been published. Yirgu, Kaleab Woldeyohannes, Amy M. Kim, and Megan S. Ryerson. 2021. “Long-Distance Airport Substitution and Air Market Leakage: Empirical Investigations in the US Midwest.” Transportation Research Record: Journal of the Transportation Research Board 2675 (10): 148–60. https://doi.org/10.1177/03611981211010797. I carried out data curation, analysis and modelling, and developed the original manuscript draft. Draft editing was conducted by Amy M. Kim and Megan S. Ryerson.


The current version of Chapter 4 is under journal review, and was also presented at the standing committee meeting of AV020 Aviation System Planning. Yirgu, Kaleab Woldeyohannes. 2023. “Airport Choices across Multiple Administrative Boundaries and their Planning Implications.” In 102nd Annual Meeting of the Transportation Research Board. Washington, DC.


Chapter 6 is currently under journal review.
# Table of Contents

Abstract........................................................................................................................ iii

Lay Summary ................................................................................................................ iv

Preface........................................................................................................................... v

Table of Contents ........................................................................................................ vi

List of Tables ................................................................................................................ ix

List of Figures ............................................................................................................... x

List of Abbreviations .................................................................................................... xiii

Acknowledgements ..................................................................................................... xv

Dedication ...................................................................................................................... xvi

Chapter 1: Introduction .............................................................................................. 1

  1.1 Background and Motivation .............................................................................. 1

  1.2 Research Objectives ....................................................................................... 3

  1.3 Terminology .................................................................................................... 3

  1.4 Thesis Organization ........................................................................................ 4

Chapter 2: Background and Literature Review ......................................................... 7

  2.1 Aviation Supply and Demand ........................................................................... 8

  2.1.1 Drivers of Air Service Disparities ............................................................... 10

  2.1.2 Passenger Airport Choices and Long-distance “Leakage” ......................... 11

  2.1.3 Airport Passenger Catchment Areas ......................................................... 14

  2.1.4 Air Passenger Data Collection Approaches ............................................. 15

  2.2 Airport Choices, Environmental Impacts and Policies .................................... 17

  2.3 Aviation Fuel Burn and Emissions Estimation ............................................... 18

  2.4 Identified Research Gaps ................................................................................. 19

Chapter 3: Research Context and Data .................................................................. 21

  3.1 Research Setting ............................................................................................... 21

  3.2 Data and Sources ............................................................................................. 22

  3.2.1 Passenger Air Tickets .............................................................................. 24

  3.2.2 Air Service Attributes and Capacity Variables ......................................... 30

  3.2.3 Aviation Fuel Consumption and Pollutant Emissions .............................. 31
List of Tables

Table 2.1 Data Collection Methods ................................................................. 16

Table 3.1 Data and Sources ........................................................................... 23

Table 3.2 Tickets and Passengers Reported on Tickets .................................... 28

Table 3.3 Population and Unemployment Summary Statistics .......................... 52

Table 4.1 MMNL Model Estimates .................................................................. 61

Table 4.2 MMNL Model Estimates without Route-based Categories .................. 69

Table 5.1 LTO Phase Fuel and Emissions Model Estimates ............................... 85

Table 5.2 CCD Phase Fuel and Emissions Model Estimates .............................. 86

Table 5.3 Elasticity of Fuel/Emission $x$ to $LF \left( \pi_{n,x}^{LF} \right)$ Based on Nonstop Flight Segments’ Origin Airport Groups ................................................................. 90

Table 6.1 Summary Statistics of the 2SLS Model Input Variables, by Quarter .......... 108

Table 6.2 2SLS Supply-and-Demand Model Estimation Results (standard errors are shown after estimates, in brackets) ................................................................. 110
List of Figures

Figure 1.1 Thesis organization................................................................. 5
Figure 2.1 Literature topics covered and connections to thesis objectives ................. 7
Figure 2.2 Supply-and-demand relationship.................................................. 8
Figure 3.1 US Midwest................................................................................. 21
Figure 3.2 Specific area defined by collection of ZIP codes ..................................... 22
Figure 3.3 Airports defining the study area ..................................................... 26
Figure 3.4 ZIP codes captured and passengers captured on sampled tickets per airport, Dubuque (DBQ, top left), Dane County Regional (MSN, top right), Indianapolis International (IND, bottom left) and Chicago O’Hare International (ORD, bottom right) ........................................... 29
Figure 3.5 All ZIP codes by passengers captured on the sampled tickets ................... 30
Figure 3.6 Airports within and close to the study area for which passenger air tickets are unavailable ................................................................. 34
Figure 3.7 Final study area and airports.......................................................... 35
Figure 3.8 Passengers in the Market Locator dataset (after data processing) as a percentage of total annual enplanement, by departure airport ......................................................... 37
Figure 3.9 “Leaking” passengers attracted and median additional miles traveled (per airport, 2013 - 2018) .............................................................................................................. 38
Figure 3.10 Proportion of passengers in air ticket dataset bypassing their nearest airport ....... 39
Figure 3.11 Air service attributes by airport ....................................................... 41
Figure 3.12 Mean aircraft size (number of seats) by airport category .......................... 42
Figure 3.13 Mean LF by airport category ........................................................... 43
Figure 3.14 Mean nonstop distance flown by airport category .................................................. 44
Figure 3.15 Mean weight per seat by airport category .............................................................. 45
Figure 3.16 LTO phase aviation fuel, CO₂, H₂O and NOₓ .......................................................... 47
Figure 3.17 LTO phase CO, HC, SOₓ and PM₂₅ ........................................................................ 48
Figure 3.18 CCD phase aviation fuel, CO₂, H₂O and NOₓ .......................................................... 50
Figure 3.19 CCD phase CO, HC, SOₓ and PM₂₅ ........................................................................ 51
Figure 3.20 Jet fuel price ............................................................................................................ 53
Figure 4.1 Estimated parameter distributions for flight frequency (left) and nonstop service (right) .................................................................................................................. 63
Figure 4.2 Estimated parameter distributions for airport access distance (left) and airfare (right) ....................................................................................................................... 65
Figure 4.3 Mean air service attributes representing hypothetical destinations per departure airport .................................................................................................................. 67
Figure 4.4 Market areas and shares of MSN (left) and MKE (right) .............................................. 70
Figure 4.5 ORD market area and shares ..................................................................................... 71
Figure 4.6 Changes in airfare and resulting market changes, MSN (mean airfare = 287 USD) .. 74
Figure 4.7 Changes in airfare and resulting market changes, MKE (mean airfare = 264 USD).. 75
Figure 4.8 Changes in airfare and resulting market changes, ORD (mean airfare = 280 USD)... 76
Figure 4.9 Market share reduction (%) at MKE caused by proportional increases in airfare (left) and decreases in flight frequency (right) .................................................................................. 78
Figure 5.1 An air passenger’s routing options through three airports ......................................... 80
Figure 5.2 Chapter overview ........................................................................................................... 81

Figure 5.3 Study routes for the AEF and MEF analysis ................................................................. 83

Figure 5.4 AEF and MEF estimates for aviation fuel, CO_2 and H_2O. “AEF-S” refers to the AEF for a small airport, “AEF-M” for medium, and “AEF-L” for large ........................................... 91

Figure 5.5 AEF and MEF estimates for NO_x, SO_x, CO, HC and PM_2.5 ...................................... 91

Figure 5.6 AEFs and MEFs of small and medium airports, as a percent increase against those of large airports .................................................................................................................... 93

Figure 6.1 Relationship among airfare, demand, capacity and emissions .................................. 98

Figure 6.2 Airfare elasticities of jet fuel, GHGs and other pollutants on routes from MSN and ORD, averaged by quarter ........................................................................................................ 114

Figure 6.3 Histogram of airfare elasticities of fuel and some pollutants ............................... 116

Figure 7.1 Thesis objectives and central outcome (taken from Figure 1.1) ............................ 119
List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AEF</td>
<td>Average emission factor</td>
</tr>
<tr>
<td>AKT</td>
<td>Aircraft-kilometer traveled</td>
</tr>
<tr>
<td>ARC</td>
<td>Airlines Reporting Corporation</td>
</tr>
<tr>
<td>ASC</td>
<td>Alternative specific constant</td>
</tr>
<tr>
<td>AOW</td>
<td>Aircraft operating weight</td>
</tr>
<tr>
<td>BADA</td>
<td>Base of Aircraft Data</td>
</tr>
<tr>
<td>BTS</td>
<td>Bureau of Transportation Statistics</td>
</tr>
<tr>
<td>CCD</td>
<td>Climb-cruise-descent</td>
</tr>
<tr>
<td>CV</td>
<td>Coefficient of variation</td>
</tr>
<tr>
<td>DOT</td>
<td>Department of Transportation</td>
</tr>
<tr>
<td>DWH</td>
<td>Durbin-Wu-Hausman</td>
</tr>
<tr>
<td>EAS</td>
<td>Essential Air Service</td>
</tr>
<tr>
<td>EEA</td>
<td>European Environment Agency</td>
</tr>
<tr>
<td>EMEP</td>
<td>European Monitoring and Evaluation Program</td>
</tr>
<tr>
<td>FAA</td>
<td>Federal Aviation Administration</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse gas</td>
</tr>
<tr>
<td>HHI</td>
<td>Herfindahl-Hirschman Index</td>
</tr>
<tr>
<td>IATA</td>
<td>International Air Transport Association</td>
</tr>
<tr>
<td>ICAO</td>
<td>International Civil Aviation Organization</td>
</tr>
<tr>
<td>IV</td>
<td>Instrumental variable</td>
</tr>
<tr>
<td>LCC</td>
<td>Low-cost carrier</td>
</tr>
<tr>
<td>LF</td>
<td>(Aircraft) load factor</td>
</tr>
<tr>
<td>LTO</td>
<td>Landing-takeoff</td>
</tr>
<tr>
<td>MAR</td>
<td>Multi-airport region</td>
</tr>
<tr>
<td>MAS</td>
<td>Multi-airport system</td>
</tr>
<tr>
<td>MEF</td>
<td>Marginal emission factor</td>
</tr>
<tr>
<td>MES</td>
<td>Minimum eigenvalue statistic</td>
</tr>
<tr>
<td>mi</td>
<td>Mile</td>
</tr>
<tr>
<td>MMNL</td>
<td>Mixed logit</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>MNL</td>
<td>Multinomial logit</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean square error</td>
</tr>
<tr>
<td>NL</td>
<td>Nested logit</td>
</tr>
<tr>
<td>nm</td>
<td>Nautical mile</td>
</tr>
<tr>
<td>OEW</td>
<td>Operating empty weight</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary least squares</td>
</tr>
<tr>
<td>PKT</td>
<td>Passenger-kilometer traveled</td>
</tr>
<tr>
<td>SAF</td>
<td>Sustainable aviation fuel</td>
</tr>
<tr>
<td>SLL</td>
<td>Simulated log-likelihood</td>
</tr>
<tr>
<td>USD</td>
<td>United States Dollar</td>
</tr>
<tr>
<td>VIF</td>
<td>Variance inflation factor</td>
</tr>
<tr>
<td>2SLS</td>
<td>Two-stage least squares</td>
</tr>
<tr>
<td>3SLS</td>
<td>Three-stage least squares</td>
</tr>
</tbody>
</table>
Acknowledgements

God is good all the time and His light will shine through the darkest night. Looking back at the last four years, I feel incredibly lucky and blessed, particularly for the memories and friends I made and the priceless life lessons I learned.

Amy, not only have you been an amazing mentor, but also a true friend who unwaveringly had my back. You taught me what good research embodies – diligence and patience. Your creativity, candidness, understanding and exceptional generosity of time are admirable. Most of all, thank you for giving me this once-in-a-lifetime opportunity to earn a PhD.

Thank you Prof. Tae J. Kwon, Prof. Karim El-Basyouny, Prof. Tony Qiu, Prof. Alex Bigazzi, Prof. Omar Swei, Prof. Emily Grise, Prof. Jeff Boisvert, Prof. Jeffrey LaMondia, and Prof. Megan Ryerson for contributing to my academic journey through your classes and critical feedbacks on my research. I also owe Natural Sciences and Engineering Research Council of Canada, The University of Alberta, Edmonton Community Foundation and The University of British Columbia deep gratitude for supporting my studies through various forms.

Shout out to my friends and colleagues Sabrena Jahan Ohi, Bryan Tran, Kevin Li, Andy Wong, Mingjian Wu, Andres Rosales, Mohammed Ahmed, Laura Cabral, Naomi Li, Can Zhang, Vivienne Li, Javad Lessan, Moein Sadeghi, Mujeeb Rahman, Thomas Stringer and Spencer Lum for making grad life less painful.

To my parents who sacrificed so much to ensure I get a fair shot at life, thank you for all you have done and for keeping me in your prayers. I am forever grateful for your guidance. Mom, though you are no longer around, you will live in my heart. To my sister Ruth, you are the personification of courage, and your journey in life has immensely inspired me to keep going. Last but not least, to my caring wife Yeloultsidk, thank you for your unconditional love and support.
To my dad and late mom
Chapter 1: Introduction

1.1 Background and Motivation

Airports have often been assumed to have geographic catchment areas from which they attract air passengers. These catchments are commonly demarcated by existing administrative boundaries, predetermined airport access times and distances, and – in the simplest form – circles of various radii around airports (Frohlich and Niemeier, 2011; Marcucci and Gatta, 2011; Suau-Sanchez, Burghouwt and Pallares-Barbera, 2014; Zhou et al., 2018; Gao, 2020; Milwaukee Mitchell Airport, 2020; Teixeira and Derudder, 2021). However, decades of study have shown that air passengers from the presumed catchment of one airport cross catchment boundaries to travel up to hundreds of kilometers to depart from a larger airport offering more attractive air services, usually in the form of cheaper, more frequent nonstop flights (Kanafani and Abbas, 1987; Kaemmerle, 1991; Zhang and Xie, 2005; de Luca, 2012). This phenomenon has been termed interregional passenger “leakage,” mainly within the North American context (Suzuki, Crum and Audino, 2003).

Data-driven studies of interregional passenger leakage have typically relied on passenger surveys collected at targeted locations, or sampled passengers within the region(s) from which passengers are hypothesized to “leak.” This means that surveys and subsequent study results are often limited in geographic scope, and do not (and are not meant to) capture passenger airport choices and “leakage” across large areas spanning multiple cities, and regional and state boundaries (Ashford and Benchemam, 1987; de Neufville et al., 2013). Sampling and surveying passengers over such large areas is challenging if not nearly impossible due to limited collaboration among regional and metropolitan planning organizations (MPOs) that have jurisdictions over these areas (Oden and Sciara, 2020; Rahman, Sciara and Ryerson, 2021).

However, the exploration of air passengers’ airport choices over large geographies, and across the different types of airports within these geographies available to passengers, can yield important insights. Disparities in air services between small and large airports have grown significantly over the last two decades. Some of the factors driving these growing disparities include the rise of low-cost carriers (LCCs) (Spitz et al., 2015), airline mergers and hub reorganizations (Ryerson and
Kim, 2014), financial crises and economic unevenness (Fuellhart et al., 2016), disruptive events (US Department of Transportation, 2002), and a global pandemic (Gao, 2022). These factors disproportionately affect air services at small and medium airports, compared to those at large airports (General Accounting Office, 2014). The disparities in air services are further exacerbated by, and lead to, air passengers from small communities bypassing their local airports to drive considerable distances to larger hubs (Atallah and Hotle, 2019). Better understanding the drivers of these choices, specifically focusing on air service characteristics and differences between services at neighboring airports, can help small airports in their planning and marketing efforts, and the federal government in making decisions within the Essential Air Services (EAS) program as the Coronavirus Aid, Relief, and Economic Security (CARES) Airport Program ends (FAA, 2020).

Air passengers’ perceptions of air service disparities and resulting airport choices also have implications for the design and application of climate mitigation behavior initiatives and price-based environmental policy tools that aim to reduce the emissions burden of flying. Under climate mitigation behavior, air passengers are encouraged to practice environment-conscious decision-making by choosing less emissions intensive air routes (Gössling and Dolnicar, 2022). However, limited efforts have been made thus far to understand the differences in emissions between routes, particularly departing from airports of different sizes and operational features. Also, the approaches used have not been considered entirely dependable by experts (BBC, 2022; The Guardian, 2022). On the other hand, price-based environmental policies include carbon taxes and carbon credits, which are studied, designed and applied on national, continental and global scales (Commission of the European Union, 2013; Wild, Mathys and Wang, 2021; Zheng and Rutherford, 2022). Nonetheless, such large-scale approaches can mask important differences in the characteristics of actual emitters (Chakravarty et al., 2009; Girod and de Haan, 2009; Gössling and Humpe, 2020), which include different air routes with distinct air service and passenger demand characteristics operated at different airports. By understanding these differences, particularly among neighboring airports which air passengers choose from, the effects of the aforementioned environmental policies can be better understood.
1.2 Research Objectives

The central objective of this thesis is to understand air passenger airport choices across a large geographic area with airports of differing sizes and air services offered, and to understand the implications of these choices for aviation emissions and price-based policies to mitigate the environmental impacts of flying. The specific objectives are as follows:

Objective 1: Explore the air service-related drivers of airport choices across a large geographic region encompassing regional and state boundaries (Ch. 4).

Mixed logit models are used to determine the effects of air service attributes and airport access distance on airport choice, using a dataset of a sample of purchased air tickets in a region of the US Midwest.

Objective 2: Compare passenger-level aviation fuel burn and emissions among air routes originating from different airports within the study area (Ch. 5).

This comparison is based on average and marginal emission factors, estimated using Modified Breguet Range equations.

Objective 3: Investigate the effect of price-based environmental policies on aviation emissions (Ch. 6).

Relationships among airfare, demand, supply (capacity variables such as aircraft size and load factors (LFs)) and emissions at the airport level are estimated using a two-stage least squares (2SLS) regression model. Resulting elasticities of emissions to airfare are compared across airport sizes.

1.3 Terminology

Important terms used throughout this thesis are described below. These descriptions are based on the uses of these terms in the literature relevant to this thesis research, and the thesis research itself. Some terms will be discussed further in Chapter 2.
• *Catchment*: the geographic area from which an airport is assumed to attract air passengers (Zhou et al., 2018; Gao, 2020). In the literature, this appears to implicitly assume departing (i.e., originating) air passengers, and this thesis focuses on the same.

• *Non-hub primary airport*: an airport that receives less than 0.05% of the annual US commercial enplanements but more than 10,000 enplanements (FAA, 2022).

• *Small hub*: an airport that receives 0.05% to 0.25% of the annual US commercial enplanements (FAA, 2022).

• *Medium hub*: an airport that receives 0.25% to 1% of the annual US commercial enplanements (FAA, 2022).

• *Large hub*: an airport that receives 1% or more of the annual US commercial enplanements (FAA, 2022).

• *Passenger leakage*: the phenomenon whereby air passengers from the catchment of a (usually) smaller airport cross the catchment boundary to access a distant (and often) major hub airport offering more air services (Suzuki, Crum and Audino, 2003).

• *Supply*: collectively refers to the air services provided by airports and airlines. For airports, these services can comprise the various aspects of groundside, airside, and terminal capacities (Dixit and Jakhar, 2021). For airlines, supply and air service features can include flight frequency (Teodorović and Krčmar-Nožić, 1989; Hsu and Wen, 2003; Pitfield, Caves and Quddus, 2010), aircraft size (Jorge-Calderón, 1997; Wei and Hansen, 2005, 2006), seats offered (Wei and Hansen, 2005; Mohammadian et al., 2019), and load factor (LF) (Ippolito, 1981; Agarwal and Talley, 1985). It is noted that the terms “supply” “capacity” and “air service” have often been used interchangeably in the literature, although some literature will distinguish between these terms towards categorizing the above listed features.

### 1.4 Thesis Organization

A conceptual overview and organization of the thesis is presented in **Figure 1.1**.
Chapter 2 presents a review of the relevant literature, including studies on aviation supply and demand, airport choices in the context of interregional passenger “leakage” over long distances, airport market catchment areas, environmental policies in aviation (with respect to both emissions and fuel use), and methods to estimate aviation emissions and fuel burn.

Chapter 3 describes the study area and input data sources. The study area comprises a large portion of the US Midwest, centering on Illinois. Data sources include air tickets and other federal datasets.
on air service and capacity variables, data from standard aviation emissions databases, and demographic indicators that affect air demand.

Chapter 4 presents the long-distance airport choice investigations in pursuit of **Objective 1**. Here, airport choices are explored relying primarily on a dataset of air ticket itineraries purchased and mixed logit models, based on key air service attributes and airport access distances.

Chapter 5 presents the passenger-level emissions estimates and comparisons of average and marginal emissions factors (AEF and MEF, respectively), as per **Objective 2**. Here, the various departure airports chosen by passengers to travel to several destinations are identified, and the differences in average and marginal emission factors on these routes are quantified and compared.

Chapter 6 presents the exploration of the price-supply-demand-emissions relationship of **Objective 3**. Aggregated demand (i.e., passenger volumes) is first modelled using airfare (representing the price-based environmental measure) and other variables such as jet fuel price and demographic indicators. A 2SLS model is used to represent the endogenous supply-and-demand relationship. From this, the responses of emissions – direct outputs of supply – to airfare are quantified through elasticity estimates.

Chapter 7 closes the thesis with a summary of the work completed and key results. It also highlights contributions to the research and practice in terms of insights into airport choices over large areas, their air service-related drivers and implications for emissions and environmental policies. Also discussed are limitations of the work, and future avenues of inquiry towards building on and continuing the work presented.
Chapter 2: Background and Literature Review

This chapter provides a review of the relevant literature, including: air service and passenger demand; passenger airport choice, environmental impacts of, and policies in, aviation; and aviation fuel burn and emissions estimation. Figure 2.1 maps the topics covered to the thesis objectives presented in Chapter 1.

Figure 2.1 Literature topics covered and connections to thesis objectives

Section 2.1 introduces studies of supply and demand in the context of air transportation. In 2.1.1, disparities in air services between airports are reviewed, followed by a discussion of the resulting passenger airport choices and passenger leakage in 2.1.2. Section 2.1.3 reviews the airport catchment definitions that underlay the concept of airport passenger “leakage,” and 2.1.4 reviews the passenger data collection approaches towards understanding airport choices. Section 2.2 discusses the environmental implications of airport and route choices, and relevant price-based environmental policies. Section 2.3 presents the various approaches used for estimating aviation fuel burn and pollutants emissions. Finally, Section 2.4 concludes with a summary of research gaps in understanding the relationships among air transportation supply, demand and emissions.
2.1 Aviation Supply and Demand

Transportation systems have been represented and assessed through the basic principle that supply and demand affect each other and are thus endogenous. Furthermore, holding all other external factors constant, higher prices of goods or services lead to more supply of those goods or services and less demand for them (Pindyck and Rubinfeld, 2014). This relationship is shown in Figure 2.2 in which the x-axis is quantity of goods or services and the y-axis is price. As price increases, the demand for goods decreases (the downward-sloping red curve) while the supply of these goods increases (the upward-sloping blue curve).

![Figure 2.2 Supply-and-demand relationship](image)

In the context of air passenger markets, price has been represented by ticket price or airfare (Zou and Hansen, 2012), whereas service can be represented by variables on the side of both airports and airlines. On the side of airports, runways and terminals have limited capacities and can accommodate flights and passenger demand within their limits (Dixit and Jakhar, 2021). On the side of airlines, services comprise capacity decision variables such as aircraft size (usually measured in number of seats), total seats offered, flight frequency and load factor (LF) (Mohammadian et al., 2019). Supply of the aforementioned services, demand for these services, and the price of these services (i.e., airfare) are related and thus, change in one is expected to trigger a response in the others (Zou and Hansen, 2012).
Following the above, airports that add more attractive air services, mainly through airlines that offer attractive services, will draw more passengers. Those with less, and less attractive service offerings will lose passengers. When air travelers have a choice of airports, they will abandon airports with poorer air services usually in the form of costlier, less frequent and connecting flights, in favor of larger airports offering cheaper, more frequent and (a larger selection of) nonstop flights. The loss of passengers from airports with poor air services cause airlines to further reduce services at these airports, in a negative reinforcement effect (Fu and Kim, 2016). As expected, airports with superior air services will attract more passengers.

The air supply-and-demand relationship has been studied for over four decades, although price (or airfare) has been treated differently in that literature. In most studies (Ippolito, 1981; Agarwal and Talley, 1985; Jorge-Calderón, 1997; Mohammadian et al., 2019), airlines are assumed to change only their capacities but not airfares to adjust for changes in passenger demand. In such cases, airfare is treated as an exogenous variable. Others assume airlines change their airfares to adjust for changes in demands, in which case airfare is treated as endogenous (Suzuki and Audino, 2003; Fu and Kim, 2016). Overall, airport demand has a positive relationship with enplanement numbers (Hansen, 1995) and flight frequency (Hsu and Wen, 2003). Another study determines that increasing flight frequency rather than aircraft size attracts more demand (Wei and Hansen, 2005), while another states that higher demand leads to greater flight frequency compared with aircraft size (Pitfield, Caves and Quddus, 2010). LFs increase with increasing demand, although the rates of increase vary by flight length (Mohammadian et al., 2019). Additionally, airport infrastructure and operational capacities also contribute to the complex interactions between air passenger demand, airfare, flight frequency, aircraft size and flight delays (Zou and Hansen, 2012).

An airline’s response (also termed capacity decision) to passenger demand changes is influenced by its long-term business strategy (Kilpi, 2007). For instance, in the case of Emirates, the use of one or two basic aircraft models reduces the cost of flight crew training and maintenance but restricts aircraft size change (Wallach, 2022). Thus, responses to changes in passenger demand are mainly observed through changes in flight frequency and networking strategy. Airlines that have more diverse aircraft fleets swap aircraft as they adjust flight frequencies. Flight frequency is largely determined by airports’ operational capacities, and changes in this attribute are likely to be
accompanied by changes in on-time performance (Zou and Hansen, 2012), which in turn, affects air passengers’ airport choices (Ishii, Jun and Van Dender, 2009).

2.1.1 Drivers of Air Service Disparities

Following the 1978 US Airline Deregulation Act, airlines quickly reorganized their routes and consolidated air services at selected hub airports, leaving smaller airports with less attractive flight options (Kahn, 1988). Deregulation also encouraged new low-cost carriers (LCCs) to begin offering services at some medium and large hubs, thus further drawing passengers from small airports through cheaper airfares (Dresner, Lin and Windle, 1996; Gillen and Lall, 2004; Graham, 2013).

Airline mergers and alliances, as well as network reorganizations, intensified in the first decade of the 21st century (Ryerson and Kim, 2014). Newly merged airlines further consolidated services at key hub airports, and reduced services on redundant and less profitable routes involving small airports that were typically operated by regional aircraft (Ryerson and Kim, 2013; Atallah and Hotle, 2019). For example, major airports in the northeast corridor of the US and leisure regions in Florida experienced increases in their air services, while airports in less populous regions such as the Rust Belt and the Inter-mountain West saw significant reduction (Fuellhart et al., 2016). Such disparities, in turn, led to considerable shifts in air travel demand away from small and medium-size airports to large hubs, sometimes hundreds of miles away (Sixel Consulting Group Inc., 2014; Fu and Kim, 2016; Michigan Department of Transportation, 2016; Delta Airports Consultants Inc., 2020).

External shocks have further exacerbated air service disparities throughout the US. The 9/11 attacks and 2008 financial crisis led to partial to complete loss of services at 30 and 23 small US airports, respectively (General Accounting Office, 2002; US Department of Transportation, 2002; Hotle and Mumbower, 2021). Similar effects are also anticipated in the COVID-19 pandemic recovery, particularly once the Coronavirus Aid, Relief, and Economic Security (CARES) Act ends. CARES mandated airlines to continue pre-pandemic operations at small airports serving small communities (US Congress, 2020). These small airports are also federally supported through programs such as the Essential Air Service (EAS) in order to prevent complete loss of air services (Drukker, 2022).
2.1.2 Passenger Airport Choices and Long-distance “Leakage”

Many air travelers have access to more than one airport. Thus, their choice of a given airport will be driven by the services offered at that airport, compared to the other(s) that are accessible to them, in addition to other socioeconomic traits and travel situations. As service disparities between airports grow, airports with better services will attract more passengers from farther afield – passengers that would have otherwise be expected to use airports closer to them, as they are presumed to originate from these nearer airports’ catchment areas. The phenomenon of air passengers bypassing their nearest airports to depart from distant, often larger airports presumably serving other catchment areas has been studied since the 1980s. The results of a small passenger survey in California (Kanafani and Abbas, 1987), and a linear regression analysis of 52 Texas communities using publicly-available aggregate data (Kaemmerle, 1991), showed that air passengers from small communities often abandon their nearby, often smaller airports with limited services in favor of major hubs in neighboring urban regions with more frequent flights. Similarly, Furuichi and Koppelman (1994), by applying a nested logit (NL) model on passenger survey data from multiple Japanese cities, explored the air routes chosen based on flight frequency and airport access times. Thompson and Caves (1993), using a survey data of passengers from Sheffield, UK and a multinomial logit (MNL) model, reported that small airports could curb passenger loss to surrounding airports more effectively using increased flight frequencies over lowered airfares. Another study applied a binary logit model on an air ticket dataset of passengers from the northern half of the province of New Brunswick, Canada, to highlight the influence of aircraft type (jet vs turboprop) and airport accessibility on passengers’ decisions to access distant major hubs (Innes and Doucet, 1990).

The phenomenon of long-distance passenger loss to larger airports was more commonly referred to as air passenger “leakage” starting in the early 2000s. More studies on interregional passenger leakage in the US emerged at that time (Suzuki, Crum and Audino, 2003; Phillips et al., 2005; Zhang and Xie, 2005). Passenger leakage from 14 single airport US regions served by medium airports, to large hubs up to 150–250 miles away, was studied using a regression model based on publicly available, aggregate data, from which airfare is reported to be the most important driver of airport leakage (Suzuki and Audino, 2003). By applying a MNL on air passenger survey data in Des Moines, Iowa, Suzuki, Crum and Audino (2003) identify airfare, nonstop services and
frequent flyer membership as important factors explaining leakage. By supplementing the same survey data with socioeconomic and population data, Suzuki, Crum and Audino (2004) implemented econometric models indicating that flights from small airports have airfares higher than optimal which drives passengers away to other distant airports. Suzuki (2007) further assumes that air passengers first choose their departure airports and then the airlines they fly with, and shows that this assumption is superior to a single step process in which passengers are assumed to choose both airports and airlines simultaneously. Using a two stage least squares (2SLS) regression model, Phillips et al. (2005) explore passenger leakage from Wyoming to airports in neighboring states before and after the 9/11 attacks. In the first stage of the 2SLS model, the authors investigate the influence of air services that differ between the two periods. Using the output from this first stage, they then explain the relationship between residual effects and other variables that do not vary between the study time periods.

A study of the Golden Triangle Region in Mississippi using logistic regression shows that flight frequency and previous air travel experience, in addition to airfare, influence air travelers’ decisions to “leak” to airports in other states (Zhang and Xie, 2005). Blackstone, Buck and Hakim (2006) estimate probit models on a survey dataset of passengers that “leaked” from Philadelphia to airports in Baltimore and New York using explanatory variables of airfare, airport access distance, directness of service, income, and parking fees. Fuellhart (2007) also investigates passenger “leakage” from a small airport in Pennsylvania to hub airports in Baltimore and Washington DC using ZIP codes gathered from vehicle drivers exiting the small airport parking lot. Passenger leakage is estimated over the area within a 75 mi radius around the small airport using simple linear regression models, with airport access distance and population information as explanatory variables. Leon (2011) shows trip purpose, trip duration and airline to be important determinants of airport choice, through application of a binary logit model on air ticket data of passengers in Fargo, North Dakota that leaked to a major hub in Minneapolis. Gao (2020), using publicly available data, spatially estimates passenger leakage from throughout Indiana to Chicago Midway International (MDW) and Chicago O’Hare International (ORD) by formulating a cost minimization problem for different trip durations and travel groups, and concludes that leisure passengers traveling in larger groups are more likely to leak. Most recently, Yirgu, Kim and Ryerson (2021) apply NL models on an air ticket dataset of passengers from Milwaukee, Madison
and Grand Rapids, to highlight the importance of airfare in these passengers’ decisions to “leak” to more distant large hubs.

Airport competition has also been studied extensively in both the European and Asian contexts within the last two decades. However, these contexts differ from that of North America, given higher population densities and smaller distances between airports, and the presence of extensive rail services nearly everywhere. Air and rail competition (Jiang and Zhang, 2016), or the situation in which passengers access larger airports farther away using intercity rail (instead of by private vehicle as per the typical North American context) (Albalate, Bel and Fageda, 2015) has been studied extensively (Adler, Pels and Nash, 2010; Dobruszkes, 2011). Using a survey of air passengers in Norway and binary logit models, Lian and Rønnevik (2011) show that air passengers will travel an additional four hours to three main airports, bypassing seven smaller regional airports, for cheaper direct services. Another study using a passenger survey in the region of Campania shows that car ownership and higher income, in addition to cheaper airfares and greater flight frequency, encourage Campania residents to “leak” from Naples Airport to two airports in neighboring Rome, while more flying experience discourages it (de Luca, 2012). This study also provides a comparison of the applications of MNL, NL and mixed multinomial logit (MMNL) models, to show that the model gains of MMNL and NL over MNL are not substantial.

With respect to transborder passenger leakage from Canada to the US, Elwakil, Windle and Dresner (2013), using a three-stage least squares (3SLS) model applied on aggregated data, estimate passenger volumes leaking from Montreal to Burlington VT, Toronto to Buffalo NY, Ottawa to Syracuse NY, Windsor to Detroit MI and Vancouver to Seattle WA, and confirm that cheaper airfare at US airports (even small ones) is the main driver of transborder leakage. Another study estimated that nearly five million air passengers, mainly from Montreal, Vancouver and Toronto, leak annually to airports in Plattsburgh, Seattle and Buffalo, respectively, also due to cheaper airfares (Kelly-Gagnon, 2015).

Passenger loss to larger neighboring airports has been a major concern for many small and medium airports in North America, and many of these airports have conducted or sponsored their own studies to understand the extent and drivers of this loss. The findings of these studies are often featured in local news. For instance, Edmonton International Airport estimated losses of up to
750,000 air passengers annually from the Greater Edmonton area to Calgary International Airport, 177 mi south of downtown Edmonton (Jang, 2010). A study of Macon, Georgia – served by the small Middle Georgia Regional Airport – estimated that of the annual 1,167,491 passengers generated by the region, 98.3% drove more than 85 mi to depart from Hartsfield-Jackson Atlanta International Airport (Sixel Consulting Group Inc., 2014). Another report showed that Orlando-Sanford International Airport experienced significant passenger loss to Orlando International Airport (Kimley-Horn & Associates, 2015a). In exceptional cases, passenger spillover from major hubs to smaller airports is observed due to congestion and unsatisfactory on-time performance at the former. At Ft. Lauderdale–Hollywood International Airport, 12% of passengers originate from Miami-Dade County, served by the large hub of Miami International Airport (Kimley-Horn & Associates, 2015b).

More recently, Milwaukee Mitchell International Airport (MKE) estimated that 30% and 80% of domestic and international travelers, respectively, from its expected catchment in Wisconsin leak to airports in Chicago, particularly O’Hare International Airport (ORD) (Milwaukee Mitchell Airport, 2020). Another study estimated passenger loss from six small airports in Georgia to range from 58.6% up to 98.9% to hub airports including Hartsfield-Jackson Atlanta International Airport, Orlando International Airport in Florida, and Jacksonville International Airport in Florida (Delta Airports Consultants Inc., 2020).

2.1.3 Airport Passenger Catchment Areas

Given that passenger leakage is predicated on the assumption that an airport has a catchment area from which it loses passengers to another airport, understanding approaches used in defining this area is critical. The simplest approach involves drawing concentric circles with radii ranging from 30-155 mi around airports (Fuellhart, 2007; Fröhlich and Niemeier, 2011; O’Connor and Fuellhart, 2016). Other approaches include identifying geographic areas within: predetermined airport access times ranging from 1-3 hours (Suzuki, Crum and Audino, 2003; Marcucci and Gatta, 2011; Zhou et al., 2018; Milwaukee Mitchell Airport, 2020); and fixed airport access distances ranging from 15 to 621 mi (Suau-Sanchez, Burghouwt and Pallares-Barbera, 2014; Huber et al., 2021). In Europe, where nearly two-thirds of the population lives within two hours of at least two airports (Blachut, 2017), the various access time/distance thresholds used to define catchment boundaries
result in considerable inconsistencies. Still others simply apply existing administrative boundaries such as state (Gao, 2020) and metropolitan area boundaries (Loo, Ho and Wong, 2005; Gupta, Vovsha and Donnelly, 2008; Teixeira and Derudder, 2021) to demarcate airport catchments.

While the aforementioned studies propose predefined and static catchment boundaries, Lieshout (2012), presents a considerably different approach in a study of Amsterdam Schiphol Airport. The author accounts for individual destinations and quality of air services at both the subject airport and surrounding airports, towards identifying areas where the subject airport has at least 1% passenger market share. The collection of these areas constitutes the catchment for the considered destination.

### 2.1.4 Air Passenger Data Collection Approaches

Air passenger survey data is often collected to understand airport choices within the context of airport leakage concerns. Such data have been collected through a variety of methods, including intercept surveys conducted at selected municipality centers (de Luca, 2012) and airports (Zhang and Xie, 2005), mail or telephone surveys (Blackstone, Buck, and Hakim, 2006) and combinations of the above (Suzuki, Crum, and Audino, 2003; Suzuki, 2007). Other methods include purchased air ticket databases sampled from travel agents (Innes and Doucet, 1990; Leon, 2011; Yirgu, Kim and Ryerson, 2021), and open access databases (Lian and Rønnevik, 2011). The data will differ significantly in geographic scope and passenger details, depending on the source. Passenger leakage studies cannot be supported by data collected by MPOs (which has been used to study airport choice in multi-airport regions (MARs) such as the San Francisco Bay Area – see Başar and Bhat (2004) and Hess and Polak (2005)) due to their geographic limitations. Thus, data to support these studies has typically been collected/sponsored by airport authorities. **Table 2.1** provides a summary of the strengths and limitations of the aforementioned data collection mechanisms.
## Table 2.1 Data Collection Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Strengths</th>
<th>Limitations</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept survey at small airport</td>
<td>Enables detailed data collection on passenger-specific attributes such as flying experience, loyalty program participation, income, car ownership, trip purpose, length of stay at destination, airport access mode, etc.</td>
<td>Does not capture travelers that go to a different airport; likely to capture a limited diversity of itineraries based on time of day and day of week.</td>
<td>(Suzuki, Crum and Audino, 2003; Zhang and Xie, 2005; Suzuki, 2007)</td>
</tr>
<tr>
<td>Intercept survey at municipality center</td>
<td>Enables detailed data collection on passenger specific attributes (as above).</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Might not capture travelers that live farther and do not regularly pass through the chosen center.</td>
<td>(de Luca, 2012)</td>
</tr>
<tr>
<td>Telephone survey</td>
<td>Allows coverage of targeted geography (through area code); enables detailed data collection on passenger specific attributes (as above).</td>
<td>Might require substantial time and resources.</td>
<td>(Blackstone, Buck and Hakim, 2006)</td>
</tr>
<tr>
<td>Mail survey</td>
<td>Allows coverage of targeted geography; enables detailed data collection on passenger specific attributes (as above).</td>
<td>Might require substantial time and resources; data quality might be poor due to incomplete or inappropriately filled forms.</td>
<td>(Suzuki, Crum and Audino, 2003; Suzuki, 2007)</td>
</tr>
<tr>
<td>Travel agencies or companies accessing</td>
<td>Covers diverse travel plans and large regions.</td>
<td>Does not provide passenger specific attributes either due to unavailability or privacy concerns.</td>
<td>(Innes and Doucet, 1990; Leon, 2011; Yirgu and Kim, 2021)</td>
</tr>
<tr>
<td>travel agency data</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open access database</td>
<td>Allows access to all researchers; captures passenger-specific attributes if provided by the data provider under privacy policy.</td>
<td>Passengers’ travel plans and geography are already defined as per the data provider.</td>
<td>(Lian and Rønnevik, 2011)</td>
</tr>
</tbody>
</table>
2.2 Airport Choices, Environmental Impacts and Policies

An air passenger’s emissions contributions vary depending on their air route taken (Gössling and Dolnicar, 2022), which in turn is dependent on the airport they choose to depart from to reach their desired destination. This is due to differences in aircraft size and weight, LF, flight distance, and type of service (nonstop versus connecting) on different routes (Zheng and Rutherford, 2021).

There are two efforts currently aiming towards raising awareness amongst passengers about the emissions impact of their airport choices. The first focuses on encouraging passengers to choose itineraries from departure airports that are less emissions-intensive, through trip planning tools such as Google Flights (Gössling and Dolnicar, 2022). These tools have been criticized for underrepresenting the actual emissions associated with air routes (BBC, 2022; The Guardian, 2022). The second involves customer (or passenger) carbon offset schemes, in which air passengers voluntarily pay fees proportional to their share of emissions created by their travel itinerary, for investment on certified carbon removal projects (Mair, 2011; ICAO, 2021). These voluntary fees are paid to third parties such as Gold Standard or to airlines, provided the airlines offer offset schemes of their own or in partnership with third parties as in the case of Qantas (Fly Carbon Neutral), Air Canada (Less Emissions), KLM Royal Dutch (CO₂ZERO), Austrian (Climate Austria) and many others.

Voluntary offsetting is on course to becoming a mandatory policy measure as governments commit to charge airlines for their carbon emissions (IATA, 2013; CBC News, 2018; Reuters, 2022), towards supporting R&D in cleaner technologies and energy sources including sustainable aviation fuel (SAF). Among these policies are the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) and European Union Emission’s Trading Scheme (EU ETS). CORSIA is the first international market-based measure that offers a harmonized mechanism to reduce emissions from international aviation. Participation by ICAO member states is voluntary for the pilot phase in 2022–2023 and first phase in 2024–2026. In the third phase of 2027-2035, CORSIA will become mandatory; airlines will need to purchase carbon credits which are tradeable certificates that entitle them to emit carbon (ICAO, 2022). Airlines, in turn, are expected to pass these charges onto passengers through a standardized and transparent mechanism (Pagoni and Psaraki-Kalouptsidi, 2016). Under the EU ETS cap for 2013–2020, airlines were allowed to release
up to 95% of their historical average emissions from 2004–2006 without having to purchase carbon credit (Ko, Jang and Kim, 2017). Beginning in 2026, the EU is expected to start charging airlines for all their carbon emissions (Reuters, 2022). In some cases such as in Switzerland, national governments directly attempt to impose carbon taxes on air tickets (Wild, Mathys and Wang, 2021).

Studies on environmental policies involve national- and international-level analyses that assume air demand responds uniformly to price-based policy measures, as evident from the application of a generic price elasticity of demand (Dray et al., 2022; Zheng and Rutherford, 2022). This is despite that the price elasticity of demand has been shown to vary greatly from one region and airport to another (Brons et al., 2002; Schiff and Becken, 2011).

2.3 Aviation Fuel Burn and Emissions Estimation

Aviation emissions have been measured through remote sensing and Fourier transform infrared spectroscopy (Schäfer, 2001; Schäfer et al., 2003), chromatography analysis of carbon species emissions (Anderson, Chen and Blake, 2006), open path devices for real-time emission indices (Schürmann et al., 2007), and sample collection from engines via probes fixed on exhaust nozzles (Agrawal et al., 2008). Other methods of estimating aviation fuel and emissions have been documented in the European Monitoring and Evaluation Programme (EMEP) / European Environment Agency (EEA) Air Pollutant Emission Inventory Multi-tier Database and Guidebook (European Environment Agency, 2013), and ICAO Engine Exhaust Emission Databank (ICAO, 2009). These documents provide procedures to estimate fuel and emissions from the landing-takeoff (LTO) and climb-cruise-descent (CCD) phases for certain aircraft models operating a known distance under some specified load, with estimates from these phases summed to determine total emissions (Kurniawan and Khardi, 2011). LTO includes aircraft operations (taxi-out, takeoff, climb to 914 m above runway, final approach, land and taxi-in) that take place below an altitude of 914 m above runway, while all activities above this altitude are classified under CCD (ICAO, 1993).

In the absence of extensive details on a flight’s 4-dimensional trajectory, and ambient as well as operational conditions, accurately estimating the emissions from a flight has remained difficult, at least without requiring substantial data collection and computational resources (Chatterji, 2011).
However, modified versions of Breguet Range equations have enabled the estimation of aviation fuel burn during different flight phases without the need for extensive details (Graham, Hall and Vera Morales, 2014; Singh and Sharma, 2015). By developing a framework that requires only publicly available data, Yanto and Liem (2018) demonstrate that Breguet Range equations can be used to estimate fuel burn with errors below 6%, while Seymour et al. (2020) propose a version of these equations that mainly rely on flight distance and several other inputs to estimate fuel burn with less than 5% estimation error. Cox, Jemiolo and Mutel (2018), in their lifecycle assessment of the Swiss commercial aircraft fleet, extend the application from fuel burn to pollutants such as carbon dioxide (CO₂), carbon monoxide (CO), hydrocarbon (HC), particulate matters at 2.5 micrometer size (PM₂.₅), nitrogen oxides (NOₓ), sulphur oxides (SOₓ) and water vapor (H₂O).

### 2.4 Identified Research Gaps

Disparities in air services among airports within and across large regions have deepened due to various events such as airline mergers, hub reorganizations, personnel shortage, financial crises and disruptive events like the COVID-19 pandemic. Consequently, air passengers from smaller regions served by smaller airports have been shown to abandon these local airports in favor of distant but larger airports offering superior services. There has been decades of study to understand these airport preferences, although data collection has been restricted. This is at least in part due to limited collaboration among neighboring MPOs, which has discouraged collection of air passenger survey data across administrative boundaries. Consequently, the insights from these existing airport leakage studies do not fully capture the airport choices of air passengers across city, state and regional boundaries.

Airport choices also play important roles in air travel mitigation behavior, in which passengers are encouraged to minimize their emissions contribution by choosing less emissions-intensive air routes. However, there is a need to better understand the emissions and fuel-use differences between routes departing from small and large airports. Furthermore, price-based environmental policies on aviation rely on analyses at the national, continental or global scales, by assuming that air demand uniformly responds to these policies. Nonetheless, such assumptions lead to oversimplification, masking variations among airports within regions, given the distinct air service
and passenger demand characteristics of different size airports throughout a large region such as the US Midwest, for example.

This thesis uses an air ticket dataset of passengers from a large section of the US Midwest spanning several administrative boundaries to: 1) provide insight into the air service-related drivers of airport choices over large regions; 2) quantify the differences in passenger-level emissions resulting from choosing large hubs over small and medium ones; and 3) explore the effect of price on emissions at airports of differing sizes by considering their respective air service and demand characteristics.
Chapter 3: Research Context and Data

This chapter introduces the geographic context of the research followed by data descriptions. There are four main data categories: 1) air tickets; 2) air service attributes and capacity decision variables; 3) aviation fuel consumption and pollutants’ emissions; and 4) socioeconomic and population data.

3.1 Research Setting

This thesis uses a sample of air tickets purchased by air passengers originating from a large eastern portion of the US Midwest, from 2013 through 2018.

Shown in Figure 3.1, the US Midwest consists of the states of Ohio (OH), Michigan (MI), Indiana (IN), Illinois (IL), Wisconsin (WI), Minnesota (MN), Iowa (IA), Missouri (MO), North Dakota (ND), South Dakota (SD), Nebraska (NE) and Kansas (KS). This region had a population of 68.9 million as of 2020 (US Bureau of Labor Statistics, 2022). Major economic activities include manufacturing, education, health, tourism, and shipping as well as logistics (Siddiqui, 2022). Demand for air services in some parts of the region is also stimulated by the entry of increasing numbers of Fortune 500 and 1000 companies (Airline Network News and Analysis, 2020).

![Figure 3.1 US Midwest](image-url)
The specific eastern portion of the US Midwest on which this thesis focuses is shown in Figure 3.2 as a collection of ZIP codes in the states of Wisconsin, Iowa, Illinois, Indiana and Michigan.

![Figure 3.2 Specific area defined by collection of ZIP codes](image)

**Figure 3.2** is shown to help orient the reader. Detailed processes used to narrow down on this specific area, which in turn are dependent on the air tickets dataset, will be further discussed in the chapter.

### 3.2 Data and Sources

A summary of data and sources is given in Table 3.1. The section under which each data will be discussed is indicated.
Table 3.1 Data and Sources

<table>
<thead>
<tr>
<th>Data</th>
<th>Source / Link</th>
<th>Data of interest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Locator (discussed in Section 3.2.1)</td>
<td>Airline Reporting Corporation (publicly available for purchase)</td>
<td>Origin airport, final destination airport, connecting airport(s), billing ZIP code (assumed as home)</td>
</tr>
<tr>
<td>DB1B (3.2.2)</td>
<td><a href="https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FHK">https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FHK</a></td>
<td>Route-level airfare</td>
</tr>
<tr>
<td>T-100 (3.2.2)</td>
<td><a href="https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=GE">https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=GE</a></td>
<td>Available seats, occupied seats, useful payload, flight frequency, and flight distance based on flight segments</td>
</tr>
<tr>
<td>Airports’ locations (3.2.2)</td>
<td><a href="https://openflights.org/data.html">https://openflights.org/data.html</a></td>
<td>Geographic coordinates of airports</td>
</tr>
<tr>
<td>ZIP codes’ locations (3.2.2)</td>
<td><a href="https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/table/">https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/table/</a></td>
<td>Geographic coordinates of ZIP codes’ centroids</td>
</tr>
<tr>
<td>Road shapefiles (3.2.2)</td>
<td><a href="https://catalog.data.gov/dataset/tiger-line-shapefile-2016-nation-u-s-primary-roads-national-shapefile">https://catalog.data.gov/dataset/tiger-line-shapefile-2016-nation-u-s-primary-roads-national-shapefile</a></td>
<td>Primary and secondary road shapefiles of the final study area</td>
</tr>
<tr>
<td>EMEP/EEA Tier 3 emissions database and inventory guidebook (3.2.3)</td>
<td><a href="https://data.mendeley.com/datasets/2psysvvg8/2/files/b51bb77f-313c-4c75-ae22-981e54ff70c6">https://data.mendeley.com/datasets/2psysvvg8/2/files/b51bb77f-313c-4c75-ae22-981e54ff70c6</a></td>
<td>Aviation fuel consumed and pollutants emitted by 78 representative aircraft at specified payloads (for different flight distances)</td>
</tr>
<tr>
<td>Aircraft characteristics (3.2.3)</td>
<td>Appendix B (also available online: <a href="https://doi.org/10.1016/j.trd.2021.103092">https://doi.org/10.1016/j.trd.2021.103092</a>)</td>
<td>Operating empty weight (OEW) and seating capacity of the 78 representative aircraft in the EMEP/EEA Emissions database</td>
</tr>
<tr>
<td>Jet fuel price (3.2.4)</td>
<td><a href="https://transtats.bts.gov/fuel.asp?pn=0&amp;disp=tt">https://transtats.bts.gov/fuel.asp?pn=0&amp;disp=tt</a></td>
<td>Monthly price of jet fuel per gallon</td>
</tr>
<tr>
<td>Population (3.2.4)</td>
<td><a href="https://data.world/lukewhyte/us-population-by-zip-code-2010-2016">https://data.world/lukewhyte/us-population-by-zip-code-2010-2016</a></td>
<td>ZIP code level annual population</td>
</tr>
<tr>
<td>Unemployment rate (3.2.4)</td>
<td><a href="https://www.bls.gov/lau/#tables">https://www.bls.gov/lau/#tables</a></td>
<td>County-level annual unemployment rate</td>
</tr>
</tbody>
</table>
3.2.1 Passenger Air Tickets

The Market Locator dataset, from the Airlines Reporting Corporation (ARC), consists of a sample of air ticket purchases made in the US for domestic itineraries. ARC is a consortium of airlines that provides air ticket transaction settlement services between airlines and all travel agencies (both traditional brick-and-mortar and online agencies such as Booking Holdings, Expedia Group, and their subsidiaries) in the US, Puerto Rico, the US Virgin Islands and American Samoa. Each ticket record on the dataset reports the number of passengers, route (departure airport, connecting airport(s) if not a nonstop route, and final destination), marketing airline, month and year, and the ZIP code of the credit card used to purchase the air ticket. Air tickets purchased through a travel agency account for 35% of all US air ticket purchases, while the remaining 65% consists of purchases made directly from airlines through their websites, call centers and ticket offices. Of the 35% purchased through travel agencies, ARC sends only 20% to a credit card processing company that matches air passengers’ tickets to their credit card billing ZIP codes. Therefore, the Market Locator is a 7% (35% x 20%) representative sample of US air ticket purchases (Drukker, 2022).

The database contains leisure and unmanaged business travelers (business travelers whose company does not have a program in place for booking business travel) to both domestic and international destinations (Drukker, 2022). Unlike members of airline alliances (Sky Team, Oneworld and Star Alliance), the LCCs of Southwest, Allegiant and Spirit Airlines are underrepresented in the Market Locator data (Sixel Consulting Group Inc., 2014) as these LCCs follow air ticket sales strategies that encourage purchases directly from airline websites instead of travel agencies (Skift, 2019; Southwest, 2022).

The ZIP codes of the credit cards used to purchase tickets are assumed to represent the home addresses of travelers, rather than that of companies in the case of corporate or business credit cards. This was considered a reasonable assumption given that leisure travelers predominantly constitute the Market Locator dataset (Drukker, 2022), although there are limitations associated with it. For example, some air passengers’ tickets may be purchased by family, friends, or relatives living elsewhere, although this is likely to be a rare occurrence. Understanding these assumptions, for each airport shown in Figure 3.3, air tickets purchased within a geographic search radius of 400 mi around the airport in question were downloaded. This 400 mi radius was deemed to be
large enough to capture air passengers residing in the supposed catchments of other airports, but flying through the airport in question.
Figure 3.3 Airports defining the study area

ATW - Appleton International
AZO - Kalamazoo/Battle Creek International
BMI - Central Illinois Regional
CMI - University of Illinois Willard
CWA - Central Wisconsin
DBQ - Dubuque International
DSM - Des Moines International
DTW - Detroit Metropolitan Wayne County
ESC - Delta County
FWA - Fort Wayne International
GRB - Austin Straubel International
GRR - Gerald R. Ford International
IMT - Iron Mountain Ford
IND - Indianapolis International
MKE - Milwaukee Mitchell International
MKG - Muskegon County
MLI - Quad City International
MSN - Dane County Regional
MSP - Minneapolis-Saint Paul International
ORD - Chicago O'Hare International
PIA - General Wayne A. Downing Peoria
RHI - Rhinelander-Oneida County
SBN - South Bend International
SPI - Abraham Lincoln International
STL - St. Louis Lambert International
UIN - Quincy Regional
The airport categorization scheme shown in the legend of Figure 3.3 follows that established by the US Department of Transportation (DOT) and Federal Aviation Administration (FAA). A large hub is defined to have 1% or more of the annual US commercial enplanements; a medium hub has 0.25% to 1%; a small hub and non-hub primary have 0.05% to 0.25% of annual US commercial enplanements and less than 0.05% but more than 10,000 enplanements, respectively.

With the search radius applied per airport, all ZIP codes that are associated with at least one air ticket purchase within this radius are captured. In some instances, multiple passengers (sometimes up to hundreds) are reported on a single ticket purchase record. Such a practice is common in other US air ticket sales datasets as it enables data size compression (Martin, Martin, and Lawford, 2010). Thus, if multiple passengers are reported on a single ticket, it cannot be assumed that those passengers traveled together as part of a single travel group. Consequently, passengers reported are treated as individual travelers. The number of air tickets and passengers reported per airport are shown in Table 3.2. A total of 11.28 million tickets containing 15.44 million passengers that flew to 2,433 international and domestic destinations were reported for the 27 subject airports. From Table 3.2 the large hub airports of ORD, MSP and DTW collectively account for 74% of sampled tickets.
Table 3.2 Tickets and Passengers Reported on Tickets

<table>
<thead>
<tr>
<th>Airport</th>
<th>Number of Tickets</th>
<th>Number of Passengers</th>
</tr>
</thead>
<tbody>
<tr>
<td>ORD</td>
<td>6,047,033</td>
<td>6,456,244</td>
</tr>
<tr>
<td>MSP</td>
<td>1,401,622</td>
<td>2,656,526</td>
</tr>
<tr>
<td>DTW</td>
<td>907,601</td>
<td>1,552,577</td>
</tr>
<tr>
<td>IND</td>
<td>577,683</td>
<td>971,383</td>
</tr>
<tr>
<td>STL</td>
<td>519,852</td>
<td>838,902</td>
</tr>
<tr>
<td>MKE</td>
<td>474,321</td>
<td>806,853</td>
</tr>
<tr>
<td>DSM</td>
<td>272,913</td>
<td>464,728</td>
</tr>
<tr>
<td>GRR</td>
<td>225,541</td>
<td>359,001</td>
</tr>
<tr>
<td>MSN</td>
<td>197,874</td>
<td>315,501</td>
</tr>
<tr>
<td>MDW</td>
<td>95,750</td>
<td>155,896</td>
</tr>
<tr>
<td>MLI</td>
<td>91,527</td>
<td>147,343</td>
</tr>
<tr>
<td>FWA</td>
<td>72,042</td>
<td>109,179</td>
</tr>
<tr>
<td>PIA</td>
<td>66,986</td>
<td>105,453</td>
</tr>
<tr>
<td>GRB</td>
<td>61,249</td>
<td>97,717</td>
</tr>
<tr>
<td>ATW</td>
<td>50,285</td>
<td>79,051</td>
</tr>
<tr>
<td>BMI</td>
<td>45,231</td>
<td>72,950</td>
</tr>
<tr>
<td>SBN</td>
<td>49,481</td>
<td>71,056</td>
</tr>
<tr>
<td>CWA</td>
<td>36,279</td>
<td>55,306</td>
</tr>
<tr>
<td>AZO</td>
<td>24,926</td>
<td>35,413</td>
</tr>
<tr>
<td>CMI</td>
<td>23,903</td>
<td>34,050</td>
</tr>
<tr>
<td>SPI</td>
<td>16,145</td>
<td>24,498</td>
</tr>
<tr>
<td>DBQ</td>
<td>10,343</td>
<td>16,251</td>
</tr>
<tr>
<td>MKG</td>
<td>5,134</td>
<td>8,169</td>
</tr>
<tr>
<td>ESC</td>
<td>3,328</td>
<td>5,655</td>
</tr>
<tr>
<td>IMT</td>
<td>1,836</td>
<td>2,767</td>
</tr>
<tr>
<td>UIN</td>
<td>1,440</td>
<td>2,287</td>
</tr>
<tr>
<td>Total</td>
<td>11,280,325</td>
<td>15,444,756</td>
</tr>
</tbody>
</table>
As an example, ZIP codes associated with the ticket dataset and the number of passengers captured by the tickets are shown for four of the 27 airports in Figure 3.4. Each chosen airport represents one of the four airport size categories of non-hub primary, small hub, medium hub and large hub.

Figure 3.4 ZIP codes captured and passengers captured on sampled tickets per airport, Dubuque (DBQ, top left), Dane County Regional (MSN, top right), Indianapolis International (IND, bottom left) and Chicago O’Hare International (ORD, bottom right)

From Figure 3.4, as airport size increases, the number of air tickets sold (and thus air passengers using an airport) and ZIP codes associated with these tickets increase. In Figure 3.5, all ZIP codes
captured through the search across all 27 airports are shown along with the distribution of passengers recorded over ZIP codes.

![Figure 3.5 All ZIP codes by passengers captured on the sampled tickets](image)

### 3.2.2 Air Service Attributes and Capacity Variables

Air service attributes such as airfare, nonstop versus connecting flight options and flight frequency, airport access distance or travel time are used as variables in the departure airport choice models. Capacity decision variables such as aircraft size and load factor (LF), in addition to flight distance, are used to compute average emission factors (AEFs), marginal emission factors (MEFs) and elasticities of emissions to airfare.

Access distance is used as a measure of airport accessibility as opposed to access time, as the latter can vary significantly by day of week and time of day. This distance is computed using the ArcGIS Network Analyst tool based on a road network built from study states’ road shapefiles downloaded from the US Census Bureau, Department of Commerce website. The coordinates of ZIP code
centroids and airports are then added to the network as origins and destinations, respectively. Under the assumption that the Market Locator dataset predominantly consists of leisure travelers, the origin ZIP codes represent the residential addresses of these travelers.

Airfare is not reported in the Market Locator dataset. Thus airfares, for each route and analysis period (i.e. quarter-year), are extracted from a matching record in the Airline Origin and Destination Survey dataset (DB1B). The DB1B is maintained by the Bureau of Transportation Statistics (BTS) and contains a 10% sample of tickets from reporting airlines. Using the same matching technique, flight frequency, seats offered, aircraft size, LF, weight per seat and nonstop distance flown are also extracted from the T-100 Domestic Segment (US Carriers) of Air Carrier Statistics (Form 41 Traffic) – US Carriers database from BTS. This database reports number of scheduled flights completed, aircraft type, available capacity/seat, occupied capacity/seat, revenue generating payload, ramp-to-ramp time, and flight distance, all for defined flight segments and time periods. Flight frequency is used in the airport choice model of Chapter 4:; while flight distance, aircraft size and LF are used as inputs in the emissions models of Chapter 5: and Chapter 6:.

3.2.3 Aviation Fuel Consumption and Pollutant Emissions

To estimate the parameters on the adopted Modified Breguet Range-based fuel and emissions model, the fuel consumption and pollutants’ emissions of 78 basic aircraft types are extracted from European Monitoring and Evaluation Programme (EMEP) and European Environment Agency (EEA) emissions database. Based on their range capabilities, fuel consumed and pollutants emitted by aircraft type are reported for flight distances ranging from 125 nautical miles (nm) (232 km) to 8,180 nm (15,149 km). The pollutants considered in this thesis are carbon dioxide (CO\textsubscript{2}), water vapor (H\textsubscript{2}O), nitrogen oxides (NO\textsubscript{X}), sulphur oxides (SO\textsubscript{X}), hydrocarbon (HC), carbon monoxide (CO) and particulate matters with maximum width of 2.5 micrometre (PM\textsubscript{2.5}).

The EMEP/EEA database assumes a flight LF of 0.6 and average passenger weight of 95 kg. Additionally, aircraft engine performance is based on 2004 technology, and engine thrust settings as well as duration of all landing and takeoff (LTO) activities follow International Civil Aviation Organization’s (ICAO’s) standard taxi time. It is noted that this 2004 engine technology assumed in the EMEP/EEA data (which is used to estimate model parameters) does not necessarily match
with the aircraft of domestic US routes on which the estimated model is later applied, given that detailed engine information on the latter are not available. Furthermore, the objective of this thesis is to estimate route level emissions based on average observations, as opposed to microscopic level computations. Emissions reported for climb-cruise-descent (CCD) phases are based on 4-D flight trajectories (time being the fourth dimension) extracted from the Central Flow Management Unit (CFMU). Furthermore, the database’s altitude and attitude dependent aircraft operation parameters affecting CCD phase fuel burn are based on Eurocontrol’s Base of Aircraft Data (BADA).

3.2.4 Other Variables

Populations, socioeconomic data, and jet fuel prices are gathered from different sources. ZIP code populations are extracted from a secondary source that uses the US Census Bureau’s 2010 baseline count and the American Community 2016 Survey. With respect to the socio-economic indicator used, unemployment rate is chosen over employment rate. This is due to inconsistencies observed in the latter across multiple data sources that rely on various bases such as total over-16 adult population and total population in the active labor market. However, the US Bureau of Labor Statistics, a primary source of socio-economic data, reports unemployment at the county rather than ZIP code level. Consequently, ZIP codes are overlaid onto counties (further described in 3.3.4) to compute the mean unemployment rate for the collection of ZIP codes belonging to a county.

Jet fuel prices are extracted from the Airline Fuel Cost and Consumption (US Carriers – Scheduled) database of BTS.

3.3 Data Description and Processing

3.3.1 Air Tickets and Geography

This section describes: 1) the air tickets and passengers captured on these tickets, and data preparation; and 2) the geographic scope refinement used to narrow down on the specific study area.

The Market Locator dataset contains a total of 11.28 million air tickets on which 15.44 million passengers are captured. Of this total, 73% had domestic final destinations while the remaining
27% were international. Furthermore, 56% of passengers captured on the ticket dataset used nonstop services and the remaining 44% connected. The dataset has 129 different marketing airlines with top ten final destination cities of Orlando, Phoenix, Las Vegas, New York, Los Angeles, Denver, San Francisco, Miami, Cancun and Dallas from the study area. However, 83% of passengers on the ticket dataset were carried by seven airlines: American, Delta, United, US Airways (which merged with American in 2016), Sun Country, Frontier and Alaska. Southwest Airlines is underrepresented in the Market Locator dataset (Sixel Consulting Group Inc., 2014), but this carrier has a 95% market share at Chicago Midway International (MDW). Thus, air tickets for routes originating from MDW are removed. Consulting reports using the Market Locator data (Sixel Consulting Group Inc., 2014; Kimley-Horn & Associates, 2015a, 2015b) overcome this limitation regarding Southwest by growing the sample in proportion to actual total origin-destination passenger demand, using datasets with full access to the global distribution system such as Sabre. However, access to such origin-destination passenger demand records was not available for this research.¹ Finally, tickets to international destinations are removed since air service attributes on international travel are not fully available from the data sources used to supplement the Market Locator dataset.

Ticket records for the non-hub primary airports of Rhinelander-Oneida County (RHI), Iron Mountain Ford (IMT), Delta County (ESC), Quincy Regional (UIN) and Muskegon County (MKG) were consistently incomplete. The data incompleteness, given that these five airports recorded the least annual enplanement among the subject airports (FAA, 2019), may be due to the lower likelihood of obtaining passenger samples from a low number of actual airport users. Thus, these five airports and ZIP codes that are closest to them are removed, as passengers most likely to use these airports are not represented.

¹ We distinguish passenger origin-demand from segment origin-destination. Passenger origin-destination demand is that between an origin airport and final destination airport, while segment origin-destination is that between an origin and destination (where this destination might be a connecting airport for passengers on connecting flights or a final destination for non-connecting passengers).
There are also several other airports (both within and outside of the study area) shown in Figure 3.6, which in reality, are available for passengers, although ticket data on these airports is unavailable. Some of these airports include Eugene F. Kranz Toledo Express (TOL), Cleveland Hopkins International (CLE), John Glenn Columbus International (CMH), Pittsburgh International (PIT), Buffalo Niagara International (BUF), James M Cox Dayton International (DAY), Cincinnati Northern Kentucky International (CVG), Rochester International (RST), St Louis Regional (ALN) and Spirit of St Louis (SUS).

![Figure 3.6 Airports within and close to the study area for which passenger air tickets are unavailable](image)

Considering passengers from the entire geography of Figure 3.5 would assume that the viable airport choices passengers have available to them are only those shown in Figure 3.3, given that ticket data is only available for these airports. In order to overcome this unrealistic assumption, passengers whose air tickets are associated with ZIP codes in Ohio and all states to the east and south of Ohio are removed. Similarly, all ZIP codes in states to the west of Minnesota and Iowa are removed. Furthermore, air tickets associated with ZIP codes closest to MSP, DSM and STL are further removed given that there are other surrounding airports (on which data is not available).
that could have been chosen by air passengers. These geographic scope refinement measures are taken simply based on driving distance proximity and state boundaries as other measures were not possible due to data limitations.

**Figure 3.7** presents the final study area, which centers around ORD, the third busiest US airport in 2018, with nonstop flights to over 210 domestic and international destinations and a total of 39.87 million passenger enplanements (FAA, 2019). That same year, extensive infrastructure and capacity expansion programs including a new terminal, dozens of new gates and more concourses were launched at an estimated budget of 8.5 billion USD (Ruthhart, 2018). ORD attracts air passengers from throughout Southern Illinois as well as from the neighboring states of Wisconsin, Indiana and even Michigan (Milwaukee Mitchell Airport, 2015; Naczek, 2019; Gao, 2020; Yirgu, Kim and Ryerson, 2021).

![Map showing airports](image)

**Figure 3.7 Final study area and airports**

On the eastern edge of the study area is DTW, which draws passengers from areas nearer to other airports (Michigan Department of Transportation, 2016; Yirgu, Kim, and Ryerson, 2021). MSP is
another large hub airport to the west of the study area attracting passengers from areas served by other closer airports (Leon, 2011). MKE, IND and STL are medium hubs that offered nonstop services to various domestic destinations (30 up to 60) during the study period of 2013–2018. The remaining small hub and non-hub primary airports in the study area offered limited scheduled flights to a number of large hubs both within and beyond the study area such as Atlanta, Denver and Dallas. LCCs provided point-to-point services at some of these small and non-hub airports during the study period.

The number of passengers finally retained in the dataset is 6.8 million, and this is broken down as a percentage of total annual enplanement per airport as shown in Figure 3.8. The total annual enplanement is taken from FAA’s Passenger Boarding (Enplanement) data (FAA, 2019). However, the total annual enplanement used as base for each airport does not distinguish between passengers that connected and started their air trips at the airport under question.
Figure 3.8 Passengers in the Market Locator dataset (after data processing) as a percentage of total annual enplanement, by departure airport

From Figure 3.8, airports that are not within the collection of ZIP codes included in the study area – such as STL, MSP and DSM – have lower percentages as expected, since records of passengers from the metropolitan areas in which these airports are located and primarily serve are not included. The large hubs of DTW and ORD have lower percentages compared to the small and
medium hubs. DTW’s low percentage might have been caused by the exclusion of air passengers from Northern Ohio that might have used the airport.

Each air ticket record is then supplemented with access distances to all study airports, computed using the ArcGIS Network Analyst tool as described in 3.2.2. In Figure 3.9, the number of sampled passengers that chose airports other than their closest ones (which is how the word “leakage” is defined for the figure titles), and the median additional miles traveled to do so, are shown for all six years of data.

According to Figure 3.9, ORD attracted the highest number of passengers who bypassed their closest airport (at 801,817) followed by MKE and MSP at 146,380 and 112,832, respectively, within the study area. Non-hub primary airports such as DBQ, CMI and SPI attracted a significantly lower number of air passengers bypassing their nearest airports, suggesting that most passengers that forego their nearest airports do so for large hubs rather than other small airports. The extra distances driven to large hubs, however, should be carefully interpreted in the context

Figure 3.9 “Leaking” passengers attracted and median additional miles traveled (per airport, 2013 - 2018)
of the study area and geographic location of these hubs. For instance, MSP is located 90 miles from the ZIP code closest to it within the study area whereas ORD is located centrally within the study area. As a result, it is expected that the median extra miles traveled by passengers leaking to ORD to be lower than that of MSP.

A map with the proportions of air ticket billing ZIP codes, purchased for trips originating at airports not the closest to the ZIP code, is shown in Figure 3.10.

![Figure 3.10 Proportion of passengers in air ticket dataset bypassing their nearest airport](image)

**Figure 3.10** shows that air passengers may forego use of their nearest airport in significantly greater proportions in ZIP codes closest to non-hub and small hubs compared to those closest to medium and large hubs. This suggests that medium and large hub airports retain a greater proportion of their nearby passengers.
3.3.2 Air Service Attributes and Capacity Variables

3.3.2.1 Air Service Attributes

The DB1B dataset is used to supplement the Market Locator data with airfares by route and quarter-year. The top and bottom ten percent of airfares are removed in order to exclude outliers that represent faulty and unrealistic reports of airfares, following Sherry (2014). Furthermore, itineraries operated by Southwest Airlines are removed as this carrier is not represented in the Market Locator dataset. The absence of Southwest is expected to have little impact on the research as this carrier only monopolizes MDW (which has been excluded) and has limited presence at the other subject airports.

Flight frequency is extracted from the T-100 dataset to further supplement the Market Locator data. Air services with a minimum of 24 flights per quarter (or, two flights per week) are considered, as these can be reasonably considered regular scheduled flights. Such measures have been used in the past to exclude “thinner” markets that are commonly associated with destinations prone to small sample bias (Windle and Dresner, 1995). Frequencies for flights operated by Southwest are also removed given that the airline is excluded from the Market Locator dataset. In Figure 3.11, mean air service attributes (averaged over quarter-year and destination) are shown. Note that mean flight frequency is presented in tens (x10) such that each value needs to be multiplied by ten.
Figure 3.11 Air service attributes by airport

Figure 3.11 shows that ORD, at 155, had the highest number of destinations served nonstop, followed by MSP and DTW at 118 and 110, respectively, by quarter. The medium hubs of MKE, IND and STL had nonstop services to 30 up to 60 destinations whereas the small hubs of GRR, DSM and MSN had services to 12 up to 21 destinations by quarter. All non-hub primary airports had ten or less destinations served nonstop per quarter on average. Similarly, large hubs had the highest average flight frequencies per destination, while non-hub primary airports recorded the highest airfares. In general, these comparisons suggest that large hubs have superior and more attractive air services.

3.3.2.2 Capacity Variables

Given that multiple completed flights are often compressed into a single record in the T-100 dataset, capacity decision variables such as aircraft size and LF are determined by dividing total available seats by total number of performed flights, and total occupied seats by total available seats, respectively. Weight per seat is also computed by dividing useful payload by number of seats. Although not considered as a capacity decision variable, nonstop flight distance, due to its
importance in CCD phase emission estimation, is also extracted. These variables are summarized by airport category by quarter-year as shown in Figures 3.12–3.15.

![Image of Figure 3.12](image)

**Figure 3.12** Mean aircraft size (number of seats) by airport category

**Figure 3.12** indicates that medium hubs had the largest average aircraft size followed by large and small hubs. Given higher flight frequencies, it is not necessarily unexpected that air routes originating from large hubs had lower mean aircraft size than those from medium hubs. Additionally, several flights connect to large hubs from small airports using regional and small aircraft, further reducing the average aircraft size at large hubs. Also, there is a general upward trend in aircraft sizes for all airport categories as the study period progresses.
Figure 3.13 Mean LF by airport category

Figure 3.13 shows that LFs ranged between 0.72 and 0.82 with non-hub primary airports registering the lowest value.
Figure 3.14 illustrates that non-hub primary and small hub airports had the lowest nonstop distances flown, as routes originating from these airports are mainly connectors to a small number of neighboring large hubs.
According to Figure 3.15, weight per seat ranged between 112 and 125 kg/seat for small, medium and large hubs, with non-hub primary airports recording values beyond 125 kg/seat for nine of 24 quarters.

### 3.3.3 Aviation Fuel and Emissions

For each of the 78 aircraft reported in the EMEP/EEA, the aircraft operating weight (AOW) is computed as shown in Equation 3.1. It should be noted that the information from these 78 aircraft are only used to estimate the parameters on the adopted aviation fuel/emissions model discussed in detail in 5.1.1.

$$AOW = OEW + (LF \times w \times a)$$  \hspace{1cm} (3.1)

Where
\( AOW \) = aircraft operating weight;
\( OEW \) = operating empty weight;
\( LF \) = 0.6 as per EMEP/EEA;
\( w \) = weight per passenger (95 kg as per EMEP/EEA); and
\( \alpha \) = aircraft size (number of seats).

Note that \( OEW \) is the basic weight of an aircraft including crew, all fluids necessary for operation such as engine oil, engine coolant, water, unusable fuel and all operator items and equipment.

For the purposes of data description and discussion, the 78 aircraft are categorized into one of the following based on Eurocontrol’s Aircraft Performance Database: corporate, tactical, utility, regional, narrow body, and wide body. This classification is chosen simply because it clearly distinguishes between aircraft types typically used in commercial and non-commercial operations. For instance, the last three groups are generally used in commercial aviation whereas the first three groups are used in non-commercial aviation. Corporate aircraft transport small groups of travelers or goods and are operated outside of scheduled commercial air travel, while tactical aircraft are capable of engaging in combat. Utility aircraft transport limited passengers or cargo and can operate on short unpaved runways. Regional aircraft have a maximum seating capacity of 70 up to 100 (with a maximum of 4 seats abreast) and are used in short flights. Narrow body aircraft accommodate a maximum of 6 seats abreast, arranged along a single aisle and are used in short to medium range flights whereas aircraft with seats arranged along double aisles are categorized as wide body. The quantity of fuel burned and pollutants emitted during LTO is then plotted along with AOW as shown in Figures 3.16–3.17. Given that LTO emissions will be modeled as a function of AOW, these plots are helpful in illustrating their relationship. From Figure 3.16, there appears to be a linear relationship between AOW on one hand, and aviation fuel burned as well as \( \text{CO}_2 \), \( \text{H}_2\text{O} \) and \( \text{NO}_x \) emitted on the other. Conversely, Figure 3.17 shows that HC and PM\(_{25}\) have no relationship with AOW.
Figure 3.16 LTO phase aviation fuel, CO₂, H₂O and NOₓ
Figure 3.17 LTO phase CO, HC, SO\textsubscript{X} and PM\textsubscript{25}
Unlike LTO phase fuel and emissions, CCD fuel and emissions are dependent on flight distance, and there are multiple separate flights reported for the same aircraft type operating different flight distances, based on range capability. Fuel and emissions for most regional aircraft are reported for flights ranging between 232–2,778 km, while those for narrow body aircraft are reported for 232–7,400 km. Wide body aircraft fuel and emissions are reported for flights ranging from 232 up to 15,120 km. Aviation fuel burned and pollutants emitted in the CCD phase are computed by passenger-kilometer travelled (PKT) for each unique flight (since number of passengers can be computed as the product of LF, i.e. 0.6 and seat number), and plotted against flight distance as shown in Figures 3.18–3.19. These plots show the general relationship between PKT level emissions and flight distance for aircraft of different categories and sizes.

In Figures 3.18–3.19, wide body aircraft burn and emit the least amount of fuel and pollutants by PKT, respectively, whereas corporate aircraft result in the greatest fuel consumption and pollutants’ emissions at the PKT level. Furthermore, as flight distance increases, reported values of fuel and pollutants decrease, with the exception of CO.
Figure 3.18 CCD phase aviation fuel, CO$_2$, H$_2$O and NO$_x$
Figure 3.19 CCD phase CO, HC, SO\textsubscript{x} and PM\textsubscript{2.5}
3.3.4 Other Data

Population and socio-economic factors are used as variables in the model for air demand in the third objective. Total annual changes in population and unemployment between successive years are assumed to occur in four even increments, to match the quarter-years used for this thesis. For instance, if population is one million during year $y$ and 1.1 million during year $y + 1$, it is assumed that populations during the first to fourth quarters of $y + 1$ are 1.025 million, 1.05 million, 1.075 million and 1.1 million, respectively.

As described in Chapter 6, MSN and ORD – each representing small, medium and large hubs, respectively – are selected for analysis from which elasticities of aviation fuel and emissions to airfare are computed. Accordingly, the geographic area from which these airports draw air passengers (market areas) are identified based on Chapter 4: and population (sum of population in ZIP codes within the market area of an airport) and mean unemployment (within the market area of an airport) are computed by quarter-year. Recall that although population is directly available at the ZIP code level, unemployment is only reported at the county level. A county contains multiple ZIP codes and thus, the mean of unemployment rates of counties spanning the airport market area ZIP codes are considered. The relevant counties are identified by overlaying counties on ZIP codes. Table 3.2 summarizes unemployment and population per airport’s market area.

Table 3.3 Population and Unemployment Summary Statistics

<table>
<thead>
<tr>
<th>Airport</th>
<th>Population (year-quarterly per ZIP code)</th>
<th>Unemployment, % (year-quarterly per county)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min.</td>
<td>Mean</td>
</tr>
<tr>
<td>MSN</td>
<td>57</td>
<td>6248</td>
</tr>
<tr>
<td>ORD</td>
<td>52</td>
<td>14,324</td>
</tr>
</tbody>
</table>

The remaining variable of jet fuel price is presented in Figure 3.20. Jet fuel price is available on a monthly basis, and is thus averaged for the three months within a quarter to determine the quarterly price.
Figure 3.20 Jet fuel price

Jet fuel prices were significantly higher during 2013 and 2014, falling in 2015 towards a low in 2016 Q1, and then increasing to the end of the study period.
Chapter 4: Long-Distance Departure Airport Choices

This chapter presents an exploration of long-distance departure airport choice. The disparities in air services offered at different airports across a large region have been further exacerbated by airline mergers, network reorganizations, personnel shortages, and external shocks such as the 9/11 attack, the 2008 financial crisis and most recently, the COVID-19 pandemic. In response to these disparities, some air passengers will travel longer ground distances to access airports with better air services compared to those available at their closest airport – a phenomenon that has been termed air passenger “leakage.” To better understand this phenomenon, both researchers and practitioners have collected and assessed air passengers’ airport choices over the last 30 years, largely through mail, telephone and intercept surveys (Innes and Doucet, 1990; Suzuki, Crum and Audino, 2003; Blackstone, Buck and Hakim, 2006; de Luca, 2012). However, these surveys and subsequent model results have been limited in geographic scope due to the constraints of survey data collection, and thus do not (and are not meant to) capture the full extent of passenger airport choices and “leakage” across large areas spanning multiple administrative boundaries (Gupta, Vovsha and Donnelly, 2008). Furthermore, there is a lack of air passenger survey data collected across geographic areas administered by multiple neighboring regional planning agencies due to barriers to coordination (Oden and Sciara, 2020; Rahman, Sciara and Ryerson, 2021).

Thus, the purpose of this work is to gain a more comprehensive understanding of how long-distance airport choices – choices to use major airports up to hundreds of miles away instead of closer but smaller airports – are influenced by these disparities in air services offered. This work is primarily supported by a dataset of air tickets purchased by travelers from a section of the US Midwest spanning several state and regional boundaries, as introduced in the previous chapter.

An earlier version of the model on which this chapter is based is published in Transportation Research Record.

4.1 Approach Overview

The analysis approach taken in this chapter is as follows. First, a mixed logit model (MMNL) is used to estimate the effects of air service characteristics on air passengers’ airport choices,
specifically on routes originating from the 21 departure study airports (Figure 3.7) and ending at 61 unique final destinations (shown in Appendix B.1). MMNL is chosen as it captures heterogeneity across decision-makers (i.e., air passengers), through model estimates that are random variables as opposed to deterministic constants. The 61 final destinations are chosen because there are records of at least one passenger traveling to each from each of the study airports. This approach assumes that all air passengers within the study area can choose among all the 21 airports. Such an assumption has some limitations given that the airports considered by a passenger are limited and depend, among other things, on sociodemographic, informational, psychological and subjective criteria specific to that person (Ben-Akiva and Boccara, 1995; Başar and Bhat, 2004). As such, an individual might decide a particular airport to be too far (or too unattractive because it is not served by an airline this individual frequently uses) to even consider while another individual might not (Başar and Bhat, 2004). Given the lack of data on the abovementioned factors, this work uses airport access distance in addition to air service variables to explain airport choices.

The routes are divided into three categories based on total flight length – short, medium and long. The resulting airport choice characteristics are compared across these categories to understand how air service attributes influence airport choices. This work is described in Section 4.2 and the results are presented in 4.3.1.

Then, for each of the 21 departure airports considered, hypothetical destinations are created by using averages of the air service attributes on all 61 destinations. Model parameters are estimated again, without using route distance categorizations, and the results are plotted for selected airports (4.3.2). Finally, the effects of growing air service disparities on airport market areas and shares are explored through a sensitivity analysis (4.3.3).

4.2 Model

4.2.1 Specification

Airfare, flight frequency, availability of nonstop services, and airport accessibility are among the most well-documented attributes affecting departure airport choice as discussed in the literature review (Section 2.1.2), and these are used in the model. Other air service and capacity-based explanatory variables such as airfare per mile, seats offered, number of flight legs and route distance were also initially considered but excluded due to multicollinearity. Different
combinations of these variables were tested for multicollinearity using correlation matrices and variance inflation factor (VIF). For VIF, an upper limit of five is applied to limit non-pairwise correlation (O’Brien, 2007), such that any combination of variables whose VIF value exceeds five is judged to exhibit collinearity. Note that passenger-specific attributes such as frequent flyer membership, income, flying experience, travel purpose (business or leisure), age, gender, travel group, airport access mode etc., which are expected to also influence airport choices are not available from the Market Locator purchased ticket dataset. The utility underlying the airport choices made by passengers represented in the Market Locator dataset, across the study geography, is show in Equation 4.1.

\[
U_{i,j,k}^q = V_{i,j,k}^q + \varepsilon_{i,j,k}^q = \alpha_{0,k} \cdot I(i) + \alpha_{1,k} f_{i,j}^q + \alpha_{2,k} D_{i,k} + \alpha_{3,k} F_{i,j}^q + \alpha_{4,k} NS_{i,j}^q + \varepsilon_{i,j,k}^q \tag{4.1}
\]

Where

\( q = \) quarter-year, \( q = 1 \ldots Q \), where \( Q \) is 24 (4 quarters per year for 6 years, 2013-2018);

\( i = \) departure airport, from \( i = 1 \ldots 21 \) airports;

\( j = \) final destination airport, \( j = 1 \ldots 61 \) airports;

\( k = \) decision maker (air passenger), \( k = 1 \ldots K \);

\( U_{i,j,k}^q = \) is the utility of choosing the route from departure airport \( i \) to final destination airport \( j \) for air passenger \( k \), in quarter-year \( q \);

\( V_{i,j,k}^q = \) is the observed utility on route \( i \) to \( j \) for \( k \), in \( q \);

\( I(i) = \) airport dummy, \( I = 1 \) if departure airport chosen is \( i \), and 0 otherwise;

\( f_{i,j}^q = \) mean airfare (USD) on route \( i \) to \( j \) in \( q \);

\( D_{i,k} = \) access distance (miles) from residential ZIP code of \( k \) to \( i \);

\( F_{i,j}^q = \) flight frequency on route \( i \) to \( j \) in \( q \);
\( NS_{i,j}^q \) = nonstop service dummy on route \( i \) to \( j \) in \( q \), \( NS_{i,j}^q = 1 \) if flight is nonstop, \( 0 \) if connecting;

\( \alpha_{0,k} \) = alternative specific constant (ASC) for \( k \);

\( \alpha_{1,k}, \alpha_{2,k}, \alpha_{3,k}, \alpha_{4,k} \) = coefficients on air service attributes for \( k \), and

\( \varepsilon_{i,j,k}^q \) = error term on route \( i \) to \( j \) for \( k \), in \( q \).

Because of limitations in the Market Locator dataset, it is impossible to account for all variables (most critically, passenger-specific attributes) that affect decision makers’ choices. Therefore, the utility of alternatives cannot be fully captured, resulting in randomly distributed error terms or unobserved portions of utilities (Bernasco, Wim; Block, 2009). However, by introducing the ASCs, the mean of the error terms can be added to the observed utility function such that the remaining error term has a mean of zero (Hess and Polak, 2005).

The MMNL treats parameters \( \alpha_0 \ldots \alpha_4 \) as random variables rather than constants, and thus model estimates are of the moments of these parameters. If they are assumed to be normally distributed, their means and standard deviations are estimated. As shown in Equation 4.2, the probability that decision maker \( k \) chooses departure airport \( i \) to fly to destination \( j \) during quarter-year \( q \), i.e. \( P_{i,j,k}^q \), is an integral of the conditional logit probability over some density distribution \( f(\alpha | \Omega) \), where \( \Omega \) represents the parameters of this distribution.

\[
P_{i,j,k}^q = \int L_{i,j,k}^q(\alpha) \cdot f(\alpha | \Omega) \, d\alpha
\]

(4.2)

Where

\[
L_{i,j,k}^q(\alpha) = \frac{e^\gamma_{i,j,k}^q}{\sum_{l=1}^l e^\gamma_{l,j,k}^q}
\]

(4.3)

Where

\( L_{i,j,k}^q(\alpha) \) = probability that \( k \) chooses \( i \) to fly to \( j \) in \( q \), conditional on \( \alpha \), and other variables as previously defined.
**Equation 4.2** has no closed form solution and must be solved by simulation. While various distribution types are possible, the normal distribution is chosen as it does not force only positive parameter estimates (Ibeas *et al.*, 2014) like, for example, the log-normal. When only positive or negative estimates are forced, the researcher must decide the signs of the estimated parameters a-priori (Hess and Polak, 2005).

**Equation 4.3** is approximated through simulation for any given value of $\Omega$ by executing the following steps: i) draw a value of $\alpha$ from $f(\alpha|\Omega)$ to be labeled as $\alpha^g$ where $g = 1$ refers to the first draw; ii) calculate $L_{i,j,k}^q(\alpha^g)$ using **Equation 4.3**, and iii) repeat steps i and ii a total of $G$ times (number of simulations), and average the results. This average is the simulated probability shown in **Equation 4.4**.

$$
\hat{p}_{i,j,k}^q = \frac{1}{G} \sum_{g=1}^{G} L_{i,j,k}^q(\alpha^g)
$$

(4.4)

For the entire set of decision makers $K$, the value of $\Omega$ that maximizes the simulated log-likelihood ($SLL$) function is searched (McFadden and Train, 2000) using **Equation 4.5**.

$$
SLL = \sum_{k=1}^{K} \sum_{i=1}^{I} d_{i,j,k}^q \hat{p}_{i,j,k}^q
$$

(4.5)

Where

$$
d_{i,j,k}^q = \text{dummy variable on } \hat{p}_{i,j,k}^q, 1 \text{ if } k \text{ chooses } i \text{ to travel to } j \text{ in } q, \text{ and } 0 \text{ otherwise.}
$$

The coefficient of variation (CV), the ratio of standard deviation to mean (Li, 2015), is a dispersion indicator which is used to measure decision-maker taste heterogeneity with respect to the attributes.

**4.2.2 Segmentation by Flight Length**

Air passengers can be categorized into more homogeneous groups, and model estimates across these different groups can be compared. In previous studies, passengers have been categorized by
trip purpose (business vs. leisure) and geography familiarity (resident vs. non-resident) (Hess and Polak 2005; Ishii, Jun, and Van Dender 2009), amongst others. Due to lack of data on such passenger-specific attributes in the Market Locator dataset, passengers are categorized based on total flight distance traveled instead (Jorge-Calderón, 1997; Lee, Li and Song, 2019; Mohammadian et al., 2019). This is done in order to understand whether the influences of air service attributes on different flight distances also differ, and by how much. Based on recommendations for domestic US operations (Hansen, 1995) and Eurocontrol’s standard classification (European Organisation for the Safety of Air Navigation, 2011), three categories are chosen: <932 mi (1,500 km) – short route, 932-1,864 mi (1,500-3,000km) – medium route, and >1,864 mi (3,000 km) – long route.

4.2.3 Passenger Sample Subset

As expected, initial attempts to implement the specified MMNL on all 2.37 million passengers in the three flight range categories (with the 61 destinations shown in Appendix B.1) did not lead to convergence of the SLL. Although other simpler model structures such as MNL and NL that more easily converge were tested, they do not achieve the specific objective of this work. As mentioned earlier, both provide one parameter estimate per each attribute, assuming that all decision makers place the same weight on each attribute included in the utility function. It was deemed important to capture that decision makers are unlikely to place the same value on an attribute (Hess and Polak, 2005). Second, certain airports are likely to be viewed as more substitutable by passengers, particularly when similar airlines serve these kinds of airports (only captured with NL and MMNL).

To achieve convergence with a smaller dataset, a subset of the total passenger dataset is drawn using Halton sequences which, when compared to simple random sampling, improves the spatial coverage of geographical data (Robertson et al., 2019). Fixed first is the minimum subset data size of the base category, chosen to be all passengers in the long route category. For population sizes over 100,000, a minimum sample size of 2,000 is considered sufficient for discrete choice models (Koppelman and Chu, 1983; de Bekker-Grob et al., 2015). Based on this, a sample size of 2,000 passengers is taken for the long route category. Once this category’s size is fixed, the subset sizes of the remaining two categories are fixed by preserving the proportion ratio observed in the total
dataset, as typically done in clustered sampling (Meng, 2013; IBM, 2021). For instance, the ratio of passengers on short routes to those on long routes is 2.12, while that of short to medium is 0.39 in the processed ticket dataset. Additionally, the ratio of passengers on medium routes to those on long routes is 5.5. Accordingly, subset sizes of 4,240, 11,000 and 2,000 passengers are taken for the short, medium and long route categories, respectively. Given that only subsets of the total dataset are used to estimate parameters, the estimates will vary depending on the data subset used. Thus, for each route category, five different subsets (all following the cluster ratios) are drawn to check if model estimates exhibit statistically significant differences.

4.3 Results and Discussion

4.3.1 Route Distance-based Model Estimates

The model estimates resulting from the abovementioned five subsets were compared using a t-test. Differences in model estimates for airfare, flight frequency, access distance and nonstop service between two data subsets were found to be statistically significant. Also, differences in ASC estimates on three of the 21 airports, i.e. MSP, DSM and STL were found to be statistically significant between all data subsets. However, the comparisons among estimates on the different route categories discussed hereafter still hold for all data subsets. With this, one data subset per route category is randomly chosen, and the estimated parameter results are discussed. The means and standard deviations of the ASCs have been excluded in the interest of length, but are contained in Appendix B.2. Parameters are estimated using the mlogit library of R and presented in Table 4.1. All estimates are significant at the 99% confidence level, and standard errors are indicated in parenthesis next to each model estimate.
Table 4.1 MMNL Model Estimates

<table>
<thead>
<tr>
<th>Air service attribute</th>
<th>Moments</th>
<th>Short routes</th>
<th>Medium routes</th>
<th>Long routes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Estimate (std. error)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Access distance</td>
<td>Mean</td>
<td>-0.102 (0.009)</td>
<td>-0.107 (0.006)</td>
<td>-0.201 (0.038)</td>
</tr>
<tr>
<td></td>
<td>Std. dev</td>
<td>0.046 (0.005)</td>
<td>0.053 (0.003)</td>
<td>0.078 (0.016)</td>
</tr>
<tr>
<td></td>
<td>CV, %</td>
<td>45.1</td>
<td>49.5</td>
<td>38.8</td>
</tr>
<tr>
<td>Flight frequency</td>
<td>Mean</td>
<td>0.001 (0.000)</td>
<td>0.001 (0.000)</td>
<td>0.003 (0.001)</td>
</tr>
<tr>
<td></td>
<td>Std. dev</td>
<td>0.000 (0.000)</td>
<td>0.001 (0.000)</td>
<td>0.005 (0.001)</td>
</tr>
<tr>
<td></td>
<td>CV, %</td>
<td>0.0</td>
<td>100.0</td>
<td>166.7</td>
</tr>
<tr>
<td>Mean airfare</td>
<td>Mean</td>
<td>-0.039 (0.004)</td>
<td>-0.039 (0.003)</td>
<td>-0.042 (0.011)</td>
</tr>
<tr>
<td></td>
<td>Std. dev</td>
<td>0.029 (0.004)</td>
<td>0.029 (0.004)</td>
<td>0.074 (0.016)</td>
</tr>
<tr>
<td></td>
<td>CV, %</td>
<td>74.4</td>
<td>74.4</td>
<td>176.2</td>
</tr>
<tr>
<td>Nonstop service</td>
<td>Mean</td>
<td>2.922 (0.370)</td>
<td>2.625 (0.180)</td>
<td>2.857 (0.801)</td>
</tr>
<tr>
<td></td>
<td>Std. dev</td>
<td>1.860 (0.493)</td>
<td>2.126 (0.239)</td>
<td>4.822 (1.561)</td>
</tr>
<tr>
<td></td>
<td>CV, %</td>
<td>63.7</td>
<td>81.0</td>
<td>168.8</td>
</tr>
<tr>
<td>Passengers sampled in data subset</td>
<td></td>
<td>4,240</td>
<td>11,000</td>
<td>2,000</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td>89,040</td>
<td>231,000</td>
<td>42,000</td>
</tr>
<tr>
<td>SLL</td>
<td></td>
<td>-3,592.317</td>
<td>-9,198.864</td>
<td>-1,559.154</td>
</tr>
<tr>
<td>McFadden R²</td>
<td></td>
<td>0.733</td>
<td>0.723</td>
<td>0.744</td>
</tr>
<tr>
<td>Adjusted McFadden R²</td>
<td></td>
<td>0.730</td>
<td>0.722</td>
<td>0.736</td>
</tr>
</tbody>
</table>

All parameter estimates are significant at the 99% confidence level

With regard to taste heterogeneity, coefficients of variation (CVs) exceeding 100% are often associated with dispersion (Bedeian and Mossholder, 2000), and are indicative of greater taste heterogeneity. The CV for access distance ranges between 38.8% and 49.5%, while for frequency it ranges between 0% and 166.7% for different route categories. Additionally, the CV on airfare for both short and medium routes is 74.4%, but increases to 176.2% for long routes. Nonstop service has a CV ranging between 63.7% for short routes up to 168.8% for long routes.

Results show that the influences of airfare, flight frequency and access distance on airport choice are very similar for short and medium routes. Airfare coefficients are -0.039 for both, while access distance coefficients are -0.102 and -0.107 for short and medium routes, respectively (about a 5% difference). The influence of nonstop service on airport choices differs at 2.92 for short vs 2.63 for medium routes (about a 10% difference).
The impacts of airfare and nonstop service on air passengers’ utilities on long routes differ compared to those on short and medium routes (-0.042 for long versus -0.039 for short/medium on airfare). For comparable airfares, the utility portion of airfare on long routes is expected to be 7% lower than those on short/medium. However, for comparable flight frequencies, passengers on long routes place three times as much weight (0.003 vs 0.001) on this frequency attribute compared to those on short and medium routes. These results are not straightforward to interpret; for nonstop routes, the frequency considered is the number of flights serving those nonstop routes. For connecting routes (which are often associated with longer flights), only the first leg flight frequencies are considered. In instances where these connecting routes are served through multiple intermediate airports, the means of flight frequencies leading to these intermediate airports are taken. Marcucci and Gatta (2011) showed that connecting air passengers attempt to minimize their wait times during connections which is in large part determined by the first flight schedule, as more options usually exist at airports where connections are made. Additionally, even when nonstop services are available, long routes are usually offered at lower frequencies than short routes, and thus passengers taking long routes are likely to place higher value on flight schedule (with lower flight frequencies further restricting passengers’ schedule preferences). Passengers on long routes, compared to those on short ones, place twice as much weight on access distance (-0.201 vs -0.102 for short-range), which seems counterintuitive as passengers flying to farther destinations would be expected to be more amenable to more distant departure airports, because of an inclination towards minimizing overall travel time, which includes the ground-based airport access trip plus the longer flight. Longer trips are associated with increased value of travel time (Athira et al., 2016; US Department of Transportation, 2016), given that passengers’ abilities to engage in other productive activities decrease as they spend more time traveling. Thus, they are willing to pay more to save a unit of time. The relatively high CVs associated with airfare (176.2), frequency (166.7) and nonstop service (168.8%) on long routes imply that passengers’ responses to these attributes are more diverse. In essence, airlines might be able to better predict how changes in these service attributes would affect passengers on short and medium routes. To further investigate, the distributions of the model coefficients are presented in Figures 4.1–4.2.
Figure 4.1 Estimated parameter distributions for flight frequency (left) and nonstop service (right).

From Figure 4.1, 11% and 12% of air passengers on short and medium routes, respectively, have negative coefficients for flight frequency. This indicates that higher flight frequency is expected...
to increase the probability of an airport being chosen by the remaining 89% and 88% of passengers. Similarly, the availability of nonstop services has a positive influence on an airport’s probability of being chosen among 94% and 89% of passengers on short and medium routes, respectively. These findings confirm that higher flight frequency and nonstop service availability lead to a positive preference response across the majority of passengers on short and medium route. However, for passengers on long-routes, both flight frequency and nonstop services positively influence an airport’s choice probability among a smaller 76% and 73% of passengers, respectively, indicating more diverse responses to these service attributes. The responses for the remaining attributes of airfare and access distance are shown in Figure 4.2.
Figure 4.2. Estimated parameter distributions for airport access distance (left) and airfare (right)

The left column graphs of Figure 4.2 show that 97%-99% of passengers across the three route categories are negatively influenced by a larger airport access distance, confirming a preference
for closer airports. Higher airfares have a negative influence on 90% and 91% of passengers on short and medium routes, respectively. This drops to 71% for passengers on long routes, meaning with all else equal, 29% of these passengers view paying more for airfare positively towards choosing an airport. Although counterintuitive, this result might suggest that there are other attributes – such as preferences for certain airlines that service these routes, or tickets that include the costs of add-ons – that have passengers choosing long-route itineraries with higher airfares.

4.3.2 Airport Choice Probabilities by Geography

Airport choice probabilities are calculated using the means of the estimated model parameters applied to hypothetical destinations. These hypothetical destinations feature the mean air service attributes for traveling to the 61 destinations identified previously. This is done as an alternative to showing probability plots for each of the 61 destinations individually, and serve the purpose of demonstrating how air service disparities impact passengers’ airport choices across the study region. The mean air service attributes are shown for all studied departure airports, by airport size classification, in Figure 4.3.
Figure 4.3 Mean air service attributes representing hypothetical destinations per departure airport

From Figure 4.3, as expected mean airfare and nonstop service are highest and lowest, respectively, at the non-hub primary airports. Large hubs have mean nonstop service indicators close to one (1 at ORD, 0.8 at DTW, and 0.9 at MSP), as most of the 61 destinations were connected to these airports via nonstop service. Medium hubs have nonstop service indicators ranging from 0.35-0.45, small hubs range from 0.16-0.24, and all non-hubs have values less than 0.15. Flight frequency is computed to consider the schedule of first leg flights for destinations not served nonstop, from all non-hub primary and small hubs with few nonstop services to the 61 destinations. As mentioned earlier, the characteristics of first leg flights are critical in passengers’ airport and itinerary choices towards reducing wait times but increasing the likelihood of catching connecting flights (Marcucci and Gatta, 2011).
Because attributes representing mean air service qualities across all destinations are considered here, the model in 4.2.1 is first estimated for all 61 destinations without the route distance categorization of 4.2.2. The minimum sample size of 2,000, Halton sequencing mechanism and five different data subset draws employed in 4.2.3 are used here as well\(^2\). Model estimates, along with their standard errors in brackets, are shown in Table 4.2 based on one data subset. Then these estimates are applied on the air service attributes of the hypothetical destinations, to find each departure airport’s probability of being chosen, by ZIP code as discussed hereafter.

\(^2\) Note that higher sample sizes that still achieve convergence were tested, and a final size of 17,000 is used. However, for the flight distance-based sampling, it was not possible to increase sample sizes while still preserving cluster ratios and achieving convergence.
Table 4.2 MMNL Model Estimates without Route-based Categories

<table>
<thead>
<tr>
<th>Air service attributes and airport dummy</th>
<th>Mean (std. error)</th>
<th>Std. dev (std. error)</th>
<th>CV, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Access distance</td>
<td>-0.095 (0.004)</td>
<td>0.037 (0.002)</td>
<td>38.9</td>
</tr>
<tr>
<td>Flight frequency</td>
<td>0.001 (0.000)</td>
<td>0.001 (0.000)</td>
<td>100.0</td>
</tr>
<tr>
<td>Mean airfare</td>
<td>-0.033 (0.002)</td>
<td>0.026 (0.003)</td>
<td>78.8</td>
</tr>
<tr>
<td>Nonstop service</td>
<td>1.765 (0.113)</td>
<td>1.839 (0.176)</td>
<td>104.2</td>
</tr>
<tr>
<td>$I(\text{ATW} = 1)$ (base)</td>
<td>0 (-)</td>
<td>0 (-)</td>
<td>-</td>
</tr>
<tr>
<td>$I(\text{AZO} = 1)$</td>
<td>-1.155 (0.435)</td>
<td>0.189 n/s (0.828)</td>
<td>16.4</td>
</tr>
<tr>
<td>$I(\text{BMI} = 1)$</td>
<td>2.740 (0.302)</td>
<td>2.437 (0.388)</td>
<td>88.9</td>
</tr>
<tr>
<td>$I(\text{CMI} = 1)$</td>
<td>-0.547** (0.320)</td>
<td>0.251 n/s (0.505)</td>
<td>45.9</td>
</tr>
<tr>
<td>$I(\text{CWA} = 1)$</td>
<td>-1.829 (0.332)</td>
<td>0.510 n/s (0.682)</td>
<td>27.9</td>
</tr>
<tr>
<td>$I(\text{DBQ} = 1)$</td>
<td>-4.305 (0.501)</td>
<td>2.725 (0.632)</td>
<td>63.3</td>
</tr>
<tr>
<td>$I(\text{DSM} = 1)$</td>
<td>5.357 (0.439)</td>
<td>5.063 (0.487)</td>
<td>94.5</td>
</tr>
<tr>
<td>$I(\text{DTW} = 1)$</td>
<td>6.799 (0.393)</td>
<td>1.214 (0.243)</td>
<td>17.9</td>
</tr>
<tr>
<td>$I(\text{FWA} = 1)$</td>
<td>2.243 (0.355)</td>
<td>0.215 (0.534)</td>
<td>9.6</td>
</tr>
<tr>
<td>$I(\text{GRB} = 1)$</td>
<td>0.282* (0.142)</td>
<td>1.319 (0.259)</td>
<td>467.7</td>
</tr>
<tr>
<td>$I(\text{GRR} = 1)$</td>
<td>3.079 (0.297)</td>
<td>2.725 (0.272)</td>
<td>88.5</td>
</tr>
<tr>
<td>$I(\text{IND} = 1)$</td>
<td>7.776 (0.401)</td>
<td>1.905 (0.271)</td>
<td>24.5</td>
</tr>
<tr>
<td>$I(\text{MKE} = 1)$</td>
<td>5.808 (0.316)</td>
<td>3.702 (0.317)</td>
<td>63.7</td>
</tr>
<tr>
<td>$I(\text{MLI} = 1)$</td>
<td>1.974 (0.264)</td>
<td>3.888 (0.521)</td>
<td>197.0</td>
</tr>
<tr>
<td>$I(\text{MSN} = 1)$</td>
<td>2.589 (0.241)</td>
<td>2.320 (0.327)</td>
<td>89.6</td>
</tr>
<tr>
<td>$I(\text{MSP} = 1)$</td>
<td>9.229 (0.493)</td>
<td>4.147 (0.535)</td>
<td>44.9</td>
</tr>
<tr>
<td>$I(\text{ORD} = 1)$</td>
<td>6.832 (0.419)</td>
<td>2.410 (0.316)</td>
<td>35.3</td>
</tr>
<tr>
<td>$I(\text{PIA} = 1)$</td>
<td>3.883 (0.425)</td>
<td>1.543 (0.743)</td>
<td>39.7</td>
</tr>
<tr>
<td>$I(\text{SBN} = 1)$</td>
<td>1.838 (0.352)</td>
<td>0.504 n/s (0.481)</td>
<td>27.4</td>
</tr>
<tr>
<td>$I(\text{SPI} = 1)$</td>
<td>-0.918 n/s (0.926)</td>
<td>0.722 n/s (0.959)</td>
<td>78.6</td>
</tr>
<tr>
<td>$I(\text{STL} = 1)$</td>
<td>10.658 (0.576)</td>
<td>5.751 (0.685)</td>
<td>54.0</td>
</tr>
</tbody>
</table>

Passengers sampled in data subset: 17,000
Observations: 357,000
SLL: -14,906.384
McFadden $R^2$: 0.718
Adjusted McFadden $R^2$: 0.717

*significant at 95% level; **significant at 90% level; n/s not significant at 90% level. All others significant at 99%.
In the interest of length, the discussion is focused on choice probability plots for one airport each from the small, medium and large categories: Dane County Regional (MSN), Milwaukee Mitchell International (MKE), and Chicago O’Hare International (ORD), respectively. ORD’s position as one of the largest US hub airports presents a unique opportunity to show the geographic extent from which an airport can attract passengers. MKE and MSN are also chosen due to their proximity and documented history of passengers within their assumed catchments “leaking” to ORD (Milwaukee Mitchell Airport, 2015; Yirgu, Kim and Ryerson, 2021).

Figures 4.4–4.5 show the airport choice probabilities for MSN, MKE and ORD after applying the mean values of model parameter estimates (Table 4.2) on the mean air service attributes of Figure 4.3. These airport choice probabilities can be interpreted as, or represent, the airport market shares (Wei and Hansen, 2005; Ryerson and Kim, 2018). State borders as well as metropolitan planning organization (MPO) boundaries are shown. All ZIP codes with market shares of at least 0.05 are included, and these are assumed to represent the market areas of airports. Furthermore, the plots are restricted to the study ZIP codes of Figure 3.7. The scales and plot extents of all plots are identical to allow for comparisons between the results.

![Map showing market areas and shares of MSN and MKE](image)

**Figure 4.4 Market areas and shares of MSN (left) and MKE (right)**
Several observations can be made from Figures 4.4–4.5. First, as airport size increases, its market area also increases. As expected, MSN has the smallest market area followed by MKE, while ORD has by far the largest and strongest. Second, the area over which ORD has complete market dominance (0.98–1.00) is larger than that of MKE. On the other hand, MSN does not have market shares exceeding 0.95 in any ZIP code. Third, small and medium airports’ market areas and shares are visibly smaller in the direction of a neighboring airport, indicating that such airports are more susceptible to competition for passengers. For instance, the market area of MSN mainly extends to its west as MKE is located to its east and ORD to its southeast (and there are no dominant airports to its west). Similarly, MKE’s market area extends primarily north, as ORD is located only 72 mi to the south and as such, passengers to the south of MKE are far more likely to access ORD. The aforementioned observations are also observed at the other study airports, results not shown here.

Administrative borders are, as expected, of little to no importance when it comes to airport passenger markets. The area over which MSN’s market shares exceed 0.90 crosses seven MPO boundaries, while ORD’s crosses 21. This does, however, raise attention to some critical surface transportation planning issues. In the US, where intercity transit services are the exception rather
than the norm (Sperry et al., 2012; Augustin et al., 2014), air passengers throughout the region access airports mainly by private vehicle, potentially accounting for up to 2.75% of average daily traffic on congested portions of interstate highways (Ryerson and Kim, 2018). MPOs, which are responsible for regional transportation planning and are mainly structured to function independently (Rahman, Sciara, and Ryerson, 2021), focus on air transport demand only within their respective jurisdictional boundaries (Hess and Polak, 2005, 2006; Regional Airport Planning Committee, 2011; Steer Davies Gleave and Mark Kiefer Consulting, 2014). Aside from limited coordination with their neighboring counterparts, these MPOs also have little to no collaboration with the operators of several airports within their region. For example, Sciara (2019) reports that only 11% of MPOs provide voting seats for airports and an even lower 2.5% have dedicated aviation committees. Particularly in the case of long-distance travel behavior, this fractured planning paradigm cannot account for the fact that travelers originating from one jurisdiction frequently use surface and air transportation facilities and services in another.

The results of Figures 4.4–4.5 also have implications for catchment-based airport demand estimates. The results clearly demonstrate that airport catchments cannot be demarcated simply based on circles of predetermined radii around airports (Fuellhart 2007; Fröhlich and Niemeier 2011; O’Connor and Fuellhart, 2016), areas within predetermined airport access times (Suzuki and Audino, 2003; Marcucci and Gatta, 2011; Zhou et al., 2018; Milwaukee Mitchell Airport, 2020) or distances (Suau-Sanchez, Burghouwt and Pallares-Barbera, 2014; Huber et al., 2021), and administrative boundaries (Loo, Ho and Wong, 2005; Gao, 2020; Teixeira and Derudder, 2021). Nonetheless, such catchment definitions have extensively been used in airport planning and demand studies (Moore and Soliman, 1982; Rengaraju and Thamizh Arasan, 1992; Zhou et al., 2018; Mohammadian et al., 2019). Lieshout (2012) is the only author to have previously explicitly accounted for air service qualities in defining an airport’s catchment, specifically that of Schiphol Airport in the Netherlands (Amsterdam). Overall, while there is general consensus that a one-size-fits-all catchment definition is insufficient (Gao, 2020; Huber et al., 2021), a lack of large-scale passenger data has largely stymied further work in this area. To this end, Adler et al. (2022) have more recently used a large dataset of anonymized GPS records generated by mobile application users to support airport catchment estimation.
4.3.3 The Impacts of Air Service Disparities on Airport Markets

Changes in air services at airports occur as new services are launched or airlines exit certain markets, due to various forces impacting passenger demand including economic growth or decline, pilot shortage, market profitability, disruptive events (such as the COVID-19 pandemic), and others (Fuellhart et al., 2016; Atallah and Hotle, 2019; Hotle and Mumbower, 2021). Such changes will not result in the same passenger responses at all airports. The following analysis provides some insights into how airports of different sizes and locations, in relation to other airports, are impacted differently.

The effects of growing disparities in air services between airports, as represented by the mean air service attributes of Figure 4.3, are investigated. These disparities are simulated by changing the mean value of one attribute at one airport, keeping all else equal across other attributes and airports. First investigated are the effects of increasing mean airfares at MSN, MKE and ORD (one at a time) in 10% increments. The results for MSN are shown in Figure 4.6, while those for MKE and ORD are shown in Figures 4.7–4.8, respectively.
Figure 4.6 Changes in airfare and resulting market changes, MSN (mean airfare = 287 USD)

As airfare increases at MSN, the area over which the airport has market share exceeding 0.05 contracts in all directions while market shares themselves also decrease. For instance, market shares are 0.90-0.95 at mean airfare in ZIP codes clustered around the airport, and these decrease to 0.70-0.90 and 0.50-0.70 at 20% and 30% higher mean airfares, respectively.
Figure 4.7 Changes in airfare and resulting market changes, MKE (mean airfare = 264 USD)

From Figure 4.7, contraction in market area and changes in market shares are observed for MKE much like MSN. However, Figure 4.8 shows that such contractions are much less observable for ORD, reinforcing previous findings that large airports can typically absorb service degradations without losing substantial market (Ryerson, 2016; Atallah and Hotle, 2019). In general, MKE and ORD – bigger and better serviced airports than MSN – do not have their market shares decrease by more than half over a substantial proportion of their market areas like MSN, owing to their larger ASCs (5.8 for MKE and 6.8 for ORD, versus 2.6 for MSN). These ASCs capture the advantages larger, better serviced airports have over other those with worse/less air services, as well as characteristics difficult to quantify such as airport reputation (Hess and Polak, 2005). As a
result, the impacts of utility reductions caused by deteriorations in air service attributes are less impactful on passenger utility for the subject airport. Ishii, Jun, and Van Dender (2009) also showed that the ASCs of larger airports that compete with smaller ones are higher, such that if air service attributes explicitly defined in the MMNL model and airport accessibility are unaccounted for, passengers would still prefer to depart from larger airports.

![Figure 4.8 Changes in airfare and resulting market changes, ORD (mean airfare = 280 USD)](image)

The impacts of decreasing mean flight frequency and mean nonstop service on the market shares of the study airports are considerably lower than those resulting from proportional percentage changes in airfare. Mean flight frequency and nonstop service at each subject airport are reduced in 10% increments up to 30% (while keeping all else at mean values), and the greatest reductions
in corresponding market shares are just under 15% and 25%, respectively. 30% increases in airfare, however, led to market share reductions exceeding 75%.

Figure 4.9 shows the reductions in market shares for MKE resulting from proportional increases in mean airfare (left column) versus decreases in mean flight frequency (right column). It is noted that only ZIP codes with choice probabilities of at least 0.05 after air service attribute changes are shown. Reduced mean flight frequency has a much smaller impact on market shares compared to proportionally increased mean airfares. Moving farther away from MKE, the reduction in market share is considerably higher for increased airfare, reaching >75%, whereas that for decreased mean flight frequency peaks at just under 15%. While the above observations are based on comparable percentage changes in the different service attributes, it should be noted that air passengers internalize airfare and other air service attributes such as frequency differently.

While flight frequency has been shown to be critical in driving airport choices within multi-airport regions (MARs) (Harvey, 1987; Windle and Dresner, 1995; Başar and Bhat, 2004; Hess and Polak, 2005), its importance has been reported to be limited or statistically insignificant in driving long distance airport choices and passenger leakage (Yirgu, Kim, and Ryerson 2021; Suzuki, Crum, and Audino 2003). This may be due to the fact that leaking passengers are predominantly made up of leisure travelers, who are more likely to prioritize price over flight schedules.
Figure 4.9 Market share reduction (%) at MKE caused by proportional increases in airfare (left) and decreases in flight frequency (right)
4.4 Recap and Summary

In this chapter, the airport choices of air passengers across a large section of the US Midwest are characterized using MMNL choice models. An air ticket dataset allows for the exploration of transportation service attributes for airports across this geography, including airport access distance, and air service attributes of airfare, flight frequency and nonstop route availability. First, the dataset is segmented by three route distances, and the model estimation results are compared across these categories. The results show that up to 29% of air passengers on long routes have a positive response to higher airfare, a somewhat counterintuitive result, compared to a much lower 10% and 9% on medium and short routes, respectively. Similarly, 24% of passengers are willing to accommodate lower flight frequencies (compared to 12% and 11% of passengers on medium and short routes, respectively). Also, 27% of these passengers (compared to 11% and 6% of passengers on medium and short routes, respectively) have a positive response to connecting flight options, which is expected as longer routes are more likely to involve connections. These findings can provide small airports, and the airlines serving these airports, with insights on how different air service attributes influence their spatial passenger markets by route length, and better retain these markets by targeting specific service-related measures over others. The findings could also be informative for federally funded programs such as the Essential Air Service (EAS) program.

Estimated model parameters were also applied to hypothetical destinations represented by the mean values of airfare, flight frequency and nonstop service at each study departure airport in the study region. The resulting airport choice probabilities were then spatially plotted. The results indicate that airports’ market areas vary considerably but clearly increase with airport size. The market areas of smaller airports diminish in the direction of nearby airports, whereas the market areas of large hubs appear strongly across large distances, well into neighboring MPOs and across state borders. This points to a need for airport operators and MPOs to collaborate with their neighbors towards a more cooperative long-distance transportation planning approach. Finally, the potential outcomes of increasing air service disparities are investigated using proportional degradations in air service attributes. Results show that proportional changes in airfare, compared with flight frequencies, have a much stronger influence on airport choice geographically.
Chapter 5: Implications of Airport Choices on Aviation Fuel and Emissions

Part of the work of this chapter is published in *Transportation Research Part D: Transport and Environment*. The published version of the work contains only average emission factors (AEFs), whereas marginal emission factors (MEFs) are also included here.

AEF is the total emissions from a flight divided by the total passenger-kilometer traveled (PKT). It has been used extensively for different transportation modes towards informing environment-related policies. MEF is the change in emissions that can be attributed to a unit change in demand and is also measured at the PKT level.

This chapter contains estimates of the differences in AEFs and MEFs among air routes originating from different airport categories to common final destinations, towards understanding how emissions from these routes vary. The airport choices and resulting air routes investigated in Chapter 4: are expected to have different emissions outcomes, with further implications for aviation-related environmental policies.

5.1 Approach

From Figure 5.1, consider a passenger (whose true point of origin is home) that chooses between a small (or non-hub), medium, and large hub airport to fly to a destination on Route 1, Route 2 and Route 3, respectively.

![Figure 5.1 An air passenger’s routing options through three airports](image-url)
Based on the service features of each of the routes (i.e., number of connections and nonstop flight segments, aircraft size, aircraft LFs, and flight segment distances), the AEFs and MEFs on each route are expected to differ. These differences are computed as per the chapter overview shown in Figure 5.2.

**Figure 5.2 Chapter overview**

Figure 5.2 shows that a fuel/emissions model formulation is first adopted from Cox, Jemiolo and Mutel (2018), and the necessary model parameters are estimated based on standard emissions database available from the European Monitoring Evaluation Program (EMEP) and European Environment Agency (EEA). The model is then applied on routes originating from small, medium
and large hubs as observed from the Market Locator dataset to estimate AEFs and MEFs on these routes. The estimates are finally compared across these airport groups.

In the adopted model, Cox, Jemiolo, and Mutel (2018) estimate the Swiss national aviation fuel consumption to within 7% accuracy of national fuel reports for a 25-year period. The model is derived from basic aerodynamic equations that predict how far an aircraft can fly given a set of constraints, and can estimate fuel burned and pollutants emitted by any kind of aircraft with a specified payload operating a known flight distance. This Breguet Range-based generalized fuel/emissions model is adopted for two reasons. First, it allows a macroscopic-level analysis in cases (such as this research) in which aircraft taxi duration, engine thrust settings, altitude/attitude dependent aircraft parameters, and other operational as well as ambient details are not available for a more detailed estimation. Second, such model formulations have consistently produced aviation fuel burn results that are within 6% accuracy (Yanto and Liem, 2018; Seymour et al., 2020).

The parameters on the adopted model by Cox, Jemiolo and Mutel (2018) were specifically estimated for five generic aircraft classes. In order to account for as many aircraft types employed in domestic US operations as possible, this thesis estimates new model parameters using a wider range of aircraft types whose information are provided in standard aircraft emission databases. Accordingly, all 78 representative aircraft types, for which fuel consumption and pollutant emissions are reported for flight distances ranging from 125-8,180 nm in the EMEP/EEA database (European Environment Agency, 2013) are used. As described in Section 3.2.3, the reported fuel consumptions and pollutants’ emissions are based on the following assumptions:

1. 0.6 aircraft LF at 95 kg/passenger (note that these assumptions are only used for estimating model parameters; the estimated parameters are then applied on LFs and weights per seat observed for US domestic routes, and these are described in Figures 3.13 and 3.15);
2. Standard International Civil Aviation Organization (ICAO) taxi time and engine thrust settings during landing and takeoff (LTO);
3. Climb-cruise-descent (CCD) emissions based on altitude and attitude dependent parameters from BADA (Base of Aircraft Data);
4. Cruise altitudes and trajectories that follow 4-dimensional (4-D) flight information from the Central Flow Management Unit (CFMU); and
5. Aircraft engine performance reflective of 2004 technology.

Details such as the OEW and seating capacity of representative aircraft in the EMEP/EEA, required to estimate the adopted model, are extracted from sources shown in Appendix A.

The origin-final destination airport pairs defining the study air routes are those shown in **Figure 5.3**, in which the 21 origin airports are again categorized by size and 61 final destination airports identified as in Chapter 4: using the Market Locator dataset. These result in 1,281 unique origin-fnal destination pairs across 24 quarters (six years total, 2013-2018). Airport pairs served by nonstop flights involve one route per pair with a single flight segment. Airport pairs served by connecting flights could be served by different routes in which different intermediate airports (where passengers make connections between their origin and final destination airports) are used. As a result, routes connecting the same origin-final destination airport could involve different flight segments.

**Figure 5.3 Study routes for the AEF and MEF analysis**

Flight distances and AOWs for the study routes identified above are obtained and computed, respectively, from the T-100 database introduced in Chapter 3. Fuel and emissions are then estimated for these routes.
5.1.1 Model Setup

**Equations 5.1–5.4**, taken from Cox, Jemiolo and Mutel (2018) estimate fuel burned and pollutants emitted from an air route consisting of a single nonstop flight segment. Fuel and pollutants from this nonstop flight segment during the LTO (landing and takeoff) phase depend only on AOW, while they depend on both flight distance and AOW in the CCD (climb-cruise-descent) phase. Emissions from the two phases are added to yield total emissions. Flight distance is irrelevant during LTO as each operating flight must taxi out, take off, climb up to 914 m above runway, approach, land and taxi in, irrespective of the flight distance. The energy required to climb from 914 m above runway to cruise altitude also heavily depends on the AOW, while the cruise stage depends both on AOW and flight distance.

\[
LTO_{x,n} = \alpha_x AOW_n^{\beta_x} \quad (5.1)
\]

\[
CCD_{x,n} = \gamma_x d_n + \delta_x \quad (5.2)
\]

\[
\gamma_x = \epsilon_x AOW_n^{\zeta_x} + \eta_x \quad (5.3)
\]

\[
\delta_x = \theta_x AOW_n^{\iota_x} \quad (5.4)
\]

Where

\( x = \) aviation fuel or pollutant type, \( x \in X = \{\text{fuel, CO}_2, \text{H}_2\text{O}, \text{NO}_x, \text{SO}_x, \text{HC, CO, PM}_{2.5}\}; \)

\( n = \) flight segment on route;

\( LTO_{x,n} = x \) from landing and takeoff on \( n \) (kg);

\( CCD_{x,n} = x \) from climb-cruise-descent on \( n \) (kg);

\( d_n = \) flight distance on \( n \) (km);

\( \alpha_x, \beta_x, \gamma_x, \delta_x, \epsilon_x, \zeta_x, \eta_x, \theta_x, \iota_x = \) parameter estimates for \( x \), and

\( AOW_n = \) aircraft operating weight on \( n \) (ton).
For the LTO phase in Equation 5.1, model parameters are directly estimated by using values of fuel and emissions reported, as well as $AOW$ computed, for each of the 78 representative aircraft in the EMEP/EEA database. However, for the CCD phase (Equations 5.2–5.4), fuel consumption and pollutant emissions are first plotted to determine slope ($\gamma_x$) and intercept ($\delta_x$) as shown in Appendix C. The slope $\gamma_x$ represents fuel and emissions per km of flight, while intercept $\delta_x$ represents the energy required to accelerate the aircraft to speed up and climb to cruise altitude. These values for $\gamma_x$ and $\delta_x$ are estimated because CCD values, unlike LTO, depend not only on $AOW$ but also on flight distance, and there are multiple observations for the same aircraft type with various flight distances (based on aircraft range) in the EMEP/EEA database. Parameters on the right-hand side of Equations 5.3–5.4 are then estimated based on $AOW$, $\gamma_x$ and $\delta_x$.

All model parameters are estimated using the mosaic library in R and verified with curve_fit from scipy.optimize in Python. Table 5.1 presents parameters estimated for the LTO phase. All parameters are significant at the 99% confidence level unless otherwise specified.

**Table 5.1 LTO Phase Fuel and Emissions Model Estimates**

<table>
<thead>
<tr>
<th>$x$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel</td>
<td>48.79</td>
<td>0.77</td>
</tr>
<tr>
<td>NOX</td>
<td>0.29</td>
<td>0.97</td>
</tr>
<tr>
<td>CO$_2$</td>
<td>153.68</td>
<td>0.77</td>
</tr>
<tr>
<td>SOX</td>
<td>0.04</td>
<td>0.77</td>
</tr>
<tr>
<td>H$_2$O</td>
<td>60.00</td>
<td>0.77</td>
</tr>
<tr>
<td>CO</td>
<td>2.95</td>
<td>0.41</td>
</tr>
<tr>
<td>HC</td>
<td>2.22</td>
<td>0.03$^{n/s}$</td>
</tr>
<tr>
<td>PM$_{25}$</td>
<td>0.01</td>
<td>0.50</td>
</tr>
</tbody>
</table>

$^{n/s}$ not significant at 90% confidence level.
All other parameters are significant at the 99% confidence level.

Model parameter estimates for the CCD phase are presented in Table 5.2. Again, all parameters are significant at the 99% confidence level unless otherwise specified.
Table 5.2 CCD Phase Fuel and Emissions Model Estimates

<table>
<thead>
<tr>
<th></th>
<th>$\chi$</th>
<th>$\varepsilon$</th>
<th>$\zeta$</th>
<th>$\eta$</th>
<th>$\theta$</th>
<th>$\iota$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel</td>
<td>0.12</td>
<td>0.83</td>
<td>0.23</td>
<td>45.80</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>NO$_X$</td>
<td>0.00*</td>
<td>1.21</td>
<td>0.00</td>
<td>0.09</td>
<td>1.24</td>
<td></td>
</tr>
<tr>
<td>CO$_2$</td>
<td>0.38</td>
<td>0.83</td>
<td>0.73</td>
<td>144.26</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>SO$_X$</td>
<td>0.00</td>
<td>0.83</td>
<td>0.00</td>
<td>0.04</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>H$_2$O</td>
<td>0.15</td>
<td>0.83</td>
<td>0.28</td>
<td>56.33</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>-3.83*</td>
<td>0.00</td>
<td>3.85</td>
<td>0.20**</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>HC</td>
<td>-2.97*</td>
<td>0.00</td>
<td>2.98</td>
<td>0.13</td>
<td>0.43*</td>
<td></td>
</tr>
<tr>
<td>PM$_{25}$</td>
<td>0.00*</td>
<td>0.40*</td>
<td>0.00</td>
<td>0.00</td>
<td>0.66</td>
<td></td>
</tr>
</tbody>
</table>

* significant at the 95% confidence level.
** significant at the 90% confidence level.
\*\* not significant at the 90% confidence level.
All other parameters are significant at 99% confidence level.

From Table 5.2, CO, HC and PM$_{25}$ have more estimates that are statistically not significant at the 90% confidence level. These pollutants, in addition to other atmospherically processed emissions not included in this thesis such as methane (CH$_4$) and aviation-induced cirrus clouds or contrails, have always presented challenges, mainly because these emissions depend on operational and ambient conditions more than on aircraft size and distance flown (Lee et al., 2009; Fuglestvedt et al., 2010; Scheelhaase et al., 2016). Consequently, more parameter estimates on CO, HC and PM$_{25}$ are not significant at the commonly accepted 90% confidence level. Nonetheless, for generalized emission estimations at the macroscopic level, such statistically insignificant model parameters have been used in the past (Cox, Jemiolo and Mutel, 2018). Also, in the absence of microscopic-level analysis, Breguet Range-based models have been shown to estimate aviation fuel burn to within 6% accuracy (Yanto and Liem, 2018; Seymour et al., 2020). Their use in estimating pollutants such as NO$_X$, CO$_2$, SO$_X$ and H$_2$O that are mainly dependent on fuel burn (which is, in turn, dependent on aircraft size and distance flown) is reasonable.
5.1.2 Model Application towards AEF and MEF Estimation

The estimated model parameters shown in Tables 5.1 and 5.2 are used to compute AEFs for each study route connecting the 1,281 origin-final destination airport pairs, according to Equation 5.5. As discussed in 5.1, while routes on airport pairs served by nonstop flights consist of single nonstop flight segments, those served by connecting flights consist of multiple nonstop flight segments that are connected. Additionally, these airport pairs could be connected through different intermediate airports. As a result, the same origin-final destination airport pairs could involve different routes, and thus different nonstop flight segments.

\[
AEF_{r,x}^{q} = \sum_{n=1}^{N_r} AEF_{n,x}^{q} = \sum_{n=1}^{N_r} \frac{LTO_{x,n}(\overline{AOW}_n^q)}{d_n \cdot \overline{\alpha}_n^q \cdot \overline{LF}_n^q} + \frac{CCD_{x,n}(\overline{AOW}_n^q, d_n)}{d_n \cdot \overline{\alpha}_n^q \cdot \overline{LF}_n^q} \tag{5.5}
\]

Where

- \( q \) = quarter-year, from \( q = 1 \ldots Q \), where \( Q = 24 \) (4 quarters per year, from 2013-2018);
- \( r \) = route (which can involve one or more flight segments based on the availability of nonstop flights to the desired destination), from \( r = 1 \ldots R \);
- \( AEF_{r,x}^{q} \) = average emission factor (kg/PKT) on \( r \) for \( x \), in \( q \);
- \( N_r \) = total number of nonstop flight segments involved in \( r \), from \( n = 1 \ldots N_r \);
- \( d_n \) and \( n \) as described after Equation 5.4;
- \( LTO_{x,n} = x \) from LTO on \( n \) (kg), Equation 5.1;
- \( CCD_{x,n} = x \) from CCD on \( n \) (kg), Equations 5.2;
- \( \overline{AOW}_n^q \) = mean aircraft operating weight (ton) on \( n \) in \( q \);
- \( \overline{\alpha}_n^q \) = mean aircraft size (number of seats) on \( n \) in \( q \); and
- \( \overline{LF}_n^q \) = mean load factor on \( n \) in \( q \).
Mean aircraft operating weight $\overline{AO威}_{n}^q$ is calculated as per Equation 5.6 below:

$$\overline{AO威}_{n}^q = \frac{\overline{O威}_{n}^q + LF_{n}^q \cdot \overline{a}_{n}^q \cdot \overline{w}_{n}^q}{1000}$$ \hspace{1cm} (5.6)

Where

- $\overline{O威}_{n}^q =$ mean operating empty weight (kg) of aircraft on $n$ in $q$;
- $\overline{w}_{n}^q =$ mean weight per passenger (kg) on $n$ in $q$, and all other variables and parameters as introduced above.

Given that the same route could be operated by more than one type of aircraft in which case weights change, continuous computation of aircraft weight can be achieved using a simple power function (Cox, Jemiolo and Mutel 2018). Accordingly, by using the EMEP/EEA aircraft database, Equation 5.7 is formulated and estimated in this thesis.

$$O威_{y} = 222.28 \cdot \overline{a}_{y}^{1.035}$$ \hspace{1cm} (5.7)

Where

- $O威_{y} =$ operating empty weight (kg) of aircraft $y$; and
- $\overline{a}_{y} =$ size (typical number of seats) of aircraft $y$.

The multiplicative and power parameters of Equation 5.7 have standard errors of 3.89 and 0.0044, respectively, and are significant at the 99% confidence level. The equation has a goodness of fit of $R^2 = 0.97$. Based on these parameters, $\overline{O威}_{n}^q$ is computed as per Equation 5.8.

$$\overline{O威}_{n}^q = 222.28 \cdot (\overline{a}_{n}^q)^{1.035}$$ \hspace{1cm} (5.8)

Next, MEFs for aviation fuel and emissions are estimated following a formulation used by Holland and Mansur (2008) and Bigazzi (2019), and is adapted into this thesis as per Equation 5.9.
\[ MEF_{r,x}^q = \sum_{n=1}^{N_r} AEF_{n,x}^q \cdot (\pi_{n,AKT}^{PKT} + \pi_{n,LF}^{PKT} \cdot \pi_{n,x}^{LF} ) \]  \hspace{1cm} (5.9)

Where

\( MEF_{r,x}^q \) = marginal emission factor (kg/PKT) on \( r \) for \( x \), in \( q \);

\( \pi_{n,AKT}^{PKT} \) = elasticity of aircraft-kilometer traveled (AKT) to passenger-kilometer traveled (PKT) on \( n \);

\( \pi_{n,LF}^{LF} \) = elasticity of \( x \) to LF on \( n \), and all other variables and parameters as introduced above.

All nonstop flight segments involved in the studied routes originate from the small hubs and non-hub airports group (referred to collectively as small airport in Table 5.3), medium hub group, and large hub group, depending on whether the route itself is nonstop or connecting, and the airport group at which connections take place. Therefore, \( \pi_{n,LF}^{LF} \) is estimated for each of the nonstop flight segments originating from the three airport groups. Accordingly, LFs on all nonstop flight segments originating from the three airport groups are first reduced by 10% and then aviation fuel and emissions are estimated using Equations 5.1–5.2. The resulting changes in fuel and emissions (in percentage) are divided by 10% to yield \( \pi_{n,LF}^{LF} \) which are shown in Table 5.3. The values of \( \pi_{n,LF}^{LF} \), per nonstop flight segments’ origin airport groups, are identical for aviation fuel, CO\(_2\), H\(_2\)O and SO\(_x\). This is because the volumes of the latter three are proportional to fuel burned as determined previously.
Table 5.3 Elasticity of Fuel/Emission $x$ to LF ($\pi_{n,x}^{LF}$) Based on Nonstop Flight Segments’ Origin Airport Groups

<table>
<thead>
<tr>
<th>Fuel/Emission, $x$</th>
<th>Airport group from which nonstop flight segment originates</th>
<th>Small airport*</th>
<th>Medium hub</th>
<th>Large hub</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aviation fuel, CO$_2$, H$_2$O and SO$_x$</td>
<td>0.17</td>
<td>0.14</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>NO$_x$</td>
<td>0.20</td>
<td>0.18</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>0.05</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>HC</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>PM$_{25}$</td>
<td>0.13</td>
<td>0.09</td>
<td>0.08</td>
<td></td>
</tr>
</tbody>
</table>

*includes small hubs and non-hub primary airports

A range of values for $\pi_{n,AKT}^{PKT}$ between 0.55 and 0.75 is adopted from Bigazzi (2019), who estimated the elasticity of $AKT$ to $PKT$ for US air travel. Small airports, compared to large and medium airports, are more likely to partially or fully lose air services for various reasons, including passenger loss due to leakage. Consequently, a change in $AKT$ caused by a change in $PKT$ is expected to be larger at small airports compared to large and medium hubs, and thus the highest value of 0.75 is assumed for $\pi_{n,AKT}^{PKT}$ on nonstop flight segments originating from these small airports. By similar reasoning, i.e., anticipated level of change in $AKT$ caused by change in $PKT$, a central value of 0.65 is taken for nonstop flight segments originating from medium hubs while the lowest value of 0.55 is adopted for those originating from large hubs.

5.2 Results and Discussion

5.2.1 AEF and MEF Estimates

AEF and MEF results are presented in Figures 5.4–5.5, after averaging over quarters and routes per airport group of origin. In the x-axis labels, “AEF-S” and “MEF-S” represents the AEF and MEF of routes originating from small airports, “-M” represents routes originating from medium hubs, and “-L” represents routes originating from large hubs.
Figure 5.4 AEF and MEF estimates for aviation fuel, CO₂ and H₂O. “AEF-S” refers to the AEF for a small airport, “AEF-M” for medium, and “AEF-L” for large.

From Figure 5.4, MEFs for each pollutant and fuel are 75%-80% of the AEFs for each route originating from small airports, 65%-70% of AEFs for those originating from medium airports,
and 55%-63% of AEFs for those originating from large hubs. These results indicate that as air services increase due to an increase in demand, the resulting emissions will be lower than those represented by AEFs due to economies of scale in operations/supply. It is also noted that both AEF and MEF decrease as the airport size group increases, which is intuitive insofar as larger airports operate air services at greater economies of scale, compared to small and medium ones (Caves, Christensen and Tretheway, 1984; Gillen, Oum and Tretheway, 1990; Brueckner and Spiller, 1994; Hansen and Zou, 2013). Smaller airports offer limited nonstop flights mainly to neighboring large airports from which passengers can connect to further destinations. As such, passengers often travel on multiple flight segments that generate more than one LTO cycle, which is more emissions intensive. Previous research has shown that a 25% increase in LTO (equivalent of one more connecting flight out of every four nonstop flights) cycle leads to an 11% increase in common pollutants (Yilmaz, 2017).

The AEF estimates of CO₂, NOₓ and SOₓ from this thesis, particularly for routes originating from small and medium airports (where more connections are often required to reach desired final destinations), are higher than previously reported values in the literature (Peeters, Szimba and Duijnisveld, 2007; Spielmann et al., 2007; Miyoshi and Mason, 2009). This is because this analysis is based on passengers’ complete routes while previous estimates are based on single nonstop flight segments. Passengers’ complete routes can often involve multiple nonstop flight segments, particularly when originating from small and medium hubs; thus, as the number of flight segments increases, total emissions increase. Comparisons of CO, HC and PM₂.₅ with previous studies are not made because these pollutants are rarely directly reported in the literature, at least in part due to the uncertainties involved in their estimation (Fuglestvedt et al., 2010; Scheelhaase et al., 2016). Recall from the discussion following Table 5.2 that estimates of these pollutants are not well explained by aircraft size and distance flown, compared with aircraft operating and ambient conditions which are not usually available for analysis (Cox, Jemiolo and Mutel, 2018) (and were not for this analysis).

There is a paucity of MEF estimates in the literature (Bigazzi, 2019), as most energy and emission intensity estimates of transportation modes and demands rely solely on AEFs to support transportation policy-making (Chester, Horvath and Madanat, 2010; Borken-Kleefeld, Fuglestvedt and Berntsen, 2013). However, analysis in the energy sector has shown that AEFs often differ
from the marginal effects of changes in demand, as such changes in demand do not uniformly impact all aspects of energy supply at differing demand levels (Siler-Evans, Azevedo and Morgan, 2012). This non-uniform relationship also holds true for air transportation, in which airlines’ service features do not proportionally change as passenger demand changes due to economies of scale and economies of density in airline operations (Caves, Christensen and Tretheway, 1984).

From Figure 5.4, a unit change (say, a unit reduction) in demand on routes originating from small hubs, represented by MEF-S, is associated with a fuel burn of 0.09 kg/PKT. This compares to 0.05 kg/PKT for routes originating from large hubs, MEF-L. To interpret, a unit reduction in demand at small hubs, compared to the same unit demand reduction at large hubs, will result in a nearly double savings in fuel burn. Similarly, the MEF-S of CO₂ is 0.29 kg/PKT, versus 0.17 kg/PKT for MEF-L. Figure 5.6 shows the proportional differences in AEF and MEF for routes originating from small and medium airports, comparing against those from large airports.

![Figure 5.6 AEFs and MEFs of small and medium airports, as a percent increase against those of large airports](chart.png)

Figure 5.6 shows that the differences in MEFs of small/medium airports to those of large airports are higher than the differences in AEFs between the groups. For example, AEFs at medium hubs
are higher than those at large airports by 18%-40% (with the exception of PM$_{25}$), but this range increases to 36%-65% for MEFs. The differences between small and large airports are greater: while AEFs are 27%-50% higher, MEFs are 63%-105% higher (again with the exception of PM$_{25}$). Thus, when an air traveler “leaks” to a large hub airport over using their local small airport, their personal contribution to air emissions resulting from this decision are lower than if they chose their local airport. When comparing the AEF and MEF estimates, the findings further indicate that the fuel and emissions savings of choosing large hubs over small airports are considerably higher than those commonly reported based on AEFs.

5.2.2 Policy Implications and Contextualization

The passenger-level average and marginal analyses from this chapter have implications on the current course of efforts aimed at decarbonizing air travel, particularly with regard to customer carbon charges and environment-conscious airport choices. Various tools including Google Flights (https://www.google.com/travel/flights) help air travelers factor environmental considerations into their trip planning by providing average passenger level emissions (AEF x flight distance) on alternative routes. Thus, an air passenger using such a tool would be viewing estimates of emissions that are larger than the more appropriate MEF estimates. However, given that the MEF differences between routes at small/medium versus large airports are larger than the AEF differences, how emissions would actually balance out would depend on the specific situation. Overall, the results of this chapter do indicate the importance of estimating and reporting MEFs to the public towards providing more accurate information. Furthermore, non-CO$_2$ emissions are not included in nearly all efforts to create environmental awareness, although these account for over a third of global warming potential$^3$ caused by aviation (Lee et al. 2021).

Engaging air travelers in climate change mitigation measures within their own personal travel choices has remained challenging. This is due to limitations in awareness and social norms (Choi

---

$^3$ Global warming potential measures how much energy the emissions of one ton of a gas will absorb over a given period of time, relative to the emissions of one ton of CO$_2$. 

and Ritchie, 2014) as well as lack of trust in the narratives on emissions communicated by the aviation industry (Guix, Ollé and Font, 2022). However, it has been shown that travelers with a thorough understanding of aviation’s contributions to climate change are just as unlikely to fly less, due to their dependence on this mode of transportation (Davison, Littleford and Ryley, 2014). A contributing factor to discouraging public involvement is the lack of reliable mechanisms of reporting passenger-level emissions and reasonable voluntary customer emission charges (Babakhani, Ritchie and Dolnicar, 2017). For example, Google Flights, introduced in October 2021 and poised to stimulate passenger engagement (Gössling and Dolnicar, 2022), has recently been accused of considerably reducing its original emission estimates and causing confusion amongst travelers (BBC, 2022; The Guardian, 2022). AEFs and MEFs based on several actual routes and easily replicable methods such as those used in this thesis may be useful in the effort towards standardizing passenger-level emissions. From such standardized emissions, reasonable carbon charges can be proposed to passengers willing to participate in voluntary carbon offsetting. Provisions to make offset payments are already made by third parties (Gold Standard for example) and directly by airlines such as Qantas (Fly Carbon Neutral), Air Canada (Less Emissions), KLM Royal Dutch (CO2ZERO), Austrian (Climate Austria), and many others. Also, more stringent new policies, such as ICAO’s Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), are expected to result in mandatory carbon charges imposed on airlines. Because airlines will, in turn, pass these charges on to passengers, standardizing passenger level emissions is critical.

MEFs were 36%-65% and 63%-105% higher at small and medium hubs, respectively, compared with their large hub counterparts. The MEF differences were also higher than the AEF differences. These results suggest that flying from large hubs results in sizable emissions and fuel savings. However, these savings must be considered alongside the well-documented negative externalities of large hubs, which cannot be ignored. These include acute local effects like high noise and air pollution concentrations in adjacent neighborhoods, and more broadly, the economic weakening of regions served by small airports due to passenger leakage (McNair, 2020).

Finally, this research has not assessed the impacts of emissions from airport ground access trips, which must be accounted for, in order to fully understand the environmental implications of airport choices. Recall from Figure 5.1 that air passengers drive different distances in accessing different
airports. Thus, the excess distance driven and emissions associated with choosing one airport over another should be included to fully understand the environmental implications for long-distance airport choices, despite that emissions from the ground access trip are estimated to be small in comparison to those of the air trip (Borken-Kleefeld, Fuglestad and Berntsen, 2013; Ottelin, Heinonen and Junnila, 2014). Unlike Europe, with its strong rail and links between airports and neighboring cities (including those other than the city they are primarily associated with), high-quality long-distance bus or rail services in most parts of North America remain the exception rather than the norm (Sperry et al., 2012; Augustin et al., 2014). Thus, in North America, air passengers from anywhere outside the most urbanized regions access airports using private vehicles. “Leaking” passengers may constitute up to 2.75% of the average annual daily traffic on busy US interstate highways (Ryerson and Kim, 2018). Although vehicle emissions are expected to decrease into the future due to the adoption of rapidly developing plug-in hybrid electric, battery electric (Gopal et al., 2018) and connected and autonomous vehicle technologies (Perrine, Kockelman and Huang, 2020), it is still critical to include the airport ground access trip in emissions and fuel use estimates.

Furthermore, when passengers “leak” to distant hubs, sometimes up to several hundreds of kilometers in private vehicles, they are often replacing a short feeder trip from their local airport to a major hub. This major hub can sometimes be the one they are “leaking” to instead. This phenomenon of competition versus cooperation (Adler, Pels and Nash, 2010; Xia and Zhang, 2016) has been studied for air and high-speed rail, most commonly in the European context. The replacement of a short feeder flight with a longer drive was not addressed in this study and should be in future work.

5.3 Recap and Summary

By using Modified Breguet Range equations whose parameters are estimated based on standard aircraft emissions database, this chapter quantified AEFs and MEFs on domestic air routes connecting 1,281 unique origin-final destination airport pairs between 2013 and 2018. The pairs consist of 21 origin airports categorized into one of three groups: small hub/non-hub, medium hub and large hub. Routes from these airports were to 61 unique domestic destinations. For all airport size groups and routes, MEFs were estimated to be lower than AEFs. Also, AEFs from medium
and small hubs/non-hubs are 18%-40% and 27%-50% higher than from large hubs, respectively, whereas MEFs are 36%-65% and 63%-105% higher. This reveals that the environmental advantages of choosing large hubs over small airports is underrepresented when using AEFs. Thus, although the environmental benefits of flying are overstated when using AEFs instead of MEFs, the benefits of flying from larger airports instead of smaller ones are underrepresented using AEFs compared to MEFs. Creating this awareness among air travelers is critical for encouraging choices towards mitigating the environmental impacts of air travel.
Chapter 6: Aviation Fuel and Emissions in a Supply-and-Demand Analysis

Climate mitigation policies in aviation aim to use price-based measures imposed on airlines and air passengers to: 1) control air travel demand, towards reducing emissions, and 2) raise funds for carbon reduction and removal processes and technologies towards achieving the 2050 net zero goal, signed by 196 countries in 2015 (UNFCCC, 2016). Studies on aviation-focused climate action policies address these financial requirements through country, continental and global level analyses, often without exploring the relationship among demand, supply and the resulting emissions (Sobieralski, 2021).

Country-, continental- and global-level analyses rely on important quantities such as the price elasticity of air demand to be applied over entire nations, assuming that this demand uniformly responds to price-based measures. In reality, demands at different airports respond differently to prices (Brons et al., 2002; Granados, Gupta and Kauffman, 2011). With the availability of air ticket data on passengers over a large region, it is possible to estimate price elasticity of demand on an airport-by-airport basis. Furthermore, given that emissions are direct outputs of capacity decision, which is influenced by demand which in turn is affected by price, the impact price ultimately has on emissions cannot be well-understood unless the relationships between price, demand, supply and emissions are explored.

6.1 Approach

Figure 6.1 shows a schematic mapping the relationship among airfare, demand (passenger volume), aircraft size and LF (capacity decision factors), and the resulting emissions.

Figure 6.1 Relationship among airfare, demand, capacity and emissions
In this thesis, airfare is used as a proxy for price-based policies, given that the introduction of such policy measures causes rises in airfares (Brueckner and Zhang, 2010; Pagoni and Psaraki-Kalouptsidi, 2016). However, it should be noted that these measures, which can include voluntary customer emissions charges, mandatory air ticket carbon charges and carbon credits, are in practice not included in but rather added onto airfares. Nonetheless, the total impact of prices is expected to have an effect on demand by potentially reducing it, in the same way as a higher airfare would (Wild, Mathys and Wang, 2021; Zheng and Rutherford, 2022). It is also noted that price (airfare) is treated as an exogenous factor given that policy interventions are external factors, and this treatment has been used previously in the literature (Jorge-Calderón, 1997; Mohammadian et al., 2019).

Demand and supply/capacity have an endogenous relationship such that change in one is expected to result in a change in the other. Thus, change in demand caused by airfare can lead to change in capacity decision, which in turn is hypothesized to lead to a change in the emissions produced. To test this idea, in this chapter, the elasticities of emissions to airfare are estimated to quantify the impact of price-based environmental measures on emissions. Elasticity is unitless, as it represents the percent change in emissions caused by a percent change in airfare. If the absolute value of this elasticity is greater than one, then emissions are considered “elastic” to airfare, and “inelastic” (or, insensitive to changes) if less than one.

Dane County Regional Airport (MSN) and Chicago O’Hare International Airport (ORD) are chosen as analysis departure airports as they represent a small and large hub, respectively. They are only 135 mi apart. They can be used to show how similar price-based policy measures may lead to different outcomes at airports that are proximate but very different in air services offered, which is in contrast to how most existing studies have assumed that outcomes are the same in regions and at airports across a nation.

Overall, this chapter maps the relationships among price, demand, supply and emissions at individual airports, offering an airport-level analysis approach to revealing the impact of price-related policy measures on emissions.
6.1.1 Empirical Supply-and-Demand Model

6.1.1.1 Description

Consider Equation 6.1 in which $S^r_q$ and $D^r_q$ are supply and demand, respectively, on route $r$ between two airports during quarter-year $q$:

$$S^r_q = \sum_{b=1}^{B} \theta_b T_{b,q}^r + \theta_d D_q^r + \zeta_q^r$$  \hspace{1cm} (6.1)

Where:

$T_{b,q}^r$ = a vector of explanatory variables ($b \in \{1, B\}$) determining $S^r_q$ and $D^r_q$;

$\theta_b, \theta_d$ = estimated parameters, and

$\zeta_q^r$ = the error term of supply on $r$, in $q$.

It is hypothesized that $D^r_q$ is correlated with $\zeta_q^r$, making it endogenous to $S^r_q$. This hypothesis can be tested using the Durbin-Wu-Hausman (DWH) test. If endogenous, the equation cannot be solved without biased estimates using ordinary least squares (OLS), and thus two-stage-least squares (2SLS) or simultaneous-equation or three-stage-least squares (3SLS) approaches must be considered. Selecting either the 2SLS or 3SLS approach mainly depends on sample size, whether lagged explanatory variables are used or not, and whether the number of model equations specified is equal to the number of variables in the instrument variable (IV)\(^4\) vector (Gujarati, 2003; Wooldridge, 2013). Additionally, 3SLS accounts for correlation of the error terms in all specified

\(^4\) IVs are variables that are used to model an explanatory variable that is endogenous to the dependent variable. For example, because demand is exogenous to supply, the latter cannot be modeled as a direct function of the former without the introduction of IVs.
model equations. Consequently, any weak relationship between independent and dependent variables in any one equation leads to estimation errors throughout the entire model.

A review of empirical aviation supply-and-demand studies shows that 3SLS models are mainly used when there are no data on some variables that explain supply and demand, and lagged variables are used (Pitfield, Caves and Quddus, 2010). 2SLS is favored in the absence of lagged variables (Jorge-Calderón, 1997; Mohammadian et al., 2019). The model presented in this chapter does not rely on lagged variables. The adopted analysis time interval, i.e., quarter-year, is not appropriate for incorporating lagged variables as there are seasonality changes between successive quarters that airlines account for. For a yearly analysis, however, lagged variables might be appropriate. Thus, a 2SLS regression in which the endogenous variable $D_q^r$ is modeled separately in the first stage as per Equation 6.2 is proposed.

$$D_q^r = \sum_{b=1}^{B} \phi_b T_{b,q}^r + \sum_{c=1}^{C} \phi_c Z_{c,q}^r + \epsilon_q^r$$ (6.2)

In Equation 6.2, $Z_{c,q}^r$ represents IVs (numbering $c = 1 \ldots C$) that satisfy three conditions: 1) the IVs determine $D_q^r$, 2) they do not determine $S_q^r$ directly but only through $D_q^r$, and 3) they are not determined by $T_{b,q}^r$, but rather, are exogenous and imposed on the model. Also, $\phi_b, \phi_c$ are estimated parameters, $\epsilon_q^r$ is an error term, and all other terms are as previously defined.

Equation 6.2 can be solved first using OLS, and the predicted value of $D_q^r$ – which is $\hat{D}_q^r$ – will then be used in Equation 6.1 in the second stage to model $S_q^r$ as shown in Equation 6.3.

$$S_q^r = \sum_{b=1}^{B} \theta_b T_{b,q}^r + \theta_d^* \hat{D}_q^r + \zeta_q^*$$ (6.3)

Whether the IV vector used in the first stage model (Equation 6.2) is appropriate or not is investigated through the weak instrument variable test (Stock, Wright and Yogo, 2002).
6.1.1.2 Variable Selection and Model Formulation

In the first-stage demand model, population and socioeconomic factors constitute the IVs. Previous studies (Jorge-Calderón, 1997; Mohammadian et al., 2019) used population within the administrative boundaries of the cities containing origin and destination airports. This chapter adopts probabilistic inputs for defining unique geographic market areas and shares, for each origin and destination airport pair studied, based on the results of Chapter 4. This is in contrast to most previous studies that relied on catchment areas based on administrative boundaries, or other measures such as circles of fixed radii. Accordingly, the mean probabilities of choosing MSN and ORD are computed for each of the studied destinations, and the collection of ZIP codes with 5% potential market is assumed to constitute the airport market area (also commonly referred to as the “catchment” area in the literature) of a departure airport for a particular destination. A similar market area definition is used by Lieshout (2012) for airports in the Netherlands, who proposes airport catchments that vary by destination based on a minimum market share of 1%.

Population and socioeconomic factors in the identified market areas are considered exogenous factors on air travel demand. All other factors not accounted for at the origin and final destination airports, including population and socioeconomic factors at the destinations, are accounted for through the use of route dummy variables.

Unemployment rate is used as a socioeconomic indicator (Wadud, 2015; Mohammadian et al., 2019). Another socioeconomic indicator that was initially considered is ZIP code-level median income. However, given the correlation between these indicators, only unemployment is finally used by comparing mean square errors (MSE) from the models that use both indicators. Also included as the last IV in the demand model is airfare, which is among the most important determinants of airport choice and represents price-based environmental policy measure (Wild, Mathys and Wang, 2021; Zheng and Rutherford, 2022).

Other well-documented explanatory variables are route-level airline competition and jet fuel price (Gillen and Hazledine, 2015; Mohammadian et al., 2019). Despite the presumed correlation between airfare and jet fuel price, historical analyses in the US (Atems, 2021) as well as several middle-income countries (Valdes, 2015) have shown that airfare mainly responds to aggregate and oil-specific demands, including fuel for other transportation modes such as gasoline and diesel,
but not to international jet fuel demand and supply shocks. Furthermore, Atems (2021) argues that the oligopolistic structure of the US market, in which the major carriers of American, Delta, United and Southwest are interdependent with regards to their pricing policies, has led to steady average airfares despite jet fuel prices generally falling since 2013. Consequently, jet fuel price is not strongly correlated with airfare, and thus may be considered suitable for use as an explanatory variable alongside airfare (Mohammadian et al., 2019). Also, airlines enter hedging contracts with jet fuel suppliers to purchase fuel at predetermined contract prices, which helps stabilize airlines’ operating costs, which further leads to more airfare stability even during volatile periods of jet fuel supply (Swidan and Merkert, 2019). Finally, the correlation coefficient of mean airfare and jet fuel prices for the study period was found to be less than 0.2, which is considered negligible (Mukaka, 2012).

Another explanatory variable considered is route-level airline competition, quantified using the Herfindahl-Hirschman Index (HHI). The HHI is the sum of squares of airlines’ market shares on a given route. It ranges from zero to one, reflecting perfect competition and monopoly, respectively.

Additionally, airlines’ supply strategies on different flight markets based on flight lengths, which is in turn dependent on the demand for these markets, are expected to differ. Thus, it is common to distinguish between short-, medium- and long-range operations in aviation supply-and-demand studies (Mohammadian et al., 2019). Flight distance group categorical variables are introduced based on the same distance classifications from Chapter 4; i.e., <1,500 km for short routes, 1,500-3,000 km for medium routes, and >3,000 km for long routes.

For the second stage, the well-documented explanatory variables of demand from the first stage, HHI, and jet fuel price are used as explanatory variables on air service. In both the first and second stage models, shown in Equations 6.4–6.6, all variables except the route dummy variables and route distance categorical variables are log transformed towards yielding coefficient estimates that directly represent elasticities.
First stage: Demand model

\[ \ln D^r_q = \mu_0 + \mu_1 \ln j_q + \mu_2 \ln HHI^r_q + \mu_3 \ln \bar{f}^r_q + \mu_4 \ln \text{Pop}^r_q + \mu_5 \]  
\[ \ln \text{Unp}^r_q + \sum_r \mu_r \text{Rt}(r) + \sum_c \mu_c \text{C}(r) + \xi^r_q \] (6.4)

Where:

\( D^r_q \) = Demand on route \( r \) in period \( q \);  
\( j_q \) = Price of jet fuel in period \( q \), USD/gallon;  
\( \bar{f}^r_q \) = Mean airfare on route \( r \) in period \( q \), USD;  
\( HHI^r_q \) = Herfindahl-Hirschman Index of airlines’ competition on route \( r \) in period \( q \);  
\( \text{Pop}^r_q \) = Sum of all population within ZIP codes whose choice probabilities for origin airport (of route \( r \)) is at least 5% in period \( q \);  
\( \text{Unp}^r_q \) = Mean unemployment rate (%) of all ZIP codes with choice probabilities for origin airport (in route \( r \)) of at least 5% in period \( q \);  
\( \text{Rt}(r) \) = Route dummy, \( \text{Rt} = 1 \) if route is \( r \), and 0 otherwise;  
\( \text{C}(r) \) = Categorical distance variable for route \( r \); “short” if flight distance on route \( r \) is <1,500 km, “medium” if \( 1,500 \leq \) flight distance \( \leq 3,000 \) km, and “long” if flight distance is > 3,000 km;  
\( \mu_0, \mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_r, \mu_c \) = Model estimates;  
\( \xi^r_q \) = Demand model error term on route \( r \) in period \( q \), and all other variables are as previously defined.

Second stage: Supply model

\[ \ln a^r_q = \lambda_0 + \lambda_1 \ln j_q + \lambda_2 \ln HHI^r_q + \lambda_3 \ln \overline{D}^r_q + \vartheta^r_q \] (6.5)
\[ \ln \overline{LF}_{rq} = \varphi_0 + \varphi_1 \ln j_q + \varphi_2 \ln HHI_{rq} + \varphi_3 \ln \widehat{D}_{rq} + \kappa_{rq} \]  

(6.6)

Where:

\( \overline{a}_{rq} \) = mean aircraft size on route \( r \) in \( q \); 

\( \overline{LF}_{rq} \) = mean load factor (%) on \( r \) in \( q \); 

\( \widehat{D}_{rq} \) = estimated demand, from first stage model (Equation 6.4); 

\( \lambda_0, \lambda_1, \lambda_3, \varphi_0, \varphi_1, \varphi_2, \varphi_3 \) = model estimates; 

\( \phi_{rq} \) = aircraft size model error term on \( r \) in \( q \); 

\( \kappa_{rq} \) = load factor model error term on \( r \) in \( q \), and all other variables are as previously defined.

### 6.1.2 Elasticities of Aviation Fuel and Emissions to Airfare

From the 2SLS model of Equations 6.4–6.6, airfare elasticity of demand (\( \mu_3 \)), demand elasticity of aircraft size (\( \lambda_3 \)) and demand elasticity of LF (\( \varphi_3 \)) are shown in Equations 6.7–6.9, respectively, following standard definitions of elasticity (Koppelman and Bhat, 2006).

\[ \mu_3 = \frac{\Delta D_{rq}}{\Delta f_{rq}} \]  

(6.7)

\[ \lambda_3 = \frac{\Delta a_{rq}}{\Delta D_{rq}} \]  

(6.8)

\[ \varphi_3 = \frac{\Delta LF_{rq}}{\Delta D_{rq}} \]  

(6.9)

All variables are as previously defined.
If airfare impacts demand, and demand in turn impacts aircraft size and LF, the latter two are indirectly impacted by airfare or price in general (Brueckner and Zhang, 2010). This impact can be quantified by introducing change in airfare, i.e., $\Delta \bar{f}_q^{r}$ (typically 10%) and rearranging Equations 6.7–6.9 as per Equations 6.10–6.11.

\[
\Delta a_q^r = \lambda_3 \Delta D_q^r = \lambda_3 \mu_3 \Delta \bar{f}_q^{r} \tag{6.10}
\]

\[
\Delta LF_q^r = \varphi_3 \Delta D_q^r = \varphi_3 \mu_3 \Delta \bar{f}_q^{r} \tag{6.11}
\]

Changes in aircraft size and LF caused indirectly by changes in airfare will ultimately lead to changes in fuel burned and pollutants emitted as shown in Equation 6.12.

\[
\frac{x_q^{r} \bar{f}_q^{r}}{\Delta \bar{f}_q^{r}} = \frac{\left( \frac{x_{q,2}^{r}}{x_{q,1}^{r}} - \frac{x_{q,1}^{r}}{x_{q,1}^{r}} \right)}{100\%} \tag{6.12}
\]

Where:

$x_q^{r}$ = fuel/pollutant $x$ on $r$ in $q$;

$e_{x_q^{r}}^{\bar{f}_q^{r}}$ = elasticity of $x_q^{r}$ to $\bar{f}_q^{r}$;

$x_{q,1}^{r}$ = jet fuel/pollutant $x$ on $r$ in $q$, computed before a 10% increase in $\bar{f}_q^{r}$;

$x_{q,2}^{r}$ = jet fuel/pollutant $x$ on $r$ in $q$, computed after a 10% increase in $\bar{f}_q^{r}$; other variables are as previously defined.
Weights of jet fuel burned and pollutants emitted per route during landing and takeoff (LTO) and cruise-climb-descent (CCD)\(^5\) before and after 10% airfare increase are estimated using **Equations 5.1–5.2** (which are flight segment based). It is noted that depending on the route, multiple flight legs could be involved in which case the emissions from these multiple legs are summed. However, as will be discussed in 6.1.3, the routes chosen for the analysis of this chapter are all based on nonstop services with single flight segments. Furthermore, the aircraft operating weight (AOW) used in **Equations 5.1–5.2** is based on **Equation 5.6**, which allows a single average AOW on a single flight segment to be estimated based on average aircraft size and LF per quarter. Flight distance, however, will remain unchanged irrespective of quarter, provided the route remains in operation.

### 6.1.3 Model Inputs

Data on nonstop segments originating from MSN and ORD are gathered from T-100 for 16 successive quarters in 2013 through 2016. The analysis scope was limited to segment demand (instead of true origin and destination demand) for two reasons. First, there is no realistic mechanism of taking a single value of LF and aircraft size on connecting routes. Second, passengers terminating their trips, continuing their trips, and joining at intermediate stops on connecting routes cannot be found from the publicly available data sources used in this thesis. Furthermore, yearly ZIP code level population data for the years 2017-2018 was not available from other sources that provide yearly ZIP code level estimations based on the US Census Bureau’s 2010 baseline count and the American Community 2016 Survey. Thus, the analysis period was limited to 2013-2016 instead of 2013-2018 as in previous chapters.

Data from a total of 177 nonstop routes is extracted (12 originating from MSN, and the remaining 165 from ORD), including distance flown, quarterly mean weight per seat, mean LF, total seats offered and total flight frequency. Some routes are seasonal and, in some cases, not necessarily offered each year. Average weight per seat is computed by dividing total payload by total seats

\[ \text{Average weight per seat} = \frac{\text{Total payload}}{\text{Total seats}} \]

---

\(^5\) Recall from **Chapter 5** that the total emissions on any route is the sum total of LTO and CCD phase emissions.
offered, while LF is computed by dividing total number of passengers by total seats offered. Similarly, average aircraft size is computed by dividing total seats offered by total flight frequency. Furthermore, passenger demand is further categorized by airline, to compute quarterly HHI as the sum of the squares of all operating airlines’ market shares on a route. Descriptive statistics of all variables, by quarter from 2013 through 2016, are shown in Table 6.1.

Table 6.1 Summary Statistics of the 2SLS Model Input Variables, by Quarter

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airfare, USD</td>
<td>314</td>
<td>80</td>
<td>21</td>
<td>688</td>
</tr>
<tr>
<td>Aircraft size (seat number)</td>
<td>88</td>
<td>44</td>
<td>14</td>
<td>348</td>
</tr>
<tr>
<td>Demand (passenger number)</td>
<td>44,701</td>
<td>61,714</td>
<td>1,157</td>
<td>413,576</td>
</tr>
<tr>
<td>LF, %</td>
<td>80</td>
<td>9</td>
<td>35</td>
<td>97</td>
</tr>
<tr>
<td>Weight per seat, kg</td>
<td>121</td>
<td>70</td>
<td>88</td>
<td>2,570</td>
</tr>
<tr>
<td>HHI</td>
<td>0.62</td>
<td>0.30</td>
<td>0.12</td>
<td>1.00</td>
</tr>
<tr>
<td>Jet fuel price, USD/gallon</td>
<td>2.30</td>
<td>0.70</td>
<td>1.27</td>
<td>3.20</td>
</tr>
<tr>
<td>Population sum over market area, 1000s</td>
<td>10,200</td>
<td>3,468</td>
<td>1,174</td>
<td>12,000</td>
</tr>
<tr>
<td>Unemployment, %</td>
<td>6.40</td>
<td>1.24</td>
<td>4.00</td>
<td>8.27</td>
</tr>
<tr>
<td>Distance flown on route, km</td>
<td>1,195</td>
<td>911</td>
<td>108</td>
<td>6,828</td>
</tr>
</tbody>
</table>

Among the variables shown in Table 6.1, only distance flown is constant while all others change across quarters. Both population and employment are available on a yearly basis rather than quarter, thus a simple linear interpolation was used to calculate values of each per quarter. For example, if population over one departure airport’s market area for a certain destination is one million during year $y$ and 1.1 million during year $y + 1$, it is assumed that populations during the first, second, third and fourth quarters of $y + 1$ are 1.025 million, 1.05 million, 1.075 million and 1.1 million, respectively.
6.2 Results and Discussion

6.2.1 Supply-and-Demand

Parameter estimates from the 2SLS supply-and-demand model, and outputs of endogeneity as well as weak instrument tests for the first-stage demand models, are presented in Table 6.2. Model estimation and hypothesis testing was carried out in StataBE 17. Standard errors are reported in parentheses next to estimates. Unless indicated otherwise, estimates are significant at the 99% confidence level. In the interest of length, parameter estimates on the route dummy variables are not shown here but included in Appendix D. In estimating the first-stage model, the population coefficient was negative, suggesting that demand for air travel decreases with increasing population. Although this is counterintuitive, the unexpected sign is likely due to the quarterly breakdown implemented over only four years of analysis, which is too short a time period for any substantial population change to meaningfully impact air travel and the aviation industry. Therefore, the demand model was estimated again without including the population variable.
Table 6.2 2SLS Supply-and-Demand Model Estimation Results (standard errors are shown after estimates, in brackets)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Routes originating from MSN</th>
<th></th>
<th>Routes originating from ORD</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First stage</td>
<td>Second stage</td>
<td>First stage</td>
<td>Second stage</td>
</tr>
<tr>
<td></td>
<td>Demand</td>
<td>Aircraft size</td>
<td>LF</td>
<td>Demand</td>
</tr>
<tr>
<td>Constant</td>
<td>11.784</td>
<td>3.146</td>
<td>1.573*</td>
<td>9.737</td>
</tr>
<tr>
<td></td>
<td>(0.693)</td>
<td>(1.150)</td>
<td>(0.638)</td>
<td>(0.289)</td>
</tr>
<tr>
<td>Jet fuel price</td>
<td>0.323*</td>
<td>-0.203</td>
<td>0.003</td>
<td>0.422</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.029)</td>
<td>(0.016)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>HHI</td>
<td>0.0652</td>
<td>0.092</td>
<td>-0.013*</td>
<td>-0.210</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.035)</td>
<td>(0.019)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Mean airfare</td>
<td>-0.423</td>
<td>n/a</td>
<td>n/a</td>
<td>-0.023**</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td></td>
<td></td>
<td>(0.031)</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>-0.742</td>
<td>n/a</td>
<td>n/a</td>
<td>-0.988</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
<td></td>
<td></td>
<td>(0.092)</td>
</tr>
<tr>
<td>Demand</td>
<td>n/a</td>
<td>0.175**</td>
<td>0.281</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.093)</td>
<td>(0.063)</td>
<td></td>
</tr>
<tr>
<td>Route Distance</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0 (base)</td>
</tr>
<tr>
<td>Long</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Medium</td>
<td>1.798</td>
<td>n/a</td>
<td>n/a</td>
<td>1.762</td>
</tr>
<tr>
<td>Short</td>
<td>(0.072)</td>
<td>n/a</td>
<td>n/a</td>
<td>(0.179)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.944</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.180)</td>
</tr>
<tr>
<td>Observations</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>2.372</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.372</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.372</td>
</tr>
<tr>
<td>R²</td>
<td>0.970</td>
<td>0.871</td>
<td>0.721</td>
<td>0.964</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.963</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.564</td>
</tr>
<tr>
<td>Root MSE</td>
<td>0.189</td>
<td>0.109</td>
<td>0.060</td>
<td>0.238</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.081</td>
</tr>
<tr>
<td>MES</td>
<td>32.960</td>
<td>n/a</td>
<td>n/a</td>
<td>58.084</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>n/a</td>
</tr>
<tr>
<td>Durbin (score) χ²</td>
<td>n/a</td>
<td>6.662</td>
<td>13.509</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>51.524</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>72.527</td>
</tr>
<tr>
<td>Wu-Hausman F statistic</td>
<td>n/a</td>
<td>5.955</td>
<td>12.168</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>48.915</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>69.484</td>
</tr>
</tbody>
</table>

*significant at 95% level; **significant at 90% level; n/s not significant at 90% level; n/a not applicable.

Unless indicated otherwise, estimates are significant at the 99% confidence level.
Models for routes originating from both MSN and ORD have minimum eigenvalue statistics (MES) of 32.96 and 58.08 for the first stage models, respectively, exceeding the minimum value of 10 which indicates the presence of a weak instrument (Stock, Wright and Yogo, 2002). Thus, the null hypothesis that the instruments are weak is rejected. With regard to the test for endogeneity, the null hypothesis that demand is exogenous to supply is rejected due to the small p-values (<0.05) of the Durbin score chi square ($\chi^2$) and Wu-Hausman F-statistics (Davidson and MacKinnon, 1993). Therefore, the use of 2SLS over OLS is justified.

The model estimates in Table 6.2 represent elasticities, and thus the effect of a 10% increase in a subject variable on another is found by multiplying the estimate by 10. Furthermore, an estimate whose magnitude equals or exceeds one is considered elastic, while less than one is inelastic. In the first stage model, jet fuel price has a positive effect on demand, with a 10% increase in the former leading to 3.2% and 4.2% increases in the latter on routes originating from MSN and ORD, respectively. This finding reinforces previous studies (Valdes, 2015; Atems, 2021) that refute a long-held presupposition that higher jet fuel price negatively influences air passenger demand by forcing airlines to increase air ticket prices. Furthermore, higher jet fuel prices have been associated with an improved economy under which air demand could be stimulated (Mohammadian et al., 2019).

All remaining variables in the first stage model negatively impact demand, except for the HHI on routes originating from MSN, which is also statistically insignificant. For example, a 10% increase in HHI, an indicator of airline monopoly, reduces demand by 2.1% on routes from ORD. A 10% increase in unemployment rate leads to 7.4% and 9.9% reductions in demand on routes originating from MSN and ORD, respectively. In a previous work, a 10% increase in unemployment rate was estimated to result in a far more modest 1.24% reduction in enplanement per capita at the national level (Wadud, 2015), which indicates that national level analysis could mask regional behavior.

The largest difference in elasticities between the airports is that of the impact of airfare on demand. A 10% increase in airfare results in a 4.2% reduction in demand at MSN but only 0.23% at ORD, supporting the notion that a small airport has a much weaker ability to retain passenger market share in the face of air service degradations, compared to a large hub airport (Fu and Kim, 2016; Ryerson, 2016). The demand reduction on routes from ORD is close to the 0.32% reduction in
demand estimated for medium-haul domestic Australian flights (Mohammadian et al., 2019), while that for MSN approaches the 5% estimated in the European context (Jorge-Calderón, 1997). One of the main motivations behind the work of this chapter is the significant variations in price elasticity of demand across different analysis levels and geography that has historically been observed, ranging from -3.20 up to 0.21 (Brons et al., 2002). The variations in these estimates support the need for an airport-by-airport or regional analysis, towards estimating the impact of monetary-based climate policy measures targeting air passenger demand.

With respect to the remaining variables in the first stage model, estimates on the distance categorical variables show that short-range domestic flights have the highest impact on demand on routes from MSN (with 1.8 compared to the base “medium”), as most services from this small hub are destined to nearby main hubs involving short flights. It should also be noted that there are no long-range operations from MSN. On routes from ORD, however, impact on demand from medium-range flight (with 1.8) is greatest followed by those on short (with 0.9) and long-range (with zero as base). Given that social and commercial interaction between origin-destination pairs are generally expected to decrease as distance increases (Mohammadian et al., 2019), it is not unexpected that demand is least impacted by long-range category flights. However, it should also be noted that the importance of air travel increases on origin-destination pairs that are significantly distant from one another, given that other travel modes become less viable on such long distances (Jorge-Calderón, 1997).

With regard to the second stage model of supply, a 10% increase in jet fuel price results in 2% and 0.7% reductions in aircraft size on routes from MSN and ORD, respectively. The effects of jet fuel price on LF are not found to be statistically significant. Airlines are known to use smaller aircraft towards the aim of greater LFs during jet fuel price shocks (McConnachie, Wollersheim and Hansman, 2013). A 10% increase in HHI leads to 0.92% and 0.97% increases in aircraft size on routes from MSN and ORD, respectively, while also resulting in a 0.76% increase in LF on routes from ORD. All these changes are negligible, in agreement with Mohammadian et al. (2019). Other studies have shown as airlines monopolize markets in the face of reduced competition, they reduce costs by increasing aircraft size and reducing flight frequency; when facing increased competition, they reduce aircraft size and add frequency (Hanlon, 1989; Borenstein and Netz, 1999). A 10% increase in demand leads to 2.8% and 2.7% increases in LF on routes from MSN and ORD,
respectively. However, it also leads to smaller increases in aircraft size on routes from MSN at 1.8%, compared to 3.1% on routes from ORD. This could be an indication of the much higher passenger volumes on routes from ORD which, if increased by 10%, would require a greater increase in aircraft size in addition to more flight frequency compared to MSN.

6.2.2 Elasticities of Emissions to Airfare

Price measures in the form of voluntary customer emission charges (Mair, 2011), carbon credits (Hofer, Dresner and Windle, 2010; Malina et al., 2012) as well as mandatory air ticket carbon taxes (Wild, Mathys and Wang, 2021) are imposed with the aim of reducing demand and subsequent emissions, and generating revenues required to support carbon removal processes. Such price measures are expected to trigger a chain of reactions on demand, supply, and ultimately, emissions, but these reactions are rarely fully explored (Sobieralski, 2021). Based on results of the work of this chapter towards exploring these interactions, some insights are discussed.

Applying Equations 6.10–6.11, a 10% increase in mean airfare leads to 0.74% and 0.07% reductions in aircraft size on routes from MSN and ORD, respectively. Additionally, a 10% increase in mean airfare leads to 1.1% and 0.06% reductions in LF on routes from MSN and ORD, respectively, indicating that capacity decision factors are inelastic to airfare. However, based only on the very small magnitudes of these inelastic values, capacity decision factors appear to respond more to airfare on routes from MSN than those from ORD.

Equation 6.12 is used to estimate the elasticities of jet fuel burned and pollutants to airfare for each route (12 originating from MSN and 165 from ORD) per quarter. The elasticities are then averaged by quarter and shown in Figure 6.2. The airfare elasticities of CO$_2$ and H$_2$O (collectively referred as GHG in the figure), and SO$_X$ are identical to that of jet fuel burned per route, as the quantities of these three pollutants emitted are proportional to jet fuel burned, which in turn is proportional to distance flown as also determined in past studies (Scheelhaase et al., 2016; Cox, Jemiolo and Mutel, 2018). However, NO$_X$, CO, HC and PM$_{2.5}$ exhibit different elasticities, largely because the emissions of these pollutants are influenced by ambient and operational conditions more than by weight of jet fuel burned and distance flown (Fuglestvedt et al., 2010; Scheelhaase et al., 2016).
Figure 6.2 Airfare elasticities of jet fuel, GHGs and other pollutants on routes from MSN and ORD, averaged by quarter

Figure 6.2 shows that jet fuel and all pollutants are inelastic to airfare on all routes originating from both MSN and ORD. Jet fuel and pollutants on the 12 routes originating from MSN respond to airfare more than the 165 routes originating from ORD. This is evident from the elasticities ranging from zero up to -0.12 (in which case a 10% increase in mean airfare results in 0-1.2% reductions in pollutants) for the former, compared against zero up to -0.015 (in which case a 10% increase in mean airfare results in 0-0.15% reductions in pollutants) for the latter. Furthermore, for all routes originating from both airports, the response to airfare is greatest for NO\textsubscript{X} followed by jet fuel and the GHGs of CO\textsubscript{2} and H\textsubscript{2}O, and SO\textsubscript{X}, while it is the smallest for HC.

Including non-CO\textsubscript{2} emissions such as NO\textsubscript{X}, SO\textsubscript{X}, HC and PM\textsubscript{2.5}, and estimating their potential response to airfare, is important for current climate mitigation measures, despite that the results show negligible response. Previous research has shown that two-thirds of aviation’s contribution to climate change arise from non-CO\textsubscript{2} emissions (Scheelhaase et al., 2016). However, in their
Nationally Determined Contributions (NDCs) (UNFCCC, no date), documents in which The Paris Accord signatory countries (excluding Germany and Austria) outline their national targets on reducing aviation emissions from domestic flights, countries do not include non-CO$_2$ pollutants (German Environment Agency, 2018; Gössling and Humpe, 2020). This is due to the exclusion of short-lived pollutants including NO$_X$ and contrails from the Paris Climate Accord (Lee et al., 2021). Even considering only carbon emissions, the UNFCCC Secretariat has determined that an irreconcilable gap exists between the emissions reductions required to achieve the net zero goal of 2050 and the reductions planned in the NDCs. Thus, the UNFCCC Secretariat has called on countries to thoroughly revisit their targets and set them higher (UNFCCC, 2021).

For a closer inspection, histograms of airfare elasticities of fuel and selected pollutants from Figure 6.2 are presented in Figure 6.3. The left column represents routes originating from MSN and right column represents those from ORD.
Figure 6.3 Histogram of airfare elasticities of fuel and some pollutants

Figure 6.3 shows that the airfare elasticities of jet fuel and pollutants on routes originating from the large hub of ORD are roughly one-tenth their counterparts from the small hub of MSN. Consequently, routes originating from such large hubs could be more challenging for emissions reductions (from their current levels) through price measures, although they are environmentally more efficient at the passenger-kilometre-traveled (PKT)-level as shown in Chapter 5. In
combination with medium-size airports, large hubs in the US account for 88% of passenger traffic, and thus, contribute the most to aviation emissions. With more passenger leakage from small to large hub airports anticipated in the COVID-19 recovery period (Hotle and Mumbower, 2021), demand is likely to continue growing disproportionately at large hubs compared to small ones. Thus, proportional emissions reductions must occur at these large hubs if the 2050 net zero goal is to be achieved. Given the weak link shown between price and emissions in this thesis, however, such proportional reductions will be challenging to achieve using reasonable monetary instruments. Prominent climate policies on aviation, such as the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) and the European Union Emissions Trading Scheme (EU ETS), are unlikely to achieve net zero in 2050 due to their overly ambitious plans to reduce emissions at very low costs (Efthymiou and Papatheodorou, 2019; Warnecke et al., 2019).

Recall that this analysis is performed at the airport and route levels. Policy decisions based on analysis at national and international levels mask critical regional variations and misplace the focus on countries rather than actual producers of emissions (Chakravarty et al., 2009; Girod and de Haan, 2009). The findings from this chapter demonstrate that demand at two airports that are within only 1.5 hr drive of each other may respond considerably differently to comparable changes in airfare, which also implies that responses to monetary environmental measures will differ between the two airports. Furthermore, national and international approaches do not align with place-based approaches to net zero, through which decarbonization efforts start at highly localized levels such as neighborhoods and cities (Wildfire et al., 2019; Krabbe, 2021; Power, 2022) and local government agencies take the lead in regulating environmental policies (Elofsson et al., 2018).

The effectiveness of monetary measures on reducing emissions remains debatable, and thus nations have taken other approaches. France has become the first major economy to ban short haul flights on intercity routes for which bus and rail services exist, with the idea that stopping travelers from flying altogether is the most promising way forward (Åkerman et al., 2021). Similarly, after providing a bailout to Austrian Airlines, the Austrian government mandated it to replace its Vienna-Salzburg flight with rail service in 2020 in order to reduce emissions (BBC, 2021). The Chinese government grew high-speed rail (HSR) ridership from 7.34 million passengers in 2008
to 961.4 million passengers in 2015, leading to a 5.6% reduction in total CO₂ emissions from domestic air travel (Wang, O'Sullivan and Schäfer, 2019).

### 6.3 Recap and Summary

In this chapter, the relationships between demand, capacity decision and emissions, triggered by airfare (used as a proxy for a price-based climate action policy measure), are investigated. As opposed to a top-down, national or international-level approach commonly taken in previous studies, a bottom-up approach focusing on air passenger demand over a small section of the US Midwest is adopted. Based on a 2SLS supply-and-demand model and elasticity analysis, a comparable 10% increase in airfare leads to 4.23%, 0.74% and 1.1% reductions in demand, aircraft size and LF, respectively, on routes from the small hub of MSN. The same 10% increase in airfare has nearly no effect on these service characteristics for routes originating at the large hub of ORD. The findings also indicate that aviation fuel and pollutants on routes from both airports are inelastic to airfare and in fact very, very small, although the magnitude of airfare elasticities of fuel/pollutants on routes from MSN are ten times those from ORD. This points towards the potentially low efficacy of price-based measures on reducing aviation emissions. Given that these airports are only approximately 1.5 hr drive apart, the results show that a uniform application of these monetary-based policy instruments for reducing emissions over entire countries may yield uneven outcomes. Replicating this more localized approach on airports in different regions of the US as well as other countries may yield a range of insights about where price-based emissions policies could have efficacy and to what extent. By comparing against the results of this thesis and other locales, further insights may be gained towards understanding how effective national-level policies may be designed.
Chapter 7: Conclusion

This chapter provides a summary of the research and results, highlights contributions, and identifies limitations of the research and future directions.

7.1 Overview of Research and Results

The central objective of this thesis is to understand air passengers’ airport choices across a large geographic area, and to investigate the implications of these choices for aviation emissions and price-based environmental policies. Towards this central objective, three specific objectives were pursued, as per Figure 7.1.

A summary of the work pursued and key results of each objective are described below.

Objective 1: Explore the air service-related drivers of airport choices across a large geographic region encompassing regional and state boundaries (Ch. 4).

Summary of Work: Air service-based drivers of airport choices – specifically, the choices of air passengers that drive long distances, bypassing their local airports in favour of large hubs father away – are explored using a mixed logit model estimated on a dataset of air tickets purchased by
domestic air passengers over a large section of the US Midwest. Then, the estimated means of variable coefficients are applied on average air service attributes at the study airports, and resulting choice probabilities are spatially plotted to observe the geographic extent of the passenger markets of the study airports. The air service attributes explored for each airport and route include airfares, airport access distances, flight frequencies and flight option (nonstop vs connecting). Air passengers are also categorized by three air route distances (short, medium and long), and the model is again estimated for each group.

**Results:** The results indicate that the geographic extent and strength/shares of airport passenger markets vary considerably, with airport market areas generally consistent within the FAA-designated size category they belong to. For small airports, their passenger market areas and market shares clearly diminish in the directions of neighboring airports. Degradations in air services also lead to sizeable contractions in the market areas and shares of small and medium hubs. In contrast, comparable air service degradations for large hub airports result in negligible contractions in market areas and shares. For small and medium airports, the contraction in market areas and shares caused by increases in airfare are greater than those caused by proportional decreases in flight frequency or nonstop service at these airports. For example, a 30% increase in mean airfare leads to market share reductions exceeding 75%, while similar proportional reductions in mean flight frequency cause only a 15% market share reduction. These results suggest that airfare is the dominant service attribute driving passengers’ choices of departure airports, leading to the hypothesis that price-based emissions policies could be impactful (this idea is explored in Objective 3). Additionally, the market areas of medium and large airports are shown to strongly cross administrative boundaries. This further reinforces the idea that MPOs, regional and state transportation planning agencies should be collaborating with one another, and with airports in their regions, to plan long-distance transportation services and infrastructures.

The model results for passengers in short, medium and long route categories reveal that responses to airport access distance and flight frequency, in choosing departure airports, vary across route categories. Passengers in the long route category place twice as much weight on airport access distance, compared to those in short route category. Although unexpected, this indicates that passengers on long flights may prioritize minimizing overall travel time in their airport choices, which includes the ground-based airport access trip. Passengers in the long route category also
place three times as much weight on flight frequency, compared to those in short route category. This could be due to the fact that long routes are operated less frequently than short routes, and thus are valued more. The differences in weights placed by passengers on nonstop services and airfare, on the other hand, are limited to within 10% across route categories. Next, it was found that 88% and 89% of passengers on short and medium categories, respectively, place more value towards airports with greater flight frequencies available, as opposed to 76% on long routes. Similarly, nonstop services are positively perceived among 94% and 89% of passengers on short and medium routes, respectively, versus 73% of passengers on long routes. Only 9%-10% of passengers on short and medium routes have a positive response to airfare, compared to 29% of passengers on long routes. Finally, nearly all passengers view shorter airport access times as positive, across all route distances. Overall, these results show that there is substantial variation in airport market areas and strengths based on the routes flown, as well as the geographic distribution of airports across the region of study.

Objective 2: Compare passenger-level aviation fuel burn and emissions among air routes originating from different airports within the study area (Ch. 5).

Summary of Work: Average emission factors (AEFs) and marginal emission factors (MEFs) on air routes originating from the 21 small, medium and large study airports, and ending in 61 unique final destinations are computed. To compute these emission factors, a Modified Breguet Range-based emission model is first adopted from an existing study, and then the required model parameters are estimated using a standard aircraft emission database. The estimated model, which requires only aircraft size, load factor (LF) and flight distance, is then applied on the identified air routes.

Results: MEFs are generally 0.75-0.80 times AEFs for routes originating from small airports, 0.65-0.70 times AEFs for those originating from medium airports, and 0.55-0.63 times AEFs for those originating from large hubs, for jet fuel and each of seven pollutants (\(\text{CO}_2\), \(\text{H}_2\text{O}\), \(\text{SO}_x\), \(\text{NO}_x\), \(\text{HC}\), \(\text{CO}\) and \(\text{PM}_{25}\)). These numbers indicate that the fuel use and pollutant volumes attributed to a unit increase or decrease in demand – represented by MEF – are smaller than average values (AEF). Although useful as general indicators of passenger-level emissions, AEFs should be coupled with MEFs towards understanding the environmental implications of demand changes caused by
changes in air services. Also, both AEF and MEF decrease as departure airport size increases. The differences in MEFs on routes from small/medium versus large airports are higher than their AEF counterparts. For instance, AEFs on routes from medium hubs are generally higher than those from large airports by only 18%-40% (with the exception of PM_{25}, which is 99% higher). However, this range increases to 36%-65% for MEFs (and PM_{25} is 132% higher). The differences on routes from small airports with those from large ones are even higher – while AEFs are 27%-50% higher (with PM_{25} 100% higher), MEFs are higher by 63%-105% (and PM_{25} 167% higher). Thus, when an air traveler “leaks” to a large hub airport over using their local small airport, their personal contribution to air emissions resulting from this decision are lower than if they chose their local airport. When comparing the AEF and MEF estimates, the findings further indicate that the fuel and emissions savings of choosing large hubs over small airports are considerably higher than those commonly reported based on AEFs.

**Objective 3: Investigate the effect of price-based environmental policies on aviation emissions (Ch. 6).**

**Summary of Work:** Based on Chapter 4 results suggesting airfare to be the dominant service attribute driving passengers’ choices of departure airports, this objective investigates the potential efficacy of price-based emissions policies. The interaction between demand, supply and emissions, triggered by price (represented by airfare in this thesis) is explored on air routes originating from a small airport and large airport using a two-stage least-squares (2SLS) regression model. The effects of airfare on demand, which is bi-directionally related to supply, in turn governs emissions. Demographic indicators, jet fuel prices and airline competition are also included as variables. In the first stage of the 2SLS model, demand is modelled using airfare and the aforementioned variables. The demand from this first stage is then used with jet fuel prices and airline competition to model aircraft size and LF in the second stage. From the first stage model, the elasticities of demand to airfare are determined, and by combining these elasticities with the elasticities of aircraft size and LF to demand, the elasticities of aircraft size and LF to airfare are indirectly computed. Aircraft size and LF determine emissions, and using the elasticities of aircraft size and LF to airfare, changes in emissions caused by changes in airfare are finally computed and again reported as elasticities.
Results: A 10% increase in airfare leads to 4.23%, 0.74% and 1.1% reductions in demand, aircraft size and LF, respectively, on routes from the small airport. A similar 10% increase in airfare leads to 0.23%, 0.07% and 0.06% reductions in demand, aircraft size and LF, on routes from the large hub airport. The elasticities of emissions to airfare range from zero to -0.12 on all studied routes, indicating that emissions are inelastic to airfare (and perfectly inelastic at 0). Despite all results being inelastic, the magnitudes of elasticity estimates on routes originating from the large hub are one-tenth of those on routes from the small hub. These results confirm those of previous studies, including that it may be very challenging to achieve measurable emission reductions on routes from large hubs using price-based measures because demand is unresponsive to price and passengers are inclined to fly through large hubs, especially with the disparities in air services between these large hubs and small airports deepening in the COVID-19 recovery era. Overall, the inelasticity of emissions to airfare indicates the potential inefficacy of price-based policies to reduce emissions.

Overview: Air travelers’ airport choices, specifically in the long-distance context of “leakage” to larger hubs farther away, are most influenced by airfare. The resulting choices for these airports entail sizeable differences in passenger-level emissions that relate to air travel mitigation behavior initiatives. However, despite its considerable influence on airport choices, higher airfares appear to have little efficacy towards emissions reductions, raising questions about the efficacy of price-based emissions policies.

7.2 Contributions

Aviation systems around the world are facing many challenges as the world emerges from the COVID-19 pandemic. In the US as well as Canada, events over the last two decades culminating with the COVID19 pandemic have led to service and passenger losses at many non-major hub airports, and it is unclear what post-pandemic trends may emerge: whether these losses will exacerbate with the end of the CARES Act, leading to further hub strengthening, or otherwise. In addition, aviation is one of the most emissions intensive sectors contributing to the climate crisis the world is experiencing. Although technology is developing quickly with respect to greener fuels and low- to no-emissions aircraft, the question remains whether growth in aviation demand – particularly the explosive growth anticipated post-COVID – will lead to more emissions in the
shorter term. Nations worldwide are seeking to combat aviation emissions through various initiatives and polices including emissions charges, air travel mitigation behavior and other means.

This thesis addresses some important questions that emerge from the above uncertainties and challenges.

First, airport choices and their air service-related drivers are explored over the largest geographic area to date. In doing so, air service disparities among airports of differing sizes, and the influence of these service disparities on passengers’ airport choices, are examined. Also, variations in airport market areas and market shares based on their geographic locations relative to other airports can be observed. The observed market areas differ significantly from airport catchments conventionally defined based on administrative boundaries or other simple measures (circles at some radii around airports, driving distances/times). Given that such catchment definitions have been extensively used to gauge airport passenger demand estimates, the results of this thesis can help improve this demand estimation and subsequent air service analyses.

Furthermore, the market areas of airports (particularly large hubs and to a certain extent medium hubs) are shown to strongly cross multiple MPO boundaries. As such, air travelers will cross these boundaries consistently to use airports and surface transportation infrastructure, potentially at high volumes, reinforcing the need for cooperative regional transportation planning. Such planning requires inter-MPO as well as MPO-airport collaboration which currently are very limited. The findings can also help small airports (and the federal EAS program) in determining the types of air services needed to better retain passengers, and thus better target their (passenger and airline) marketing efforts.

Second, the emissions implications resulting from airport choices are also studied. Passenger-level emissions on complete air routes (which may involve one or more flight segments) are estimated, as opposed to previous work that focused on single flight segments. Differences in passenger level emissions on alternative routes are estimated using both AEFs and MEFs. MEFs are considered to be appropriate indicators for quantifying changes in emissions attributable to changes in demand within the energy sector, although they have been largely absent in the air transportation literature asides from a few key studies. The route-level emissions comparisons can support air travel mitigation behavior initiatives in which passengers are encouraged to choose departure airports
and routes involving less emissions. The findings are also relevant in terms of quantifying the emissions outcome pertaining to changing aviation operations during the COVID-19 recovery, when more and more airlines are strongly pushing for terminating services involving regional jets and small airports, which in turn, are expected to exacerbate passenger leakage.

Finally, the potential impact of price-based environmental policies on emissions are explored on an airport-by-airport basis. This is done in light of the distinct geographic location, air service and demand characteristics of airports, and by considering the interaction between these services and demand which is often overlooked in studies guiding environmental policies on aviation. Findings show that despite the dominant role it plays in air passengers’ airport choices, higher airfare will not have measurable impacts on emissions from air travel, based on the airport-level analysis of this thesis. Thus, price-based environmental policies, although critical to incentivize and generate revenues necessary for carbon reduction processes and technologies (including but not limited to SAF), are expected to have limited efficacy in directly combating emissions.

7.3 Research Limitations and Future Work

There are some methodological, scope and data limitations in this thesis that could be addressed in future works.

First, the air ticket dataset used offers extensive passenger geographic coverage but lacks passenger-specific attributes such as travel purpose (business versus leisure), frequent flier membership, flying experience, previous airport experience, income, airport access mode, travel group size, time of ticket booking and other attributes that are well-documented to influence airport choices. Furthermore, with more time investment, information on additional attributes that also influence airport choices such as presence of LCCs, on-time performance, parking fees, airport amenities, ease of check in, and shuttle and train services (and costs) can be collected towards improving the current choice model. Also, by analyzing the trade-offs between model estimates on different air service attributes and implementing other choice modelling techniques (including non-parametric approaches), other airport choice characteristics could be uncovered. Additionally, systematic definitions of choice sets could be tested instead of assuming all passengers’ choice sets consist of all available airports.
Second, the emission model applied estimates pollutants as a function of aircraft size, LF and flight distance. While this approach is suitable for fuel burn and CO₂, H₂O and SOₓ emissions, it is limited in its ability to accurately estimate HC and PM₂₅ as evident from the higher number of statistically insignificant model parameter estimates. Thus, other model formulations that account for aircraft operational and ambient conditions should be developed and tested. Furthermore, instead of evenly distributing emissions across all seats in an aircraft as done in this thesis, detailed aircraft seat class configurations could be accounted for in future studies, as the carbon footprints from business and first-class seats have been reported to be between three to nine times higher than economy seats (Gössling and Humpe, 2020). Emissions from airport ground access trips should also be incorporated, in order to complete a full picture of the environmental implications of airport choice and air travel.

Third, the impact of price on emissions can also be explored further. It should be analyzed at several other airports of different sizes both within and outside of the study region, as results could vary considerably from large airports to smaller ones (as shown in this research). In addition to airport size, it is also necessary to consider the primary market type served. Airports (and routes) largely serving leisure markets are likely to be more impacted by price-based environmental policies, as leisure trips are optional and often directly paid for by passengers themselves. Such policies are expected to have less impacts at airports (and for routes) mainly serving business passengers, given that business travel is mainly non-optional and paid for by companies. Furthermore, true origin and destination passenger volumes should be considered instead of segment volumes in the supply-and-demand analysis, if available, as the former is the correct way of quantifying the air volumes generated between two airports. Also, by considering a longer study period, it is possible to investigate the long-term price elasticity of demand and emissions. Elasticity estimates could also be obtained using machine learning approaches. Additionally, the difficulties of implementing price-based policies at different geographic scales (and potentially on an airport-by-airport or route basis) should be considered in analyses such as the one presented in this thesis.

Finally, this thesis relies on the assumption that price-based environmental policies on aviation will impact passenger demand in a manner similar to airfare. Nonetheless, this assumption might not be sufficiently realistic given that such policies (implemented in the form of air ticket carbon
taxes, carbon offset charges, carbon credits (bought by airlines and passed onto passengers) and others) are not imposed as integral parts of airfare. By exploring the various pathways (such as impact on fuel costs, and thus operational costs of airlines) through which such price-based policies ultimately enter airfare, the current assumption could be improved.
Bibliography


ICAO. 2022. “Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA).”
https://www.icao.int/environmental-protection/CORSIA/Pages/default.aspx.


Appendices

Appendix A Aircraft Characteristics

These sources were used to find the operating empty weight (OEW) and seating capacity of the 78 representative aircraft in the EMEP/EEA Emissions database.

https://www.airbus.com/aircraft.html
https://www.boeing.com/commercial/airports/plan_manuals.page
https://contentzone.eurocontrol.int/aircraftperformance/default.aspx?
https://www.airliners.net/aircraft-data/canadair-cl-600-regional-jet-crj-100-200/125
https://aviation-safety.net/database/types/Bombardier-CRJ100-200-440/specs
https://www.globalair.com/aircraft-for-sale/Specifications?specid=1635
https://www.airlines-inform.com/commercial-aircraft/dornier-228.html
http://www.flugzeuginfo.net/acdata_php/acdata_dc10_en.php
https://modernairliners.com/douglas-dc8/
http://www.flugzeuginfo.net/acdata_php/acdata_dhc8_en.php
https://www.planemapper.com/aircrafts/C-GZJC
https://www.predictivemobility.com/family-DASH
http://www.flugzeuginfo.net/acdata_php/acdata_emb110_en.php
https://www.embraercommercialaviation.com/wp
content/uploads/2017/02/Embraer_spec_145_web.pdf
https://www.embraercommercialaviation.com/commercial-jets/e170/
https://www.fokkerservices.com/media/53peaal2/fokker100_informationbooklet.pdf
https://aviation-safety.net/database/types/Fokker-F-27-Friendship/specs
Appendix B  Airport Choice Supplementary Inputs and Outputs

The 61 final destinations used in Chapters 4 and 5, and estimates on airport dummy variables (representing alternative specific constants (ASCs)) from the route distance-based MMNL choice modelling work (Chapter 4) are presented.

B.1  Final Destinations
### B.2 MMNL ASC Estimates for Short, Medium and Long Routes

<table>
<thead>
<tr>
<th>Airport dummy</th>
<th>Moment</th>
<th>Short route</th>
<th>Medium route</th>
<th>Long route</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Estimate (std. error)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(I(\text{ATW} = 1)) (base)</td>
<td>Mean</td>
<td>0 (-)</td>
<td>0 (-)</td>
<td>0 (-)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0 (-)</td>
<td>0 (-)</td>
<td>0 (-)</td>
</tr>
<tr>
<td>(I(\text{AZO} = 1))</td>
<td>Mean</td>
<td>-1.718(^{**}) (0.884)</td>
<td>-1.928 (0.440)</td>
<td>-0.626(^{n/s}) (1.758)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0.147(^{**}) (1.314)</td>
<td>1.640(^{**}) (0.883)</td>
<td>0.811 (1.526)</td>
</tr>
<tr>
<td>(I(\text{BMI} = 1))</td>
<td>Mean</td>
<td>0.001(^{n/s}) (0.721)</td>
<td>2.049 (0.435)</td>
<td>8.761 (1.974)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>3.370 (0.624)</td>
<td>3.230 (0.367)</td>
<td>5.698 (1.565)</td>
</tr>
<tr>
<td>(I(\text{CMI} = 1))</td>
<td>Mean</td>
<td>-3.946 (1.102)</td>
<td>-1.480 (0.531)</td>
<td>2.430(^{n/s}) (1.508)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>3.948 (0.796)</td>
<td>1.352(^{**}) (0.760)</td>
<td>4.965 (1.863)</td>
</tr>
<tr>
<td>(I(\text{CWA} = 1))</td>
<td>Mean</td>
<td>-2.508 (0.774)</td>
<td>-2.799 (0.470)</td>
<td>-5.264 (1.907)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>1.703(^{**}) (1.230)</td>
<td>0.975(^{n/s}) (0.750)</td>
<td>0.417 (2.299)</td>
</tr>
<tr>
<td>(I(\text{DBQ} = 1))</td>
<td>Mean</td>
<td>-5.670 (1.117)</td>
<td>-6.985 (1.068)</td>
<td>-0.919(^{n/s}) (1.911)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0.981(^{n/s}) (1.124)</td>
<td>1.919(^{n/s}) (2.892)</td>
<td>3.495 (1.609)</td>
</tr>
<tr>
<td>(I(\text{DSM} = 1))</td>
<td>Mean</td>
<td>3.737 (0.994)</td>
<td>6.525 (0.587)</td>
<td>8.642(^{*}) (4.116)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>3.301 (0.568)</td>
<td>6.285 (0.647)</td>
<td>8.972 (3.383)</td>
</tr>
<tr>
<td>(I(\text{DTW} = 1))</td>
<td>Mean</td>
<td>7.677 (0.922)</td>
<td>7.167 (0.547)</td>
<td>16.509 (3.291)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>2.161 (0.694)</td>
<td>1.068(^{*}) (0.427)</td>
<td>2.082(^{n/s}) (1.677)</td>
</tr>
<tr>
<td>(I(\text{FWA} = 1))</td>
<td>Mean</td>
<td>4.124 (0.808)</td>
<td>1.862 (0.600)</td>
<td>5.343 (1.587)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>-0.215(^{n/s}) (0.346)</td>
<td>-0.314(^{n/s}) (0.338)</td>
<td>0.465(^{n/s}) (0.729)</td>
</tr>
<tr>
<td>(I(\text{GRB} = 1))</td>
<td>Mean</td>
<td>3.523 (0.727)</td>
<td>3.586 (0.418)</td>
<td>7.571 (2.178)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>2.563 (0.680)</td>
<td>3.087 (0.380)</td>
<td>4.825 (1.262)</td>
</tr>
<tr>
<td>(I(\text{GRR} = 1))</td>
<td>Mean</td>
<td>8.210 (0.878)</td>
<td>8.241 (0.600)</td>
<td>17.587 (3.367)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0.376(^{n/s}) (0.340)</td>
<td>0.156(^{n/s}) (0.395)</td>
<td>4.382 (1.053)</td>
</tr>
<tr>
<td>(I(\text{IND} = 1))</td>
<td>Mean</td>
<td>5.993 (0.686)</td>
<td>7.542 (0.482)</td>
<td>13.447 (2.560)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0.358(^{n/s}) (0.497)</td>
<td>4.161 (0.389)</td>
<td>2.751 (1.764)</td>
</tr>
<tr>
<td>(I(\text{MKE} = 1))</td>
<td>Mean</td>
<td>9.237 (1.044)</td>
<td>9.707 (0.643)</td>
<td>-12.067(^{n/s}) (2.718)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>6.275 (1.491)</td>
<td>0.228(^{n/s}) (0.468)</td>
<td>14.408 (3.973)</td>
</tr>
<tr>
<td>(I(\text{MSN} = 1))</td>
<td>Mean</td>
<td>9.616 (1.018)</td>
<td>10.163 (0.670)</td>
<td>12.508 (2.720)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>3.716 (0.584)</td>
<td>3.559 (0.392)</td>
<td>0.059 (1.590)</td>
</tr>
<tr>
<td>Airport dummy</td>
<td>Moment</td>
<td>Short route</td>
<td>Medium route</td>
<td>Long route</td>
</tr>
<tr>
<td>---------------</td>
<td>--------</td>
<td>-------------</td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td></td>
<td>Estimate (std. error)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( I(PIA = 1) )</td>
<td>Mean</td>
<td>1.651* (0.784)</td>
<td>3.563 (0.581)</td>
<td>13.504 (3.032)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>1.736* (1.020)</td>
<td>0.705(^{n/s}) (0.887)</td>
<td>4.547 (2.204)</td>
</tr>
<tr>
<td>( I(SBN = 1) )</td>
<td>Mean</td>
<td>2.542 (0.762)</td>
<td>1.202* (0.593)</td>
<td>3.133** (1.898)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>2.092* (0.823)</td>
<td>1.640* (0.747)</td>
<td>2.518 (1.671)</td>
</tr>
<tr>
<td>( I(SPI = 1) )</td>
<td>Mean</td>
<td>-2.192** (1.281)</td>
<td>0.904(^{n/s}) (0.720)</td>
<td>6.552 (2.316)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>0.022(^{n/s}) (2.792)</td>
<td>6.310* (2.479)</td>
<td>6.550 (4.496)</td>
</tr>
<tr>
<td>( I(STL = 1) )</td>
<td>Mean</td>
<td>2.671* (1.081)</td>
<td>4.494 (0.892)</td>
<td>10.273 (2.927)</td>
</tr>
<tr>
<td></td>
<td>St. dev</td>
<td>6.360 (1.078)</td>
<td>4.829 (0.797)</td>
<td>6.892 (2.075)</td>
</tr>
</tbody>
</table>

* significant at the 95% confidence level.
** significant at the 90% confidence level.
\(^{n/s}\) not significant at the 90% confidence level.
All other parameters are significant at 99% confidence level.
Appendix C Supplementary Description and Inputs for Emissions Modelling

Cruise-climb-descent (CCD) phase fuel and pollutants’ plots from which $\gamma_x$ and $\delta_x$ are estimated (in the Modified Breguet Range emissions model), are presented based on European Monitoring and Evaluation Program (EMEP) and European Environment Agency (EEA) emissions database.

C.1 CCD Phase Fuel
C.2  CCD Phase H$_2$O
C.3  CCD Phase CO$_2$
C.4 CCD Phase NOx
C.5  CCD Phase SO\textsubscript{x}

![Image of graph showing SO\textsubscript{x} emissions versus flight distance with aircraft data points]
C.6  CCD Phase CO
C.7 CCD Phase HC

![Graph showing HC vs Flight distance for different aircraft types]

**Aircraft**
- A306
- A310
- A318
- A319
- A320
- A321
- A332
- A333
- A343
- A346
- A388
- AT43
- AT45
- AT72
- B190
- B462
- B721
- B722

**Legend:**
- C130
- C550
- CRJ1
- CRJ2
- C38
- CRJ9
- D228
- D328
- DC10
- DC85
- DC87
- DC94
- DHA
- DH8A
- DH8C
- DH8D
- E110
- E120
- E145
- E170
- E190
- F27
- F28
- F2
- F50
- JS31
- JS41
- MD11
- MD82
- MD83
- MD8
- PA27
- PAY3
- RJ85
- SB20
- SF34
- SH36
- SW4
- T134
- T154

**Graph Details:**
- Y-axis: HC (kg)
- X-axis: Flight distance (km)
C.8  CCD Phase PM$_{25}$
Appendix D  Estimates on Route Dummy Variables (First Stage of 2SLS Supply-and-Demand Model)

D.1 Routes Originating from MSN

<table>
<thead>
<tr>
<th>Route</th>
<th>Estimate (std. error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSN_CLE</td>
<td>-1.565 (0.109)</td>
</tr>
<tr>
<td>MSN_CLT</td>
<td>-1.030 (0.122)</td>
</tr>
<tr>
<td>MSN_CVG</td>
<td>-2.042 (0.085)</td>
</tr>
<tr>
<td>MSN_DCA</td>
<td>-1.752 (0.073)</td>
</tr>
<tr>
<td>MSN_DEN</td>
<td>0.031&lt;sup&gt;n/s&lt;/sup&gt; (0.078)</td>
</tr>
<tr>
<td>MSN_DFW</td>
<td>-0.534 (0.069)</td>
</tr>
<tr>
<td>MSN_DTW</td>
<td>0.513 (0.071)</td>
</tr>
<tr>
<td>MSN_EWR</td>
<td>-1.952 (0.073)</td>
</tr>
<tr>
<td>MSN_LGA</td>
<td>-1.22 (0.071)</td>
</tr>
<tr>
<td>MSN_MSP</td>
<td>0.486 (0.072)</td>
</tr>
<tr>
<td>MSN_ORD</td>
<td>0.802 (0.092)</td>
</tr>
<tr>
<td>MSN_SLC</td>
<td>0 (base)</td>
</tr>
</tbody>
</table>

<sup>n/s</sup> not significant at the 90% confidence level.

All other parameters are significant at 99% confidence level.
### D.2 Routes Originating from ORD

<table>
<thead>
<tr>
<th>Route</th>
<th>Estimate (std. error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ORD_ABQ</td>
<td>-0.424 (0.087)</td>
</tr>
<tr>
<td>ORD_ACY</td>
<td>-0.003* (0.111)</td>
</tr>
<tr>
<td>ORD_ALB</td>
<td>0.996 (0.087)</td>
</tr>
<tr>
<td>ORD_ALO</td>
<td>-0.388 (0.086)</td>
</tr>
<tr>
<td>ORD_ANC</td>
<td>1.568 (0.180)</td>
</tr>
<tr>
<td>ORD_ART</td>
<td>-0.636 (0.116)</td>
</tr>
<tr>
<td>ORD_ASE</td>
<td>-1.228 (0.085)</td>
</tr>
<tr>
<td>ORD_ATL</td>
<td>2.964 (0.089)</td>
</tr>
<tr>
<td>ORD_ATW</td>
<td>0.400 (0.086)</td>
</tr>
<tr>
<td>ORD_AUS</td>
<td>0.963 (0.088)</td>
</tr>
<tr>
<td>ORD_AVL</td>
<td>-0.061* (0.088)</td>
</tr>
<tr>
<td>ORD_AVP</td>
<td>-0.362 (0.087)</td>
</tr>
<tr>
<td>ORD_AZA</td>
<td>-0.271* (0.246)</td>
</tr>
<tr>
<td>ORD_AZO</td>
<td>0.281 (0.086)</td>
</tr>
<tr>
<td>ORD_BDL</td>
<td>1.562 (0.090)</td>
</tr>
<tr>
<td>ORD_BGR</td>
<td>-1.641 (0.114)</td>
</tr>
<tr>
<td>ORD_BHM</td>
<td>0.187* (0.086)</td>
</tr>
<tr>
<td>ORD_BIL</td>
<td>-2.221 (0.134)</td>
</tr>
<tr>
<td>ORD_BIS</td>
<td>-0.988 (0.101)</td>
</tr>
<tr>
<td>ORD_BMI</td>
<td>-0.116** (0.086)</td>
</tr>
<tr>
<td>ORD_BNA</td>
<td>1.761 (0.088)</td>
</tr>
<tr>
<td>ORD_BOI</td>
<td>-0.739 (0.087)</td>
</tr>
<tr>
<td>ORD_BOS</td>
<td>3.082 (0.088)</td>
</tr>
<tr>
<td>ORD_BTV</td>
<td>0.513 (0.088)</td>
</tr>
<tr>
<td>ORD_BUF</td>
<td>1.498 (0.090)</td>
</tr>
<tr>
<td>ORD_BWI</td>
<td>1.845 (0.089)</td>
</tr>
<tr>
<td>ORD_BZN</td>
<td>-0.830 (0.085)</td>
</tr>
<tr>
<td>ORD_CADE</td>
<td>-0.053* (0.086)</td>
</tr>
<tr>
<td>ORD_CAK</td>
<td>0.335 (0.087)</td>
</tr>
<tr>
<td>ORD_CHA</td>
<td>-0.793 (0.087)</td>
</tr>
<tr>
<td>ORD_CHO</td>
<td>-0.091* (0.088)</td>
</tr>
<tr>
<td>ORD_CHS</td>
<td>0.458 (0.087)</td>
</tr>
<tr>
<td>ORD_CID</td>
<td>1.239 (0.091)</td>
</tr>
<tr>
<td>ORD_CLE</td>
<td>2.149 (0.091)</td>
</tr>
<tr>
<td>ORD_CLT</td>
<td>2.763 (0.087)</td>
</tr>
<tr>
<td>ORD_CMH</td>
<td>1.886 (0.090)</td>
</tr>
<tr>
<td>Route</td>
<td>Estimate (std. error)</td>
</tr>
<tr>
<td>----------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>ORD_CMI</td>
<td>0.740 (0.087)</td>
</tr>
<tr>
<td>ORD_CMX</td>
<td>-0.369 (0.088)</td>
</tr>
<tr>
<td>ORD_COS</td>
<td>0.475 (0.086)</td>
</tr>
<tr>
<td>ORD_COU</td>
<td>-0.386 (0.087)</td>
</tr>
<tr>
<td>ORD_CRW</td>
<td>-0.540 (0.087)</td>
</tr>
<tr>
<td>ORD_CVG</td>
<td>1.666 (0.093)</td>
</tr>
<tr>
<td>ORD_CWA</td>
<td>0.298 (0.087)</td>
</tr>
<tr>
<td>ORD_DAY</td>
<td>1.254 (0.092)</td>
</tr>
<tr>
<td>ORD_DBQ</td>
<td>-0.021^{n.s} (0.086)</td>
</tr>
<tr>
<td>ORD_DCA</td>
<td>2.833 (0.088)</td>
</tr>
<tr>
<td>ORD_DEN</td>
<td>3.003 (0.087)</td>
</tr>
<tr>
<td>ORD_DFW</td>
<td>3.244 (0.086)</td>
</tr>
<tr>
<td>ORD_DLH</td>
<td>0.228 (0.088)</td>
</tr>
<tr>
<td>ORD_DSM</td>
<td>1.578 (0.092)</td>
</tr>
<tr>
<td>ORD_DTW</td>
<td>2.308 (0.095)</td>
</tr>
<tr>
<td>ORD_DCA</td>
<td>2.833 (0.088)</td>
</tr>
<tr>
<td>ORD_EAU</td>
<td>-0.627 (0.088)</td>
</tr>
<tr>
<td>ORD_EGE</td>
<td>-1.059 (0.123)</td>
</tr>
<tr>
<td>ORD_ELM</td>
<td>-0.547 (0.105)</td>
</tr>
<tr>
<td>ORD_ELP</td>
<td>-0.808 (0.085)</td>
</tr>
<tr>
<td>ORD_ERI</td>
<td>-0.357 (0.098)</td>
</tr>
<tr>
<td>ORD_EVV</td>
<td>0.363 (0.086)</td>
</tr>
<tr>
<td>ORD_EWR</td>
<td>2.818 (0.086)</td>
</tr>
<tr>
<td>ORD_FAI</td>
<td>0.471* (0.195)</td>
</tr>
<tr>
<td>ORD_FAR</td>
<td>0.726 (0.087)</td>
</tr>
<tr>
<td>ORD_FCA</td>
<td>-1.279 (0.134)</td>
</tr>
<tr>
<td>ORD_FLL</td>
<td>1.323 (0.088)</td>
</tr>
<tr>
<td>ORD_FNT</td>
<td>0.465 (0.087)</td>
</tr>
<tr>
<td>ORD_FOE</td>
<td>-0.922 (0.152)</td>
</tr>
<tr>
<td>ORD_FSD</td>
<td>0.820 (0.088)</td>
</tr>
<tr>
<td>ORD_FWA</td>
<td>0.725 (0.087)</td>
</tr>
<tr>
<td>ORD_GRB</td>
<td>0.950 (0.087)</td>
</tr>
<tr>
<td>ORD_GRR</td>
<td>1.466 (0.091)</td>
</tr>
<tr>
<td>ORD_GSO</td>
<td>0.255 (0.088)</td>
</tr>
<tr>
<td>ORD_GSP</td>
<td>0.198* (0.087)</td>
</tr>
<tr>
<td>ORD_HDN</td>
<td>-1.629 (0.115)</td>
</tr>
<tr>
<td>ORD_HNL</td>
<td>2.101 (0.179)</td>
</tr>
<tr>
<td>ORD_HPN</td>
<td>0.657 (0.087)</td>
</tr>
<tr>
<td>ORD_HSV</td>
<td>-0.315 (0.086)</td>
</tr>
<tr>
<td>Route</td>
<td>Estimate (std. error)</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>ORD_IAD</td>
<td>1.953 (0.086)</td>
</tr>
<tr>
<td>ORD_IAH</td>
<td>2.918 (0.086)</td>
</tr>
<tr>
<td>ORD_ICT</td>
<td>0.987 (0.088)</td>
</tr>
<tr>
<td>ORD_IND</td>
<td>1.892 (0.092)</td>
</tr>
<tr>
<td>ORD_JAC</td>
<td>-0.641 (0.088)</td>
</tr>
<tr>
<td>ORD_JAN</td>
<td>-0.705 (0.087)</td>
</tr>
<tr>
<td>ORD_JAX</td>
<td>0.745 (0.091)</td>
</tr>
<tr>
<td>ORD_JFK</td>
<td>1.787 (0.089)</td>
</tr>
<tr>
<td>ORD_LAN</td>
<td>0.074^{ns} (0.086)</td>
</tr>
<tr>
<td>ORD_LAS</td>
<td>1.864 (0.089)</td>
</tr>
<tr>
<td>ORD_LAX</td>
<td>2.584 (0.088)</td>
</tr>
<tr>
<td>ORD_LBE</td>
<td>-0.402* (0.181)</td>
</tr>
<tr>
<td>ORD_LEX</td>
<td>0.639 (0.087)</td>
</tr>
<tr>
<td>ORD_LGA</td>
<td>3.508 (0.089)</td>
</tr>
<tr>
<td>ORD_LIT</td>
<td>0.900 (0.087)</td>
</tr>
<tr>
<td>ORD_LNK</td>
<td>0.356 (0.086)</td>
</tr>
<tr>
<td>ORD_LSE</td>
<td>0.259 (0.086)</td>
</tr>
<tr>
<td>ORD_MBS</td>
<td>0.038^{ns} (0.086)</td>
</tr>
<tr>
<td>ORD_MCI</td>
<td>1.895 (0.093)</td>
</tr>
<tr>
<td>ORD_MCO</td>
<td>1.869 (0.088)</td>
</tr>
<tr>
<td>ORD_MDT</td>
<td>1.089 (0.089)</td>
</tr>
<tr>
<td>ORD_MEM</td>
<td>1.104 (0.091)</td>
</tr>
<tr>
<td>ORD_MHK</td>
<td>-0.299 (0.086)</td>
</tr>
<tr>
<td>ORD_MHT</td>
<td>-0.089^{ns} (0.086)</td>
</tr>
<tr>
<td>ORD_MIA</td>
<td>1.940 (0.085)</td>
</tr>
<tr>
<td>ORD_MKE</td>
<td>1.676 (0.091)</td>
</tr>
<tr>
<td>ORD_MKG</td>
<td>-0.798 (0.091)</td>
</tr>
<tr>
<td>ORD_MLI</td>
<td>0.839 (0.092)</td>
</tr>
<tr>
<td>ORD_MOB</td>
<td>-1.160 (0.089)</td>
</tr>
<tr>
<td>ORD_MQT</td>
<td>-0.917 (0.086)</td>
</tr>
<tr>
<td>ORDMSN</td>
<td>1.390 (0.092)</td>
</tr>
<tr>
<td>ORD_MSO</td>
<td>-1.830 (0.115)</td>
</tr>
<tr>
<td>ORD_MSP</td>
<td>2.902 (0.096)</td>
</tr>
<tr>
<td>ORD_MSY</td>
<td>1.486 (0.090)</td>
</tr>
<tr>
<td>ORD_MTJ</td>
<td>-1.739 (0.190)</td>
</tr>
<tr>
<td>ORD_MYR</td>
<td>0.017^{ns} (0.089)</td>
</tr>
<tr>
<td>ORD_OAK</td>
<td>-0.530 (0.095)</td>
</tr>
<tr>
<td>ORD_OGG</td>
<td>0.836 (0.218)</td>
</tr>
<tr>
<td>Route</td>
<td>Estimate (std. error)</td>
</tr>
<tr>
<td>------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>ORD_OKC</td>
<td>0.994 (0.089)</td>
</tr>
<tr>
<td>ORD_OMA</td>
<td>1.571 (0.091)</td>
</tr>
<tr>
<td>ORD_ORF</td>
<td>0.519 (0.091)</td>
</tr>
<tr>
<td>ORD_PAH</td>
<td>-0.511 (0.088)</td>
</tr>
<tr>
<td>ORD_PBI</td>
<td>-0.002(^{\text{n/s}}) (0.084)</td>
</tr>
<tr>
<td>ORD_PDX</td>
<td>1.291 (0.087)</td>
</tr>
<tr>
<td>ORD_PHL</td>
<td>2.800 (0.088)</td>
</tr>
<tr>
<td>ORD_PHX</td>
<td>2.027 (0.087)</td>
</tr>
<tr>
<td>ORD_PIA</td>
<td>0.677 (0.089)</td>
</tr>
<tr>
<td>ORD_PIT</td>
<td>1.874 (0.091)</td>
</tr>
<tr>
<td>ORD_PNS</td>
<td>-1.171 (0.093)</td>
</tr>
<tr>
<td>ORD_PSP</td>
<td>-0.402 (0.092)</td>
</tr>
<tr>
<td>ORD_PVD</td>
<td>0.322 (0.086)</td>
</tr>
<tr>
<td>ORD_PWM</td>
<td>0.257 (0.087)</td>
</tr>
<tr>
<td>ORD_RAP</td>
<td>-0.454 (0.095)</td>
</tr>
<tr>
<td>ORD_RDU</td>
<td>1.812 (0.088)</td>
</tr>
<tr>
<td>ORD_RIC</td>
<td>1.174 (0.091)</td>
</tr>
<tr>
<td>ORD_RNO</td>
<td>-0.493 (0.084)</td>
</tr>
<tr>
<td>ORD_ROA</td>
<td>-0.104(^{\text{n/s}}) (0.086)</td>
</tr>
<tr>
<td>ORD_ROC</td>
<td>1.300 (0.090)</td>
</tr>
<tr>
<td>ORD_RST</td>
<td>0.387 (0.086)</td>
</tr>
<tr>
<td>ORD_RSW</td>
<td>0.884 (0.088)</td>
</tr>
<tr>
<td>ORD_SAN</td>
<td>1.480 (0.086)</td>
</tr>
<tr>
<td>ORD_SAT</td>
<td>0.342 (0.091)</td>
</tr>
<tr>
<td>ORD_SAV</td>
<td>0.091(^{\text{n/s}}) (0.087)</td>
</tr>
<tr>
<td>ORD_SBN</td>
<td>0.428 (0.091)</td>
</tr>
<tr>
<td>ORD_SCE</td>
<td>-0.243 (0.092)</td>
</tr>
<tr>
<td>ORD_SDF</td>
<td>1.253 (0.090)</td>
</tr>
<tr>
<td>ORD_SEA</td>
<td>1.898 (0.089)</td>
</tr>
<tr>
<td>ORD_SFO</td>
<td>2.568 (0.086)</td>
</tr>
<tr>
<td>ORD_SGF</td>
<td>0.892 (0.088)</td>
</tr>
<tr>
<td>ORD_SIC</td>
<td>0.198(^*) (0.084)</td>
</tr>
<tr>
<td>ORD_SJU</td>
<td>2.089 (0.181)</td>
</tr>
<tr>
<td>ORD_SLC</td>
<td>1.003 (0.090)</td>
</tr>
<tr>
<td>ORD_SMF</td>
<td>0.089(^{\text{n/s}}) (0.085)</td>
</tr>
<tr>
<td>ORD_SNA</td>
<td>1.173 (0.086)</td>
</tr>
<tr>
<td>ORD_SPI</td>
<td>0.062(^{\text{n/s}}) (0.089)</td>
</tr>
<tr>
<td>ORD_SRQ</td>
<td>-0.679 (0.086)</td>
</tr>
<tr>
<td>Route</td>
<td>Estimate (std. error)</td>
</tr>
<tr>
<td>-----------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>ORD_STC</td>
<td>-1.064 (0.135)</td>
</tr>
<tr>
<td>ORD_STL</td>
<td>2.195 (0.091)</td>
</tr>
<tr>
<td>ORD_STT</td>
<td>0.087 (0.087)</td>
</tr>
<tr>
<td>ORD_SUX</td>
<td>-0.289 (0.086)</td>
</tr>
<tr>
<td>ORD_SYR</td>
<td>1.142 (0.089)</td>
</tr>
<tr>
<td>ORD_TOL</td>
<td>0.086&lt;sup&gt;n/s&lt;/sup&gt; (0.087)</td>
</tr>
<tr>
<td>ORD_TPA</td>
<td>1.276 (0.088)</td>
</tr>
<tr>
<td>ORD_TTN</td>
<td>-0.058&lt;sup&gt;n/s&lt;/sup&gt; (0.126)</td>
</tr>
<tr>
<td>ORD_TUL</td>
<td>1.012 (0.090)</td>
</tr>
<tr>
<td>ORD_TUS</td>
<td>0 (base)</td>
</tr>
<tr>
<td>ORD_TVC</td>
<td>0.737 (0.088)</td>
</tr>
<tr>
<td>ORD_TYS</td>
<td>0.869 (0.086)</td>
</tr>
<tr>
<td>ORD_UST</td>
<td>-0.573 (0.182)</td>
</tr>
<tr>
<td>ORD_XNA</td>
<td>1.062 (0.086)</td>
</tr>
</tbody>
</table>

* significant at the 95% confidence level.
** significant at the 90% confidence level.
<sup>n/s</sup> not significant at the 90% confidence level.
All other parameters are significant at 99% confidence level.