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Supply-and-demand models for exploring relationships between smaller airports and neighboring hub airports in the U.S.

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We explore the issue of air passenger leakage at small and medium-size airports

We model relationships between passenger volume and air services at neighbouring airports

We present a supply-and-demand feedback model of airport choice

The existence of feedback is demonstrated – more passengers, more attractive services

Supply-and-demand models for exploring relationships between smaller airports and neighboring hub airports in the U.S.

Abstract

Airport passenger leakage is the phenomenon of air passengers choosing to travel longer distances to access more extensive air services offered by airlines at an out-of-region hub (or, substitute) airport, instead of using their local airports. Airport leakage can cause further reduction in services offered by airlines at a local airport, thereby causing even further leakage, and so on, which can significantly impact an airport's role in the growth of the local economy. This paper explores the geographic and operational attributes of local-and-substitute airport pairs in the United States, explicitly accounting for the interactive feedback relationship between passenger volumes and air service characteristics that contribute to the onset, persistence, and exacerbation of airport passenger leakage. A two-stage least squares regression model of air passenger demand at small- and medium-sized airports is first presented, where local passengers may travel by vehicle to larger, out-of-region hub airports. The results confirm that airfare and passenger volume relationships exist between the local and substitute airport pairs included in the dataset, and that lower airfares at the substitute airport have a greater impact on airport choices made by larger travel groups. They also suggest the existence of positive feedback in that if an airport attracts increasingly smaller passenger numbers with fewer air services and fewer air services with fewer passengers, without external intervention airport leakage impacts may be irreversible and exacerbate over time. A conceptual market share equilibrium analysis is used to illustrate the mechanisms of a direct two-way feedback relationship between passenger volumes at a local airport and air service characteristics at both the local and substitute airports. With data, this quantitative framework can help guide airport planners in further assessing and verifying suspected passenger leakage issues at their airport. The results suggest that without intervention, airport leakage impacts may be difficult to reverse; further exacerbating the trend are technological advancements that make driving cheaper and easier (connected and autonomous vehicles). However, the results can also guide planners in choosing the types and degrees of infrastructure investments and airline incentives that may be used to expand or retain air services to attract passengers.

Keywords

Airport leakage; empirical model; airport planning.

1. Introduction

Passengers at many small- and medium-sized U.S. airports are increasingly provided fewer flight options and higher airfares as a result of airline mergers, alliances, and various decisions made to cut operational costs and increase efficiency (Sharkey, 2014a; Sharkey, 2015), in addition to constraints on opportunities to expand infrastructure capacity. For instance, airlines are increasing their use of larger and more efficient jet aircraft over regional jets, which make hub airports more preferable for these airlines to operate from (Sharkey, 2014b). This in turn increases airline competition and decreases the concentration level of airlines at hub airport as measured by the Herfindahl–Hirschman Index (HHI) (Detzen, Jain, Likitapiwat, & Rubin, 2012; Lijesen & Rietveld, 2002), which may be associated with more airfare discounts (Stavins, 2001). As a result, passengers that would typically use their smaller local airports may respond by driving relatively long distances to larger out-of-region hub airports (termed substitute airports) in order to take advantage of better flight options, lower airfares, and other airport amenities. This phenomenon has been termed airport leakage (Elwakil, Windle, & Dresner, 2013; Fuellhart, 2007; Suzuki & Audino, 2003; Suzuki, Crum, & Audino, 2004).

As airports play an important role in connecting regions nationally and globally and supporting local economic development, the loss of passengers at these small- and medium-sized airports can have significant and long-term impacts (Ottawa Macdonald-Cartier International Airport Authority, 2012; De Neufville, 1995). It may contribute to increased traffic and congestion at substitute airports. A shrinking passenger base at the local airport makes that airport less attractive to airlines, eventually leading to fewer flight options (Pitfield, Caves, & Quddus, 2010), then fewer passengers and even fewer flight options, and so on – a positive supply-and-demand feedback, or the “vicious cycle of local air services” (Kanafani & Abbas, 1987). For instance, after airline deregulation, air carriers reduced their services at Meadows Field Airport in Bakersfield, California, encouraging a large portion of travelers in the Bakersfield area to drive approximately 110 miles to Los Angeles International Airport (LAX). The shrinking market and revenues at Meadows Field resulted in fewer air carriers and flight options, which further drove local passengers to LAX (Kanafani & Abbas, 1987). Without incentive programs (Ryerson, 2016), other investments by local governments, or the benefits of external economic forces, passenger losses may be difficult to reverse (Sharkey, 2014b). It is important to have some quantitative insights into the mechanisms driving passenger leakage at these local airports to major out-of-region hub airports, with respect to the service characteristics of these airports, and vice versa, in order to gauge the need for (and degree of) investments that may help to stem this passenger leakage.

This paper explores the operational attributes of local-and-substitute airport pairs in the United States. We explicitly account for the interactive feedback relationship between passenger volumes (demand) and air service characteristics (supply) that contribute to the onset, persistence, and exacerbation of airport passenger leakage.

We first present a two-stage least squares regression model of air passenger demand at small- and medium-sized airports, where local potential passengers may travel by vehicle to larger, out-of-region hub airports. The results confirm that airfare and passenger volume relationships exist between the local and substitute airport pairs included in the dataset, and that lower airfares at the substitute airport have a greater impact on airport choices made by larger travel groups. After confirming the existence of this relationship, we then present a conceptual market share equilibrium analysis to illustrate the mechanisms of a direct two-way feedback relationship between passenger volumes at a local airport and air service characteristics at both the local and substitute airports. They also suggest the existence of positive feedback in that if an airport attracts increasingly smaller passenger numbers with fewer air services and fewer air services with fewer passengers, without external intervention, airport leakage impacts may be irreversible and exacerbate over time.

The contributions of this paper include the confirmation of relationships between airport leakage and explanatory factors such as travel group size and airport enplanement, and explicit consideration of the interaction between demand and supply in both the empirical model and the equilibrium analysis. Most importantly, this paper proposes a quantitative framework that can help guide airport planners in further assessing and verifying suspected passenger leakage issues at their airport. If an airport suspected of passenger leakage to an out-of-region hub airport exhibits characteristics similar to those in the regression model dataset, data collection to estimate and populate the proposed feedback model may be justified. The model results can be used, in turn, to quantitatively verify or refute the existence and severity of leakage. Analysis results can be used by local jurisdictions and airport planning authorities to gauge what types of, and to what degree, infrastructure investments and incentive programs should be considered in expanding or retaining air services to attract passengers back to the airport in question. More specifically, the results can provide some indication of how impactful intervention decisions may be in disrupting the positive feedback of air passenger leakage and service cutbacks, such that appropriate types and levels of investment can be applied.

2. Literature review

The study of airport passenger leakage implicitly assumes that air travelers within a certain distance of an airport, or within a defined region in which the airport is located, are expected to use that airport when flying (Fröhlich & Niemeier, 2011). These travelers presumed to be in the catchment area of that airport may “leak” to a larger airport for which they are not expected to be in the catchment. This phenomenon can be categorized as an airport passenger competition problem (Fuellhart, 2007; Lieshout, 2012). Although airport competition and passenger choice has been extensively studied for multi-airport regions (MARs), it has received far less attention in the context of airports experiencing expected passenger loss to larger, out-of-region hub airports. The passenger leakage problem has been studied using the same analysis methods applied to MARs problems, insofar as both deal with understanding the mechanisms that determine how airports attract (and compete for) passengers with two or more airport options. Differences arise as the geographic scope of the leakage problem is interregional, while that of the multi-airport region problem is within a single metropolitan area. The service characteristics of these airports differ, as do the factors that influence passengers' airport choice.

Despite that interregional air passenger leakage is considered to be an issue of significance (Lian & Rønnevik, 2011; Jang, 2010; Sharkey, 2014b), it has not been studied as much as the MARs problem due to a number of reasons. Firstly, it is often the case that the local metropolitan planning organization (MPO) collects various transportation data within the region it oversees. These agencies are not typically easily able (or willing) to collect data – particularly the disaggregate survey data required for discrete choice models – beyond their jurisdictions. Coordinated data collection by multiple regional authorities is difficult due to institutional structure and therefore happens very rarely (Miller, 2004). As a result, most past studies on airport leakage have been based on data collected specifically to study the problem by the airports experiencing the leakage (Suzuki, Crum, & Audino, 2003; Fuellhart, 2007; Kimley-Horn and Associates, Inc., 2012). Secondly, although airports and regions that experience passenger leakage may have anecdotally identified the issue, without an investment in data collection, it may be more difficult to determine whether the issue is severe enough to warrant further infrastructure investments and how much.

Interregional air passenger leakage is also relevant within the context of the Essential Air Service (EAS) program (Grubesic & Matisziw, 2011). Passenger retention at small community airports in the EAS program, as well as overall program efficiency, has been studied by several researchers (Kaemmerle, 1991; Zhang & Xie, 2005; Grubesic & Wei, 2012). Consistent with conclusions from airport leakage studies, it has been found that the quality and quantity of air services at small community airports, as well as the distances between them and other larger airports, are very important in retaining passengers at these EAS airports (Kaemmerle, 1991; Zhang & Xie, 2005). A study indicates that federal expenditures can be reduced by ending subsidies to some small community airports that share spatial market coverage (i.e. overlapped passenger catchment areas) with larger hub airports (Grubesic & Matisziw, 2011).

Airport leakage has been studied from both the demand and supply (service) perspective. From the perspective of demand, airport leakage has been demonstrated to be a function of passenger market share, passengers' airport choice, and airport ground access choice (Tam, Lam, & Lo, 2011; Chang, 2013; Cohas, Belobaba, & Simpson, 1995), and will be discussed in the following section. Also, different airports offer markedly levels of accessibility to the air transportation network, as measured, for example, by the number of direct connections from an airport. Airports also offer different levels of ground access as well (Matisziw & Grubesic, 2010). The airport supply-side consists of the service characteristics (airside, groundside, and in the terminal) at an airport.

Previous studies focused on how decisions regarding air services are made by the airport and airlines, and also, how accessible an airport is to the passenger market that they expect to serve (Budd, Ison, & Ryley, 2011). Although the previous studies relevant to airport leakage can be broadly divided into those that consider demand-side issues, supply-side issues, or both interactively, methodological approaches vary greatly. We will discuss the relevant existing literature by categorizing general study approaches, which consists broadly of passenger airport choice, supply-and-demand equilibrium and game theoretic approaches, and regression.

2.1 Airport choice

Discrete choice models have been applied extensively to study passenger airport choice in MARs (Harvey, 1987; Windle & Dresner, 1995; Hess & Polak, 2005; Loo, 2008), in addition to joint choices of airport, airline and ground access modes (Pels, Nijkamp, & Rietveld, 2000; Pels, Nijkamp, & Rietveld, 2001; Hess S. , 2004; Hess, Adler, & Polak, 2007; Tierney & Kuby, 2008). The results and findings of these studies vary significantly, at least partly due to the different modeling structures employed. Some studies have found that airport choice is most heavily influenced by ground access mode characteristics (Pels, Nijkamp, & Rietveld, 2003) while other studies have found that air services characteristics are more important (Harvey, 1987). Overall, the most important factors reported by these studies to impact airport choice include access time and/or distance, travel party size, car ownership, trip purpose (business or personal), airfare, flight frequency, flight time, direct or indirect flight, past delays, aircraft types used, etc. (de Luca, 2012). In addition, an early study has looked at the choice made between five airports throughout England using a basic multinomial logit model (Ashford & Bencheman, 1987).

Discrete choice models have also been applied to study airport leakage, but as mentioned above, to a far lesser extent due to data availability. It has been found that leisure travelers are more likely to leak to substitute airports than business travelers; also, past experiences at an airport, access time, airfare, age and income have significant impacts on passengers' airport choices (de Luca, 2012; Suzuki, Crum, & Audino, 2003). Based on survey data collected to gain understanding about passenger leakage from the Des Moines airport to neighboring airports, Suzuki (2007) has studied the joint airport and airline choice problem as a two-stage decision process to better represent the actual decision making process.

2.2 Supply-and-demand equilibrium and game theoretic models

As demonstrated above, there is extensive literature on how service attributes impact passenger demands, particularly in MARs. However, there has been less work in understanding how passengers' airport choice in turn can influence airlines and airports in their provision of air services (supply), and so on – a two-way feedback relationship. In the few existing studies considering feedbacks, discrete choice models of air passenger demand have been used in combination with other models to study this endogeneity. A key example of this is by Hansen (1995), who has treated the supply-side characteristics of airports in a MAR as endogenous in a disaggregate model of airport choice. Predicted equilibrium market shares have been found to show high agreement with actual market shares at the San Francisco and Oakland airports. Another study, again based on data from the San Francisco Bay Area, has estimated a nested logit model and considered that airport and airlines would respond competitively to maximize their benefits (Pels, Nijkamp, & Rietveld, 2000). They report that the elasticity of demand to flight frequency should be less than one as a sufficient condition for a competitive equilibrium to exist.

In the context of the airport leakage problem, Suzuki et al. (2004) has combined an airline profit function with a multinomial logit market share model, and conducted a simulation experiment to investigate the relationship between passenger volumes and airfares. They find the optimal airfare required to maximize an airline's profit, which is lower than the actual airfares offered at Des Moines airport. The paper suggests that underestimation of airport leakage may be the reason why airlines set higher airfares than is optimal (Suzuki, Crum, & Audino, 2004).

2.3 Regression models

Airport leakage has been studied to its largest extent using regression models. In one study, airport passenger traffic "leaking" from local airports to substitute hub airports has been estimated, where the number of "leakage" passengers is determined from the tickets sold at a travel agent in the local airport's region for flights departing at substitute airports (Phillips, Weatherford, Mason, & Kunce, 2005). The first step consists of a regression model of the proportion of "leaking" passengers. In the second step, the residuals from the first-step model are regressed on explanatory variables that only vary with respect to routes. The findings indicate that airfare differentials, the distance between the local airport and the substitute airport, and whether regional jets are provided are the three most important factors determining leakage from small community airports in Wyoming. In another study, a two-stage least squares model has been constructed for 14 U.S. airport pairs to capture the endogeneity of supply-side and demand-side attributes (Suzuki & Audino, 2003). It estimates airfare in the first stage, and then uses the predicted airfare variable in a second-stage model. The airfare and driving distance interaction variable indicates that air passengers may be attracted to a substitute airport that is up to 250 miles away (Suzuki & Audino, 2003). However, other studies limit this distance to one ranging between 100 and 200 miles (Grubesic & Matisziw, 2011; Kanafani & Abbas, 1987; Lin, 1977; Kaemmerle, 1991). Fuellhart (2003) has used linear regression models that suggest the leakage of passengers from Harrisburg and Philadelphia airports to Baltimore – distances of 70 to 90 miles – is due to fare differentials, low-cost carrier service, and other factors. With zip code data collected for vehicles parking at Harrisburg airport, GIS and regression analysis suggest strong leakage patterns from Harrisburg to Baltimore-Washington airport (Fuellhart, 2007). The author has used route level data to demonstrate relationships between airfare differentials and passenger volumes. Elwakil et al. (2013) has constructed a three-stage least squares model to explore the impact of competition in U.S. cities near the Canadian border. The study finds airfare differentials – which are significant between Canada and the U.S. – to be a potential cause of airport leakage for the transborder market (Elwakil, Windle, & Dresner, 2013).

This paper attempts to combine two of the modeling approaches from above to present a framework for analysis of airport leakage. Firstly, we provide a systematic local-substitute airport pair selection process and autocorrelation correction for the two-stage least squares model proposed by Suzuki and Audino (2003), using more recent data. After confirming a relationship between passenger volumes and air service characteristics from the empirical analysis, we represent the endogenous (feedback) relationship between airfares and passenger volumes through an equilibrium analysis that utilizes the estimated airfare model and a simple binary airport choice model. This feedback model is used to explore the sensitivities of airport market share to airfares and vice versa.

3. Models of supply and demand

In this section, we will present two analyses of the feedback effects between supply and demand in airport leakage, through an econometric model and a conceptual market share equilibrium analysis. The econometric model explores the (geographically) generalized relationships using an empirical two-stage model as well as the positive feedback mechanism. Based on the results from the econometric model, the market share equilibrium analysis further explores the hypothesized relationships in an equilibrium context. This section has four subsections: hypothesized relationships between supply and demand variables, econometric model, conceptual market share equilibrium analysis, and overview of relationships between supply and demand variables.

3.1 Hypothesized relationships between supply and demand variables

According to the literature review, airfare is an important contributor to airport passenger leakage (Suzuki & Audino, 2003; Hansen, 1995; Pels, Nijkamp, & Rietveld, 2000). We begin with the hypothesis that higher airfares at the local airport will encourage more passengers to use substitute airports, resulting in fewer passengers at the local airport. In turn, fewer passengers at the local airport are expected to result in higher airfares at local airport. Similarly, lower airfares at the substitute airport will result in more passengers leaking to the substitute airport. We also assume that more flight legs, absence of low-cost carriers, lower flight frequencies at the local airport, lower populations (in the area intended to be served by the local airport), and closer distances between the local and substitute airports will contribute to airport leakage. We will examine the above assumptions using the econometric model. Attributes that we assume are related to airport passenger volumes but may not specifically be related to airport leakage include seasonal fluctuations of airport passenger volumes. These will also be tested in the econometric model.

In the conceptual model, we will examine the impacts of airfares at the local and substitute airports, flight frequencies, and ground access distance on airport choice and airport market share (after confirmation through the empirical model).

3.2 Econometric model of supply (airfare) and demand (passenger volumes)

In this section, we introduce a two-stage least squares regression model of airfare and passenger volumes, based on that proposed by Suzuki and Audino (2003). Airfare is a function of exogenous variables in the first stage, and passenger volumes are a function of the predicted airfare (and other exogenous variables) in the second stage:

First-stage model: $$F = f(P, \boldsymbol{U}) \tag{1}$$

Second-stage model: $$P = f(\hat{F}, \boldsymbol{V}) \tag{2}$$

Where, F is airfare; $\hat{F}$ is the fitted airfare variable; P is passenger volumes; and $\boldsymbol{U}, \boldsymbol{V}$ are other exogenous explanatory variables. Our model builds on the previously developed model by including a systematic airport selection process, new variable specifications, and bias corrections. The original model has accounted for air cargo volumes, airfares at substitute airport, driving distances between local and substitute airports, seasonality, and number of flight legs from the substitute airport (Suzuki & Audino, 2003). To consider seasonal fluctuations in passenger volumes, we use total quarterly passenger enplanement from all U.S. airports to each destination airport (included the dataset), excluding enplanement volumes from the local and substitute airports. The local and substitute airport passenger volumes were removed to reduce endogeneity between the seasonality variable and both the passenger and enplanement variables. We have explored additional variables including total passenger enplanement from the local and substitute airports to all U.S. airports. Explanatory variables are identified in Sections 3.2.3, 3.2.4 and 3.2.5.

As the data exhibits autocorrelation and heteroscedasticity, a feasible generalized least squares (FGLS) model structure is adopted to account for these issues (Wooldridge, 2012). Time series data (such as we have here) is collected through repeated measurements of the same variables. Therefore, if there is a source of measurement error, it is likely to be repeated, resulting in autocorrelation (Maddala, 1992; Asteriou & Hall, 2007). Another possible source of autocorrelation is the omission of other important variables from the model. These variables may exhibit a trend over time and impact the dependent variable, but may not be included because the data is unavailable (Maddala, 1992; Asteriou & Hall, 2007). For instance, aircraft maintenance costs will impact overall airline operating costs, and possibly, in turn, airfare; in addition, maintenance costs in some quarter is likely related to those of previous quarters. However, maintenance cost are not captured in the dataset and therefore, any impact it may have on airfares is thus included in the error term in the airfare model. The following four subsections describe the airport/region data selection process, specifications of the first-stage and second-stage models, and presentation and discussion of model estimation results.

3.2.1. Data Sources

U.S. airport passenger traffic, airline services, driving distances, census information, and aviation fuel costs are obtained from five sources. Airport passenger traffic and airline services data are from the Airline Origin and Destination Survey (DB1B) and the Air Carrier Statistics (T-100), both of which are available from the U.S. Department of Transportation (DOT) website (www.transtats.bts.gov). Driving distances between airports are from the Google Maps website (maps.google.com). Census data, including population and income, are from the U.S. Census, Department of Commerce (factfinder.census.gov/faces/nav/jsf/pages/index.xhtml). Aviation fuel cost data are available from the U.S. Department of Transportation.

Table 1 Data sources

Data source	Information extracted
Airline Origin and Destination Survey (DB1B)[1]	Origin, destination, time, airfare, flight leg, group size
Air Carrier Statistics (T-100)[2]	Origin, destination, time, passenger traffic, flight frequency, non-stop miles, carrier, freight
U.S. Census[3]	Population, per capita income
Google Maps[4]	Driving distance[6]
Aviation Fuel Cost[5]	Aviation fuel cost and consumption

1 http://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=125

2 www.transtats.bts.gov/Fields.asp?Table_ID=258

3 factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml

4 maps.google.com

5 transtats.bts.gov/fuel.asp?pn=0&display=data1

6 The shortest driving distance on the website is used. Data was extracted on November 25, 2015.

Data from 2005 through 2013 have been obtained for this work. Departure airport, destination airport, airfare, number of flight legs, passenger volumes, carrier name, non-stop flight distance, flight frequency, group size, and population information are available in the DB1B, T-100, and census datasets.

3.2.2. Airport Selection Procedure

We first identify small- to medium-size airports hypothesized to experience some level of air passenger leakage to larger hub airports. This selection is based on the supposition that if airport passenger leakage is occurring, this is caused by, and contributes to, the substitute airport having significantly higher passenger volumes and better air service provision by airlines (i.e., cheaper and more frequent flights to common destinations) than the local airport. The output of the selection process will be a local airport, its substitute airport, and the destination airport (identifying an origin-destination (OD) pair). Figure 1 shows the filtering criteria applied to obtain the twenty local/substitute/destination airport combinations used in the model estimation.

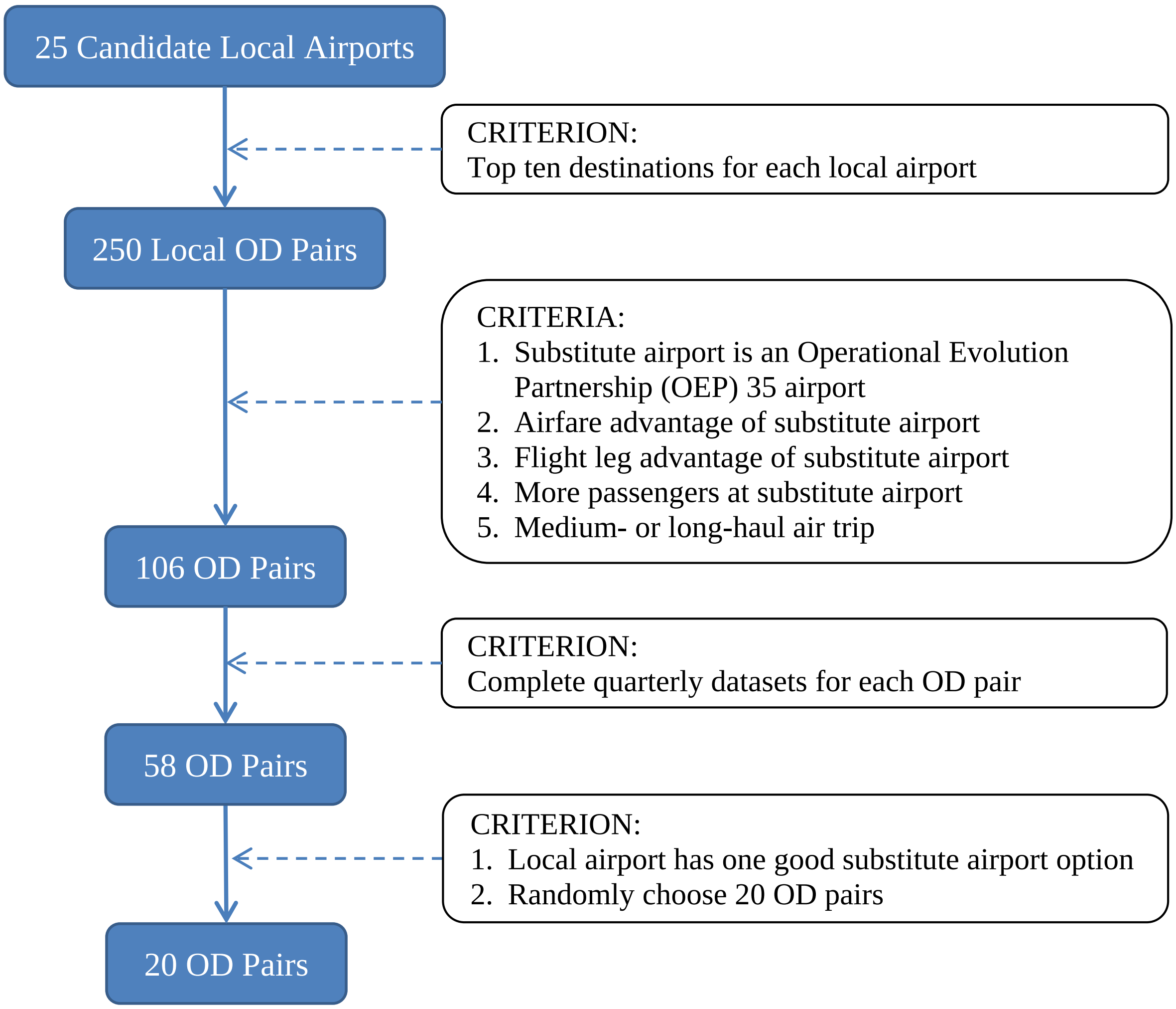

Figure 1 Local airport selection process

As shown in **Figure 1**, the first step involves the selection of 25 candidate local airports and their corresponding substitute airports (to which passenger leakage from the local airports may occur). This step is based on a search for small- to medium-size airports in single-airport regions, with major hub airports within reasonable driving distances (Lin, 1977; Kaemmerle, 1991; Grubesic & Wei, 2012). We also considered anecdotal evidence when setting such driving distance criteria. For instance, passengers in the Huntsville region have been reported to "leak" to Hartsfield–Jackson Atlanta International Airport (ATL) even though ATL is more than 200 miles away (Huntsville International Airport, 2013). In Canada, residents in the Edmonton Capital Region in Alberta are known to drive over 200 miles to use Calgary International Airport rather than Edmonton International Airport (Jang, 2010). Hence, we felt it appropriate to include and explore local-substitute airport pairs as far as 200 miles apart in our airport selection.

The top ten destinations with the highest number of passengers are identified for each candidate local airport based on nine years of Airline Origin and Destination Survey (DB1B) data (from 2005 through 2013). Then, five filtering criteria are applied as follows:

1) Substitute airports are included in the 35 Operational Evolution Partnership (OEP) airports designated by the Federal Aviation Administration (FAA), which are the 35 busiest commercial airports in the United States (Federal Aviation Administration, 2015).
2) Average airfare to the destination from the local airport is higher than from the substitute airport.
3) Average number of flight legs to the destination from the local airport is higher than from the substitute airport.
4) Passenger volumes between the substitute and destination airport are no smaller than 1.5 times the volumes between the local and destination airport. This is to ensure that the substitute airport does have greater market share to the destination airport when compared to the local airport.
5) Distance from the local airport to the destination airport is greater than 500 miles.

After application of these conditions, 106 OD pairs remain. Then, the third filter ensures that there are sufficient quarterly data from both the DB1B and T-100 datasets, leaving 58 OD pairs remaining. The final filter ensures that each local airport has only one good candidate substitute airport. Twenty OD pairs have then been randomly selected for use. The resulting set of local airports, corresponding substitute airports, destination airports, and flight distances (from local to destination) are shown in Table 2.

Table 2 Final set of origin airports (local and substitute) and destinations

Local Airport	Substitute Airport	Distance, local to substitute airport (miles)	Destination Airport	Flight distance from local airport (miles)
Jacksonville (JAX)	Orlando (MCO)	173	Philadelphia (PHL)	742
			Newark (EWR)	821
Tucson (TUS)	Phoenix (PHX)	117	Seattle–Tacoma (SEA)	1,216
Milwaukee (MKE)	Chicago Midway (MDW)	94.9	Orlando (MCO)	1066
Oklahoma City (OKC)	Dallas/Fort Worth (DFW)	195	Atlanta (ATL)	761
Grand Rapids (GRR)	Detroit (DTW)	147	Atlanta (ATL)	640
Quad City (MLI)	Chicago O'Hare (ORD)	164	Denver (DEN)	752
Columbia Metropolitan (CAE)	Charlotte Douglas (CLT)	105	LaGuardia (LGA)	617
			Chicago O'Hare (ORD)	666
Portland Jetport (PWM)	Boston (BOS)	105	Chicago O'Hare (ORD)	900
			Charlotte (CLT)	812
Manchester–Boston Regional (MHT)	Boston (BOS)	53.7	Chicago O'Hare (ORD)	843
Bradley (BDL)	Boston (BOS)	113	Chicago O'Hare (ORD)	783
Charleston (CHS)	Charlotte (CLT)	204	LaGuardia (LGA)	641
Chattanooga Metropolitan (CHA)	Atlanta (ATL)	123	Washington National (DCA)	523
Colorado Springs Municipal (COS)	Denver (DEN)	86.9	Los Angeles (LAX)	833
Eugene (EUG)	Portland (PDX)	130	Denver (DEN)	997
Huntsville (HSV)	Atlanta (ATL)	201	Washington National (DCA)	613
			Dallas/Fort Worth (DFW)	603
Shreveport Regional (SHV)	Dallas/Fort Worth (DFW)	202	Atlanta (ATL)	551

We then searched for empirical evidence and anecdotal claims of leakage at the airports listed in Table 2. Chattanooga Metropolitan Airport, Columbia Metropolitan Airport, Huntsville International Airport, and Charleston International Airport were included in the dataset used by Suzuki & Audino (2003). Jacksonville International Airport is striving to attract more flights by offering incentives to airlines (Webner, 2015), given that residents of Jacksonville have been observed to drive two or more hours to Orlando International Airport. Passengers have also been observed to travel from Tucson to Phoenix Sky Harbor International Airport by bus because of better connections and better airfares (Sharkey, 2015). On social media, Gerald R. Ford International Airport in Grand Rapids, MI encourages patronage by local residents in order to stem losses of flight routes and frequency, acknowledging that passenger leakage occurs due to lower airfares offered elsewhere (Gerald R.

Ford International Airport, 2015). Approximately 40% passenger loss from Portland International Jetport (PWM) to Logan Airport in Boston has been claimed (Portland International Jetport, 2012). As mentioned above, a 2012 leakage study estimates that around 5% of passengers in the Huntsville service region use Hartsfield–Jackson Atlanta International Airport despite that it is more than 200 miles away from Huntsville (Huntsville International Airport, 2013). Finally, significant passenger leakage has been observed from Shreveport Regional Airport to Dallas/Fort Worth International Airport (Shreveport Airport Authority, 2014).

3.2.3. Dataset and Descriptive Statistics

Based on the data from data sources as mentioned in Section 3.2.1 and the airports we obtain from Section 3.2.2, we develop a dataset of all the variables that are hypothesized in the model as shown in Equation 1-2. The dataset has 719 observations, meaning almost all of the 20 local airports have 36 quarterly datasets each. Variables include the number of passengers, airfare, flight leg, non-stop miles, freight, group size, fuel cost, seasonality, enplanement, passengers using low-cost carriers, the number of flight departures, population, per capita income, driving distance between the local and substitute airport, quarter indicator variables, and local airport indicator variables. Among them, the seasonality variable represents total passenger enplanement per quarter from all U.S. airports, excluding the local airport and substitute airport, to the destination airport (Suzuki & Audino, 2003). The seasonality variable implicates quarterly fluctuations in air passenger volumes in the U.S., which is expected to have a positive relationship to passenger volumes at the local airport. There are two enplanement variables: one represents the passenger volume from the local airport to all U.S. destinations, excluding the subject destination airport; and the other represents passenger volume from the substitute airport to all U.S. destinations at quarter. We expect the local airport enplanement to have a positive relationship with local passenger volumes and the substitute enplanement variable a negative relationship. The explanations as well as expectations of the signs and relationships of the variables only in the final version of the model will be described in detail in the following sections.

Descriptive statistics for the independent variables of the model are shown in Table 3. As the variables for airfare, flight leg, group size and non-stop miles shown are constructed from DB1B data, the number of observations in DB1B per quarter per origin-destination pair is also provided in Table 4.

Table 3 Descriptive statistics for model independent variables

Variable	Explanation	Mean	Std. Dev.	Min.	Max.
F_{ijt}	Airfare at local airport($)	210.24	51.15	102.35	372.67
P_{ijt}	Passenger volume	19,430	16,023	1,029	114,105
L_{ijt}	Flight leg	1.31	0.19	1.06	2.03
M_{ij}	Non-stop miles(mile)	768.98	173.31	523.00	1,216.00
SZ_{ijt}	Travel group size	1.70	0.52	1.04	4.47
$F_{(-i)jt}$	Airfare at substitute airport($)	162.34	24.73	90.14	259.57
S_{ijt}	Seasonality	5,259,274	2,474,262	1,653,233	10,610,022
E_{it}	Enplanement at local airport	286,747	246,564	37,122	1,256,864
$E_{(-i)t}$	Enplanement at substitute airport	4,645,724	2,413,309	1,336,676	10,822,651
C_t	Unit Aviation Fuel Cost($/gallon)	2.45	0.60	1.36	3.49

Table 4 Observations per quarter per origin-destination (OD) pair in DB1B

	Number of observations per quarter			Number of observations per quarter	
Local OD	**Min.**	**Max.**	**Substitute OD**	**Min.**	**Max.**
JAX-PHL	781	1533	MCO-PHL	2125	3624
JAX-EWR	591	1369	MCO-EWR	1408	3218
TUS-SEA	734	1088	PHX-SEA	2398	3603
MKE-MCO	894	2653	MDW-MCO	880	2411
OKC-ATL	473	859	DFW-ATL	2413	3797
GRR-ATL	317	743	DTW-ATL	1722	3219
MLI-DEN	106	261	ORD-DEN	2086	3666
CAE-LGA	215	615	CLT-LGA	1364	4575
CAE-ORD	191	532	CLT-ORD	1395	3365
PWM-ORD	264	647	BOS-ORD	2010	6255
PWM-CLT	144	556	BOS-CLT	800	2364
MHT-ORD	286	766	BOS-ORD	2010	6255
BDL-ORD	852	1898	BOS-ORD	2010	6255
CHS-LGA	303	1440	CLT-LGA	1364	4575
CHA-DCA	142	263	ATL-DCA	1959	2770
COS-LAX	174	887	DEN-LAX	2761	4456
EUG-DEN	100	349	PDX-DEN	1223	2946
HSV-DCA	385	798	ATL-DCA	1959	2770
HSV-DFW	196	374	ATL-DFW	2381	3820
SHV-ATL	109	295	DFW-ATL	2413	3797

For example, for JAX-PHL, it has 36 quarterly observations in the final dataset. For each quarterly observation in the final dataset, the average airfare variable is from DB1B in that particular quarter. The maximum number of DB1B records in one quarter is 1533 while the minimum is 781. As mentioned in Section 3.2.1, not all variables are from DB1B data. Thus, Table 4 only applies to five variables in the model: airfare at the local airport, airfare at the substitute airport, flight legs, non-stop miles, and group size.

3.2.4. First-stage (Airfare) Model

The first-stage airfare model is specified as follows:

$$\begin{aligned}
&\ln(F_{ijt}) = \sum_i \lambda_i \cdot I(i=1) + \alpha_1 \ln(P_{ijt}) + \alpha_2 \ln(F_{(-i)jt}) + \alpha_3 \ln(C_t \cdot M_{ij}) + \mu_t \\
&\mu_t = \rho_1 \mu_{t-1} + \epsilon_t
\end{aligned} \tag{3}$$

Where variables are defined as:

F_{ijt}	Average airfare per passenger from local airport i to destination airport j in quarter t (USD).
$I(i=1)$	Local airport indicator variable. $I=1$ if the route is from local airport i; and $I=0$ otherwise.
P_{ijt}	Passenger volume from local airport i to destination airport j at quarter t.
$F_{(-i)jt}$	Average airfare per passenger from substitute airport $(-i)$ to destination airport j at quarter t (USD).
C_t	Unit aviation fuel cost per gallon for domestic services provided by U.S. carriers at quarter t.
M_{ij}	Non-stop miles from local airport i to the destination airport j.
μ_t	Airfare model error term at quarter t.
μ_{t-1}	Airfare model error term at quarter $t-1$.
ρ_1	First-order autoregressive parameter.
ϵ_t	Error term for the autoregressive error model, assumed normally and independently distributed with mean 0 and variance σ_1^2, such that $\epsilon_t \sim N(0, \sigma_1^2)$.

The first-order autoregressive parameter specification is included because the results of a Durbin-Watson test indicate presence of first-order autocorrelation (higher-order autocorrelation was not found to exist). Parameter estimation results for all included variables are discussed in Section 3.2.6.

3.2.5. Second-stage (Passenger Volumes) Model

The second-stage local airport passenger volume model is a function of the predicted airfare (from stage 1) and other exogenous explanatory variables.

$$\begin{aligned}
\ln(P_{ijt}) = &\sum_i \delta_i \cdot I(i=1) + \beta_1 \ln(\widehat{F_{ijt}}) + \beta_2 \ln(L_{ijt}) + \beta_3 \ln(S_{ijt}) + \beta_4 \ln(F_{(-i)jt}) \\
&+ \beta_5 \cdot (SZ_{ijt} \cdot \ln(F_{(-i)jt})) + \beta_6 \ln(E_{it}) + \beta_7 \ln(E_{(-i)t}) + \varepsilon_t \\
\varepsilon_t = &\ \rho_2 \varepsilon_{t-1} + v_t
\end{aligned} \tag{4}$$

In addition to the variables that were introduced previously, such as local airport indicator variable and airfare at the substitute airport, the following are also included:

$\widehat{ln(F_{ijt})}$	Fitted log of airfare per passenger from local airport i to destination airport j at quarter t.
L_{ijt}	Average number of flight legs per passenger from local airport i to destination airport j at quarter t.
S_{ijt}	"Seasonality" variable – total passenger enplanement per quarter from all U.S. airports, excluding local airport i and substitute airport $(-i)$, to destination airport j at quarter t.
SZ_{ijt}	Average passenger group size from local airport i to destination airport j at quarter t.
E_{it}	Enplanement variable for the local airport – passenger volume from local airport i to all U.S. destinations, excluding the subject destination airport, at quarter t.
$E_{(-i)t}$	Enplanement variable for the substitute airport – passenger volume from the substitute airport $(-i)$ to all U.S. destinations at quarter t.
ε_t	Passenger volume model error term at quarter t.
ε_{t-1}	Passenger volume model error term at quarter $t-1$.
ρ_2	First-order autoregressive parameter.
v_t	Error term for the autoregressive error model, normally and independently distributed with mean 0 and variance σ_2^2, $v_t \sim N(0, \sigma_2^2)$.

Again, the first-order autoregressive parameter specification is included because the results of a Durbin-Watson test indicate presence of first-order autocorrelation.

3.2.6. Results

The model has been estimated using Statistical Analysis System (SAS) software. The estimation results for the first-stage model and second-stage model are shown in Table 5 and Table 6, respectively.

Table 5 Estimation results, first-stage model

Coefficient	Variable	Estimate	*t*-value
λ_{JAX}	$\mathrm{I}(JAX = 1)$	2.83	10.26
λ_{TUS}	$\mathrm{I}(TUS = 1)$	2.70	9.79
λ_{MKE}	$\mathrm{I}(MKE = 1)$	2.65	9.34
λ_{OKC}	$\mathrm{I}(OKC = 1)$	3.12	10.98
λ_{GRR}	$\mathrm{I}(GRR = 1)$	3.20	11.53
λ_{MLI}	$\mathrm{I}(MLI = 1)$	2.88	10.72
λ_{CAE}	$\mathrm{I}(CAE = 1)$	2.85	10.67
λ_{PWM}	$\mathrm{I}(PWM = 1)$	2.88	10.56
λ_{MHT}	$\mathrm{I}(MHT = 1)$	2.83	10.17
λ_{BDL}	$\mathrm{I}(BDL = 1)$	2.98	10.19
λ_{CHS}	$\mathrm{I}(CHS = 1)$	2.79	10.06
λ_{CHA}	$\mathrm{I}(CHA = 1)$	2.65	10.26
λ_{COS}	$\mathrm{I}(COS = 1)$	2.90	10.62
λ_{EUG}	$\mathrm{I}(EUG = 1)$	2.74	10.02
λ_{HSV}	$\mathrm{I}(HSV = 1)$	3.20	11.76
λ_{SHV}	$\mathrm{I}(SHV = 1)$	3.17	11.44
α_1	P_{ijt}	-0.11	-6.81
α_2	$F_{(-i)jt}$	0.36	8.77
α_3	$C_t \cdot M_{ij}$	0.22	10.25
ρ_1	Autoregressive Parameter	0.75	28.14
Model fit statistics	σ_1^2	0.008	
	Regress R-Square	0.996	
	Total R-Square	1.000	

Table 6 Estimation results, second-stage model

Coefficient	Variable	Estimate	t-value
δ_{JAX}	$\mathrm{I}(JAX = 1)$	-4.41	-4.05
δ_{TUS}	$\mathrm{I}(TUS = 1)$	-4.79	-4.34
δ_{MKE}	$\mathrm{I}(MKE = 1)$	-4.51	-4.23
δ_{OKC}	$\mathrm{I}(OKC = 1)$	-4.55	-4.04
δ_{GRR}	$\mathrm{I}(GRR = 1)$	-4.85	-4.41
δ_{MLI}	$\mathrm{I}(MLI = 1)$	-4.87	-4.30
δ_{CAE}	$\mathrm{I}(CAE = 1)$	-4.94	-4.57
δ_{PWM}	$\mathrm{I}(PWM = 1)$	-4.72	-4.41
δ_{MHT}	$\mathrm{I}(MHT = 1)$	-5.24	-4.82
δ_{BDL}	$\mathrm{I}(BDL = 1)$	-4.42	-4.06
δ_{CHS}	$\mathrm{I}(CHS = 1)$	-4.23	-3.97
δ_{CHA}	$\mathrm{I}(CHA = 1)$	-4.72	-4.15
δ_{COS}	$\mathrm{I}(COS = 1)$	-4.78	-4.30
δ_{EUG}	$\mathrm{I}(EUG = 1)$	-4.65	-4.44
δ_{HSV}	$\mathrm{I}(HSV = 1)$	-3.71	-3.27
δ_{SHV}	$\mathrm{I}(SHV = 1)$	-4.16	-3.70
β_1	F_{ijt}	-0.52	-7.24
β_2	L_{ijt}	-1.00	-9.71
β_3	S_{ijt}	0.87	16.17
β_4	$F_{(-i)jt}$	0.24	3.31
β_5	$SZ_{ijt} * \ln\left(F_{(-i)jt}\right)$	0.02	3.82
β_6	E_{it}	0.53	7.48
β_7	$E_{(-i)t}$	-0.27	-2.85
ρ_2	Autoregressive Parameter	0.76	28.39
Model fit statistics	σ_2^2	0.020	
	Regress R-Square	0.996	
	Total R-Square	1.000	
Durbin-Watson Test		2.051	

The results of the Durbin-Watson tests in both models indicate that first-order autocorrelation has not been detected in the FGLS model specification. All variables in the airfare model and passenger model are significant at the 95% confidence level. Local airport indicator variables have controlled some geographically specific characteristics of each local airport market that are not captured by other variables. The first-stage (airfare) model estimation results indicate that airfare $\left(F_{ij}\right)$ from a local airport i to destination j has a negative relationship to the number of passengers $\left(P_{ij}\right)$ from i to j. This confirms that when passenger volumes to a destination increase at the local airport, air service from the local airport will be provided by the airlines at a lower cost per passenger, reflecting economies of density (Caves, Christensen, & Tretheway, 1984).

Furthermore, higher passenger traffic attracts more airlines to the airport and intensifies airline competition, which can also reduce airfares (Borenstein, 1989; Borenstein & Rose, 1991). The value of α_1 is quite small given the difference in absolute magnitude of airfare (in USD) versus quarterly passenger volumes between a local airport and a destination. Airfares from the local and substitute airports to a destination (F_{ij} and $F_{(-i)j}$, respectively) are positively related, as one would expect that the major drivers of airfare are major economic and airline industry factors not controlled for in the model. Increases in the interaction variable of fuel cost and non-stop miles $\left(C_t \cdot M_{ij}\right)$ from i to j will also increase airfares from i to j. Higher per gallon fuel cost and/or greater flight distances will increase flight costs and, therefore, airfares (Caves, Christensen, & Tretheway, 1984; Vowles, 2006).

The second-stage model results indicate that increases in airfare (F_{ijt}) at the local airport will negatively impact passenger volumes (P_{ijt}). This is as expected – when travelers can choose an origin airport, they will place significant weight on how airfares to their destination will compare, and lower airfares will attract more passengers (Suzuki & Audino, 2003). The average number of flight legs (L_{ijt}) required to reach destination j has a negative impact on passengers (P_{ijt}). If airlines at the local airport do not provide good direct flight options, passengers traveling from the local airport will decrease. This implies that they will either choose to fly from the out-of-region substitute airport, or not travel at all. In addition to direct flight availability, layover time between connecting flights is also important in passengers' choices (Innes & Doucet, 1990). The total travel time, which includes layover time, certainly impacts air passengers' travel choices (Adler, Falzarano, & Spitz, 2005), but travel time information is unavailable in the dataset. As mentioned above, the seasonality variable (S_{ijt}) represents quarterly fluctuations in air passenger volumes in the U.S., which as expected has a positive relationship to passenger volumes at the local airport. Also as anticipated, airfare ($F_{(-i)jt}$) to destination j from the substitute airport ($-i$) has a positive relationship to passenger volumes to j from the local airport. This implies that as $F_{(-i)jt}$ increases but F_{ijt} (or, fares from the local airport i) remains constant, passenger volumes to j from the local airport will increase. The impact, however, is smaller than the impact of local airport airfares to j on passengers from i to j, based on the estimated values for β_1 and β_4.

Airfares at the substitute airport will impact travelers' decisions differently depending on the size of their travel group. The positive parameter estimate on the interaction variable of group size and airfare $\left(SZ_{ijt} \cdot \ln\left(F_{(-i)jt}\right)\right)$ indicates that the impact of lower airfares (offered at the substitute airport) on decreasing local airport passenger volumes is magnified with larger group sizes. Anecdotally, we expect that group travelers are more likely to be families on leisure travel, that have the flexibility and motivation to travel a longer distance by car if there are savings to be gained on the purchase of multiple flight tickets. As a result, we expect that lower fares offered by airlines at an out-of-region airport are more impactful when travel group sizes are larger. We also expect airfares to have a larger impact on leisure travel decisions compared to business travel (Hess, Adler, & Polak, 2007; Zhang & Xie, 2005); therefore, the impact is magnified with leisure group travel. Travel purpose is not available in the data. However, it would be interesting to further assess how travel group size impacts travel decisions such as airport choice.

Another second-stage model result is that overall enplanement $\left(E_{ijt}\right)$ increases at the local airport lead to higher passenger volumes (P_{ijt}), to j, while increases in enplanement at the substitute airport $\left(E_{(-i)jt}\right)$ have a negative impact on P_{ijt}. If an airport retains higher overall levels of passenger traffic, it is also likely to retain passengers traveling to a particular destination j. However, as overall traffic levels at the substitute airport increase, it is likely that they offer better service to many destinations and as a result may draw passengers away from the local airport. This supports the notion that an airport with higher passenger volumes will in turn attract more passengers, leading to a positive feedback effect (Hansen, 1995).

In summary, the model results indicate an inverse relationship between airfare and passenger volumes at a small- to medium-size airport within a (long-distance) drive of a major hub airport. This in turn suggests that more passengers at a local airport will lead to lower airfares offered by airlines at the local airport, and lower airfares would in turn attract more passengers. The influence of out-of-region hub airports within a long-distance drive on the local airport are also captured; lower airfares and higher overall enplanement volumes at substitute airports may encourage lower passenger volumes at the local airport. However, we also demonstrate that the impact of airfares at substitute airports on passenger volumes at local airports will vary by travel group size. Significantly, airports with higher overall levels of passenger traffic are likely to attract more passengers to individual routes as well.

3.3 Conceptual market share equilibrium analysis

In Section 3.2 we have empirically confirmed the existence of a relationship between airfares at the local airport, and passenger volumes at both the local and substitute airports (in addition to several other attributes). Therefore, we now present an equilibrium analysis of how airport supply characteristics can impact passenger "leakage" to substitute airports or, the supply-and-demand feedback mechanisms at play (Hansen, 1995). This model proposes the use of the empirical airfare model with a binary logit model, to investigate the sensitivity of airport leakage to airfare, flight frequency, and ground access distance in a numerical equilibrium analysis.

3.3.1. Model Specification and Assumptions

We assume that air travelers can choose to depart from one of two airports – their local airport, and a larger hub airport up to 200 miles away. We represent this aggregate airport choice (or, market share) scenario using a binary logit model. We also use the airfare model of Equation 3 to capture the impacts of airport demand levels (market share) on airfares at the local airport, thereby completing the supply-and-demand feedback loop. For the airfare model, we arbitrarily choose variable and coefficient values for the route from Jacksonville Airport (JAX) to Philadelphia Airport (PHL) (substitute Orlando, or MCO).

For the binary logit model, we assume airfare, flight frequency, and ground access distance are the major drivers of airport choice, as these attributes are well-documented to have the most significant impact (Hess S. , 2005; Hess & Polak, 2010). The air passenger utility function and market share model are as follows:

$$U_i = V_i + \varepsilon_i = \alpha F_i + \beta\, log(f_i) + \gamma\, log(g_i) + \varepsilon_i, i = 1\ or\ 2 \tag{5}$$

$$MS_i = \frac{exp(V_i)}{exp(V_1) + exp(V_2)} \tag{6}$$

Where,

i is the departure airport; $i = 1$ is the local airport while $i = 2$ is the substitute airport.

U_i is the utility of choosing Airport i to travel to the destination airport.

V_i is the deterministic utility of choosing Airport i.

ε_i is the stochastic error term.

F_i is the average airfare from Airport i to the destination airport.

f_i is the flight frequency from Airport i to the destination airport.

g_i is the average ground access distance to Airport i.

α, β, γ are coefficients.

MS_i is the market share of Airport i; the total air passenger volume for the metropolitan region of Airport 1 is T, and therefore passenger volumes at airport 1 can be expressed as $P_1 = T \cdot MS_1$.

3.3.2. Numerical Analysis

In this numerical analysis, we find the sensitivity of an airport's equilibrium market share with respect to different variables, which we define as a market share value that satisfies Equation 3, 5, and 6. In the numerical analysis, we assume some values for the parameters based on previous studies (de Luca, 2012), the route specification from Jacksonville (JAX) to Philadelphia (PHL) airports, and that airlines at the substitute airport (Airport 2) provide more flight frequencies than the local airport (Airport 1), as shown below.

Table 7 Variable and coefficient values in market share and airfare functions

Market share model (Eqn. 5)		
α	Coefficient of airfare	-0.04
β	Coefficient of frequency	0.36
γ	Coefficient of ground access distance	-0.85
f_1	Flight frequency at Airport 1 per quarter	100
f_2	Flight frequency at Airport 2 per quarter	200
g_1	Ground access distance to Airport 1 (miles)	30
g_2	Ground access distance to Airport 2 (miles)	144
Airfare model (Eqn. 3)		
λ	Coefficient for JAX-PHL route	2.83
α_1	Coefficient for passenger volumes at Airport 1	-0.11
α_2	Coefficient for average airfare at Airport 2	0.36
α_3	Coefficient for fuel cost and non-stop flight distance interaction term	0.22
T	Total passenger demand	100,000
F_2	Airfare at Airport 2 (USD)	200
C	Unit aviation fuel cost (USD/gallon)	3
M_1	Non-stop flight miles from Airport 1 to destination (miles)	742

Figure 2 shows equilibrium values for market share based on the numerical values in Table 7, for four values of the airfare coefficient (α). The x-axis represents input values of market share, which we input to Equation 3 to obtain values for F_1. By inputting the F_1 values into Equation 5, we can in turn obtain MS_1 values again, which are called output market share values as represented by the y-axis. Equilibrium only exists where each curve (corresponding to a specific α value) intersects the 45^{o} reference line. There are two types of equilibria: stable and unstable. A stable equilibrium exists when the curve cuts the 45^{o} reference line from above, when input market share increases. The market share will return to a stable equilibrium if a disturbance should happen to change the market share at any point (Sharov, 1996; Hansen, 1995). However, if a disturbance should occur to disrupt an unstable equilibrium, the market share will not return to that equilibrium (Sharov, 1996). By definition, unstable equilibria are unlikely to exist over the long term (Taylor & Jonker, 1978). As a result, we have focused our attention on stable equilibria.

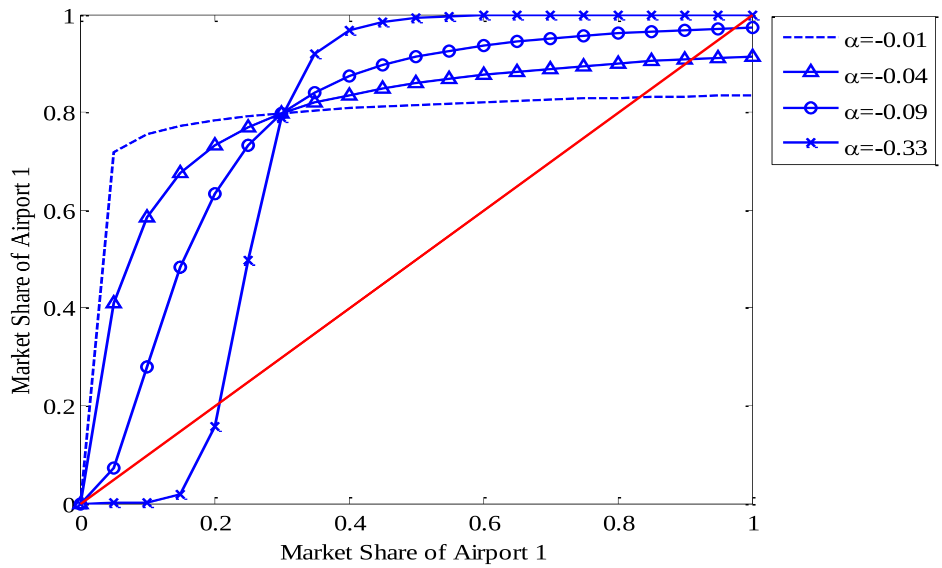

Figure 2 Equilibria under alternative airfare coefficient (α) values

The results for $\alpha = -0.09$ and $\alpha = -0.33$ are discussed here. They indicate that the number of equilibrium solutions changes as α decreases. We have focused our discussion on positive stable equilibria points because they are able to reflect the sensitivity of market share in airport leakage. The trend of positive stable equilibria is that the equilibrium market share of the local airport (MS_1) increases with respect to the increase of the absolute value of α. Given that α represents how much weight a passenger assigns to airfare (relative to frequency and ground distance) when choosing an airport, more passengers will use the local airport when airfare is increasingly important to passengers, under the circumstances that airfare at the local airport is lower than the substitute airport. As more passengers use the local airport, airfares will also decrease due to economies of density (Lijesen, Rietveld, & Nijkamp, 2001), further magnifying the airfare advantage of the local airport. Thus, under the condition that airfare is highly important (i.e., the absolute value of α increases) and the local airport's airfares are lower, more passengers will use their local airport. This positive feedback effect suggests that an airport with higher passenger traffic will attract more passengers (Hansen, 1995), and so on. However, if airfare is less important to passengers $(-0.33 < \alpha < 0)$, more passengers will use the substitute airport because airlines offer greater flight frequency than at the local airport (i.e. $f_1 = 100, f_2 = 200$). Consequently, airlines increase airfares at the local airport, making travel from the local airport less attractive to passengers.

The sensitivity of MS_1 with respect to the substitute airport's airfare F_2 is also impacted by the fact that F_1 will also change when F_2 changes. As a result, we will discuss the combined effect of F_1 and F_2 on the stable equilibrium for market share, using the numerical values in Table 7 but varying the values for substitute airport airfare (F_2). As shown in Figure 3, when F_2 decreases, F_1/F_2 increases and MS_1 decreases. Based on Equation 5, when F_2 decreases, F_1 also decreases but at a slower rate. This means that when the substitute airport has increasingly lower airfares compared to the local airport, the substitute airport will take more market share from the local airport. Even when F_1 equals F_2 (i.e. $F_1/F_2 = 1$), market share at the substitute airport (MS_2) is approximately 80% and airport leakage still occurs, due to the flight frequency at the substitute airport being higher than at the local airport (recall $f_1 = 100$ and $f_2 = 200$).

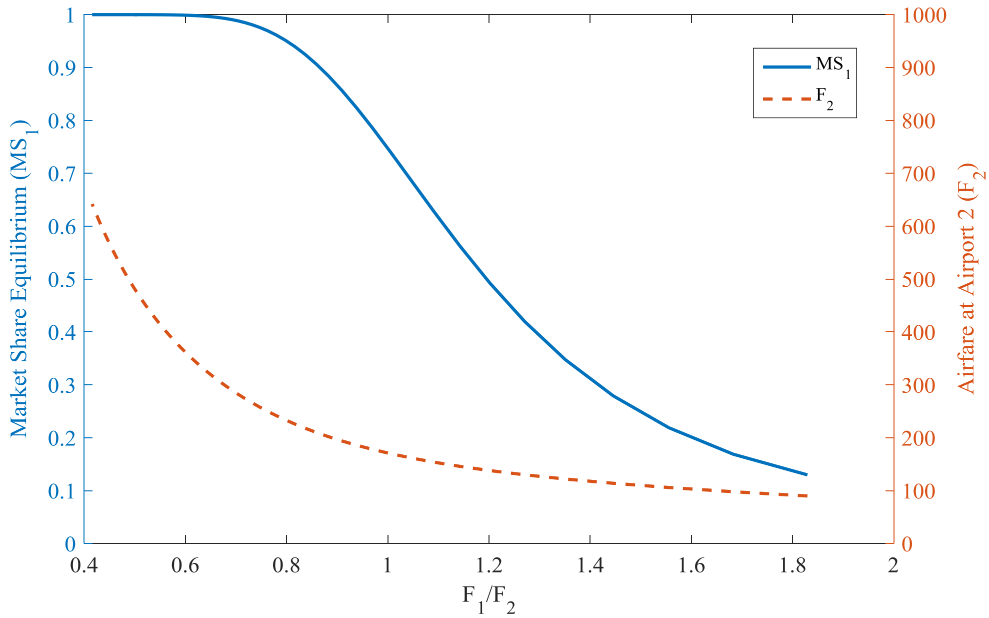

Figure 3 Market share equilibria as a function of F_1/F_2

3.4 Overview of relationships between supply and demand variables

An overview of how various factors impact local airport passenger market share, as found in the model results presented earlier, is presented in Table 8. Table 8 is meant to summarize the highly generalized insights about these relationships, without geographic specificity. We find that some of the hypotheses of Section **Error! Reference source not found.** are confirmed. For instance, if fewer passengers are using the local airport, this goes hand-in-hand with lower airfares at the substitute airport, more flight legs required (to fly to particular destinations) at the local airport, and higher flight frequencies at the substitute airport. In the econometric model, the airfare at the local airport has been confirmed to have a negative relationship with traffic volume at the local airport. Moreover, higher flight frequency and shorter ground access distance of the local airport is positively related to the market share at the local airport. Inversely, if the substitute airport provides lower airfares, higher flight frequency, or has shorter ground access distance, the market share at the local airport will reduce. As indicated by the conceptual market share equilibrium analysis, the weights of airfare, flight frequency, and ground access distance, which implicate the importance of the three attributes in passengers' airport choices, contribute to market share local airport differently.

Table 8 Sensitivities of demand or market share of local airport

Analysis	Feature	If it should:	Then passenger market share for that destination, at local airport, may:
Econometric model	Airfare at local airport	↑	↓
	Flight legs (connections) from local airport	↑	↓
	Seasonality (attractiveness of destination airport)	↑	↑
	Enplanement at local airport	↑	↑
	Enplanement at substitute airport	↑	↓
Market share equilibrium analysis	Airfare at substitute airport (F_2)	↓	↓[1]
	Flight frequency at local airport (f_1)	↑	↑
	Flight frequency at substitute airport (f_2)	↑	↓
	Ground access distance to local airport (g_1)	↓	↑
	Ground access distance to substitute airport (g_2)	↑	↑
	Weight of airfare (α)	↑	↑
	Weight of flight frequency (β)	↑	↓
	Weight of ground access distance (γ)	↑	↑

[1] Based on the econometric model, this effect is larger when travel group sizes are larger as well.

Table 8 provides generalized results that do not pertain to specific geographic contexts. These relationships may of course vary or demonstrate different trends in specific geographic contexts. However, the purpose of the table is to provide some general insight into the relationships, as a starting point for further analysis. To analyze a specific geographic area (and local airport market) using the analytical modeling method, market-specific airfare models and a passenger market share model should be estimated using locally collected data. The utility coefficients for the market share model can be generated from local traveler survey data, which would require a targeted data collection effort by municipal planners and/or airport planners looking to operationalize this model to obtain quantitative evidence of leakage. There are limited instances of data collection and assessment of leakage in past literature, due to the challenges of collecting (and generally limited availability of) data covering a geographic scope that crosses municipal jurisdiction boundaries (Suzuki, Crum, & Audino, 2004; Fuellhart, 2007; Kimley-Horn and Associates, Inc., 2012). However, if airport passenger leakage is considered to be a critical regional issue, and investments in a quantitative study of the problem are to be made, the proposed modeling effort is a potential candidate.

4. Conclusions and discussion

This paper has presented models for understanding the relationships between small- and medium-sized (local) airports and major hub (substitute) airports serving larger neighboring regions that are within a long-distance drive. The first model estimates how substitute airports can impact passenger volumes at small- and medium-sized airports in the U.S. while capturing the endogeneity between airfare and passenger volumes. Refinements and updates to this model from previous work (Suzuki & Audino, 2003) include a systematic process to select local airports and correction of time series-related biases. Then, a conceptual equilibrium analysis of supply-and-demand feedback combines the empirical airfare model with a market share model to investigate the sensitivities of airport market share to air service characteristics of airfare and flight frequency. Both models capture the interactions and feedback between air services and airport passenger demand (or market share).

The empirical model provides some generalized insights into major trends of airport leakage in the U.S. The modeling results suggest that when airfares at the local airport decrease, the airport will indeed retain higher passenger volumes. In addition, the attraction of lower airfares at the substitute airport is stronger when passengers travel in larger groups. Also, the higher the overall passenger traffic at a local airport, the more passengers the airport will retain; the higher the traffic at a substitute airport, the more passengers the substitute airport will attract. This result implies that positive supply-and-demand feedback – where an airport will attract more passengers if it has higher passenger volumes already, and so on – does exist. After confirming the existence of this feedback mechanism, we then explore equilibrium passenger market share between a local and substitute airport, utilizing a logit choice model with the empirical airfare model.

The contributions of this paper include the confirmation of relationships between airport leakage and explanatory factors such as travel group size and airport enplanement, and explicit consideration of the interaction between demand and supply in both the empirical model and conceptual market share equilibrium analysis. Most importantly, however, the models presented in this paper may be used by practitioners to provide quantitative support in planning infrastructure investment strategies and other interventions. For example, with proper data collection, the conceptual model may be operationalized by airport and municipal planners in quantifying the severity of the potential leakage problem faced. As the results of this paper suggest that airport leakage impacts may be highly difficult to reverse without targeted intervention, the results of an operationalized model can guide planners in choosing suitable infrastructure investment strategies and other interventions that can expand or retain air services in attracting passengers back to the local airport. Possible strategies include the provision of airline incentives by municipalities (Ryerson, 2016), involving airlines in local airport planning processes, expansion planning of airport access facilities (Bieger & Wittmer, 2006), and advocating higher efficiency at local airports than major hubs, which of the later may have more delays (Bazargan & Vasigh, 2003). Investment should be based on planning that is strategic, incremental and flexible (De Neufville, 1995). Operationalized model results can provide indications of how impactful potential intervention decisions may be in disrupting the positive feedback mechanism of air passenger leakage and service cutbacks, such that appropriate types and levels of investment can be advocated for and planned accordingly. It should also be considered that leakage problems may be further exacerbated without intervention in the future, as it becomes cheaper and easier to drive with technologies such as connected vehicles and autonomous vehicles.

There are limitations in this work that should be further investigated, and key ways by which it can be extended. In the empirical model, the 20 origin-destination (OD) pairs are assumed to be independent, despite that several of these OD pairs have the same local, substitute or destination airports. It would be helpful to understand to what degree this impacts results. In addition, the application of conclusions from the empirical model is limited to the airports included in the dataset and possibly those that have similarities. More critically, in the equilibrium analysis, the numerical analysis results are based on assumed values for variables and coefficients, and thus are not geographically specific. A next step in moving this line of research forward is to conduct a survey of air travelers in a metropolitan region suspected of leaking air travelers to an out-of-region hub airport, in order to operationalize the model. Finally, the impacts of group size on leakage to out-of-region hub airports would be of great interest to further investigate, also through the collection of survey data. If data on other factors that influence passenger leakage are collected in the future, such as trip purposes and layover time, they could be used an explanatory variables in the models.

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