

Understanding the Factors Affecting Airport Level Demand (Arrivals and Departures) Using a Novel Modeling Approach

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Submitted To: Journal of Air Transport Management

Submission Date: September 19, 2022

Declarations of Interest: None

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ABSTRACT

The current study proposes a novel modeling approach for modeling airline demand. Specifically, we develop a joint panel generalized ordered probit model system with observed thresholds for modeling air passenger arrivals and departures while accommodating for the influence of observed and unobserved effects on airline demand across multiple time periods. The proposed model is estimated using airline data compiled by Bureau of Transportation Statistics for 510 airports in the US at a quarterly level for five annual time points. A host of independent variables including demographic characteristics, built environment characteristics, spatial and temporal factors are considered. From the model estimation, the important factors affecting airline demand include metropolitan statistical area (MSA) population, median income, education attainment, airport location and temporal factors. A validation exercise is also performed using a holdout sample to highlight the superior performance of the proposed model. Finally, to illustrate how the proposed demand model allows agencies to understand changes to airline demand with changes to independent variables, a policy analysis is conducted.

Keywords: Joint panel generalized ordered probit model, airline demand, arrivals, departures, unobserved effects.

1 INTRODUCTION

1.1 Background

In the United States, commercial aviation sector is a significant contributor to the economy. About 7.3% of the US job sector is attributed to commercial aviation sector contributing about 5.2% of US Gross Domestic Product (FAA, 2022). Further, airline industry is closely intertwined with tourism, hospitality, and related auxiliary business (such as rental cars). An important metric to examine the health of the aviation sector is passenger demand – arrivals and departures - at airports. Airline passenger demand and revenue has steadily increased at an annualized growth rate of 2.9% and 5.4% respectively between 2009 and 2019. Given the importance of the airline industry to US economy, understanding the factors affecting airline demand at US airports is important for long-term planning (such as airport runway and terminal design and expansion, intermodal transportation facilities) and operational decisions (such as crew management for airport services). The main objective of the proposed research is to develop a mathematical model of airline demand with the objective of identifying important determinants of demand as well as quantifying their impact. To be sure, airline industry is in a precarious situation as Coronavirus Disease 2019 (COVID-19) pandemic continues to affect the economy and the travel sector. In these conditions, understanding the factors influencing airline demand at various airports will be of utmost importance to the industry. Specifically, analyzing how airline demand at airports evolved over time (over several years) and identifying the factors contributing to this evolution will allow us to build a template of a possible recovery path in the coming years.

To be sure, several studies have examined airline passenger demand. Table 1 provides a summary of earlier research efforts related to air passenger travel demand modeling with information on the study, study region, demand resolution, study objectives, methodology and independent variables considered¹. From Table 1, we can make several important observations. First, earlier research on air travel demand can be categorized into two groups based on the spatial unit of demand data analyzed: (a) airport level and (b) regional level. In the former category, studies analyze passenger demand data for individual airports while in the latter category, the analysis is conducted by aggregating demand at a regional level. From the review, a majority of earlier research focused on analyzing aggregate demand (we found only five studies that explored data at the airport level). Second, the factors identified to affect airline demand have been consistent including socio-demographic factors (population, education, age distribution), socio-economic factors (income, unemployment rate, GDP), built environment (number of trade centers, tourist attractions), level of service factors (average air fare and distance) and lag variables (historical demand). Third, in terms of mathematical frameworks employed for analyzing data, we found two predominant approaches: (a) prediction methods using data and (b) distribution or assignment methods. The majority of prediction methods focused on one dimension – trip departures from the spatial unit of interest. Thus, these studies resorted to employing univariate models of passenger demand such as regression models and their variants such as repeated measures models and regression trees, Artificial neural networks, and Fuzzy models. The second set of studies employ approaches to match the pairwise origin destination demand using approaches such as gravity models, bi-level optimization, and continuous equilibrium approach.

¹ The reader would note that we focused on earlier research examining airline demand. For studies exploring itinerary shares or individual level airline survey data analysis see Li & Wan, 2019; Chi, 2014; Kuo & Tang, 2011; Carson et al., 2011; Wei & Hansen, 2006 and Coldren et al., 2003.

Finally, studies of air travel demand have primarily employed cross-sectional data for estimating demand.

1.2 Contributions of the current study

While earlier research has offered significant insights on airline travel demand, there is scope for enhancing our understanding of factors influencing airline demand. The *first contribution* of our study to the literature arises from spatial and temporal data enhancement of airline demand data from Bureau of Transportation Statistic (BTS). Spatially, the proposed research is conducted at the disaggregate resolution of airport to better incorporate the local factors in modeling airline demand. Earlier studies that conducted airport level prediction analysis have employed a small number of airports in the US (with the highest number of airports considered being 176²). In our study, we conduct our analysis considering 510 airports across the country. For these airports, we augmented the airline demand data with a host of independent variables including demographic characteristics and built environment characteristics at metropolitan statistical area (MSA), spatial and temporal factors. Temporally, the current study examines airline demand at a quarterly level for five annual time points (2010, 2012, 2014, 2016 and 2018). Thus, for every airport, we have 20 observations (5 years * 4 quarters per year). Also, in our study we consider two airport level variables - arrivals and departures. Given the obvious interaction between these two variables, we develop a bivariate multiple time period framework that recognizes the influence of common unobserved factors.

The presence of multiple dependent variables and repeated observations requires the analysis methodology to accommodate for the influence of observed and unobserved factors affecting airline demand. The inclusion of observed factors within the model framework is reasonably straightforward. However, unobserved effects in the current context provide multiple levels of hierarchies including airport level, airport – year, airport – quarter, quarter only, departures and arrivals. The reader would note that in some cases there is an apparent nesting across the hierarchies while in other cases there is some overlap. The *second contribution* of the research is on empirically examining the appropriate hierarchy of unobserved factors that affect airline demand. Finally, earlier research has predominantly considered linear regression and its variants as a framework for such analysis. This is expected due to continuous nature of airline demand variables (such as natural logarithm of airline demand). However, linear regression models impose a linear restriction on parameter impacts for independent variables. While these restrictions can be addressed to some extent by considering indicator variables and/or polynomial terms, the restrictions still exist. Further, it is far from straightforward to test for polynomial terms for all variables. To address this limitation, we recast a recently developed model structure referred to as the grouped response framework for developing a non-linear regression framework that is analogous to the linear regression model system without the restrictions of linear regression (Tirtha et al., 2020; Bhowmik et al., 2019; Rahman et al., 2019). The proposed non-linear system is a recasting of the generalized ordered probit (GOP) model. In the traditional GOP model, the ordered alternatives are modeled by estimating the threshold parameters that demarcate the different alternatives. For identification reasons, the variance of the GOP error term is normalized to 1. However, in our current context, the data is a continuous value, and the demarcations can be predefined. To elaborate, we are translating the scale of the latent propensity to actual observed data. Thus, in the proposed approach, with observed thresholds, we can estimate the variance of

² Li & Wan, 2019 considered 449 airports in their analysis. However, their approach involved a bi-level optimization model that is different from the proposed data driven exercise.

the error term. The only data processing required is categorizing the data appropriately. If the data are finely categorized the model will represent a non-linear version of the traditional linear regression. In fact, we can establish that the proposed non-linear system subsumes the linear regression model system. Further, the proposed framework can be employed to generate a prediction output that is analogous to the linear regression model (details presented in Section 2).

The rest of the paper is organized as follows: Section 2 provides a discussion of the methodology and presents the procedures for employing the proposed framework to obtain continuous prediction. Section 3 presents data compilation procedures and summarizes the data employed for model development. In Section 4, we conduct a comparison of the model performance of various model systems considered. The results from the models are discussed in Section 5. Section 6 and 7 conduct model validation and policy analysis respectively. Finally, the last section concludes the paper.

Table 1 Summary of Literature Review

Study (Study region)	Demand resolution (dependent variable definition)	Objectives	Methodology	Independent Variables Considered				
				Socio- Demo.	Socio- Econ.	Built Env.	Service Factors	Lag Variable
Li & Wan, 2019 (US; 2017)	Airport (Departures)	Model originating air travel demand and its geographical distribution	Bi-level optimization model	Yes	Yes	No	No	No
Mostafaiepour et al., 2018 (Iran; 2011-2015)	Regional (Pairwise; total passenger)	Predict air travel demand	Artificial neural network	Yes	Yes	No	No	No
Zhou et al., 2018 (22 airports, Western Australia; 2016-2017)	Airport (Pairwise; total available seats)	Model air travel demand and find the effects of catchment area on the factors	Gravity model	Yes	Yes	Yes	Yes	No
Valdes, 2015 (32 middle income countries; 2002-2008)	Regional (Total passenger)	Find air travel demand determinants	Linear regression	No	Yes	No	No	No
Chang, 2014 (Countries in APEC region; 2006-2007)	Regional (Pairwise; total passenger)	Identify determinants of air passenger flows	Non-parametric multivariate adaptive regression spline	No	Yes	No	Yes	No
Chi, 2014 (US and 11 other countries; 2012)	Regional (Arrivals and departures)	Identify socio-economic factors on air travel demand	Autoregressive lag modeling approach	No	Yes	No	No	Yes
Kalić et al., 2014 (Serbia, 2001-2011)	Regional (Pairwise; Total passengers)	Model trip generation and trip distribution	Fuzzy models	Yes	Yes	No	No	No
Li et al., 2013 (US; 1995)	Airport (Pairwise; total passengers)	Estimate historical air travel demand	Route-based optimization model	No	No	No	Yes	No
Ba-Fail et al., 2000 (Soudi Arabia; 1971-1994)	Regional (Total passengers)	Estimate domestic air travel demand	Regression analysis	Yes	Yes	No	No	No
Hwang & Shiao, 2011 (Taiwan; 2007)	Airport (Pairwise; air cargo)	Determine the factors of international air cargo flows	Gravity model	Yes	Yes	No	Yes	No

Study (Study region)	Demand resolution (dependent variable definition)	Objectives	Methodology	Independent Variables Considered				
				Socio- Demo.	Socio- Econ.	Built Env.	Service Factors	Lag Variable
Carson et al., 2011 (US; 1990-2004)	Regional and airport (logarithm of departures/population)	Forecast originating air travel demand	Quasi-AIM approach	No	Yes	No	No	Yes
Suryani et al., 2010 (Taiwan; 1996-2007)	Airport (Total passengers)	Forecast air passenger demand	System dynamics model	Yes	Yes	No	Yes	No
Endo, 2007 (US and Japan; 2000-1992)	Regional (Pairwise; import and export)	Identify effect of bi-lateral aviation framework on air service imports	Regression analysis	No	Yes	No	Yes	No
Grosche et al., 2007 (Germany and 28 European countries; 2004)	Regional (Pairwise, total passengers)	Model air passenger volume between cities	Gravity model	Yes	Yes	No	Yes	No
Loo et al., 2005 (Hong Kong–Pearl River Delta region; 2000)	Airport (passengers/year)	Model geography of air passenger flows	Continuous equilibrium approach	No	Yes	No	No	No
Wei & Hansen, 2006 (Hub Airports, US; 2000)	Airport and airlines (Pairwise; logarithm of departures)	Model aggregate air passenger traffic	Log-linear demand model	Yes	Yes	No	Yes	No
Matsumoto, 2004 (Asia and outside Asia; 1998)	Regional (Pairwise; Total passengers and cargo)	Identify the pattern of international air passenger and cargo flows	Gravity model	Yes	Yes	No	Yes	No
Coldren et al., 2003 (US; 2000)	Air carrier (Pairwise; Total passengers)	Model market share of air carriers	Aggregate multinomial logit	No	No	No	Yes	No
Abed et al., 2001 (Saudi Arabia; 1971-1992)	Regional (Total passengers)	Model the demand for international air travel	Stepwise regression analysis	No	Yes	No	No	No
Rengaraju & Arasan, 1992 (40 city pairs, India; 1986)	Regional (Pairwise; total passenger)	Model demand of air travel	Stepwise multiple linear regression	Yes	Yes	No	No	No

Study (Study region)	Demand resolution (dependent variable definition)	Objectives	Methodology	Independent Variables Considered				
				Socio- Demo.	Socio- Econ.	Built Env.	Service Factors	Lag Variable
Hakim & Merkert, 2016 (8 South Asian Country;1973–2014)	Country (Total passengers and Freight)	Identify causal relationships between aviation and economic growth	Pedroni/Johansen cointegration test, Granger long-run and Wald short-run causality tests	No	Yes	No	No	Yes
Hakim & Merkert, 2019 (8 South Asian Country;1973–2015)	Country (Total passengers and Freight)	Identify the determinants of air transport demand	Panel regression and error correction mechanism approach	Yes	Yes	No	No	Yes
Jin et al., 2020 (3 Airports, China; 2006-2017)	Airport (Total passengers)	Propose a new hybrid approach to forecast air passenger demand	Hybrid approach: variational mode decomposition, autoregressive moving average model and kernel extreme learning machine	No	No	No	No	No
Kağan Albayrak et al., 2020 (47 provinces, Turkey; 2004-2014)	Regional (Total passengers)	Identify determinants of air traffic in an emerging economy	Panel Regression Model	Yes	Yes	Yes	Yes	No
Hanson et al., 2022 (US; 1970-2018)	National (Total passengers)	Identify causal relationship between income and air travel demand	Autoregressive distributed lags bound testing approach	No	Yes	No	No	No
Iyer & Thomas, 2021 (57 airports, India; 2018-2019)	Airport (Total passengers)	Analyze the domestic air traffic demand in regional airports	Multiple Regression Analysis	Yes	Yes	Yes	No	No

2 ECONOMETRIC METHODOLOGY

2.1 Model Formulation

Let q ($q = 1, 2, \dots, Q$) be an index to represent airports, r represent the demand dimension ($r = 1$ represents arrivals and $r = 2$ represents departures), t ($t = 1, 2, 3, \dots, T = 5$) represent the different years, l ($l = 1, 2, 3, \dots, L = 4$) represent different quarters and j ($j = 1, 2, 3, \dots, J = 14$) be an index to represent the logarithm of quarterly passenger arrivals or departures data. We consider fourteen categories for the air travel demand analysis and these categories are: Bin 1 = ≤ 3 ; Bin 2 = 3-4; Bin 3 = 4-5, Bin 4 = 5-6, Bin 5 = 6-7, Bin 6 = 7-8, Bin 7 = 8-9, Bin 8 = 9-10, Bin 9 = 10-11, Bin 10 = 11-12, Bin 11 = 12-13, Bin 12 = 13-14, Bin 13 = 14-15 and Bin 14 = > 15 . Then, the equation system for modeling demand may be written as follows:

$$D_{qrtl}^* = (\alpha_r' + \gamma_{qr}')x_{qrtl} + (\eta_k)x_{qrtl} + \varepsilon_{qrtl}, D_{qrtl} = j \text{ if } \psi_{j-1} < D_{qrtl}^* \leq \psi_j \quad (1)$$

In equation 1, D_{qrtl}^* is the latent (continuous) propensity for total airline demand dimension r at airport q , for the year t and quarter l . This latent propensity D_{qrtl}^* is mapped to the actual demand category j by the ψ thresholds, in the usual ordered-response modeling framework. In our case, we consider $J = 14$ and thus the 15 ψ values are as follows: $-\infty, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15$ and $+\infty$. x_{qrtl} is a matrix of attributes that influence passenger arrivals and departures (including the constant); α is the vector of coefficients corresponding to the attributes and γ_q is a vector of coefficients representing the impact of unobserved factors moderating the influence of corresponding element of x_{qrtl} . Further, ε_{qrtl} is an idiosyncratic random error term assumed independently normally distributed with variance λ_{Dr}^2 .

The variance vectors for arrivals and departures are parameterized as a function of independent variables as follows: $\lambda_{Dr} = \exp(\theta_r' x_{qrtl})$. The parameterization allows for the variance to be different across the airports accommodating for heteroscedasticity. Finally, to allow for alternative specific effects, we also introduce threshold specific deviations in the model as $\rho_{jr} = \tau'_{jr} x_{qrtl}$.

η_k represents the vector of coefficients representing the impact of common unobserved factors that jointly influence quarterly passenger arrivals and departures across repetition level k . As discussed earlier, in the current study context, we estimate η_k for different levels (k) of repetition measures including airport specific, year specific, quarter specific, airport-year specific, airport-quarter specific and year-quarter specific. The flexibility offered by testing for unobserved heterogeneity enhances the model development exercise. In accommodating unobserved effects at different repetition levels, random numbers are assigned to the appropriate observations of the repetition measures. For example, at airport level, we have 510 airports. Thus, in evaluating unobserved effect at the airport level, 510 sets of different random numbers are generated specific to 510 airports and assigned to the data records based on their airport ID. The random numbers are assigned for other repetition levels following the same analogy in estimating the model. The reader would note that the multiple levels identified here also allows for the joint correlation across the two dependent variables (arrivals and departures). For instance, at observational level (airport-year-quarterly), this η_k will be different across the observations but same across the two dependent variables which implies that the unobserved factors that increase the propensity for arrivals for a given reason, also increase the propensity for departures. Thus, the proposed framework by

allowing for additional flexibility allows the analyst to avoid conflation of unobserved effects on quarterly arrivals and departures at an airport for different years.

To complete the model structure of the Equations (1) and (2), it is necessary to define the structure for the unobserved vectors γ_{qr} and η_k . In this paper, we assume that the three vectors are independent realizations from normal distributions as follows: $\gamma_{qr} \sim N(0, \sigma_r^2)$ and $\eta_k \sim N(0, \varrho^2)$.

With these assumptions, the probability expressions for the air travel demand category may be derived. Conditional on γ_{qr} and η_k the probability for airport q to have arrivals and departures in category j in year, t and quarter, l is given by:

$$P(D_{qrtl})|\gamma, \eta = \Lambda \left[\frac{\psi_j - ((\alpha'_r + \gamma'_{qr})x_{qrtl} + (\eta_k)x_{qrtl} + \rho'_{jr})}{\lambda_{Dr}} \right] - \Lambda \left[\frac{\psi_{j-1} - ((\alpha'_r + \gamma'_{qr})x_{qrtl} + (\eta_k)x_{qrtl} + \rho'_{j-1,r})}{\lambda_{Dr}} \right] \quad (2)$$

where $\Lambda(\cdot)$ is the cumulative standard normal distribution.

The complete set of parameters to be estimated in the bivariate model system of Equations (2) are α_r , τ_r and θ_r vectors and the following standard error terms: σ_r and ϱ . Let Ω represent a vector that includes all the standard error parameters to be estimated. Given these assumptions the joint likelihood for airport level quarterly arrivals and departures is provided as follows:

$$L_q|\Omega = \prod_{t=1}^T \prod_{l=1}^L \prod_{r=1}^2 \prod_{j=1}^J [P(D_{qrtl})|\gamma, \eta]^{d_{qrtlj}} \quad (3)$$

where d_{qrtlj} are dummy variables taking a value of 1 if an airport q has the demand dimension, r within the j^{th} category for year, t and quarter, l and 0 otherwise. Finally, the unconditional likelihood function may be computed for airport q as:

$$L_q = \int_{\Omega} (L_q|\Omega) d\Omega \quad (4)$$

Now, we can express the likelihood function as follows:

$$\text{LL} = \sum_{q=1}^Q \ln L_q \quad (5)$$

The likelihood function in Equation (5) involves the evaluation of a multi-dimensional integral of size equal to the number of rows in Ω . We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood

function and maximize the logarithm of the resulting simulated likelihood function (See Bhat, 2001; Yasmin & Eluru, 2013 for more details).

2.2 Model Prediction

In the preceding discussion we presented the model estimation approach. In this sub-section, we outline the formula for generating the demand prediction from the proposed model. The approach recognizes that the continuous latent propensity score (D_{qrtl}^*) generated serves as the estimate of airline demand. However, in the presence of alternative specific variables (ρ_{jr}), the latent propensity score needs to be adjusted accordingly. The resulting equation for continuous demand from the proposed model is expressed as follows:

$$p_{qrtl} = (\alpha'_r + \gamma'_{qr})x_{qrtl} + (\eta_k)x_{qrtl} + \sum_{j=2}^J(\alpha'_r x_{qrtl} > (\psi_j - \rho_{jr})) \times \rho_{jr} \quad (6)$$

where, p_{qrtl} represents the total airline demand for dimension r , at airport q , for the year t and quarter l and x_{qrtl} is a matrix of attributes that influence passenger arrivals and departures. p_{qrtl} generated will allow us to estimate all measures of comparison applicable for linear regression such as squared residuals, R^2 and adjusted R^2 .

2.3 Equivalent Log-Likelihood Generation Using Linear Regression

The adjusted R^2 measure represents the squared error in the model. However, it is worth noting that the squared error might not penalize the error in observations adequately. To develop a more reliable comparison metric to investigate the model performance, an equivalent linear regression log-likelihood was generated. The reader would note that linear regression model log-likelihood represents the probability density function of the difference between the observed and predicted value. However, in the proposed model, we do not differentiate between any values within each category. Thus, a direct comparison of log-likelihoods is not appropriate. Hence, we present an equivalent log-likelihood that allows for an appropriate comparison. The probability for airport q to have arrivals and departures in category j in year, t and quarter, l using linear regression model is given by:

$$P(D_{qrtl}) = \Lambda \left[\frac{\psi_j - (\omega'_r x_{qrtl})}{\kappa_r} \right] - \Lambda \left[\frac{\psi_{j-1} - (\omega'_r x_{qrtl})}{\kappa_r} \right] \quad (7)$$

where, ω and κ^2 represent the vector of coefficients and the error variance respectively estimated from the linear regression model and ψ is same as defined earlier in Equation 1. The probability thus generated is employed to compute the likelihood function following same equations as presented in 3, 4 and 5.

3 DATASET DESCRIPTION

The airport demand data are sourced from the airline origin and destination survey (DB1B) dataset provided by Bureau of Transportation Statistics (BTS). BTS provides detailed information about 10% of the tickets collected from domestic airlines operating in the US from 1993 through 2022. For our current analysis, we confined our attention to the domestic air travelers from 2010 to 2018 across the 51 states in US covering five major regions including south, west, north-east, mid-west and pacific regions. Further, we consider both arrivals and departures at an airport for every quarter over the study period. Hence, passenger trips in origin and destination survey are aggregated at quarters and airports and scaled appropriately (as they represent 10% of the total domestic trips) to estimate the quarterly airport level travel demand. In the airport selection process, our focus was to consider all of the public-use airports located in the US. In this effort, we consider 510 airports for which itinerary information are available in origin and destination survey. We ignored the smaller airports that do not have itinerary information available. For the selected airports, we extract the demand data for every two years interval (2010, 2012, 2014, 2016 and 2018). The reader would note that some airports did not have all 20 records for various reasons (such as airports that were opened for passengers at a later time or closed in the time frame). After cleaning the data, we obtain a total of 8,477 observations for estimation.

In preparation of dependent variables, we performed log transformation of arrivals and departures, and then considered 14 categories (≤ 3 , $>3-4$, $>4-5$, $>5-6$, $>6-7$, $>7-8$, $>8-9$, $>9-10$, $>11-12$, $>12-13$, $>13-14$, $>14-15$, >15) of the transformed variables. Distribution of the dependent variables are shown in Figure 1. The transformed variable reasonably represents a normal distribution.

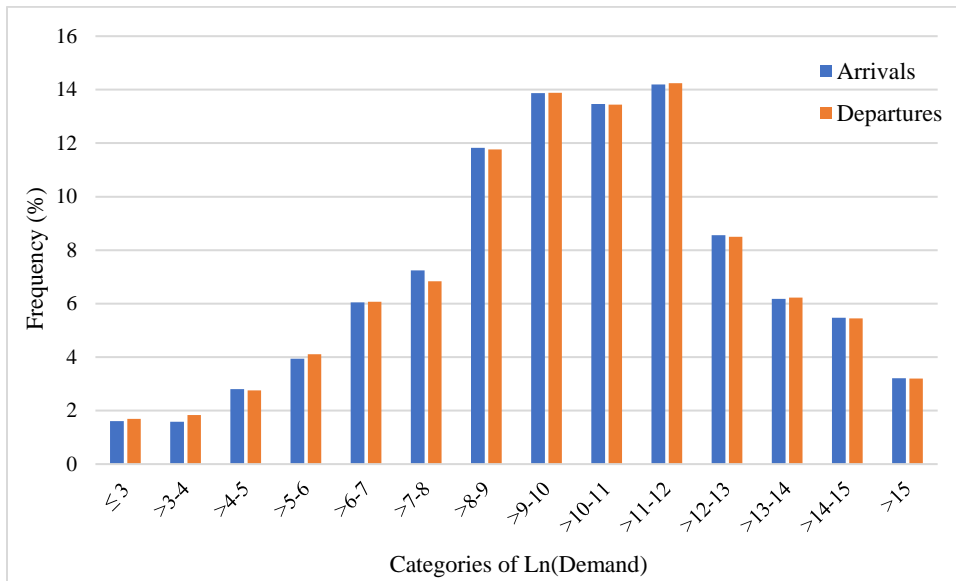


Figure 1 Distribution of the dependent variables

The BTS airline data is also augmented with a host of independent variables. These variables are sourced from American Community Survey (ACS) and other secondary sources (County health ranking and roadmaps (Roadmaps) for crime data; (Insider)). Independent variables are grouped into four broad categories, namely, demographic characteristics, built environment characteristics, spatial and temporal factors. Demographic factors include population,

household median income, employment, out of state employment and education level of the residents in the corresponding metropolitan statistical area (MSA). Built environmental characteristics include number of airports in 50mile buffer area around the airport of interest and tourism ranking of the corresponding state. Spatial factors include location of the airport in terms of region including south, north-east, west, mid-west and pacific region. Temporal factors include year and quarter of the analysis. Detailed descriptions of functional form and summary statistics of the independent variables are provided in Table 2 for categorical and continuous variables.

Table 2 Description of the Independent Variables

Variables	Definition	Frequency	Percentage
<i>Categorical Independent Variables</i>			
<i>Demographic characteristics</i>			
Education Status			
High	Percentage of adults not having high school degree in the MSA <=12%	4713	55.597
Low	Percentage of adults not having high school degree in the MSA >12%	3764	44.403
<i>Built environment factors</i>			
Tourist attraction			
Top10	The state is among top 10 tourist attraction states	2252	26.566
Bottom10	The state is among bottom 10 tourist attraction states	948	11.183
Others	The state is other than top and bottom tourist attraction states	5277	62.251
<i>Spatial Factors</i>			
Region			
South		2465	29.100
North-East		1079	12.700
West		2176	25.700
Mid-West		1958	23.100
Pacific		799	9.426
<i>Temporal factors</i>			
Quarter			
Quarter 1	January-March	2101	24.785
Quarter 2	April-June	2142	25.268
Quarter 3	July-September	2128	25.103
Quarter 4	October-December	2106	24.844
<i>Continuous Independent Variables</i>			
Variables	Definition	Mean	Min/Max
<i>Demographic characteristics</i>			
Population	Population in million in corresponding MSA	1.101	0.013/20.031
Median Income	Household median income in 100K in corresponding MSA	0.541	0.276/1.147
Employment	Ln(number of workers in thousands in corresponding MSA)	4.848	2.029/9.166

Out of State Employment	Fraction of job holders in corresponding MSA working out of state	0.029	0.000/0.273
<i>Built environment factors</i>			
Number of airports	Ln(Number of airports in 50 mile buffer area)	1.711	0.000/3.664
<i>Ordinal Independent Variables</i>			
<i>Temporal factors</i>			
Year	Ordinal year variable with 2010 as the base year	3.900	0.000/8.000

4 MODEL SELECTION

The empirical analysis begins with comparing the performance of the proposed generalized ordered probit (GOP) model with the performance of a linear regression model. The reader would note that the two model systems are generally estimated using different approaches. The linear regression model is estimated using the least squares estimator (and evaluated based on adjusted R^2) and the GOP model employs a log-likelihood maximization procedure (evaluated using log-likelihood). In our effort to compare the two frameworks, we build equivalent measures for the two models from both approaches i.e., generate adjusted R^2 and log-likelihood for both models (equations presented in section 2.2 and 2.3).

The linear regression model for arrivals (departures) with 12 (12) parameters resulted in an adjusted R^2 value of 0.401 (0.397). For the GOP arrivals (departures) model with 15 (16) parameters resulted in an adjusted R^2 value of 0.408 (0.405). The reader would note, even after accounting for the additional parameters in the GOP framework, we observe that GOP model outperforms the linear regression model structure.

The log-likelihood and Bayesian Information Criterion (BIC) value for the equivalent linear regression framework appropriately aggregated to reflect the GOP structure is -37,363.3 (with 24 parameters) and 74,876.2, respectively. The log-likelihood and BIC value for the proposed GOP system is -37,128.0 (with 31 parameters) and 74,449.3, respectively. The comparison of the adjusted R^2 , log-likelihood and BIC measures clearly illustrate the superiority of the proposed model structure for the present empirical case study.

After establishing the superiority of the GOP framework (versus the linear regression approach), we estimate advanced model structures in the GOP regime to account for the presence of two dependent variables and repeated measures. Prior to doing this, we recognized that the arrivals and departures models have similar coefficients for a substantial number of parameters. Hence, to arrive at a parsimonious specification, we restrict the variables with close parameter values and re-estimate the model. The re-estimated model offers no significant loss of fit. Finally, with this specification we estimate the joint panel GOP model. The fit measures - log-likelihood (parameters) - for the three models are as follows: Independent GOP model: -37,128.0 (with 31 parameters); 2) Restricted GOP model: -37,128.2 (with 19 parameters) and 3) Joint Panel GOP model: -30,175.2 (with 20 parameters). We also compute the BIC value for these three frameworks to determine the best model. The BIC values for the three models are as follows: a) 74,449.3, b) 74,374.9 and c) 60,475.1. Based on the BIC values, the joint panel model that accommodates for the presence of unobserved heterogeneity significantly outperforms the respective independent models highlighting the importance of accommodating for the influence of common unobserved

factors affecting the two dependent variables (and their repeated measures). For the sake of brevity, only the joint panel GOP model results are presented in the paper³.

5 ESTIMATION RESULTS

In the model estimation process, we explored various transformations of the independent variables and chose the best transformation based on model fit. Table 3 shows the effects of exogenous variables on passenger arrivals and departures. Positive (negative) coefficients in the model indicate that an increase of a variable increases (decreases) the propensity for higher demand. From Table 3, the reader would note the variables for arrivals and departures offer identical parameters as they were restricted to be the same based on initial estimations that offered very close values across the two variables. Given the similarity, we will discuss the variable effects for both arrivals and departures together by variable groups.

5.1 Demographic Characteristics

Among the various demographic characteristics considered in the model, population, median income in an MSA, out of state employment and education status offer significant impact on the quarterly demand. As is evident from Table 3, we can see that population - a surrogate for air travel demand exposure is positively associated with demand (arrivals and departures) (please see Kağan Albayrak et al., 2020; Zhou et al., 2018 and Grosche et al., 2007 for similar findings). The finding is intuitive and highlights the role of MSA population on airline demand; as population in the catchment area increases, airline demand increases. Further, results show that the air travel demand is positively associated with median income in an MSA (please see Hakim & Merkert, 2019 for similar findings). Increased income, in general, corresponds to increased affordability for personal travel and higher business activity in the region. Thus, it is possible that airports in MSA's with higher median income are likely to have higher demand profiles.

The variable specific to out of state employment represents the percentage of employees working out of state and reveals a negative association with the air travel demand. This may indicate that as out of state workers are not actively present in the MSA, consequently, increase of such population may reduce total number of passenger arrivals and departures. Further, from the results it appears that education status in an MSA is an important determinant influencing the air travel demand. Results show that if percentage of adults without high school degree is more than 12%, then air travel demand decreases.

5.2 Built Environment Characteristics

The variable number of airports in a 50-mile buffer represents the number of available airports in close proximity (50 mile radius) of an airport. Interestingly, we found that increased number of airports in 50 mile buffer results in higher air travel demand in the MSA. The result indicates that increased number of airports in close proximity contribute to increased air travel demand in the region (Tirtha et al., 2022). Further, we considered the tourism status of an MSA in our analysis as demand for travel to these destinations can increase air travel demand. For this purpose, we identify the top and bottom 10 desirable states with respect to tourism activity and use that indicator variables as predictors in our model system. As expected, we find that the likelihood of higher air

³ It is possible that independent variables considered in demand modelling might be correlated with each other. To test for possible multicollinearity, we estimate Pearson correlation coefficients between each variable pair. The result of the analysis is provided in the supplementary material. The result highlights that our analysis is unaffected by multicollinearity issue.

travel demand is greater in an airport located in top 10 tourists' attraction states while a reduced propensity for air demand is observed for an airport located in the least 10 visiting states.

5.3 Spatial Factors

Location of the airports in terms of US region has a significant effect on the total number of arrivals and departures through those airports. In general, compared to the airports in the west and the mid-west region, demand is observed to be higher for an airport in the south region. On the other hand, airports in the north-east and pacific regions experience lower level of demand. Airports in south region might have larger catchment areas compared to other regions resulting in higher demand at the airports located in this region.

5.4 Temporal Factors

Quarterly effects are found to be significant in the model and the results indicate that travel demand is lowest for quarter 1 (January – March) and highest for quarter 3 (July – September). These trends can be attributed to presence of seasonal variation in air travel demand.

5.5 Category Specific Deviations

The proposed model also allows for category specific deviations on various predefined thresholds. In our air passenger arrivals and departures estimation, we consider various category specific deviations based on model fit and sample sizes across each trip count categories. The estimation results of these parameters are reported in the third-row panel of Table 3. These deviation parameters are similar to a constant in discrete choice models and do not have an interpretation after incorporating other variables.

5.6 Effect of Unobserved Factors

In our proposed model, we estimated unobserved effects at multiple levels: airports, year, quarter, airport – year and airport – quarter. Among different levels we considered, we found that the airport – year and airport – quarter level effects have significant influence on air travel demand. The estimation results of these standard deviations are presented in last row panel of Table 3. The significant standard deviation parameters at different repetition measures provide evidence toward supporting our hypothesis that it is necessary to incorporate these unobserved effects in examining air travel demand. These variables indicate that the air passenger arrivals and departures may vary for different airports based on the unobserved effects specific to different levels.

Table 3 Model Estimation Results

Variables	Arrivals		Departures	
	Estimate	t-statistic	Estimate	t-statistic
<i>Propensity Components</i>				
Constant	5.6422 ¹	48.4330	5.6235	48.2630
<i>Demographic characteristics</i>				
Population	0.2681	32.0980	0.2681	32.0980
Median income	3.5463	17.1210	3.5463	17.1210
Out of state employment	-0.6236	-1.7920	-0.6236	-1.7920
Education Level (Base: High (% of adults not having high school degree <=12%))				
Low	-0.6030	-15.0460	-0.6030	-15.0460
<i>Built Environment Factors</i>				

No. of airports	1.3622	41.6110	1.3622	41.6110
Tourist's Attraction (Base: Others)				
Top10	0.8160	15.5210	0.8160	15.5210
Bottom10	-0.4552	-6.7810	-0.4552	-6.7810
<i>Spatial Factors</i>				
Region (Base: West and Mid-West)				
South	1.1928	20.9990	1.1928	20.9990
North-East	-1.4536	-21.4080	-1.4536	-21.4080
Pacific	-2.9293	-36.1590	-2.9293	-36.1590
<i>Temporal Factors</i>				
Quarter (Base: Quarter 1)				
Quarter 2&4	0.1161	2.8440	0.1161	2.8440
Quarter 3	0.2044	4.5600	0.2044	4.5600
<i>Variance Components</i>				
Constant	0.3767	42.6490	0.3855	43.6470
<i>Threshold Specific Constant</i>				
Threshold 11	-0.1275	-5.7110	-0.1309	-5.8620
Threshold 13	-0.4185	-7.7620	-0.4282	-7.9420
Threshold 14	-1.6344	-17.2810	-1.6498	-17.3010
<i>Unobserved Effects</i>				
Variables	Estimate		t stat	
Airport-Year specific effect	1.9572		38.3520	
Airport-Quarter specific effect	0.3668		19.8320	

¹= Significant at 90% confidence level

6 MODEL VALIDATION

The holdout sample with quarterly passenger arrivals and departures for year 2017 is used to perform the validation test. The validation set consists of 1,609 observations for 415 airports. To test the predictive performance of the proposed model, a validation exercise is performed in this study following the same procedures outlined in Section 4. First, we compared the performance of the traditional linear regression with the independent GOP model. To perform the validation analysis, 25 data samples, of 100 airports each, are randomly generated from the hold out validation sample consisting of 415 airports. Predicted R^2 and Log-likelihood values for linear regression model and GOP model are plotted in Figure 2. Figure 2 clearly highlights the enhanced performance of the GOP model over LR across most of the samples for both arrival and departure rate. Specifically, for the arrival model, the GOP model performs better than LR model in 43 out of 50 cases (R^2 : 21 and LL: 22) while for the departure model, the GOP model performs better in 45 cases (R^2 : 22 and LL: 23). While the improvements in predicted R^2 might be small, the consistency of the improved performance of the GOP model indicates its superiority over the LR model. Subsequently, we compared the performance of the three GOP model systems (LL and BIC): (1) independent GOP: -6972.12 and 14,131.12, (2) restricted GOP: -6972.13 and 14,058.80 and (3) joint panel GOP: -5868.40 and 11,857.37. The LL and BIC values computed using the

validation dataset also clearly highlights the superiority of the joint panel GOP model relative to the other two systems.

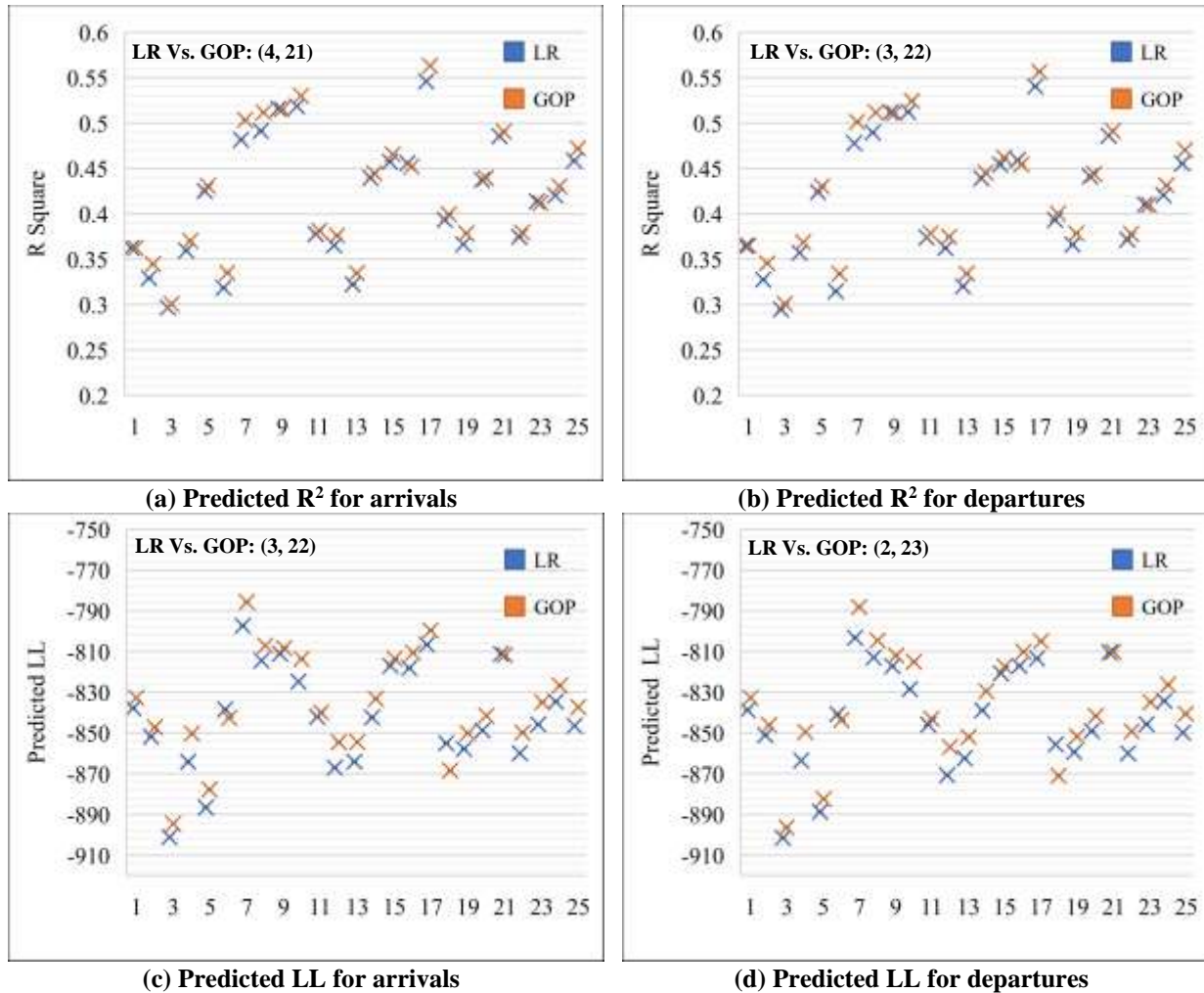


Figure 2 Predicted R^2 and LL Comparison Between LR and GOP Model

7 POLICY ANALYSIS

The proposed model framework is a non-linear regression model. Hence, the variable parameters do not directly provide the magnitude of variable impacts. In order to highlight the effect of various attributes on air passenger arrivals and departures, an elasticity analysis is conducted (see Eluru & Bhat, 2007 for a discussion on the methodology for computing elasticities). The emphasis of the elasticity analysis is to illustrate the contribution of each independent variable to airline demand. To elaborate, we compute the percentage change of aggregate probability of the demand categories because of the change in the factors considered. To compute the elasticity effects, specific approaches by variable category are employed. For continuous variables, the change in the probability of airline demand categories is examined in response to a 10% increase in the independent variable. For indicator variables, the change is computed by evaluating the changes in the probability of airline demand categories by converting the indicator value from 0 to 1 and

vice-versa. The change resulting from 1 to 0 is reversed and added to the change from 0 to 1 to obtain the overall change corresponding to the indicator variable. The variables considered include MSA level population, household median income, out of state employment, education status, number of airports in close proximity, and tourism related variables. The results of elasticity analysis are presented in Table 4. From the table, we can see the percentage change in arrival and departure categories due to changes in independent variables. For example, if MSA population increases by 10%, the share of the lowest arrival (departure) category decreases by 1.91% (1.84%) and the share of the highest arrival (departure) category increases by 23.66% (23.86%). This result indicates that demand propensity shifts to the higher demand categories significantly in response to population increase. Several observations can be made from the results. First, airport location in tourism driven states has a significant impact on air travel demand. Further, we observe that increased air travel demand is associated with number of airports in proximity, population, and median income. Second, air travel demand is adversely affected by MSA level education status (higher proportion of adults without high school education) and state's presence in the bottom tier of tourist attractions. These findings illustrate how the proposed approach can be employed to understand how air travel demand is affected by various independent variables. The model framework developed will acquire even more significance with the country and economy recovering from the Corona Virus Disease 2019 (COVID-19). Airport agencies and tourism stakeholders across the country can employ our model to predict how airline demand patterns are likely to evolve over time (see Tirtha et al., 2022 for a recent study examining COVID-19 impact explicitly). Specifically, using our model, expected airline demand volumes can be predicted for airports in regions with changing population patterns across the country. For example, cities in the South that are experiencing large growth rates in population can proactively plan for increased airline demand, terminal, and intermodal facility design. Further, these regions should also work closely with urban transportation agencies to proactively improve multi-modal transportation connectivity to the airport to alleviate potential congestion with growing airline demand. The analysis also provides encouraging trends for tourism heavy states highlighting how locations in the Top 10 rank contribute to increased demand. State and urban tourism agencies can dedicate additional marketing funds to promote tourism in the state and urban regions within the state.

Table 4 Elasticity Analysis Results

Arrivals categories	Bins													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Population	-1.91 ²	-1.13	-0.74	-0.56	-0.49	-0.46	-0.45	-0.42	-0.39	-0.31	-0.18	-0.24	-0.35	23.66
Median income	-37.41	-30.71	-25.26	-20.36	-15.79	-11.32	-6.82	-2.34	1.97	6.05	9.22	11.26	10.54	19.38
Out of state employment	0.31	0.28	0.24	0.18	0.14	0.10	0.06	0.02	-0.02	-0.06	-0.09	-0.10	-0.03	-0.27
Education Status (Low)	183.12	133.79	101.85	75.75	53.36	34.10	17.83	4.12	-7.75	-18.81	-27.69	-32.32	-25.45	-45.00
No. of airports	-10.54	-12.39	-13.85	-14.58	-14.05	-12.07	-8.82	-4.62	0.30	5.85	10.92	14.87	15.27	32.43
Top10	-113.58	-96.89	-84.41	-72.42	-59.54	-45.27	-29.67	-12.78	5.43	25.34	42.53	52.02	44.11	60.03
Bottom10	122.85	93.18	73.40	56.82	41.78	27.59	14.34	2.54	-7.30	-15.23	-20.49	-22.80	-19.85	-29.87
Departures categories	Bins													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Population	-1.84	-1.10	-0.73	-0.55	-0.49	-0.46	-0.45	-0.42	-0.38	-0.31	-0.18	-0.25	-0.24	23.86
Median income	-36.87	-30.26	-24.92	-20.08	-15.57	-11.13	-6.68	-2.24	2.02	6.06	9.21	11.23	10.56	19.49
Out of state employment	0.31	0.28	0.23	0.18	0.13	0.10	0.06	0.02	-0.02	-0.06	-0.09	-0.10	-0.03	-0.27
Education Status (Low)	178.94	131.10	99.98	74.39	52.39	33.44	17.42	3.87	-7.89	-18.86	-27.64	-32.17	-25.49	-45.26
No. of airports	-10.69	-12.52	-13.91	-14.56	-13.96	-11.94	-8.69	-4.50	0.38	5.89	10.91	14.82	15.31	32.62
Top10	-112.20	-95.87	-83.59	-71.67	-58.83	-44.64	-29.14	-12.36	5.71	25.46	42.44	51.78	44.15	60.22
Bottom10	120.35	91.52	72.22	55.92	41.07	27.05	13.98	2.34	-7.38	-15.24	-20.45	-22.73	-19.89	-29.96

² = percentage change of aggregate probability of the demand categories

8 CONCLUSION

Understanding the factors affecting airline demand at US airports is important for long-term planning and operational decisions. The current study contributes to the existing literature along multiple directions. The first contribution our study to the literature arises from spatial and temporal data enhancement of airline demand data from BTS. Also, in presence of airport level variables - arrivals and departures, we develop a bivariate framework that recognizes the influence of common unobserved factors. The second contribution of the research is on empirically examining the appropriate hierarchy of unobserved factors that affect airline demand. Finally, to address the inherent limitations of traditional linear models, we employ the generalized response framework for developing a non-linear framework that subsumes the linear regression model system. In summary, the proposed research develops a joint panel generalized ordered probit model system with observed thresholds for modeling air passenger arrivals and departures. The proposed model is estimated using airline data compiled by Bureau of Transportation Statistics for 510 airports across the US. A host of exogenous variables including demographic characteristics, built environment characteristics, spatial and temporal factors are considered in the model estimation.

The empirical analysis shows that the flexible structure of generalized ordered probit model (GOP) allows us to capture the non-linearity between air travel demand and its contributing factors resulting in better data fit compared to linear regression model. To arrive at a parsimonious specification, we estimated a restricted GOP model without any significant loss of data fit. Finally, the joint panel model that accommodates for the presence of unobserved heterogeneity performs the best in terms of empirical context highlighting the importance of accommodating for the influence of common unobserved factors affecting the two dependent variables (and their repeated measures). Finally, to illustrate how the enhanced demand model allows policy agencies to understand changes to airline demand with changes to independent variables a policy analysis is conducted. The results identify important predictors for airline demand. In particular, they highlight the role of tourism in the state, regional population, and median income.

However, this study is not without limitations. Augmenting the data in our research with local economic indicators and airport specific attributes might improve the model. In addition, as the proposed model is at the airport level causation is far from straightforward to determine. Each airport might have specific factors affecting their airline demand that are not explicitly considered in our analysis. Examining the causal relationship between airline demand and the independent variable considered would be an avenue for future research.

The data employed in our paper is entirely pre-COVID-19. Thus, the model developed does not consider the impact of COVID-19. In response to COVID-19 pandemic, domestic airline demand in the US experienced a sharp drop, and it has only started to recover in recent months with widespread vaccination programs across the world. While the models developed do not explicitly account for COVID-19 related impacts, the proposed model can contribute to long-term planning as airline demand recovers from the pandemic levels (see Tirtha et al., 2022 for study explicitly examining the impact of COVID-19 on airline demand).

ACKNOWLEDGMENT

The authors would like to acknowledge Bureau of Transportation Statistics (BTS) for providing access to their airline origin and destination survey dataset.

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