THE TRENDS OF REGIONAL AND HUB AIRPORTS IN THE CASE OF NEW YORK STATE

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

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Master of Science

by

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ABSTRACT

Airports have been an important topic of recent study. This research examines trends of small to hub airports in New York State and attempts to understand the impetus for sustaining these airports. This thesis fills the literature gap regarding airport activity and accessibility by vehicle. It contributes to a broader discussion about the health of regional airports in a New York State context.

The main argument is that small and regional airports struggle to retain flight commercial services. Shadowed by the influence of hubs, small airports often have difficulties maintaining their operations, which may signal either the end of regional airports or the beginning of rebranded, or re-strategized, regional airports. The thesis aims to demonstrate applications of regional science by surveying issues that trouble airport managements and their local communities at the county scale in New York State.

The study has found the trends from 2000 through 2014 that the non-primary and small primary airports in New York State have encountered a decrease in their enplanements in contrast to a slight increase in the large primary airports' enplanements. The results highlight that the small primary airports have the lowest number of enplanements, compared to the other airport groups, when accounting for the determinants (vehicle, median household income, population density, primary, and catchment area).

BIOGRAPHICAL SKETCH

Sun Kyo Chung was born in Seoul, South Korea. He earned his Bachelor of Arts at Harding University in Arkansas, USA, in 2011. After years of work in the Republic of Korea Air Force and industry, he began his graduate program in Regional Science at the College of Architecture, Art, and Planning (AAP) at Cornell University in the fall of 2016. While working on multiple research projects as a research assistant for professors, he completed the Master of Science degree in Regional Science in 2019.

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TABLE OF CONTENTS

Biographical Sketch iii

Acknowledgements iv

Table of Contents v

List of Figures vi

List of Tables vii

List of Abbreviations viii

Chapter 1: Introduction 1

1.1 The Characteristics of Aviation and Airports

Chapter 2: Literature Review 4

2.1 Historical Context: The Rise and Fall of Aviation Industry

2.2 Issues of Small and Regional Airports

Chapter 3: The Case of New York State 11

3.1 Commercial Service Airports and Their Operations in Their Catchment Areas

3.2 Leakage to Hub Airports and Ground Access by Car

Chapter 4: Empirical Analysis 24

4.1 The Model

4.2 Testing of the Econometric Model

Chapter 5: Conclusion and Discussion 52

5.1 Conclusion

5.2 Discussion

Appendix A: Data 58

Appendix B: Similar Econometric Studies 61

Bibliography 63

LIST OF FIGURES

Figure 1. Locations of the Commercial Service Airports in New York State 12

Figure 2. Watertown Airport Homepage 14

Figure 3.1. Enplanements of the Commercial Service Non-primary Airports 16

Figure 3.2. Enplanements of the Commercial Service Small Primary Airports 16

Figure 3.3. Enplanements of the Commercial Service Large Primary Airports 17

Figure 3.4. Natural Log Scale of the Study Airports' Enplanements 17

Figure 4 Population Density by County 19

Figure 5.1 New York State Vehicle Registrations 22

Figure 5.2 Percentage of Personal Vehicles Available 23

Figure 6 Median Household Income by County 28

Figure 7.1 Service Areas of the Non-primary Airports 31

Figure 7.2 Service Areas of the Small Primary Airports 32

Figure 7.3 Service Areas of the Large Primary Airports 32

Figure 8.1 Linearity between Enplanements and Vehicles 44

Figure 8.2 Linearity between Enplanements and Median Household Income 45

Figure 8.3 Linearity between Enplanements and Population Density 45

Figure 9.1 The Residuals vs. Vehicles 47

Figure 9.2 The Residuals vs. Median Household Income 48

Figure 9.3 The Residuals vs. Population Density 48

Figure 10 The Residuals vs. Predicted 49

Figure 11 Normal Q-Q Plot 50

LIST OF TABLES

Table 1. Sum of Enplanements from 2000 through 2014 15
Table 2. Categories of the Airports 30
Table 3. Fixed Effects Regression Output 34
Table 4. Testing for Heteroscedasticity 36
Table 5. Robust Fixed Effects Regression Output 37
Table 6. Different Aggregation Scheme: Categories of the Airports 38
Table 7. Different Aggregation Scheme: Regression Output 39
Table 8. Instrumental Variables (IV) Estimation 41
Table 9. The Hausman Test 43
Table 10. Non-linearity: Regression with Quadratic Terms 46
Table 11. Cross-sectional dependence 50

LIST OF ABBREVIATIONS

ALB Albany International Airport

ART Watertown International Airport

BGM Greater Binghamton Airport

BUF Buffalo Niagara International Airport

ELM Elmira Corning Regional Airport

HPN Westchester County Airport

ISP Long Island MacArthur Airport

ITH Ithaca Tompkins Regional Airport

JFK John F. Kennedy International Airport

JHW Chautauqua County Jamestown Airport

LGA LaGuardia Airport

MSS Massena International - Richards Field

OGS Ogdensburg International Airport

PBG Plattsburgh International Airport

ROC Greater Rochester International Airport

SLK Adirondack Regional Airport

SWF Stewart International Airport

SYR Syracuse Hancock International Airport

FAA The Federal Aviation Administration

LCCs Low Cost Carriers

CHAPTER 1. INTRODUCTION

1.1 The Characteristics of Aviation and Airports

Airports have evolved to become one of the most important transportation modes around the globe. With a surge in air traffic demand since the early 1920s, airports have transformed from airplane lots to major economic hubs. Among local governments' long-term investments, airports can be the largest investment to spur economic development. Aviation presents a new model of economic impacts by linking places globally that otherwise have been disconnected (Florida, Mellander, & Holgersson, 2015, p. 198). In other words, airport development in a city or region can bring a long-haul impact.

Airports hold an important role in prompting regional productivity through positive externalities. The agglomeration economies develop around these locations (Florida et al., 2015, pp. 198–199). As resources often aggregate toward lucrative markets, airports feature a similar pattern of spatial competition. Such concentrations fall under two categories: hub and regional networks. Hub networks are considered to be airports having the capacity to accommodate large airplanes with multiple runways in metropolitan areas. Regional networks refer to airports handling smaller aircrafts. Over time, hub networks have structured a core periphery system with fewer airlines and headquarters. Regional networks, in the meanwhile, have encountered a deduction in routes (Lian & Rønnevik, 2011, p. 85).

In the United States, the Federal Aviation Administration (FAA) administers overall airport operations. According to the FAA, the categories of airport activities are the following[1]:

Commercial Service Airports are publicly-owned facilities that receive scheduled passenger service with at least 2,500 passenger boardings each calendar year. These commercial airports are then categorized by primary and non-primary. Primary airports enplane more than 10,000 passenger boardings each calendar year. Non-primary airports operate scheduled air service of at least 2,500 passenger boardings each calendar year.

Cargo Service Airports can have both commercial and cargo services, but they are largely for cargo air transportation with an annual total of more than 100 million pounds of weight.

Reliever Airports serve as congestion relief for Commercial Service Airports and improve general aviation access to communities.

General Aviation Airports have no scheduled air service or hold less than 2,500 passenger boardings annually. Civilians can fly at General Aviation airports.

Of the airport characteristics, the thesis focuses on Commercial Service Airports, the most common air transportation mode for leisure and business travelers. The thesis attempts to understand why non-primary airports – widely known as small, rural, or regional airports – may struggle to maintain flight commercial services or to

[1] https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/categories/

compete with larger airports for passengers. The questions to consider are: (a) what is the relationship between major airports and small airports? (b) How are enplanements affected for hubs and small airports?

The thesis is organized into five parts. It begins with an examination of the air travel industry in the United States. Second, it reviews the relevant literature to discuss the historical development of aviation in the U.S. in the 1970s. A particular theme from this timeframe punctuates the deregulation of aviation as a significant factor in expanding or weakening once-government-operated airports. Third, it analyzes the trends of New York State's commercial service airports and factors leading to airport leakage to hub airports. Fourth, it presents a fixed effects model and the empirical findings. The conclusion describes the implications of the factors to improve small airports and the findings pertinent to policy discussions and future research.

CHAPTER 2. LITERATURE REVIEW

2.1 Historical Context: The Rise and Fall of Aviation Industry

Previous research has focused on major airports and their global networks of aviation. Considerable research has detailed aggregate impacts of air service on economic development and behaviors of passengers, but much less research is conducted on the sustainability of small and regional airports in remote, scattered areas. Particularly, airport accessibility by personal vehicle, instead of public transportation, has received less attention. This thesis fills a gap in the airport activity and leakage literature to understand determinants that deteriorate small and regional airports. It furthers an understanding of the relationship between airport activity and access by vehicle. It contributes to a broader discussion about the health and operation of regional airports in a New York state context by exploring air service trends across different airport sizes.

Air service growth varies in direction and scale among airports, since air service patterns, air transport connectivity, and airports' opportunity costs of capital are all different (Allroggen & Malina, 2014, p. 1). Economic impact of air service underlines that airfreight output spurs local and regional economic development (Button & Yuan, 2013, p. 329), and passenger enplanements increase employment (Brueckner, 2003, p. 1455). Air transport enhances productivity by promoting a flow of ideas and face-to-face interactions apart. As a regional amenity, airports can boost population growth and market access for natural resources (Tveter, 2017, p. 50).

In the U.S., nearly 550 commercial airports, differing in activity and size from small to large airports, have been operating. Most of the airports were locally-

managed in the 1920s and 1930s. The developments of air travel including jet airlines, air commerce deregulation for air passenger market growth, and local economic development initiatives opened a new era of airports since the 1940s. Air transportation has been vital for promoting supermodernity, globalization, and mobility by moving cargo and people to places. On the other hand, scholars have voiced concern over excessive funding allocated to passenger growth. Municipally owned airports started expanding runways, terminals, and landmark structures to attract more passenger markets. Such efforts breathed new life into some airports and their communities, but others were left behind due to airline acquisitions, route mergers, or bankruptcies following the Airline Deregulation Act of 1978 (Bednarek, 2016, pp. 1–4).

The deregulation in the U.S. has drastically changed the landscape of the airport industry. In the review of Bailey, Graham, and Kaplan's Deregulating the Airlines, Meyer (1986) writes that once-nationally-owned carriers became independent to secure revenues. They encountered stiff competition against each other to achieve quality and productivity. Consumers, on the other hand, benefitted from more convenient flight times, departing locations, and destinations. The competition created by the deregulation not only led to lower fares compared to a regulated system, but also marked the beginning of hub and regional airports through network consolidations (pp. 461–465).

The deregulated environment brought three significant changes: ownership, airline-airport relations, and financial fragility. In many cases, local governments discontinued the ownership and route subsidies. Profitable routes triumphed over less popular ones. Small and rural airports with an insufficient passenger base were no longer guaranteed to belong to a route network. This shifted the market power to airlines in the form of airlines as an employer and airports as an employee. Even if

airports upgraded their parts of infrastructure, airlines could choose to withdraw the next day, a business decision driven by airlines' revenue models (Donehue & Baker, 2012, p. 233).

Commercial service airports employ different lease agreements and fee structures such as airline rentals, terminal concessions, aircraft landing fees, parking fees, and fuel sales to maximize revenues. When airports encounter reductions or consolidations of airline service, their capabilities to generate revenues are in danger. Airports increase charges to airlines or passengers to fill in the revenue hole to cover operational costs. Passengers flying out of a small or regional airport usually pay higher fares because of reduced airlines. In other words, a discontinued carrier or route can cause financial burdens for these airports (New York State Department of Transportation, 2010, pp. 12–14).

Donehue and Baker (2013) point that the prominence of hub airports has been locked into a "mono-dimensional pattern." This system precludes direct flights between regional routes. It necessitates passengers to fly to hub locations before travelling to regional airports. Regional airport networks become part of an overall hub network rather than individual airports. The incapability to direct individual routes weakens regional airports and general aviation in their respective communities (p. 235). If they belong to a group of hub networks, they achieve less non-aeronautical revenues and operational efficiency, compared to standalone counterparts. The reasons include the failure to establish new commercial opportunities, utilize subsidies, and produce in-house, ground-handling activities (Adler, Ülkü, & Yazhemsky, 2013, pp. 29–30).

In the study of Bogdański (2014), the Warmińsko-Mazurskie Voivodship is a less developed region with a low population density in Poland. In order to raise the province's competitiveness, the regional authorities decided to transform the old

military airport to a revamped regional passenger airport. Even with its well-proposed accessibility to services and goods outside the region, the evaluation of the decision resulted economically negative due to the Szymany airport's small catchment area. The bigger airports near Gdańsk and Warsaw limited Szymany's catchment area and potential airport users, leading to reduced capacity to generate profits (pp. 15–23).

2.2 Issues of Small and Regional Airports

Small regional airports are integral infrastructure that connects local communities to urban centers socially and economically, but since the deregulation in the U.S., the operation of these airports has been under financial stress. The infrastructure requires constant, expensive maintenance for the runways, terminal buildings, security, and navigational equipment. Other expenditures related to training and recruiting qualified personnel to manage operations add more stresses. Any infrastructure decision becomes a financial risk for vulnerable airport owners. The economic viability and financial uncertainty of operation remain causes of concern without sufficient funding. This potential demise of the airports may result in fewer airports for general aviation, disaster relief, or emergency responses (Donehue & Baker, 2012, pp. 232–239).

Low-cost carriers (LCCs) are further slicing small airports' revenues. They have first inhabited small and regional airports to take advantage of low capacity utilization and affordable fees, but LCCs begin to operate increasingly at major airports. They become more competent with their prices and services, while imposing their growth and expansion strategies beyond small airports. This change leads to more competition between small and large airports (Dobruszkes, Givoni, & Vowles, 2017, p. 50). LCCs also exert influences in contracts that work against small airports' aeronautical revenues. Small airports then attempt to compensate by increasing fees to passengers (Francis, Fidato, & Humphreys, 2003, p. 267).

Passenger leakage due to airport inaccessibility is another central issue for small airports. Passengers may choose an alternative major airport over the local airport due to inconvenient access times, infrequent flight schedules, or few destination choices. Small community airports often lack transportation infrastructure,

economic activities, and population bases to maintain the travel demand for airlines. When still-operating airports in small communities encounter a reduction in air service and revenues, inaccessibility at these locations heightens and causes a lower share of airport users. For example, Golden Triangle Regional Airport in Mississippi is a small community airport that is viewed as a less-accessible airport. Lately, airport users have been choosing more accessible, bigger airports in Jackson, Birmingham, and Memphis (Yunlong Zhang & Xie, 2005, pp. 442–443).

Marcucci and Gatta (2011) further study airport decision attributes that constrain small airports. Access times, air fares, flight frequency, parking policy, and airline connectivity have an important hand in passengers' airport choice. Business travelers prefer the previously chosen airport, while leisure travelers opt for low-cost flights (pp. 70–71, 82). Flight delays and cancellations at small airports also cause local residents to drive to a nearby airport. These flight interruptions negatively impact small community airports (Stone, 2018, p. 214).

Unlike hubs, small regional airports are more vulnerable to economic shocks and route productivity. If exchange rate or commodity price volatiles, traffic volumes to offset fixed costs are directly influenced by the economy. Small airport performance relies on major route production. Airlines' network effects or inter-firm competition decides the fate of various routes (Yahua Zhang, Wang, & Fu, 2017, p. 484). Airport capacity utilization depends heavily on the airlines as they select which profitable routes and airports to exploit. The interests of airlines are often not parallel with airport shareholders or regional interests (Humphreys & Francis, 2002, pp. 257–258).

Overall, small and regional airports face a variety of challenges. The deregulation in the U.S. has left local governments to handle their airport management and development. Most of them have little financial or human resources to sustain operations. A recent finding on Australian rural airports reveals that the number of

small airports serving rural areas of Australia has dropped from 268 to 138 active airports between 1985 and 2008. Small and regional airports across the regions share a variety of contextual concerns that can be pertinent to New York State, particularly when the rural airports in Australia and New York both feature widely distributed towns and distances between population centers (Donehue & Baker, 2012, p. 232).

CHAPTER 3. THE CASE OF NEW YORK STATE

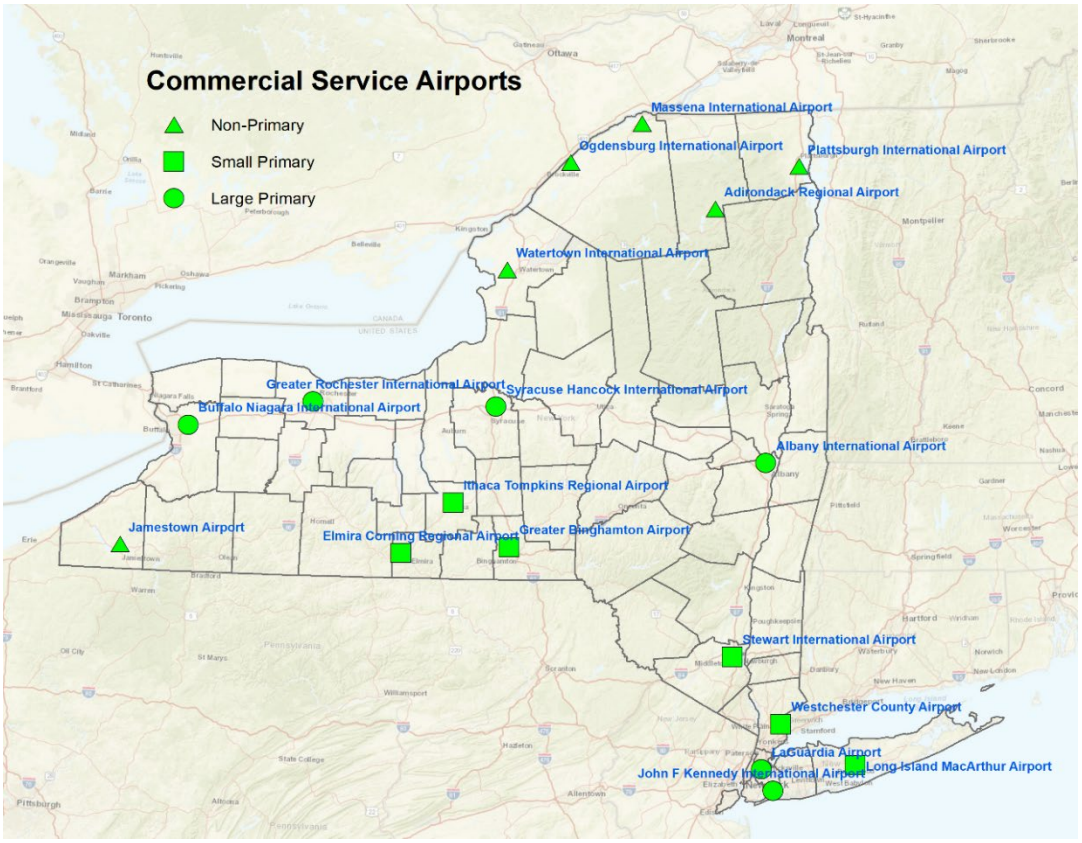
3.1 Commercial Service Airports and Their Operations in Their Catchment Areas

New York State has 90 public-use airports in the State Aviation System Plan. 18 are commercial service airports that provide scheduled airline passenger service. 72 are general aviation airports for medical emergencies, charter flights, law enforcement, flight training, and recreational flying. In New York State, two percent of total income stems from aviation. Aviation generates $50 billion in annual economic activity for businesses. Notably, economic activity from John F. Kennedy International Airport and LaGuardia Airport drives almost 84% of the aviation economic impact in the state (New York State Department of Transportation, 2010, pp. ii–vii).

The New York State Department of Transportation lists commercial service airports as the following[2]: *Adirondack Regional Airport (SLK), Albany International Airport (ALB), Buffalo Niagara International Airport (BUF), Chautauqua County Jamestown Airport (JHW), Elmira Corning Regional Airport (ELM), Greater Binghamton Airport (BGM), Greater Rochester International Airport (ROC), John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA), Long Island MacArthur Airport (ISP), Massena International Airport (MSS), Ogdensburg International Airport (OGS), Plattsburgh International Airport (PBG), Stewart International Airport (SWF), Syracuse Hancock International Airport (SYR), Ithaca Tompkins Regional Airport (ITH), Watertown International Airport (ART), and Westchester County Airport (HPN).*

[2] https://www.dot.ny.gov/divisions/operating/opdm/aviation/directories/commercial-service

Figure 1 Locations of the Commercial Service Airports in New York State



Each airport serves its catchment area. The New York State Thruway is a highway system of controlled-access through the heart of the state. It consists of Albany International, Buffalo Niagara International, Greater Rochester International, and Syracuse Hancock, covering most of the population across upstate New York. The suburban areas of New York City are serviced by Long Island MacArthur, Westchester County Airport, and Stewart International. In the Southern Tier of New York State, Elmira Corning Regional, Greater Binghamton, and Ithaca Tompkins Regional feed businesses and universities by connecting key airline hubs. Adirondack Regional, Chautauqua County, Massena International, Ogdensburg International, Plattsburgh International, and Watertown International receive schedule service daily

on commuter airlines to remote areas of the state (New York State Department of Transportation, 2010, p. 11).

The information below surveys the non-primary airports' activity to understand the supply variations in their respective airport markets:

Adirondack Regional Airport[3]

One airline with two routes: The airport operates one airline that connects to Boston Logan International Airport and Saranac Lake.

Chautauqua County Jamestown Airport[4]

Currently, commercial airline service at Jamestown Airport is not available. Chautauqua County is working with the U.S. Department of Transportation, regional municipalities, and business partners to revive commercial air service at the airport.

Massena Int'l Airport/Richards Field[5]

One airline with a route: Massena International Airport to Boston Logan International Airport.

Ogdensburg International Airport[6]

Two airlines with four destinations: the airport serves Albany, NY; Boston, MA; Orlando, FL; and Toronto, Canada.

[3] https://www.adirondackairport.com/
[4] https://www.co.chautauqua.ny.us/330/Jamestown-Airport-JHW
[5] http://massenainternationalairport.com/en/
[6] https://ogsair.com/flight-info/flight-tracker/

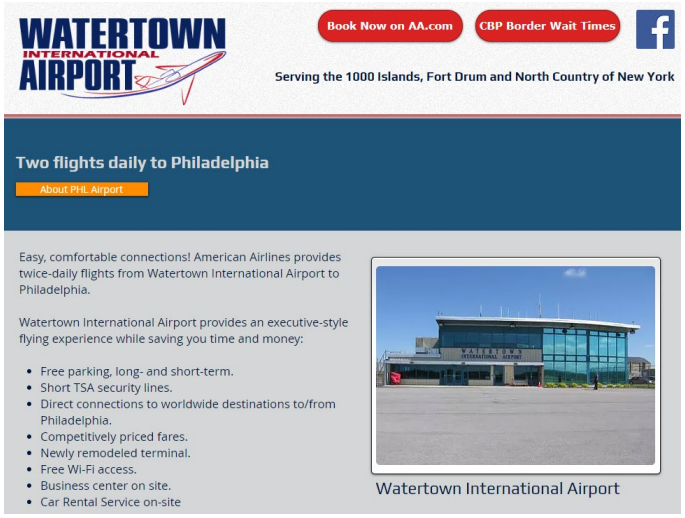
Plattsburgh International Airport[7]

Three airlines with multiple destinations: The airport serves D.C. and major cities in Florida.

Watertown International Airport[8]

One airline with a route: The airport serves Northern New York, Southern Ontario, and the Fort Drum region with twice-a-day service to Philadelphia International Airport by American Airlines.

Figure 2 Watertown Airport Homepage[9]



As seen in the information above, most of the non-primary airports operate infrequent flights. Chautauqua County Jamestown Airport is currently inoperative due to the insufficient demand. Watertown Airport makes conscious efforts to advertise its free amenities as a means to attract more passengers for maintaining its operation as

[7] http://flyplattsburgh.com/
[8] https://www.watertownairport.com/about-us
[9] https://www.watertownairport.com/passenger-service

shown in Figure 2. Such examples imply that airport activities at these locations are minimal, which can lead to reduced revenues to cover fixed operational costs. According to Halpern and Graham (2015), low-performing airports can note that marketing to customers with electronic information, loyalty programs, and sponsorship is not effective in generating revenues over time. Passenger airport choices fluctuate when airport locations or airline services are weighted. Airports should turn their attention to direct marketing to airlines. Airports' route development initiatives to attract more services and new airlines would have more success in overcoming operational costs (pp. 213–214).

The information above also illustrates deteriorating air services across the state. Table 1 lists total enplanement numbers for the commercial service airports from 2000 through 2014. In the airport industry, an enplanement is a passenger boarding that represents an airport's operational health, or total activity.

Table 1 Sum of Enplanements (in Thousand) from 2000 through 2014[10]

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
ADIRONDACK REGIONAL	4	3	3	2	3	3	3	3	4	5	6	6	6	6	5
ALBANY INTERNATIONAL	1407	1464	1401	1406	1536	1533	1443	1424	1366	1303	1250	1217	1222	1197	1211
BINGHAMTON REGIONAL AIRPORT	129	115	112	126	134	122	107	120	108	98	109	108	105	95	83
BUFFALO-NIAGARA INTERNATIONAL	2140	2204	2059	2039	2206	2437	2522	2677	2745	2657	2603	2583	2593	2568	2378
CHAUTAUQUA CO.-JAMESTOWN MUNI.	18	14	10	9	11	7	4	4	4	4	4	3	3	3	3
CLINTON COUNTY/PLATTSBURGH INTL	9	4	2	1	2	2	2	3	46	73	88	140	112	151	140
ELMIRA-CORNING REGIONAL	113	105	88	87	97	87	83	99	105	115	131	153	145	130	159
GREATER ROCHESTER INTERNATIONAL	1218	1133	1176	1233	1365	1450	1417	1431	1350	1274	1262	1191	1203	1209	1174
ITHACA/TOMPKINS REGIONAL	100	88	80	68	72	80	77	86	92	110	121	122	120	104	90
JOHN F. KENNEDY INTERNATIONAL	16155	14554	14369	15676	18587	20260	21072	23401	23621	22710	22927	23665	24521	25036	26245
LA GUARDIA	12697	11352	11068	11367	12313	13014	12926	12530	11568	11084	12002	11989	12819	13372	13535
LONG ISLAND - MAC ARTHUR	1121	1010	962	940	986	1056	1138	1168	1083	930	859	781	668	663	646
MASSENA INT'L.-RICHARDS FIELD	4	3	3	2	3	3	3	2	1	3	3	4	5	5	5
OGDENSBURG INTERNATIONAL	2	2	2	2	2	2	2	3	1	2	2	4	5	5	6
STEWART INTERNATIONAL	274	198	176	202	250	200	157	455	392	198	202	210	185	164	159
SYRACUSE-HANCOCK INTERNATIONAL	1061	936	944	954	1130	1223	1128	1179	1105	1017	1025	983	974	992	987
WATERTOWN INTERNATIONAL	3	2	2	2	4	5	4	7	1	2	2	4	17	19	19
WESTCHESTER COUNTY	507	456	461	427	463	462	512	823	904	965	1000	972	893	764	756

[10] Source: The New York State Department of Transportation (https://data.ny.gov/)

Figure 3.1 Enplanements of the Commercial Service Non-primary Airports

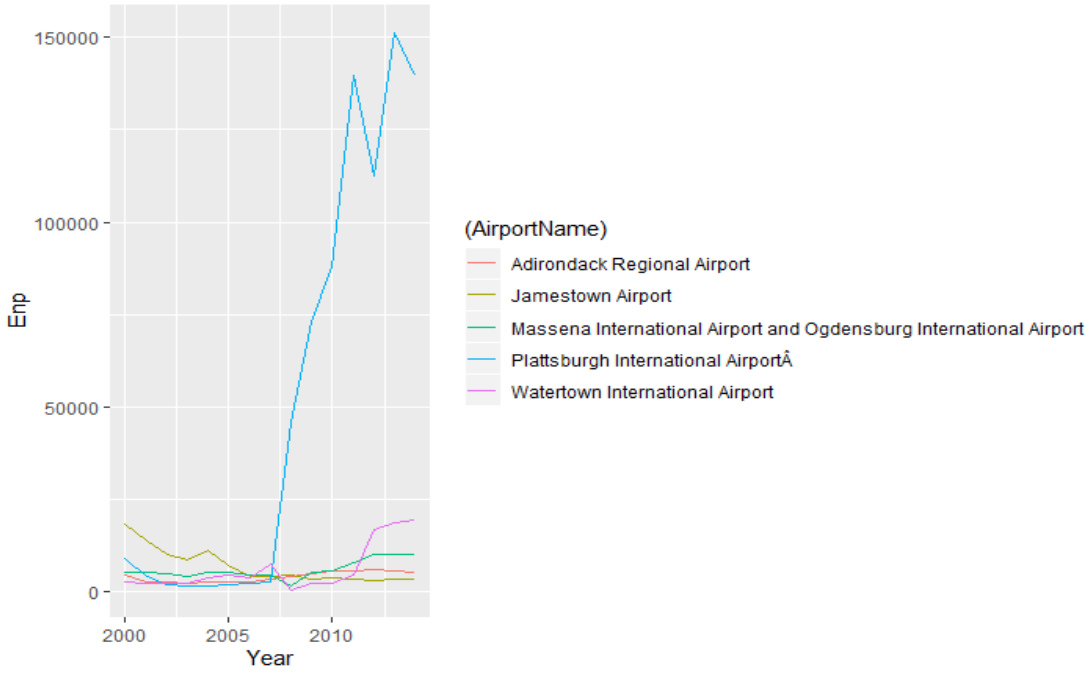


Figure 3.2 Enplanements of the Commercial Service Small Primary Airports

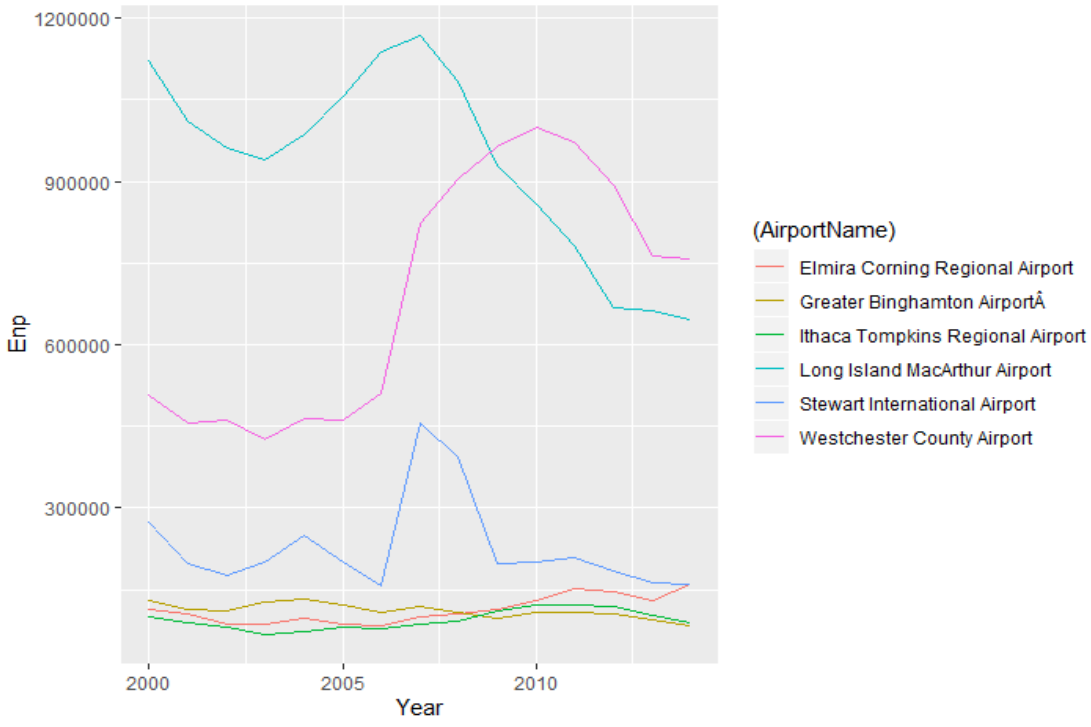


Figure 3.3 Enplanements of the Commercial Service Large Primary Airports

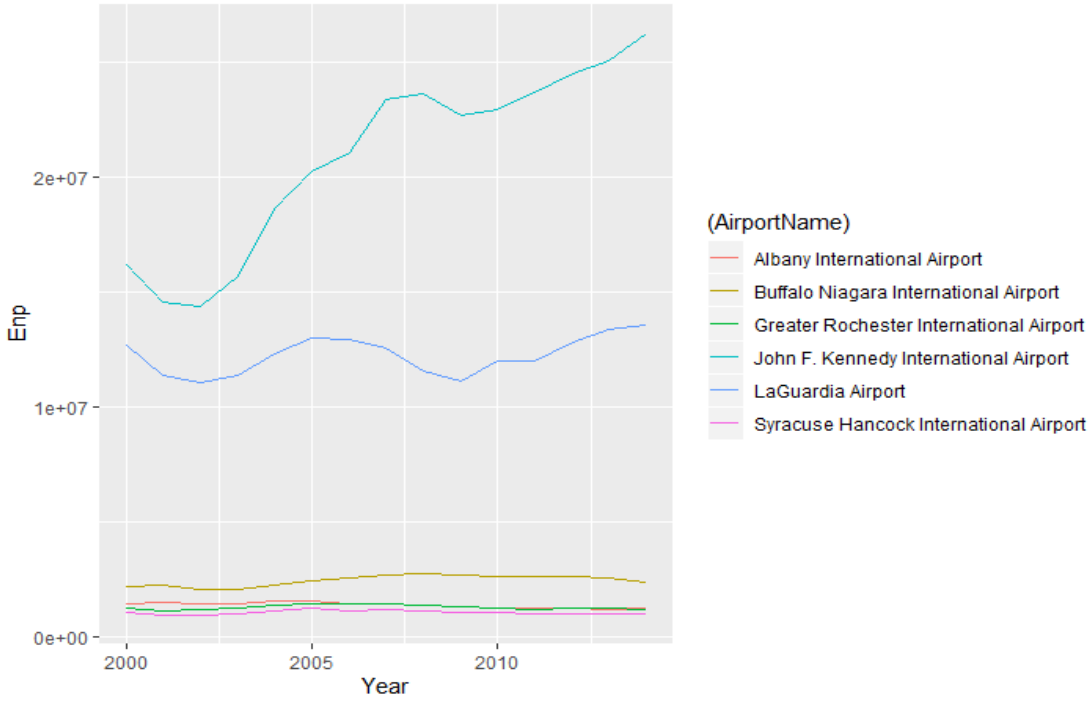
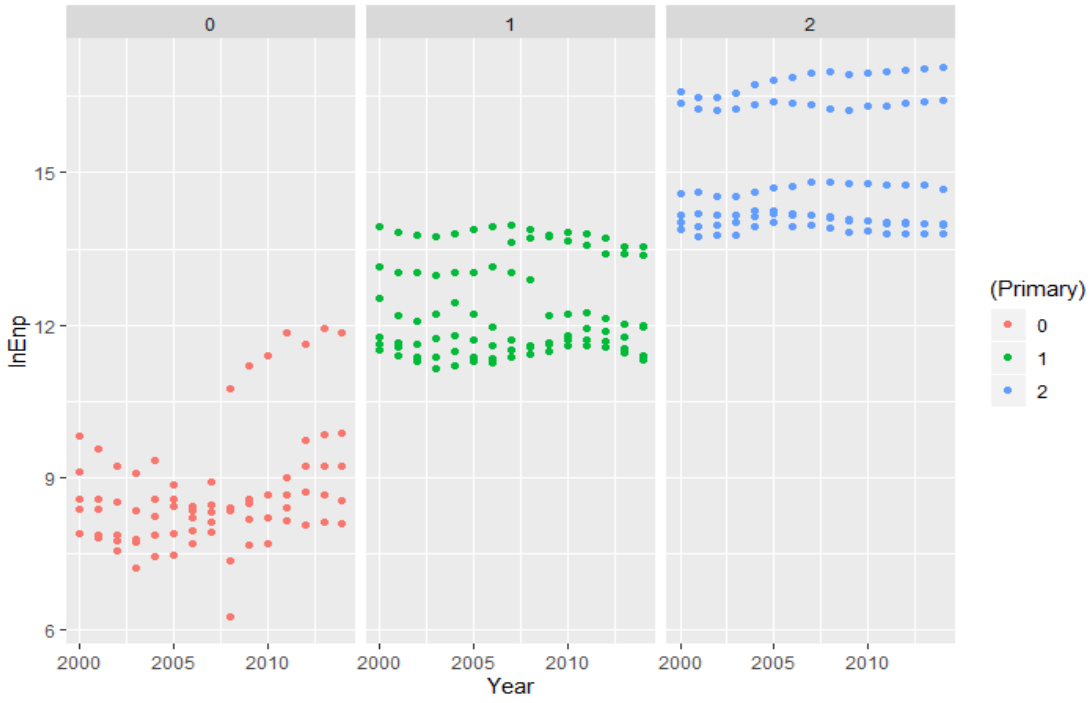


Figure 3.4 Natural Log Scale of the Study Airports' Enplanements



A variety of flights at each airport is essential for thriving populations and businesses, but expanded air services come to a halt if enplanements continue to decline. In Figure 3.1, the non-primary airport group mostly experienced a decrease in their enplanements. The four airports near the Canadian border (Watertown International Airport, Massena International Airport, Ogdensburg International Airport, and Plattsburgh International Airport) gained enplanements in the recent years. In Figure 3.2, the small primary airport group had either a drastic drop or no growth in enplanements over time.

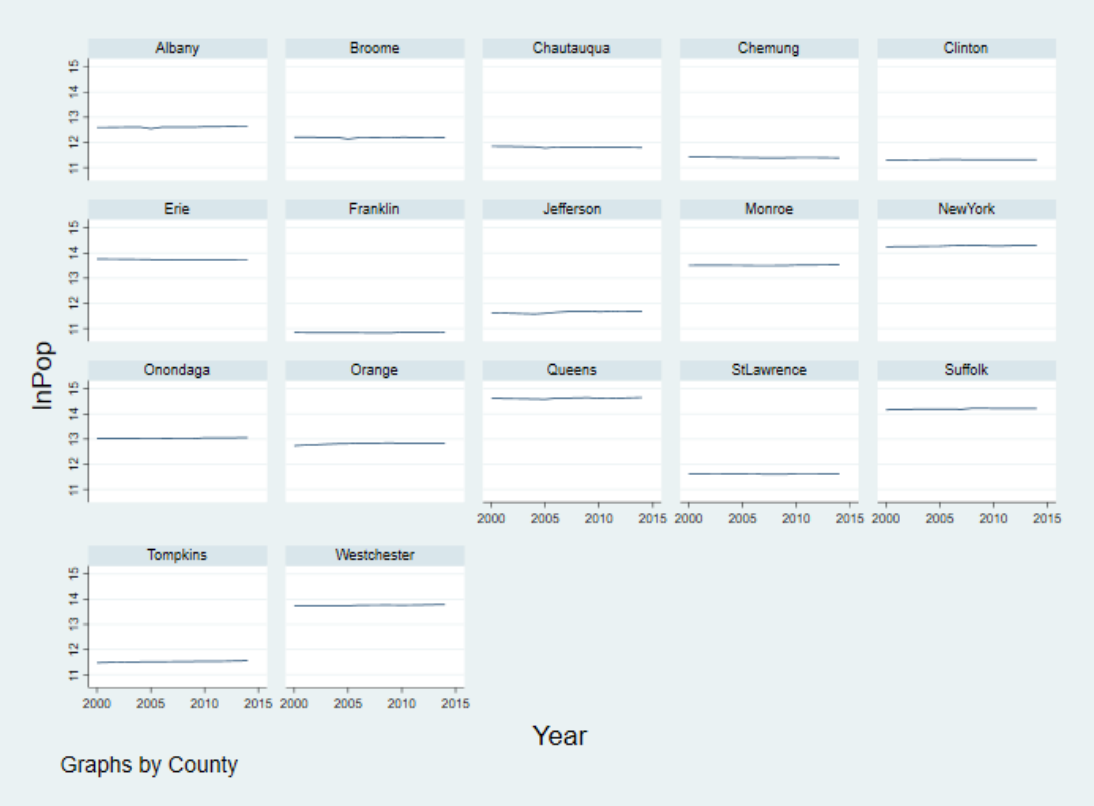
Figure 3.1 stresses two aspects. First, insufficient demand is reflected in the relatively low number of enplanements. Second, most of the airports' enplanements have generally negative trend lines, implying that the enplanements at these airports have not grown in the past. Similarly, Figure 3.2 highlights the diminishing airport activities for even the smaller primary airports after a brief upturn. Their enplanements mostly faded across the data lines. On the other hand, Figure 3.3 illustrates a steady upward trend in the enplanements for the large primary airports. Figure 3.4 then compiles a summary of the relative enplanements. Except for the large primary airport group, the rest of the airports do not show distinctive upward mobility.

Around the year 2008, these smaller airports saw a particular dip in their enplanements. A major economic recession hit these airports between 2007 and 2009 (Fuellhart, Ooms, Derudder, & O'Connor, 2016, p. 1253). In this economic turmoil, New York State's air passenger traffic recorded a 6.9 percent drop between 2007 and 2009. The recession caused airline revenues to wane, because even business travelers or core travelers cut back on travel (New York State Department of Transportation, 2010, pp. iii, 12). The smaller airports were more susceptible to outside influences compared to large hubs. The primary airports nevertheless performed relatively well without a drop during the economic downturn. These figures narrate a reality of

insufficient consumer demand that the non-primary or small primary airports have faced.

One may raise a point that small populations can be responsible for insufficient demand in the counties where the commercial service airports operate. Figure 4 dives into the counties' population trends to answer whether they attribute to a low number of enplanements.

Figure 4 Population Density by County



The population densities have remained fairly unwavering since 2000. Ironically, the enplanements of the non-primary airports diminished even with the steady population bases. These counties' populations have either remained unchanged or risen slightly, but the non-primary or small airports enplaned fewer passengers. This raises a question of why these non-primary or small primary airports faltered even when the population bases did not fall. It may be that the airports had to depress frequencies so that low-load flights would not depart. It may be that air passengers used an alternative airport that offered better services and amenities. The next section explores how the airport market leakage to an alternative airport may explain the weakening of the small regional airports.

3.2 Leakage to Hub Airports and Ground Access by Car

The majority of the population across the globe still has little access to some form of motorized ground transport or personal vehicles. This, however, is rapidly changing with the growth of urban transport activity (Kahn Ribeiro & Kobayashi, 2007, p. 325). In the U.S., private vehicles have the largest intercity travel market share below 600 miles. Passengers on freeways have risen since the 2008 economic recession (Kim & Ryerson, 2018, pp. 238, 243). Access by private cars to large airports accounts for 65% of ground journeys and up to 99% to regional airports, where regular transport services are inadequate (Humphreys & Ison, 2005, p. 1).

Airport passenger leakage refers to passengers traveling to a different airport location, instead of choosing to fly at the local airport in the area. This phenomenon first occurred in the 1980s and 1990s at smaller airports near hub airports (Kim & Ryerson, 2018, p. 240). Between 2000 and 2010, airlines in the U.S. lessened services to small and medium airports that are marginally profitable after network consolidations to hub airports. Airline mergers not only widened the air service gap between airports apart from each other, but also allowed larger airports to enlarge their catchment areas by drawing travelers from smaller airports with little service. The passenger leakage from smaller communities to a larger airport can worsen the flow of revenue for the local airport and may eventually split the economic potential across cities. This intense cycle of increased airfares and reduced flights continues to affect various groups of passengers (Ryerson & Kim, 2018, p. 238).

The ground travel market for airport access has largely three segmentations: travel purpose, destination, and traveler residence. Transport literature often separates among business travel, leisure, and commute (Merkert & Beck, 2017, p. 30). Travel purpose is a behavioral difference between business and leisure. Business passengers

value access time and reliability, while most leisure travelers are more sensitive to cost. Considerations of destination, trip length, and luggage weight alter ground mode choices for domestic or international trips. Regarding residency, local residents are flexible because of available automobiles and trip proximity to the airport, but international passengers are likely to prefer taxis or buses due to the unfamiliarity of driving in a foreign environment (Gupta, Vovsha, & Donnelly, 2008, p. 8).

The overall leakage in various regions of the U.S. is estimated between 15% and 32%, which implies that ground travel to a hub is substantial. Passengers traveling to large airports account for 0.05% to 12% of daily highway traffic. Local airports retain 80% of passengers seeking a non-stop itinerary but below 50% of passengers on multiple connecting flights (Ryerson & Kim, 2018, pp. 248–249). Transitioning from a national context to New York State, Figure 5.1 below displays the state's vehicle trend.

Figure 5.1 New York State Vehicle Registrations

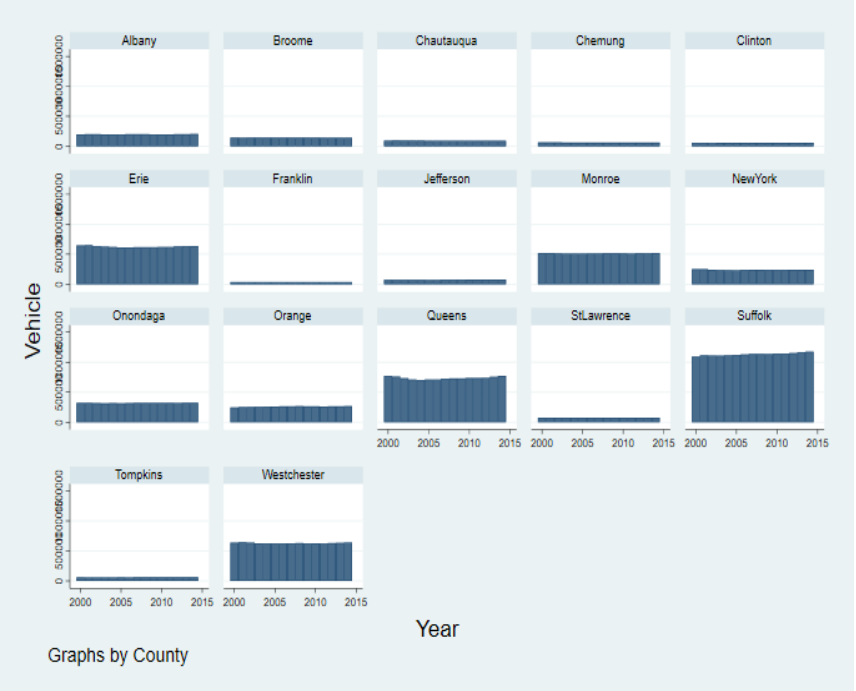


Figure 5.2 Percentage of Personal Vehicles Available

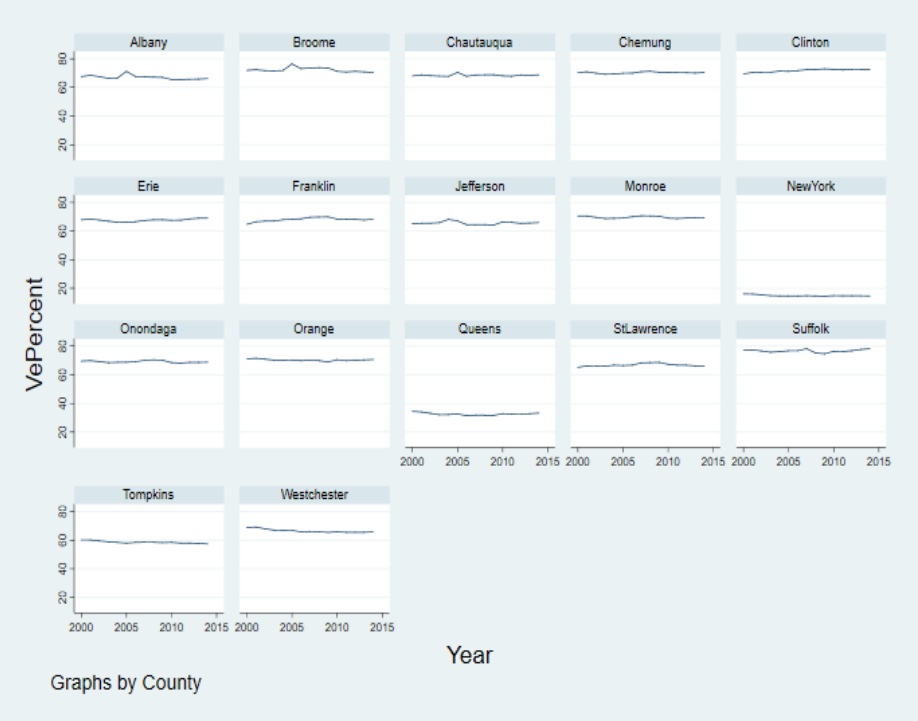


Figure 5.1 presents the steady trend of individual car ownership in the counties where the airports operate. Figure 5.2 illustrates the high utility of personal cars. The share of population that owns a car mostly sits between 60% and 80%. One can infer that a high volume of personal vehicles can allow travelers to drive extra miles to arrive at a distant airport. Considering the state's substandard interregional transportation, the usage of vehicles may further propel the exodus to hubs to capitalize on airfare differences, schedule frequencies, and amenities. These added benefits for travelers can nullify extra driving distances for air service (Ryerson & Kim, 2018, p. 240).

It can be derived that distinctive local airport markets are either complementary to hub networks or cannibalizing each other. Furthermore, the ground travel leakage to hubs deepens operational challenges against small regional airports and their respective communities.

CHAPTER 4. EMPIRICAL ANALYSIS

4.1 The Model

The previous chapters have surveyed the evolution of airports and identified the potential factors that contribute to the decline of small and regional airports in New York State. The influence of the airport competition in the catchment areas, the population bases, and the ground travel market leakage have affected the enplanements one way or the other. The growth of enplanements is especially important, because it provides essential junctions for mobility to remote locations. It is also a local economic driver for communities that depend on aeronautical revenues. Therefore, understanding the subtleties of the withering small regional airports can bring a perspective on sustaining enplanements.

4.1.1 Methodology

This section focuses on how enplanements are affected through a comparison among hub, small primary, and non-primary airports. It explores empirically the relationship between the enplanements and the determinants through the panel data of 17 commercial service airports between 2000 and 2014 in New York State. Panel data allow observations of the behavior of entities and control for time-invariant factors across time.

In the data generating process, endogeneity may be inherent, because an unobserved shock can increase enplanements in the region. This means that the

dependent variable may be correlated with the error term. To address the heterogeneity across the cross-sections and autocorrelation within, a county-specific fixed effects model can be used (Bilotkach, 2015, p. 1582). The model is designed to analyze the causes of changes within the airports and only the impact of the variables that vary over time. By reducing the effect of the time-invariants, the fixed effects model produces the net effects of the variables across fixed time *t* and airport *i* on the outcome variable. The 17 airports remain the same unit at each location across the years with the independent variables varying in value year by year.

The fixed effects model's equation below:

$$
\begin{aligned}
lnEnplanements_{it} &= B_1\, lnVehicles_{it} + B_2\, lnVehicles_{it} * Primary_{1\,it} + B_3\, lnVehicles_{it} \\
&* Primary_{2\,it} + B_4\, lnVehicles_{it} * Catchment_{1\,it} \\
&+ B_5\, lnMedian\ Household\ Income_{it} + B_6\, lnMedian\ Household\ Income_{it} \\
&* Primary_{1\,it} + B_7\, lnMedian\ Household\ Income_{it} * Primary_{2\,it} \\
&+ B_8\, lnMedian\ Household\ Income_{it} * Catchment_{1\,it} \\
&+ B_9\, lnPopulation\ Density_{it} + B_{10}\, lnPopulation\ Density_{it} * Primary_{1\,it} \\
&+ B_{11}\, lnPopulation\ Density_{it} * Primary_{2\,it} + a_i + u_{it}
\end{aligned}
$$

lnEnplanements: the natural log of the total annual enplanements at each airport

lnVehicles: the natural log of the total annual vehicle registrations in each county

lnMedian Household Income: the natural log of the annual median household income in each county

lnPopulation Density: the natural log of the total annual population in each county

Primary: Airport categories according to large primary airports = 2; small primary airports = 1; non-primary airports = 0

Catchment: the presence of an alternative airport in the 70-mile service area from each airport by road

a_i: Fixed but unexplained intercept *i*

u_{it}: Error term for unit *i* and at time *t*; captures time-invariant unobservables

4.1.2 The variables

The enplanements vary greatly from Adirondack Airport to John F. Kennedy Airport. The natural log transformation linearizes a relationship between the outcome variable and regressors. The transformation of the dependent and independent variables into natural logarithms can also minimize heteroscedasticity by shrinking the variables' scale (Kaemmerle, 1991, p. 107).

Enplanements

An enplanement is a passenger boarding that includes a passenger on a connecting flight. Each airport reports its annual enplanements to the FAA as enplanement numbers represent the airport's total activity. Then, the FAA determines the amount of federal aid that an airport can obtain based on the enplanement numbers (Kaemmerle, 1991, p. 103).

The enplanements of Massena International Airport and Ogdensburg International Airport have been combined as one entity for the purpose of the model. The reasons are: (a) travel time between the two airports is only 40 minutes; (b) both are located near the US-Canada border line; (c) they are similar in terms of size and

airline services; (d) all the other study airports are unique to each respective county, but St. Lawrence County is the only county with two commercial service airports.

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
Enp	255	2437842	5495841	524	2.62e+07

Data source: New York State Government website

Vehicles

The variable refers to cars, trucks, and rental cars that passengers or passengers' guests can ride from point A to B. The variable has the total number of the New York State vehicle registrations by county where the study airports operate.

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
Vehicle	255	309179	304563.9	33097	1175291

Data source: https://dmv.ny.gov/

Median Household Income

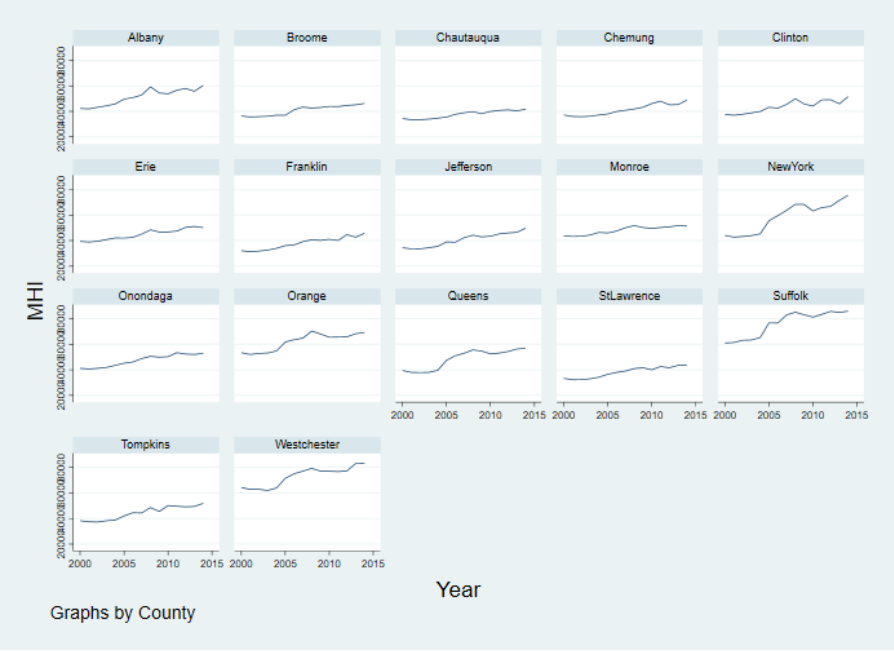
Median household income is an indicator of a regional economic measure. The variable is utilized instead of gross domestic products (GDP), because this variable holds the best coverage for the time frame from 2000 through 2014 at the county level. The variable is an aggregate of each county's median household income (dollars, not seasonally adjusted).

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
MHI	255	49059.85	12872.97	31302	85886

Data source: https://fred.stlouisfed.org/categories/29191

Figure 6 Median Household Income by County



Population Density

The variable (population per square mile) refers to the population densities of the New York State counties where each commercial service airport is located. Population density provides a more accurate measure of population for large, rural counties, since most of the New York State counties are agricultural and remotely dispersed.

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
PopDens	255	5763.906	16509.57	30.81	71671.84

Data source: https://www.health.ny.gov/

Primary

The FAA distinguishes commercial service airports between non-primary and primary. The primary airports are further broken into two groups at the threshold of one million passengers per year to capture passengers travelling from a small primary airport to another primary airport. Each airport is assigned a value from 0 to 2. A non-primary airport (with enplanements of at least 2,500 per year) is assigned a value of 0. A small primary airport (with enplanements of less than one million per year) is assigned a value of 1. A large primary airport (with enplanements of more than one million per year) is assigned a value of 2. The reference level for interpretation is 0.

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
Primary	255	1.058824	.8038237	0	2

Table 2 Categories of the Airports

Values	Category	NYS Commercial Service Airport Names
0	Non-Primary Airports	Adirondack Regional Airport Jamestown Airport Massena International Airport & Ogdensburg International Airport Plattsburgh International Airport Watertown International Airport
1	Small Primary Airports	Elmira Corning Regional Airport Greater Binghamton Airport Ithaca Tompkins Regional Airport Long Island MacArthur Airport Stewart International Airport Westchester County Airport
2	Large Primary Airports	Albany International Airport Buffalo Niagara International Airport Greater Rochester International Airport John F. Kennedy International Airport LaGuardia Airport Syracuse Hancock International Airport

Data source: https://www.faa.gov/

Catchment Area

The variable refers to the presence of an alternative airport around the 70-mile radius by road. According to the Iowa Department of Transportation, researchers often assume that passengers can travel about 70 miles to reach an airport. The one-hour

radius from an airport often defines the airport's service area (Suzuki & Audino, 2003, p. 40). The variable is coded as 0 or 1. If there is an alternative airport equivalent or larger than the local airport, the airport is assigned a value of 1. If there is no substitute airport in the catchment area, then the airport is assigned a value of 0.

Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
Catchment	255	.8235294	.3819697	0	1

Data source: FAA, Google Maps, and Google Flights

Figure 7.1 Service Areas of the Non-primary Airports

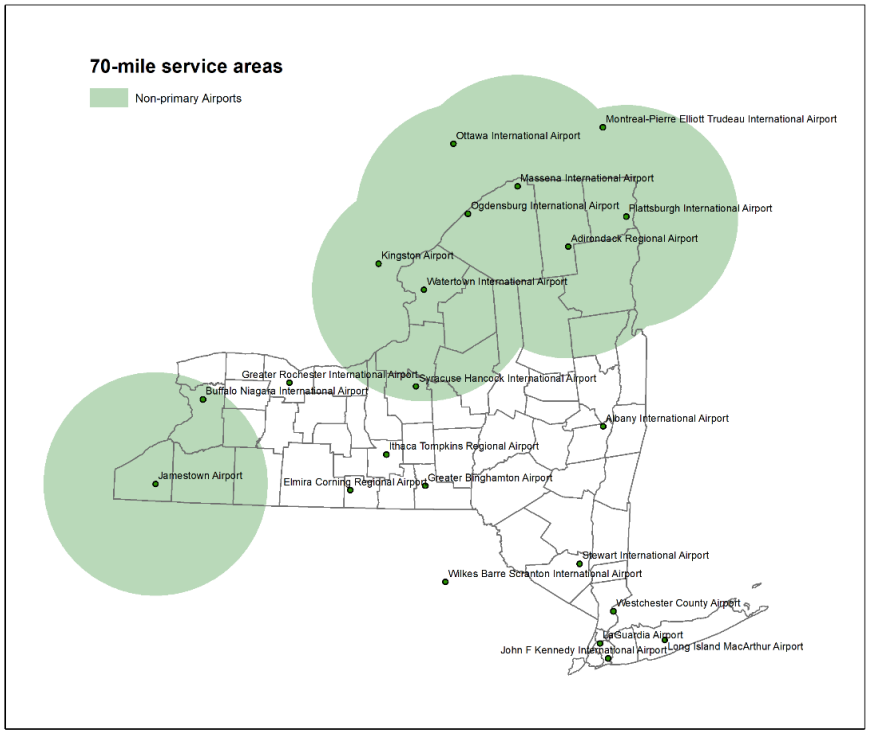


Figure 7.2 Service Areas of the Small Primary Airports

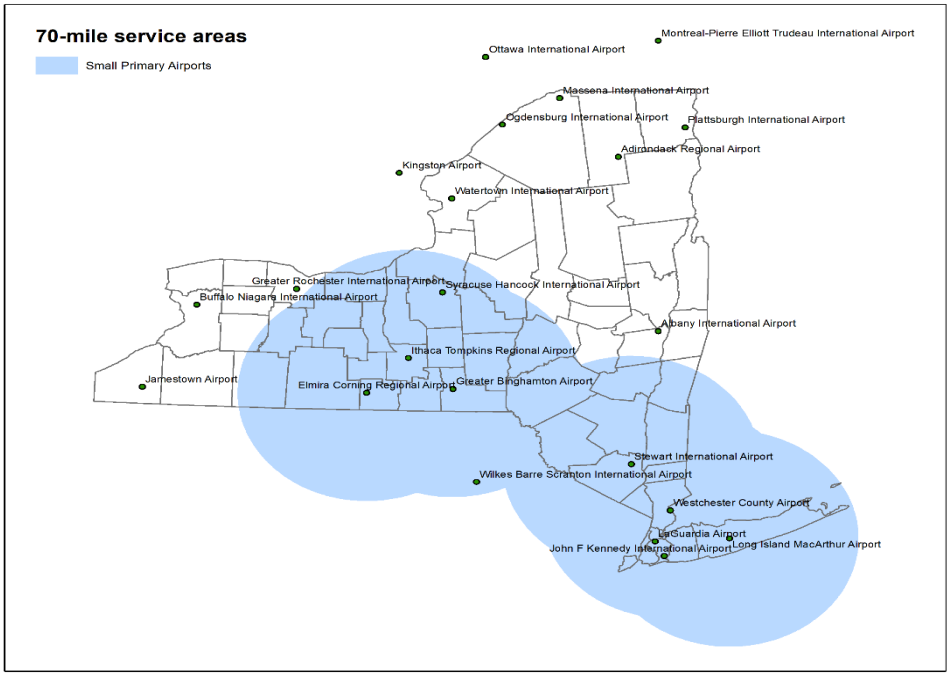
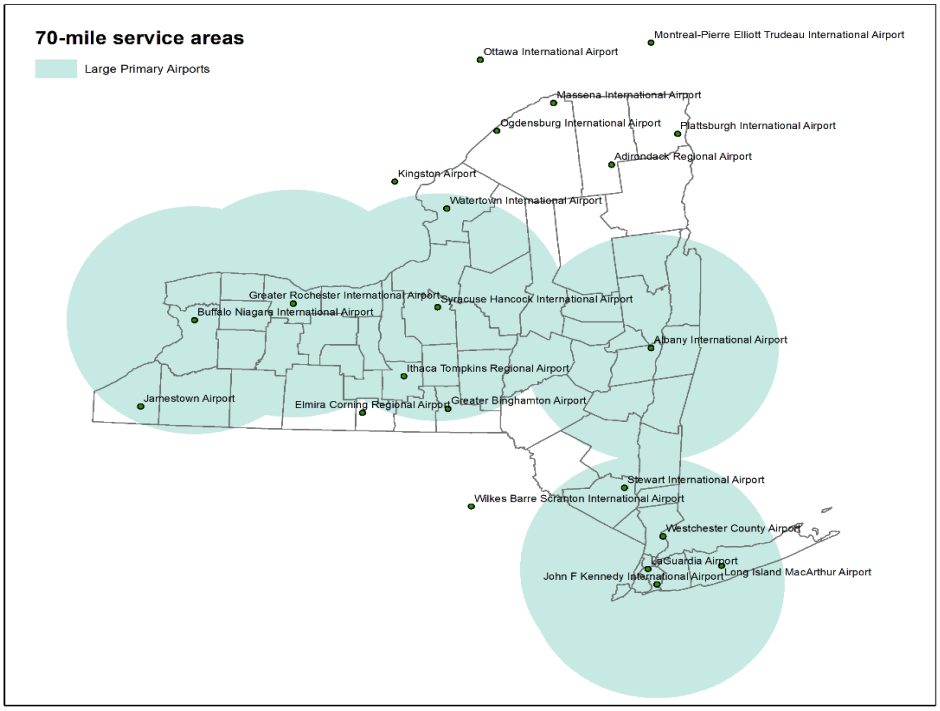


Figure 7.3 Service Areas of the Large Primary Airports



4.1.3 Hypotheses and Data Analysis

The study presumes that higher flight fares at a small local airport will influence travelers to leak to alternative airports, which can lead to fewer enplanements at the local airport. Another assumption on the airport passenger leakage to bigger airports is attributed to the small airports' infrequent flights, additional flight legs, and proximity to alternative airports (Fu & Kim, 2016, p. 70). Some researchers also assume that airfare can be excluded, because multicollinearity can be present. Airfare is often highly correlated with geographic distances. (Zhou et al., 2018, pp. 92–93). Harvey (1987) also notes that airline fares have more variations among fare classes than flights or airports. The actual pay by each traveler is not known between hub and regional airports (p. 445).

Hypotheses

H1: An increase in airport competition in the catchment area leads to a lower number of enplanements for smaller airports.

H2: To an extent, the usage of personal vehicles decreases enplanements.

H3: To an extent, the median household income is a predictor for enplanement growth.

Table 3 Fixed Effects Regression Output

```
Fixed-effects (within) regression               Number of obs     =       255
Group variable: AirportName1                    Number of groups  =        17

R-sq:                                           Obs per group:
     within  = 0.2630                                         min =        15
     between = 0.2297                                         avg =      15.0
     overall = 0.2195                                         max =        15

                                                F(11,227)         =      7.36
corr(u_i, Xb)  = -0.9998                        Prob > F          =    0.0000

------------------------------------------------------------------------------
       lnEnp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnVehicle |   29.48988   7.795878     3.78   0.000     14.12834    44.85142
             |
  Primary#c.lnVehicle |
             1  |  -15.73644   6.395068    -2.46   0.015    -28.33773   -3.135153
             2  |  -7.272065   5.369821    -1.35   0.177    -17.85313    3.309004
             |
Catchment#c.lnVehicle |
             1  |  -23.70287   8.682513    -2.73   0.007     -40.8115   -6.594246
             |
       lnMHI |   1.031418   1.137886     0.91   0.366    -1.210751    3.273588
             |
      Primary#c.lnMHI |
             1  |  -1.939549   .9887307    -1.96   0.051    -3.887813     .008715
             2  |  -2.562861   .9806593    -2.61   0.010    -4.495221   -.6305021
             |
    Catchment#c.lnMHI |
             1  |   2.337744   .9163479     2.55   0.011     .5321087     4.14338
             |
       lnPopD |   .0097763    .783995     0.01   0.990    -1.535062    1.554614
             |
     Primary#c.lnPopD |
             1  |   1.679643   4.572228     0.37   0.714    -7.329792    10.68908
             2  |  -1.572985   2.353255    -0.67   0.505    -6.210002    3.064031
             |
        _cons |  -20.30847   27.40408    -0.74   0.459    -74.30738    33.69044
-------------+----------------------------------------------------------------
     sigma_u |  133.38707
     sigma_e |  .51907667
         rho |  .99998486   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(16, 227) = 6.84                     Prob > F = 0.0000
```

The results in Table 3 show that estimates of parameters associated with *Vehicle*, *Primary 1*Vehicle*, *Catchment 1*Vehicle*, *Primary 2*Median Household Income*, and *Catchment 1*Median Household Income* are statistically significant at the 95% confidence level. For *Vehicle*, the enplanements of the non-primary airports (0's) surge by 0.29% when one percent of vehicle increases with no substitute airport available, while holding other variables constant. If a substitute airport exists in the

catchment area, the enplanements increase only by 0.06% with a one-percent increase in vehicle. This implies that travelers do drive to a substitute airport.

For the small primary airports (1's), the enplanements rise by 0.14% when one percent of vehicle increases with no substitute airport available, while holding other variables constant. If these airports have an alternative airport in the catchment area, their enplanements decrease by 0.1% with an additional percent of vehicle. For the large primary airports (2's), the effect of vehicle is not statistically significant at the 95% confidence level. Compared to the non-primary airports, the small primary airports have fewer enplanements when there is a one-percent increase in vehicle with no substitute airport, while holding other variables constant.

The median household income variable is statistically significant for the large primary airports (2's). Their enplanements drop by 0.02% with a one-percent increase in the median household income when a substitute airport does not operate in the service area, while holding other variables constant. With at least one alternative airport in the area, the large primary airports' enplanements grow by 0.01% with a one-percent increase in the median household income.

Table 4 Testing for Heteroscedasticity

```
Breusch-Pagan test

data:  lnEnp ~ lnVehicle + lnVehicle * Primary + lnVehicle * Catchmen
t +     lnMHI + lnMHI * Primary + lnMHI * Catchment + lnPopD + lnPopD
 *     Primary + factor(County)
BP = 836.26, df = 27, p-value < 2.2e-16
```

Homoscedasticity is an important assumption in regression, signaling that the errors are evenly scattered. Heteroscedasticity means that the residuals associated with different observations are distributed with different variances. The Breusch-Pagan test indicates the presence of heteroscedasticity. The null hypothesis of the test is the constant variance of errors (homoscedasticity). The alternative hypothesis is that the constant variance of errors is not equal. The computed p-value of the test above is less than 0.05; so, the null hypothesis is rejected in support of the alternative hypothesis. A possible solution to address heteroscedasticity includes employing an estimator that yields robust errors.

The regression model estimated by generalized least squares (GLS) with the xtreg-fe option in Stata yields robust standard errors presented in Table 5 below. The robust option makes the appropriate adjustments on standard errors to account for heteroscedasticity. In Table 5, estimates of parameters associated with *Vehicle*, *Primary 1*Vehicle*, *Catchment 1*Vehicle*, *Catchment 1*Median Household Income*, and *Primary 2*Population Density* are statistically significant at the 95% confidence level. Compare to the pre-robust regression results, *Primary 2*Median Household Income* is no longer statistically significant, but *Primary 2*Population Density* has the statistical significance at the 95% confidence level.

Table 5 Robust Fixed Effects Regression Output

```
Fixed-effects (within) regression               Number of obs     =       255
Group variable: AirportName1                    Number of groups  =        17

R-sq:                                           Obs per group:
     within  = 0.2630                                         min =        15
     between = 0.2297                                         avg =      15.0
     overall = 0.2195                                         max =        15

                                                F(11,16)          =     20.12
corr(u_i, Xb)  = -0.9998                        Prob > F          =    0.0000

                                 (Std. Err. adjusted for 17 clusters in AirportName1)
------------------------------------------------------------------------------
                     |               Robust
               lnEnp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
           lnVehicle |   29.48988   7.429847     3.97   0.001      13.7393    45.24045
                     |
  Primary#c.lnVehicle |
                   1 |  -15.73644   5.859075    -2.69   0.016    -28.15712   -3.315755
                   2 |  -7.272065   5.447406    -1.33   0.201    -18.82005    4.275919
                     |
Catchment#c.lnVehicle |
                   1 |  -23.70287   9.453353    -2.51   0.023    -43.74309   -3.662661
                     |
               lnMHI |   1.031418   2.437457     0.42   0.678    -4.135759    6.198596
                     |
      Primary#c.lnMHI |
                   1 |  -1.939549   2.536211    -0.76   0.456    -7.316076    3.436979
                   2 |  -2.562861   2.645668    -0.97   0.347    -8.171426    3.045703
                     |
    Catchment#c.lnMHI |
                   1 |   2.337744   .8132605     2.87   0.011     .6137091    4.061779
                     |
             lnPopD |   .0097763   .6463979     0.02   0.988    -1.360526    1.380079
                     |
     Primary#c.lnPopD |
                   1 |   1.679643   1.547217     1.09   0.294    -1.600311    4.959597
                   2 |  -1.572985   .6996108    -2.25   0.039    -3.056094   -.0898766
                     |
               _cons |  -20.30847   19.00861    -1.07   0.301    -60.60493    19.98798
---------------------+--------------------------------------------------------------
             sigma_u |  133.38707
             sigma_e |  .51907667
                 rho |  .99998486   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

4.1.4 Different Aggregation Scheme

The initial aggregation scheme for the primary airports is the one-million enplanement threshold, because a distinctive trend of less than one million enplanements is noticeable for the small airports. Any cut-off scheme above one million enplanements is not meaningful, because only JFK and La Guardia will belong to the large primary airport group (a value of 2). A different aggregation scheme incorporates a 0.5 million enplanement mark. If a primary airport enplanes more than a half million passenger boardings, the airport is assigned a value of 2. A primary airport with less than a half million enplanements is assigned a value of 1.

Table 6 Different Aggregation Scheme: Categories of the Airports

Values	Category	NYS Commercial Service Airport Names
0	Non-primary Airports	Adirondack Regional Airport Jamestown Airport Massena International Airport & Ogdensburg International Airport Plattsburgh International Airport Watertown International Airport
1	Small Primary Airports	Elmira Corning Regional Airport Greater Binghamton Airport Ithaca Tompkins Regional Airport Stewart International Airport
2	Large Primary Airports	Albany International Airport Buffalo Niagara International Airport Greater Rochester International Airport John F. Kennedy International Airport LaGuardia Airport Long Island MacArthur Airport Syracuse Hancock International Airport Westchester County Airport

Table 7 Different Aggregation Scheme: Regression Output

```
Fixed-effects (within) regression               Number of obs     =        255
Group variable: AirportName1                    Number of groups  =         17

R-sq:                                           Obs per group:
     within  = 0.2585                                         min =         15
     between = 0.3357                                         avg =       15.0
     overall = 0.3210                                         max =         15

                                                F(11,16)          =     131.72
corr(u_i, Xb)  = -0.9998                        Prob > F          =     0.0000

                                  (Std. Err. adjusted for 17 clusters in AirportName1)
------------------------------------------------------------------------------
                     |               Robust
                lnEnp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
            lnVehicle |    28.7095   8.226246     3.49   0.003     11.27063    46.14836
                      |
  Primary#c.lnVehicle |
                    1 |   -12.3545   7.771806    -1.59   0.131    -28.82999    4.120995
                    2 |  -9.303151   5.876735    -1.58   0.133    -21.76127    3.154971
                      |
Catchment#c.lnVehicle |
                    1 |  -22.71267   10.40114    -2.18   0.044    -44.76209   -.6632428
                      |
                lnMHI |   .9569576   2.474594     0.39   0.704    -4.288947    6.202862
                      |
      Primary#c.lnMHI |
                    1 |   -1.72143    2.53041    -0.68   0.506    -7.085659    3.642799
                    2 |  -2.468629   2.694502    -0.92   0.373    -8.180718    3.243459
                      |
    Catchment#c.lnMHI |
                    1 |     2.3717   .8557164     2.77   0.014     .5576619    4.185737
                      |
              lnPopD |   .0162422   .6538864     0.02   0.980    -1.369935    1.402419
                      |
     Primary#c.lnPopD |
                    1 |   .0889132   4.075214     0.02   0.983    -8.550154    8.727981
                    2 |  -1.704361    .756767    -2.25   0.039    -3.308635   -.1000868
                      |
                _cons |  -25.38295   22.31462    -1.14   0.272    -72.68783    21.92193
---------------------+--------------------------------------------------------------
              sigma_u |  122.94641
              sigma_e |  .52065492
                  rho |  .99998207   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Compared to the regression output in Table 5, the different aggregation scheme (0.5 million enplanements) produces the similar results in the coefficients and computed p-values. This indicates that the model can be consistent with a different scheme.

4.1.5 Endogeneity and Instrumental Variables

Endogeneity bias can lead to misleading inferences and inconsistent estimates. Endogeneity refers to the condition when (a) one of the explanatory variables correlates with the residuals; (b) the dependent variable simultaneously correlates with an explanatory variable; and (c) omitted variable bias or measurement errors occur. Statistically ensuring that endogeneity bias is completely resolved is not almost possible, because exogenous variables cannot be precisely exogenous or the error term in endogeneity is not observable (Ullah, Akhtar, & Zaefarian, 2018, pp. 69–70).

Instrumental Variable (IV) estimation is used to help address endogeneity. An instrumental variable correlates with the explanatory variable but has no correlation with u and no effect on y. The instrumental variables used in this model are the following.

Driver licenses

This variable is defined as the annual number of NY State driver licenses by county. Driver licenses are directly correlated with *Vehicles*, because drivers need the license to operate a car, but at the same time licenses themselves are uncorrelated with *Enplanements*.

Data source: the New York State Department of Motor Vehicles

Marriage occurrences

This variable is defined as marriages of occurrence by county in New York State. Marriages are correlated with *Household Income*, because married couples are involved in financial activities together but are uncorrelated with *Enplanements*.

Data source: the New York State Department of Health

Table 8 Instrumental Variables (IV) Estimation

First-stage within regression

Fixed-effects (within) regression — Number of obs = 255
Group variable: AirportName1 — Number of groups = 17

R-sq:
within = 0.3235
between = 0.5205
overall = 0.4035

Obs per group:
min = 15
avg = 15.0
max = 15

F(3,235) = 37.47
corr(u_i, Xb) = -0.9978 — Prob > F = 0.0000

lnMHI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnPopD	.4659094	.1388777	3.35	0.001	.1923051	.7395137
lnMarry	-.4049566	.0600102	-6.75	**0.000**	-.5231834	-.2867298
lnLic	1.949888	.3099729	6.29	**0.000**	1.339207	2.560568
_cons	-12.86897	3.708368	-3.47	0.001	-20.17486	-5.563072
sigma_u	2.4491712					
sigma_e	.10161667					
rho	.99828152	(fraction of variance due to u_i)				

F test that all u_i=0: F(16, 235) = 36.37 — Prob > F = 0.0000

First-stage within regression

Fixed-effects (within) regression — Number of obs = 255
Group variable: AirportName1 — Number of groups = 17

R-sq:
within = 0.2251
between = 0.9096
overall = 0.9093

Obs per group:
min = 15
avg = 15.0
max = 15

F(3,235) = 22.75
corr(u_i, Xb) = 0.8484 — Prob > F = 0.0000

lnVehicle	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnPopD	.0318185	.0226038	1.41	0.161	-.0127135	.0763505
lnMarry	.0137554	.0097673	1.41	0.160	-.0054872	.0329981
lnLic	.3767146	.0504514	7.47	**0.000**	.2773199	.4761094
_cons	7.229366	.6035761	11.98	0.000	6.040255	8.418477
sigma_u	.61122134					
sigma_e	.01653919					
rho	.99926833	(fraction of variance due to u_i)				

F test that all u_i=0: F(16, 235) = 470.79 — Prob > F = 0.0000

```
Fixed-effects (within) IV regression            Number of obs     =         255
Group variable: AirportName1                    Number of groups  =          17

R-sq:                                           Obs per group:
     within  = 0.0196                                         min =          15
     between = 0.5182                                         avg =        15.0
     overall = 0.4892                                         max =          15

                                                F(20,235)         =      2.82
corr(u_i, Xb)  = -0.9247                        Prob > F          =     0.0397

------------------------------------------------------------------------------
       lnEnp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnMHI |   1.706966   .7410648     2.30   0.022     .2469864    3.166945
   lnVehicle |  -3.170582   5.571332    -0.57   0.570    -14.14672    7.805555
      lnPopD |   .2862488   .9003421     0.32   0.751    -1.487524    2.060022
       _cons |   30.48763   62.82551     0.49   0.628    -93.28553    154.2608
-------------+----------------------------------------------------------------
     sigma_u |  5.1322263
     sigma_e |  .58839342
         rho |  .98702663   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F  test that all u_i=0:     F(16,235) =    42.33          Prob > F    = 0.0000
------------------------------------------------------------------------------
Instrumented:   lnMHI lnVehicle
Instruments:    lnPopD lnMarry lnLic
------------------------------------------------------------------------------
```

Table 8 shows that estimates of parameters associated with *Marriage* and *License* are statistically significant at the 95% confidence level. For *Median Household Income*, *Marriage* and *License* are statistically significant. For *Vehicle*, *License* is statistically significant. The instrumental variables are validated, but in the IV regression, only *Median Household Income* becomes statistically significant at the 95% confidence level. Then, the Hausman Test is performed to test the validity of the IV regression.

Table 9 The Hausman Test

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       iv           .          Difference          S.E.
-------------+------------------------------------------------------------------
       lnMHI |    1.706966     .8959105        .8110551        .6653599
   lnVehicle |   -3.170582     5.981905       -9.152487        5.160193
      lnPopD |    .2862488      .188411        .0978378        .4447008
------------------------------------------------------------------------------
                        b = consistent under Ho and Ha; obtained from xtivreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =         3.19
                Prob>chi2 =       0.3625
```

The Hausman test is routinely utilized to detect endogeneity of individual explanatory variables. This test determines the correlation between the error term and the explanatory variables (Ullah et al., 2018, p. 74). The test result above is not statistically significant at the 95% confidence level. The null hypothesis is not rejected. The difference in the coefficients between the IV and Fixed Effects regressions is not systematic.

4.1.6 Specification Tests

The fixed effects model's R-squared is 0.2195. This means that 22% of the dependent variable variation is explained by the model. The model's F-test of overall significance is statistically significant at the 95% confidence level. The model fits the data better than the model with no predictors. This model is also tested for any non-linear specification below.

Figure 8.1 Linearity Between Enplanements and Vehicles

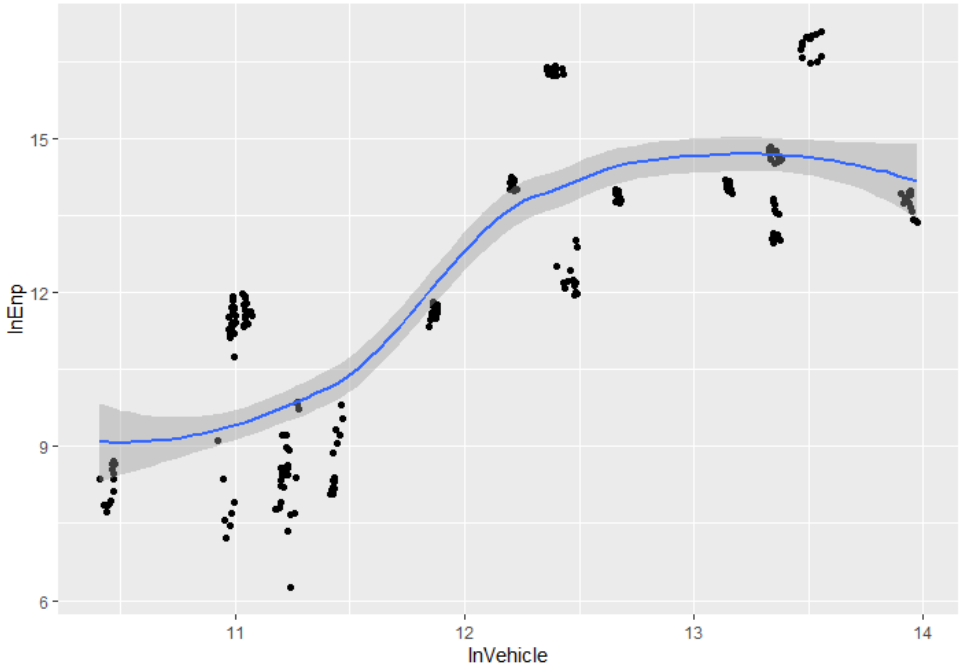


Figure 8.2 Linearity Between Enplanements and Median Household Income

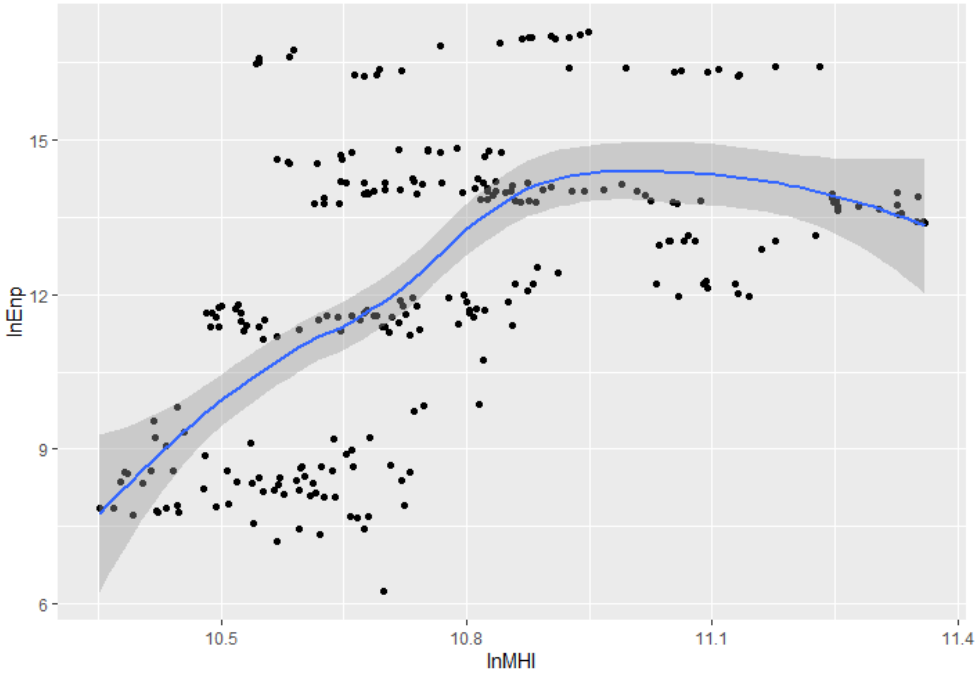


Figure 8.3 Linearity Between Enplanements and Population Density

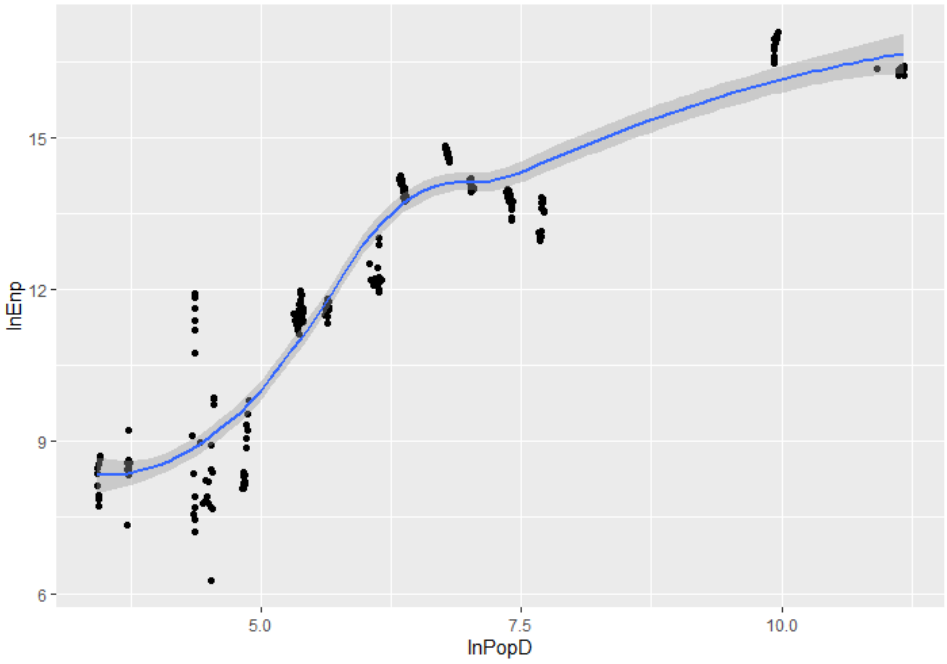


Table 10 Non-linearity: Regression with Quadratic Terms

```
Fixed-effects (within) regression               Number of obs     =       255
Group variable: AirportName1                    Number of groups  =        17

R-sq:                                           Obs per group:
     within  = 0.2733                                         min =        15
     between = 0.1757                                         avg =      15.0
     overall = 0.1677                                         max =        15

                                                F(13,16)          =     34.10
corr(u_i, Xb)  = -0.9992                        Prob > F          =    0.0000

                                (Std. Err. adjusted for 17 clusters in AirportName1)
------------------------------------------------------------------------------
                   |               Robust
             lnEnp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          lnVehicle |   30.71244   45.72209     0.67   0.511    -66.21405    127.6389
              lnVsq |  -.1701692   2.105803    -0.08   0.937    -4.634273    4.293934
                    |
    Primary#c.lnVsq |
                1   |  -.5843487   .3618045    -1.62   0.126     -1.35134    .1826426
                2   |  -.1468312   .3984413    -0.37   0.717     -.991489    .6978266
                    |
  Catchment#c.lnVsq |
                1   |  -.9179763   .4025594    -2.28   0.037    -1.771364   -.0645884
                    |
             lnMHI |  -34.28439   33.14878    -1.03   0.316    -104.5567    35.98789
           lnMHIsq |   1.670346   1.648426     1.01   0.326     -1.82416    5.164853
                    |
  Primary#c.lnMHIsq |
                1   |  -.1204931   .1473432    -0.82   0.425    -.4328466    .1918605
                2   |  -.1492206    .146415    -1.02   0.323    -.4596065    .1611653
                    |
Catchment#c.lnMHIsq |
                1   |    .101114   .0357203     2.83   0.012     .0253903    .1768377
                    |
            lnPopD |   .0576547   .6121827     0.09   0.926    -1.240115    1.355424
                    |
   Primary#c.lnPopD |
                1   |  -.2479514   2.535278    -0.10   0.923      -5.6225    5.126597
                2   |  -1.931273   .8745148    -2.21   0.042    -3.785162   -.0773845
                    |
              _cons |   .6556876   320.8812     0.00   0.998     -679.582    680.8934
-------------------+----------------------------------------------------------------
           sigma_u |  65.013796
           sigma_e |  .51771048
               rho |  .99993659   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

As Figures 8.1 and 8.2 show a partial parabola, the quadratic terms are utilized to capture non-linearity. The regression results in Table 10 show that the quadratic terms for *lnVehicle* and *lnMHI* are not statistically significant at the 95% confidence level. The model's R-squared is lower compared to the previous model. The non-linear relationship is not justified; so, the current fixed effects model is reasonable.

4.2 Testing of the Econometric Model

A fixed effects model accounts for the effects of unobserved time-invariants that influence the dependent variable one way or another. The model reduces potential omitted variable biases by removing these time-invariant characteristics. The model assumes that (a) the error term should have a normal distribution and a constant variation; (b) the error term should be uncorrelated with the predictor variables for the time *t* and the entity *i*; (c) individual-specific characteristics are correlated with the predictor variables (Allison, 2009).

Figure 9.1 The Residuals vs. Vehicles

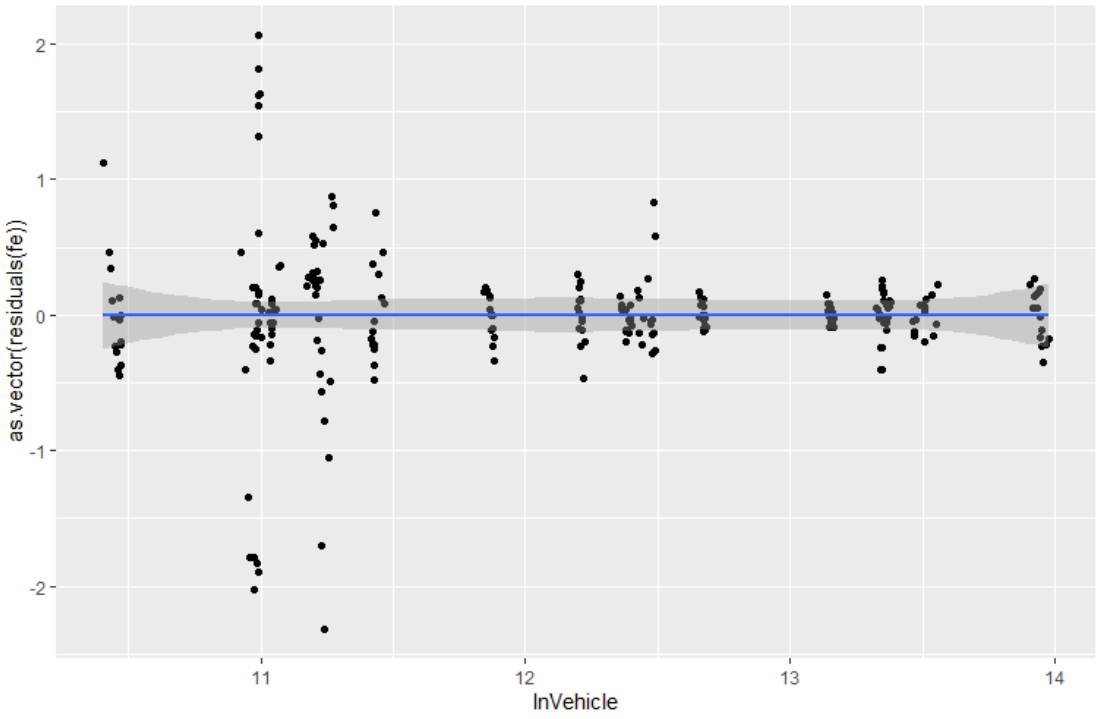


Figure 9.2 The Residuals vs. Median Household Income

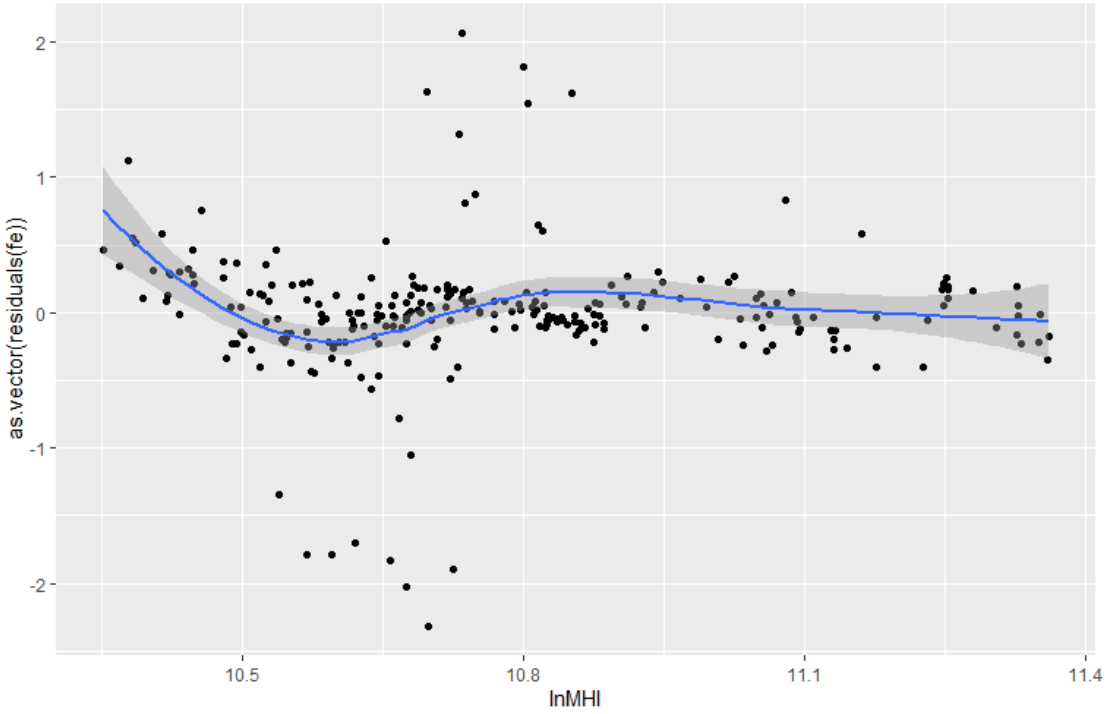
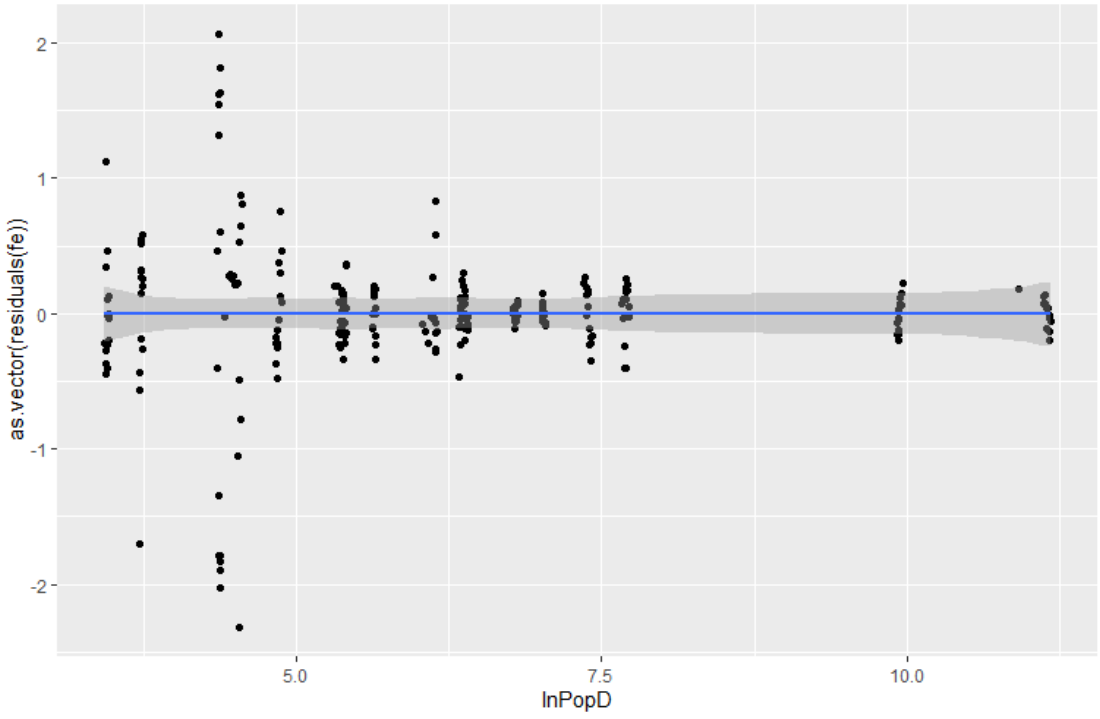
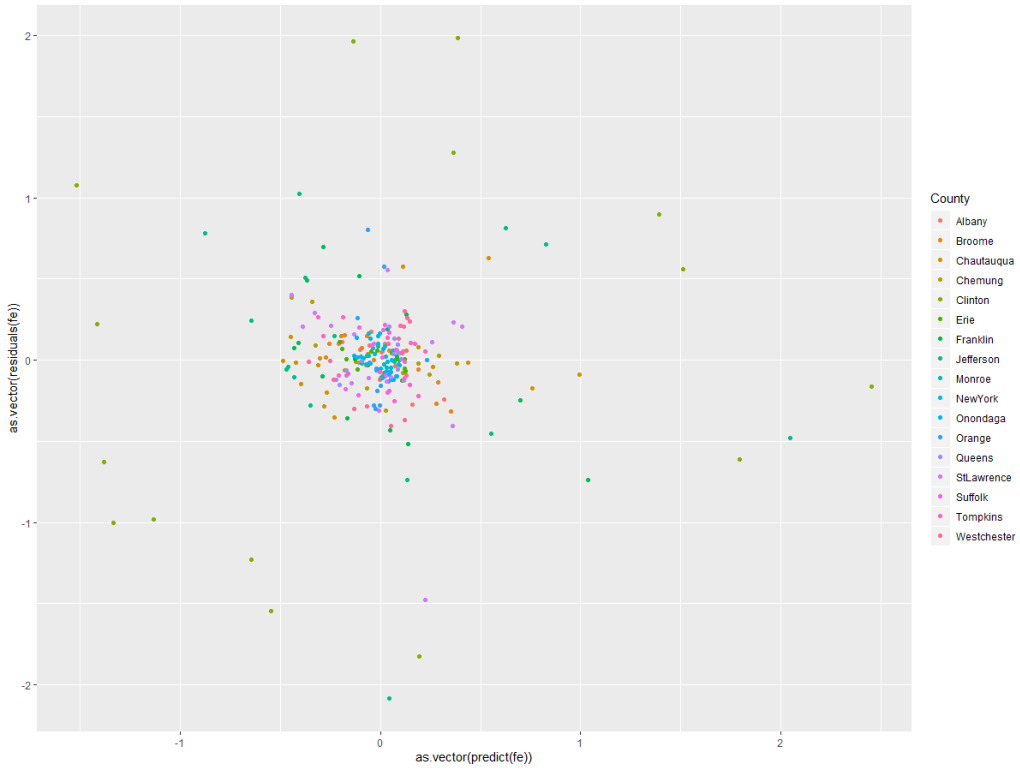


Figure 9.3 The Residuals vs. Population Density



Figures 9.1 and 9.3 show the independence of error. In essence, the error term has a constant variation around a mean of zero. Figure 9.2 displays a similar variation of the error term around zero.

Figure 10 The Residuals vs. Predicted



Based on Figure 10, the model's error term appears to be uncorrelated with the predictor variables, since the errors are scattered without a certain pattern. Note that Clinton County has some residuals not fully predicted by the explanatory variables, as seen in a few errors scattered away from zero. It can be inferred that outside influences unrelated to vehicle, median household income, population density, catchment area, and non-primary category may be causing some unexplained errors in that county.

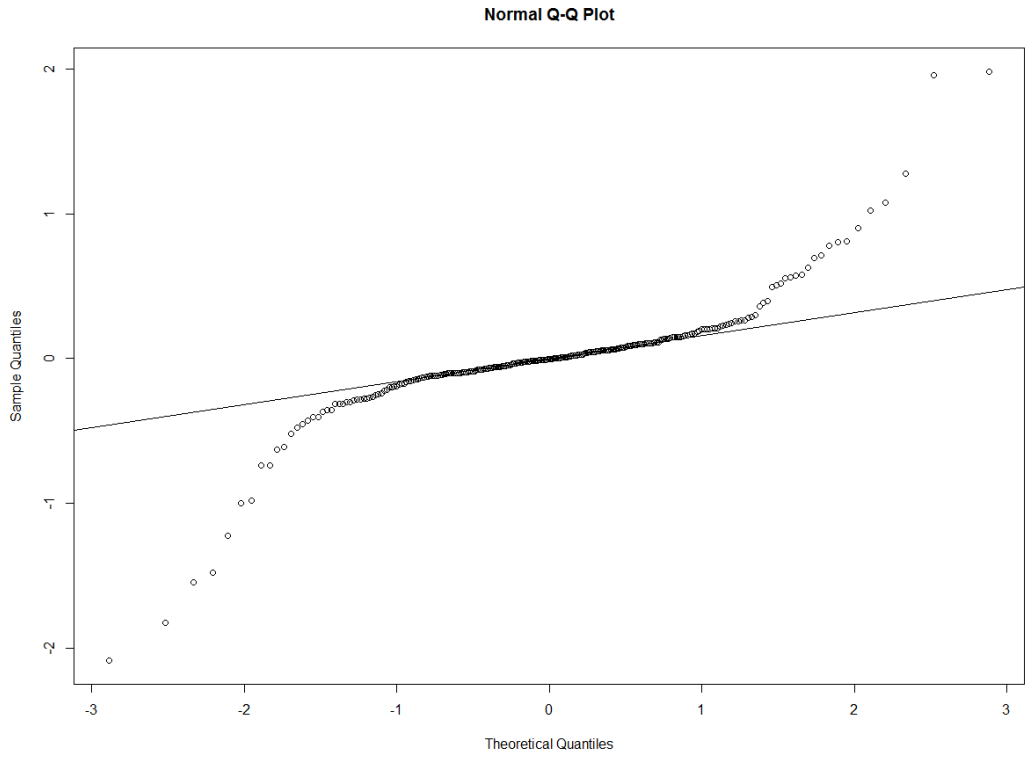
Table 11 Cross-sectional dependence

```
Pesaran CD test for cross-sectional dependence in panels

data:  lnEnp ~ poly(lnVehicle, 2) + poly(lnVehicle, 2) * Primary + po
ly(lnVehicle,     2) * Catchment + poly(lnMHI, 2) + poly(lnMHI, 2) *
Primary +     poly(lnMHI, 2) * Catchment + lnPopD + lnPopD * Primary
z = 1.3877, p-value = 0.1652
alternative hypothesis: cross-sectional dependence
```

A panel data model may possess interdependencies across cross-sections. The Pesaran CD test is used to detect cross-sectional dependence and contemporaneous correlation. The null hypothesis is that residuals across entities are not correlated. The test gives the computed p-value of 0.16, which is greater than 0.05. The null hypothesis is not rejected, and there is no cross-sectional dependence.

Figure 11 Normal Q-Q Plot



The Normal Q-Q Plot assesses the assumption of normality. The plot in Figure 11 reveals that the normal distribution holds, since the data points form along a straight line. Some data points at each end have flatter tales. This tail behavior may be due to extreme values or a result of Clinton County. The data satisfy the model's goodness of fit.

CHAPTER 5. CONCULSION AND DISCUSSION

5.1 CONCULSION

The thesis has reviewed the relative importance of each determinant that has contributed to the development or decline of the commercial service airports in New York. Chapter 1 observed the characteristics of the aviation industry in the modern-day travel. Chapter 2 reviewed the historical trace of the aviation. The government's decision to deregulate the airline market substantially changed airline commercial services. The stiff competition among the airports to survive on their own lowered airline fares, improved airline service quality, and importantly marked the beginning of the airport market divide. Chapter 3 dived into the 17 commercial service airports operating scheduled passenger services to comprehend enplanements, populations, catchment, and car ownership. Chapter 4 employed fixed effects regressions to analyze the relationship between the enplanements and the explanatory variables (*Vehicle, Median Household Income, Population Density, Primary,* and *Catchment*). The results underlined that the small primary airport group would have the lowest number of enplanements when the determinants are accounted for, compared to the other airport groups.

Hypotheses revisited:

H1: An increase in airport competition in the catchment area leads to a lower number of enplanements for smaller airports.

Some literature in the previous chapters discussed that air passengers would travel to another substitute airport to capitalize on bigger airports' advantages. The result supports that when a similar or bigger airport operates around the 70-mile radius, the enplanements decrease by 0.24% for the non-primary airports and shrink by 0.39% for the small primary airports, compared to a single airport in the service area. This increased competition indicates that the smaller airports in their respective areas are being used less with the effect of vehicle, because passengers have a choice to board a flight at another airport in a reasonable driving distance.

The competition among the airports further aggravates small airport issues. These airports have scarce-to-mediocre resources, or manpower, to combat against the larger players. The matter becomes worse when poor public intercity transportation infrastructure is rarely optimal and distant from population centers. They also struggle to maintain their operational costs and attract new airlines, while the large primary airports draw passengers from different catchment areas by utilizing their advantages and amenities.

H2: To an extent, the usage of personal vehicles decreases enplanements.

The availability of personal vehicles allows travelers to drive to airports in a state where cars function as a major mode of transportation access in place of the mediocre bus and rail infrastructure. The ground travel to airports is substantial, and car ownership in most of the counties generally rose. Therefore, there is actually a modest increase in the non-primary airports' enplanements by 0.29% with the effect of vehicle. However, for the small primary airports like Greater Binghamton Airport, Ithaca Tompkins Regional Airport, etc., the usage of personal vehicles reduces their

enplanements by 0.16%. The effect of vehicle on the large primary airports is not statistically significant at the 95% confidence level. This indicates that passengers may be choosing their local hub to fly or may not be driving to an airport. Based on the result from the small primary airport group, personal cars influence individuals to bypass a local airport and drive to a more distant airport, leading to a decrease in enplanements. This outflow of travelers can further dampen the operations of the small to medium primary airports.

H3: To an extent, the median household income is a predictor for enplanement growth.

In this model, the median household income is not a direct indicator for enplanement growth. This may indicate that households with more income can utilize more options to fit their flight needs. Interestingly, with a one-percent income hike, enplanements magnify by 0.03% when an additional airport in the catchment area operates.

This thesis' regression analysis on the 17 airports has provided an inferential explanation of the factors through geographic, economic, and market nuances. More importantly, the study is centered on the small regional airports to improve air service and maintain their operations in their local communities, while co-existing with the larger hubs. Policy makers can be aware that diversifying transportation access to airports between catchment areas, funding infrastructure, subsidizing route development activities, regulating revenues from major airline networks can advance the small and regional aviation markets in the long run. Considering New York State's

reliance on the agriculture industry and low population densities, the sustainability of small and regional airports is important despite their geographic isolation or reduced roles. They are key nodes to aviation networks and local communities relying on aeronautical revenues or natural resources. The trends explored in the thesis can be pertinent to other similar states to improve small and regional airports.

Future trends entail further growth in air transport, high-speed rail, and vehicles. Faster transport modes will flourish, because consumers can achieve more spatially distant trips in a shorter time. Air service may see a five-fold gain, especially in emerging economies due to a rise in income, population, and car ownership. Road transport volumes across regions will continue to expand. Light-duty vehicles like cars and trucks are expected to hike 2.5 times higher by 2050. Mere car travel volumes though will be slow in advanced economies due to a combination of fuel prices and saturated demand. Constructing high-speed rail tacks can be costly at first, but trains remain roughly constant with low variable costs. Once built and operated, high-speed rails have the potential to attract a wide range of passengers (Proost & Van Dender, 2011, p. 48–50).

The next generation of air service will continue to be affected by network consolidations, market segmentations, and LCCs. Route consolidations will continue to create large carriers. Market segmentations will further the divide between business and leisure passengers. Business travelers will consider better value-for-money air travel for short-haul trips, fueled by the advancements of web-based and video-conferencing communication technology. LCCs' market will be restructured to a fewer number of large LCCs. The long-haul market competition will remain intense, while small carriers will hold onto an independent role of "point-to-point" networks as well as feeder services to hubs (Mason & Alamdari, 2007, p. 310).

5.2 DISCUSSION

This thesis has focused on three aspects. The first concerns the trends of small and regional airports in local communities. The second examines the factors that contributed to these airports' decline in the state. The third evaluates the relationship between the primary and non-primary airports. The thesis now concludes with a discussion of the government programs, airports' refined goals in the era of hub airports, and future research.

Government grants or subsidized programs can help enhance small airport operations. For example, Europe utilizes two subsidy strategies: incentive programs and bilateral agreements. Most large airports exploit public incentive programs to reduce transaction costs without having to negotiate with airlines. Bilateral agreements entail public funds for regional public authorities to promote route and passenger volumes in their respective airports (Núñez-Sánchez, 2015, p. 94). In the U.S., three federal programs are well-known to help maintain service levels of smaller airports. Essential Air Service is a subsidized program to connect unlucrative routes between rural and large airports (Grubesic & Matisziw, 2011, p. 24). The Small Community Air Service Development Program funds airports and communities to retain or expand air service (Mills & Kalaf-Hughes, 2017, p. 119). The FAA Airport Improvement Program funding aids projects for runways and airport infrastructure improvements (Ryerson & Woodburn, 2014, pp. 140–141). Such programs upgrade infrastructure, promote regional marketing efforts, and address issues related to air service deficiencies.

A refined goal for the small airports should be to increase airport activity. Most hubs today, particularly privately-owned, are becoming less dependent on aeronautical revenues. They have resources to market the facility, manage leased properties, lobby

airlines for improved service, and convert non-aeronautical land to profit. Small and regional airports with declining activity can attempt to establish a stream of non-aeronautical revenues such as leasing more airport property to tenants. For example, Griffiss International Airport manages maintenance-repair shops for aircrafts, creating 900 direct and indirect jobs along with $170 million worth of economic activity. This segment of excess land development around the airport secures long-term revenues (New York State Department of Transportation, 2010, p. 21). Non-aeronautical developments through a more suitable land use pattern can present a financial opportunity to recover or improve operations of airports and public transport accessibility (Orth, Frei, & Weidmann, 2015, pp. 44–45).

Future research can be related to knowledge sharing, behavioral passenger-airport interactions, and non-commercial air service. Airports not only help maintain populations, but also attract talent and educated individuals that stimulate economic growth. A brain drain or a low economic productivity can occur in locations without airports (Chen, Chi, & Chi, 2018, p. 326). Also, between airports express buses are rapidly growing. The influence of public buses on air passenger behaviors such as access time, seasonal air fares, destination choices, trip length, travel group size, and loyalty programs can be interesting areas of research. Bao (2016) reiterates that advancing the comprehensive attractiveness of small airports and their respective communities requires not only to expand air routes, but also to improve airport access by establishing an external transportation system (p. 60). Lastly, a further look into cargo and reliever airports through the lens of general aviation would provide an overall picture of the impact of the aviation system.

APPENDIX A: DATA

This appendix provides a detailed background of the dataset used for the study. The panel data consist of 17 New York State counties where the commercial service airports operate from 2000 through 2014. This is a balanced panel that each individual *i* is observed in each time period *t*. All the cross sections have the same time span at the county level. This balanced data have no missing *n* units or *t* times. The variables are downloaded from different web sources and are processed into a single dataset to run the fixed effects model.

Enplanements

The data come from the New York State Government (https://data.ny.gov/browse/select_dataset?tags=enplanements&q=enplanement&sortBy=relevance&utf8=%E2%9C%93). The government collects digital data and makes them accessible. The government website provides a variety of open data for analysis on policies and programs. This dataset has the number of passengers boardings at New York State commercial service airports between 2000 and 2014. The data quality can be assured.

Vehicle

The data are from the New York State Department of Motor Vehicles (https://dmv.ny.gov/). The department keeps track of vehicle registrations by county and publishes them annually online. The data processing involves filtering out unsuited columns like trailer, motorcycle, moped, and others that cannot travel to airports. To download each year's data, one can use the website called archive.org. This website allows users to time-travel to the DMV website url in 2000 and to search

for the captures for that year. Under publications and statistical summaries, the registrations in force section has the data. The data quality can be assured. https://web.archive.org/web/20010915231846/http://www.nydmv.state.ny.us/regin2000.htm

Population Density

The data come from the New York State Department of Health (https://www.health.ny.gov/). The department collects data through records and surveys to publish regular reports and studies. The data are found in the Vital Statistics of New York State annual report by county. A google search for this title with a year returns the link for the statistics in Table 2. The data quality can be assured. https://www.health.ny.gov/statistics/vital_statistics/2000/table02.htm

Median Household Income

The data come from Economic Research at the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/categories/29191). The Division produces high-quality original research and data related to applied microeconomics, macroeconomics, and banking. The data can be found under Estimate of Median Household Income for every county in New York.

New York State Driver Licenses

The data also come from the New York State Department of Motor Vehicles (https://dmv.ny.gov/). Using the archive.org. website, one can find the data in New York State Licenses on File by County for each year under publications and statistical summaries. The data quality can be assured.

https://web.archive.org/web/20010917213352/http://www.nydmv.state.ny.us/license2000.htm

Marriage Occurrences

The data come from the New York State Department of Health. (https://www.health.ny.gov/statistics/vital_statistics/2014/). The data can be found in Table 47 under the Vital Statistics of New York State annual report. The total records for each NY county are included in the table. The data quality can be assured.

APPENDIX B: SIMILAR ECONOMETRIC STUDIES

This appendix summarizes other similar econometric studies relevant to this thesis. Several studies have focused on air services and economic impact. Recent research has explored an airport leakage trend by air service characteristics such as flight frequencies, access times, fares, etc., but few studies have addressed the relationship between airport activity and accessibility by vehicle. This is the gap where this thesis contributes to an understanding of air service trends at small airports.

Research	Method	Findings
Passenger leaks and the fate of small community air service Phillips and Weatherford (2005)	Two-step regressions	Distance between the hub and local airport, fare differences, and the proportion of planes at small community airports are determinants that affect passenger leaks to a hub. Otherwise, small community airports would have more enplanements.
Exploring the determinants for airport profitability: Traffic characteristics, low-cost carriers, seasonality and cost efficiency Zuidberg (2017)	Fixed-effects panel data regression	A quadratic relationship exists between seasonality and airport profitability. Capital cost efficiency positively impacts on profitability. Hub airports depend on global economies. Regional airports depend on regional economies and population growth.
Up in the air: The role of airports for regional economic development Florida, Mellander, Holgersson (2012)	Multiple regression	Airports are more feasible to operate in bigger cities with warmer winters. Airports promote regional development such as economic output per capita. Regional development by airport occurs when they transport people and freight. Their impact on regional growth varies depending on scale and size.
Factors affecting airport route development activity and performance Halpern and Graham (2016)	Multiple regression	Larger airports and private airports are more active. Route development activity positively impacts on airport performance, specifically market growth.

Estimating the demand for small community air service Kaemmerle (1991)	Multiple regression	Total county income, driving to a hub, weekly flights directly to hubs, aircraft size, and community status as a hub airport are relevant determinants to estimate annual enplanements at small community airports in Texas.
Airport size and urban growth Sheard (2017)	Ordinary least square and (OLS) and two-stage least squares	Airport size positively impacts on local GDP, number of firms, employment rate, population, and local employment, with an elasticity of 0.03.
Air service and urban growth: Evidence from a quasi-natural policy experiment Blonigen and Cristea (2015)	OLS regression and two-stage least squares	Air services affect local population, income growth, and employment growth. If a city's traffic growth rate increases by 50 percent, an additional income of 7.4% of real GDP is generated over 20 years.
Airport competition – Regional airports losing ground to main airports Lian and Rønnevik (2011)	Logistic regression	Traffic leakage by car to nearby major airports is high if regional airport connections are indirect. Travel leakage is evident for leisure travelers. Increased competition at main airports raises leakage levels.
Small community airport choice behavior analysis: A case study of GTR Zhang and Xie (2005)	Logistic regression	Fare differences, flight schedules, and previous experiences with the airport are important factors for passenger choices between small and more distant major airports.
The effect of airports on regional development: Evidence from the construction of regional airports in Norway Tveter (2017)	Difference-in-difference	A comparison of control municipality groups by a shorter distance to the nearest airport indicates a 5% increase in the population near the constructed airports from 1970 to 1980.
The impacts of transport accessibility on population change across rural, suburban and urban areas: A case study of Wisconsin at sub-county levels Chi (2011)	OLS regression Spatial regime model	In rural areas of Wisconsin, airport access and highway development spur population growth. In suburban areas, airport accessibility has an effect on population growth, but neither is statistically significant in urban areas.
Economic contribution of essential air service flights on small and remote communities Özcan (2014)	Two-stage least squares estimation	The Essential Air Service Program is implemented to help small and remote communities develop economically and socially. One percent increase in EAS airports' air passenger traffic results in a 0.12% increase in per capita income for that community.
Are airports engines of economic development? A dynamic panel data approach Bilotkach (2015)	Dynamic panel data generalized method of moment	Passenger traffic volume increases average wage and creates jobs, with a more robust impact from non-stop flights.

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