USE AGREEMENTS AND ECONOMIC PERFORMANCE OF U.S. AIRPORTS

A Dissertation
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Fecri Karanki

In Partial Fulfillment of the Requirements
for the Degree of
DOCTOR OF PHILOSOPHY

Major Program:
Transportation and Logistics

March 2020

Fargo, North Dakota

North Dakota State University
Graduate School

Title

USE AGREEMENTS AND ECONOMIC PERFORMANCE OF U.S. AIRPORTS

By

Fecri Karanki

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

SUPERVISORY COMMITTEE:

Dr. Siew Hoon Lim
Chair

Dr. John Bitzan

Dr. Joseph Szmerekovsky

Dr. Alan Dybing

Approved:

06/19/2020 Tim O. Peterson
Date Department Chair

ABSTRACT

In the U.S., airport use agreements are developed based on three common rate-setting approaches: the residual, compensatory, and hybrid methods. Under a residual agreement, the financial risk of the host airport is borne by the signatory airlines, and in return, the signatory airlines pay reduced user fees. Under a compensatory agreement, however, the airport bears its own financial risks and offers no reduced user fees to airlines. A hybrid agreement combines the features of residual and compensatory agreements. Under a hybrid agreement, the airport usually bears its own financial risks in terminal operations while the signatory airlines take over the financial risks in airfield operations. This dissertation aims to contribute to air transportation literature concerning the implication of use agreements on airport economic performance and rate differentials. Using the data of 59 U.S. hub airports from years 2009 to 2016, I studied the effects of use agreements on airport operational efficiency (in Chapter 2) and on cost efficiency (in Chapter 3), as well as the sources of aeronautical charge differentials between use agreements (in Chapter 4). The major findings of this dissertation are (1) airports with residual-type agreements tend to have lower operational efficiency compared to their peers adopting either the compensatory or hybrid agreement; (2) airports adopting the residual rate-setting method is less cost-efficient than the airports adopting either the hybrid or compensatory method; (3) compensatory airports have the highest average aeronautical and non-aeronautical charges; (4) non-aeronautical charges are a significant determinant of compensatory airports' aeronautical charges; (5) airports adopting the hybrid method have lower aeronautical charges than the airports adopting the other two methods due to differences in the average cost level. The first two results imply that under a residual agreement, increased airport inefficiency may undercut any potential benefits of signatory airlines, and this result may indicate the presence of

a moral hazard problem in the contractual relationship between the airlines and airports as a result of unequal risk-sharing and information symmetry.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deep gratitude to Prof.Siew Hoon Lim for her consistent encouragement and guidance during my entire Ph.D. program. She was not only an advisor for me but also a mentor who taught me how to become a good scholar. I am indebted to her patience and faith in my research. Without her dedicated support, this dissertation would not have been possible.

I would also like to express my sincere appreciation to Prof.John Bitzan for being always supportive. Due to his unique ideas, I could improve my research further.

I wish to extend my special thanks to Prof.Joseph Szmerekovsky for his insightful suggestions and constructive comments on this dissertation.

Last but not the least, my sincere thanks also go to Prof.Alan Dybing for providing motivation and immense support during the compilation of this dissertation.

DEDICATION

To my parents: Fatma and Cevat

To my siblings: Necmi, Vejdi, Serpil, and Selda

To my wife: Esin

To my twins: Janset and Jem

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. Vertical Relationships

U.S. airports are owned and operated by governments. The five financial sources of U.S. airports include airport user charges (aeronautical and non-aeronautical revenues)[1], state/local grants, the Airport Improvement Program (AIP) grants[2], revenue bonds and passenger facility charges (PFC) (Folkes, Koletsky, & Graham, 1987)[3]. Airport user charges are usually used to recover operating expenditures and debt services cost less passenger facility charges (FAA, 1999). Grants are allocated by the Federal Aviation Association (FAA) based on passenger volume and project basis (Fuhr & Beckers, 2009). PFC and AIP are complementary, AIP funds are adjusted based on the amount of PFC. However, government funding resources are not sufficient to finance airport capital projects and to sustain airport operations. Airports are increasingly pressured to reduce reliance on government resources (Fu, Homsombat, & Oum, 2011). Accordingly, airports need additional funding opportunities to sustain their capital projects and reduce financial uncertainty. Hence, having a close business relationship with airlines is essential for airports to sustain operations and to maintain a steady stream of income (Barbot, 2011).

Meanwhile, many airlines are seeking increased values or returns from their relationships with airports. Besides user fees' discounts, airlines also want to increase their connections and

---

[1] Aeronautical user charges include landing fees, apron, gate-use or parking fees, fuel-flowage fees, and terminal charges for rent or use of passenger hold rooms, ticket counters, baggage claims, administrative support, hangar space, and cargo buildings. Non-aeronautical user charges include rentals and fees to terminal concessionaires, automobile parking, rental car fees, rents and utilities for facilities, non-aviation development fees and communication fees (FAA, 1999).
[2] The AIP was established to support a nationally integrated airport system (Graham, 2004).
[3] Passenger facility charges are the fees collected via airline tickets and are used to recover debt service cost which is the principal and interest payments of revenue bonds. The remaining amount of debt service cost is recovered by user charges. Revenue bonds are used for new capital investments.

abilities to offer a wider range of services to passengers at their hubs. Their increased willingness to shop around also reflects the contestability of the airline industry (Carney & Mew, 2003). For airlines, in addition to securing airport facilities for operations, a vertical contractual relationship with an airport could enable airlines to expand market power by controlling and even potentially foreclosing upstream airport facilities from downstream rivals in the long run. Competition in the downstream air travel market also means that airlines must be strategic about their decisions on routes, connections, service levels and their dealings with airports. Moreover, airlines could avoid higher airport fees through long-term contractual agreements with airports (Barbot, 2011).

1.2. Use Agreements

The use of contracts in air transportation is fundamental and integral to the daily operations of airports and airlines in the U.S. An effective coordination has great potential not only to increase air transportation efficiency but also to result in lower prices and improved quality of air travel services.

U.S. airports use three rate-setting approaches to formulate airport use agreements with airlines. The three types of use agreements based on the rate-setting approaches are the residual, compensatory and hybrid methods. In a residual agreement, the host airport obtains financial mitigation by turning over its day-to-day financial risk to the signatory airlines. In turn, the signatory airlines may have reduced airport fees. Unlike the compensatory method, the airport bears all financial risk alone, and the tenant airlines pay the fees according to their use level. The hybrid approach is relatively new; it is a combination of the features of residual and compensatory methods. For example, under a hybrid method, the airport adopts the residual method for aeronautical operations and uses the compensatory method for non-aeronautical operations.

The vertical contractual relationships of airports and airlines can be evaluated in two dimensions: risk and reward. Table 1 below, by Wu (2015), helps us visualize the contract types and their associated tradeoffs between risk and reward. The compensatory method provides more rewards such as airport managerial freedom, non-aeronautical revenues, while it brings more risk to the airport. If an airport chose a residual method, it would bear less financial risk but the reward would be lower as well. The hybrid method is a balance between the first two methods, and therefore the risk and reward of this method are moderate.

Table 1. Risk and Reward Evaluation

		Reward	
		Low	**High**
Risk	**Low**	*Residual*	*Hybrid*
	High	*Hybrid*	*Compensatory*

Source: Wu (2015).

1.3. Objectives

Since vertical business agreements between airlines and airports are the bread and butter of the U.S. air transportation system, and the relationship between airlines and airports could be advantageous and risky, the implications of the use agreements warrant a thorough examination. Although use agreements are the most common and important formal business arrangements between airports and airlines, the effects of use-agreements on airport economic performance have not been well studied yet. In this dissertation, I seek to answer three empirical research questions examined separately in 3 essays. Specifically, the three research objectives of this dissertation are:

1. To examine the three types of airport use agreements and their impacts on airport operational performance (Essay 1);
2. To examine the impacts of the three types of use agreements on cost efficiency (Essay 2);
3. To determine the sources of aeronautical charge differentials between use agreements (Essay 3)

Essay 1 is motivated by the stark contrast between residual and compensatory airport use agreements, namely the unequal risk-bearing of the two agreements. As mentioned earlier, under the residual method, the airport's financial risk is covered by signatory airlines, and in return, the signatory airlines obtain a discount on their user fees. Thus should there be any deficits in its financial standing as a result of its projects and operations, an airport could rest assured that the signatory airlines would help to cover the financial losses. This feature of the residual method could potentially result in a moral hazard problem of the airports. On the contrary, the compensatory method requires airports to bear all financial responsibilities for their operations, and all airlines pay only the cost of the facilities they use or lease at the host airport. Thus, airport operators are more susceptible to economic downturns. Since the airport operators must bear the financial risk of operations, which means they also receive financial rewards if they perform well, they must strive to be efficient and diligent in operations. Therefore, under this method, moral hazard might be less of a concern since each party is responsible for its own financial risk, and neither party can shift its own risk to the other.

In Essay 2, I examine whether the moral hazard problem extends beyond operational inefficiency. Because airports adopting the residual agreement are financially secured due to the financial guarantee of signatory airlines, the airports may also have a diminished focus on operating expenditures (Faulhaber, Schulthess, Eastmond, Lewis & Block, 2010). This could result in non-optimal use of inputs which in turn leads to cost inefficiency, thereby forcing the signatory airlines to bear more financial risk for their airports, and this may, in turn, result in higher user fees paid by the signatory airlines. Thus, the expected benefits of signatory airlines from the residual agreement may not be as high as what they might expect to get. While Essay 1 examines the implications of airport use agreements on airport operational efficiency, it does not address how the use agreement types affect operations in monetary terms. In Essay 2, I focus on airport operating costs, which not only reflect airport managerial performance but also cost performance. This allows me to measure the impact of non-optimization due to the use agreements from a cost perspective and in monetary terms.

Airport operational and cost efficiency are without questions integral to the airport-airline relationship and coordination. However, Essays 1 and 2 do not answer the question how use agreements may affect the aeronautical charges that airlines pay. In Essay 3, I examine how aeronautical charges differ by use agreement and the sources of aeronautical charge differential. The determinants of aeronautical charges have been scarcely analyzed since U.S. airports are public infrastructure. Although the use agreements are developed based on three different rate-setting methods, the impact of these methods on aeronautical charges and charge differential are not well understood. How much of the aeronautical charge differential, if any, is explained by the use agreements? Do residual airports charge lower fees relative to their counterparts using the compensatory or hybrid method? Do lower aeronautical charges mean higher non-aeronautical charges? The findings from Essay 3 will shed light on the airport's pricing strategy.

1.4. Methodology and Data

For Objective 1, I employ a two-stage semi-parametric method developed by Simar and Wilson (2007, or SW) to determine if use agreements affect the operational efficiency of 59 U.S.

hub airports from 2009 through 2016. The two-stage method is a double-bootstrap procedure involving the use of data envelopment analysis in Stage 1 and a truncated regression in Stage 2. The SW method is an improvement over the traditional DEA-regression two-stage method because the latter disregards the fact that DEA efficiency scores are serially correlated and not censored. Therefore, when applying the scores as the dependent variable in a regression model in stage 2, the results are biased, and inferences are invalid (Simar & Wilson, 2007).

For Objective 2, I employed three stochastic cost frontier models: a pooled Aigner, Lovell and Schmidt (1977) model, a Battese and Coelli (1995) model, and a "true" random-effects (TRE) model. In each model, use agreements were used as explanatory variables to measure the impact of use agreements on variable cost efficiency. The TRE model isolates time-invariant airport heterogeneity from inefficiency and enables us to remove bias from inefficiency resulting from time-invariant unobservable factors.

For Objective 3, I examined the determinants of aeronautical charges as well as the sources of the aeronautical charge differentials between use agreements using a two-fold Oaxaca decomposition. Airports are first clustered into three groups in accordance with the use agreement types. My model also accounts for potential endogeneity problems.

I used the data of 30 large hubs and 29 medium hub airports in the years between 2009 and 2016. The information on airport use agreement types was obtained from LeighFisher (2016). The main source of our airport data is the Certification Activity Tracking System (CATS) Database which holds the financial reports of all U.S. commercial airports obtained from the Airport Financial Reporting Program. The information on aeronautical revenues, non-aeronautical revenues, operating expenditures, debt service costs after passenger facility charges, as well as all input and output data were obtained from this database. The financial data were adjusted for inflation using the U.S. gross domestic product deflator.

1.5. Summary of Key Findings

I find that during the study period (2009-2016), airports that chose either the compensatory or hybrid contracts outperformed their peers that adopted the residual contract. In other words, airports choosing compensatory or hybrid contracts were more efficient than the airports choosing residual contracts.

On airport cost performance, I find the mean cost efficiency was 0.935, suggesting that U.S. airports could lower the operating costs by an average of 6.5%. To put things in perspective this value can be translated into $17.93 million in annual cost savings for an average U.S. airport. Moreover, cost inefficiencies differ across use agreement types. The mean cost efficiency of residual airports is 0.925 while it is 0.931 for compensatory airports and 0.948 for hybrid airports. Thus, airports adopting the compensatory and hybrid methods are more cost-efficient than the ones adopting the residual method. This implies that airports under compensatory or hybrid agreements manage their input use more efficiently compared to the airports under the residual method. Hence, lower airport operational and cost efficiency may undercut any benefits that the signatory airlines expect to receive through residual-typed contracts.

In addition, I find that average aeronautical charges are lowest at hybrid airports, and compensatory airports have the highest average aeronautical and non-aeronautical charges. The relationship between aeronautical and non-aeronautical charges is negative under compensatory agreement while it is insignificant for residual and hybrid airports.. The difference in the responsiveness of aeronautical charges to non-aeronautical charges can be explained by the difference in the business practices of use agreements. The main characteristic leading to the aeronautical charge differential between use agreements is average costs.

1.6. Contributions

To the best of my knowledge, the implications of the use agreements on airport economics performance with respect to airport cost and operational efficiency and airport pricing have not been previously studied. This study seeks to fill the void in the literature by looking into the outcomes of the use agreements. The results will shed light on the vertical relationships between airports and airlines and enhance our understanding of the effect of the use agreements on air transport economics. Therefore, this study enables airport and airline management to make informed decisions on balancing risk and rewards.

Specifically, the results point out that the hybrid method may be more preferable to the other two. Although there appears to be no statistical difference in cost and operational efficiency between airports that use the compensatory and hybrid methods, the airports adopt a compensatory agreement have higher aeronautical and non-aeronautical charges, while the airports that adopt a hybrid agreement have the lowest aeronautical charges compared to their counterparts that adopt either of the other two methods. This differential is driven predominantly by their lower average costs. The lower aeronautical charges coupled with a more balanced risk-sharing arrangement between the airports and the signatory airlines under the hybrid method may produce greater benefits to the air transportation sector as well as the society at large in terms of social welfare.

1.7. Dissertation Outline

This dissertation is organized as follows. Chapter 2 is the first essay that examines the effects of use agreements on airport operational efficiency (Objective 1). The second essay, which is focused on the use agreement effects on cost efficiency (Objective 2), is presented in Chapter 3. The third essay, which analyzes aeronautical charge differential (Objective 3), is in Chapter 4. In Chapter 5, I conclude the dissertation with a summary of the research findings, implications, and suggestions for future research.

CHAPTER 2: THE EFFECTS OF USE AGREEMENTS ON AIRPORT EFFICIENCY

2.1. Abstract

Bilateral contracting is integral to the working relationship between airports and airlines. In the U.S., the three common types of airport use agreements are the residual method, the compensatory method, and the hybrid method. Under a residual agreement, the financial risk of the host airport is borne by the signatory airlines, and in return, the signatory airlines pay reduced user fees. Under a compensatory agreement, however, airports bear their own financial risks in the absence of a signatory airline. A hybrid agreement combines the features of residual and compensatory agreements. For example, under a hybrid agreement, airports usually bear their own financial risks in terminal operations while the signatory airlines take over the financial risks in airfield operations. This paper aims to determine whether these three types of business agreements affect airport operational efficiency. Using 2009 to 2016 yearly data of 59 U.S. hub airports, I find that airports with residual-type agreements tend to have lower operational efficiency. This implies that, although under a residual agreement, the signatory airlines pay favorable airport fees, increased airport inefficiency may undercut any potential benefits of the agreement.

2.2. Introduction

In the U.S., while airlines and airports are separate entities, they form an absolutely inseparable vertical relationship in air transportation. The close coordination of the two entities, through their roles and activities in the air transportation network, is indispensable and highly critical for the greater interests of efficiency and welfare beyond the entities themselves. In light of the vast importance of their coordination and mutual reliance, bilateral contracting is integral to the business relationship between airports and airlines.[4]

While airlines in the U.S. are privately owned and managed, airports in the U.S. are owned and operated by local governments or port authorities and financed by local governments. The main financial sources of U.S. airports are user charges, state/local government programs, Airport Improvement Program (AIP) grants, and passenger facility charges (Graham, 2004). Airport user charges are basically aeronautical revenues and non-aeronautical revenues. User charges are used to recover operating expenditures and debt service costs (FAA, 1999). The AIP was established for the purpose of supporting a national integrated airport system. Grants are allocated by the Federal Aviation Association (FAA) based on passenger volume and project basis (Fuhr & Beckers, 2009). Passenger facility charges are enplanement fees charged directly to passengers. Passenger facility charges are usually used for capital projects and maintenance/repair expenditures (FAA, 1999). Yet these sources are not sufficient to fund capital projects and sustain airport operations. For example, airports in the U.S. needed approximately $14.3 billion per year between 2005 and 2009, but the AIP supported just over $3.5 billion in 2006, leaving a gap of $10.8 billion to be funded with other sources (National Academy of Sciences, Engineering, 2007). Thus, airports must seek additional funding opportunities to sustain their capital projects and reduce financial uncertainty.

Having a stable stream of revenues from passenger and cargo services as well as non-aeronautical businesses helps airports maintain a sound financial footing. Although non-

---

[4] In support of competition in air transportation services, current U.S. federal laws require airports to provide access to qualified airlines without unjust discrimination and on reasonable terms, and airports are prohibited from granting exclusive access to any airline (FAA, 1999). In addition, collusion among airlines is illegal under U.S. antitrust laws, and collusive behaviors are prosecuted (Shepherd and Brock, 2013).

aeronautical revenues have been vital for break-even budgets in recent years, airports need to establish various contractual agreements with airlines to cover potential financial risks. Especially in recent decades following the deregulation in 1978, financial volatility within the airline industry could easily spill over to airports as a result of increased airline bankruptcies and cessations of unprofitable service routes. Meanwhile, many airlines are seeking increased values or returns from their relationships with airports. Besides user fees' discounts, airlines also want to increase their connections and abilities to offer a wider range of services to passengers at their hubs. Their increased willingness to shop around also reflects the contestability of the airline industry (Carney & Mew, 2003). Thus, forging a strong and mutually beneficial business relationship with airlines is paramount to airports. When entering a contractual agreement with a tenant airline, an airport must balance between risk and reward, and it must ensure that the outcomes of the agreement are beneficial not only to itself but also to the airline.

For airlines, in addition to securing airport facilities for operations, a vertical contractual relationship with an airport could enable airlines to expand market power by controlling and even potentially foreclosing upstream airport facilities from downstream rivals in the long run. Moreover, airlines could avoid higher airport fees through long-term contractual agreements with airports (Barbot, 2011). However, increased air traffic volumes in recent years have put a substantial constraint on airport capacity. According to the *FAA Aerospace Forecast* (2017), passenger volume in the U.S. is expected to rise by an average of 1.9% per year over the next 20 years. Airport capacity is important to airlines, and airports need reliable partners in the airline industry to ascertain sufficient passengers or customers that are fundamental to the long-term growth and financial stability of the airport. Competition in the downstream air travel market also means that airlines must be strategic about their decisions on routes, connections, service levels and their dealings with airports.

Therefore, vertical contractual agreements between airlines and airports are the bread and butter of the U.S. air transportation system. Besides serving as a legally binding document, contracts enable and motivate the parties involved to work together and take actions that benefit each other. Nevertheless, if either party cannot fully observe or control the other party's action or behavior, the problem of moral hazard may arise (Holmstrom, 1979). Moral hazard in this context refers to the lack of effort on the part of the agent (Eisenhardt, 1989). In other words, the agent may "shirk" or may not put forth sufficient effort. This could have implications for air transportation efficiency since the signatory airlines, as the principal, is not able to control the host airport's performance in operations.

In the U.S., residual, compensatory and hybrid are three common types of airport use agreements. Airports adopting residual agreements obtain a financial guarantee from signatory airlines, and in return, signatory airlines pay reduced airport fees depending on the airport's operating expenditures and non-aeronautical revenues. Unlike the residual method, the compensatory method requires that airports bear their own financial risks in the absence of signatory airlines. The hybrid method is a combination of residual and compensatory methods. Under a hybrid agreement setting, the residual method is usually applied to airfield operations while the compensatory method is utilized in terminal operations.

In this study, I examine these three common types of airport-airline agreements and their impacts on airport operational performance. To the best of our knowledge, the implications of the three common use agreement methods on airport operational efficiency have not been previously studied. This study seeks to fill the void in the literature by looking into the outcomes of the use agreements. The results will shed light on the vertical relationships between airports and airlines and enhance our understanding of the effect of their use agreements on the operational performance of airports. Additionally, the outcomes of this research will enable airport management to make informed decisions on balancing risks and rewards and to sustain and improve airports' coordination with their tenants for the greater benefits of society.

This paper is organized as follows. In Section 2.3, I discuss the three use agreement methods. In Section 2.4, I give a brief review of the studies on the airport-airlines vertical relationship and airport efficiency. Section 2.5 presents the model, and the empirical data are discussed in Section 2.6. I discuss the analysis and empirical results in Section 2.7. Section 2.8 concludes with additional discussions on the effects of use agreements between airports and airlines on airport efficiency.

2.3. Airport Use Agreements

The use of contracts in air transportation is fundamental and integral to the daily operations of airports and airlines in the U.S. An effective coordination has great potential not only to increase air transportation efficiency but also to result in lower prices and improved quality of air travel services. Through various forms of business arrangements, airlines and airports in the U.S. form a close, inseparable partnership in air transportation.

Airport use agreements are one of the most important and common vertical contractual arrangements in the U.S. air transportation industry. The agreement between an airport and its airlines provides both parties privileges, obligations and rights. Through airport use agreement, business arrangement and rate-setting between airports and airlines are established. In addition, the agreements may also stipulate both parties' control spans on airport investment management, responsibilities for financial risks, and conditions for revenue sharing.

An important element of the vertical agreements between airports and airlines is the extent of risk-sharing between the two parties. Economists first explored the risk-sharing problems among collaborating parties (Eisenhardt, 1989). In a principal-agent relationship, problems arise when, according to Eisenhardt (1989, page 58):

"(a) the desires and goals of the principal and agent conflict, and (b) it is difficult or expensive for the principal to verify what the agent is actually doing. The problem here is that the principal cannot verify that the agent has behaved appropriately. The second is the problem of risk sharing that arises when the principal and agent have different attitudes toward risk."

If the agent's behavior is not observable, then the principal can (i) discover the agent's behavior through investing in information systems, and (ii) co-align the agent's preferences with those of the principal's (Eisenhardt, 1989). For example, solution (i) may require the agents to fulfill certain reporting obligations, and solution (ii) aims to motivate the agent through an outcome-based contract. That is, the principal rewards the agent based on the outcome, which may be the agent's output or performance, and this solution inherently shifts some risk to the agent, so the principal does not bear all the risk in the vertical relationship.

In the U.S., the three primary airport use agreement approaches are the residual method, the compensatory method and the hybrid method (FAA, 2009). Under the residual method, the airport's financial risk[5] is covered by signatory airlines, and in return, the signatory airlines obtain a discount on their operation fees. Thus should there be any deficits in its financial standing as a result of its projects and operations, an airport could rest assured that the signatory airlines would help to cover the financial losses. Hence, airports always achieve a break-even point. Under this agreement setting, airports tend to have a large debt to equity ratio and limited

[5] Here the financial risk refers to the risk associated with the airport operator's day-to-day operations (Faulhaber et al, 2018), rather than the risks of catastrophic events, risks that may arise outside a normal business environment, or any risks that result from the signatory airlines' bankruptcy or merger that leads to de-hubbing.

cash availability. In addition, most of the residual agreement includes a majority in interest (MII) clause in which airports' decisions and levels of control are restricted and capital projects may need to be reviewed and approved by the signatory airlines that bear the airport's financial risk (Faulhaber et al., 2010; Van Dender, 2007).

Although the signatory airlines obtain benefits from a residual-typed agreement by avoiding high user fees, and by fortifying their competitive advantage in the downstream market, taking on extra-financial risks might substantially raise the financial burden of airlines that are already facing operating and other financial risks of their own. Airport's moral hazard problem might further exacerbate the problem. Therefore, if the airports do not have enough incentive to strive for better operational and cost efficiency, the signatory airlines might experience additional problems in operations in addition to the financial and economic risks they already bear. Besides these, because of the nature of long-term contracts, both sides may encounter hold-up problems down the road. Since transaction costs are high in this type of agreement, contracts will be binding during the contract term. In the past, especially prior to the Airline Deregulation Act of 1978, most agreements followed the residual method. These residual contractual agreements are still common at airline hub airports, allowing them to pass on operating costs to the signatory airlines that demand most of the facility (Faulhaber et al., 2010).

Contrary to the residual method, the compensatory method requires airports to bear all financial responsibilities for their operations, and they do not prioritize any airlines, and all airlines pay only the cost of the facilities they use or lease at the host airport. Without the revenue assurance of signatory airlines, a compensatory airport must consider the break-even constraint, that is the total revenues from the airline and non-airline sources must be enough to offset all airport expenditures.[6] Considering that they have more control over their own projects and operations, airports need to constantly evaluate their operations as well as long-term projects and plans. Thus, airport operators are more susceptible to economic downturns. Since the airport operators must bear the financial risk of operations, which means they also receive financial rewards if they perform well, they must strive to be efficient and diligent in operations. Therefore, under this method, the moral hazard that may potentially arise from the principal-agent relationship is less of a concern since each party is responsible for its own financial risk, and neither party can shift its own risk to the other.

As inferred by the name, the hybrid method is a combination of residual and compensatory methods. An airport may choose to adopt the residual method in airfield operations and a compensatory method in terminal operations. Depending on the level of risk each party is willing to bear, according to Faulhaber et al. (2010), the options for a hybrid contractual scenario is "endless." Under the hybrid agreement, the financial risk burden is shared between the airports and their signatory airlines. Besides this, the contract may include revenue sharing contingent upon excess non-aeronautical revenue at the airport (Faulhaber et al. 2010). [7] Therefore, airport operators have more freedom over the use of their resources and surplus funds, but they usually give up some control over capital plans besides sharing revenues with airlines. Under a hybrid agreement, airports do not have to bear the financial risk on airfield operations since that risk may be covered by signatory airlines, which in turn obtain a deduction on the

[6] U.S. hub airports are government owned or operated. The business goal is to break even rather than aiming for the maximum profits. In fact, the FAA strictly prohibits airports from making any revenue surpluses (FAA, 2008).
[7] Fu and Zhang (2010) found that airport's revenue sharing has potential implications on welfare and airline competition. Since airports rely on airlines to bring in travelers to consume airports' commercial services, sharing concession revenues with airlines may help improve the financial returns to both airports and airlines. However, Fu and Zhang (2010) found that revenue sharing may also harm downstream competition.

operation fees paid to their host airports. But since non-aeronautical operations are separated from aeronautical operations under the hybrid method, the airport must bear the financial risk in non-aeronautical operations. This creates a balanced risk-sharing mechanism between the airport and the signatory airlines, unlike the residual approach that has the signatory airlines be the financial risk bearer of their host airport, and unlike the compensatory approach that has the host airport as the sole financial risk bearer for its aeronautical and non-aeronautical operations. Therefore, the hybrid method creates a more balanced risk sharing and can help overcome the under-effort problem and restore losses in the utility of both airports and airlines (Hihara, 2012). Table 2 below highlights and summarizes the differences in the three agreement methods, and I discuss three airport examples below.

Table 2. Differences in the Three Agreement Methods

	Residual	**Compensatory**	**Hybrid**
Prioritized signatory airlines[8]	Yes	No	Yes - Airfield operations No - Terminal Operations
Airfield	Signatory airlines pay the residual amount after non-aeronautical revenues and revenues from non-signatory airlines. Non-signatory airlines pay higher landing fee, usually 125% the calculated landing fee of signatory airlines.*	All airlines pay the same rate according to the levels of use	Signatory airlines pay the residual amount after non-aeronautical revenues and revenues from non-signatory airlines. Non-signatory airlines pay higher landing fee, usually 125% the calculated landing fee of signatory airlines.*

[8] All airlines signing contracts with the airport are signatory airlines under all three rate setting methods. However, prioritized signatory airlines obtain reduced fees and have control over airport capital investments.

Table 2. Differences in the Three Agreement Methods (continued)

	Residual	Compensatory	Hybrid
Terminal	Signatory airlines pay the residual amount after non-aeronautical revenues and revenues from non-signatory airlines.	All airlines pay the same rate according to the levels of use	All airlines pay the same rate according to the levels of use
Airlines provide a financial guarantee to airports	Yes	No	Yes - Airfield operations No - Terminal operations
Airport shares non-aeronautical revenue with signatory airlines	Yes	Yes & No	Yes
Airport financial risk bearer	Signatory airlines	Airport	Signatory airlines - Airfield operations Airport - Terminal operations
Majority-in-interest clause	Yes	No	Yes - Airfield operations No - Terminal operations

*Generally, there are two primary types of residual rate-setting mechanisms. The first is the "airport residual" method or the "single cash register" method by which the landing fee is calculated to cover all the residual airport costs that are not covered by revenues from all (airline and non-airline) sources. Thus, the landing fee is a balancing mechanism to ensure that the airport will not incur a deficit. The second residual rate-setting mechanism is the "cost center residual" method by which airport costs and revenues are allocated to airline cost centers (e.g. airfield, terminal, and other areas) from which airline rates (in the airfield, terminal buildings, and apron areas) are derived. Details on the two methods and rate calculations are discussed in Faulhaber et al. (2010).

On the west coast of the U.S., San Francisco International Airport (SFO) has adopted the residual method since 1981. Under the airport's 2011 Lease and Use Agreement guideline[9], the signatory airlines offer a financial guarantee by covering SFO's expenditures. For example, "Under the Lease and Use Agreement, the airlines are required to pay terminal rents and landing fees in amounts that, when aggregated with certain other Airport revenues, will be equal to the

[9] The 2011 Lease and Use Agreement went into effect on July 1, 2011 and will expire on June 30, 2021.

Airport's expenditures for: operating expenses other than depreciation and amortization; principal and interest on outstanding debt; annual service payments to the City; and certain acquisitions of capital assets. Airline payments are also required to cover expenses treated as "Operations and Maintenance Expenses" under the Master Bond Resolutions. Other capital asset additions are funded with proceeds of revenue bonds for which the airlines are required to fund debt service (San Francisco International Airport, 2018, page 47)."[10]

Additionally, in return for the financial guarantee they offer to SFO, the signatory airlines receive 85% of the airport's concession revenues (San Francisco International Airport, 2011). Meanwhile, non-signatory airlines operate under short-term month-to-month operating permits and are required to pay a 25% premium over the landing fees paid by the signatory airlines. For example, in 2019, the landing fee for signatory airlines at SFO was $5.80 per 1000 pounds of landed weight, compared to $7.25 per 1000 pounds for non-signatory airlines (San Francisco International Airport, 2019). In addition, in return for the financial guarantee provided by the signatory airlines, under the majority-in-interest (MII) [11]clause in the use agreement, all proposed airport projects at SFO exceeding the Charge Trigger Amount of $672,500 (in the 2014/15 fiscal year) are subject to review by the signatory airlines. SFO gives the signatory airlines 45 days to review or object to the airport's proposed capital project. The signatory airlines may ask SFO to defer a proposed project no longer than 6 months to allow more time for discussion. The lease

[10] If in a fiscal year there exists a difference in the actual airport revenues and expenditures and estimates of airline fees and charges, the landing fees and terminal rental rates in the subsequent year will be adjusted.

[11] The MII is defined as more than 50% of the number of airlines on schedule; these airlines must account for more than 50% of the aggregate revenue aircraft landed weight by the signatory airlines in the previous fiscal year (San Francisco International Airport, 2014).

and use agreement does allow SFO to move forward with the project after a six-month waiting period (San Francisco International Airport, 2014).

Unlike SFO, Boston's Logan International Airport (BOS) uses the compensatory method on which the landing fees and terminal rentals are determined every year (in October) by the Massachusetts Port Authority (MASSPORT) to cover the direct and allocated costs of capital, administration, maintenance, and operations. In 2018, the landing fee for all airlines was $4.6 per 1000 pounds of landed weight. The landing fees and terminal rental rates are calculated based on the airport's historical capital costs and projected landed weights as well as the budgeted direct and allocable indirect operating costs of the fiscal year. If deemed necessary, MASSPORT may adjust the landing fees and terminal rental rates during the year to recover its actual capital and budget operating costs. MASSPORT also has significant control over terminal facilities (Massachusetts Airport Authority, 2018). BOS does not share its non-aeronautical revenues with airlines (LeighFisher, 2016). [12]

In the Midwest, Minneapolis-St. Paul International Airport (MSP) has used the hybrid method for over 20 years. It adopts a blend of the compensatory method for its terminal building cost center and the residual method for the airfield cost center. In airfield operations, the landing fees[13] are residual, so the signatory airlines pay or guarantee 100% of the cost of the airfield. Non-signatory airlines are required to pay a 25% premium over the landing fee paid by the signatory airlines. In terminal operations, the terminal building costs are calculated on a compensatory basis by which the airlines pay for their own share of rentable space in the

[12] Some compensatory airports share their non-aeronautical revenues with airlines. Examples: the international airports in Los Angeles, Orlando, Houston, Salt Lake City, Columbus, etc.
[13] Landing fees consist of direct operations, maintenance and debt services expenses, plus allocated police, fire, labor and administration costs.

terminal at MSP (e-mail communication with MSP's Metropolitan Airport Commission, August 29, 2019). MSP also shares with airlines 25% or 50% of its annual gross revenues for selected concessions, if the gross revenues reach certain predetermined thresholds. The portions are reduced if the minimum revenue requirement is not met. Supplemental revenue sharing is also given to airlines if the volume of enplaned passengers exceeds a predetermined level in a given fiscal year.

Before airline deregulation, airport-airline agreements were based on mostly the residual method, and the contract duration could be as long as 30 years. The length of the agreement has shortened after deregulation due to increased variability in the air transportation sector for both airlines and airports. In recent years, contract durations for medium and large airports may be as long as 10-25 years, shorter durations are negotiable or available at some airports. The coordination and working relationship between airports and airlines also come in many varieties in addition to airport use agreements. Since the relationship between airlines and airports could be advantageous to both parties strategically, operationally and financially, other forms of airline-airport relationships, ranging from various joint ventures to risk sharing, have existed. Fu, Homsombat and Oum (2011) discussed the different arrangements in detail.

In summary, in a normal day-to-day business environment, residual agreements offer more financial insulation to airport operators compared to the other two types of agreements. For example, residual agreements reduce the host airport's risk of having a budget shortfall because of the financial guarantee provided by the signatory airlines. It is noteworthy, however, that none of the three agreement methods mitigates catastrophic event risks or any risks associated with circumstances outside a normal day-to-day business environment. Regardless of the types of agreements, airline mergers and bankruptcies, for example, could disrupt the day-to-day operations of the host airports and could potentially result in hub abandonment by the tenant airlines. Nevertheless, compared to compensatory and hybrid agreements, residual agreements provide airports with more financial security during the normal course of business.

2.4. Literature Review

As part of a broader network industry, airport operational efficiency is essential for air transportation and the overall system efficiency. For airport efficiency analyses, data envelopment analysis (DEA) has been a popular method. Using DEA models, Sarkis (2000) studied the efficiency of 44 US airports with data between 1990 and 1994; the study found that the overall mean efficiency of US airports was increasing due to increased competition and better resource utilization. Also using DEA, Bazargan and Vasigh (2003) analyzed the efficiency of 45 U.S. hub airports of large, medium and small sizes as classified by the FAA. Under the constant returns to scale assumption, they found that smaller airports were more efficient.

Another popular method for evaluating airport efficiency is stochastic frontier analysis (SFA). Pels, Nijkamp and Rietveld (2003), for example, conducted an efficiency analysis of 33 European airports between 1995 and 1997 using both DEA and SFA models. In their parametric SFA model, Pels at al. (2003) tried to explain inefficiency using dummy variables for slot-coordinated airports and time restriction. After that, a second production frontier was estimated with air passenger movements (APM) being the output variable and the predicted ATM from the first production frontier estimation was used as one of the explanatory variables. In this second frontier model, the inputs are the number of check-in desks and the number of baggage claim units. The variables explaining inefficiency were a time dummy and airlines' load factor. For the non-parametric (DEA) model, the ATM and APM outputs were analyzed separately as in the parametric model but all inputs were used simultaneously for the production of the two outputs.

Results from the first parametric model indicate that slot-coordinated airports and airports with limited hours of operation were less inefficient. The latter result, as explained by Pels et al. (2003), may be due to the reason that airports with no time restriction (open for 24 hours) experience too little traffic during night time. In the second parametric model, Pels at al. (2003) found that efficiency increases with carriers' load factors. Pels et al. (2003) did not report the estimated inefficiency scores from the parametric models, but results from the DEA model show that, on average, airports operated under constant returns to scale, but the smallest airports operated under increasing returns to scale and had low scale efficiency. They found that airports were inefficient in general but some privately owned or corporatized ones seemed to perform better on average (Pels et al., 2003).

Many airport efficiency studies in the past 2 decades focused on airport governance, namely the effect of privatization on airport efficiency. For example, using an unbalanced panel dataset of 109 airports around the world and considering six categories and types of airport ownership and institutional forms, Oum, Yan and Yu (2008) analyzed the cost efficiency of airports via a Bayesian SFA model. As an extension to Oum et al. (2008), Assaf and Gillen (2012) analyzed the effect of economic regulation on airport efficiency using DEA and a Bayesian distance stochastic frontier model.

While the non-parametric DEA is a more common method for estimating the technical efficiency of multi-output firms, SFA can also be modeled with multiple outputs by means of a parametric distance function approach (Coelli & Perelman, 2010). For example, Abrate and Erbetta (2010); Martini, Scotti, and Volta (2013), and Scotti, Malighetti, Martini, and Volta (2012) analyzed Italian airports' technical efficiency with a stochastic distance function approach.

In addition to the above parametric and nonparametric approaches, some semiparametric methods are used for analyzing airport efficiency. Semiparametric methods relax certain constraints of both parametric and nonparametric methods. In the semiparametric method, multi-output can also be used whereas the effects of environmental variables can be analyzed in the second stage. For example, D'Alfonso, Daraio and Nastasi (2015) analyzed the effects of competition on the technical efficiency of 34 Italian airports in 2010 using a two-stage analysis method following the study of Badin, Daraio and Simar (2012). They concluded that competition among airports negatively affects efficiency.

Another semi-parametric analysis of airport efficiency was conducted by Barros and Dieke (2008). They evaluated 31 Italian airports' technical efficiency for 2001-2003 using a semi-parametric method proposed by Simar and Wilson (2007, SW henceforth). The SW method involves a bootstrap procedure with the use of DEA and a truncated regression model. In the regression model, the potential efficiency determinants they considered, besides a time trend, were hubs (regional hub = 1, 0 otherwise), workload unit (WLU)[14], management type (private vs. public)[15] and a regional dummy (Northern Italian = 1, 0 otherwise). They found that private ownership and hub airports are more efficient than others. However, Barros and Dieke (2008) did Not further break down the types and extent of private ownership and governance. The above-mentioned studies are summarized in Table 3.

---

[14] 1 WLU = 1 passenger or 100 kg of freight (Doganis, 1978). Since WLU is composed of passenger and cargo volumes, rather than being considered a determinant of airport efficiency, it is traditionally used as an aggregated output with a ratio of 10:1 passenger-cargo relationship for airports (Doganis, 2005). See Humphreys and Francis (2002), Martini et al. (2013), Scotti et al. (2014), among others.

[15] Barros and Dieke (2008) considered two categories of ownership using a dummy variable which is equal to 1 for airports fully managed by private organizations and zero otherwise.

Table 3. Summary of Airport Efficiency Studies

Authors	Sample	Model	Inputs	Outputs
Gillen and Lall (1997)	21 Major US airports for 1989-1993	DEA (VRS-CRS)/ Output	➢ Runways ➢ Terminal space(m^2), ➢ Gates, ➢ Employees ➢ Baggage collection belts ➢ Car parking spots ➢ Airport area ➢ Runway area	➢ Passengers, ➢ Cargo (tons) ➢ Air Traffic Movements (ATM) ➢ Commuter ATM
Parker (1999)	22 UK airports for 1979-1995, 1988-1996	DEA (VRS-CRS)/ Input	➢ Employees ➢ Capital input ➢ Operation costs	➢ Passengers ➢ Cargo
Sarkis (2000)	44 major Airports	DEA (VRS-CRS)/ Input	➢ Operation costs ➢ Employees ➢ Gates ➢ Runways	➢ Operational revenue ➢ Passengers ➢ ATM ➢ Cargo ➢ General aviation movements
Martin & Roman (2001)	37 airports in Spain for 1997	DEA (VRS)/Output	➢ Labor ➢ Capital ➢ Material	➢ Passengers ➢ Cargo (tons), ➢ ATM
Pels et al. (2003)	33 European airports for 1995-1997	DEA (VRS) & SFA / Input	➢ Surface area ➢ Runways ➢ Check-in desks ➢ Baggage claim units ➢ Parking position terminal ➢ Remote parking position	➢ Passengers ➢ ATM
Bazargan and Vasigh (2003)	45 US airports for 1996-2000	DEA (CRS)/Input	➢ Operation cost ➢ Non-operating cost ➢ Runways ➢ Gates	➢ Passengers ➢ ATM ➢ Commuters ➢ Aeronautical revenues ➢ Non-aeronautical revenue ➢ %ontime operation

Table 3. Summary of Airport Efficiency Studies (continued)

Authors	Sample	Model	Inputs	Outputs
Oum, Yan and Yu (2008)	109 international airports for 2001-2004	Bayesian SFA Model	➢ Runways ➢ Terminal size ➢ Number of employees ➢ Non-labor variable cost	➢ Passengers ➢ Aircraft movements ➢ Non-aeronautical revenues
Barros and Dieke (2008)	31 Italian airports for 2001-2003	Simar and Wilson Model	➢ Labor cost ➢ Capital invested ➢ Operational costs less labor costs Environmental variables: ➢ Time trend ➢ Hubs ➢ WLU ➢ Management type ➢ Regional factors	➢ Number of aircrafts ➢ General cargo ➢ Aeronautical sales ➢ Commercial Sales ➢ Number of Passengers ➢ Handling receipts
Abrate and Erbetta (2010)	26 Italian airports for 2001-2005	Translog stochastic input distance function	➢ Labor cost ➢ Material and services expenditures ➢ Quaxi-fixed capitial inputs: • Apron area for aircraft parking • Surface area	➢ Number of passengers ➢ Ground handling revenues (revenues from services related to aeronautical operations) ➢ Commercial (non-aeronautical) revenues
Scotti, Malighetti, Martini and Volta (2012)	38 Italian airports for 2005-2008	Translog stochastic output distance function	➢ Max number of authorized flights per hour ➢ Number of aircraft parking positions ➢ Terminal surface area ➢ Number of check-in desk ➢ Number of baggage claims ➢ Number of full-time-	➢ ATM ➢ APM ➢ Tons of freight

Table 3. Summary of Airport Efficiency Studies (continued)

Authors	Sample	Model	Inputs	Outputs
Assaf and Gillen (2012)	73 International Airports for 2003-2008	Bayesian distance SFA	➢ Number of employees ➢ Operational costs ➢ Number of Runways ➢ Terminal size	➢ Passengers ➢ Aircraft movements ➢ Non-aeronautical revenues
Martini, Scotti and Volta (2013)	33 Italian Airports for 2005-2008	Classical distance function and Hyperbolic distance function.	➢ Max. number of authorized flights per hour ➢ The number of aircraft parking position ➢ The terminal surface area ➢ The number of check-in desks ➢ The number of baggage claims ➢ The number of employees	➢ Aircraft movements ➢ WLU ➢ Weighted Local Pollution
D'Alfonso, Daraio and Nastasi (2015)	34 Italian Airports for 2010	Conditional nonparametric frontier analysis	➢ Airport area(m^2) ➢ Number of runways ➢ Number of passenger terminals ➢ Number of gates ➢ Number of check-in counters ➢ Number of employees	➢ Number of passengers ➢ Number of aircraft movements ➢ Amount of cargo
Gallego, San Roman and Sanchez (2017)	Spanish Airports for 2009-2014	Input oriented distance model: Parametric and error component	➢ Labor ➢ Capital ➢ Intermediate consumptions	➢ WLU ➢ Operation revenues

The effects of the vertical relationship between airports and airlines on airport efficiency have been scarcely analyzed in the literature. The earliest study I found was conducted by Gillen and Lall (1997) who analyzed the technical efficiency of 21 US airports between 1989 and 1993 using a two-stage DEA-regression approach. In their DEA model (stage 1), they used two outputs (number of passengers and pounds of cargo) and six inputs (number of runways, number of gates, terminal area, number of employees, number of baggage collection belts and number of public parking spots) to measure terminal and airside efficiency. After they obtained the relative efficiency scores of airports in stage 1, at the second stage, they regressed the logged efficiency scores on environmental (annual service volume), structural (number of runways, land area and number of gates) and managerial (use of gates, financing regime, noise strategies, proportion of general aviation traffic, existence of hubs at airport) variables in a Tobit regression. One of the managerial variables they considered was the type of airport use agreements. They argued that residual financing was more efficient for airside operations whereas compensatory was more efficient for terminal operations. This result could imply that airports with a hybrid agreement might be more efficient. However, Gillen and Lall (1997) did not examine any form of vertical business agreement in their model. While very commonly used, the two-stage DEA-regression method in Gillen and Lall (1997) was later deemed inappropriate by Simar and Wilson (2007) -- a point I will discuss later.

Vasigh and Hamzaee (1998) developed a model to understand which agreement method is most desirable for airports in terms of their financial performance. They compared the airport's financial performances under the compensatory method, the residual method, the hybrid method, and privatization. The results of this study show that the marginal contribution of the residual method to airport profitability is about $0.63 per enplaned passenger, while the marginal contribution of the compensatory method is $2.11 per enplaned passenger. Based on these results, they argued that a compensatory arrangement contributes more to the profit of an airport. In addition, they argued that airports prefer to recoup their own expenses via non-aeronautical revenues rather than aviation revenues.

Focusing on productivity, Oum, Zhang and Zhang (2004) examined the effects of use agreements on total factor productivity and capital input productivity of airports when they analyzed the effects of single till [16] and dual till. They matched compensatory agreement with the dual till, and residual agreement with the single till. In the empirical part of the paper, they examined the effects of airport productivity indicators on capital input productivity and total factor productivity for 60 airports in 1999; the sampled airports include 11 airports in Asia, 18 airports in Europe, and 31 airports in North America. They also assessed the effect of single-till and dual-till variables on airport productivity. They found that airport capital input productivity is higher under single-till pricing (or a residual agreement). On the contrary, total factor productivity is higher under dual-till pricing (or compensatory).[17]

Much of the literature on airport performance has thus far focused mostly on the effects of governance and privatization on airport efficiency, and airport productivity. A few studies noted above had attempted to examine the airport-airline vertical relationship and airport pricing, but none has examined the three agreement methods in-depth and their effects of airports. Our study aims to fill this gap in the literature. The results will shed light on the efficiency implications of the current standard practice in U.S. airport-airline relationships.

2.5. Method

DEA is a non-parametric mathematical programming technique for frontier estimation and analysis. The measurement of productive efficiency was first proposed by Farrell (1957)

[16] Single-till refers to an airport's decision about aeronautical charges based on both aeronautical and non-aeronautical revenues. Dual-till price cap refers to an airport's current aeronautical charges that are based only on its aeronautical revenues. Bilotkach, Clougherty, Mueller and Zhang (2012) examined the effects of single-till and dual till on aeronautical charges, and found that single till decreases aeronautical charges.

[17] It is important to note that, albeit related, productivity and (operational) efficiency are two different economic measures. Productivity can be broadly defined as the ratio of outputs to inputs, whereas operational or technical efficiency measures the ability of a firm to achieve a maximum output with a set of inputs, or the ability to obtain a given level of output with the least inputs (Coelli, Rao, O'Donnell and Battese, 2005). Oum, Zhang and Zhang (2004) referred specifically to airport productivity.

using a piece-wise linear convex hull approach. Charnes, Cooper and Rhodes (1978) then developed a mathematical programming efficiency measurement. DEA is used to determine an envelopment surface which is the efficient frontier through these DMUs. DMUs located on the frontier are considered efficient, whereas DMUs that are located away from the frontier are considered inefficient. After that, the distances between the inefficient DMUs to the efficient frontier are measured. There are in general two types of DEA models. The first of which was proposed by Charnes et al. (1978), and it assumes a constant return to scale (CRS). The other type was proposed by Banker, Charnes and Cooper (1984); it is an extension of the first to account for variable returns to scale (VRS) in production processes. As their names indicate, VRS exists when there are increasing or decreasing returns to scale.

As discussed in the previous section, DEA has been widely used in airport efficiency studies because of its capability of incorporating multiple outputs and inputs of decision-making units (DMUs). In our DEA model, each DMU uses a set of inputs to produce outputs. I assume the goal of airports is to maximize their output levels given the available inputs and prevailing production technology. Thus an output-oriented DEA model is developed.

There are $i = 1, \dots, n$ DMU's (or airports), and each DMU uses k inputs to produce m outputs. The output-oriented measure of technical efficiency for the i^{th} DMU can be obtained by solving the following linear programming problem:

$$\max_{\omega,\lambda} \omega; \tag{2.1}$$

$$s.t. -\omega y_i + Y\lambda \geq 0,$$

$$x_i - X\lambda \geq 0,$$

$$\lambda \geq 0,$$

where

y_i is an $m \times 1$ vector of output quantities for the i^{th} DMU,

x_i is a $k \times 1$ vector of input quantities for the i^{th} DMU,

Y is an $n \times \text{m}$ matrix of output quantities for all n DMUs,

X is an $n \times \text{k}$ matrix of output quantities for all n DMUs, and

λ is an $n \times 1$ vector of weights, and ω is a scalar.

Model (1) assumes CRS technology, which means that airports are assumed to be operating at an optimal scale. One can invoke the VRS technology assumption by incorporating a convexity constraint, $\sum_{i=1}^{n} \lambda = 1$, in the linear programming model (1). The mathematical programming problem (1) is solved n times, once for each of the n DMUs. The solution to (1) is greater than 1, that is, $1 \leq \omega < +\infty$. This is a Farrell (1957) output-oriented measure of inefficiency. If $\omega = 1$, the DMU is considered technically or operationally efficient. If $\omega > 1$, the DMU is operationally inefficient, and $1 - \omega$ measures the proportional expansion of output that could be achieved by the i^{th} airport without changing its level of input use. It is common to invert the Farrell (1957) measure to get the Shephard (1970) measure of operational efficiency, $\theta = \frac{1}{\omega}$ so $0 < \theta \leq 1$, where $\theta = 1$ implies operational efficiency, and $\theta < 1$ implies operational inefficiency. Since I would like to assess the variation in efficiency and to interpret the effect of airport characteristics on airport efficiency in percentage terms, the Farrell inefficiency scores ω are inverted to create a Shephard's measure of operational efficiency, θ, in the second-stage regression.

The input variables in Model (1) are the number of employees, the effective number of standard runways, airport land area, number of gates, and total operating expenditures minus personnel expenditures. The output variables are WLU and non-aeronautical revenues. Although

Model (1) provides the efficiency scores of airports, the variation of the scores is yet to be explained. For this purpose, traditionally, the efficiency scores obtained from DEA are regressed on potential environmental factors in a second- stage which commonly involves estimating a Tobit model (a censored regression), an OLS model, or a logit fractional regression model. This two-stage approach is ubiquitous in the literature, however, the problem of it is that the DEA efficiency scores in stage 1 are serially correlated in an unknown way. Moreover, the fact that environmental variables are not independent respect to output and input leads to a correlation between error terms and environmental variables at the second stage. Therefore, when applying the scores as the left-hand-side variable in a regression model in stage 2, the results are biased, and inferences are invalid (Simar & Wilson, 2007). Moreover, the use of a Tobit regression model is inappropriate because the efficiency scores are not censored.

Since the objective of this study is to determine the effects of use agreement types on efficiency, I estimate a regression model to explain the variation in the efficiency scores. I use a two-stage semi-parametric method developed by Simar and Wilson (2007) to address the weakness associated with the regression model of the traditional two-stage approach. The truncated regression is given by:

$$\hat{\theta}_i = \mathbf{z_i}\beta + \varepsilon_i \tag{2.2}$$

where $\hat{\theta}_i$ are the Shephard efficiency estimates from Model (1), and ε_i are drawn from a two-sided truncated normal distribution at $-z_i\hat{\beta}$ on the left and at $(1 - z_i\hat{\beta})$ on the right. This ensures that the Shephard output-oriented measures are bounded between 0 and 1. Moreover, ε_i is independent of $\mathbf{z_i}$, which is a vector of explanatory variables. I follow Algorithm 2 proposed in SW, which is a bootstrap procedure that uses bias-corrected efficiency scores as the dependent variable in (2).[18] I take into account the two-sided truncation in the SW Algorithm 2 bootstrap procedure and estimate our model using the Stata command developed by Badunenko and Tauchmann (2018).

Because I would like to evaluate the effects of use agreement types on technical efficiency, the explanatory variables in the second-stage regression model include binary variables for the contract types. Since there are three contract types, only two binary contract variables were incorporated into the model. The first binary variable is *Compensatory*, which is equal to 1 for airports adopting the compensatory method, and 0 otherwise. The second method is *Hybrid*, which is equal to 1 for airports adopting the hybrid method, and 0 otherwise. The control group is airports that adopt the *Residual* method. Besides the contract types, the regression model also accounts for airport governance that may potentially affect operational efficiency. Following Kutlu and McCarthy (2016), airport governance is classified into these four categories: *Port/Airport Authority, City, State and County*. *Port/Airport Authority* was selected as the control group while *City, State, and County* are used as binary variables in the model. In addition, airport size was included as an explanatory variable in the regression model. Specifically, to control for airport operating size, the regression model also incorporates large-size hubs as a binary variable, so medium hubs are in the base group. [19]Thus,

$$\mathbf{z_i}\beta = \beta_0 + \beta_1 Compensatory_i + \beta_2 Hybrid_i + \beta_3 County_i + \beta_4 City_i + \beta_5 State_i + \beta_6 LargeHub_i \tag{2.3}$$

[18] Details on the bootstrap procedures are discussed in Simar and Wilson (2007). A two-sided truncation adjustment was made in the estimation procedure to account for the unit interval of the efficiency scores (Badunenko and Tauchmann, 2018).
[19] The regression model does not account for airport capacity since it is inherently controlled for by the number of standard runways, airport land area and gates along with other input and output variables in the DEA model, and the DEA scores reflect airport efficiency given these input levels.

where the parameters β_1 through β_6 provide measures of the effects of use agreement types, governance and hub-size on airport operational efficiency, $\hat{\theta}_i$. In particular, positive estimates of β_1 or β_2 would imply that, relative to the residual method, the compensatory method or the hybrid method contributes positively to airport operational efficiency. The variables $Compensatory$ and $Hybrid$ are intrinsically exogenous since the methods were determined or "grandfathered in" from years or decades ago, and current airport operators just develop their budgets and calculate their charges, fees, and rentals based on the method already set in place.[20] On governance, β_3 through β_5 are expected to have negative signs, meaning county-, city- and state-operated airports are expected to have lower efficiency relative to port- or airport authority-operated airports, since Craig, Airola and Tipu (2012, page 726) found that airport authorities tended to be more efficient because these entities "allows an institutional structure to evolve that is considerably streamlined compared to that from general-purpose governments."[21] Zhao, Choo and Oum (2014) also found that airport authorities tend to be more cost-efficient compared to airports operated by a government branch.

2.6. Data

The main source of the data is the Certification Activity Tracking System (CATS) Database. Under the FAA Authorization Act of 1994, all commercial service airports are required to report their annual financial data to the FAA. The information submitted by airports

[20] For examples, SFO has used its current (residual) agreement method since 1981 and MSP has used the hybrid method for over 20 years. In 2013, Chicago-Midway (MDW) decided to retain the residual method for another 15 years, and Denver International Airport (DEN) is currently using a hybrid method until 2025 for a total of 30 years (LeighFisher, 2016). Additionally, some contract durations can be as long as 25 years at some airports; while switching is possible, it is difficult for airports to unilaterally switch from one method to another in any given year without violating the terms and conditions that they had previously agreed on with the signatory airlines.
[21] Craig et al. (2012) compared efficiency of airports managed by airport authorities and city governments.

under the Airport Financial Reporting Program is then available to the public through the CATS. I examined the data of 59 large and medium hub airports classified by the FAA. The data covers the years between 2009 and 2016. From the CATS, I obtained the number of employees, operating expenses, personnel expenditures, number of passengers, landed weights in pounds, and total non-aeronautical revenues. In addition to these variables, the number of gates was obtained from airports' websites while the runway data were obtained from FAA Aeronautical Information Services[22]. Besides, I obtained airport land area data from the Airport GIS data portal of FAA[23]. The input variables in Model (1) include the number of airport employees, the effective number of standard runways[24], airport land area, the number of gates, and total operating expenditures minus personnel expenditures.

There are two output variables in Model (1). Following Martini et al. (2013), Scotti et al. (2014), McCarthy (2016), Gallego, San Román and Sánchez (2017), I include WLU as one of the output variables for airport's aeronautical operations. The second output variable in Model (1) captures the commercial or non-aeronautical output of airports and is measured by non-aeronautical revenues. The descriptive statistics of the variables are shown in Table 4. I used use-agreement types, hub size and governance forms as determinants of airport operational efficiency in the regression model. The information on use-agreement types and hub sizes for each airport was obtained from LeighFisher (2016). The information on governance forms was

[22] https://www.faa.gov/air_traffic/flight_info/aeronav/aero_data/Airport_Data

[23] https://airports-gis.faa.gov

[24] Since there is no standard measurement for runways, using the number of runways as an input measure can be biased. The effective number of standard runways introduced by McCarthy (2014) sought to address this issue. It is measured by $\sum_r (Length_{rit})(Width_{rit})/1{,}500{,}000$ for the r^{th} runway of i^{th} airport in t^{th} year. Since a runway having dimensions 10,000 by 150 feet can be used for aircrafts of most sizes except for some extreme aircraft sizes, the runway measure can be standardized.

obtained from the National Academies of Sciences, Engineering, and Medicine (2009). Appendix A presents the classifications of the airports by governance form, hub size and agreement type.

Table 4. Descriptive Statistics for Outputs and Inputs

		OUTPUTS		INPUTS				
YEARS		**WLU ($x10^6$)**	**NON-AERO. REV. ($x10^6$)**	**OP. EXP. less LABOR COST($x10^6$)**	**Gates**	**Employees**	**ENSR**	**Land Area ($x10^3$)**
2009	MEAN	17.8	95.4	154.8	72.8	557.9	3.4	4.8
	SD	16.0	72.9	132.4	46.3	508.5	2.04	5.3
2010	MEAN	18.5	97.7	159.2	72.8	547.4	3.4	4.8
	SD	17.6	75.2	133.9	46.3	495.4	2.04	5.3
2011	MEAN	18.7	104.9	168.7	72.8	552.0	3.4	4.8
	SD	17.2	83.1	146.2	46.3	493.8	2.04	5.3
2012	MEAN	18.7	109.1	175.2	72.8	554.8	3.4	4.8
	SD	17.1	86.9	151.7	46.3	510.8	2.04	5.3
2013	MEAN	19.1	115.3	181.9	72.8	553.2	3.4	4.8
	SD	17.5	92.7	158.6	46.3	504.5	2.04	5.3
2014	MEAN	19.5	121.8	190.2	72.8	564.6	3.4	4.8
	SD	17.8	99.6	165.8	46.3	516.7	2.04	5.3
2015	MEAN	20.7	127.4	191.0	72.8	569.7	3.4	4.8
	SD	19.6	104.6	162.3	46.3	509.4	2.04	5.3
2016	MEAN	21.6	136.0	202.3	72.8	579.5	3.4	4.8
	SD	20.1	111.7	172.6	46.3	520.6	2.04	5.3

2.7. Analysis

Following Simar and Wilson (2007), we performed a year-by-year analysis. A DEA was conducted for each year. Thus, airports are benchmarked against their peers in the same year only. The summary statistics of the efficiency scores are reported in Table 5. The CRS and VRS DEA scores are reported respectively in Appendices B and C. The results in Table 5 show that the average efficiency of 59 airports under VRS technology is higher than the average efficiency score derived with CRS technology.

Table 5. Summary Statistics of DEA Scores for Each Year

Years	Mean	SD	Min.	Max.
		CRS		
2009	0.7646	0.1890	0.4147	1
2010	0.7879	0.1839	0.4056	1
2011	0.7684	0.1833	0.3803	1
2012	0.8082	0.1738	0.4370	1
2013	0.8296	0.1574	0.4651	1
2014	0.8306	0.1605	0.4822	1
2015	0.8304	0.1577	0.4676	1
2016	0.8086	0.1535	0.4685	1
		VRS		
2009	0.8502	0.1801	0.4158	1
2010	0.8589	0.1750	0.4546	1
2011	0.8404	0.1844	0.3857	1
2012	0.8627	0.1674	0.4591	1
2013	0.8792	0.1548	0.4792	1
2014	0.8864	0.1551	0.4737	1
2015	0.8880	0.1559	0.5108	1
2016	0.8789	0.1532	0.4711	1

Following the DEA in Stage 1, the second-stage SW bootstrap procedure with bias-corrected efficiency scores in a two-sided truncated regression was conducted with 1,000 bootstrap replications. The estimates of the year-by-year bootstrapped truncated regression are displayed in Table 6.

Table 6. SW Truncated Regression Results by Year†

	CRS		**VRS**	
2009	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.521***	0.049	0.436***	0.040
Compensatory	0.179***	0.049	0.248***	0.040
Hybrid	0.191***	0.051	0.216**	0.040
City	-0.021	0.041	-0.007	0.035
County	0.062	0.063	0.122**	0.048

Table 6. SW Truncated Regression Results by Year (continued)

	CRS		VRS	
2009	**Parameter**	**BSE**	**Parameter**	**BSE**
State	**-0.195****	**0.086**	**-0.223****	**0.084**
Large Hub	0.025	0.037	0.141***	0.031
2010	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.573***	0.049	0.499***	0.043
Compensatory	0.142***	0.047	0.201***	0.043
Hybrid	0.177***	0.048	0.215***	0.043
City	-0.044	0.041	-0.089**	0.035
County	0.065	0.065	0.095*	0.052
State	-0.159*	0.085	-0.316***	0.088
Large Hub	0.022	0.036	0.132***	0.033
2011	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.516***	0.043	0.425***	0.037
Compensatory	0.152***	0.041	0.206***	0.37
Hybrid	0.213***	0.044	0.178***	0.036
City	-0.045	0.036	-0.017	0.032
County	0.089	0.055	0.119***	0.046
State	-0.116	0.072	-0.266***	0.082
Large Hub	0.023	0.030	0.191***	0.030
2012	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.548***	0.038	0.469***	0.039
Compensatory	0.141***	0.037	0.170***	0.041
Hybrid	0.207***	0.039	0.198***	0.039
City	-0.057*	0.032	0.013	0.035
County	0.059	0.050	0.079	0.051

Table 6. SW Truncated Regression Results by Year (continued)

	CRS		VRS	
2009	**Parameter**	**BSE**	**Parameter**	**BSE**
State	**-0.087**	**0.067**	**-0.315*** **	**0.071**
Large Hub	0.024	0.030	0.167***	0.031
2013	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.563***	0.035	0.517***	0.037
Compensatory	0.146***	0.037	0.183***	0.038
Hybrid	0.195***	0.035	0.218***	0.037
City	-0.050	0.031	0.002	0.034
County	0.017	0.043	0.075	0.048
State	-0.127**	0.054	-0.225***	0.062
Large Hub	0.053**	0.027	0.120***	0.030
2014	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.607***	0.034	0.626***	0.030
Compensatory	0.141***	0.034	0.151***	0.030
Hybrid	0.186***	0.033	0.181***	0.030
City	-0.070**	0.029	-0.062	0.026
County	0.028	0.042	0.034	0.038
State	-0.153**	0.059	-0.269***	0.053
Large Hub	0.033	0.025	0.025***	0.022
2015	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.643***	0.041	0.573***	0.039
Compensatory	0.148***	0.042	0.237***	0.041
Hybrid	0.181***	0.044	0.243***	0.041
City	-0.062*	0.037	-0.045	0.036
County	0.015	0.054	0.075	0.05

Table 6. SW Truncated Regression Results by Year (continued)

	CRS		VRS	
2009	**Parameter**	**BSE**	**Parameter**	**BSE**
State	-0.221***	0.074	-0.492***	0.068
Large Hub	0.038	0.033	0.121***	0.033
2016	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.570***	0.040	0.564***	0.036
Compensatory	0.190***	0.041	0.201***	0.037
Hybrid	0.231***	0.041	0.202***	0.036
City	-0.021	0.036	-0.036	0.031
County	0.089	0.054	0.151***	0.049
State	-0.240***	0.063	-0.477***	0.065
Large Hub	0.002	0.029	0.095***	0.028

***, ** and * denote 1%, 5% and 10% significance levels, respectively.
† BSE is the bootstrap standard error

The effects of compensatory and hybrid agreements on efficiency are positive and significant every year. This suggests that during these years, airports that chose either the compensatory or hybrid contracts outperformed their peers that adopted the residual contract. In other words, airports choosing compensatory or hybrid contracts were more efficient than the airports choosing residual contracts. However, based on the Wald test results in Table 7, there is no significant difference in the effects of compensatory and hybrid contract types on airport efficiency between 2009 and 2016.

On airport governance, airports operated by a state government is less efficient than their counterparts operated by a port or airport authority. This result is consistent with earlier findings by Craig et al. (2012) and Zhao et al. (2014). That is port or airport authorities tended to be more efficient because the structure of these special-purpose entities is considerably streamlined compared to that of general-purpose governments and therefore allowing them to a better transportation service.

Table 7. Comparison of Hybrid and Compensatory Effects on Efficiency

Years	Chi^2	Pr> Chi^2
		VRS
2009	0.99	0.3204
2010	0.43	0.5137
2011	0.84	0.3584
2012	0.39	0.5327
2013	0.30	0.5815
2014	1.40	0.2372
2015	0.01	0.9112
2016	0.19	0.6612
		CRS
2009	0.10	0.7465
2010	0.62	0.4316
2011	3.00*	0.0834
2012	3.29*	0.0698
2013	2.20	0.1379
2014	1.90	0.1678
2015	0.51	0.4750
2016	1.10	0.2945

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

The effect of large hub airports on efficiency is positive and significant every year under VRS technology, implying large hub airports are more efficient than medium hub airports. On the other hand, the effect of large hub airport is significant and positive in only 2013 under CRS technology. The insignificant results in the CRS model is expected because of the lack of convexity constraints under CRS technology. The CRS DEA model assumes all airports are operating at the optimal scale, and this may not be the case for U.S. airports, so the CRS DEA scores are confounded by scale inefficiency. Under the VRS assumption, the DEA frontier is the convex combination of DMU's and allows for inefficient airports to be benchmarked against other airports like them in terms of size.

The mechanism by which use agreements affect airport operational efficiency is of interest. Airports alone are not capable of producing WLU since they must work with airlines in order to jointly provide aeronautical services, but airports are responsible for the production of non-aeronautical outputs over which the signatory airlines of a residual contract may not have direct control. This lack of direct control and observation raises the issue of a potential moral hazard problem that may arise from the residual contract.[25] Based on the regression results, I infer that airports with residual agreements may have less incentive to increase non-aeronautical revenues since they are in a financial comfort zone. Coupled with the lack of direct control over the agent's behavior, the lopsidedly unequal risk sharing relationship -- when the principal bears all risks – inevitably leads to underperformance by the agent. Because of the financial safety net provided by signatory airlines, airports that adopt the residual method are less motivated to increase non-aeronautical output and service levels. This, in turn, may result in them being less operationally efficient than their peers. Consequently, the benefits that airlines gain from signing a residual-type contract with an airport may be undermined by the moral hazard problem. Our results suggest that airports choosing either compensatory or hybrid methods are more efficient;

---

[25] While the signatory airlines at residual airports may in theory exploit the MII clause by using it as an anti-competitive tactic to limit airport's ability to serve other non-signatory airlines and cause inefficiency, such exploitations may not be practical for two reasons: (1) airports have been able to move forward with their capital projects after the project review period and with additional discussions with the airlines (San Francisco International Airport, 2014); (2) if signatory airlines' anti-competitive actions, if any, adversely affect non-signatory airlines, the latter can change their status to signatory, since the signatory status is available to all airlines that want to sign a use agreement with the airport, and especially since being signatory yields additional economic benefits that are otherwise not available to non-signatory airlines. Such status change would thwart any anti-competitive actions of the existing signatory airlines.

this finding is consistent with those of Oum et al. (2004). Gillen and Lall (1997), and Vasigh and Hamzaee (1998).

During the study period, two of the airports following the residual method experienced airline exits, and getting de-hubbed caused significant shrinkage in airport operations. This may potentially lead to bias estimates in our results because the operational inefficiency of residual-typed airports may be due to dehubbing instead of the features of the residual agreement. In 2009, following the merger of America West and US Airways, the merged carrier abandoned Las Vegas McCarran International Airport (LAS) as its hub. Cleveland Hopkins International Airport (CLE) was de-hubbed in 2014 by United Airlines following the latter's acquisition of Continental Airlines (Rupp and Tan, 2019). Both de-hubbings occurred within our study period (2009 – 2016). Prior to 2009, St. Louis (STL), a residual airport, was de-hubbed by American Airlines in 2004 following the latter's acquisition of TWA, and Pittsburgh (PIT) was de-hubbed by US Airways in 2008 (Rupp and Tan, 2019). Both incidents occurred outside our study period. As a robustness check, I first conducted the analysis without LAS and CLE to explicitly account for the airline exits at these two residual airports. After that, I conducted another analysis without all 4 residual airports (LAS, CLE, STL and PIT), as an additional robustness check. The descriptive statistics of the new sets of DEA scores and the truncated regression results are presented in Tables 8 and 9. As seen in Table 8, despite dropping the de-hubbed airports, the efficiency scores are largely similar to those reported in Table 5. In addition, the truncated regression results in Table 9 are by and large consistent with those displayed in Table 6. Specifically, the positive effects of compensatory and hybrid on airport efficiency remain significant even among airports that did not experience de-hubbing.

Table 8. Descriptive Statistics of DEA Scores of Airports without Hub Abandonment

	Without 2 De-hubbed Residual Airports				Without 4 De-hubbed Residual Airports			
Years	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
		CRS				CRS		
2009	0.7642	0.1906	0.4147	1	0.7823	0.1770	0.4315	1
2010	0.7887	0.1854	0.4056	1	0.8073	0.1715	0.4057	1
2011	0.7686	0.1849	0.3803	1	0.7882	0.1690	0.4272	1
2012	0.8084	0.1753	0.4370	1	0.8279	0.1580	0.4880	1
2013	0.8316	0.1580	0.4651	1	0.8498	0.1405	0.5296	1
2014	0.8384	0.1524	0.4676	1	0.8510	0.1396	0.5388	1
2015	0.8381	0.1566	0.4822	1	0.8505	0.1448	0.5061	1
2016	0.8167	0.1483	0.5070	1	0.8278	0.1390	0.5100	1
		VRS				**VRS**		
2009	0.8510	0.1810	0.4158	1	0.8731	0.1551	0.5143	1
2010	0.8598	0.1762	0.4546	1	0.8813	0.1532	0.4665	1
2011	0.8414	0.1855	0.3857	1	0.8641	0.1611	0.4276	1
2012	0.8639	0.1685	0.4591	1	0.8854	0.1444	0.4887	1
2013	0.8817	0.1549	0.4792	1	0.9016	0.1320	0.5377	1
2014	0.8956	0.1468	0.4806	1	0.9095	0.1294	0.5713	1
2015	0.8966	0.1495	0.5152	1	0.9099	0.1343	0.5150	1
2016	0.8878	0.1452	0.5127	1	0.9012	0.1292	0.5270	1

Table 9. Truncated Regression Results After Dropping 2 and 4 Dehubbed Airports†

	Without 2 De-hubbed Residual Airports††				Without 4 De-hubbed Residual Airports†††			
	CRS		**VRS**		**CRS**		**VRS**	
2009	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.519***	0.05	0.430***	0.041	.5703***	0.056	.5110***	0.040
Compensatory	0.179***	0.052	0.255***	0.043	.1337*	0.054	.2019***	0.040
Hybrid	0.198***	0.049	0.224***	0.043	.1450**	0.054	.1528***	0.042
City	-0.022	0.044	-0.011	0.034	-0.009	0.042	-0.019	0.032
County	0.029	0.065	0.088	0.054	0.001	0.065	0.0398	0.047
State	-0.196**	0.09	-0.230**	0.089	-.1804*	0.085	-.2960***	0.065
Large Hub	0.019	0.039	0.146***	0.032	-0.012	0.039	.0969***	0.028
2010	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.577***	0.052	0.515***	0.039	.5956***	0.059	.6087***	0.044
Compensatory	0.140***	0.051	0.173***	0.041	.1276*	0.056	.1154**	0.042
Hybrid	0.177***	0.052	0.179***	0.04	.1691**	0.055	.1202**	0.043
City	-0.043	0.045	-0.069**	0.032	-0.036	0.046	-.080*	0.033
County	0.069	0.065	0.074	0.051	0.0509	0.072	0.025	0.052
State	-0.158*	0.086	-0.432***	0.07	-.2521**	0.086	-.386***	0.064
Large Hub	0.024	0.039	0.139***	0.031	0.0121	0.040	.0880**	0.030

Table 9. Truncated Regression Results After Dropping 2 and 4 Dehubbed Airports (continued)

	Without 2 De-hubbed Residual Airports††				Without 4 De-hubbed Residual Airports†††			
	CRS		**VRS**		**CRS**		**VRS**	
2011	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.514***	0.041	0.469***	0.037	.5581***	0.047	.513***	0.040
Compensatory	0.154***	0.042	0.173***	0.037	.1152**	0.044	.1466***	0.036
Hybrid	0.210***	0.043	0.148***	0.036	.1721***	0.044	.1151**	0.037
City	-0.046	0.034	-0.035	0.029	-0.037	0.035	-0.0215	0.031
County	0.082	0.056	0.093**	0.046	0.0584	0.056	.09504*	0.045
State	-0.117	0.075	-0.266***	0.075	-0.106	0.070	-.2447**	0.076
Large Hub	0.027	0.032	0.180***	0.027	-0.0045	0.033	.1463***	0.028
2012	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.550***	0.038	0.479***	0.039	.5585***	0.048	.5732***	0.041
Compensatory	0.140***	0.04	0.170***	0.038	.1322**	0.045	.1018**	0.039
Hybrid	0.207***	0.04	0.196***	0.04	.2140***	0.046	.1294***	0.039
City	-0.059*	0.032	0.014	0.033	-0.048	0.038	0.0112	0.032
County	0.046	0.051	0.079	0.049	0.044	0.057	0.0245	0.046
State	-0.086	0.07	-0.240***	0.081	-.1965**	0.065	-.2676***	0.062
Large Hub	0.018	0.03	0.146***	0.031	0.0072	0.034	.0996***	0.028
2013	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.566***	0.036	0.557***	0.035	.6309***	0.036	.6094***	0.038
Compensatory	0.144***	0.037	0.146***	0.034	.0885*	0.035	.1059**	0.037
Hybrid	0.195***	0.036	0.171***	0.035	.1341***	0.035	.1424***	0.037
City	-0.053*	0.031	-0.007	0.03	-0.0426	0.029	0.0151	0.031
County	0.012	0.049	0.068	0.047	-0.0122	0.042	0.0616	0.044
State	-0.143*	0.058	-0.135**	0.061	-0.0756	0.051	-.1498**	0.051
Large Hub	0.062*	0.028	0.107***	0.027	0.0234	0.027	.0692**	0.027
2014	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.615***	0.037	0.616***	0.031	.6609***	0.037	.7449***	0.031
Compensatory	0.135***	0.035	0.159***	0.033	.0975**	0.036	.0658*	0.029
Hybrid	0.179***	0.035	0.200***	0.032	.1413***	0.035	.1068***	0.030
City	-0.065**	0.029	-0.052**	0.026	-.0638*	0.028	-.0694**	0.024
County	0.03	0.046	0.039	0.043	0.0117	0.043	-0.03	0.036
State	-0.150**	0.059	-0.308***	0.048	-.1441**	0.055	-.2095***	0.044
Large Hub	0.027	0.026	0.015	0.025	0.0066	0.026	-.0617**	0.023
2015	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.653***	0.044	0.587***	0.034	.70716***	0.048	.67023***	0.038
Compensatory	0.144***	0.044	0.218***	0.036	.09525*	0.045	.1657***	0.038
Hybrid	0.175***	0.046	0.231***	0.035	.1234**	0.045	.1677***	0.037
City	-0.056	0.039	-0.032	0.03	-0.057	0.036	0.059	0.031
County	0.022	0.06	0.086**	0.044	-0.013	0.052	0.0341	0.045
State	-0.220***	0.076	-0.339***	0.071	-.2130**	0.070	.4288***	0.058
Large Hub	0.034	0.034	0.082***	0.028	0.0138	0.032	.06303*	0.027

Table 9. Truncated Regression Results After Dropping 2 and 4 Dehubbed Airports (continued)

	Without 2 De-hubbed Residual Airports††				Without 4 De-hubbed Residual Airports†††			
	CRS		**VRS**		**CRS**		**VRS**	
2016	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**	**Parameter**	**BSE**
Constant	0.577***	0.04	0.579***	0.033	.62568***	0.042	.6955***	0.033
Compensatory	0.181***	0.04	0.175***	0.033	.1376***	0.039	.1077***	0.032
Hybrid	0.221***	0.04	0.178***	0.035	.1783***	0.041	.1045***	0.031
City	-0.015	0.036	-0.024	0.028	-0.0176	0.033	-.0558*	0.025
County	0.103*	0.056	0.164***	0.049	0.07	0.051	.0894*	0.040
State	-0.241***	0.061	-0.440***	0.058	-.1976***	0.058	-.4059***	0.049
Large Hub	0.001	0.031	0.088***	0.025	-0.0203	0.029	0.0399	0.023

***, ** and * denote 1%, 5% and 10% significance levels, respectively.
† BSE is the bootstrap standard error
†† Excluding LAS and CLE
††† Excluding LAS, CLE, STL and PIT

As a final robustness check, following Barros and Dieke (2008), I pooled the data of the 59 US hub airports from years 2009 through 2016 and conducted the efficiency analysis with a total of 472 observations (or DMUs). The descriptive statistics of efficiency scores under CRS and VRS technology are reported in Appendix D.[26] Following the first-stage DEA, I conducted a second-stage analysis using the SW procedures with 1,000 bootstrap replications. The results of the regression model are reported in Appendix E. Both use-agreement variables remain positive and significant at 1% level.

2.8. Conclusion

Following the deregulation of the U.S. airline industry in 1978, both airlines and airports in the U.S. encountered increased competition. Changes like the adoption of the hub-and-spoke system, the rise of low-cost carriers, and increased airline competition compelled both airports and airlines to be strategic about their operations. Although airports and airlines are vertically separated in the U.S., their operations are inseparable; thus forging a strong vertical relationship is important to both. The most common form of vertical business arrangements between airports

[26] The full set of efficiency scores from the pooled data is available from upon request.

and airlines in the U.S. is airport use agreements that generally follow a residual, compensatory or hybrid method.

Under the residual method, airports may obtain financial support from signatory airlines with which they can forge long-term business relationships to help alleviate financial stress and uncertainty. In turn, the signatory airlines may benefit from low user fees as compared to other airlines, with access to airport facilities secured and prioritized over rivals. However, host airports may have less incentive to increase non-aeronautical revenues and have a diminished focus on operating expenditures. These two factors may lead to a moral hazard problem in the context of asymmetric information.

In light of this, I conducted a two-stage semiparametric efficiency analysis to examine the effects of contractual agreement type on airport efficiency using U.S. airport data from 2009 to 2016. The results show that the efficiency contribution of both compensatory and hybrid methods was evident in U.S. airports. Specifically, airports that follow either of these two methods outperformed those that followed the residual method. This might be that, compared to the compensatory and hybrid counterparts, residual-typed airports do not bear the financial risk of operations, but their signatory airlines do. This financial guarantee offered by the signatory airlines (the principal) creates unequal risk-sharing which in turn disincentivizes the airport (the agent) from striving for greater operational efficiency especially in areas where the signatory airlines cannot fully observe. Hence, a lower airport efficiency may undercut any benefits that the signatory airlines expect to receive through the residual-typed contracts. While I reached this conclusion, the model postulated the agreement methods as exogenous variables since airport operators develop their operating budgets and calculate the user fees based on the agreement method already in place. Nevertheless, since the distribution of use agreements may not be completely random, there may be potential estimation issues associated with possible endogeneity of the agreement method variables.

Besides use agreements, I analyzed the effects of governance forms and hub size on airport efficiency. According to the regression results, airports governed by the state are less efficient than the airports governed by port/airport authorities. In addition, large hub airports exhibit higher efficiency than medium hub airports. Since U.S. airports are public infrastructure managed and operated by governments, they are prohibited to seek revenue surpluses (FAA, 2008). Thus my study focused on airport technical efficiency as opposed to profitability which may be of interest to private airports in other parts of the world.

Lastly, although the results suggest no statistically significant difference between hybrid- and compensatory-typed agreements, both airports and airlines may benefit most from hybrid-typed agreements. This is because hybrid contracts are flexible and require both parties to invest in equal efforts. The reduction in risk through a more balanced risk-sharing mechanism increases the utility of airports and airlines (Hihara, 2012). On one hand, under a hybrid agreement, the airport is motivated to optimize non-aeronautical operations since they bear the risk and receive the benefits of terminal operations. On the other hand, the airport obtains financial support from the signatory airlines in airfield operations. Furthermore, an airport's freedom to make project decisions is not restricted by the hybrid contract. Potentially, the signatory airlines could obtain a share from non-aeronautical revenues if they agreed on revenue-sharing in the hybrid agreement. Under a compensatory contract, the under-effort problem of the airport is less of a concern, but since all financial risk falls on the airport, it becomes more susceptible to economic downturns. Thus, among the three types of agreements analyzed for this paper, the hybrid agreement seems to be the fairest for both airlines and airports, and it guards against the moral hazard problem which we observe in residual agreements.

CHAPTER 3: AIRPORT USE AGREEMENTS AND COST EFFICIENCY OF U.S.AIRPORTS

3.1. Abstract

In this study, I examined the impact of airport use agreements on the cost efficiency of 59 U.S. hub airports in the years between 2009 and 2016 by estimating three stochastic cost frontier models. The major finding in this research is that airports adopting the residual rate-setting method is less cost-efficient than the airports adopting either the hybrid or compensatory method. This cost inefficiency of residual airports may be an indicator of a lack of vigilance over airport operating costs, which in turn may translate into higher user fees for the signatory airlines. This result lends credence to the finding in Chapter 2 that residual agreements may exert a moral hazard problem of airport management due to the risk-shifting feature of the agreements that shield the airports from fiscal uncertainty.

3.2. Introduction

In the years following the Airline Deregulation Act in 1978, the U.S. air transportation industry experienced higher air traffic, a higher number of passengers and lower airfares (Peterson, 2018). Besides, airlines had to deal with more intense competition (D'Alfonso, 2011). Between 1979 and 2018, 180 airlines had filed for Chapter 11 bankruptcy, and 24 airlines filed for Chapter 7 bankruptcy[27]. In this unsettled environment, airlines need a reliable airport partner for their operations and for maintaining and enhancing their positions in the downstream market. The airport use agreement is one of the most important and common vertical contractual arrangements in the U.S. air transportation industry. The agreement between an airport and the

[27] http://airlines.org/dataset/u-s-bankruptcies-and-services-cessations/

signatory airlines provides both parties privileges, obligations and rights. Through airport use agreements, business arrangement and rate-setting between airports and airlines are established. In addition, the agreements may also define both parties' control spans on airport management, responsibilities for airport's financial risks, and conditions for airport revenue sharing. In the U.S., airport use agreements are commonly categorized into three types in accordance with the three rate-setting methods adopted by airports; they are the residual method, the compensatory method, and the hybrid method (FAA, 2009).

Under the residual method, the signatory airlines agree to bear the financial risks of normal business operations of the host airport. If there is a budget deficit, the signatory airline pays the "residual" amount of operating costs and the debt-service costs for bonds after the revenues generated from other airlines and non-aeronautical activities (FAA, 1999). In the case of a budget surplus, the excess revenue will be credited to the signatory airlines. Therefore, the host airport can break even under the residual method. Because of their commitment to bear the airport's financial risk, the signatory airlines pay lower airport fees. For example, the landing fee of non-signatory airlines is usually 1.25 times the fee paid by the signatory airlines. Thus, the residual method may have implications on downstream airline competition and new air carrier entry (FAA, 1999). Although the residual agreements provide financial assurance for the host airport, airports face a trade-off between risk and autonomy on capital expenditures. Due to the majority in interest (MII) clause in residual agreements, airports' control span on capital projects is narrowed. Since the cost of the capital projects could lead to an increase in the rates of signatory airlines, the airport must seek the approval of the signatory airlines on new capital projects under the MII clause.

The compensatory method is the opposite version of the residual method. Airlines' fees are determined according to their usage; there are no reduced user fees for airlines under this method, and the airport bears the entire financial risks of its operations. However, the airport also reaps the rewards of all revenue surplus from non-aeronautical operations, and a compensatory airport has full control over its investment decisions. The compensatory method has become more popular in recent years because of the lucrativeness of non-aeronautical airport business. Non-aeronautical revenues have becomes a vital income source of airports that enable them to strengthen their financial position in recent years (Barbot & D'Alfonso, 2014; D'Alfonso, Jiang & Wan, 2013; Zhang, Fu & Gavin, 2010).

The hybrid method is a combination of residual and compensatory methods. Under this method, a common arrangement is for an airport to adopt the residual method in airfield operations and a compensatory rate-setting method in terminal operations. The financial risk of airfield operations is borne by the signatory airline while the airport bears the financial risk of terminal operations. Besides, the hybrid contract may include revenue sharing contingent upon excess non-aeronautical revenue at the airport (Faulhaber et al. 2010). The signatory airlines may benefit from the extra revenues of the host airport's non-aeronautical operations. Meanwhile, the host airport has more freedom over the use of its resources and surplus funds. However, airports usually share non-aeronautical revenues with the signatory airlines to increase demand for the non-airline services at the airport.

According to Faulhaber et al. (2010), the airports adopting the residual agreement are less incentivized to increase non-aeronautical revenues leading to more operational inefficiency (Karanki & Lim, 2020). On the other hand, because of the financial guarantee of signatory airlines, the airports adopting the residual method also have a diminished focus on operating expenditures (Faulhaber et al., 2010), especially since the signatory airlines have no control over airport operating costs. This results in non-optimal use of resources or inputs which leads to cost inefficiency. The airport's lack of vigilance over operating expenditures may be a result of a moral hazard problem of residual airports forcing the signatory airlines to bear more financial risk for their airports, and this may, in turn, result in higher user fees paid by the signatory airlines. Thus, the expected benefits of signatory airlines from the residual agreement may not be as high as what they might expect to get.

Chapter 2 of this dissertation examines the implications of airport use agreements on airport operational efficiency, but the chapter does not address how the use agreement types affect operations in monetary terms. In this chapter, I focus on airport operating costs, which not only reflect airport managerial performance but also cost performance. This allows me to measure the impact of non-optimization due to the use agreements from a cost perspective. The results and information from this study will be useful for airports as they seek to improve their performances through efficient resource allocation, and for airlines as when they execute long-term agreements with airports. To this end, I employ three stochastic frontier analyses to examine the implications of residual agreements on airport cost efficiency. To the best of my knowledge, the effects of use agreements on airport cost efficiency have not been previously analyzed. This study aims to identify differential in cost efficiency between use agreements. The analysis and results in this chapter lend support to the finding in Chapter 2 that the financial protection provided by airlines to residual airports may lead to airport underperformance as evidenced by higher inefficiency in operations and higher airport operating (variable) cost. The higher variable cost could then lead to higher charges for airlines.

The chapter is organized as follows: In Section 3.3, I review the studies on airport cost-efficiency. In Section 3.4, I present the method to analyze cost efficiency. After that, I describe the empirical data used in this research in Section 3.5. In Section 3.6, I discuss the results. In the last section, I conclude with the findings and implications.

3.3. Literature Review

Airport cost efficiency is scarcely seen in the literature. Barros (2008), Oum, Yan and Yu (2008) and Martin, Roman and Voltes-Dorta (2009) are among the first to conduct airport cost-efficiency studies. Barros (2008) analyzed the efficiency changes of Portuguese airports between 1990 and 2000 with a stochastic frontier model. He employed a translog total cost frontier to measure airport cost efficiency. Oum, Yan and Yu (2008) analyzed the relationship between airport cost efficiency and ownership forms by employing a Bayesian method on a stochastic cost frontier model. They developed a system of a translog variable cost function and the associated cost-share equations. Using a method similar to Oum et al. (2008), Martin, Roman and Voltes-Dorta (2009) analyzed Spanish airports' cost-efficiency using a Markov Chain Monte Carlo process to estimate a stochastic frontier model of an equation system that includes a translog total cost function and cost-share equations.

Assaf (2010) analyzed the cost efficiency of Australian airports using a Bayesian panel stochastic frontier. For the panel stochastic frontier analysis, he employed the Battese and Coelli (1992) time-decay model of a Cobb-Douglas cost function. Martín, Rodríguez-Déniz and Voltes-Dorta (2013) analyzed the drivers of cost efficiency of 194 airports worldwide between 2007 and 2009. For this analysis, they employed a Bayesian approach on a stochastic frontier model by estimating a seemingly unrelated regression to estimate a cost frontier along with cost-share equations. After they obtained the efficiency scores from a stochastic frontier analysis, they regressed these scores on environmental factors: ownership, the Herfindahl-Hirschman Index, the share of charter traffic, the share of low-cost carrier flights, annual passenger traffic in millions, maximum takeoff weight, share of material costs, the share of commercial over total revenues. They concluded that airline dominance increased cost efficiency in the US, whereas it has a negative effect in Europe; low-cost carriers (LCCs) increased cost efficiency because of their less demanding nature for airport services compared to full service airlines; outsourcing has a negative effect on costs in a recession.

Kutlu and McCarthy (2016) analyzed the effects of various management forms in the U.S. on cost efficiency. They used a translog variable cost function with cost-share equations by estimating a true fixed effects model proposed by Greene (2005a). Through this method, the authors analyzed the governance effects on cost efficiency. The authors reported that medium-sized airports are more cost-efficient than large-sized airports, and local ownership, multi-airports in the metropolitan area, multi-airport joint ownership in the metropolitan area reduce cost-efficiency. The above studies are summarized in Table 10.

Table 10. Summary of Airport Cost Efficiency Studies

Authors	Functional Form	Model	Explanatory Variables	Quasi Fixed Capital Inputs	Input Prices	Outputs
Oum, Yan, and Yu (2008)	Translog Variable Cost Function with Share Equations	Bayesian SFA Model, SUR	Ownership Forms	• Number of Runways, • Terminal Size	• Labor, • Non-Labor	• Number of Passengers, • Number of Aircraft Movements (ATM) • Non-Aeronautical Revenue
Barros (2008)	Translog Total Cost Function	SFA Model	NA	NA	• Labor • Capital	• Sales to Passenger, • Sales to Planes

Table 10. Summary of Airport Cost Efficiency Studies (continued)

Authors	Functional Form	Model	Explanatory Variables	Quasi Fixed Capital Inputs	Input Prices	Outputs
Martin, Roman, and Voltes-Dorta (2009)	Translog Total Cost Function with Share Equations	Bayesian SFA Model, SUR	NA	NA	• Labor • Material • Capital	• Aircraft Movements • Work Load Units
Assaf (2010)	Cobb-Douglas Total Cost Function	Bayesian Panel SFA, Battese and Coelli (1992)	NA	NA	• Labor • Capital	• Total Passengers, • ATM, • Total Cargo
Martín, Rodríguez-déniz, and Voltes-Dorta (2013)	Translog Variable Cost Function with Share Equations and Hedonic Function	Bayesian SFA Model, SUR	• Ownership • HHI, • Share of Charter Traffic, • Share of LCC Flights, • Passenger, • Max. Takeoff Weight, • Share of Material Costs, • Share of Commercial Rev. • Pre-crisis Level Efficiency	• Terminal floor area • Total runway length	• Labor • Material	• ATM, • Domestic Passengers, • International Passengers, • Cargo, • Commercial Revenues
Kutlu and McCarthy (2016)	Translog Variable Cost Function with Share Equations	Bayesian Panel SFA, Greene (2005a)	• Ownership Forms in the US.(Multi-airport, Multi-airport Joint Ownership, Local Ownership) • Hub Status	Effective Number of Standard Runways	• Labor, • Repair/ Maintenance, • General Operations	• Departures

None of the above studies have examined the use agreement effects on airport cost efficiency. However, a few studies have focused on airport technical efficiency and use agreements. The earliest study I found was conducted by Gillen and Lall (1997) who analyzed the technical efficiency of 21 US airports between 1989 and 1993. They argued that the residual method led to more efficient airside operations whereas the compensatory method led to more efficient terminal operations. This result could imply that airports with a hybrid agreement might be more efficient. However, Gillen and Lall (1997) did not examine any specific form of vertical agreements. Vasigh and Hamzaee (1998) developed a model to understand which agreement method is most desirable for U.S. airports in terms of their financial performance. They found that a compensatory arrangement contributes more to the profit of an airport.

Apart from the effect of vertical agreements on airport efficiency, Richardson, Budd and Pitfield (2014) analyzed the effects of use agreements on the financial performances of 23 US large hub airports for the year 2011/2012. In their study, they determined the key financial performance indicators through an interview series with 12 large hub airports' managers. The five financial performance indicators are revenue generation, capital investment, commercial performance, cost-effectiveness, and financial profitability. The main findings in this study are compensatory airports generate higher revenues than residuals, residual airports are the most cost-effective airports, residual airports have higher commercial revenues than other two methods, and the compensatory airports are the most financially profitable. Oum, Zhang and Zhang (2004) examined the effects of use agreements on total factor productivity and capital input productivity of airports when they analyzed the effects of single till price cap[28] and dual till price cap on airport efficiency. They regarded the compensatory method as the U.S. version of the dual till price-cap approach and the residual method as a U.S. equivalent of the single till price cap approach. In the empirical part of the paper, they examined the effects of airport productivity indicators on capital input productivity and total factor productivity of 60 airports in 1999; the sampled airports include 11 airports in Asia, 18 airports in Europe and 31 airports in North America. They found that airport capital input productivity is higher under single-till pricing (or a residual agreement). On the contrary, total factor productivity is higher under dual-till pricing (or a compensatory agreement) since the under-investment problem in capacity under single-till is higher than the one under dual till.

3.4. Theoretical Framework and Model

3.4.1. Stochastic Frontier Analysis

The stochastic frontier analysis (SFA) was originally developed by Aigner, Lovell, and Schmidt (1977) (ALS) and Meeusen and Van Den Broeck (1977) for cross-sectional data. Pitt and Lee (1981) (PL) extended the ALS model for panel data. The PL stochastic production frontier is given by

$$y_{it} = \alpha + x_{it}'\beta + \nu_{it} - u_i, \tag{3.1}$$

where y_{it} is the output for $i = 1,\ldots, n$ cross-sectional units at $t = 1,\ldots, T$ periods, and x_{it} is a vector of input variables. The term ν_{it} is the error term distributed $N(0, \sigma_v^2)$, and u_i is the one-sided time-invariant inefficiency term distributed $N^+(0, \sigma_u^2)$. Similar to ALS, the PL model can

[28] Single-till price cap refers to an airport's decision to base their current period aeronautical charges on both aeronautical and non-aeronautical revenues in the preceding period. Dual-till price cap refers to an airport's current aeronautical charges that are based only on its aeronautical revenues in the preceding period.

be estimated by the maximum likelihood method. However, PL has still two limitations. Firstly, the model assumes uncorrelatedness between inefficiency and the explanatory variables. Secondly, the model assumes time-invariant inefficiency (Greene, 2004). The first limitation implies that although inefficiency includes the heterogeneity, it is uncorrelated with explanatory variables. Although firm-specific heterogeneity is neither input prices nor output quantity, it has explanatory power on the inefficiency term (Greene, 2005). Therefore, firm-specific heterogeneity in inefficiency may be correlated with the explanatory variables. Thus, the parameter estimates in the PL model are biased. PL also does not allow the inefficiency to vary over time, and this may not be a realistic assumption with long periods.

The heterogeneity limitation can be relaxed first by a fixed-effects model offered by Schmidt and Sickles (SS, 1984). In the SS production model (2). which is estimated by OLS, all heterogeneity is stacked into $\alpha_i = \alpha - u_i$:

$$y_{it} = \alpha_i + x_{it}'\beta + v_{it}, \text{ and}$$

$$\hat{u}_i = max_i(\hat{\alpha}_i) - \hat{\alpha}_i \geq 0 \tag{3.2}$$

where the estimates of u_i, $\hat{u}_i$, capture all heterogeneity, $v_{it} \sim (0, \sigma_v^2)$, and the SS model allows for individual effects. However, there is still a time-invariant inefficiency problem in SS (Battese and Coelli, 1992; Battese and Coelli, 1995). According to Greene (2004), one major limitation of the model is that any time-invariant heterogeneity will appear in α_i and $\hat{u}_i$. Thus, Battese and Coelli (BC, 1992) proposed a model in which inefficiency may vary over time. Accordingly, inefficiency is defined as

$$u_{it} = \eta_t |U_i|, \tag{3.3}$$

where $\eta_t = \exp[-\eta(t - T)]$, and η is an unknown scalar parameter. Through this setting, BC allows inefficiency to decrease, stay constant or increase over time when $\eta < 0, \eta = 0, \eta > 0$, respectively. Battese and Coelli (1995) (BC95) also proposed a model addressing the heterogeneity problem. The technical inefficiency term u_{it} is specified as

$$u_{it} = z_{it}\delta + w_{it}, \tag{3.4}$$

where z_{it} is a vector of explanatory variables for u_{it}, δ is unknown coefficients to be estimated, and w_{it} is a random variable distributed truncated normal. However, BC95 does not separate cross-unit heterogeneity and inefficiency. Greene (2004) argued that the conventional panel data stochastic frontier models stack heterogeneity and inefficiency in one disturbance term. Greene (2005a) addressed these issues by reformulating conventionally fixed and random effects models with "true" fixed and random-effects models. In "true" random-effects model (TRE), he isolated time-invariant cross-unit heterogeneity (w_i) from inefficiency (u_{it}). Hence, the basic difference between BC95 and TRE is the location of random firm-specific heterogeneity in the stochastic frontier model. In TRE, w_i is a time-invariant cross-sectional unit-specific term, and it is assumed to be uncorrelated with the with all the other terms in the model (3.5):

$$y_{it} = (\alpha + w_i) + \beta' x_{it} + v_{it} - u_{it}, \tag{3.5}$$

where w_i follows a normal distribution $N(0, \sigma_w^2)$, v_{it} follow $N(0, \sigma_v^2)$, and u_{it} follows $N^+(0, \sigma_u^2)$. Thus, TRE offers three disturbance terms (v_{it}, u_{it}, w_i). In this way, TRE aims to remove bias from inefficiency resulting from time-invariant unobservable factors.

3.4.2. Short-Run Cost Frontier

To examine the effects of use-agreements on cost efficiency, I employed BC95 and TRE methods which consider time-invariant cross-unit heterogeneity and time-varying inefficiency. In addition, I compared the BC95 and TRE results with those derived from a pooled ALS model which considers heterogeneity in inefficiency. In this study, an airport chooses an optimal level of input use to minimize the cost of production given the prevailing technology and input prices.

Airport costs can be analyzed in a short or long-run context. In economics, a long-run production refers to a time in which firms can adjust all inputs to their optimal levels, whereas in short-run production, one or more inputs are invariable. Since airport capital inputs are invariable, in this study I conduct a short-run analysis. In the short run, the total cost is composed of fixed and variable costs as in equation (3.6) where $R_{it}K_{it}$ represents the total fixed costs, while $C^v(W_{it}, Y_{it}, K_{it}, \delta)$ represents the total variable costs for airport *i* at time *t*:

$$C_{it}^s = C^v(W_{it}, Y_{it}|K_{it}, \delta) + R_{it}K_{it}, \tag{3.6}$$

where the variables cost is a function of the input prices ($W_{it} = (w_{1t}, w_{2t} \dots w_{jt})$), outputs ($Y_{it} = (y_{1t}, y_{2t} \dots y_{mt})$), given the level of fixed capital input (K_{it}) and the state of technology (δ). The fixed cost component is the sum of the products of capital input price and capital input quantity, and R_{it} is the vector of capital prices ($R_{it} = (r_{1t}, r_{2t}, \dots r_{3t})$), and K_{it} is the vector of fixed capital quantity ($K_{it} = (k_{1t}, k_{2t} \dots k_{nt})$). In the short run, the airport cannot change its capital inputs, and they focus on minimizing variable costs.

Input prices in this study are wage, maintenance/repair price, and operating price other than wage and maintenance/repair; outputs are airport's workload units (WLU)[29] and non-aeronautical revenues; the fixed inputs are the effective number of runways[30] and airport surface area. Since U.S. airports are heterogenous, hub-size was added to the model as an explanatory variable. A time trend (*t*) was also included in the model to control the technical change in the variable cost over the years. Following Farsi, Filippini and Kuenzle (2006) and Filippini and Maggi (1992), the effects of the input price variables on operating costs are assumed to be

[29] 1 WLU = 1 passenger or 100 kg of freight (Doganis, 2005).

[30] The effective number of standard runway is defined as $\sum_f (Length_{fit})(Width_{fit})/1{,}500{,}000$ (McCarthy, 2014).

constant over time. Since the use agreement types do not vary for the overwhelming majority of airports, these variables are not interacted with the time trend as well. The variable cost function was specified as a translog form (Christensen, Jorgenson and Lau, 1973) and all variables (excluding time trend and hub-size) were normalized by dividing them by their sample means,

$$\ln(C_{it}^{v}) = \beta_0 + \beta_1 S_i + \beta_2 t + \sum_j \beta_j \ln\left(\frac{w_{jt}}{\bar{w}_j}\right) + \sum_n \beta_n \ln\left(\frac{k_{nt}}{\bar{k}_n}\right) + \sum_m \beta_m \ln\left(\frac{y_{mt}}{\bar{y}_m}\right)$$

$$+ \frac{1}{2}\sum_j \sum_p \beta_{jp} \ln\left(\frac{w_{jt}}{\bar{w}_j}\right) \ln\left(\frac{w_{pt}}{\bar{w}_p}\right) + \frac{1}{2}\sum_m \sum_l \beta_{ml} \ln\left(\frac{y_{mt}}{\bar{y}_m}\right) \ln\left(\frac{y_{lt}}{\bar{y}_l}\right) + \frac{1}{2}\sum_n \sum_o \beta_{no} \ln\left(\frac{k_{nt}}{\bar{k}_n}\right) \ln\left(\frac{k_{ot}}{\bar{k}_o}\right)$$

$$+ \sum_j \sum_m \beta_{jm} \ln\left(\frac{w_{jt}}{\bar{w}_j}\right) \ln\left(\frac{y_{mt}}{\bar{y}_m}\right) + \sum_j \sum_n \beta_{jn} \ln\left(\frac{w_{jt}}{\bar{w}_j}\right) \ln\left(\frac{k_{nt}}{\bar{k}_n}\right) + \sum_n \sum_m \beta_{nm} \ln\left(\frac{k_{nt}}{\bar{k}_n}\right) \ln\left(\frac{y_{mt}}{\bar{y}_m}\right) \quad (3.7)$$

The difference between a variable cost function in (3.7) and a variable cost frontier is the inefficiency term u_{it} as demonstrated below:

$$\ln(C_{it}^{v}) = \ln(C_{it}^{v*}) + v_{it} + u_{it}, \quad (3.8)$$

where $\ln(C_{it}^{v})$ is the observed log variable cost, and $\ln(C_{it}^{v*}) + v_{it}$ constitutes the variable cost frontier attainable. If an airport is a variable cost-inefficient, $u_{it} > 0$, then the observed variable cost is higher than the variable cost frontier. If an airport is a variable cost-efficient, $u_{it} = 0$, the observed variable cost is equal to the minimum variable cost. In the pooled ALS model, v_i follows a normal distribution $N(0, \sigma_v^2)$, and u_i follows a one-sided $N^+(0, \sigma_{ui}^2)$ distribution where $\sigma_{ui}^2 = \exp(z_i'\psi)$ where z_i is a vector of binary variables for the agreement types, and ψ are the unknown parameters to be estimated (Caudill, Ford & Gropper, 1995; Hadri, 1999). In the BC95 model, u_i is distributed $N^+(z_{it}\delta, \sigma^2)$ and v_i follows a normal distribution. In TRE, v_i is assumed to distribute normal, while u_i follows an exponential distribution with σ_{uit}^2 mean.

Christensen and Greene (1976) imposed two restrictions on the translog functional forms by considering a well-behaved cost function assumptions: (i) homogeneity of degree 1 in input prices which provides the condition that total cost increases in response to a proportional increase in factor prices, and (ii) symmetry of the cross-partials for the continuity assumption. To satisfy these assumptions, total operating cost and input prices are normalized by an arbitrarily chosen input price which is operating price. Accordingly, the following restrictions are imposed:

$$\beta_{jp} = \beta_{pj},\ \sum_j \beta_j = 1,\ \sum_j \beta_{jp} = 0\ \forall\, p,\ \ \sum_j \beta_{jm} = 0\ \forall\, m\,,\ \ and\ \ \sum_j \beta_{jn} = 0\ \forall\, n \qquad (3.9)$$

3.5. Data

I used an unbalanced panel dataset of 30 large hub airports and 29 medium hub U.S. airports for the years between 2009 and 2016. The data were mainly obtained from the Certification Activity Tracking System (CATS) Database. From the CATS, I obtained the data on the number of employees, labor expenditures, operating expenses, maintenance/repairs expenditures, number of enplanements, landed weights in pounds, and total non-aeronautical revenues. Seventeen[31] out of 472 observations were eliminated from the analysis because the data on maintenance/repairs were not reported to CATS.

Since airports are multiproduct firms, the non-aeronautical operations should be represented as well as aeronautical operations in the cost function. The vast majority of current studies employ non-aeronautical revenue as the output of non-aeronautical operations (Bottasso & Conti, 2012; McCarthy, 2016; Oum et al., 2008; Voltes-Dorta & Lei, 2013). Thus, I used non-aeronautical revenues as the output of non-aeronautical operations along with WLU as the output of aeronautical operations. The fixed inputs are the effective number of standard runways and

---

[31] The maintenance/repair data of the following airports are not available in the CATS: Albuquerque International Sunport (ABQ) in 2011, Hartsfield-Jackson Atlanta International Airport (ATL) in 2009, Austin-Bergstrom International Airport (AUS) in 2009, Bradley International Airport (BDL) in 2012, Nashville International Airport (BNA) in 2009, Buffalo Niagara International Airport (BUF) in 2009 and 2010, Louis Armstrong New Orleans International Airport (MSY) in 2009 and 2013, Palm Beach International Airport (PBI) in 2009 and 2010, Seattle-Tacoma International Airport (SEA) in 2009, John Wayne Airport (SNA) in 2010, and St. Louis Lambert International Airport (STL) in 2009, 2011, 2012 and 2013.

airport surface area. Based on the capital intensive structure of airports, a change in capital inputs would require a higher level of investment in the long run. Therefore, runways and airport surface area are considered as fixed capital inputs in the short run. The runway data were obtained from the FAA Aeronautical Information Service,[32] while the airport surface area was obtained from the Airport GIS data portal of FAA[33]. The effective number of standard runways was calculated by following McCarthy (2014). A common practice in the literature is that labor price can be obtained by dividing total expenditures for employees by the number of employees (Bottasso & Conti, 2012; Martin et al., 2009). The employee total expenditures include wages, health insurance and other benefits paid to the airport's employees. The other input price apart from wages and maintenance/repair prices were calculated by dividing the remaining operating expenditures by the number of aircraft movements (Bottasso & Conti, 2017; Martin et al., 2009). In the same fashion, maintenance/repair prices were obtained by dividing maintenance/repairs expenditures by the number of aircraft movements (Bottasso & Conti, 2017). The number of aircraft movements was obtained from the Operations Network Web Data System[34]. I controlled for heterogeneity among airports with hub size. The hub size classifications were determined by the FAA according to the number of passenger boardings annually. Public commercial service airports that have more than 10,000 passenger boardings each year are considered primary airports, and of which, those that account for 1% or more of the annual passenger boardings in the U.S. are classified as large hubs airports, while primary airports that account for at least 0.25% but less than 1% of the boardings are considered medium hub airports[35]. Hub-sizes were

---

[32] https://www.faa.gov/air_traffic/flight_info/aeronav/aero_data/Airport_Data/
[33] https://airports-gis.faa.gov
[34] https://aspm.faa.gov/opsnet/sys/main.asp
[35] https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/categories/

obtained from LeighFisher (2016). Medium hub size was chosen as a control variable so a large hub size binary variable was added to the model. Hub takes on the value of 1 for large hubs, and 0 otherwise. In addition, use-agreement types were used as determinants of airport cost inefficiency in the stochastic frontier model. The information on use-agreement types for each airport is obtained from LeighFisher (2016). According to the data, eleven of the large hub airports adopted the compensatory method while eight of them used the hybrid method, and eleven of them followed the residual method. Eleven of the medium-hub airports preferred the hybrid method, ten of them used the residual method, and eight of them adopted the compensatory method. I assigned residual airports as the control group; this means that airports adopting the residual method are chosen to be the base group. Table 11 shows a summary of the variables used in the model. Appendix A contains information on airport hub size and the use agreement types.

The descriptive statistics of the variables are presented in Table 12. As Table 12 depicts, total operating cost increased by about 30% between the years 2009 and 2016 while operating prices other than wages and maintenance prices went up by 25.8%, maintenance prices increased by 38.9% and wages increased by 19.5%. The largest annual mean operating expenditure was observed in 2016. The annual averages of the two fixed inputs remained constant throughout the study period.

Table 11. Variable Descriptions

Variable	Description/Unit of Measurement	Source
Outputs		
WLU (y_1)	Workload Unit (1 WLU = 1 passenger or 100 kg of freight)	CATS
Non-aeronautical revenues ($y2$)	Annual revenues from non-aeronautical operations ($)	CATS
Input prices		
Wage (w_1)	Total labor expenditure /#employees ($)	CATS
Price of Maintenance (w_2)	Total maintenance-repair expenditures /aircraft movements ($)	CATS/ Operations Network Web Data System
Operating price (w_3)	Operating expenditures other than maintenance-repair and labor expenditures/aircraft movements ($)	CATS/ Operations Network Web Data System
Fixed Inputs		
Area (k_1)	Airport surface area (acres)	Airport GIS data portal of FAA
ENSR (k_2)	The Effective Number of Standard Runways	FAA Aeronautical Information Service
Other variables		
Large Hub	A dummy variable (Hub = 1 for large hubs, 0 otherwise)	Leigh Fisher
Use agreements	A dummy variable (1 for Compensatory airports, 0 otherwise; 1 for Hybrid airports, 0 otherwise, Residual is the control group.)	Leigh Fisher

Table 12. Descriptive Statistics of Cost Efficiency Data

			OUTPUTS		INPUT PRICES			FIXED INPUTS	
YEAR		**Total Operating Cost ($x10^6$)**	**WLU ($x10^6$)**	**Non-Aero. Rev ($x10^6$)**	**Other inputs**	**Wages ($x10^3$)**	**Maintenance**	**ENSR**	**Area ($x10^3$)**
2009	MEAN	211.84	17.8	95.4	421.67	107.8	93.04	3.4	4.8
	SD	178.47	16.0	72.9	191.52	84.3	112.88	2.04	5.3
2010	MEAN	216.43	18.5	97.7	432.68	109.9	102.91	3.4	4.8
	SD	180.56	17.6	75.2	199.81	88.2	119.17	2.04	5.3
2011	MEAN	226.55	18.7	104.9	452.78	110.9	109.01	3.4	4.8
	SD	193.05	17.2	83.1	211.07	91.0	122.99	2.04	5.3
2012	MEAN	234.36	18.7	109.1	478.78	112.7	114.31	3.4	4.8
	SD	201.46	17.1	86.9	218.15	94.7	110.64	2.04	5.3
2013	MEAN	241.76	19.1	115.3	485.92	117.1	126.10	3.4	4.8
	SD	208.45	17.5	92.7	229.69	100.6	117.07	2.04	5.3
2014	MEAN	253.71	19.5	121.8	498.12	116.2	144.66	3.4	4.8
	SD	220.23	17.8	99.6	227.87	82.1	124.28	2.04	5.3
2015	MEAN	260.62	20.7	127.4	516.50	120.6	132.04	3.4	4.8
	SD	227.09	19.6	104.6	231.50	92.9	115.01	2.04	5.3
2016	MEAN	275.79	21.6	136.0	530.51	128.8	129.20	3.4	4.8
	SD	242.40	20.1	111.7	224.21	94.5	112.91	2.04	5.3

In addition to Table 12, I also reported the descriptive statistics of the data by use agreement type in Table 13. Looking at Table 13 in more detail, we observe that the mean total operating cost of compensatory airports is the highest among the three groups of airports. The residual airports follow the compensatory airport in terms of operating costs. While the average non-aeronautical revenues of compensatory airports are higher than the other two airport groups', the average WLU of residual airports is the highest compared to the other two. Besides, compensatory airports appeared to have the highest average input prices.

Table 13. Descriptive Statistics by Use Agreement

		C_{it}^{v}	OUTPUTS		INPUT PRICES			FIXED INPUTS	
Use Agreements		**Total Opt. Cost (x10^6)**	**WLU (x10^6)**	**Non-Aero. Rev ($). (x10^6)**	**Other Input**	**Wages (x10^3)**	**Maintenance**	**ENSR**	**Area (x10^3)**
Compensatory	MEAN	302	19.2	136	509.68	152.80	172.29	3.5	4.64
	SD	255	15.2	107	225.71	140.72	166.88	2.7	4.07
Hybrid	MEAN	188	17.4	103	427.24	89.84	98.57	3.3	5.74
	SD	141	16.6	78.8	201.26	23.67	63.19	1.7	7.46
Residual	MEAN	250	22.8	107	507.04	108.06	98.01	3.6	4.06
	SD	204	21.5	87.3	230.00	54.81	74.37	1.4	2.72

3.6. Results

To examine the cost efficiency of the sampled airports, I estimated three models: pooled ALS, BC95 and TRE. As discussed in section 3, ALS was originally developed for cross-sectional data. Thus, in a pooled ALS model, an airport appears multiple times in the data, but each appearance is assumed to be independent of the other appearances of the same airport. In other words, the pooled ALS model assumes each observation to be independently and identically distributed across time. Thus, this is a limitation of the pooled frontier model. Besides, ALS does not allow analyzing the effects of environmental factors on inefficiency. This limit is relaxed by scaling inefficiency distribution ($u_i \sim N^{+}(0, \sigma_{ui}^2),\ \sigma_{ui}^2 = \exp(z_i'\psi)$). In this way, the effects of use agreements on cost inefficiency can be examined.

By employing BC95, we are able to account for the panel structure of the data. Furthermore, BC95 allows inefficiency to vary over the years and considers the heterogeneity in the context of random-effects analysis. However, we need to separate heterogeneity from inefficiency to generate consistent results on the effects of use-agreement. Accordingly, we employed TRE to separate the unobserved cross-sectional airport heterogeneity from airport inefficiency. The descriptive statistics of efficiency scores obtained from these models are reported in Table 14.

Table 14. The Descriptive Statistics of Efficiency Scores

Model	Mean	SD	Min	Max
BC95	0.904	0.058	0.629	0.968
TRE	0.935	0.106	0.596	0.999
Pooled	0.911	0.055	0.633	0.969

As seen in Table 14, the mean efficiency estimate from the TRE model is 0.935, implying that the cost-saving potential was approximately 6.5%, while the mean efficiency estimates from the pooled and BC95 models are 0.911 and 0.904, respectively. The mean differences were compared with the paired t-test. Accordingly, the mean efficiency scores of TRE is greater than those derived from the other two models[36]. Moreover, as seen in Figure 1, the mean and standard deviations of distribution in TRE are higher than the ones from BC95 and Pooled ALS. The mean TRE cost efficiency score suggests that U.S. airports could reduce their operating cost by an average of 6.5%. To put this in perspective, considering the average annual operating cost in 2016 ($275.79 million), a 6.5% potential cost reduction implies that a U.S. airport could reduce its operating cost by $17.93 million in 2016.

[36]The mean TRE cost efficiency is statistically greater than the mean cost efficiency of BC95 (t =-4.3174; p-value=0.000). The mean TRE cost efficiency is greater than the mean cost efficiency of pooled ALS. t =-3.2602, p-value=0.000). Additionally, the mean cost efficiency of pooled ALS is greater than the mean efficiency score of BC95 t- = 36.3620:p-value=0.000).

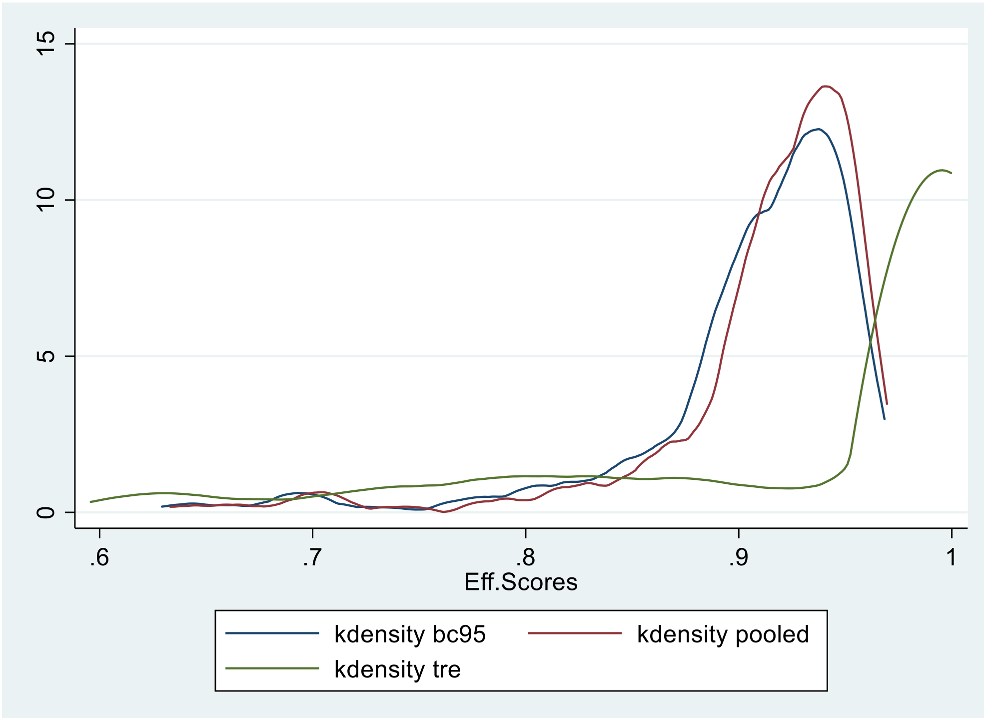

Figure 1. Kernel Density Distributions of Three Models

The estimates of the three models are reported in Table 15. According to the Wald statistics, all three models are significant. Outputs (WLU and non-aeronautical revenue), input prices (wages and price of maintenance/repairs), and fixed inputs (area and ENSR) are significant and positive. A positive fixed input parameter estimate is common in airport cost analysis[37], and it can be explained by over-capitalization (Cowing & Holtmann, 1983; Oum & Zhang, 1991). In other words, if a firm holds an excessive amount of capital stock, an increase in fixed inputs leads to an increase in variable cost. Since U.S. airports face the lumpy capacity[38] problem (Gillen & Lall, 1997; Pels, Van Vuuren, Ng & Rietveld, 2016), the variable cost of airports increases when fixed inputs increases. Although the coefficient estimates in pooled ALS

[37] See Oum et al. (2008), Martín et al. (2013), Kutlu & McCarthy (2016) and Zhao et al. (2014).
[38] Airports face lumpy capacity problem when they hold excess capacity in the short-run by considering their long run capacity needs in advance (Doganis, 1992, page 47).

and BC95 are very close, the ones in TRE show some departures from the estimates of the other two, plausibly due to unobserved airport heterogeneity that was not captured by ALS and BC95. Therefore, we should expect inefficiency derived from BC95 and pooled ALS to be biased (Farsi, Filippini & Greene, 2005). Besides, the time trend is significant and negative, implying that cost reduced over the years. Large-hub size has a significant and positive effect on cost; that is a large hub has approximately 34% higher variable cost in the TRE model. However, the estimated effect is approximately 18.50% in both pooled ALS and BC95.

The contributions of ENSR (approximately 18%) and maintenance/repairs price (14%) in TRE are higher than the ones in the other two models. In addition to these, I did not detect a significant time-variant parameter (η) in BC95, implying airport inefficiency does not vary over time. Besides, in TRE, the unobserved heterogeneity (σ_w) is significant, confirming the importance of the separation of heterogeneity from cost inefficiency in our model.

Table 15. BC95, TRE, and Pooled ALS Analysis Results

Parameter	**TRE**		**BC95**		**Pooled ALS**	
	Estimate	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Constant	-0.1165***	0.022	0.0613	0.052	-0.0520	0.051
Time (t)	-0.0156***	0.001	0.01862***	0.004	-0.01865***	0.004
Large-Hub (s1)	0.3358***	0.027	0.1842***	0.039	0.1850***	0.039
Area (k1)	0.1048***	0.016	0.1037***	0.024	0.1046***	0.024
Ensr (k2)	0.1793***	0.036	0.1348***	0.049	0.1321**	0.049
Wages (w1)	0.2802***	0.013	0.3937***	0.025	0.3948***	0.025
Maintenance/Repairs (w2)	0.1411***	0.006	0.1172***	0.017	0.1176***	0.017

Table 15. BC95, TRE, and Pooled ALS Analysis Results (continued)

Parameter	**TRE**		**BC95**		**Pooled ALS**	
	Estimate	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
WLU (y1)	0.3456***	0.016	0.3588***	0.029	0.3603***	0.029
Non-Aeronautical Rev.(y2)	0.1282***	0.021	0.2357***	0.033	0.2346***	0.033
k1*k1	-0.0268	0.018	-0.0287	0.028	-0.0294	0.028
k1*k2	0.0153	0.024	0.0002	0.035	-0.0022	0.035
k1*y1	0.0655***	0.017	0.1145***	0.030	0.1158***	0.030
k1*y2	-0.0861***	0.018	0.0133	0.034	0.0154	0.034
k1*x1	0.0190	0.015	0.1171***	0.033	0.11808***	0.033
k1*x2	-0.0033	0.004	0.0308**	0.014	-0.0306**	0.013
k2*k2	0.1430**	0.055	0.1804*	0.104	0.1766*	0.104
k2*y1	-0.1085**	0.036	0.0519	0.056	0.0488	0.056
k2*y2	-0.0245	0.039	0.2654***	0.068	-0.2614***	0.068
k2*x1	0.0030	0.029	0.2768***	0.063	-0.2793***	0.063
k2*x2	0.0006	0.011	0.0646**	0.031	0.06537*	0.031
x1*x1	0.0703***	0.005	0.0832***	0.012	0.08356***	0.011
x1*x2	0.0187**	0.008	0.1032***	0.023	-0.1031***	0.022
x1*y1	-0.0921***	0.015	0.1359**	0.046	0.13702**	0.046
x1*y2	-0.0050	0.015	0.1078**	0.050	-0.1081**	0.050
x2*x2	0.0517***	0.005	0.1249***	0.017	0.12505***	0.017
x2*y1	-0.0043	0.006	0.0434**	0.018	-0.0436**	0.018
x2*y2	-0.0025	0.006	-0.0478**	0.019	-0.0483**	0.019
y1*y1	-0.0506**	0.023	0.0675*	0.040	0.0688*	0.040
y1*y2	0.1291***	0.016	0.1299***	0.033	0.1307***	0.033
y2*y2	-0.003	0.028	0.2628***	0.058	-.02670***	0.058

Table 15. BC95, TRE, and Pooled ALS Analysis Results (continued)

Parameter	**TRE**		**BC95**		**Pooled ALS**	
	Estimate	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
$\boldsymbol{\sigma_U}$						
Compensatory	-0.5701**	0.288	-0.4740*	0.272	-0.9111**	0.451
Hybrid	-0.8238**	0.368	-0.4912*	0.268	-1.0428**	0.524
Constant	-5.4526***	0.214	1.2636	3.084	-4.0262***	0.442
$\boldsymbol{\sigma_V}$	-8.8634***	1.020	3.9296***	0.210	-3.894***	0.200
$\boldsymbol{\sigma_w}$	0.1822***	0.004				
$\boldsymbol{\eta}$			1.7451	6.410		
Wald Test	41384.20***		6792.93***		6784.26***	

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

The agreement variables (compensatory and hybrid) in all three models are significant and negative. These results imply that compensatory and hybrid airports are more cost-efficient than their peers that adopt the residual method. On the other hand, there is statistical difference in the cost efficiency scores between compensatory and hybrid airports according to the Wald test result (χ^2=0.62 and p-value=0.4322). The impacts of use agreements on cost inefficiency in the pooled ALS model are quite high because the model disregards the panel data structure. Moreover, the use agreements are significant at a 10% level in BC95. When the airport heterogeneity effect is accounted for in the inefficiency term in TRE, use agreements are significant at the 5% level. Cost inefficiency results in higher operating cost which could both increase the likelihood of airport budget deficit and increase in the airport fees paid the signatory airlines at residual airports. For the signatory airlines at residual airports, they are responsible for the budget deficit of the airports. Therefore, cost inefficiency could severely impact the benefits of the airlines.

3.7. Conclusion

Employing three stochastic variable cost frontier models (pooled ALS, BC95, and TRE), I examined the effects of rate-setting methods (or airport use agreement types) on airport cost efficiency. The analysis was conducted using an unbalanced panel data of 59 large and medium U.S. airports covering the years 2009-2016. According to TRE, the mean cost efficiency was 0.935, suggesting that U.S. airports could lower the operating costs by an average of 6.5%, which can be translated into $17.93 million in annual cost savings for an average U.S. airport. Moreover, cost inefficiencies differ across use agreement types. Airports adopting either the compensatory or hybrid method are more cost-efficient than the ones adopting the residual method. This implies that airports under compensatory or hybrid agreements manage their input use more efficiently compared to the airports under the residual method. This conclusion lends further support to the findings in Chapter 2 that, due to the financial assurance provided by signatory airlines, airports adopting the residual method may have a diminished focus on operating expenditures. The cost inefficiency of residual airports may lead to higher airport fees for the signatory airlines and could undercut any benefits that the latter expect to gain from executing a residual contract. This situation is a classic moral hazard problem that arises from unequal risk sharing in the agreement and from information symmetry in the airport-airline relationship.

CHAPTER 4: THE SOURCES OF U.S. AIRPORT AERONAUTICAL CHARGE DIFFERENTIAL: AN OAXACA DECOMPOSITION

4.1. Abstract

The decisions on aeronautical charges are crucial not only for the entire air transportationindustry but also for society. In the U.S., as public entities, airports must balance between achieving break-even with less government financial support and offering attractive charges to retain or increase their clienteles. U.S. airports adopt 3 rate-setting methods to formulate their charges. Under the residual method, the airports always achieve a break-even condition because any budget deficits (or surplus) would be covered by (credited to) the signatory airlines. In return, the signatory airlines pay reduced fees for bearing the airports' financial risk. Under the compensatory approach, the airports alone bear their own financial risk. All airlines pay charges according to their levels of facility usage. The hybrid method is a combination of these two methods. In this study, I examined the determinants of aeronautical charges as well as the sources of the aeronautical charge differential using an Oaxaca decomposition. I find that airports adopting the hybrid method have lower aeronautical charges than the airports adopting either the compensatory or residual method due primarily to the difference in airport average cost. The difference in aeronautical charges between residual and compensatory airports is not statistically significant. The results also show that non-aeronautical charges are an important determinant of aeronautical charges for airports using the compensatory method. This can be explained by the differences in the use agreements.

4.2. Introduction

After the Airline Deregulation Act in 1978, airline competition and harsh market and economic conditions had resulted in 204 airlines bankruptcies between 1979 and 2018[39] in the U.S. Airline bankruptcies directly affect airports in a profoundly negative way as they could lead to hub abandonment (Rupp and Tan, 2019; Karanki and Lim, 2020). Airlines and airports have developed strategies to mitigate the risks of operating in a market full of uncertainty and situations beyond their control. Some of the common forms of formal business arrangements between them are use agreements, revenue sharing, risk sharing, revenue bonds for airlines, etc. With a business arrangement with the airports, airlines could solidify their network, obtain lower aeronautical fees, and have a competitive advantage in the downstream market. It would be very difficult for airlines to carry out these strategies without a working and stable relationship with airports (Fu et al., 2011).

U.S. airports are public infrastructure owned and controlled by governments (Kutlu and McCarthy, 2016). They are not allowed to create revenue surpluses that exceed the airport operating costs (FAA, 2009). While air traffic volume has risen in recent years, and airports are operating at limited capacity, government funding resources are not sufficient to meet airports' needs for capacity expansion. For instance, the U.S. airport industry estimates almost $100 billion for infrastructure development for the years between 2017 and 2021, but only $61 billion are not met by the federal government's airport improvement program[40] (Dillingham, 2017). Moreover, lately, airports are expected to reduce their reliance on government resources (Fu et

[39] http://airlines.org/dataset/u-s-bankruptcies-and-services-cessations/

[40] Airport improvement program is a grant program provided by Federal government to public airports for their capital project. (https://www.faa.gov/airports/aip/overview/).

al., 2011). Thus, airports must ascertain stable and sufficient revenues from their operations to maintain a solid financial footing. Airlines are important business partners to airports, and their relationship is symbiotic (Faulhaber et al., 2010). They need each other to survive and thrive.

It is very common for airports and airlines in the U.S. to formalize their business relationship by executing an airport use agreement. The use agreements can be categorized into three types based on the three rate-setting methods in the U.S. (FAA, 1999): residual, compensatory and hybrid. The three methods dictate how fees are to be calculated and how airport financial risks may be shared in each agreement type.

In this study, I examined the determinants of aeronautical charges and the source of differences in aeronautical charges between the use agreement types using an Oaxaca decomposition. In performing the Oaxaca decomposition, the gap was decomposed into two parts: the explained part resulting from the difference in characteristics of determinants of aeronautical charges the use agreements, and the unexplained part resulting from the difference in the way the determinants' characteristics impact aeronautical charges.

To the best of my knowledge, this is the first study to shed light on the sources of the differences in aeronautical charges between airport use agreement types. Although the differences in aeronautical charges between use agreements are lucid, the sources of these differences are scarcely studied or understood. Consequently, it is difficult for both airline and airport management to identify the implicit and explicit factors of aeronautical charge differential. This study aims to identify these implicit or explicit sources. The major findings of this study are (1) airports adopting the hybrid method charges lower aeronautical fees than those that adopt either the compensatory or residual method; (2) the charge gap can be explained by differences in airport average cost; (3) the aeronautical charges between residual and compensatory based airports are not statistically significantly different; (4) non-aeronautical charges are an important determinant of aeronautical charges under the compensatory agreement; (5) the impact of non-aeronautical charges on aeronautical charges differs across the use agreement methods because of the difference in the use agreements.

I describe the three rate-setting methods in the following section. Section 4.3 belows gives an overview of the rate setting methods used by U.S. airports. In Section 4.4, I give a summary of previous studies regarding the determinants of aeronautical charges. The relationship between aeronautical and non-aeronautical charges is discussed in Section 4.5. Following the presentation of the model in Section 4.6, the data are described in Section 4.7. I discuss the results in Section 4.8. In Section 4.9, I conclude the chapter with the results' implications.

4.3. Rate Setting Methods and Airport Use Agreements

Use agreements are an important vertical business arrangement between airports and airlines in the U.S. They can be categorized into three types based on the three rate-setting methods (FAA, 1999): residual, compensatory and hybrid.

Under a residual method, the signatory airlines pay reduced user fees as they provide financial guarantees to the host airport. The financial risk of the airport is borne by the signatory airlines, allowing the host airport to always achieve break-even. However, the host airport's control span on capital investment is limited by a majority-in-interest (MII) clause under the residual agreement. Under the MII, the host airport has to have the approval of the signatory airlines to begin a new capital project since the bond debt service costs are covered by the signatory airlines. Under the residual method, the aeronautical fees paid by the signatory airlines is determined by the residual amount after deducting non-airline revenues and non-signatory airlines' payments from the total cost. At the end of the year, if there is a surplus in non-aeronautical operations, it is credited to the signatory airlines. However, any airport budget deficit would be covered by the signatory airlines. The residual method resembles the single-till approach which considers all airport activities, both aeronautical and non-aeronautical when calculating the airport charges (Oum et al., 2004). Based on the information from Landrum & Brown[41], non-signatory airlines usually pay 25% more than the landing fee paid by the signatory airlines. This implies that there is a positive correlation between the charges between signatory and non-signatory airlines. Therefore, non-aeronautical revenues indirectly impact the aeronautical charges for non-signatory airlines, i.e., a surplus leads to a decrease in aeronautical charges for non-signatory airlines.

Unlike the residual method, the host airport bears its own financial risk under the compensatory method. This implies that the break-even condition for the airport is not guaranteed. With this rate-setting method, airlines pay the fees according to their levels of airport use. Besides, airport management has full control over capital projects and investment decisions.

The third method is a hybrid approach, which is a combination of the residual and compensatory methods. A common arrangement under the hybrid approach can be that the compensatory method is applied for terminal operations while the residual method is used for airfield operations. Hence, the overall airport financial risk is shared, i.e. the risk of terminal operations may be borne by the airport while the risk of airfield operations may be covered by the airlines. This risk-sharing brings a financial assurance toairports since the financial risk of airfield operations is covered by the airlines against uncertainty in the airline industry and the

[41] My e-mail discussion with Landrum & Brown on August 8 ,2019.

economy, while the airport is incentivized to increase non-aeronautical revenues (FAA, 1999). In this system, a hybrid airport may share its non-aeronautical revenues with signatory airlines (Faulhaber et al, 2010). In this way, airport management incentivizes signatory airlines to increase their operations at the airport (Fu et al., 2011).

4.4. Determinants of Aeronautical Charges

The determinants of aeronautical charges have been scarcely analyzed in literature since airports are seen as infrastructure rather than a business entity (Bilotkach, Clougherty, Mueller & Zhang, 2012). Four empirical studies on aeronautical charges published in the last decade focused on the airports in Europe and the U.S. Van Dender (2007) is the first to study the determinants of aeronautical charges. He analyzed the market structure effects on airfares, aeronautical charges, and non-aeronautical charges by using the data of 55 U.S. airports in the years 1998 through 2002. Van Dender (2007) found that aeronautical charges decrease with the number of flights. Additionally, his findings related to aeronautical charges were that airports facing competition charge lower fees, the hub effect is not significant while aeronautical charges increase with Herfindahl–Hirschman Index (HHI), flight distance and the share of international flight.

A second related study was conducted by Bel and Fageda (2010) who focused on the effects of market power and regulation/ownership on aeronautical charges using the data of 100 European airports in 2007. They found that private owned-regulated airports tend to charge higher fees, and aeronautical charges decrease with the percentage of domestic traffic while they increase with total traffic. The study also found that there is no difference between the single-till and dual till approaches when it comes to aeronautical charges; airports having higher traffic charge more; the existence of neighbor airports in 100 km reduces aeronautical charges;

aeronautical charges decrease with HHI; lastly, the aeronautical charges for domestic flights are lower than those for international flights.

The study by Bilotkach et al. (2012) also focused on the aeronautical charges of European airports using the data of 61 airports in the years between 1990 and 2007. Bilotkach et al. (2012) found that the single-till approach leads to lower aeronautical charges while non-aeronautical revenues per passenger have no significant effect on aeronautical charges. They found that privatized airports tend to charge lower fees, airports adopting ex-post regulation[42] apply lower fees, and aeronautical charges are higher at airports with a hub status. Unlike Van Dender (2007) and Bel and Fageda (2010), Bilotkach et al (2012) did not detect any significant effect of the presence of nearby airport on aeronautical charges.

The latest study on aeronautical charges was conducted by Choo (2014) who analyzed the aeronautical charges of 59 U.S. airports in the years 2002 through 2010. The effects of hub status, governance types, percentage of international and connecting flights, and competition among airports on aeronautical charges were examined in this study. Choo (2014) found that U.S. airports use cross-subsidization, and airport operating cost is reflected on aeronautical charges. Similar to Bilotkach et al. (2012), Choo (2014) found hub airports charge higher fees. Furthermore, the author did not find any evidence of the effects of neighbor airports, which is measured by the number of airports in a 100 km radius, on aeronautical charges. Lastly, airport governance types, connecting traffic, and the share of dominant airlines have no significant effect on aeronautical charges as well.

---

[42] In an ex-post regulation regime, the regulator does not regulate the airports unless the latter violates the price, profit, and service quality thresholds.

4.5. Non-Aeronautical and Aeronautical Charges

Non-aeronautical and aeronautical operations are interdependent. Zhang and Zhang (1997) found that social welfare gains in aeronautical operations are higher than the loss in non-aeronautical operations when airports cross-subsidizing the two operations. In recent years, non-aeronautical revenues have become more important for airports (D'Alfonso et al., 2013; Kidokoro, Lin & Zhang, 2016; Zhang & Czerny, 2012; Zhang et al., 2010), and non-aeronautical revenues are seen by most airports as a major revenue source (D'Alfonso et al., 2013). Van Dender (2007) found that non-aeronautical revenue share is more than half of the total revenues of the 55 U.S. airports during the period1998-2002. Zhang and Zhang (2010) found that aeronautical charges are lower due to non-aeronautical operations. This implies that cross-subsidizing aeronautical operations with lucrative non-aeronautical operations may be feasible and practical for airports. Czerny (2006) and Lu and Pagliari (2004) contributed to the literature by finding that the single-till[43] approach improves social welfare. In the European airport industry, single-till is considered a way of cross-subsidization (Bilotkach et al., 2012). Ivaldi et al. (2015) analyzed 31 U.S. airports by accounting for the two-sided structure of the airport operations. They concluded that U.S. airports apply profit-maximizing prices for non-aeronautical operations while they set Ramsey prices for aeronautical operations[44], implying that cross-subsidization is not used by U.S. airports. Additionally, according to the simulation results, Ivaldi et al. (2015) found the single-till approach enhances social welfare. On the other hand,

[43] The single-till approach refers to an airport's decision to base their aeronautical charges on both aeronautical and non-aeronautical revenues in the preceding period. The dual-till approach refers to an airport's method of calculating aeronautical charges based only on its aeronautical activities (Smyth & Pearce, 2007).

[44] Ramsey pricing is a strategy to set prices inversely to the price elasticity of demand. Ramsey pricing is seen as the second best solution for the social welfare if marginal cost pricing cannot be applied due to high fixed costs. It is the second best solution since it allows the maximum possible social welfare which is lower than the ones at marginal cost pricing while firm is achieving break-even (Bitzan, 2000).

contrary to previous studies, Kidokoro et al. (2016) argued that the dual-till approach yields higher welfare, and cross-subsidizing does not lead to welfare maximization.

4.6. Conceptual Framework and Model

In this study, aeronautical charges (a) are modeled as a function of average cost (*AC*), non-aeronautical revenues per passenger (*NR*), delays (*D*), the Herfindahl-Hirschman Index for the market concentration of airlines (*HHI*), governance types (*G*), horizontal tie (*Htie*) and a time trend (*T*):

$$a = f(AC, D, HHI, Htie, G, NR, T) \tag{4.1}$$

Following the literature, aeronautical charges are defined as aeronautical revenues per aircraft movement (Bilotkach et al., 2012; Choo, 2014; Dender, 2007). Since U.S. airports are not allowed to earn excess revenue more than their costs, aeronautical charges may reflect the cost level of airports (Choo, 2014). If the averge cost is high, the aeronautical charge must rise; if the average cost is low, and the airport must reduce the aeronautical charge since any revenue surplus is not permitted. Since airport total revenues (aeronautical revenues and non-aeronautical revenues) are used to recover both operating expenditures and revenue bond debt-services (FAA, 1999), I consider the sum of operating costs and debt service costs as the total cost. Therefore, I calculated the average cost by dividing airport'stotal cost by the number of aircraft movements. To capture the effect of congestion on aeronautical charges, I used the number of delays as a proxy for congestion. Delays are considered a social cost affecting the aeronautical charges (Zhang & Zhang, 1997). Accordingly, we expect an increase in delays leads to an increase in aeronautical charges. However, the optimal aeronautical charges of a congested airport are disputable in the literature. Some researchers suggest that airports should apply higher aeronautical charges or congestion pricing to reduce delays (Brueckner, 2001; Daniel, 1995;

Zhang & Zhang, 2006). Nevertheless, D'Alfonso et al. (2013) proposed lower aeronautical fees considering the positive correlation between non-aeronautical revenues and dwell time, thus, the lower aeronautical charges at a congested airport would lead to an increase non-aeronautical revenues. Van Dender (2007) and Bel and Fageda (2010) used the HHI to measure airline market density at the airport ($HHI = \sum_i \tau_i^2$, where τ_i is the market share of ith airline). One may expect lower aeronautical fees at airports with higher concentration since the dominant airline has a higher bargaining power on aeronautical charges. Governance types may also be a factor affecting aeronautical charges (Choo, 2014). Based on the differences in the contributions of the local/state grants to airport financial portfolios, the decisions on aeronautical charges may vary across airports governed by different entities. Thus, we considered four common airport governance types: city, county, state and port/airport authority. Besides, I also examine the horizontal (administrative or ownership) tie between airports. Specifically, some airports may have a horizontal relationship with each other as they are managed by the same governing entity (Van Dender, 2007). The control of an airport cluster increases the negotiation power of the airport governing body, thus, one may expect airports that have a horizontal tie with other airports in the same geographical cluster to have higher aeronautical charges compared to their peers. In our sample, there are three such clusters: O'Hare International Airport and Chicago Midway Airport are governed by the Chicago Department of Aviation; JFK, LaGuardia and Newark airports are governed by the Port Authority of New York and New Jersey; Dulles International and Reagan Washington National Airports are governed by the Metropolitan

Washington Airport Authority.[45] Lastly, following Bilotkach et al. (2012), I used non-aeronautical revenue per passenger (or non-aeronautical charges) to control for potential interdependence between aeronautical and non-aeronautical operations. One may expect a negative relationship between non-aeronautical and aeronautical charges due to the complementary relationship between the two.

This model setting raises some endogeneity concerns due to the reverse or simultaneous causality of aeronautical charges with the explanatory variables such as delays, average cost and non-aeronautical revenue per passenger. The interdependence between aeronautical and non-aeronautical operations implies that airports consider both aeronautical and non-aeronautical charges simultaneously under an overall budget constraint. Thus, there is a two-way relationship between aeronautical and non-aeronautical revenue charges which makes the latter endogenous. Secondly, because aeronautical output and charges are directly related, an increase in aeronautical output leads to higher charges, and the latter in turn exert downward pressure on the aeronautical output demanded and result in even higher unit costs.. Accordingly, I consider the average cost variable endogenous as well. As discussed previously, aeronautical charges may have an impact on delays, i.e., higher aeronautical charges may alleviate congestion. Consequently, this two-sided relationship leads to an endogeneity problem between delays and aeronautical charges. Following Bilotkach et al. (2012), I addressed the endogeneity problems of non-aeronautical charge and average costs by using the time-lagged values of these two variables as instruments. Indeed, as long as the lagged values are not a part of the equation and are

[45] The Chicago Department of Aviation adopts the residual method; the Port Authority of New York and New Jersey uses the compensatory method for all three airports; the Metropolitan Washington Airport Authority uses the hybrid method.

sufficiently correlated with the endogenous variable, using lagged values of endogenous variables provides an effective estimation (Reed, 2015). In addition, delays were instrumented by the number of the gates which is one of the explanatory factors of delays.

To examine the differences in aeronautical charges between rate-setting methods, I modified the Oaxaca two-fold decomposition (Oaxaca, 1973):

$$E(\ln a_i) - E(\ln a_j) = E + U \tag{4.2}$$

where a_i is the aeronautical charge of airports adopting method *i*, and a_j is the aeronautical charge of airports adopting method *j*; E is the part of the aeronautical charge differential that can be explained by differences in *X* which is a set of determinants for aeronautical charges, while *U* is the unexplained part that captures the portion of the charge differential that cannot be explained by the differences in X.[46] The unexplained part may be attributed to the differences in the rate-setting methods. The explained and unexplained parts are given by

$$E = [E(X_i) - E(X_j)]'\beta^* \tag{4.3}$$

$$U = E(X_i)'(\beta_i - \beta^*) + E(X_j)'(\beta^* - \beta_j) \tag{4.4}$$

where $E(X_i)$ is the expected value of the determinants for aeronautical charges of airports adopting method *i*, while $E(X_j)$ is the expected value of the determinants for aeronautical charges of airports adopting method *j*. The mean values, $\bar{X}_i$ and $\bar{X}_j$, can be used as estimators of $E(X_i)$ and $E(X_j)$, respectively. The parameters β_i and β_j are the coefficients associated with the determinants for methods *i* and *j*, respectively. Finally, β^* is the arithmetic mean of the coefficients in the two groups without weighing the use agreements unequally (Reimers, 1983),

[46] Oaxaca (1973) originally developed this model to examine the wage differences between male and female workers.

that is $\beta^* = 0.5\beta_i + 0.5\beta_j$. The Oaxaca decomposition is demonstrated in Figure 2 in which an explanatory variable, x, is assumed to have a positive effect on aeronautical charges. In our study, the parameters β_i and β_j are estimated by the two-stage least squares method due to the endogeneity concerns in the model.

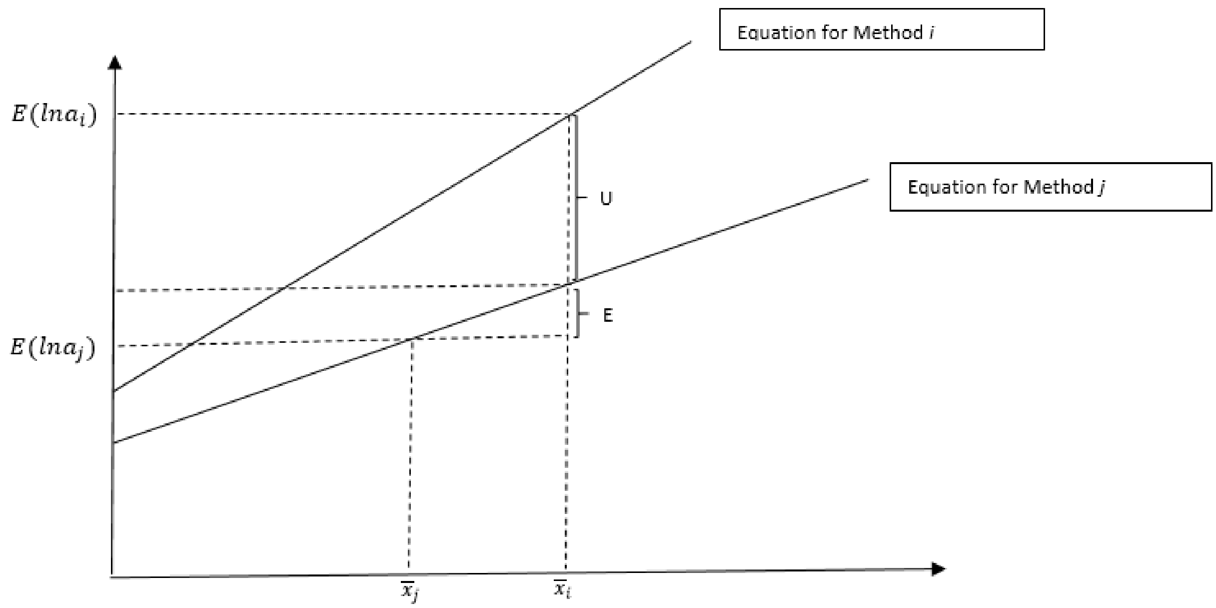

Figure 2. Graphical Illustration of Oaxaca Decomposition

In looking at Figure 2, the vertical distance between $E(\ln a_i)$ and $E(\ln a_j)$ represents the charge differential; E is the portion of the mean aeronautical charge differences resulting from the differences in between methods *i* and *j* that can be explained by *x*. If both methods had the same characteristics, the mean aeronautical charge difference could be eliminated. Another portion of the mean aeronautical charge difference, U, is the differential not explained by *x;* U may include any potential differences in the variables that are not observed by the model which may be attributed to the differences in the use agreements. In other words, although each use agreement had the same characteristics, mean aeronautical charges would still be different due to the differences in the ways the unobserved variables affect aeronautical charges.

To perform the Oaxaca decomposition, firstly, the following equation was estimated for each rate-setting method:

$$\ln a_{kit} = \beta_o + \beta_1 \ln AC_{kit} + \beta_2 \ln NR_{kit} + \beta_3 \ln HHI_{kit} + \beta_4 \ln D_{kit} + \beta_5 g1_{kit} + \beta_6 g2_{kit} + \beta_7 g3_{kit} + \beta_8 T + \beta_{15} Htie_{kit} + \varepsilon_{kit,} \quad (4.4)$$

where

a_{kit} is the aeronautical charge of *ith* airport adopting method k at year *t*, and *k: {Compensatory*, *Residual*, *Hybrid}*,

AC_{kit} is the annual average total cost,

NR_{kit} is non-aeronautical revenue per passenger,

HHI_{kit} is the Herfindahl-Hirschman index of airlines,

D_{kit} is the number of delays measured by the number of flights that arrive or depart 15 minutes or more than their scheduled times,

$g1_{kit}$ is the dummy variable for city governance,

$g2_{kit}$ is the dummy variable for county governance,

$g3_{kit}$ is the dummy variable for state governance,

$Htie_{kit}$ is the dummy variable for airports that have a horizontal administrative relationship with another airport, and

T is the year trend.

Because the model contains time-invariant variables, a fixed-effects (FE) model is not feasible. Thus, equation (4.4) is a random effects model, and ε_{kit} is a composite error term that encompasses the time-invariant unobserved effects and time-variant disturbance term. Additionally, it is assumed that any unobserved airport-specific effect is not correlated with the explanatory variables.

4.7. Data

I used a panel dataset of 30 large hubs and 29 medium hub airports in the years between 2009 and 2016. The data were clustered according to use agreement types to perform the Oaxaca decomposition. Use agreement types were obtained from LeighFisher (2016). The main source of our data is the Certification Activity Tracking System (CATS) Database which holds the financial reports of all U.S. commercial airports obtained from the Airport Financial Reporting Program. Information on aeronautical revenues, non-aeronautical revenues, operating expenditures, debt service cost after passenger facility charges, and the number of employees was obtained from this database. The financial data were adjusted for inflation using the U.S. gross domestic product deflator. To obtain aeronautical charges, we divided total aeronautical revenues by the number of aircraft movements. Aircraft movement data were obtained from the aircraft activity system of the FAA[47]. Aircraft movements cover all takeoffs and landings. The data on the number of delays were obtained from the Bureau of Transportation Statistics[48]. The number of gates were obtained from airports' websites. Flights are considered delayed if the aircraft arrive or depart 15 or more minutes than their scheduled time. The governance types were obtained from the National Academies of Sciences, Engineering, and Medicine (2009). I classified governance types into 4 categories: port/airport authority, county, city and state (Kutlu & McCarthy, 2016). Port/airport authority was selected as the control variable while city, county, and state were included as binary variables in the model. The airline's *HHI* was calculated with the information obtained from the Bureau of Transportation Statistics[49]. The values of *HHI* vary

---

[47] https://aspm.faa.gov/opsnet/sys/Main.asp?force=atads
[48] https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236
[49] https://www.transtats.bts.gov/airports.asp

between 0 and 10,000. Values closer to 10,000 imply a more concentrated downstream market at the airport. The descriptive statistics of the data are reported in Table 16.

Table 16. Descriptive Statistics of the Data

		Compensatory	**Hybrid**	**Residual**
Aeronautical Charges (*a_{kit}*)	Mean	512.436	318.177	440.094
	SD	414.531	166.709	234.066
Delays (*D*)	Mean	14381.87	13269.38	12122.37
	SD	10914.03	13207.54	10359.13
HHI	Mean	2404.125	3163.894	2783.366
	SD	1046.549	1722.554	1756.887
Non-aeronautical Charge (*NR*)	Mean	11.10	10.56	10.09
	SD	3.40	2.96	4.11
Average Cost (*AC*)	Mean	1003.12	821.96	1009.87
	SD	502.59	406.80	451.07
Horizontal Tie (*Htie*)	Mean	0.15	0.09	0.11
	SD	0.35	0.29	0.32
Port/Airport Authority	Mean	0.5	0.48	0.26
	SD	0.5	0.5	0.44
City (*g1*)	Mean	0.35	0.37	0.39
	SD	0.47	0.48	0.49
County (*g2*)	Mean	0.1	0.04	0.28
	SD	0.3	0.21	0.45
State (*g3*)	Mean	0.05	0.09	0.06
	SD	0.22	0.29	0.23
Number of Airports		20	21	18

As displayed in Table 16, the aeronautical charge of compensatory airports averaged $512.5 per aircraft movement, which is the highest of the three airport rate-setting methods. The difference in the average charges between compensatory and hybrid airports is large compared to the average charge difference between compensatory and residual airports. Compensatory airports too have the highest average non-aeronautical charge at $11.1 per passenger, compared to $10.6 for hybrid airports and $10.1 for residual airports. The airline market concentration at hybrid airports is the highest, followed by residual airports. Lastly, the average number of delays at compensatory airports was the highest of the three airport types.

4.8. Empirical Analysis

Firstly, the Durbin-Wu-Hausman was performed to check the endogeneity of *AC*, *NR*, and *Delays* following Wooldridge (2015). The null hypothesis of the test is that these variables in the regression can be treated as exogenous. Under the null hypothesis, the test statistic follows a Chi-squared distribution. The rejection of the null hypothesis implies that the endogeneity of the variable in question is affirmed. According to the test results (χ^2 statistic = 42.02, p-value =0.000), I rejected the null hypothesis of the Durbin-Wu-Hausman test, implying that the *AC, NR* and *Delays* are endogenous with this model setting[50]. Following the Hausman test, I assessed the relevance of instrumental variables which are the time-lagged values of endogenous variables with a null hypothesis that the instruments are uncorrelated to the endogenous variables. According to the test results (the χ^2 statistic for the instrument of *Delay* is 7287.93 (p-value=0.0000), the χ^2statistic of the instrument of *NR* is 2659.97 (p-value=0.0000), and the

[50] Since the number of instrumental variables is limited, i.e., the number of endogenous variables equals the number of instrumental variables, the over-identification test cannot not be performed to check for the exogeneity of instrumental variables.

χ^2statistic of the instrument of *AC is* 803.66 (p-value=0.0000)), we can conclude that there is sufficient evidence of the relevance of the instruments.

To perform the Oaxaca (1973) decomposition, I estimated a random-effects regression model for the three groups of airports according to the rate-setting method they use. The estimation results for the three sets of results are reported in Table 17. In looking at Table 17, the parameter estimates differ across the three methods. As expected, the average cost is significant and positive. A 1% increase in the average costs of the residual airports is estimated to increase aeronautical charges by 1.21%. For compensatory airports, this estimated effect is 1.28%, while it is 0.74% for hybrid airports. Unlike Bilotkach et al. (2012), my results showa significant effect of non-aeronautical charges on aeronautical charges for compensatory airports, and the effect is negative suggesting that the two lines of airport operations are highly dependent on each other especially for airports adopting the compensatory method. A 1% increase in non-aeronautical charges is estimated to decrease aeronautical charges by 0.59% at compensatory airports. The effect of non-aeronautical charges in not significant for the residual and hybrid airports. Residual airports are guaranteed a budget breakeven by the signatory airlines, hence the sensitivity of aeronautical charges in response to any changes in non-aeronautical charges is less since any budget shortfall (surplus) in the two operations will be covered by (credited to) the signatory airlines. Thus, the two charges at residual airports are less responsive to each other. On the contrary, compensatory airports must rely on their own to balance their budgets, and they must ensure that any non-aeronautical revenue reduction is compensated by increased revenues in aeronautical operations or reduced total costs to break even. Thus, compared to residual airports, the aeronautical charges of compensatory airports are nearly three times more sensitive to any changes in non-aeronautical charges; the two lines of business are more dependent on each other.

Due to the financial assurance of the signatory airlines in the airfield operations of airports adopting the hybrid method, the responsiveness of non-aeronautical charges on aeronautical charges of a hybrid airport is between those of the compensatory and residual airports.

Table 17. Second-Stage Estimation Results of Equation (4) for the Three Methods

	RESIDUAL		**COMPENSATORY**		**HYBRID**	
	ESTIMATES	**ROBUST S.E.**	**ESTIMATES**	**ROBUST S.E.**	**ESTIMATES**	**ROBUST S.E.**
ln(AC)	1.208***	0.235	1.281***	0.200	0.736***	0.183
ln(NR)	-0.183	0.360	-0.585***	0.213	-0.087	0.381
ln(D)	-0.092	0.143	-0.039	0.107	0.026*	0.167
ln(HHI)	-0.003	0.076	-0.192	0.130	-0.108	0.058
g1	0.352	0.256	0.011	0.135	0.014	0.119
g2	0.246	0.225	0.294*	0.154	-0.149	0.243
g3	0.692*	0.319	0.026	0.199	0.378**	0.184
Htie	0.536***	0.247	0.739***	0.120	0.410***	0.170
T	-0.006	0.009	0.013	0.009	0.000	0.005
Intercept	-1.282	1.496	0.277	0.976	1.541	1.608
R^2	0.8947		0.9351		0.8421	
Wald Stat	89.75***		328.57***		106.98***	
Number of observations	142		160		170	

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Looking at the effect of delays (or congestion) on aeronautical charges, it is not significant for compensatory and residual airports but it is significant and positive for the hybrid airports at the 10% level. This implies that congestion may force hybrid airports to increase aeronautical charges. The variable *HHI* is not significant for all airports regardless of the rate-setting methods. Under the hybrid method, state-governed airports charge higher fees than those managed by a port/airport authority. Besides, under the compensatory method, county governed airports charge higher fees than the ones governed by a port/airport authority. The horizontal tie is an important indicator of regional market dominance. It is significant and positive for all three rate-setting methods. Tellingly, residual[51] and hybrid[52] airports with horizontal ties are predicted to charge between 41-54% higher fees, and compensatory airports[53] with horizontal ties are estimated to charge 74%[54] higher fees than their counterparts with no horizontal ties due to their bargaining power in their respective regions. Lastly, no significant change in aeronautical charges was observed over the years.

The Oaxaca decomposition results based on the random-effects model estimates are reported in Tables 18, 19 and 20. Table 18 shows the results of the Oaxaca decomposition for compensatory (*i*) and hybrid (*j*) airports. I observed that the log mean charge differential between compensatory (*i*) and hybrid (*j*) airports is 0.366. In other words, compensatory airports' average charge is higher than that of hybrid airports, and 73.7% (0.270/0.366) of this gap results from differences in the determinants between these two groups of airports, while 27.3% (0.096/0.366) is due to the differences in the coefficients on the determinants or the differences in the two methods in how the determinants affect aeronautical charges. The log mean aeronautical charge of hybrid airports would increase by 0.270 if they had the same characteristics as compensatory airports. Furthermore, if the ways the determinants impact aeronautical charges were the same for compensatory and hybrid airports, the log mean aeronautical charges hybrid airports would be 0.096 higher.

---

[51] O'Hare and Midway Airports in Chicago.
[52] Dulles and Reagan Airports in Washington DC.
[53] JFK, LaGuardia and Newark Airports in New York and New Jersey.
[54] The observed airport data show that there is a large gap in the aeronautical charges between the airports with a horizontal tie and those without. For example, the mean aeronautical charges of JFK, LaGuardia and Newark was $1272.85 per aircraft movement in the years between 2009 and 2016, while the same charges of other compensatory airports averaged just $378.24 in the same period.

As reported in column (1), the average cost and HHI are the only significant variables in the explained differential in aeronautical charges. This means that the explained charge differential between compensatory and hybrid airports can be attributed to the mean difference in the airports' average cost and HHI which contribute positively to the charge differential.

Table 18. Oaxaca Decomposition (Compensatory vs. Hybrid)

	Estimates	**S.E.**		
Difference	0.366***	0.088		
Explained	0.270***	0.070		
Unexplained	0.096**	0.067		
	EXPLAINED (1)		**UNEXPLAINED (2)**	
	Estimates	**S.E.**	**Estimates**	**S.E.**
Intercept			-1.355	1.921
ln(AC)	0.226***	0.065	3.654**	1.822
ln(NR)	-0.015	0.016	-1.134	1.035
ln(D)	-0.001	0.011	-0.571	1.858
ln(HHI)	0.034*	0.018	-0.607	1.111
g1	0.000	0.003	-0.004	0.066
g2	0.004	0.008	0.032	0.022
g3	-0.009	0.009	-0.026	0.021
Htie	0.032	0.023	0.039	0.026
T	0.000	0.002	0.068	0.053

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Column (2) shows that the difference in the determinants' coefficients between compensatory and hybrid airports or the ways the determinants impact aeronautical charges of the two airport groups. If the coefficients between the two groups of airports are the same, then the unexplained part collapses to zero, and all charge differentials are due to the explained part. In other words, the aeronautical charge differential with respect to a given airport characteristic is only observed when the compensatory and hybrid coefficients for the variable in question are not equal. Considering the role of AC in the differential in aeronautical charges, the mean difference in AC is significant for the (explained) charge differential. Furthermore, based on the result in Column (2), the impact of AC on charges is larger for compensatory airports compared to hybrid airports. Table 19 shows the Oaxaca decomposition of the differences in aeronautical charges between compensatory (*i*) and residual airports (*j*). The log differential in aeronautical charges between compensatory and residual airports is 0.026 which is not statistically significant because the explained part is offset by the unexplained part.

Table 19. Oaxaca Decomposition (Compensatory vs. Residual)

	Estimates	**S.E.**		
Difference	0.026	0.094		
Explained	-0.102	0.078		
Unexplained	0.129	0.078		
	EXPLAINED (1)		**UNEXPLAINED (2)**	
	Estimates	**S.E.**	**Estimates**	**S.E.**
Intercept			1.559	1.786
ln(AC)	-0.018	0.066	0.500	2.108
ln(NR)	-0.044	0.029	-0.927	0.965
ln(D)	-0.011	0.016	0.489	1.637
ln(HHI)	0.007	0.008	-1.459	1.164
g1	-0.008	0.013	-0.127	0.108
g2	-0.049*	0.028	0.009	0.052
g3	-0.002	0.010	-0.035	0.022
Htie	0.024	0.027	0.027	0.036
T	0.000	0.001	0.094	0.066

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

In Table 20, the Oaxaca decomposition results for residual (*i*) and hybrid (*j*) airports are reported. The logarithmic mean difference in the aeronautical charges between residual and hybrid airports is 0.337. In other words, residual airports charge higher aeronautical fees than do hybrid airports. This gap can be explained by only the differences in the characteristics since the unexplained part is statistically insignificant. The decomposition results in column (1) show the aeronautical charge differential between residual and hybrid airports are predominantly explained by the differences in average costs; the mean log difference of average cost accounts for over 91% of the explained charge differential.

Table 20. Oaxaca Decomposition (Residual vs. Hybrid)

	Estimates	S.E.		
Difference	0.337***	0.087		
Explained	0.257***	0.087		
Unexplained	0.080	0.101		
	EXPLAINED (1)		**UNEXPLAINED (2)**	
	Estimates	**S.E.**	**Estimates**	**S.E.**
Intercept			-2.823	2.196
ln(AC)	0.233***	0.065	3.171	1.999
ln(NR)	0.010	0.020	-0.220	1.199
ln(D)	0.002	0.007	-1.075	2.008
ln(HHI)	0.009	0.009	0.822	0.751
g1	0.004	0.011	0.131	0.109
g2	0.011	0.039	0.065	0.055
g3	-0.020	0.018	0.024	0.028
Htie	0.009	0.018	0.013	0.031
T	0.000	0.001	-0.026	0.052

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

4.9. Conclusion

The determination of aeronautical charges is crucial for airport management. In this study, I examined the determinants of aeronautical charges by considering the relationship between aeronautical and non-aeronautical charges at U.S. airports. Besides, the sources of the differences in aeronautical charges between the rate setting methods adopted by the airports were examined by the Oaxaca decomposition method.

The results show the relationship between aeronautical and non-aeronautical charges is negative under the compensatory method while it is insignificant for residual and hybrid airports The impact of non-aeronautical charges on aeronautical charges differs across the methods plausibly due to the mechanisum by which the rate setting methods affect airport operations. Residual airports, for example, are guaranteed a budget breakeven by the signatory airlines, hence the sensitivity of aeronautical charges in response to any changes in non-aeronautical charges is less since any budget shortfall (surplus) in the two operations will be covered by (credited to) the signatory airlines. For hybrid airports, the impact of non-aeronautical charges on aeronautical charges is between the ones of the compensatory and residual methods. This is expected since the hybrid method incorporates features of the other two methods. In addition to the above, I find that if airports have a horizontal administrative tie with other airport in close proximity, they tend to charge higher aeronautical fees possibly because of their market power in the region in which they operate. In addition, I also found that the aeronautical charges of compensatory and residual airports are higher than those of hybrid airports. Moreover, there is no significant difference in aeronautical charges between residual and compensatory airports. There are, however, charge differentials between hybrid airports and their compensatory and residual counterparts. The main characteristic leading to the differentials is the average costs. As a result of lower unit cost at hybrid airports, holding all other factors constant, the aeronautical charges of hybrid airports are about 23% lower than compensatory and residual airports.

In conclusion, the three rate-setting methods have significant influence over aeronautical charge differentials of U.S. airports. This study shows that airportunit cost is the largest factor that consistently explained the charge differentials between hybrid airports and their residual and compensatory counterparts. This suggests that cost saving is essential for aeronautical charge reduction, particularly for compensatory and residual airports.

CHAPTER 5: CONCLUSION

This dissertation examined the implications of use agreements on airport economic performance and aeronautical charge differentials. Use agreements are the most common vertical business arrangements in the U.S. air transportation industry. Within the use agreements, terms and conditions are stipulated including the user fees and other responsibilities. In the U.S., the use agreements can be categorized into three types according to the three common rate-setting methods: residual, compensatory and hybrid.

Under a residual agreement, airports may obtain financial support from signatory airlines with which they can forge long-term business relationships to help alleviate financial stress and uncertainty. In turn, the signatory airlines may benefit from low user fees as compared to other airlines, with access to airport facilities secured and prioritized over rivals. However, as a result of the financial assurance, the host airports may underperform and may pay less attention to cost control. These two factors could undercut the benefits of the signatory airlines. In light of this, I examined the airports' cost and operational efficiency in Chapters 2 and 3 to determine the impacts of use agreements on airport economic performance.

In Chapter 2, I performed a two-stage semiparametric efficiency analysis to examine the effects of the use agreement types on airport operational efficiency using U.S. airport data from 2009 to 2016. The results show that the efficiency contribution of both compensatory and hybrid methods was evident in U.S. airports. Specifically, airports that follow either of these two methods outperformed those that followed the residual method. This might be that, compared to the compensatory and hybrid counterparts, residual airports do not bear the financial risk of operations, but their signatory airlines do. This financial guarantee offered by the signatory airlines (the principal) creates unequal risk-sharing which in turn disincentivizes the airport (the agent) from striving for greater operational efficiency especially in areas where the signatory airlines cannot fully observe. Hence, a lower airport efficiency may undercut any benefits that the signatory airlines expect to receive through the residual-typed contracts implying a moral hazard problem in the business arrangement.

In Chapter 3, three stochastic variable cost frontier models (pooled ALS, BC95 and TRE) were employed to examine the effects of the rate-setting methods (or airport use agreement types) on airport cost efficiency. The analysis was conducted using an unbalanced panel data of 59 large and medium U.S. airports covering the years 2009-2016. I find that the mean cost efficiency was 0.935, suggesting that U.S. airports could lower the operating costs by an average of 6.5%, which can be translated into $17.93 million in annual cost savings for an average U.S. airport. Moreover, the cost inefficiency scores differ across the three use agreement types. Airports that adopt either the compensatory or hybrid method are more cost-efficient than the ones adopting the residual method. This implies that airports under compensatory or hybrid agreements manage their input use more efficiently compared to the airports that adopt the residual method. This conclusion lends support to the finding in Chapter 2 that airports adopting the residual method have a diminished focus on operating expenditures due to the financial mitigation provided by the signatory airlines. The cost inefficiency of residual airports may lead to higher airport fees for the signatory airlines and could undercut any benefits that the latter expect to gain from executing a residual contract. This situation is a classic moral hazard problem that arises from unequal risk sharing in the agreement and from information symmetry in the airport-airline relationship.

In Chapter 4, besides examining the determinants of aeronautical charges by considering the relationship between aeronautical and non-aeronautical charges of U.S. airports, I also evaluated the sources of aeronautical charge differentials between airports that adopt the three rate-setting methods. The sources of the differencials were examined using the Oaxaca decomposition method. The results show the relationship between aeronautical and non-aeronautical charges is negative under the compensatory method while it is insignificant for residual and hybrid airports. Residual airports are guaranteed a budget breakeven by the signatory airlines, hence the sensitivity of aeronautical charges in response to any changes in non-aeronautical charges is less since any budget shortfall (surplus) in the two operations will be covered by (credited to) the signatory airlines. Based on the structure of a hybrid agreement, the impact of non-aeronautical charges on aeronautical charges is between the ones of the compensatory and residual agreements. In addition, I found that the aeronautical charges of hybrid airports are about 23% lower than the aeronautical charges of compensatory and residual airports after controlling for all other factors. The main characteristic leading to the aeronautical charge differentials between hybrid airports and their compensatory and residual counterparts is the average costs. That is, hybrid airports have lower unit costs that allow them to charge lower aeronautical fees. There is no significant difference in the aeronautical charges between compensatory and residual airports.

While the results suggest no statistically significant difference between hybrid- and compensatory-typed agreements in terms of cost and operational efficiency, both airports and airlines may benefit most from hybrid-typed agreements. This is because hybrid contracts are flexible and require both parties to invest with equal efforts. The reduction in risk through a more balanced risk-sharing mechanism increases the utility of airports and airlines (Hihara, 2012). On one hand, under a hybrid agreement, the airport is motivated to optimize non-aeronautical operations since they bear the risk and receive the benefits of terminal operations. On the other hand, the airport obtains financial support from the signatory airlines in airfield operations. Furthermore, an airport's freedom to make project decisions is not restricted by the hybrid contract. Potentially, the signatory airlines could obtain a share from non-aeronautical revenues. Moreover, lower aeronautical charges also make the hybrid method more attractive. Among the three rate-setting methods analyzed in this dissertation, the hybrid method seems to be the fairer and most beneficial for both airlines and airports, and it guards against the moral hazard problem which we observe in residual-typed agreements. Airports that adopt the hybrid method alsooffers lower aeronautical charges because of lower unit costs

This study fills the gap in the literature by looking into the implication of the airport use agreements (or rate-setting methods) on airport economic performance and aeronautical charge differentials. The results shed light on the economic implications of the three commonly use rate-setting methods on airport operational and cost efficiency ae well as on aeronautical charge differentials.The relationship between airports and airlines are symbiotic. Future studies could examine how the relationship between airports and airlines helps them mitigate economic tough times and uncertainty.

REFERENCES

Abrate, G., & Erbetta, F. (2010). Efficiency and patterns of service mix in airport companies : An input distance function approach. *Transportation Research Part E*, *46*(5), 693–708. https://doi.org/10.1016/j.tre.2009.12.003

Aigner, D., Lovell, K., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, *6*, 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Assaf, A. (2010). The cost efficiency of Australian airports post privatisation: A Bayesian methodology. *Tourism Management*, *31*(2), 267–273. https://doi.org/10.1016/j.tourman.2009.03.005

Assaf, G. A., & Gillen, D. (2012). Measuring the joint impact of governance form and economic regulation on airport efficiency. *European Journal of Operational Research*, *220*(1), 187–198. https://doi.org/10.1016/j.ejor.2012.01.038

Badin, L., Daraio, C., & Simar, L. (2012). How to measure the impact of environmental factors in a nonparametric production model. *European Journal of Operational Research*, *223*(3), 818–833. https://doi.org/10.1016/j.ejor.2012.06.028

Badunenko, O., & Tauchmann, H. (2018). Simar and Wilson two-stage efficiency analysis for Stata. *FAU Discussion Papers in Economics*.

Banker, R.D., Charnes, A., and Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092.

Barbot, C. (2011). Vertical contracts between airports and airlines: Is there a trade-off between welfare and competitiveness? *Journal of Transport Economics and Policy*, *45*(2), 277–302.

Barbot, C., & D’Alfonso, T. (2014). Why do contracts between airlines and airports fail? *Research in Transportation Economics*, *45*, 34–41. https://doi.org/10.1016/j.retrec.2014.07.005

Barros, C. P. (2008). Technical change and productivity growth in airports: A case study. *Transportation Research Part A: Policy and Practice*, *42*(5), 818–832. https://doi.org/10.1016/j.tra.2008.01.029

Barros, C. P., & Dieke, P. U. C. (2008). Measuring the economic efficiency of airports: A Simar-Wilson methodology analysis. *Transportation Research Part E: Logistics and Transportation Review*, *44*(6), 1039–1051. https://doi.org/10.1016/j.tre.2008.01.001

Battese, G E, & Coelli, T. J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Emprical Economics*, 325–332.

Battese, George E., & Coelli, T. J. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *The Journal of Productivity Analysis*, *3*, 153–169.

Bazargan, M., & Vasigh, B. (2003). Size versus efficiency: A case study of US commercial airports. *Journal of Air Transport Management*, *9*(3), 187–193. https://doi.org/10.1016/S0969-6997(02)00084-4

Bel, G., & Fageda, X. (2010). Factors Explaining Charges in European Airports : Competition , Market Size , Private Ownership and Regulation by Germà Bel Factors Explaining Charges in European Airports : Competition , Market Size , Private Ownership and Regulation. *Journal of Regulatory Economics*, (37), 142–161.

Bilotkach, V., Clougherty, J. A., Mueller, J., & Zhang, A. (2012). Regulation , privatization , and airport charges : panel data evidence from European airports. *Journal of Regulatory Economics*, *42*(1), 73–94. https://doi.org/10.1007/s11149-011-9172-1

Bitzan, J. (2000). *Railroad Cost Conditions - Implications for Policy*.

Bottasso, A., & Conti, M. (2012). The Cost Structure of the UK Airport Industry. *Journal of Transport Economics and Policy*, *46*(3), 313–332.

Bottasso, A., & Conti, M. (2017). The Cost Structure of the Airport Industry : Methodological Issues and Emprical Evidence. In *The Economic Regulation of Airports* (pp. 181–212). https://doi.org/10.1108/S2212-160920170000006008

Brueckner, J. K. (2001). Internalization of Airport Congestion. *Journal of Air Transport Management*, *8*, 141–147.

Carney, M., & Mew, K. (2003). Airport governance reform: A strategic management perspective. *Journal of Air Transport Management*, *9*(4), 221–232. https://doi.org/10.1016/S0969-6997(03)00003-6

Caudill, S. B., Ford, J. M., & Gropper, D. M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business and Economic Statistics*, *13*(1), 105–111. https://doi.org/10.1080/07350015.1995.10524583

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Choo, Y. Y. (2014). Factors affecting aeronautical charges at major US airports. *Transportation Research Part A: Policy and Practice*, *62*, 54–62. https://doi.org/10.1016/j.tra.2014.02.006

Christensen, L.R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental Logarithmic Production Frontiers. *The Review of Economics and Statistics*, *55*(1), 28–45.

Christensen, Laurits R, & Greene, W. H. (1976). Economies of Scale in U . S . Electric Power Generation. *Journal of Political Economy*, *84*(4), 655–676.

Coelli, T., & Perelman, S. (2010). Technical efficiency of European railways : a distance function approach. *Applied Economics*, *32*(15), 1967–1976. https://doi.org/10.1080/00036840050155896

Cowing, T. G., & Holtmann, A. G. (1983). Multiproduct Short-Run Hospital Cost Functions: Empirical Evidence and Policy Implications from Cross-Section Data. *Southern Economic Journal*, *49*(3), 637. https://doi.org/10.2307/1058706

Craig, S. G., Airola, J., & Tipu, M. (2012). General purpose or special district governance? Technical efficiency versus rent dissipation in airport finances. *Public Finance Review*, *40*(6), 712–735. https://doi.org/10.1177/1091142112448415

Czerny, A. I. (2006). Price-cap regulation of airports : single-till versus dual-till. *Journal of Regulatory Economics*, 85–97. https://doi.org/10.1007/s11149-006-0010-9

D'Alfonso, T. (2011). *Vertical Relations Between Airports and Airlines: Theory and Implications*. University of Bergamo.

D'Alfonso, T., Daraio, C., & Nastasi, A. (2015). Competition and efficiency in the Italian airport system: New insights from a conditional nonparametric frontier analysis. *Transportation Research Part E: Logistics and Transportation Review*, *80*, 20–38. https://doi.org/10.1016/j.tre.2015.05.003

D'Alfonso, T., Jiang, C., & Wan, Y. (2013). Airport Pricing , Concession Revenues and Passenger Types. *Journal of Tranport Economics and Policy*, *47*(January), 71–89.

Daniel, J. I. (1995). Congestion Pricing and Capacity of Large Hub Airports : A Bottleneck Model with Stochastic Queues. *Econometrica*, *63*(2), 327–370.

Dillingham, G. L. (2017). *FAA's and Industry's Cost Estimates for Airport Development*.

Doganis, R. (1992). *The Airport Business*. Routledge/Taylor& Francis Group.

Doganis, R. (2005). *The Airline Business in the Twenty-first Century*. London & New York: Routledge/Taylor& Francis Group.

FAA. (1999). *Airport Business Practices and Their Impact on Airline Competition*. Retrieved from https://www.faa.gov/airports/aip/media/airport-business-practices-and-their-impact-on-airline-competition.pdf

FAA. (2009). *Policy Regarding the Establishment of Airport Rates and Charges*. Retrieved from https://www.faa.gov/airports/airport_compliance/media/airports-rates-charges-policy-with-amendments.pdf

FAA. (2017). *FAA Aerospace Forecast*. Retrieved from https://www.faa.gov/data_research/aviation/

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, *120*(3), 253–290. Retrieved from http://www.aae.wisc.edu/aae741/Ref/Farrell 1957.pdf

Farsi, M., Filippini, M., & Kuenzle, M. (2006). Cost efficiency in regional bus companies: An application of alternative stochastic frontier models. *Journal of Transport Economics and Policy, 40*(1), 95–118.

Faulhaber, J. M., Schulthess, J. J., Eastmond, A. C., Lewis, S. P., & Block, R. W. (2010). *Airport/Airline Agreements Practices and Characteristics*. https://doi.org/10.17226/22912

Filippini, M., & Maggi, R. (1992). The Cost Structure of the Swiss Private Railways. *International Journal of Transport Economics*, *19*(3), 307–327.

Folkes, V. S., Koletsky, S., & Graham, J. L. (1987). A Field Study of Causal Inferences and Consumer Reaction : The View from the Airport. *Oxford University Press*, *13*(4), 534–539.

Fu, X., Homsombat, W., & Oum, T. H. (2011). Airport-airline vertical relationships, their effects and regulatory policy implications. *Journal of Air Transport Management*, *17*(6), 347–353. https://doi.org/10.1016/j.jairtraman.2011.02.004

Fu, X., & Zhang, A. (2010). Effects of airport concession revenue sharing on airline competition and social welfare. *Journal of Transport Economics and Policy*, *44*(2), 119–138.

Fuhr, J., & Beckers, T. (2009). Contract design, financing arrangements and public ownership-an assessment of the US airport governance model. *Transport Reviews*, *29*(4), 459–478. https://doi.org/10.1080/01441640802465656

Gallego-Hidalgo, S., Martínez-San Román, V., & Núñez-Sánchez, R. (2017). Estimation of Allocative Efficiency in Airports for a Pre-Privatization Period. In *The Economics of Airport Operations* (pp. 69–95). https://doi.org/10.1108/S2212-160920170000006004

Gillen, D., & Lall, A. (1997). Developing measures of airport productivity and performance: an application of data envelopment analysis. *Transportation Research Part E: Logistics and Transportation Review*, *33*(4), 261–273. https://doi.org/10.1016/S1366-5545(97)00028-8

Graham, A. (2004). The Regulation of US Airports. In *The Economic Regulation of Airports* (pp. 63–74). London: Routledge/Taylor& Francis Group.

Greene, W. (2004). Distinguishing between heterogeneity and inefficiency: Stochastic frontier analysis of the World Health Organization's panel data on national health care systems. *Health Economics*, *13*(10), 959–980. https://doi.org/10.1002/hec.938

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, *126*, 269–303. https://doi.org/10.1016/j.jeconom.2004.05.003

Hadri, K. (1999). Estimation of a doubly heteroscedastic stochastic frontier cost function. *Journal of Business and Economic Statistics*, *17*(3), 359–363. https://doi.org/10.1080/07350015.1999.10524824

Hihara, K. (2012). An analysis of an airport – airline relationship under a risk sharing contract. *Transportation Research Part E*, *48*(5), 978–992. https://doi.org/10.1016/j.tre.2012.03.002

Holmstrom, B. (1979). Moral Hazard and Observability. *The Bell Journal of Economics*, *10*(1), 74–91. https://doi.org/10.2307/3003320

Ivaldi, M., Sokullu, S., & Toru, T. (2015). Airport Prices in a Two-sided Market Setting : Major US Airports. *CEPR Discussion Paper No.DP10658*. Retrieved from https://ssrn.com/abstract=2619233

Karanki, F., & Lim, S. H. (2020). The effects of use agreements on airport efficiency. *Journal of Air Transport Management*, *84*, 101767. https://doi.org/10.1016/j.jairtraman.2020.101767

Kidokoro, Y., Lin, M. H., & Zhang, A. (2016). A general-equilibrium analysis of airport pricing, capacity, and regulation. *Journal of Urban Economics*, *96*, 142–155. https://doi.org/10.1016/j.jue.2016.10.001

Kutlu, L., & McCarthy, P. (2016). US airport ownership , efficiency , and heterogeneity. *Transportation Research Part E*, *89*, 117–132. https://doi.org/10.1016/j.tre.2016.03.003

LeighFisher. (2016). *Emerging Trends in Airport-Airline Agreements AAAE / LeighFisher Rates and Charges Workshop*.

Lu, C. C., & Pagliari, R. I. (2004). Evaluating the potential impact of alternative airport pricing approaches on social welfare. *Transportation Research Part E: Logistics and Transportation Review*, *40*(1), 1–17. https://doi.org/10.1016/S1366-5545(03)00031-0

Martín, J. C., Rodríguez-Déniz, H., & Voltes-Dorta, A. (2013). Determinants of airport cost flexibility in a context of economic recession. *Transportation Research Part E: Logistics and Transportation Review*, *57*, 70–84. https://doi.org/10.1016/j.tre.2013.01.007

Martin, J. C., Roman, C., & Voltes-Dorta, A. (2009). A stochastic frontier analysis to estimate the relative efficiency of Spanish airports. *Journal of Productivity Analysis*, 163–176. https://doi.org/10.1007/s11123-008-0126-2

Martini, G., Scotti, D., & Volta, N. (2013). Including local air pollution in airport efficiency assessment : A hyperbolic-stochastic approach. *Transportation Research Part D*, *24*, 27–36. https://doi.org/10.1016/j.trd.2013.05.002

McCarthy, P. (2014). US Airport Costs and Production Technology A Translog Cost Function Analysis. *Journal of Transport Economics and Policy*, *48*(3), 427–447.

McCarthy, P. (2016a). Multi-Product Cost Analysis of US Airports. In *Airline Efficiency* (pp. 243–281). https://doi.org/10.1108/S2212-160920160000005010

McCarthy, P. (2016b). Multi-Product Cost Analysis of US Airports. In *Airline Efficiency* (Vol. 5, pp. 243–281). Emerald Group Publishing Limited. https://doi.org/10.1108/S2212-160920160000005010

Meeusen, W., & Van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *Institute of Social and Economic Research*, *18*(2), 435–444.

National Academies of Sciences, Engineering, and M. (2009). *Airport Governance and Ownership*. Washington, DC: The National Academies Press. https://doi.org/10.17226/23010

National Academy of Sciences, Engineering, and M. (2007). *Innovative Finance and Alternative Sources of Revenue for Airports*. https://doi.org/10.17226/14041

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets Author. *International Economic Review*, *14*(3), 693–709.

Oum, T. H., Yan, J., & Yu, C. (2008). Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. *Journal of Urban Economics*, *64*(2), 422–435. https://doi.org/10.1016/j.jue.2008.03.001

Oum, T, & Zhang, Y. (1991). Utilisation of Quasi-Fixed Inputs and Estimation of Cost Functions : an Application To Airline Costs. *Journal of Transport Economics and Policy*, *25*(2).

Oum, Tae, Zhang, A., & Zhang, Y. (2004). Alternative Forms of Economic Regulation and their Efficiency Implications for Airports. *The Journal of Transport Economics and Policy*, *38*(2), 217.

Pels, E., Nijkamp, P., & Rietveld, P. (2003). Access to and competition between airports: A case study for the San Francisco Bay area. *Transportation Research Part A: Policy and Practice*, *37*(1), 71–83. https://doi.org/10.1016/S0965-8564(02)00007-1

Pels, E., Van Vuuren, D., Ng, C., & Rietveld, P. (2016). An Emprical Analysis of Airport Operational Costs. In *Airport Competition: The European Experience* (pp. 103–118). Routledge/Taylor& Francis Group.

Peterson, R. (2018). Impacts of Airline Deregulation. *TR News*, 8. Retrieved from http://onlinepubs.trb.org/onlinepubs/trnews/trnews315airlinedereg.pdf

Pitt, M. M., & Lee, L. F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, *9*(1), 43–64. https://doi.org/10.1016/0304-3878(81)90004-3

Reed, W. R. (2015). On the Practice of Lagging Variables to Avoid Simultaneity. *Oxford Bulletin of Economics and Statistics*, *77*(6), 897–905. https://doi.org/10.1111/obes.12088

Reimers, C. W. (1983). Labor Market Discrimination Against Hispanic and Black Men. *The Review of Economics and Statistics*, *65*(4), 570–579.

Richardson, C., Budd, L., & Pitfield, D. (2014). The impact of airline lease agreements on the fi nancial performance of US hub airports. *Journal of Air Transport Management*, *40*. https://doi.org/10.1016/j.jairtraman.2014.04.004

Sarkis, J. (2000). Analysis of the operational efficiency of major airports in the United States. *Journal of Operations Management*, *18*(3), 335–351. https://doi.org/10.1016/S0272-6963(99)00032-7

Schmidt, P., & Sickles, R. C. (1984). Production Frontiers and Panel Data. *Journal of Business & Economic Statistics*, *2*(4), 367–374.

Scotti, D., Malighetti, P., Martini, G., & Volta, N. (2012). The impact of airport competition on technical efficiency : A stochastic frontier analysis applied to Italian airport. *Journal of Air Transport Management*, *22*, 9–15. https://doi.org/10.1016/j.jairtraman.2012.01.003

Shephard, R. W. (1970). *The Theory of Cost and Production Functions*. *The Economic Journal* (Vol. 82). https://doi.org/10.2307/2230285

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Smyth, M., & Pearce, B. (2007). IATA Economics Briefing No 6: Economic Regulation. *Iata*.

Van Dender, K. (2007). Determinants of fares and operating revenues at. *Journal of Urban Economics*, *62*(February 2006), 317–336. https://doi.org/10.1016/j.jue.2006.09.001

Vasigh, B., & Hamzaee, R. G. (1998). A comparative analysis of economic performance of US commercial airports. *Journal of Air Transport Management*, *4*(4), 209–216. https://doi.org/10.1016/S0969-6997(98)00028-3

Voltes-Dorta, A., & Lei, Z. (2013). The Impact of Airline Differentiation on Marginal Cost Pricing at UK Airports. *Transportation Research Part A: Policy and Practice*, *55*, 72–88. https://doi.org/10.1016/j.tra.2013.08.002

Wooldridge, J. M. (2015). *Introductory econometrics : A Modern Approach* (6th Editio). Cengage Learning.

Wu, D. (2015). Classifying Airline Rates and Charges Methodologies. *DWU Consulting LLC*.

Zhang, A., & Czerny, A. I. (2012). Economics of Transportation Airports and airlines economics and policy : An interpretive review of recent research. *Economics of Transportation*, *1*(1–2), 15–34. https://doi.org/10.1016/j.ecotra.2012.08.001

Zhang, A., Fu, X., & Gavin, H. (2010). Revenue sharing with multiple airlines and airports. *Transportation Research Part B*, *44*(8–9), 944–959. https://doi.org/10.1016/j.trb.2010.02.001

Zhang, A., & Zhang, Y. (1997). Concession revenue and optimal airport pricing. *Transportation Research Part E: Logistics and Transportation Review*, *33*(4), 287–296.

Zhang, A., & Zhang, Y. (2006). Airport capacity and congestion when carriers have market power. *Journal of Urban Economics*, *60*(2), 229–247. https://doi.org/10.1016/j.jue.2006.02.003

Zhang, A., & Zhang, Y. (2010). Airport capacity and congestion pricing with both aeronautical and commercial operations. *Transportation Research Part B: Methodological*, *44*(3), 404–413. https://doi.org/10.1016/j.trb.2009.09.001

Zhao, Q., Choo, Y. Y., & Oum, T. H. (2014). The effect of governance forms on North American airport efficiency: A comparative analysis of airport authority vs. government branch. *Journal of the Transportation Research Forum*, *53*(2), 93–110. https://doi.org/10.5399/osu/jtrf.53.2.4237

APPENDIX A. AIRPORT CLASSIFICATIONS

ID	AIRPORTS	CITY	GOVERNANCE FORMS	HUB SIZE	AGREEMENT TYPES
ABQ	Albuquerque International Sunport	Albuquerque, New Mexico	City	Medium	Hybrid
ANC	Ted Stevens Anchorage International Airport	Anchorage, Alaska	State	Medium	Residual
ATL	Hartsfield–Jackson Atlanta International Airport	Atlanta, Georgia	City	Large	Hybrid
AUS	Austin-Bergstrom International Airport	Austin, Texas	City	Medium	Compensatory
BDL	Bradley International Airport	Hartford, Connecticut	Port/Airport Authority	Medium	Compensatory
BNA	Nashville International Airport	Nashville, Tennessee	Port/Airport Authority	Medium	Hybrid‡
BOS	Gen. Edward Lawrence Logan International Airport	Boston, Massachusetts	Port/Airport Authority	Large	Compensatory
BUF	Buffalo Niagara International Airport	Buffalo, New York	Port/Airport Authority	Medium	Compensatory
BWI	Baltimore/Washington International Thurgood Marshall Airport	Baltimore, Maryland	State	Large	Compensatory
CLE	Cleveland-Hopkins International Airport	Cleveland, Ohio	City	Medium	Residual
CLT	Charlotte/Douglas International Airport	Charlotte, North Carolina	City	Large	Hybrid
CMH	John Glenn Columbus International Airport	Columbus, Ohio	Port/Airport Authority	Medium	Hybrid
CVG	Cincinnati/Northern Kentucky International Airport	Hebron, Kentucky	Port/Airport Authority	Medium	Hybrid
DCA	Ronald Reagan Washington National Airport	Arlington, Virginia	Port/Airport Authority	Large	Hybrid
DEN	Denver International Airport	Denver, Colorado	City	Large	Hybrid
DFW	Dallas/Fort Worth International Airport	Dallas-Fort Worth, Texas	City	Large	Compensatory
DTW	Detroit Metropolitan Wayne County Airport	Detroit, Michigan	County	Large	Residual
EWR	Newark Liberty International Airport	Newark, New Jersey	Port/Airport Authority	Large	Compensatory
FLL	Fort Lauderdale–Hollywood International Airport	Fort Lauderdale, Florida	County	Large	Residual
HNL	Daniel K. Inouye International Airport	Honolulu, Hawaii	State	Large	Hybrid
HOU	William P. Hobby Airport	Houston, Texas	City	Medium	Hybrid
IAD	Washington Dulles International Airport	Dulles, Virginia	Port/Airport Authority	Large	Hybrid
IAH	George Bush Intercontinental Airport	Houston, Texas	City	Large	Compensatory

ID	AIRPORTS	CITY	GOVERNANCE FORMS	HUB SIZE	AGREEMENT TYPES
IND	Indianapolis International Airport	Indianapolis, Indiana	Port/Airport Authority	Medium	Residual
JAX	Jacksonville International Airport	Jacksonville, Florida	Port/Airport Authority	Medium	Residual
JFK	John F. Kennedy International Airport	New York, New York	Port/Airport Authority	Large	Compensatory
LAS	McCarran International Airport	Las Vegas, Nevada	County	Large	Residual
LAX	Los Angeles International Airport	Los Angeles, California	City	Large	Compensatory
LGA	LaGuardia Airport (and Marine Air Terminal)	Queens, New York	Port/Airport Authority	Large	Compensatory
MCI	Kansas City International Airport	Kansas City, Missouri	City	Medium	Compensatory
MCO	Orlando International Airport	Orlando, Florida	Port/Airport Authority	Large	Hybrid
MDW	Chicago Midway International Airport	Chicago, Illinois	City	Large	Residual
MIA	Miami International Airport	Miami, Florida	County	Large	Residual
MKE	General Mitchell International Airport	Milwaukee, Wisconsin	County	Medium	Residual
MSP	Minneapolis–St. Paul International Airport	Minneapolis, Minnesota	Port/Airport Authority	Large	Hybrid
MSY	Louis Armstrong New Orleans International Airport	New Orleans, Louisiana	City	Medium	Residual
OAK	Oakland International Airport	Oakland, California	Port/Airport Authority	Medium	Hybrid
OGG	Kahului Airport	Kahului, Hawaii	State	Medium	Hybrid
OKC	Will Rogers World Airport	Oklahoma City, Oklahoma	City	Medium	Compensatory
OMA	Eppley Airfield	Omaha, Nebraska	Port/Airport Authority	Medium	Compensatory
ONT	Ontario International Airport	Ontario, California	Port/Airport Authority	Medium	Residual
ORD	Chicago O'Hare International Airport	Chicago, Illinois	City	Large	Residual
PBI	Palm Beach International Airport	West Palm Beach, Florida	County	Medium	Hybrid
PDX	Portland International Airport	Portland, Oregon	Port/Airport Authority	Large	Hybrid
PHL	Philadelphia International Airport	Philadelphia, Pennsylvania	City	Large	Residual
PHX	Phoenix Sky Harbor International Airport	Phoenix, Arizona	City	Large	Compensatory
PIT	Pittsburgh International Airport	Pittsburgh, Pennsylvania	Port/Airport Authority	Medium	Residual

ID	AIRPORTS	CITY	GOVERNANCE FORMS	HUB SIZE	AGREEMENT TYPES
RDU	Raleigh-Durham International Airport	Raleigh, North Carolina	Port/Airport Authority	Medium	Compensatory
RSW	Southwest Florida International Airport	Fort Myers, Florida	Port/Airport Authority	Medium	Hybrid
SAN	San Diego International Airport	San Diego, California	Port/Airport Authority	Large	Compensatory
SAT	San Antonio International Airport	San Antonio, Texas	City	Medium	Hybrid
SEA	Seattle–Tacoma International Airport	Seattle / Tacoma (SeaTac), Washington	Port/Airport Authority	Large	Compensatory
SFO	San Francisco International Airport	San Francisco, California	City	Large	Residual
SJC	Norman Y. Mineta San José International Airport	San Jose, California	City	Medium	Hybrid
SLC	Salt Lake City International Airport	Salt Lake City, Utah	City	Large	Hybrid
SMF	Sacramento International Airport	Sacramento, California	County	Medium	Compensatory
SNA	John Wayne Airport	Santa Ana, California	County	Medium	Compensatory
STL	St. Louis Lambert International Airport	St. Louis. Missouri	City	Medium	Residual
TPA	Tampa International Airport	Tampa, Florida	Port/Airport Authority	Large	Hybrid

APPENDIX B. CRS DEA SCORES

ID	2009	2010	2011	2012	2013	2014	2015	2016
ABQ	0.800	0.778	0.711	0.720	0.745	0.711	0.753	0.758
ANC	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ATL	1.000	1.000	1.000	0.968	1.000	0.976	0.940	0.904
AUS	0.851	0.885	0.864	0.856	0.899	0.909	1.000	0.985
BDL	0.520	0.577	0.597	0.681	0.669	0.722	0.574	0.707
BNA	0.912	0.951	0.821	0.890	0.900	0.899	0.939	1.000
BOS	0.756	0.812	0.810	0.907	0.936	0.900	0.926	0.923
BUF	0.652	0.744	0.721	0.785	0.820	0.754	0.715	0.711
BWI	0.549	0.406	0.484	0.586	0.674	0.539	0.506	0.510
CLE	0.420	0.451	0.408	0.437	0.513	0.472	0.502	0.469
CLT	0.953	1.000	0.838	0.936	0.952	0.962	0.884	0.886
CMH	0.903	0.892	0.813	0.814	0.808	0.816	0.860	0.840
CVG	0.504	0.841	0.869	0.861	0.872	0.889	0.864	0.844
DCA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DEN	0.598	0.656	0.689	0.716	0.776	0.821	0.865	0.846
DFW	0.721	0.782	0.666	0.709	0.771	0.820	0.773	0.756
DTW	0.534	0.554	0.577	0.638	0.620	0.627	0.587	0.649
EWR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FLL	0.800	0.963	0.941	1.000	1.000	1.000	0.993	0.949
HNL	0.661	0.713	0.689	0.717	0.871	0.710	0.682	0.618
HOU	0.726	0.641	0.549	0.653	0.772	0.802	0.759	0.693
IAD	0.650	0.576	0.602	0.536	0.596	0.639	0.683	0.698
IAH	0.514	0.481	0.472	0.492	0.558	0.579	0.605	0.543
IND	0.626	0.699	0.663	0.784	0.810	0.820	0.849	0.789
JAX	0.898	0.893	0.803	0.817	0.869	0.895	0.967	0.799
JFK	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LAS	0.788	0.743	0.754	0.798	0.712	0.733	0.733	0.682
LAX	0.967	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LGA	1.000	1.000	1.000	1.000	1.000	1.000	0.992	0.859
MCI	0.604	0.636	0.669	0.718	0.725	0.754	0.715	0.766
MCO	0.868	0.910	0.994	1.000	1.000	1.000	1.000	1.000
MDW	0.663	0.779	0.686	0.700	0.927	0.759	0.758	0.753
MIA	0.583	0.588	0.601	0.720	0.715	0.759	0.654	0.699
MKE	1.000	1.000	1.000	1.000	1.000	1.000	0.835	0.904
MSP	0.813	0.910	0.895	0.923	0.891	0.915	0.910	0.876
MSY	0.431	0.465	0.427	0.488	0.530	0.573	0.553	0.571
OAK	0.580	0.701	0.703	0.696	0.733	0.721	0.726	0.742
OGG	0.633	0.867	0.895	1.000	1.000	1.000	1.000	0.947
OKC	1.000	1.000	1.000	1.000	1.000	1.000	0.982	0.849
OMA	0.827	0.885	0.724	1.000	0.831	0.861	0.904	1.000
ONT	0.680	0.598	0.545	0.606	0.607	0.687	0.686	0.651
ORD	0.480	0.633	0.526	0.546	0.628	0.587	0.824	0.533
PBI	0.693	0.727	0.718	0.811	0.787	0.835	0.853	0.821
PDX	0.695	0.736	0.685	0.774	0.797	0.819	0.852	0.833
PHL	0.524	0.579	0.577	0.636	0.649	0.617	0.567	0.622
PHX	0.942	0.885	0.850	1.000	0.906	0.901	0.918	0.808
PIT	0.413	0.447	0.445	0.474	0.503	0.518	0.512	0.507

ID	2009	2010	2011	2012	2013	2014	2015	2016
RDU	0.935	0.826	0.783	0.820	0.881	0.876	0.896	0.853
RSW	0.951	1.000	0.991	0.957	0.953	0.929	0.932	0.781
SAN	0.936	0.909	0.932	0.923	1.000	1.000	1.000	1.000
SAT	0.957	1.000	0.941	1.000	1.000	1.000	1.000	0.953
SEA	0.791	0.762	0.729	0.737	0.790	0.872	0.901	0.859
SFO	0.977	1.000	1.000	1.000	1.000	1.000	1.000	0.869
SJC	0.774	0.583	0.824	0.993	1.000	1.000	1.000	1.000
SLC	0.699	0.715	0.683	0.744	0.721	0.730	0.746	0.775
SMF	1.000	0.968	0.904	0.760	0.808	0.840	0.896	0.836
SNA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
STL	0.415	0.441	0.380	0.443	0.465	0.468	0.482	0.524
TPA	0.890	0.899	0.888	0.917	0.945	0.983	0.958	0.958

APPENDIX C. VRS DEA SCORES

ID	2009	2010	2011	2012	2013	2014	2015	2016
ABQ	0.848	0.812	0.788	0.782	0.823	0.875	0.946	0.825
ANC	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ATL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
AUS	0.869	0.896	0.892	0.910	0.924	0.919	1.000	0.986
BDL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
BNA	0.917	0.965	0.839	0.890	0.901	0.899	0.947	1.000
BOS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
BUF	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
BWI	0.654	0.467	0.543	0.603	0.688	0.571	0.515	0.527
CLE	0.425	0.455	0.410	0.460	0.520	0.474	0.511	0.471
CLT	0.960	1.000	0.864	0.980	0.997	1.000	0.975	0.897
CMH	1.000	0.992	0.866	0.924	0.898	0.892	0.913	0.876
CVG	0.514	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DCA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DEN	0.857	0.902	0.894	0.880	0.913	0.933	0.987	1.000
DFW	1.000	1.000	0.982	0.996	1.000	1.000	0.978	1.000
DTW	0.605	0.592	0.629	0.666	0.642	0.664	0.650	0.746
EWR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FLL	0.833	1.000	1.000	1.000	1.000	1.000	1.000	1.000
HNL	0.692	0.735	0.722	0.723	0.872	0.724	0.688	0.631
HOU	0.972	0.697	0.575	0.755	0.880	0.931	0.825	0.709
IAD	0.715	0.674	0.661	0.598	0.610	0.649	0.688	0.749
IAH	0.535	0.512	0.521	0.536	0.571	0.607	0.636	0.588
IND	0.653	0.707	0.709	0.808	0.839	0.856	0.852	0.794
JAX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
JFK	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LAS	0.881	0.832	0.806	0.806	0.746	0.771	0.775	0.782
LAX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LGA	1.000	1.000	1.000	1.000	1.000	1.000	0.995	0.864
MCI	0.612	0.644	0.670	0.718	0.769	0.778	0.788	0.768
MCO	0.983	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MDW	0.766	0.794	0.883	0.904	0.934	0.759	0.758	0.761
MIA	0.842	0.877	0.987	1.000	0.994	1.000	0.950	0.964
MKE	1.000	1.000	1.000	1.000	1.000	1.000	0.838	0.911
MSP	0.837	0.935	0.953	0.926	0.895	0.936	0.966	0.950
MSY	1.000	1.000	0.428	0.489	0.538	0.603	0.554	0.612
OAK	0.605	0.734	0.713	0.716	0.754	0.740	0.739	0.742
OGG	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
OKC	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
OMA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ONT	0.680	0.615	0.548	0.612	0.658	0.985	1.000	1.000
ORD	0.853	0.930	0.900	0.941	1.000	1.000	1.000	1.000
PBI	0.746	0.740	0.725	0.835	0.804	0.859	0.864	0.964
PDX	0.702	0.752	0.708	0.775	0.797	0.823	0.862	0.850
PHL	0.534	0.639	0.665	0.691	0.661	0.624	0.593	0.688
PHX	1.000	1.000	1.000	1.000	0.986	1.000	1.000	0.924
PIT	0.421	0.463	0.457	0.484	0.540	0.548	0.544	0.513

ID	2009	2010	2011	2012	2013	2014	2015	2016
RDU	0.975	0.826	0.784	0.829	0.883	0.880	0.896	0.864
RSW	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.877
SAN	0.945	0.910	0.940	0.926	1.000	1.000	1.000	1.000
SAT	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.960
SEA	0.933	0.879	0.830	0.824	0.826	0.900	0.946	0.951
SFO	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SJC	0.777	0.632	0.827	0.996	1.000	1.000	1.000	1.000
SLC	0.703	0.729	0.683	0.759	0.758	0.770	0.800	0.778
SMF	1.000	0.973	0.910	0.787	0.827	0.844	0.898	0.845
SNA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
STL	0.416	0.455	0.386	0.459	0.479	0.481	0.519	0.527
TPA	0.902	0.911	0.889	0.917	0.951	1.000	1.000	0.965

APPENDIX D. DESCRIPTIVE STATISTICS OF EFFICIENCY SCORES

(POOLED DATA)

	CRS	VRS
Mean	0.7278	0.7859
SD	0.1680	0.1714
Min	0.3518	0.3668
Max	1	1

APPENDIX E. STAGE-2 TRUNCATED REGRESSION RESULTS (POOLED DATA) †

	CRS		VRS	
	Parameter	*BSE*	*Parameter*	*BSE*
Constant	0.5603***	0.0166	0.6067***	0.0161
Compensatory	0.1643***	0.0168	0.1640***	0.0169
Hybrid	0.1614***	0.0171	0.1315***	0.0170
City	-0.0549***	0.0143	-0.0661***	0.0148
County	0.0741***	0.0218	0.0452**	0.0214
State	-0.1065***	0.0253	-0.1909***	0.0257
Large Hub	0.0418***	0.0132	0.0768***	0.0131

***, ** and * denote 1%, 5% and 10% significance levels, respectively.
† BSE is the bootstrap standard error