THE DETERMINANTS OF AERONAUTICAL CHARGES OF U.S. AIRPORTS:

A SPATIAL ANALYSIS

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota

State University's regulations and meets the accepted standards for the degree of

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ABSTRACT

Using U.S. airport data from 2009 through 2016, this thesis examines the determinants of aeronautical charges of large and medium hub airports and accounts for the spatial dependence of neighboring airports in a spatial panel regression model. The major finding of this thesis are (1) U.S. airports' aeronautical charges are spatially dependent, and neighboring airport charges are spatially and positively correlated; (2) there is evidence of airport cost recovery through non-aeronautical revenues; (3) airports sharing non-aeronautical revenues with airlines charge lower aeronautical fees than their peers that do not share revenues; (4) aeronautical charges increase with higher delays.

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DEDICATION

To my lovely wife, Esin and our twins, Janset and Jem.

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1. INTRODUCTION

In recent years, U.S. airports are increasingly expected to reduce their reliance on government financial support. Due to limited government financial resources, airports must strive to balance its budget through revenues in aeronautical and non-aeronautical operations. Since aeronautical and non-aeronautical operations are interdependent, and airports provide services to both airlines and passengers, they are essentially a two-sided[1] market platform through which the passenger demand for airports is a derived demand from airline services (Ivaldi, Sokullu, & Toru, 2015). Accordingly, as the airport's non-aeronautical revenue depends on passengers' flow in airports, there is a positive externality between air travel demand and the demand for airport non-aeronautical services (D'Alfonso & Nastasi, 2014). Zhang and Czerny (2012) briefly explained this relationship: an increase in aeronautical charges could cause a decrease in passenger flow which is the main source of non-aeronautical revenues for the airport. Starkie (2002) emphasized that motivated airport management maximizes its profit by focusing on increasing passenger throughput. To achieve this goal, airports must spark airlines' enthusiasm to bring in more passengers. Thus, the aeronautical charges that airlines pay could have implications on both aeronautical and non-aeronautical operations. Empirically, Van Dender (2007), Bel and Fageda (2009), Bilotkach et al. (2012) and Choo (2014) have examined airport pricing and the effect of airport competition on aeronautical charges using a control variable such as the number of airports within a prespecified cluster or distance. However, the

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[1] A two-sided market is a market that has two interdependent product (or service) platforms through which the end-users of the products (or services) interact, and the platform provider must determine the appropriate charges for one side by considering the impact of that on the other side (Rochet & Tirole, 2006). An airport is essentially a two-sided market because its aeronautical and non-aeronautical operations depend on interactions between airport end users like airlines and travelers, so the charges it imposes on the two sides must be appropriate in order for the two sides to participate effectively.

implicit assumptions are that, regardless of the distance between them, airports are independent of each other even for airports in the same region, and any competition effect on airport charges is the same. But there is no reason to assume that the strategies, operations and characteristics of neighboring airports are independent of each other especially when their catchment areas are close and likely to be overlapped. Moreover, if a sample observation has location components, the spatial dependence cannot be ignored.

In light of this, this thesis attempts to examine three empirical research questions:

(1) Are airport aeronautical charges spatially interdependent?

(2) What are the determinants of aeronautical charges?

(3) What is the relationship between aeronautical and non-aeronautical charges?

For these objectives, we employ a combined spatial random effects model based on Cliff and Ord (1975) to control for both spatial interaction and bias resulting from the spatial data structure. The model includes a spatial autoregressive model with spatial autoregressive disturbance term of order (1,1), namely, SARAR(1,1). We used the data of 30 large hubs and 29 medium hub airports in the U.S. between the years 2009 and 2016.

The results show that U.S. airports' aeronautical pricing decisions are spatially dependent. This implies that, when an airport determines the aeronautical charges, it considers neighbor airports' pricing strategies as well. Thus, if neighboring airports' aeronautical charges increased, the airport would increase its charges as well. Furthermore, non-aeronautical revenues are a determinant of aeronautical charges. An increase in non-aeronautical charges leads to a decrease in aeronautical charges. This may suggest some degree of cross-subsidization. Revenue sharing also negatively impacts aeronautical charges, i.e., airports sharing non-aeronautical

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revenues with airlines charge lower fees than their peers that do not share revenues. Besides this, aeronautical charges increase with higher delays.

To the best of our knowledge, this is the first study that accounts for the spatial interdependence of airport's aeronautical pricing decisions. The results will shed light on the airport pricing strategies and the spatial impact of neighboring airports on an airport's aeronautical charges.

The thesis is organized as follows. The literature review is presented in Chapter 2. Following that, I provide details on the economic and statistical aspects of the model in Chapter 3. I describe the data in Chapter 4. In Chapter 5, we discuss the results. In the last chapter, we conclude the thesis with our findings and discuss the implications.

2. LITERATURE REVIEW

Other than government resources, the largest income source of U.S. airports is user charges which come from aeronautical and non-aeronautical activities. Non-aeronautical revenues have been a vital income source for airports in current years (D'Alfonso, Jiang, & Wan, 2013; D'Alfonso & Nastasi, 2014; Zhang, Fu, & Gavin, 2010) especially given the increased pressure on government-run airports to be financially independent (Zhang & Zhang, 1997). Zhang and Zhang (1997) suggested a cross-subsidization solution to reduce the aeronautical charges to achieve optimum social welfare other than Ramsey pricing. Ramsey pricing is seen as the second-best solution for social welfare if marginal cost pricing cannot be applied due to high fixed costs. According to Zhang and Zhang (1997), airports shift some non-aeronautical revenues to relax the budget constraints on aeronautical operations. Thus, airports can reduce aeronautical charges under the assumption that the welfare gains in aeronautical operations outweigh the welfare loss in non-aeronautical operations. Czerny (2006) and Lu and Pagliari (2004) analyzed the single- and dual-till approaches of aeronautical charges in Europe airport systems. With the single-till setting, aeronautical charges are determined according to aeronautical and non-aeronautical revenues in the period before. Under dual-till pricing, aeronautical charges are based only on its aeronautical revenues (Smyth & Pearce, 2007). Both studies favored the single-till approach since they found that it enhances social welfare.

Ivaldi, Sokullu and Toru (2015) stressed the importance of considering the interdependence of aeronautical and non-aeronautical operations. They found that U.S. airports follow a profit-maximizing strategy in non-aeronautical operations while they apply Ramsey pricing in aeronautical operations implying that airports do not internalize positive externalities. U.S. airports are controlled by governments, hence the financial goal is not to maximize profits

but to seek full cost recovery (or to break even). However, they suggested that two-sided profit-maximizing prices can be welfare-enhancing for some airports. Overall, airports can relax the budget constraint on aeronautical operations via cross-subsidization. Therefore, the presence of cross-subsidization may be an important factor for aeronautical charges.

On the other hand, the airport's vertical relationships with their tenant airlines may also be another important factor affecting aeronautical charges (Van Dender, 2007). One of the incentives that airports offer to their tenant airlines is revenue sharing. The goal of airport's revenue sharing is to attract, retain and expand airline clientele base for airports, which through revenue sharing with airlines, may experience higher passenger throughput and as a result experience increased non-aeronautical revenues (Saraswati & Hanaoka, 2014). Zhang et al. (2010) pointed out that airports facing higher competition tend to share non-aeronautical revenues more, and Fu and Zhang (2010) found that airports adopting revenue sharing also tend to apply higher aeronautical charges. Thus, conventional demand theory would predict competition with other airports may lead to lower aeronautical charges, a larger degree of revenue sharing, however, may lead to higher aeronautical charges even in the face of airport competition.

In addition to cross-subsidization and revenue sharing, spatial dependence between neighboring airports may impact airport aeronautical charges as well. Although large and medium hub airports are often perceived as local monopolies, the proximity effect of neighboring airports could stifle these airports' monopoly power. Starkie (2002) points out that the market power of an airport depends on the availability of proximate airports that can provide substitute goods and services. In fact, according to an International Air Transport Association (IATA) report by Wiltshire (2013), for every 1% increase in distance between two neighboring

airports the likelihood of passengers flying from the closest airport declines on average by 4%. In the same report, in terms of price, on average, for every 1% increase in distance between two neighboring airports, a 1% change in relative prices at a nearby airport would persuade passengers to travel to the more distant airport. Dmitry (2012) remarks that spatial competition among airports is usually based on the concept of catchment areas. A catchment area's size can usually be defined by geographical distance, by travel time, and by travel cost (Dmitry, 2012). Drawing concentric circles of travel distances around the airport are the most common way to define an airport's catchment area. Bel and Fageda (2009) and Choo (2014) have considered the number of airports in the catchment area to measure the impact of neighboring airports on aeronautical charges. However, the lack of consideration of spatial interaction among neighboring airports may lead to biased and inconsistent estimates.

Using the data on 55 large US airports between 1998 and 2002, Van Dender (2007) found that airports in competition tend to charge lower aeronautical fees. In addition, he found that hub airports charge higher aeronautical fees. Furthermore, Van Dender (2007) found a negative relationship between the number of passengers and airfares, a decrease in average aeronautical charges at airports serving more flights, and a decrease in average non-aeronautical charges at airports serving more passengers. The average aeronautical charge is the aeronautical revenues divided by the number of departing flights, and the average non-aeronautical charge is measured by concession revenues per passenger. Lastly, Van Dender (2007) also found that concession revenues were attributed more to international passengers than to domestic passengers.

Bel and Fageda (2009) also analyzed the determinants of airport prices with a cross-sectional analysis of 100 European airports in 2007. The authors analyzed the effects of airports' market power and regulation/ownership on aeronautical charges. In order to control for airports'

market power, the percentage of national air traffic, the number of nearby airports in 100 km, airlines' Herfindahl-Hirschman Index (HHI) and airport's island location were used in the model. Additionally, they used private/non-regulated and public/regulated dummy variables to control for airport regulation and ownership. Regulation refers to price regulations for public airports: rate of return and price cap. They found that neither the rate regulation mechanisms (rate of return or price cap) nor the scope of the regulation (single-till/dual-till) affects airport charges. They, however, found that airports having higher traffic charge more, and charges on domestic flights tend to be less because of competition from other modes. Bel and Fageda (2010) found the aeronautical charges of a mainland airport that is not under a centralized pricing system are lower, particularly when it faces a higher number of airports within a distance of 100 km. Some countries, like Greece (except Athens) and Norway, apply a centralized price system in which airports charge identical prices (Bel & Fageda, 2010). Bel and Fageda (2010) also pointed out that mainland airports that are not under price regulations charge lower fees if the downstream market is more concentrated.

Following Bel and Fageda (2009), Bilotkach, Clougherty, Mueller and Zhang (2012) analyzed airport charges in terms of privatization and economic regulations using the data of 61 European airports between 1990 and 2007. Considering the autocorrelation problem, they used a dynamic panel data model, i.e., the lagged value of aeronautical charges was added to the right-hand side of the regression. Bilotkach et al. (2012) found that a single-till approach leads to lower aeronautical charges, and they concluded that privatized airports and airports adopting ex-post regulation tend to charge lower fees. In an ex-post regulation regime, the regulator does not regulate the airports unless the latter violates the price, profit, and service quality thresholds. In addition, hub airports charge higher rates. Unlike Van Dender (2007) and Bel and Fageda

(2009), Bilotkach et al. (2012) did not detect a significant effect of nearby airports on aeronautical charges.

Choo (2014) examined the determinants of aeronautical charges of 59 U.S. airports between 2002 and 2010. She examined the effects of operating costs, cross-subsidization, hub status, governance types, percentage of international and connecting traffic, and competitive forces. Choo (2014) found a negative relationship between the ratio of non-aeronautical revenues to total revenues and aeronautical charges. Thus, the study concluded that there was cross-subsidization at U.S. airports. In addition, Choo (2014) found a substitution effect between terminal and landing fees, and higher aeronautical fees at hub airports. She concluded that the number of airports in 100 km, governance structure, connecting traffic, the share of dominant airlines all has no significant effect on aeronautical charges.

3. METHOD

3.1. Economic Aspects

We model aeronautical charges of U.S. airports as a function of the ratio of non-aeronautical revenues to operating costs, average cost, delays, downstream market structure, airport revenue sharing status, and airport governance. In this function, aeronautical charges are defined as the aeronautical revenues per aircraft movement (Bilotkach et al., 2012; Choo, 2014; Van Dender, 2007). To control for the possibility of airport's cross-subsidization, we use the ratio of non-aeronautical revenues to total cost which is the sum of operating cost and debt service cost less passenger facility charges (PFC). PFC is used to pay for some of the airport's debt service costs, and it is collected by airlines in the ticket prices on behalf of airports. The remaining debt service cost and airport operating costs are covered by aeronautical and non-aeronautical revenues. Thus, PFC is deducted from the total cost to reflect the extent of the actual cost covered by non-aeronautical revenues. Therefore, the ratio of non-aeronautical revenues to total cost may be an indicator of cross-subsidization. A negative relationship between the ratio and aeronautical charges may indicate some degree of cross-subsidization that leads to lower aeronautical charges. Nevertheless, the insight into the extent of cross-subsidization is limited by this ratio. The ratio of non-aerenautical revenue share to non-aerenautical cost share would provide a better insight into cross-subsidization. However, the inseparability of aeronautical and non-aeronautical operating costs in the airport financial data precludes us from calculating the non-aeronautical cost share. Besides this ratio variable, we also consider two close alternatives in our regression models: (1) non-aeronautical revenues per passenger (*Nrevp*) as in Bilotkach et al. (2012), and (2) the ratio of non-aeronautical revenues to total revenues (*Choo's ratio*) proposed by Choo (2014) as a measure of cross-subsidization.

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In addition, aeronautical charges should reflect airport marginal costs. However, because of the difficulty of obtaining and measuring marginal cost, we use airport average cost, which is measured by total cost per passenger, to capture the additional cost to the airport as output rises. Next, we consider delays as a proxy for airport congestion since it would not be rational for a congested airport to reduce aeronautical fees. Brueckner (2001) and Daniel (1995) showed that airports should apply higher aeronautical charges or congestion pricing as a remedy for delays. On the other hand, D'Alfonso et al. (2013) suggested that since there is a positive correlation between non-aeronautical revenues and dwell time, aeronautical charges should be kept at a lower level to increase passenger throughput. In order to understand the congestion effect on aeronautical charges, my model also accounts for congestion using the total number of delays.

Downstream competition may influence the airport's decision on aeronautical charges. Airports facing a more concentrated downstream market charge lower fees due to the greater negotiating power of the dominant airlines (Bel & Fageda, 2010). Market structure in the downstream is controlled by the airlines' HHI at the airport. The vertical relationship between airports and airlines may be another significant factor for aeronautical charges (Van Dender, 2007). To control for the vertical relationships between airports and airlines, I consider the airport's revenue-sharing strategy. Revenue sharing, a common business practice of U.S. airports, is used to incentivize airlines to increase their operations and business at the airport. With a revenue-sharing strategy, airports share their non-aeronautical revenues with airlines. However, airports adopting revenue sharing may tend to apply higher aeronautical charges (Fu & Zhang, 2010). The sampled airports' revenue-sharing strategies in this study are reported in the appendix. In addition to HHI and airport-airline vertical relationships, airports' governance can be considered an important determinant of aeronautical charges. Airports' pricing strategy may

differ across governance types due to the differences in funding formulae and managerial practices. Therefore, we consider four categories of airport governance commonly seen in the U.S.

Spatial competition among airports is another factor that needs to be considered (Fröhlich & Niemeier, 2011). Tobler (1970, page 236) pointed out that "everything is related to everything else, but near things are more related to each other further". Choo (2014) and Bel and Fegada (2009) used the number of airports in 100 km to analyze the proximity effects on airport charges; Van Dender (2007) clustered airports according to the possibility of competition to examine the proximity effects; Bilotkach et al. (2012) considered the presence of nearby airports to identify potential airport competition effects. These models are explicitly associated with airport competition, but implicitly the airports are assumed to be independent of each other, and the competition effect on aeronautical charges of airports within a predetermined distance, cluster or catchment area is assumed to be the same relative to other airports. However, besides competition, spatial dependence could also arise in economic network space (Anselin, Gallo, & Jayet, 2008). Airports interact with one another in such an economic network. For instance, an airport benchmarks neighboring airports' revenue-sharing strategy when they make a decision about it. If the common strategy in an area is sharing revenue with airlines, then an airport in the area cannot independently go against the norm. Therefore, spatial dependence is inevitable in the airport industry. Ignoring the spatial dependence of airports may lead to biased and inconsistent estimation.

3.2. Statistical Models

Van Dender (2007), Bel and Fageda (2010), Bilotkach et al. (2012) and Choo (2014) have applied different methods to explain the determinants of aeronautical charges. Van Dender

(2007) employed a three-stage least squares method to address the endogeneity problems in a system of equations. Bel and Fageda (2009) analyzed the determinants of airport prices using a two-stage least squares method. This method was chosen by considering the possibility of endogeneity between price and demand (total airport traffic) variables. To address the possible endogeneity problems, Bilotkach et al. (2012) replaced all independent variables with their lagged values in the model. Following this, Bilotkach et al. (2012) used twice lagged output variables to instrument lagged output variables. Moreover, Bilotkach et al. (2012) employed a system GMM model to address the endogeneity problem between aeronautical charges and the lagged values of aeronautical charges. Choo (2014) employed the Hausman-Taylor model and the error component two-stage least squares method along with conventional fixed and random effects models.

In this study, the base model of the relationship between aeronautical charges and the economic factors can be described by a random-effects (RE) regression (1):

$$\ln R_{it} = \beta_0 + \beta_1 Ratio_{it} + \beta_2 \ln AC_{it} + \beta_3 \ln Delay_{it} + \beta_4 \ln HHI_{it} + \beta_5 Z + \sum_j \beta_j X_{jit} + e_{it}, \ (1)$$

where R_{it} is the aeronautical charges of airport i in year t, $Ratio_{it}$ is the ratio of non-aeronautical revenues to total operating costs, AC_{it} is the average costs, $Delay_{it}$ is the delays of the airport, HHI_{it} is airlines' HHI at the airport i, Z is a time trend, and X_{jit} is a set of other control variables, including the airport's revenue-sharing status, and airport's governance types, e_{it} is the composite error term including time-invariant unobserved effects and time-variant disturbance term. The model assumes that any unobserved airport-specific effect is not correlated with the control variables in equation (1). Since the model contains time-invariant

variables such as airport's revenue-sharing status and airport governance variables, a fixed-effects (FE) model is not feasible.

There are, however, two potential endogeneity problems in equation (1). First, there is potential reverse causality between aeronautical charges and *Ratio* as well as *AC* since a decrease in aeronautical charges could lead to an increase in outputs like the number of passengers which is the determinant of non-aeronautical revenues and average cost. Thus, *Ratio* and *AC* may be endogenous. A second potential endogeneity problem may arise from the bi-directional causal relationship between delays and aeronautical charges. While delays are determinants of aeronautical charges, aeronautical charges are also determinants of the delays. As discussed in Brueckner (2001) and Daniel (1995), a congested airport could raise aeronautical charges to alleviate congestion and thereby decrease delays. To address the endogeneity problems, the variables *Ratio*, *AC* and *Delays* were instrumented by their respective time-lagged values. Instrumenting endogenous variables with lagged values is seen also in Bilotkach et al. (2012). This type of estimation is consistent and unbiased as long as the lagged variable does not belong to the model and is strongly correlated to the endogenous variable (Reed, 2015).

The next issue concerning Model (1) is the spatial dependence of rivaling airports. That is aeronautical charges may be spatially correlated when airports closer to each other may set charges similar to those of their regional rivals, and Model (1) does not consider this effect. Classical panel data models, like Model (1), assume that observations are spatially independent (LeSage, 2008). If a sampled unit has a location component, the model should consider two important factors: (i) spatial dependence between the observations, and (ii) spatial heterogeneity in the relationships. Ignoring these two factors leads to biased and inconsistent estimates (LeSage, 2008).

Spatial dependence can be explained by spatially lagged dependent variables or spatial autoregressive disturbances. Spatial lag models are preferred when the research interest is spatial interactions (Anselin, 2003). Spatial disturbance models are appropriate when the concern is to correct any potential bias arising from using the spatial data structure. We employed a combined spatial random effects model based on Cliff and Ord (1975) to control for both spatial interaction and bias resulting from the spatial data structure. The model includes a spatial autoregressive model with spatial autoregressive disturbance term of order (1,1), SARAR(1,1), and is represented by equation (2):

$$\ln R_{Nt} = \beta_0 + \lambda(I_T \otimes W_N)\ln R_{Nt} + \beta_1 \ln Ratio_{Nt} + \beta_2 \ln AC_{Nt} + \beta_3 \ln Delay_{Nt} + \beta_4 \ln HHI_{Nt} +$$

$$\beta_5 Z + \sum_j \beta_j X_{jNt} + u_{Nt} \tag{2}$$

where R_{Nt} is an $Nt \times 1$ vector representing aeronautical charges of the sampled airports, I_T is an identity matrix with dimension T, W_N is $N \times N$ weight matrix, and λ is the spatial autoregressive parameter ($|\lambda| < 1$). The weight matrix is a symmetric matrix which has zero diagonal elements ($w_{ii} = 0$). Diagonal elements are set to zero to avoid predicting airports' own effects. The rows of weight matrix were normalized so that each row-normalized w_{ij}, where $i \neq j$, can be referred to as the portion of the spatial influence of airport j on airport i. The error term (u_{Nt}) is the spatially lagged regression disturbance vector that follows a spatial autoregressive process (Kapoor, Kelejian, & Prucha, 2007),

$$u_{Nt} = \rho(I_T \otimes W_N)u_{Nt} + \varepsilon_{Nt,} \tag{3}$$

where ρ is a spatial autoregressive coefficient ($|\rho| < 1$), and $\varepsilon_{Nt} = (\iota_T \otimes I_N)\mu_N + v_{Nt}$ is the innovation vector where ι_T is a vector of ones, I_N is an $N \times N$ identity matrix, μ_N is a vector of airport-specific effects, and v_{Nt} a vector of innovations that vary across airports and over time.

First of all, based on the necessity of the diagnosis of the presence of spatial error correlation (ρ) and random effects (μ_{Nt}), a Lagrange multiplier (LM) test by Baltagi et al. (2003) for spatial panel data analysis was used. In Baltagi et al. (2003)'s one-sided joint LM test, the null hypothesis is $H_0: \rho = \sigma_\mu^2 = 0$. With this test, we could determine if the model has a spatial error correlation component and random effects. Following this, we added spatially lagged aeronautical charges into the model. However, the spatially lagged dependent variable is endogenous due to simultaneity with the dependent variable (Anselin, 2003). The endogeneity problem was addressed by instrumenting spatially lagged aeronautical charges with spatially lagged explanatory variables except for the time-invariant variables (Kelejian & Prucha, 1998). Since we normalized the spatial weight by its row, time-invariant variables (revenue sharing status and governance types) are excluded for this process (Mutl & Pfaffermayr, 2011). Three steps were conducted in the estimation process. In the first step, we eliminate spatial autocorrelation by Cochrane-Orcutt transformation. In the second step, since ρ is unknown, we estimated $\hat{\rho}$ with a spatial generalized method of moments (GMM) method by following Kapoor et al. (2007). In the final step, using $\hat{\rho}$, we estimated model parameters via the feasible generalized least squares (FGLS) method.

4. DATA

We examined a balanced panel data of 30 large hub airports and 29 medium hub airports classified by the Federal Aviation Administration (FAA). The distributions of the sampled airports are demonstrated in Figure.1. The data cover the years between 2009 and 2016. The primary 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 under the Airport Financial Reporting Program is then available to the public through the CATS. From the CATS system, we obtained the data on airport operating expenditures, debt service costs, aeronautical revenues, non-aeronautical revenues, and the number of passengers. All these variables were adjusted for inflation using the U.S. gross domestic product deflator with the base year 2009.

Figure 1. Sampled Hub Airports in the Contiguous U.S.

The sum of airport operating expenditures and debt services costs are recovered by airport user charges from aeronautical and non-aeronautical operations (FAA, 1999). Accordingly, we developed the ratio of non-aeronautical revenues to the total cost to control for any potential cross-subsidization effects on aeronautical charges. Besides this ratio, following Bilotkach et al. (2012), we calculated non-aeronautical revenue per passenger, and following Choo (2014), the ratio of non-aeronautical revenues to total revenues as alternative measures of cross-subsidization. Aeronautical charges are calculated by dividing total aeronautical revenues by aircraft movements. Aircraft movements were obtained from the aircraft activity system of the FAA[2]. Aircraft movements include all takeoffs and landings. The number of delays was obtained from the Bureau of Transportation Statistics[3]. Delays are measured by the number of flights that arrive or depart 15 minutes or more than their scheduled times. We used revenue sharing to control the vertical relationship between airlines and airports. The information on revenue sharing was obtained from LeighFisher (2016). Airports that do not share revenues with airlines are in the control group. That is, revenue sharing takes the value 1 for airports that share revenues, and 0 otherwise. The model also controls for airport governance types, and the information was obtained from the National Academies of Sciences, Engineering and Medicine (2009). Since the governance classifications are not straight forward, we followed the four classifications in Kutlu and McCarthy (2016), and the types of governance include port/airport authority, county, city and state governments. The governance types of the sampled airports are reported in the appendix. Airports governed by either a port/airport authority are in the control group. Airline's HHI at the sampled airports was calculated with the information obtained from

[2] https://aspm.faa.gov/opsnet/sys/Main.asp?force=atads
[3] https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236

the Bureau of Transportation Statistics[4] ($HHI = \sum_i \tau_i^2$, where τ_i^2 is the market share of

airline i). HHI varies between 0 and 10,000. The HHI closer to 10,000 implies a concentrated

market of airline at the sample airport. The descriptive statistics of the data is reported in Table

1.

Table 1. Descriptive Statistics of the Data

Years		Aircraft Movements (x10³)	Aeronautical Revenues (x10⁶)	Aeronautical Charges	Non-aeronautical Revenues (x10⁶)	Average Cost	Ratio	Delay	HHI
2009	Mean	288.766	124.133	383.387	95.402	26.490	0.421	14253	2734
	SD	184.710	139.777	281.46	72.927	11.396	0.143	12106	1626
2010	Mean	288.683	128.228	398.067	96.478	27.454	0.399	14008	2766
	SD	190.212	145.771	295.915	74.255	10.757	0.124	12194	1579
2011	Mean	288.841	129.909	400.308	101.557	27.098	0.408	13227	2774
	SD	190.538	146.996	291.906	80.447	10.386	0.120	11536	1574
2012	Mean	284.352	131.533	414.001	103.702	27.384	0.410	13329	2786
	SD	191.678	151.819	307.109	82.629	10.211	0.122	12009	1554
2013	Mean	282.816	137.429	430.649	107.831	27.452	0.419	12924	2796
	SD	191.720	154.188	307.019	86.667	10.120	0.119	12232	1565
2014	Mean	280.170	142.238	443.403	111.610	28.781	0.420	12417	2853
	SD	189.733	164.463	318.978	91.789	14.723	0.134	11158	1578
2015	Mean	282.099	145.928	447.637	115.827	26.307	0.436	12868	2850
	SD	190.391	166.463	308.542	95.071	9.539	0.127	11627	1583
2016	Mean	287.200	149.635	448.199	121.985	25.737	0.440	12381	2772
	SD	192.352	177.937	313.251	100.205	8.927	0.117	10802	1573

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[4] https://www.transtats.bts.gov/airports.asp

As Table 1 shows, average real aeronautical charges increased over the years. For instance, the mean aeronautical charge was $383 in 2009 compared to $448 in 2016, an increase of 17%. In addition, the increase in aeronautical revenues was less than the increase in non-aeronautical revenues. The mean non-aeronautical revenues between 2009 and 2016 rose by about 28%, while the mean aeronautical revenues between the same years increased by about 20%. Besides, the ratio of non-aeronautical revenues to total cost increased by only 4.5%, and the average cost was almost the same in the same years. These facts imply the presence of cross-subsidization between non-aeronautical revenues and aeronautical operations in the U.S. airport industry. Meanwhile, the data depicts the number of delays gradually decreased by 13% and there is no large change in HHI over the years.

5. RESULTS

As discussed in Chapter 3, due to possible reverse causality, a potential endogeneity problem may arise between aeronautical charges and *Delay*, aeronautical charges and *Ratio*, and aeronautical charges and *AC*. Firstly, we performed a Hausman test to assess the endogeneity of *Ratio, AC* and *Delay* following Wooldridge (2015). The test is performed with the null hypothesis that *Delay, AC* or *Ratio* can be treated as exogenous. The X^2 statistic in the Hausman test is 37.87 (p-value=0.000), implying there is sufficient evidence to reject the null hypothesis of exogeneity. After this, we assessed if the instruments (time-lagged values of the endogenous variables) are strongly correlated to the endogenous variables. If the instruments are weak, the resulting estimates would be biased and inconsistent (Wooldridge, 2015). Under the null hypothesis, the instruments are poorly correlated to the endogenous variable. The X^2 statistic for *Delay* is 13832.47 (p-value=0.0000), thus we conclude that the instrument is strongly correlated with *Delay*. The same test procedure was repeated for *Ratio* and *AC*. Based on the X^2 statistic of *Ratio*, 743.00 (p-value=0.0000), and the X^2 statistic of *AC,* 1354.65 (p-value=0.0000), there is sufficient evidence of the relevance of the instruments. On the other hand, the Hausman test results show that both ln(*Nrevp*) (X^2=36.15, p-value=0.0000) and *Choo's ratio* (X^2=27.15, p-value=0.0000) are also endogenous. Accordingly, we instrumented them with their time-lagged values as well. The χ^2 statistic for *Nrevp* is 2334.22 (p-value=0.0000), and χ^2 statistic for *Choo's ratio* is 3917.57 (p-value=0.0000).

Following the endogeneity and weak instrument tests, we estimated a pooled OLS, a conventional random effects (RE) model without IVs, and a conventional random-effects model with IVs (REIV). The estimates of these models are reported in Table 2. In all three models, *AC*, *Delay* and the time trend are significant and positive. Airports with higher average cost and

higher delays charge higher fees, and aeronautical charges increased over the years. The *Ratio*

and city governance variables are significant and negative only in the pooled OLS model.

However, the pooled OLS model fails to account for the panel structure and disregards the

endogeneity problems, and as a result, the estimates are biased and inconsistent. The RE model

accounts for the panel data structure but disregards the endogeneity issues discussed earlier.

Table 2. The Estimates of Pooled OLS, RE and REIV Models

	POOLED		RE		REIV	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Intercept	0.366	0.528	3.685***	0.662	-1.304	1.553
ln(*AC*)	0.676***	0.064	0.459***	0.072	1.171***	0.205
Ratio	-1.259***	0.189	0.205	0.179	-0.133	0.551
ln(*HHI*)	-0.009	0.040	-0.055	0.041	-0.048	0.057
State	0.109	0.083	0.008	0.233	0.229	0.245
County	0.095	0.054	0.104	0.154	0.075	0.158
City	-0.167***	0.055	-0.036	0.157	-0.044	0.162
ln(*Delay*)	0.389***	0.027	0.097**	0.041	0.391***	0.089
Rev. Sharing	0.007	0.038	-0.008	0.013	0.000	0.019
Time Trend	0.040***	0.007	0.027***	0.003	0.041***	0.005
R^2	0.6187		0.3594		0.5555	

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

The cross-subsidization variable, *Ratio*, is insignificant for aeronautical charges in the

REIV model in Table 2. In addition to *Ratio*, we also considered two alternatives, ln(*Nrevp*) and

Choo's ratio, in the REIV model. The results are reported in Table 3. *Choo's Ratio* has a

significant and negative effect on aeronautical charges, while ln(*Nrevp*) does not have an impact

on aeronautical charges. None of the models in Tables 2 and 3 accounts for the spatial

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relationship of airports. However, the disturbances may be spatially autocorrelated. Therefore, the estimates in Tables 2 and 3 may be biased and inconsistent.

Table 3. The Estimates of REIV with ln(*Nrevp*) and *Choo's Ratio*

	REIV with *Choo's Ratio*		REIV with ln(*Nrevp*)	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Intercept	2.311**	1.133	-0.802	1.220
ln(*AC*)	0.839***	0.150	1.318***	0.221
Choo's Ratio	-2.321***	0.398		
ln(*Nrevp*)			-0.273	0.233
ln(*HHI*)	-0.146*	0.194	-0.061	0.059
State	0.025	0.118	0.153	0.258
County	-0.118	0.122	0.065	0.163
City	-0.146	0.194	-0.068	0.167
ln(*Delay*)	0.257	0.065	0.359	0.089
Rev. Sharing:	0.000	0.012	-0.002	0.019
Time Trend	0.043***	0.003	0.043***	0.005
R^2	0.7711		0.5685	

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

Next, we performed a one-sided joint LM test of Baltagi, Song, and Koh (2003) to test for random effects and spatial error autocorrelation. According to the test results (LM =86.486, p-value=0.000), there is sufficient evidence to reject the null hypothesis: $\rho = \sigma_\mu^2 = 0$. Accordingly, our model is specified as a random-effects model with a spatially lagged dependent variable and a spatial autoregressive error term of order 1, namely SARAR(1,1). In addition, to account for the endogeneity problems discussed earlier, we also estimate a SARAR model with IVs, SARARIV(1,1). The results are reported in Table 4.

Table 4. The Estimates of SARAR(1.1) with and without IVs

	SARAR(1,1) with *Ratio* (1)		SARARIV(1,1) with ln(*Nrevp*) (2)		SARARIV(1,1) (3)		SARARIV (1,1) with *Ratio* (4)	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
λ	0.415***	0.050	0.534***	0.057	0.236***	0.054	0.507***	0.058
Intercept	-0.621	0.505	-2.240***	0.534	0.662	0.556	-0.635	0.784
ln(*AC*)	0.623***	0.057	1.138***	0.070	0.731***	0.060	0.622***	0.100
Ratio	-1.283***	0.169					-1.544***	0.280
Choo's Ratio					-2.203***	0.160		
ln(*Nrevp*)			-0.474***	0.083				
ln(*HHI*)	-0.031	0.036	-0.006	0.037	-0.067**	0.029	-0.030	0.038
State	0.139**	0.065	0.065	0.074	-0.073	0.058	0.147**	0.069
County	-0.027	0.048	-0.034	0.048	-0.042	0.040	-0.007	0.050
City	-0.187***	0.038	-0.158***	0.040	-0.196***	0.032	-0.149***	0.040
ln(*Delay*)	0.305***	0.025	0.263***	0.046	0.329***	0.033	0.258***	0.044
Revenue Sharing	-0.111***	0.034	-0.108***	0.035	-0.079***	0.028	-0.110***	0.035
Time Trend	0.036***	0.007	0.035***	0.007	0.039***	0.005	0.036***	0.006
ρ	0.0116		-0.1741		0.1831		-0.0278	

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

In looking at Table 4 in more detail, we observed some similarities between SARARIV(1,1) and SARAR(1,1) models. However, the estimates of SARAR(1,1) are inconsistent due to the endogeneity problems. In all models in Table 4, the parameter for spatially lagged aeronautical charges, λ, has a positive and significant effect on aeronautical charges, implying unambiguously that an increase in aeronautical charges of neighboring airports would lead to an increase in aeronautical charges of the airport. According to the results in Column (4), a 1% increase in neighboring airport charges leads to a 0.507% increase in the airport charges. In a similar way, a 1% increase in neighboring airports' charges is estimated to

increase an airport's charges by 0.534% in Column (2) and by 0.236% in Column (3). These results suggest that airports in close proximity may be competing with each other in pricing their services to airlines. In addition, we find that airports with higher average costs would charge higher aeronautical fees, and this is largely consistent with economic theory. Furthermore, in all four models in Table 4, we observe a negative relationship between aeronautical changes and the variables representing cross-subsidization. For instance, in Column (2) a 10% increase in non-aeronautical revenue per passenger leads to a 4.7% decrease in aeronautical charges, *ceteris paribus*. In Column (3), a 10% increase in the revenue share of non-aeronautical operations is estimated to decrease aeronautical charges by 19.8%.[5] Similarly, in Column (4), a 10% increase in non-aeronautical revenue relative to the total cost, would lead to a 14.3%[6] decrease in aeronautical charges. These results might be indicative of cross-subsidization, i.e., U.S. airports subsidize aeronautical operations with non-aeronautical revenues. In addition, holding everything else constant, we found that the effects of delays on aeronautical charges are significant and positive. In other words, congested airports charge higher fees. For example, a 10% increase in delays leads to between 2.6% and 3.3% increases in aeronautical charges. Airlines' HHI is negative and significant only in Column (3). City governance is significant in all four models, implying that airports governed by a city charge lower aeronautical fees than the ones governed by a port/airport authority. Looking at the effects of revenue sharing strategy on aeronautical charges, the revenue sharing strategy is significant in all SARAR models whereas it is insignificant in conventional REIV models. Airports adopting a revenue-sharing strategy charge 8-11% lower aeronautical fees than the airports preferring not to share revenues. Lastly,

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[5] [exp(-2.203 * 0.1) – 1] *100 ≈ -19.7722.
[6] [exp(-1.544 * 0.1) – 1] * 100 ≈ -14.3071 or -14.3%.

as in the case of the conventional REIV models in Tables 1 and 3, the time trend variables is significant and positive in all spatial models in Table 4.

Aside from these models, horizontal ties between airports in an administrative cluster are a potentially important factor in explaining aeronautical charges (Van Dender, 2007). In our data, there are 3 clusters of airports that fall into this category. O'Hare International Airport and Midway International Airport in Chicago are governed by the Chicago Department of Aviation, and geographically they are closer to each other than to other hub airports. The other two clusters include JFK, LaGuardia, and Newark, which are governed by the Port Authority of New York and New Jersey, and Dulles and Reagan International Airports which are governed by the Metropolitan Washington Airport Authority. Since airports governed by the same owner may have similar pricing strategies, the geographical proximity between them does not necessarily reflect the spatial dependence of their charges but the decision of their governing body or a central decision-maker. Failure to control for the horizontal ties of the sister airports would lead to biased spatial regression results. As a precaution, we re-estimate the spatial regression model (2) by dropping sister airports from the data. In the new sample, we kept New York JFK, Chicago O'Hare and Washington Dulles which are the largest airports in each group. Firstly, we re-tested the existence of spatial autocorrelation in disturbances with the LM test of Baltagi, Song and Koh (2003). According to the test results (LM =50.006, p-value=0.000), spatial autocorrelation in disturbance exists in the new sample. The estimates of SARARIV(1,1) without sister airports are also reported in Table 5. As Table 5 shows, the estimates of SARARIV (1,1) without sister airports are similar to the estimates of SARARIV(1,1) in Table 4. Spatially lagged aeronautical charges are significant in all SARARIV (1,1) models without sister airports, suggesting evidence of spatial dependence among neighboring airports. Specifically, the positive

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estimate of λ implies that airports react positively to any changes in aeronautical charges of other airports nearby. When one airport raises the fee, rival airports are likely to follow suit.

Table 5. Estimations of SARARIV(1,1) without Sister Airports.

	SARARIV (1,1) with Ratio (1)		SARARIV (1,1) with ln(*Nrevp*) (2)		SARARIV (1,1) with *Choo's ratio* (3)	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
λ	0.343***	0.109	0.580***	0.106	0.385***	0.096
Intercept	-2.990***	0.842	-2.795***	0.602	0.613	0.661
ln(*AC*)	0.980***	0.126	1.133***	0.072	0.607***	0.083
Ratio	-0.626*	0.329				
Choo's Ratio					-2.625***	0.216
ln(*Nrevp*)			-0.476***	0.099		
ln(*HHI*)	-0.044	0.039	-0.020	0.041	-0.058**	0.028
State	0.253***	0.073	0.090	0.081	-0.112	0.065
County	-0.081	0.050	-0.115**	0.051	-0.075**	0.036
City	-0.162***	0.040	-0.162***	0.043	-0.242***	0.028
ln(*Delay*)	0.454***	0.055	0.302***	0.057	0.303***	0.046
Revenue Sharing	-0.034	0.038	-0.056	0.038	-0.106***	0.027
Time Trend	0.041***	0.007	0.041***	0.007	0.043***	0.005
ρ	0.1345		-0.0368		0.4165	

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

Besides this, ln(*Nrevp*), *Choo's ratio,* and *Ratio* remain negative and significant in SARARIV(1,1) in Table 5, further confirming the results in Table 4 that airports may be cross-subsidizing aeronautical operations with revenues of non-aeronautical activities. Moreover, *Delay* is still positive and significant in the models without sister airports in Table 5.

6. CONCLUSION

In recent years, airports have been considered as a business entity in addition to serving as critical public infrastructure. As a consequence, they face a dilemma. They are increasingly expected to be self-reliant while they are tasked with maximizing social welfare under a break-even constraint. Thus, their decisions on aeronautical charges are critical for the airport's long-term sustainability. Higher aeronautical charges could lead to fewer airlines and reduced social welfare while lower aeronautical charges may lead to a financial loss. Thus, the determinants of aeronautical charges must be considered strategically by airport management. In light of this, we examined three important elements of airport pricing strategy: the relationship between aeronautical and non-aeronautical charges, airport-airline relationships, and spatial dependence between airports.

This thesis is the first study that considers spatial dependence between airports in terms of aeronautical charges. We examined airports' pricing decisions with two spatial dependence components: spatial autocorrelation and spatially lagged aeronautical charges. The results show the presence of spatial dependence between neighboring airports, i.e., the airport's pricing decision is positively influenced by its neighboring airports' decision. Another major finding is the complementary relationship between aeronautical and non-aeronautical revenues in U.S. airport operations. Using a ratio of non-aeronautical revenues to the total cost, non-aeronautical revenues per passenger (or ln(*Nrevp*) as in by following Bilotkach et al. (2012)), and the ratio of non-aeronautical revenues to total revenues as in Choo (2014), we found evidence of a complementary relationship between non-aeronautical operations and aeronautical charges. This result is similar to Choo's (2014) which first documented some results on cross-subsidization at U.S. airports. In addition, to the best of our best knowledge, this study is the first to consider the

implication of airport revenue sharing strategy on aeronautical charges. We found the aeronautical charges of an airport adopting revenue sharing are lower than those that do not share revenues. We also found that more congested airports charge higher aeronautical fees. Lastly, airports governed by a city government charge lower fees than the ones governed by a port/airport authority.

In conclusion, the spatial regression results suggest that U.S. airports benchmark neighboring aeronautical charges when they make a decision about pricing, implying that they are in price competition with each other even though they are government-owned infrastructure. Thus airport competition may not be just a phenomenon among privately owned and operated airports. In the case of the U.S., airports also seek to increase aeronautical outputs through lower aeronautical fees, and they then cross-subsidize aeronautical operations or recoup the cost of operations through non-aeronautical services. This practice incentivizes airlines to bring in more air travelers, but the captive air travelers who pay for the non-aeronautical services they consume are also indirectly subsidizing aeronautical operations at the airport. Future studies should examine whether such cross-subsidization produces desirable economic outcomes, that is whether the welfare gains in aeronautical operations outweigh the welfare loss in non-aeronautical operations as a result of cross-subsidization.

REFERENCES

Anselin, L. (2003). Spatial Econometrics. In *A Companion to Theoretical Econometrics* (pp. 310–330). Blackwell Publishing Ltd. https://doi.org/10.1002/9780470996249

Baltagi, B. H., Song, S. H., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, *117*(1), 123–150. https://doi.org/10.1016/S0304-4076(03)00120-9

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

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

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

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., Jiang, C., & Wan, Y. (2013). Airport Pricing , Concession Revenues and Passenger Types. *Journal of Tranport Economics and Policy*, *47*(January), 71–89.

D'Alfonso, T., & Nastasi, A. (2014). Airport–Airline interaction: some food for thought. *Transport Reviews*, *34*(6), 730–748. https://doi.org/10.1080/01441647.2014.971470

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

Dmitry, P. (2012). Airport Benchmarking and Spatial Competition: A Critical Review. *Transport and Telecommunication*, *13*(2), 123–137. https://doi.org/10.2478/v10244-012-0010-z

Fröhlich, K., & Niemeier, H. M. (2011). The importance of spatial economics for assessing airport competition. *Journal of Air Transport Management*, *17*(1), 44–48. https://doi.org/10.1016/j.jairtraman.2010.10.010

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.

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

Kapoor, M., Kelejian, H. H., & Prucha, I. R. (2007). Panel data models with spatially correlated error components. *Journal of Econometrics*, *140*, 97–130. https://doi.org/10.1016/j.jeconom.2006.09.004

Kelejian, H. H., & Prucha, I. R. (1998). A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *Journal of Real Estate Finance and Economics*, *17*(1), 99–121. https://doi.org/10.1023/A:1007707430416

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

LeSage, J. P. (2008). *An introduction to spatial econometrics*. *De Boeck Supérieur*. https://doi.org/10.4000/rei.3887

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

Mutl, J., & Pfaffermayr, M. (2011). The Hausman test in a Cliff and Ord panel model. *The Econometrics Journal*, *14*(1), 48–76. https://doi.org/10.1111/j.1368-423X.2010.00325.x

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

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

Saraswati, B., & Hanaoka, S. (2014). Airport – airline cooperation under commercial revenue sharing agreements : A network approach. *Transportation Research Part E*, *70*, 17–33. https://doi.org/10.1016/j.tre.2014.06.013

Smyth, M., & Pearce, B. (2007). IATA Economics Briefing No 6: Economic Regulation. *Iata*. Retrieved from https://www.iata.org/whatwedo/documents/economics/economicregulation_web.pdf

Starkie, D. (2002). Airport regulation and competition. *Journal of Air Transport Management*, *8*(1), 63–72. https://doi.org/10.1016/S0969-6997(01)00015-1

Stock, H. J., & Yogo, M. (2005). Asymptotic Distributions of Instrumental Variables Statistics with Many Instruments. In *Identification and Inference for Econometric Models:Essays in Honor of Thomas Rothenberg* (pp. 109–120). Cambridge University Press.

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, *46*, 234–240.

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

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

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.

APPENDIX A. AIRPORT CLASSIFICATION

ID	AIRPORTS	CITY	GOVERNANCE FORMS†	REVENUE SHARING††
ABQ	Albuquerque International Sunport	Albuquerque, New Mexico	City	Yes
ANC	Ted Stevens Anchorage International Airport	Anchorage, Alaska	State	Yes
ATL	Hartsfield–Jackson Atlanta International Airport	Atlanta, Georgia	City	Yes
AUS	Austin-Bergstrom International Airport	Austin, Texas	City	No
BDL	Bradley International Airport	Hartford, Connecticut	Port/Airport Authority	Yes
BNA	Nashville International Airport	Nashville, Tennessee	Port/Airport Authority	Yes
BOS	Gen. Edward Lawrence Logan International Airport	Boston, Massachusetts	Port/Airport Authority	No
BUF	Buffalo Niagara International Airport	Buffalo, New York	Port/Airport Authority	No
BWI	Baltimore/Washington International Thurgood Marshall Airport	Baltimore, Maryland	State	No
CLE	Cleveland-Hopkins International Airport	Cleveland, Ohio	City	Yes
CLT	Charlotte/Douglas International Airport	Charlotte, North Carolina	City	Yes
CMH	John Glenn Columbus International Airport	Columbus, Ohio	Port/Airport Authority	Yes
CVG	Cincinnati/Northern Kentucky International Airport	Hebron, Kentucky	Port/Airport Authority	Yes
DCA	Ronald Reagan Washington National Airport	Arlington, Virginia	Port/Airport Authority	Yes
DEN	Denver International Airport	Denver, Colorado	City	Yes
DFW	Dallas/Fort Worth International Airport	Dallas-Fort Worth, Texas	City	Yes
DTW	Detroit Metropolitan Wayne County Airport	Detroit, Michigan	County	Yes

ID	AIRPORTS	CITY	GOVERNANCE FORMS†	REVENUE SHARING††
EWR	Newark Liberty International Airport	Newark, New Jersey	Port/Airport Authority	No
FLL	Fort Lauderdale–Hollywood International Airport	Fort Lauderdale, Florida	County	Yes
HNL	Daniel K. Inouye International Airport	Honolulu, Hawaii	State	Yes
HOU	William P. Hobby Airport	Houston, Texas	City	Yes
IAD	Washington Dulles International Airport	Dulles, Virginia	Port/Airport Authority	Yes
IAH	George Bush Intercontinental Airport	Houston, Texas	City	No
IND	Indianapolis International Airport	Indianapolis, Indiana	Port/Airport Authority	Yes
JAX	Jacksonville International Airport	Jacksonville, Florida	Port/Airport Authority	Yes
JFK	John F. Kennedy International Airport	New York, New York	Port/Airport Authority	No
LAS	McCarran International Airport	Las Vegas, Nevada	County	Yes
LAX	Los Angeles International Airport	Los Angeles, California	City	Yes
LGA	LaGuardia Airport (and Marine Air Terminal)	Queens, New York	Port/Airport Authority	No
MCI	Kansas City International Airport	Kansas City, Missouri	City	No
MCO	Orlando International Airport	Orlando, Florida	Port/Airport Authority	Yes
MDW	Chicago Midway International Airport	Chicago, Illinois	City	Yes
MIA	Miami International Airport	Miami, Florida	County	Yes
MKE	General Mitchell International Airport	Milwaukee, Wisconsin	County	Yes
MSP	Minneapolis–St. Paul International Airport	Minneapolis, Minnesota	Port/Airport Authority	Yes
MSY	Louis Armstrong New Orleans International Airport	New Orleans, Louisiana	City	Yes
OAK	Oakland International Airport	Oakland, California	Port/Airport Authority	Yes

ID	AIRPORTS	CITY	GOVERNANCE FORMS†	REVENUE SHARING††
OGG	Kahului Airport	Kahului, Hawaii	State	Yes
OKC	Will Rogers World Airport	Oklahoma City, Oklahoma	City	No
OMA	Eppley Airfield	Omaha, Nebraska	Port/Airport Authority	No
ONT	Ontario International Airport	Ontario, California	Port/Airport Authority	Yes
ORD	Chicago O'Hare International Airport	Chicago, Illinois	City	Yes
PBI	Palm Beach International Airport	West Palm Beach, Florida	County	Yes
PDX	Portland International Airport	Portland, Oregon	Port/Airport Authority	Yes
PHL	Philadelphia International Airport	Philadelphia, Pennsylvania	City	Yes
PHX	Phoenix Sky Harbor International Airport	Phoenix, Arizona	City	No
PIT	Pittsburgh International Airport	Pittsburgh, Pennsylvania	Port/Airport Authority	Yes
RDU	Raleigh-Durham International Airport	Raleigh, North Carolina	Port/Airport Authority	No
RSW	Southwest Florida International Airport	Fort Myers, Florida	Port/Airport Authority	Yes
SAN	San Diego International Airport	San Diego, California	Port/Airport Authority	No
SAT	San Antonio International Airport	San Antonio, Texas	City	Yes
SEA	Seattle–Tacoma International Airport	Seattle / Tacoma (Sea Tac), Washington	Port/Airport Authority	Yes
SFO	San Francisco International Airport	San Francisco, California	City	Yes
SJC	Norman Y. Mineta San José International Airport	San Jose, California	City	Yes
SLC	Salt Lake City International Airport	Salt Lake City, Utah	City	Yes
SMF	Sacramento International Airport	Sacramento, California	County	No
SNA	John Wayne Airport	Santa Ana, California	County	No
STL	St. Louis Lambert International Airport	St. Louis. Missouri	City	Yes

ID	AIRPORTS	CITY	GOVERNANCE FORMS†	REVENUE SHARING††
TPA	Tampa International Airport	Tampa, Florida	Port/Airport Authority	Yes

APPENDIX B. R CODE

 # Creating spatial weight matrix

library(spfrontier)

w=constructW(cbind(aport$Lon,aport$Lat),aport$ID)

w=rowStdrt(w)

w.lw=mat2listw(w, style="W")

z=constructW(cbind(aports$lon,aports$lat),aports$ID)

z=rowStdrt(z)

z.lw=mat2listw(z, style="W")

#Creating variables

airports$lareva=log(airports$arevpd/airports$atm)

airports$lnrev=log(airports$nrevpd/airports$pas)

airports$del=log(airports$totaldelay)

airports$lhhi=log(airports$hhi)

library(fastDummies)

airports=dummy_cols(airports, select_columns="ownership")

airports=dummy_cols(airports, select_columns="rs")

airports$lexp=log(airports$tcpd/airports$pas)

airports$ratio=(airports$nrevpd/airports$tcpd)

airports$cratio=airports$nrevpd/(airports$arevpd+airports$nrevpd)

airport1$lareva=log(airport1$arevpd/airport1$atm)

airport1$lnrev=log(airport1$nrevpd/airport1$pas)

airport1$del=log(airport1$totaldelay)

airport1$lhhi=log(airport1$hhi)

library(fastDummies)

airport1=dummy_cols(airport1, select_columns="ownership")

airport1=dummy_cols(airport1, select_columns="rs")

airport1$lexp=log(airport1$tcpd/airport1$pas)

airport1$ratio=(airport1$nrevpd/airport1$tcpd)

airport1$cratio=airport1$nrevpd/(airport1$arevpd+airport1$nrevpd)

#GM-IV Spatial Panel Analysis

fm=(lareva~lhhi+ownership_state+ownership_county+ownership_city+rs_Yes+time)

#LM Tests

bsktest(fm,data=airports,index=c("ID","year"),listw=w.lw,test="LMH")

bsktest(fm,data=airport1,index=c("ID","year"),listw=z.lw,test="LMH")

#SARARIV(1,1)

ssa1=spgm(fm,airports,w.lw,index=c("ID","year"),model="random",lag=TRUE,spatial.error=TR

UE, endog=~del+lexp+ratio,instruments=~lldel+llexpp+lratio, moment="fullweight")

summary(ssa1)

#SARARIV(1,1) without Sister Airports

spgm(fm,airport1,z.lw,index=c("ID","year"),model="random",lag=TRUE,spatial.error=TRUE,

endog=~del+lexp+ratio,instruments=~lldel+llexpp+lratio, moment="fullweight")

summary(ssa2)