

An Airport Level Framework for Examining the Impact of COVID-19 on Airline Demand

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ABSTRACT

In this study, we examine the influence of Coronavirus disease 2019 (COVID-19) on airline demand at the disaggregate resolution of airport. The primary focus of our proposed research effort is to develop a framework that provides a blueprint for airline demand recovery as COVID-19 cases evolve over time. Airline monthly demand data is sourced from Bureau of Transportation Statistics for 380 airports for 24 months from January 2019 through December 2020. The demand data is augmented with a host of independent variables including COVID-19 related factors, demographic characteristics and built environment characteristics at the county level, airport specific factors, spatial factors, temporal factors, and adjoining county attributes. The effect of COVID-19 related factors is identified by considering global and local COVID-19 transmission, temporal indicators of pandemic start and progress, and interactions of airline demand predictors with global and local COVID-19 indicators. Finally, we present a blueprint for airline demand recovery where we consider three hypothetical scenarios of COVID-19 transmission rates – expected, pessimistic and optimistic. The results at the airport level from these scenarios are aggregated at the state or regional level by adding the demand from all airports in the corresponding state or region. These trends are presented by State and Region to illustrate potential differences across various scenarios. The results highlight a potentially slow path to airline demand recovery until COVID-19 cases subside.

Keywords: COVID-19, Airline Demand, Linear Mixed Model, Airport level, Scenario Analysis

1 INTRODUCTION

Coronavirus disease 2019 (COVID-19), as of August 25th, with a reported 214.7 million cases and 4.5 million fatalities has affected nearly every country in the world (Worldometer, 2021). In the United States, 38.2 million cases and 629 thousand fatalities have been reported (CDC, 2021). The pandemic has affected every facet of life in the world significantly burdening social, health and economic systems. Among these affected industries, airline industry ranks as one of the worst affected industries (S & P global, 2020). The estimated annual drop in global passenger demand and revenue amounts to 2.70 billion passenger trips and 371 billion dollars respectively (ICAO, 2021). The US airline domestic passenger demand reduced by 476.4 million in 2020 compared to the previous year (BTS, 2021a). Airline demand in the recent months has started to recover from April 2020 lows as precautions at airports, access to testing and mask mandates has encouraged some air travel. However, the magnitude of the challenge facing the airline industry is highlighted by the current state of operations. Airline demand in December 2020 still represents only 39.1% of the demand in December 2019.

The emergency use authorization of vaccines offers promise in curbing the pandemic and supporting the recovery. As the recovery begins airlines and airports would need to address supply side shortages with growing demand. This is particularly critical as airline supply (flights) has reduced by about 70% relative to the previous year (BTS, 2021b). Understanding the potential path to recovery will allow airlines, airport management agencies to design plans for increasing flight availability and hiring staff for airline and airport operations. In this context, the primary focus of our proposed research effort is to develop a framework that provides a blueprint for airline demand recovery at a high resolution as COVID-19 cases evolve over time. As airline travel involves traversing across various parts of the country, the proposed demand prediction framework needs to accommodate for the global and local impact of COVID-19 transmission rates while controlling for a host of independent variables (and their interactions with COVID-19 transmission) that are closely associated with airline demand.

While COVID-19 affected airline demand across the US, variations in COVID-19 spread across the country has resulted in varying range of impacts across different parts of US. In December 2020, the reduction in airline demand relative to December 2019 amounted to 71.6% across airports in the North-East and 55.0% across airports in the South. As opposed to examining aggregate airline demand, a high resolution demand prediction framework would provide a better understanding of the demand reduction and the potential path for recovery. Towards achieving this broad objective, the current study develops a model for analyzing airport level passenger demand data characterized as monthly departures at the airport level. A linear mixed modeling method that examines monthly airport level passenger demand from January 2019 through December 2020 is estimated with a host of independent variables including (a) global and local COVID-19 factors, (b) county level demographic characteristics, (c) built environment characteristics, (d) airport specific factors, (e) spatial factors, (f) temporal factors and (g) adjoining county attributes. The model developed is employed to generate predictions for airline demand under various scenarios of future COVID-19 transmission in response to vaccinations and other guidelines. The research develops a potential band of airline recovery demand over time by considering expected, pessimistic and optimistic scenarios.

The rest of the paper is organized as follows: Section 2 describes relevant earlier research and positions the current study. Section 3 presents details of the dataset and modeling approach employed in the research. The next section presents the model estimation results. In Section 5, we undertake a validation exercise to compare observed and predicted demand to evaluate the model performance. The results of policy analysis are presented in section 6. Finally, concluding remarks are included in the last section.

2 CURRENT STUDY IN CONTEXT

2.1 *Relevant Earlier Work*

The literature relevant to the current study context can be categorized into three major streams: a) studies investigating the factors influencing airline demand, b) studies examining the influence of external shocks (such as September 11 attacks) or health pandemics such as Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) and c) studies investigating the impacts of Covid-19.

The first group of studies develop airline demand prediction frameworks considering a host of independent variables. The demand prediction exercise is typically conducted at two spatial resolutions: (a) airport level (Li & Wan, 2019; Loo et al., 2005; Suryani et al., 2010; Wei & Hansen, 2006; Zhou et al., 2018) and (b) regional level (Abed et al., 2001; Chang, 2014; Chen et al., 2009; Chi, 2014; Chi & Baek, 2013; Endo, 2007; Grosche et al., 2007; Grubb & Mason, 2001; Kalić et al., 2014; Matsumoto, 2004; Mostafaeipour et al., 2018; Rengaraju & Arasan, 1992; Tsui et al., 2014; Valdes, 2015). 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 (such as state level or census region level). Across the two spatial resolutions, the factors affecting airline demand include 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 airfare and distance) and historical demand (considered as lag variables). In terms of mathematical frameworks employed for analyzing demand, prevalent approaches include: (a) prediction methods using data and (b) distribution or assignment methods. The majority of prediction methods focused on trip departures from the spatial unit of interest employing passenger demand models such as regression models and their advanced variants (Abed et al., 2001; Chang, 2014; Chi, 2014; Endo, 2007; Rengaraju & Arasan, 1992; Valdes, 2015), artificial neural networks (Mostafaeipour et al., 2018), Holt–Winters method (Chen et al., 2009; Grubb & Mason, 2001), seasonal autoregressive integrated moving average (Chen et al., 2009; Tsui et al., 2014; Xu et al., 2019) and fuzzy models (Kalić et al., 2014). The second set of studies match the pairwise origin destination demand using approaches such as gravity models (Grosche et al., 2007; Matsumoto, 2004; Zhou et al., 2018), bi-level optimization (Li et al., 2013; Li & Wan, 2019) and continuous equilibrium approach (Loo et al., 2005).

The second group of studies considered include research efforts that examined the impact of external shocks (such as September 11th attacks) or health shocks such as SARS and MERS on airline industry. Ito & Lee, 2005a assessed the influence of September 11 terror attacks on US airline demand using monthly observations of revenue passenger miles. The study found a sudden

reduction of about 30% in demand in response to the shock. Further, the authors also found that the reduction in demand took well over 2 years to dissipate while controlling for various independent variables (such as economic and seasonal factors). In a subsequent paper (Ito & Lee, 2005b), the authors extended the work to examine the impact of the terror attack on international airline markets. The subset of studies examining health shocks also developed similar approaches. Chi & Baek, 2013 employed autoregressive distributed lag model to study relationship between economic growth and airline demand while controlling for the impact of SARS outbreak. The results indicate that SARS epidemic decreased US air passenger demand by 6%. Pine & McKercher, 2004 also studied the impact of SARS outbreak on tourism and airline industry and presented a descriptive analysis of reductions induced by the epidemic.

The third group of studies, conducted after the onset of COVID-19 pandemic, can be broadly characterized as preliminary research studying the impact of Covid-19 on airline demand. Maneenop & Kotcharin, 2020 identified three crucial announcements that triggered the airline demand reduction including (a) the first case reported outside China, (b) Italy outbreak and (c) the global pandemic declaration issued by WHO. Nižetić, 2020 performed descriptive analysis to see how Covid-19 affected air transport mobility concluding that the number of flights in the EU region dropped by more than 89% in April 2020 (relative to April 2019). Gudmundsson et al., 2020 analyzed world air transport industry employing time series models to study air traffic volume recovery timeline. The authors developed models employing economic indicators (such as Gross Domestic Product and Oil prices) and COVID-19 indicators and conclude that air transport recovery is likely to take about 2.4 years starting from 2020 with the most optimistic estimate of recovery in latter half of 2021. Gallego & Font, 2020 examined a large data of airline passenger searches and picks to evaluate airline demand and recovery patterns. The analysis using Big Data approaches suggests an L-shaped recovery as the pandemic progresses. Sun et al., 2020 employed data from 150 airlines and 2751 airports across the world to evaluate the impact of COVID-19 on airline industry between January 2020 and May 2020 employing complex network approaches. The study concluded that airport networks in the southern hemisphere experienced more significant disruptions relative to airport networks in the northern hemisphere.

2.2 Limitations of Current Research and Contributions of the Current Study

The review of literature highlights the exhaustive research on developing airline demand prediction frameworks. The research on measuring the impact of shocks (external or health) on airline demand focused on a retrospective analysis as opposed to offering insights for the potential recovery of demand in response to the shock. While earlier research provides the building blocks of demand prediction systems and some insights on modeling demand in the presence of shocks, these frameworks have not been employed to study demand recovery patterns.

The proposed research builds on the demand prediction frameworks at the airport level by accommodating for the influence of COVID-19. Specifically, the study contributes to our understanding of the unprecedented drop in air passenger demand by examining airline data from the Bureau of Transportation Statistics (BTS) at the disaggregate resolution of airport using a linear mixed model. The study contributes to the airline demand literature along multiple directions. First, research on COVID-19 impact on airline industry is in the nascent stages and has predominantly focused on global or regional effects. In our research, we examine the influence of

COVID-19 at the disaggregate resolution of airport to incorporate the interplay of local and global factors on airline demand. The interaction between local and global factors is considered by considering global and local COVID-19 transmission, temporal indicators of pandemic start and progress, and interactions of airline demand predictors with global and local COVID-19 indicators. In our study, we conduct our analysis considering 380 airports across the country. For these airports, we augmented the airline demand data with a host of independent variables including COVID-19 related factors, demographic characteristics and built environment characteristics at the county level, spatial factors, temporal factors, and adjoining county attributes. Second, the research study employs a robust modeling framework to analyze airline demand variable. The study examines monthly airline demand (transformed to the natural logarithm) for 24 months from January 2019 through December 2020. A linear mixed model system that accommodates for the presence of repeated measures is developed. An exhaustive specification exercise is conducted to evaluate the impact of various COVID-19 factors while controlling for other attributes affecting airline demand. Finally, the proposed model is employed to undertake a scenario analysis that will allow us to provide a blueprint to the path to recovery for airline demand. The research team considers three scenarios – expected, pessimistic and optimistic – to generate the recovery patterns for airline demand. The results at the airport level were aggregated at the state or regional level by adding the demand from all airports in the corresponding state or region. These trends are presented by State and Region to illustrate potential differences across various scenarios.

3 DATA AND RESEARCH METHODS

3.1 Data Preparation and Summary

In this current study, we consider monthly airline demand for 24 months from January 2019 through December 2020. The dependent variable is sourced from T-100 Domestic Market dataset provided by Bureau of Transportation Statistics (BTS). Flight passenger counts are aggregated over origin airports for each month to generate the dependent variable. For selection of the airports, we consider the top 400 busiest airports in the US. After removing airports with missing records 380 airports remain in the estimation sample. The final dataset consists of 9,120 records in total (24 records for each airport). A representation of the monthly demand across the 380 airports is presented in Figure 1. The total demand is partitioned by region including South, West and Mid-West and rest of the country. The figure clearly illustrates the shock to the airline industry beginning in March 2020. The demand has started recovering in June 2020. However, the airline demand in December 2020 is still only a fraction of the previous year flows.

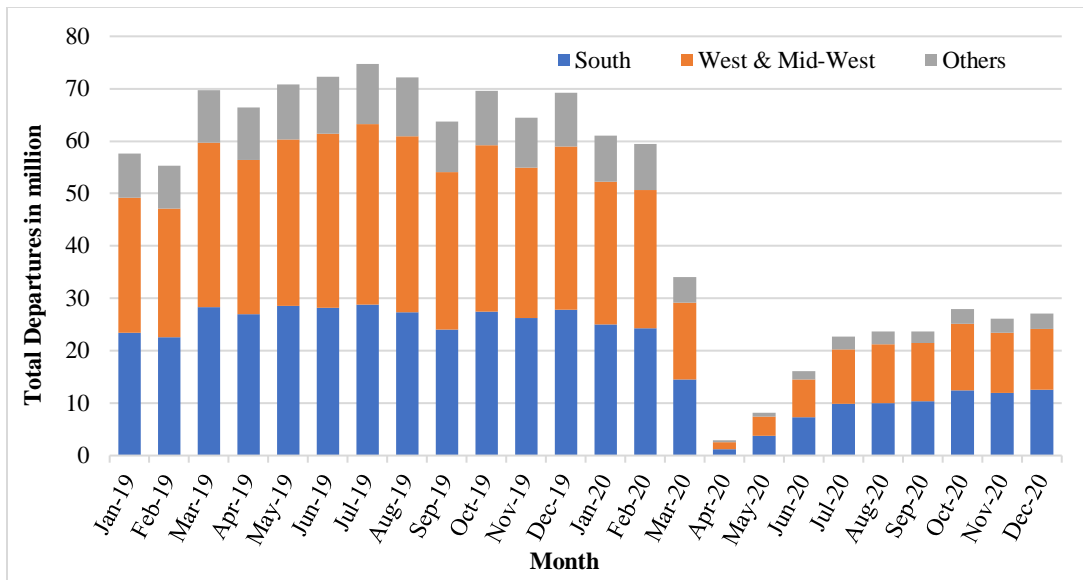


Figure 1 Domestic Air Passenger Departure Rate by Month and Region

A more detailed examination of demand during pandemic months (March through December) is presented in Figure 2. Specifically, Figure 2 presents the monthly percentage change in airline demand relative to the previous year. The results highlight the varying recovery patterns across the various regions. From the figures we can observe that demand in the Southern region is recovering slightly faster than the rest of the country.

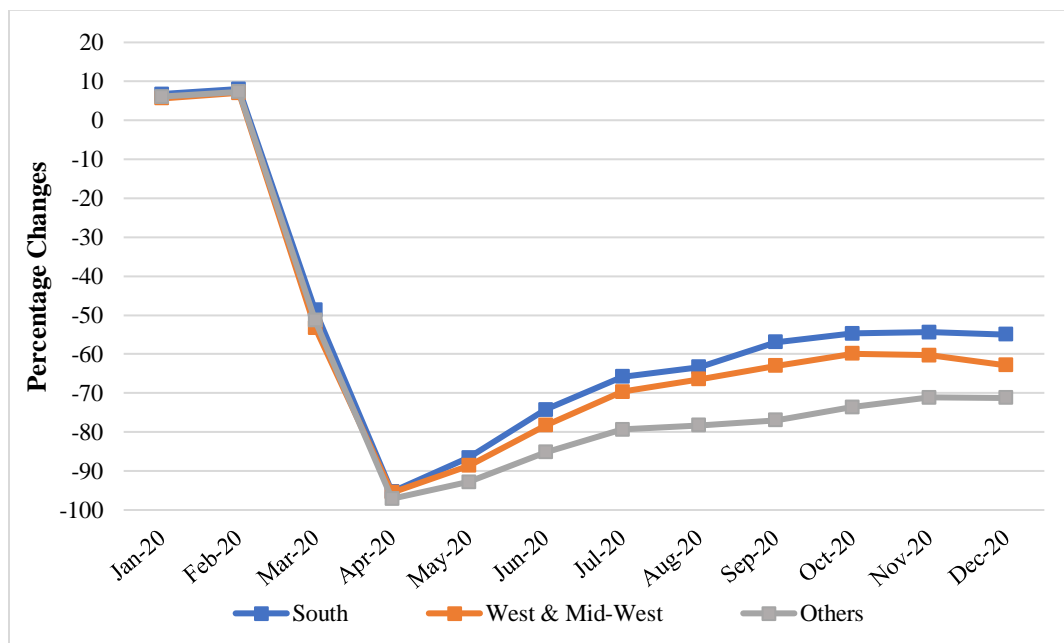


Figure 2 Changes of Air Passenger Demand across Different Regions

3.2 Independent Variable Compilation

The airline demand variable is augmented with a comprehensive set of independent variables including COVID-19 related factors, county level demographic characteristics, built environment

characteristics at the county level, airport specific factors, spatial factors, temporal factors, and adjoining county attributes. COVID-19 related factors include both global and local effects of COVID-19 on airline demand. Global factors capture the change of demand across the months since the pandemic started while controlling for the number of local COVID-19 cases. In our study, we considered several binary variables as global factors including pandemic started month, May 2020 or later, July 2020 or later, October or later variables and their interactions with other variables. The local effects of COVID-19 represent the impact of county level Covid-19 cases on airline demand. In this study, we consider natural logarithm of past month’s new cases at the county level of the airport as the local effect. County level monthly cases are processed from the COVID-19 dataset from Center for Systems Science and Engineering (CSSE) Coronavirus Resource Center at Johns Hopkins University (CSSE, 2021). Total cases in the US by month from January 2020 to August 2021 is presented in Figure 3. The figure highlights the new surge in COVID-19 cases starting from July 2021.

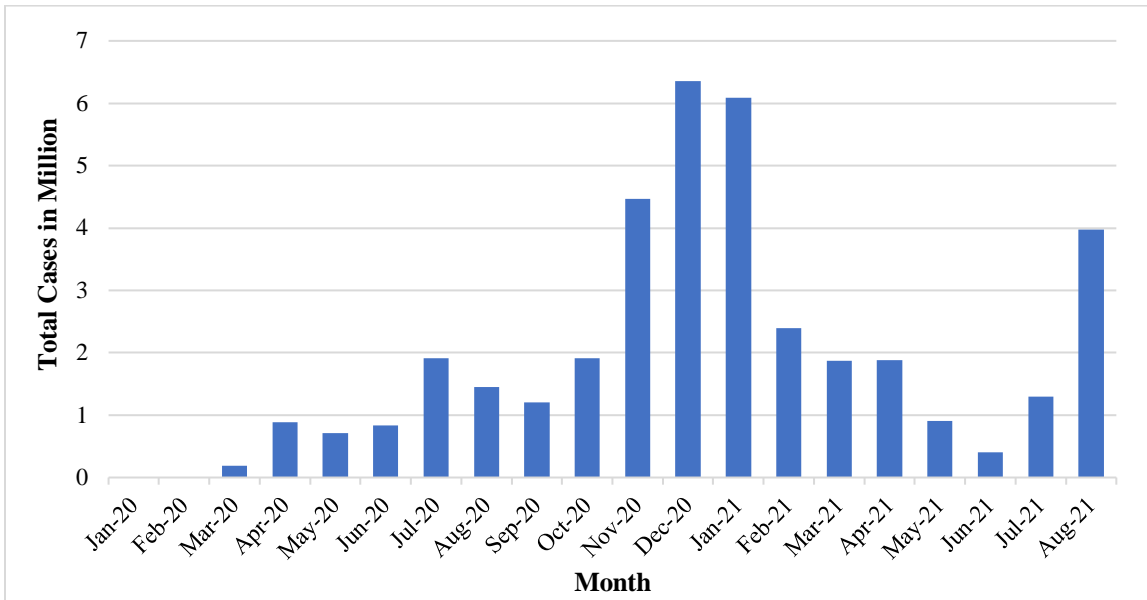


Figure 3 Total COVID-19 Cases by Month

County level demographic characteristics considered include population, median income, unemployment rate, percentage of senior residents and percentage of households with 2 or more vehicles. Demographic data are sourced from American Community Survey (ACS) data. Built environment characteristics tested include number of airports in 50-mile buffer area and state level tourism ranking. Airport specific factors include the type of airport. In this study, we consider a binary classification of the airport categorized as large and small airports. Operational Evolution Partnership (OEP 35) airports are marked as the large airports and remaining airports are marked as the small airports. Spatial factors include location of the airport in terms of US regions. The regions include South, North-East, West, Mid-West and Pacific regions. Temporal factors include quarters and month of the year. Finally, we consider the effect of attributes of adjoining counties (spillover effect) on airline demand. Spillover attributes include mean of different attributes of the neighboring counties such as population, median income, unemployment rate, vehicle ownership

level and new COVID-19 cases in the preceding month. A descriptive analysis summary of the independent variables is presented in Table 1.

Table 1 Descriptive Analysis of the Independent Variables

Variables	Description	Frequency	Percentage
Categorical Variables			
<i>Built Environment Characteristics</i>			
State level tourism			
Top 10	The state is among top 10 tourists' attraction state	109	28.7
Bottom 10	The state is among bottom 10 tourists' attraction state	39	10.3
Others	The state is not among top 10 or bottom 10 states	232	61.1
<i>Airport Specific Factors</i>			
Operational Evolution Partnership (OEP) airports			
Yes		35	9.2
No		345	90.8
<i>Spatial Factors</i>			
Region			
South	The airport is located in South region	122	32.1
North-East	The airport is located in North-East region	45	11.8
West	The airport is located in West region	91	23.9
Mid-West	The airport is located in Mid-West region	84	22.1
Pacific	The airport is located in Pacific region	38	10.0
<i>Temporal Factors</i>			
Month			
June 2019		380	4.2
July 2019		380	4.2
November 2019		380	4.2
December 2019		380	4.2
Other months		7600	83.3
<i>COVID-19 Related Factors</i>			
Pandemic started			
Yes	Month is March 2020 or later	3800	41.7
No	Month is before March 2020	5320	58.3
May or later			
Yes	Month is May 2020 or later	3040	33.3
No	Month is before May 2020	6080	66.7
July or later			
Yes	Month is July 2020 or later	6840	75.0
No	Month is before July 2020	6912	25.0
October or later			
Yes	Month is October 2020 or later	1140	12.5
No	Month is before October 2020	7980	87.5
Continuous Variables			
Variables	Description	Mean	Min/Max
<i>County Level Demographic Characteristics</i>			
Population	Population in million	0.518	0.000/10.160
Median income	Ln(Median income in thousands)	10.944	10.350/11.820

Unemployment	County level unemployment rate	4.346	2.000/19.900
Senior population	% of population having age 65 and over	15.658	5.877/39.444
Vehicle 0	% of HH with 0 vehicle	8.982	1.700/87.800
Vehicle 1	% of HH with 1 vehicle	33.329	10.000/47.800
Vehicle 2	% of HH with 2 vehicles	37.034	2.100/48.200
Vehicle 3+	% of HH with 3 or more vehicles	20.658	0.100/38.100
<i>Built Environment Characteristics</i>			
Ln(Airport)	Ln(No. of airports in 50-mile buffer area)	1.842	0.000/3.740
<i>COVID-19 Related Factors</i>			
Ln(COVID-19 cases)	Ln(County level new COVID-19 cases in the past month)	2.138	0.000/11.670
<i>Adjoining County Attributes (Spillover Effects)</i>			
Population	Average population in neighboring counties in million	0.207	0.000/4.520
Median Income	Ln(average median income in neighboring counties in thousand)	3.935	0.000/4.690
Unemployment	Unemployment rate	4.612	0.000/16.470
Vehicle 0	% of HH with 0 vehicle	8.102	0.000/68.400
Vehicle 1	% of HH with 1 vehicle	29.723	0.000/57.400
Vehicle 2	% of HH with 2 vehicles	35.989	0.000/44.450
Vehicle 3+	% of HH with 3 or more vehicles	24.084	0.000/44.700
Ln(COVID-19 cases)	Ln(average new COVID-19 cases in the past month in neighboring counties)	1.801	0.000/10.680

3.3 Econometric Methodology

The airport level monthly departure variable is a continuous value and can be analyzed using linear regression models. However, the traditional linear regression model is not appropriate for data with multiple repeated observations. In our empirical analysis, we observe monthly airline demand at the same airport for twenty four months. Hence, we employ a linear mixed modeling approach that builds on the linear regression model while incorporating the influence of repeated observations for the same airport (see Bhowmik et al., 2021; Bhowmik and Eluru, 2021 for similar approach). The linear mixed model collapses to a simple linear regression model in the absence of any airport specific effects.

Let $z = 1, 2, \dots, Z = 380$ be an index to represent each airport, $t = 1, 2, \dots, 24$ be index to represent the month for which data is compiled for each airport. The dependent variable (airport level monthly departures) is modeled using a linear regression equation with the following structure:

$$y_{zt} = \beta X_{zt} + \varepsilon_{zt} \quad (1)$$

where y_{zt} is the natural logarithm of monthly airline demand, X is a $K \times 1$ column vector of attributes and the model coefficients, β , is a $K \times 1$ column vector. The random error term ε_{zt} , is assumed to be normally distributed across the dataset. In our analysis, each airport is repeated 24 times, once for each month. These repetitions over months can result in common unobserved factors affecting the dependent variable. In our model, we used first order autoregressive moving average as the repeated covariance structure. The exact functional form of the covariance structure assumed is shown below:

$$\Omega = \sigma^2 \begin{pmatrix} 1 & \phi\rho & \dots & \phi\rho^{n-1} \\ \phi\rho & 1 & \dots & \phi\rho^{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \phi\rho^{n-1} & \phi\rho^{n-2} & \dots & 1 \end{pmatrix} \quad (2)$$

The covariance structure allows for a dampening relationship over time. The parameters estimated in this correlation structure are σ , ρ and ϕ . The models are estimated in SPSS using the Restricted Maximum Likelihood Approach (REML). The REML approach estimates the parameters by computing the likelihood function on a transformed dataset. The approach is commonly used for linear mixed models (Harville, 1977).

4 ANALYSIS AND RESULTS

In our study, we analyzed airport level monthly air passenger departures using a linear mixed model. A host of independent variables were considered in the model development process. As the main focus of our study is on understanding the impact of COVID-19, variables related to COVID-19 and various interactions were tested in the model specification. However, we also included different factors that have been identified as important determinants of airline demand. In summary, the model estimation process was guided by earlier research, variable interpretability and parameter statistical significance.

The final model results are presented in Table 2. The positive (negative) value of the parameter estimates indicates increase of a parameter increases (decreases) the airline demand. The results are discussed in detail in the following subsections by the attribute levels.

4.1 County Level Demographic Characteristics

Demographic characteristics are expected to serve as controls for airline demand. As expected, counties with larger population are likely to have higher airline demand as population serves as a surrogate measure for demand (please see Grosche et al., 2007; Zhou et al., 2018 for similar results). On the other hand, a higher percentage of senior population is found to be negatively associated with the air passenger demand. The parameter for county level unemployment rate highlights the negative association of unemployment rate with airline demand. The result is plausible as increased unemployment rate, in general, corresponds to decreased affordability for personal travel and fewer business activity in the region.

4.2 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. We found that an increased number of airports in the 50-mile buffer results in higher air travel demand at an airport. The presence of additional airport(s) in close proximity reflects higher demand in the region. Further, we considered the tourism status of the state in our analysis by identifying the top and bottom 10 desirable states with respect to tourism activity. As expected, we find that air travel demand is higher (marginally significant) in an airport located in top 10 tourist attraction states while a reduced air demand is observed for an airport located in the bottom 10 visiting states (see Sivrikaya & Tunç, 2013 for similar results). The reader would note that tourism ranking in our analysis is considered at a state resolution. Ideally, county level tourism measures such as expenditures or hotel beds would be

preferred variables. However, access to such data across the country is not readily available and is a direction for future research.

4.3 Airport Specific Factors

In this study, we consider the type of airport as an airport specific factor. We classified the airports as Operational Evolution Partnership (OEP) airports and other airports. OEP airports capture approximately 70% of the total domestic airline demand in US and are identified as large airports in the analysis. The positive coefficient of binary OEP airport variable indicates that air passenger departure rate is higher in OEP airports compared to other airports. The result reflects the higher demand in OEP airports in the US.

4.4 Spatial Factors

Location of the airports across various US regions has a significant effect on the total number departures from those airports. In general, compared to the airports in the other regions, the demand is observed to be higher for an airport in the South region. An examination of the airports in the South region reveals that some of the busiest airports in the US (3 of the top 10 busiest airports (Travel, 2021)) are from this region. Further, we also find that airports in the South are located further away from one another relative to airports in the North-East and West. It is possible that these airports have much larger catchment areas, and the South indicator variable possibly serves as a surrogate for the larger catchment size.

4.5 Temporal Factors

Monthly and Quarterly indicator variables were tested in the model to allow for seasonal effects. In our model estimation, the results indicate that travel demand was higher in the months of June, July and December 2019 and lower in November 2019 compared to other months while controlling for other factors. These results can be attributed to presence of seasonality in air travel demand.

4.6 COVID-19 Related Factors

COVID-19 related factors considered in this study include both global and local effects of COVID-19 on airline demand. Global factors were considered in the model in various functional forms including continuous (such as linear, square and other polynomial) and indicator variables (such as month indicator for pandemic, pandemic from May or later and Pandemic from July or later). Local COVID-19 factors considered include the natural logarithm of county level total new COVID-19 cases in the preceding month. The reader would note that the net effect of COVID-19 is a sum of the global effect and the local case specific effect.

As expected, the pandemic variable (set to 1 for all months from March 2020) has a negative coefficient indicating that airline demand dropped significantly after the pandemic started. The positive coefficient of May or later variable indicates that airline demand recovered after May (while controlling for other variables). The positive coefficient of July or later and October or later variables indicate that airline demand increased further since these time periods. However, airline demand was negatively influenced by local COVID-19 data in the airport county for these months. The result indicates that the air travel is likely to reduce in the presence of increasing COVID-19 cases in the preceding month. It should be noted that while some recovery has happened as reflected in May or later, July or later and October or later indicator variables, the

net change in airline demand relative to the corresponding month in 2019 has been negative across the country.

In addition to the main effects described, we also tested for several interaction effects of COVID-19 variables with other factors affecting airline demand. The positive coefficient of the interaction of pandemic variable and population indicates that the initial drop of demand in March and April of 2020 due to COVID-19 was lower in the airports located in a county with higher population. The interaction analysis also found that the larger airports (OEP airports) exhibit slightly different trends. Specifically, we found that the initial drop of demand in March and April of 2020 is slightly lower in OEP airports. The coefficient for May or later at OEP airports further highlights higher recovery in these airports. A negative coefficient for July or later variable indicates a reduced differential with other airports from July. Finally, interaction of south region and pandemic started variable is found significant. The positive coefficient of the interaction term indicates that the initial drop in airline demand in the airports in the south region is lower compared to the airports in other regions. The finding might be attributed to reduced adherence to public health guidelines in many states from this region.

4.7 Adjoining County Attributes (spillover effects)

The parameter estimates indicate that airline demand is also influenced by the attributes of adjoining counties. We found that mean population, median income, and new COVID-19 cases in the neighboring counties influence airline demand at the airport level in an intuitive manner. The effects of population and median income indicate that increased population and median income in the neighboring counties increase airline demand. The effect of neighboring county COVID cases indicates that increased new COVID cases in the adjoining counties significantly decreases airline demand.

4.8 Covariance Parameters

The last row panel of Table 2 present the results for the covariance parameters (σ^2 , ρ and ϕ). As expected, these parameters are significant and highlight the presence of common unobserved factors affecting the repeated airline demand data for each airport.

Table 2. Parameter Estimates for Liner Mixed Model

Parameter	Estimates	Std. Error	t stat
Fixed Effects			
Intercept	9.293	0.696	13.354
<i>County Level Demographic Characteristics</i>			
Population in million	0.379	0.088	4.304
Senior population	-0.070	0.019	-3.696
Unemployment rate	-0.304	0.036	-8.411
<i>Built Environment Characteristics</i>			
Ln(No. of airports in 50 mile buffer)	0.448	0.119	3.750
State level tourism (Base: Others)			
Top10	0.353	0.193	1.829
Bottom10	-0.593	0.266	-2.232

<i>Airport Specific Factors</i>			
OEP airports (Base: No)			
Yes	3.082	0.310	9.930
<i>Spatial Factors</i>			
Region (Base: Other regions)			
South	0.552	0.184	2.998
<i>Temporal Factors</i>			
Month (Base: Other months)			
June 2019	0.053	0.027	2.008
July 2019	0.114	0.027	4.293
November 2019	-0.105	0.027	-3.972
December 2019	0.059	0.027	2.241
<i>COVID-19 Related Factors</i>			
Pandemic started (Base: No)			
Yes	-0.957	0.039	-24.352
May or later (Base: No)			
Yes	1.621	0.035	46.143
July or later (Base: No)			
Yes	0.958	0.032	29.886
October or later (Base: No)			
Yes	0.183	0.030	6.105
Ln(County Level Covid-19 Cases in the last month)	-0.304	0.012	-25.356
Population × Pandemic started	0.059	0.028	2.070
OEP airports × Pandemic started	0.181	0.113	1.601
OEP airports × May or later	0.171	0.104	1.641
OEP airports × July or later	-0.292	0.104	-2.817
South × Pandemic started	0.213	0.064	3.322
<i>Adjoining County attributes (spillover effects)</i>			
Average population (million)	0.572	0.240	2.379
Ln(average median income in thousand)	0.299	0.131	2.277
Ln(average COVID-19 cases in past month)	-0.107	0.015	-7.350
Covariance Parameters			
σ^2	3.201	0.175	18.252
ρ	0.965	0.003	349.007
ϕ	0.940	0.003	272.200

5 MODEL PERFORMANCE

The performance of the linear mixed model was compared with the performance of the traditional linear regression model using log-likelihood and Bayesian Information Criterion (BIC)¹. The log-likelihood (BIC) values for the models are as follows: linear regression model: -17247.95 (34505.01) and linear mixed model: -8720.29 (17467.92). From the comparison, it is evident that the linear mixed model offers improved fit in our data.

We also evaluate the performance of the proposed model in predicting the demand. Specifically, we compare the total observed demand and predicted demand in US (see Figure 4). An examination of Figure 4 plot illustrates that the proposed model represents the demand trends before and after the pandemic. The model successfully captures the demand drops after the start of the pandemic and the slow continuing recovery after the initial months. The reader would note that the airline demand data is available only till December 2020. In our prediction exercise, we also generate demand for January 2021 through September 2021 by employing COVID-19 data available up to August 21, 2021. For COVID-19 cases in the full month of August (as required to predict demand for September), we assumed same infection rate in the remaining days of August as it was in the first 21 days of the month. The figure shows that the demand may decrease in the future months, especially in September, due to recent increase of COVID-19 cases.

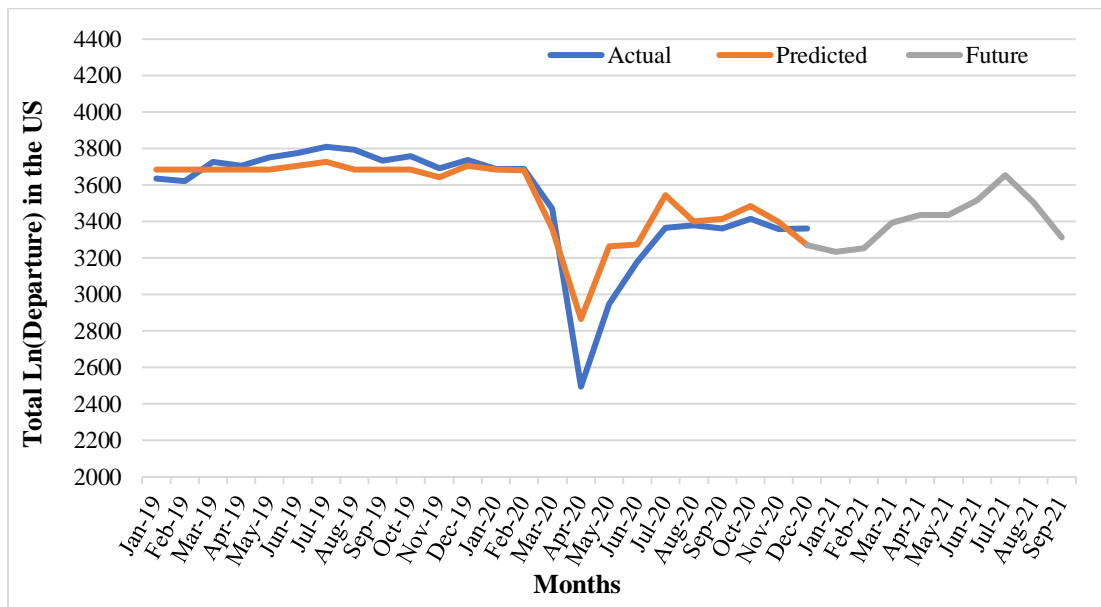


Figure 4 Predictive Performance of the Proposed Model

6 POLICY ANALYSIS

As discussed in the study objectives, the model development exercise was motivated by the need to present a blueprint for airline demand recovery. To illustrate the model applicability for generating monthly airline demand estimates, we consider three hypothetical scenarios of COVID-19 transmission rates – expected, pessimistic and optimistic. In these scenarios, a rate of increase

¹ The reader would note that due to the inherent structure of linear mixed models, traditional goodness of fit measures such as R^2 are not readily applicable and require more involved approaches to computing the measure (see Nakagawa & Schielzeth, 2013 for more details).

or decrease for COVID-19 is considered. While the rate considered is uniform across the country, the actual change in cases will depend on current transmissions in the counties. Thus, we will be accommodating for a spatially varying COVID-19 case load in the country. The exact assumptions for the scenarios are described below:

- 1) **Expected Scenario:** The scenario is based on the expected increase in vaccinations of the approved vaccines such as Pfizer BionTech and Moderna across US. Hence, in this scenario COVID-19 cases are likely to increase marginally in September 2021 (August is at a high and plateauing). As increased proportions of the population are vaccinated, we expect the transmissions to drop in the subsequent months as follows: October 2021 (15%), November 2021 (20%), December 2021 (20%), and January 2022 (20%). The reader may see IHME, 2021 to find similar expected scenario of COVID-19 transmission rate.
- 2) **Pessimistic Scenario:** The proportion of vaccinated population does not increase significantly, and infection rate keeps increasing following the trend in recent months. We assume the infection rate will increase by 20% in September 2021 and October 2021 followed by 10% increases in each of the months from November 2021 through January 2022.
- 3) **Optimistic Scenario:** The scenario assumes a better-than-expected impact of vaccination due to rapidly increased vaccination rate and possible emergence of booster doses. In this scenario, we assume that the infection rate will increase by 5% in September and booster doses will be available by end of September causing 25% decrease in COVID cases in October 2021. Finally, cases will decrease by 35%, 50% and 50% in the following months.

Table 3 Percentage Changes in New COVID-19 Cases Compared to the Preceding Month

Month	Expected	Pessimistic	Optimistic
Sep-21	10%	20%	5%
Oct-21	-15%	20%	-25%
Nov-21	-20%	10%	-35%
Dec-21	-20%	10%	-50%
Jan-22	-20%	10%	-50%

The rate of change of COVID-19 cases for different scenarios by month are summarized in Table 3. Based on these assumptions, the airline demand is predicted using the proposed linear mixed model and the demand is aggregated to identify the total airline demand for the months of interest. Then, we perform a month-by-month comparison of airline demand for months September 2021 through February 2022 with the corresponding months in 2019. To facilitate the understanding of recovery process across the country, the numbers are aggregated by US region. The results of the analysis are then presented in Figure 5. Figure 5 shows the future percentage changes in airline demand in the US by month across different regions. From Figure 5, the following observations can be made for the three scenarios considered:

- 1) **Expected Scenario:** In this scenario, airline demand will decrease in September 2021 and October 2021, followed by a small increase in November 2021. Airline demand will further decrease in December 2021. Finally, the demand will start recovering starting from January 2022. If we compare the demand changes for the four regions, we can see that south region

experienced the lowest drop in demand and may also recover faster than the other regions in the US.

- 2) Pessimistic Scenario: In this scenario, airline demand will continue decreasing and drop by 87% by February 2022. Airports across all regions may experience similar decrease in demand but airports in West region may have the highest decrease estimated at 90%.
- 3) Optimistic Scenario: In this scenario, airline demand may keep decreasing till October 2021. But in response to the improved COVID-19 condition, the recovery will start from November 2021 and accelerate in the latter months. By February 2022, airline demand in the US may reach 38% of the typical demand. If we compare the recovery rate for regions, we can see that South region will recover faster and the demand may be 50% of original demand by February 2022.

To offer further insights on the predictions generated, we aggregate the demand at the State level based on all airports in the state and present the estimates for all scenarios (see Figure 6). Figure 6 shows percentage change of airline demand from September 2021 through February 2022 compared to the usual demand from 2019 at the state level. The results follow expected scenario specific trends. We recognize that the policy assumptions are unlikely to be matched exactly. The objective of this exercise is to illustrate the insights that can be generated from the model. These plots generated can be customized with more up to date information on COVID-19 cases to arrive at accurate expected demand.

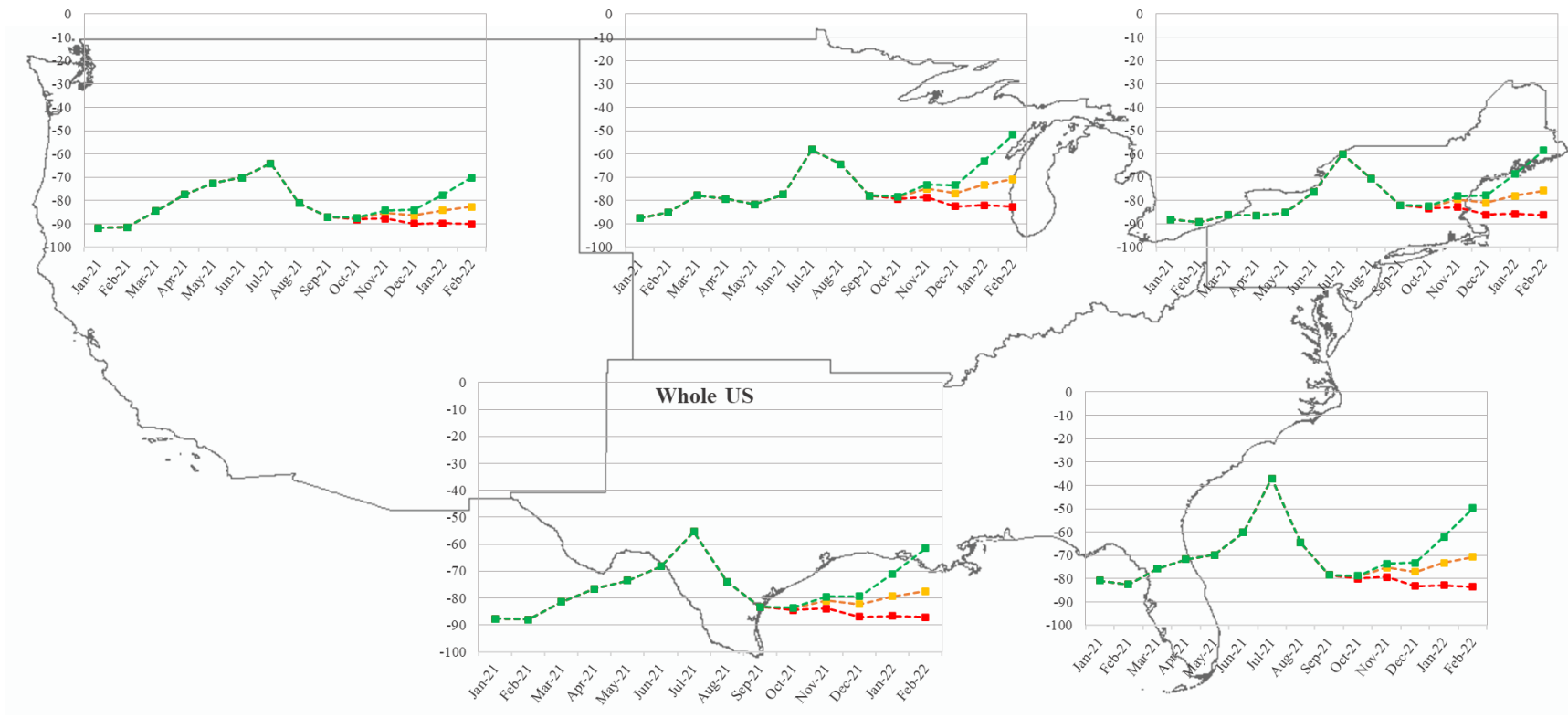
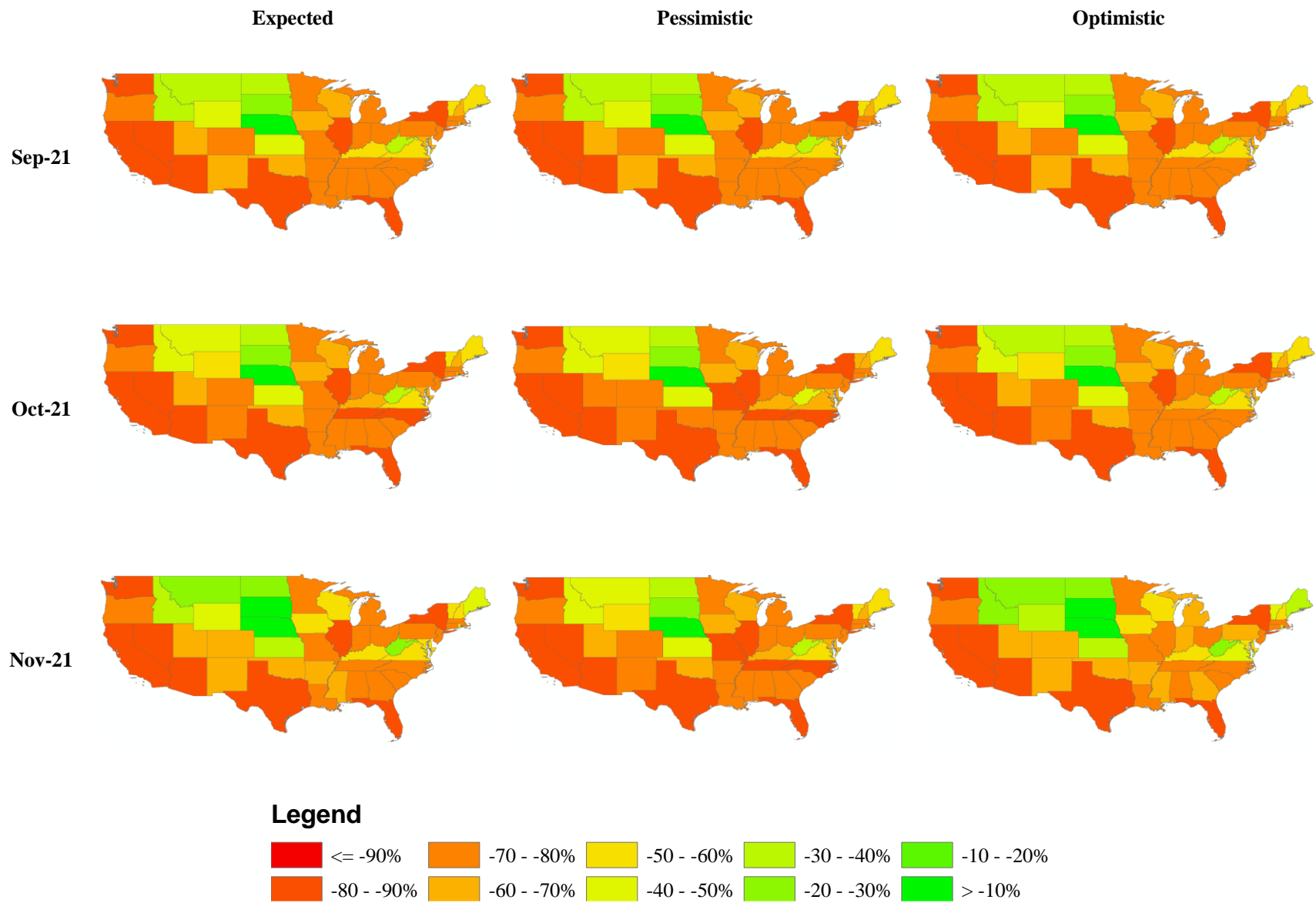


Figure 5 Future Demand Based on Hypothetical Scenarios



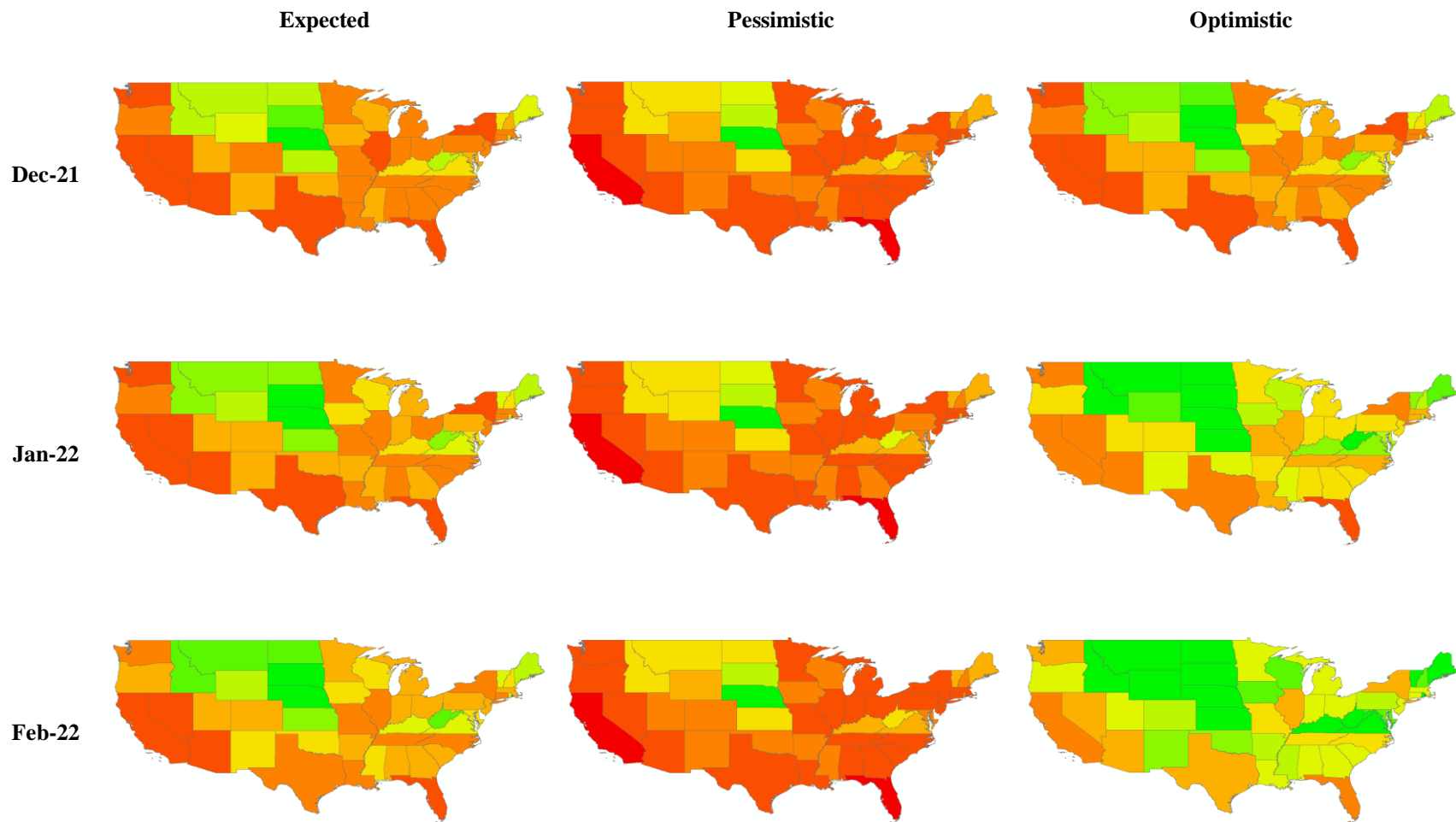


Figure 6 Future Airline Demand at the State Level

7 CONCLUSION

The COVID-19 pandemic has affected every facet of life in the world significantly burdening social, health and economic systems. Among these affected industries, airline industry ranks as one of the worst affected industries. The emergency use authorization of vaccines offers promise in curbing the pandemic and supporting the recovery. As the recovery begins airlines and airports would need to address supply side shortages with growing demand. In this context, the primary focus of our proposed research effort is to develop a framework that provides a blueprint for airline demand recovery at a high resolution as COVID-19 cases evolve over time. In our study, we conduct our analysis considering 380 airports across the country. Airline data employed in this study is sourced from Bureau of Transportation Statistics (BTS) for 24 months from January 2019 through December 2020 which is augmented with a host independent variables including COVID-19 related factors, demographic characteristics and built environment characteristics at the county level, airport specific factors, spatial factors, temporal factors, and adjoining county attributes. COVID-19 related factors include both local and global factors by considering global and local COVID-19 transmission, temporal indicators of pandemic start and progress, and interactions of airline demand predictors with global and local COVID-19 indicators. We employ a linear mixed model system that accommodates for the presence of repeated measures for modelling airline demand.

The linear mixed model identifies several important determinants of airline demand while also capturing the impact of global and local COVID-19 effects on demand. The performance of the model is examined by comparing observed and predicted demand for all airports across the US. The result indicates that model successfully captures the demand drops after the start of the pandemic and the slow continuing recovery after the initial months. Subsequently, we present a blueprint for airline demand by considering three hypothetical scenarios of COVID-19 transmission rates – expected, pessimistic and optimistic. The results at the airport level from these scenarios are aggregated at the state or regional level by adding the demand from all airports in the corresponding state or region. These trends are presented by State and Region to illustrate potential differences across various scenarios. The result from the expected scenario presents a path to slow recovery as COVID-19 cases reduce. The various scenarios clearly illustrate how the proposed model can be employed to generate airline demand estimates at the airport level, state, region or country level.

The study is not without limitations. In our analysis, data was generated at the airport county level. Thus, when the same county has multiple airports, the model includes substantially similar information for these airports (except OEP 35 indicator and number of airports in a 50-mile buffer). While only 22 of the 354 counties in our data had multiple airports, it might be interesting to explore how aggregation of the demand for these airports affects the findings. Moreover, the airline demand data is available only till December 2020 which restricted us from employing linear and non-linear functions of continuous temporal variables. Given the data availability for the next few months, continuous temporal variables could be considered to enhance the current model. Further, COVID-19 pandemic is an evolving situation, and it is appropriate to consider updating the models with newer airline demand (as they become available), local vaccination data and local COVID-19 cases. Finally, the airport level analysis conducted in the paper can be augmented by examining airport level actions/strategies (such as changes to fare,

priority for freight movement) in response to COVID-19 pandemic. The research might have to be conducted for a subset of airports where such data is available.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: NE, TB, SDT; data collection: SDT, TB, NE; model estimation: SDT, TB, NE; analysis and interpretation of results: SDT, TB, NE; draft manuscript preparation: SDT, TB, NE. All authors reviewed the results and approved the final version of the manuscript.

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