PREDICTING A DRAMATIC CONTRACTION IN THE 10-YEAR PASSENGER DEMAND

Daniel Y. Suh
Department of City & Regional Planning
University of Pennsylvania
Philadelphia, PA USA
dansuh@design.upenn.edu

Abstract—A cornerstone of any airport master plan is an aviation demand forecast, the forecast of future airport activity. A decision to plan and expand a runway, which typically spans a period of 10 years from the planning to completion, predicates on the accuracy of the projected future passenger demand. Yet aviation demand forecasts are known to be inaccurate at best and biased at worst. In this research, I develop a data-driven procedure to help airport planners evaluate the uncertainty of a dramatic contraction in passenger demand in the next 10 years using publicly available aviation and US census data. I show that socioeconomic trend metrics can be good indicators of a dramatic contraction in passenger demand in the next 10 years. This insight carries a significant relevance to airport planners especially in their airport master planning and aviation demand forecasting processes for runway expansions, as it could help them reconsider unwise investment decisions.

Airports maintain and update their infrastructures to ensure they are able to serve airlines and passengers efficiently. Airport planners often meet this challenge by expanding airport capacity via runway expansions following the federally mandated planning process known as airport master planning [1]. A cornerstone of any airport master plan is an aviation demand forecast, the forecast of future airport activity. A decision to plan and expand a runway, which typically spans a period of 10 years from the planning to completion, predicates on the accuracy of the projected future passenger demand. Yet aviation demand forecasts are known to be inaccurate at best and biased at worst.

One of the major challenges to aviation demand forecast accuracy is uncertainty in the planning environment. Major sources of this type of uncertainty include changes in global, regional, or local economic conditions, airline strategy, policy change, shock events, and statistical/model error [2]. Literature shows that the common approach to addressing uncertainty in aviation demand forecasts is to produce a range of forecasts using High, Medium, and Low assumptions about the underlying conditions (i.e., input variables). However, this approach perpetuates any statistical/model errors into each scenario. Furthermore, forecasters and decision-makers inevitably must choose a scenario they prefer and make decisions based on this forecast, essentially providing only cursory treatment to uncertainty. Consequently, the majority of 10-year aviation demand forecasts are inaccurate and optimistic (i.e., produce positive forecast errors).

This has very real and wildly different impacts on airport infrastructure investment decisions and their outcomes. For example, cities such as St. Louis and Pittsburgh experienced a dramatic contraction in passenger traffic at their major airports, never recovering the same levels of passenger demand subsequently, in the midst of expanding them based on inaccurate/optimistic forecasts. Now their newly built infrastructures are left rarely used and these airports are spending even more money to attract and recapture the lost demand [3]. On the other hand, there are airports such as ones in Miami, FL (MIA) and San Francisco, CA (SFO) whose demand, although inaccurately/optimistically forecasted, eventually caught up to the level forecasted. These airports may be able to justify (post facto) heavy investments in expansion while those in contraction may see their investments (typically in the hundreds of millions of dollars) wasted. In other words, when the overwhelming majority of aviation demand forecasts are known to be inaccurate and optimistic, and investments are justified post facto, the relevant question to consider becomes whether the uncertainty of a dramatic contraction in demand is properly addressed.

In this research, I develop a data-driven procedure to help airport planners evaluate the risk of experiencing a dramatic contraction (the empirical definition will be discussed in the methodology section) in passenger demand in the next 10 years. This insight carries a significant relevance to airport master planning and aviation demand forecasting processes for runway expansions, as it could help airport planners reconsider unwise investment decisions. Specifically, I build a predictive model using binary logistic regression that estimates the
probability that an airport will experience a dramatic contraction in passenger demand in the next 10 years. Using the Federal Aviation Administration (FAA)'s official 10-year demand forecasts (Terminal Area Forecasts or TAFs) for the 64 large, medium, and small hub airports (as defined by the FAA based on the share of total traffic moved) that are located within the top 50 metropolitan statistical areas (MSAs) by population, I first define distinct patterns of changes in the 10-year passenger demand. I dichotomize the forecasts into that of a dramatic contraction and of cyclical changes. I then build a binary logistic regression model using several airport and MSA explanatory variables to predict the binary outcome. My results indicate that the regional socioeconomic trends can be robust predictors of a dramatic contraction in demand at airport.

I begin first by conducting exploratory analysis on aviation demand forecast accuracy and demand growth in order to motivate the problem. Then I introduce my methodology and expound on the procedure. Finally, I discuss the applicability and effectiveness of the model and summarize the results.

II. BEYOND FORECAST ACCURACY

In literature, the limited number of available research on aviation demand forecast accuracy shows aviation demand forecasts are overwhelmingly inaccurate. For instance, the Airport Cooperative Research Program (ACRP), an industry-driven research program, produced a report [2] that evaluated a number of forecasts and concluded they were wildly inaccurate. Maldonado [4] provides more detailed and nuanced evaluation of aviation demand forecast accuracies for the forecasts used in master plans for airports in the FAA New England region and likewise concludes that these forecasts were highly inaccurate. At the same time, Ryerson and Kim [5] suggest that airports have experienced drastically different and disproportionate changes in the 21st century due to changes in the economy, fluctuations in the fuel price, and airline mergers. Beyond the well-established notion that the aviation demand forecasts are inaccurate, these dynamic changes and uncertainty require more nuanced understanding of forecast accuracy. Specifically, we need to understand different patterns of demand growth/contraction in order to justify airport infrastructure investments instead of relying solely on the forecast accuracy (precisely because we know the forecasts are inaccurate).

Towards generating this foundational knowledge about the relationship between forecast accuracy and demand patterns, I use the official aviation demand forecasts of Federal Aviation Administration (FAA) known as Terminal Area Forecast (TAF). As the federal entity in charge of regulating US air transportation, FAA produces TAFs annually for all US airports to help federal, state, and local authorities plan in regards to airport and air traffic operations [6]. Because the TAFs are updated in coordination with local sponsors engaged in the airport master planning process and are readily available online, they serve as good barometers for the forecasts used in airport master plans for airport expansions and other functions.

Figure 1 shows the annual passenger demand (boardings) at airports in Miami (MIA) and San Francisco (SFO) from 1995 to 2016 along with the 10-year TAF forecasts with a base year 1995 and a target year 2005 (shown in red). As suspected, the 10-year forecasts for both MIA and SFO (red bars) overestimated by substantial margins. This observation falls in line with the general pattern of optimistic forecasts uncovered in literature. At the same time, the annual demand for both MIA and SFO (grey bars) show a pattern of growth subsequently to the forecast target year (2005).

![Figure 1. Annual passenger demand and 10-year TAF forecast (base year 1995, target year 2005) for growing airports](image)

Based strictly on the measure of forecast accuracy, heavy infrastructure investments at these airports may not be advisable. However, the general growth patterns in demand in the subsequent years may act as post facto justification for the investments. In other words, the construction of a new runway, for instance, at these airports may be justified by the eventual growth in demand.

On the other hand, there are airports that may not be able to justify infrastructure investments either way. Figure 2 also shows the 10-year TAF forecasts (red bars) and annual demand (grey bars) for airports in St. Louis (STL) and Pittsburgh (PIT). The margins of error are even more pronounced for these forecasts. In fact, the forecasts overestimated by more than twice the actual demand in 2005. Additionally, the annual demand for both STL and PIT show a pattern of a dramatic contraction; the annual demand in 2015 was almost half of the demand in 1995 both airports.

![Figure 2. Annual passenger demand and 10-year TAF forecast (base year 1995, target year 2005) for declining airports](image)
These airports for St. Louis and Pittsburgh, formerly prosperous industrial cities, have lost tremendous amounts of passengers along with population since their peak from decades ago. Airline strategies contributed to the major contractions in passengers at these airports because the airports’ major hub airlines experienced financial difficulties and declared bankruptcies during this period [7]. Consider that while the contraction was happening in St. Louis, STL was in the middle of constructing a new runway at a cost of $1.1 billion. The new runway is now largely sitting unused.

The difference between airports like SFO and MIA and those similar to STL and PIT is drastic in terms of the future growth and planning needs. Investments in new runways at the former types of airports may be contested but will likely be necessary and justified given continual growth in passenger demand. On the other hand, same type of investments at airports such as STL and PIT are clearly unwise and wasteful considering that the future passenger trend will never justify the significant investments in runways that last for a long time regardless of whether they are used or not. Because the baseline assumption for airport planning is growth in demand, detecting the signs of a future passenger contraction is an important insight into airport planning that may prevent wasteful investments.

III. METHODOLOGY

Towards understanding indicators of a future contraction in passenger demand, I build a predictive model using data mining and statistical modeling. In this section, the methodology and the data used for this research are presented.

A binary logistic regression model is used to predict the binary outcome of a severe contraction in passenger volumes. The primary purpose of this research is to identify and understand the explanatory variables that impact the outcome of a severe contraction in passenger volumes, rather than to achieve the highest predictive performance. Other predictive algorithms such as ensemble methods can potentially result in higher predictive power but make it difficult to interpret the relationships between the explanatory variables and the outcome. A binary logistic regression can illuminate these relationships much more clearly and is more suitable for the purpose of this research.

A. Study Airports

I scope the sample to the 64 large, medium, and small hub airports (as defined by the FAA based on the share of total traffic moved) that are located within the top 50 metropolitan statistical areas (MSAs) by population (Figure 3). These airports served about 90% of total passengers in the US in 2016 [8].

B. Research Framework

A binary regression model describes the relationship between the explanatory variable and the binary outcome variable. Since my outcome variable of 10-year change in passenger volumes is continuous rather than binary, I first need to dichotomize the outcome variable.

Step 1: Identifying 10-year passenger demand patterns

First, I need to dichotomize the 10-year passenger demand patterns into that of severe contraction and otherwise stable patterns. Percent changes in passenger volumes in a 10-year period are used to denote 10-year passenger demand patterns. The literature is relatively scarce on the empirical definition of a severe contraction in passenger volumes, that is, there is no clear cut-off point for what can be considered as a severe contraction. Instead, a data-driven approach can distinguish distinct patterns in the 10-year percent changes in passenger volumes. Specifically, a model-based clustering algorithm such as Gaussian mixture model can tease out these distinct patterns and enable dichotomization of the outcome variable.

Step 2: Predicting 10-year contraction

Once the outcome variable is dichotomized, I use both point-in-time metrics and change-over-time metrics of airport operations and socioeconomic conditions as explanatory variables in the model. These explanatory variables will be discussed in more detail later in the chapter.

IV. IDENTIFYING 10-YEAR DEMAND PATTERNS

The literature is relatively scarce on the empirical definition of a severe contraction in passenger volumes. The de-hubbing literature, the literature on the situation where an airline with a
predominant presence at an airport scales back or discontinues their service (de-hubs) from the airport, for example, tend to use a mix of empirical and qualitative definitions of de-hubbing to identify a narrow timeframe of the de-hubbing event itself [7]. Instead, I am looking at the 10-year window which is the average length of time from the planning and completion of a new runway and the changes in passenger volumes during this period.

Given the lack of a clear definition in the literature, I use a data mining technique to let the data inform the cutoff point for the binary outcome. The data in this case are the 10-year percent changes in the passenger volumes for the 64 airports for all base years from 1995 to 2005 (i.e., total of 704 10-year percent changes). The mean and the median are 14.39 and 13.11, respectively (i.e., 14.39% growth in passenger volumes and 13.11% growth in passenger volumes) (TABLE I). However, there seems to be a wide spread in the data as indicated by the standard deviation of 34.91. There are also some extreme values as big as 395.70 and as small as -80.79.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>10-year percent changes in passenger volumes (N = 704)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>14.39</td>
</tr>
<tr>
<td>Median</td>
<td>13.11</td>
</tr>
<tr>
<td>Standard Dev.</td>
<td>34.91</td>
</tr>
<tr>
<td>Max</td>
<td>395.70</td>
</tr>
<tr>
<td>Min</td>
<td>-80.79</td>
</tr>
</tbody>
</table>

The left histogram in Figure 4 shows the distribution of these 10-year percent changes in passenger volumes. The distribution almost seems normal (i.e., Gaussian) but there are a few spikes in the distribution towards the left tail as well as a very long right tail. One approach to clustering such data points is by using a model-based algorithm such as Gaussian Mixture Model, which assumes the data points are generated from a mixture of Gaussian distributions with unknown parameters. This method uses the Expectation-Maximization (EM) algorithm, an iterative algorithm that estimates the parameters of the distributions, and produces the posterior probabilities, the probabilities of each data point generated from a particular distribution. This method essentially allows for clustering of similar data points together by assigning each data point to a distribution with the highest posterior probability.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Growth Cluster (n=9)</th>
<th>Cyclic Cluster (n=559)</th>
<th>Contraction Cluster (n=136)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>167.20</td>
<td>22.40</td>
<td>-28.61</td>
</tr>
<tr>
<td>Median</td>
<td>138.70</td>
<td>18.09</td>
<td>-22.00</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>87.51</td>
<td>23.08</td>
<td>18.26</td>
</tr>
<tr>
<td>Max</td>
<td>395.70</td>
<td>99.15</td>
<td>-11.23</td>
</tr>
<tr>
<td>Min</td>
<td>110.00</td>
<td>-10.74</td>
<td>-80.79</td>
</tr>
</tbody>
</table>

I decide to code the 559 data points in the cyclical cluster as 0 (non-event) and the 136 data points in the contraction cluster as 1 (event) for the total of 695 data points for the binary outcome variable. The data points in the growth cluster are extreme outliers that may skew the data and because there are only 9 of them, I decide to remove them from the data.
V. PREDICTING TEN-YEAR CONTRACTION IN PASSENGER DEMAND

Once the outcome variable is dichotomized, a binary logistic regression model is used to predict the probability of an airport experiencing the outcome of a dramatic contraction in passenger volumes.

A. Binary Logistic Regression

Binary logistic regression estimates the probability that an event will occur given the values of explanatory variables. For a binary outcome variable \( Y \) and a set of explanatory variables \( X = (X_1, X_2, \ldots, X_k) \), the model takes on the following expression

\[
\pi_i = \Pr(Y_i = 1|X_i = x_i) = \frac{\exp(\beta x)}{1 + \exp(\beta x)}
\]

or

\[
\text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1 - \pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}
\]

Once the parameters \( \beta \) are estimated, the coefficients are typically interpreted in exponents (\( \exp(\beta_i) \)), i.e., odds ratio. An odds ratio indicates that for every unit increase in \( X_i \), the odds of an event happening is multiplied by \( \exp(\beta_i) \).

B. Selection of Explanatory Variables

Literature on air travel demand shows that there is intrinsic relationship between airport passenger demand as well as airline strategy and sociodemographic characteristics of its host city/region \([9,10,11,12]\). Therefore, I selected explanatory variables pertaining to both airports and the MSAs that host them. I use 9 such variables for the base year figures (i.e., point-in-time numbers in base years) as well as 5-year average annual percentage change (5AAC) in these 9 variables up to the base year \([13]\). For example, population of 2 million in the base year 1995 for an MSA is a point-in-time figure while 5AAC would be 5% (averaged over 5% change during ’90-’91, 3% during ’91-’92, 2% during ’92-’93, 4% during ’93-’94, 3% during ’94-’95). In total, I start with 18 explanatory variables (9 point-in-time and 9 5AACs).

C. Description of Explanatory Variables

**Passenger enplanements (Passengers)**

In typical aviation demand forecasts, the trend of historic passenger enplanements becomes an essential piece of the model. Because my outcome variable tracks dramatic contractions in demand, prior enplanement trends may not serve as a good predictor. However, I include this variable to reflect the overall volume of traffic at an airport.

<table>
<thead>
<tr>
<th>Variables in base year numbers</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passengers</td>
<td>Persons (millions)</td>
<td>8.42</td>
<td>7.95</td>
<td>FAA</td>
</tr>
<tr>
<td>Airport competition</td>
<td>Unitless</td>
<td>3.74</td>
<td>5.57</td>
<td>FAA</td>
</tr>
<tr>
<td>Connecting passenger share</td>
<td>Proportion</td>
<td>0.47</td>
<td>0.11</td>
<td>BTS DB1B</td>
</tr>
<tr>
<td>Avg. number of seats per aircraft</td>
<td>Seats</td>
<td>118.40</td>
<td>26.87</td>
<td>BTS T-100</td>
</tr>
<tr>
<td>Avg. ticket price</td>
<td>Dollars</td>
<td>227.70</td>
<td>53.01</td>
<td>BTS DB1B</td>
</tr>
<tr>
<td>HHI</td>
<td>Unitless</td>
<td>0.35</td>
<td>0.20</td>
<td>BTS T-100</td>
</tr>
<tr>
<td>Population</td>
<td>Persons (millions)</td>
<td>3.56</td>
<td>3.44</td>
<td>Census</td>
</tr>
<tr>
<td>Per capita income</td>
<td>Dollars (thousands)</td>
<td>45.87</td>
<td>7.91</td>
<td>BEA</td>
</tr>
<tr>
<td>Service sector employment</td>
<td>Persons (millions)</td>
<td>0.92</td>
<td>0.91</td>
<td>Census</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables in 5-year avg. annual % change up to base year</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passengers (5AAC)</td>
<td>%</td>
<td>4.00</td>
<td>7.76</td>
<td>FAA</td>
</tr>
<tr>
<td>Airport competition (5AAC)</td>
<td>%</td>
<td>1.97</td>
<td>3.49</td>
<td>FAA</td>
</tr>
<tr>
<td>Connecting passenger share (5AAC)</td>
<td>%</td>
<td>0.53</td>
<td>4.51</td>
<td>BTS DB1B</td>
</tr>
<tr>
<td>Avg. number of seats per aircraft (5AAC)</td>
<td>%</td>
<td>-1.68</td>
<td>3.02</td>
<td>BTS T-100</td>
</tr>
<tr>
<td>Avg. ticket price (5AAC)</td>
<td>%</td>
<td>-2.94</td>
<td>3.39</td>
<td>BTS DB1B</td>
</tr>
<tr>
<td>HHI (5AAC)</td>
<td>%</td>
<td>0.44</td>
<td>7.52</td>
<td>BTS T-100</td>
</tr>
<tr>
<td>Population (5AAC)</td>
<td>%</td>
<td>1.12</td>
<td>0.90</td>
<td>Census</td>
</tr>
<tr>
<td>Per capita income (5AAC)</td>
<td>%</td>
<td>1.77</td>
<td>1.27</td>
<td>BEA</td>
</tr>
<tr>
<td>Service sector employment (5AAC)</td>
<td>%</td>
<td>4.76</td>
<td>3.45</td>
<td>Census</td>
</tr>
</tbody>
</table>
Airport competition

Large metropolitan areas, including Boston, Chicago, Los Angeles, and New York, are typically served by several nearby airports. In these multiple-airport regions, the main airport faces competition from the secondary airports which may offer different types of accessibility, charges, and quality of service to compete for passenger traffic. Passengers may also consider tradeoffs between the quality of service offered at competing airports and distance to travel to the airports [14]. I estimate the potential airport competition for airport \( a_i \) by summing annual passenger enplanements (in 100,000s) for airports within 100 miles divided by distance from airport \( a_i \).

\[
\text{Airport competition (}\text{AC}_{ai}\text{)} = \sum_n \left( \frac{E_{ni}}{100000} \right) \frac{d_{na_i}}{d_{na_i}},
\]

where \( n \in N \) (set of airports within 100 miles from airport \( a_i \)), \( E_{ni} \) = annual passenger enplanements at airport \( a_{ni} \), \( d_{na_i} \) = distance in miles of airport \( a_{ni} \) from airport \( a_i \).

Connecting passenger share

An airport with a high proportion of connecting passengers as opposed to origin–destination (O-D) passengers tends to be a major hub airport and may have different facility needs, such as more gates and terminal space to accommodate connecting passengers, than one with mainly O-D traffic [5].

Average number of seats per aircraft

Fleet mix of aircraft at an airport indicate types of destinations and travel demand at the airport. I estimate the fleet mix by using the average number of seats per aircraft at each airport as a proxy.

Average ticket price

Also considered is the average O-D (direct flight) ticket prices and percentage of seats flown by low-cost airlines. Ticket prices indicate the level of competition among airlines. Low-cost airlines have different business models than legacy airlines and serve different types of passengers (more O-D passengers) than legacy airlines.

HHI

Airline decisions about service level at an airport greatly influence the vitality of the airport. When a few airlines have a large share of airport operations, the impacts of the airlines’ decisions are more powerful than if a large number of airlines use the airport. A hub airline’s decision to de-hub from an airport, for example, has a long-lasting impact on the airport, leaving it with excess capacity and overbuilt infrastructure [7]. Airline concentration is measured here by using the Herfindahl–Hirschman index (HHI), a frequently applied economic concept that measures the amount of competition among firms in an industry. HHI is computed as a sum of squared market shares of companies, which in this analysis are airlines at an airport

\[
\text{HHI}_{ai} = \sum_l m_{il}^2
\]

where \( m_{il} \) is market share of an airline \( l \) at airport \( a_i \) as estimated by proportion of seats provided by airline \( l \) over total seats by all airlines. A higher HHI indicates a higher concentration, while a lower HHI means greater competition among airlines.

Population, per capita income, and service sector employment

Air traffic has historically been correlated with economic conditions [10]. The study period between 1995 and 2015 captured one of the biggest economic downturns in U.S. history. Therefore, I considered economic conditions in each of the top 50 MSAs as key variables for predicting contraction in demand. The economic variables are population, income, employment in service sectors. Service sector employment as opposed to total employment was used because the literature indicated a stronger systematic relationship between employment in that sector and air passenger demand.

Collinearity

Correlated explanatory variables could result in biased coefficient estimates. Upon inspecting correlation among explanatory, I decided to remove population in base year variable as it is highly correlated with service sector employment.

D. Train-Test Data Split

In order to prevent overfitting, I split the data 80-20 into a training set (n = 556) and a test set (n = 139). I fit the binary logistic regression model on the training set and evaluate its performance on the test set.

E. Model Selection

I selected the final model in TABLE IV using backward-stepwise regression. I started with a model with all the explanatory variables (minus base population due to collinearity, and standardized) and eliminated a variable at a time based on its p-value until AIC is minimized. I tested the
selected model on the test data set and achieved 71% accuracy, 70% true positive rate, and 30% false positive rate. The purpose of this research is to identify the operational and socioeconomic metrics that are predictive of the demand uncertainty and therefore, the predictive performance is a secondary issue although it is reflected in the model selection. I report the odds ratios \((\exp(\beta))\) instead of log-odds \((\beta)\) for the ease of interpretation in \textbf{TABLE IV}.

\textbf{TABLE IV. SUMMARY TABLE FOR THE BINARY LOGISTIC REGRESSION} \\

| Odds ratio | \(P > |z|\) |
|------------|-------------|
| (Intercept) | 0.120 | 0.000*** |
| Airport competition \(\%\) change (5AAC) | 0.612 | 0.000** |
| Connecting passenger share | 1.555 | 0.000*** |
| Connecting passenger share \(\%\) change (5AAC) | 0.962 | 0.005** |
| Avg. number of seats per aircraft | 0.709 | 0.000*** |
| Avg. ticket price | 0.612 | 0.000*** |
| HHI | 2.234 | 0.004** |
| HHI \(\%\) change (5AAC) | 1.346 | 0.003** |
| Population \(\%\) change (5AAC) | 0.201 | 0.000** |
| Per capita income | 1.539 | 0.001** |
| Service sector employment | 0.406 | 0.001** |

\(n = 556\)

\(\text{AIC} = 422.66\)

\(*p < 0.1\quad **p < 0.01\quad ***p < 0.001\

\textit{MODEL}\

\textbf{F. Discussion of Results}\

As all the explanatory variables were standardized before fitting the model, \textit{unit for each selected variable reported in TABLE IV is one standard-deviation}. The following discussion of each of the selected variables assumes that all other variables are held constant (\textit{ceteris paribus}).

\textit{Airport competition 5-year avg. annual \% change (5AAC)} (odds ratio = 0.612)

One unit increase in the 5AAC of airport competition reduces the likelihood of experiencing a severe contraction in passenger volumes by almost a half. In other words, if the airlines in the neighboring airports have been offering more seats or services in the past 5 years, the airport of interest is less likely to experience a severe contraction in passenger volumes. The airlines’ decision to provide more service in the region may indicate that the regional as a whole is a growing market and airports in this region are less likely to experience a sudden disruption in the passenger trends.

\textit{Connecting passenger share} (odds ratio = 1.555) and \textit{5-year avg. annual \% change (5AAC)} (odds ratio = 0.965)

My model indicates that one unit increase in the connecting passenger shares will increase the likelihood of experiencing a severe contraction in passenger demand by a factor of 1.5. This falls in line with the fact that the airports with high connectivity are typically the hub airports and the hub airports have historically experienced a sudden disruption in passenger volumes due to de-hubbing. On the other hand, one unit increase in the 5-year average annual \% change (5AAC) in the connecting passenger shares slightly reduces the likelihood of a severe contraction in passenger volumes. The gain in the connectivity can be interpreted as gaining more passengers in general because the connectivity indicates that the airlines are pooling passengers at the airport.

\textit{Average number of seats per aircraft} (odds ratio = 0.709)

One unit increase in the average number of seats per aircraft at an airport reduces the likelihood of a severe contraction in passenger volumes by a factor of 0.71. The literature indicates that the small aircraft size is related to the high frequency routes (i.e., short domestic routes) [15] and conversely, the large aircraft size can indicate longer routes including international destinations. My model indicates that airports with larger aircraft potentially serving international routes are less likely to experience a severe contraction in passenger volumes.

\textit{Average ticket price} (odds ratio = 0.612)

One unit increase in the average ticket price decreases the likelihood of a severe contraction in passenger volumes by a factor of 0.61. This is in line with the findings just discussed above. Higher ticket prices often indicate longer routes including international destinations. In addition, the literature indicates that the higher ticket prices may be explained by the mix of leisure and business passengers [16].

\textit{HHI} (odds ratio = 2.234) and \textit{5-year avg. annual \% change (5AAC)} (odds ratio = 1.346)

One unit increase in HHI, a measure of market concentration, increases the likelihood of a severe contraction in passenger volumes by a factor of 2.2. This result finds support from many case studies in which the dominant airline with a large share of the market at the airport discontinues their service at the airport resulting in a sharp contraction in passenger volumes. Similarly, one unit increase in the 5-year
average annual % change (5AAC) in HHI also increases the likelihood by a factor of 1.3. This indicates that as fewer and fewer airlines start gaining larger shares of the market at the airport, the airport is more likely to experience a severe contraction in passenger volumes.

Population 5-year avg. annual % change (5AAC) (odd ratio = 0.201)

One unit increase in 5-year average annual % change (5AAC) in MSA population reduces the likelihood of a dramatic contraction in passenger demand in the next 10 years by more than a half. This result supports the existing literature that links air travel demand and socio-demographic conditions of airport host cities/regions [10].

Per capita income (odds ratio = 1.539)

One unit increase in the per capita income increases the odds of a severe demand contraction by a factor of 1.5. This result is somewhat counterintuitive as it indicates that airports in the MSAs with higher per capita income are more likely to experience a sudden disruption in passenger volumes. This may be a case where the MSAs with higher per capita income tend to host hub airports and by definition, hub airports are at a greater risk for “de-hubbing”. The literature, however, is not conclusive on this point.

Service sector employment (odds ratio = 0.406)

One unit increase in the service sector employment reduces the likelihood of a severe contraction in passenger volumes by a factor of 0.41. This result supports the findings in the literature that show a strong positive relationship between employment in service sector and air passenger volumes [17]. In other words, airports located in the MSAs with strong service sector employment base have stable passenger volumes bolstered by the service sector employment.

VI. SUMMARY

The result of this research finds support among air transportation literature, particularly those linking air travel demand to socioeconomic characteristics, and provides valuable insight into measuring the future health of airport.

My research shows that hub airports that have lost connecting passenger shares as well as international passenger demand within the past 5 years are more likely to experience a contraction in overall passenger demand in the next 10 years. In addition, if fewer airlines start to dominate the market at these airports, the probability of such a contraction increases significantly. Put another way, these airports are more and more relying on point-to-point services (i.e., origin-destination vs connecting routes) with fewer international services on fewer airlines. Such situation puts airports at a great risk of losing passenger demand because of the potential risk and the detrimental impact of a dominating airline cutting back service. This indicates that airports with relatively competitive airline market (i.e., more airlines sharing the market more evenly) and stable international demand may be able to hedge against the impact of a single airline’s decisions.

At the same time, my research shows that regional health of cities and metropolitan areas play an important role in air passenger demand. Airports in the metropolitan areas that are gaining population with strong service sector employment are far less likely to experience a dramatic contraction in passenger demand. Similarly, when airports within a region are gaining passengers over time, they are less likely to contract in demand because of the shared socioeconomic benefits in the region.

These results give airport planners greater insights into how to assess the health of their airports as they plan for the future. In a planning environment where airport planners act on aspirational goals based on success stories of other airports without understanding their proper context, my research provides challenges and opportunities for them to learn from their and other airports’ past. Passenger travel demand does not materialize just because airports build a new runway [18]. Airport planners need to incorporate a wider range of metrics into evaluation of passenger demand in order to make more considered and appropriate planning decisions.

REFERENCES


