International Travel Patterns: Exploring Destination Preferences and Airfare Trends to and from the USA

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ABSTRACT

Approximately one quarter of all U.S. air-passenger trips (involving US airlines only) are to and from foreign destinations, accounting for around 4.5 percent of total US person miles in 2019. Travel demand modeling and US travel surveys often overlook this overseas travel. Therefore, this study assesses travel demand, patterns, and costs (in time and money) between major US and foreign airports worldwide, as well as ground trips to Mexico and Canada, using 2019 DB1B flight ticket data, the 2016-17 National Household Travel Survey (NHTS), and border crossing data. A model of trip distribution, from 334 US airports to 1,028 foreign airports, shows how trip flows fall about 41% with every 7-hour increase in flight start to end time. Destinations hosting tourist attractions (like London, Barcelona, Milan, Paris, Dubai, etc.) are also a practically significant variable in the model, increasing flows by 48%. Flight fares (for one-way itineraries) increase by \$0.078 per mile for coach class and \$0.163 per mile for business class and higher, according to feasible generalized least-squares models. These fares are higher for English-speaking destinations than non-English-speaking destinations, as well as for trips from April to June as compared to January to March with similar distances, flight classes, etc. Understanding international travel is important for local and global economics, the evolution of transportation technology and social networks, and the future of global climate and air quality.

Keywords: International Travel, Demand Modeling, Air Fare, Destination Choice

INTRODUCTION

The fiscal significance of international tourism in the United States cannot be underestimated. In 2019, U.S. tourism supported 9.5 million employment and contributed to 2.9% of GDP, for a total economic impact of \$1.9 trillion. Foreign tourists spend more money in the U.S. than they do in any other country (14.5 percent of all foreign tourists' money) (Travel & Tourism Industry, ITA, 2019). On average, an American spent \$1,487 per person and \$2,429 per travel party on an international trip outside the US in 2019 (APIS/I-92 Monitor, ITA, 2019). According to a more recent ITA release in 2021, Americans spent \$73.9 billion dollars (51% more than in 2020) on international trips, resulting in a trade excess of \$6.2 billion (\$2.1 billion was added just in December 2021) (ITA Data Release, 2021). According to the US Bureau of Transportation Statistics (BTS), the person-miles traveled (PMT) in 2019 was 7.7 trillion, of which 4.5% were international person-miles involving US air carriers (Travel and Tourism Research, 2019). BTS air passenger data suggest that the “average” American makes 0.37 international trips (inbound and outbound) per year by air, boat, road, and train. This implies an international departure by air every 5.43 years (APIS/I-92 Monitor and Travel and Tourism Research, ITA, 2019). The major purposes of these trips (84% of the total) were leisure or visiting friends and relatives (APIS/I-92 Monitor, ITA, 2019). Air travel accounts for 60% of international travel from U.S., land travel accounts for more than 39% (to Mexico and Canada) and travel through water (to Canada) is less than 1% (Travel and Tourism Research, 2019; BTS 2019). In addition to being a key source of household expenditure and national GDP contributor, air travel is a significant source of travel-based emissions and passenger-miles traveled. Thus, analyzing overseas travel and associated destinations is significant in the advancement of future tourism policies, including the regulation of prices, provision of adequate infrastructure and control of environmental quality (Li et al., 2006).

Travel demand modeling studies and U.S. travel surveys regularly miss international travel. Most studies focus on domestic trips, and very few include questions on long-distance trips (from the past month or year, rather than simply catching the few that happen on the survey day).

However, international trips are a notable source of travel cost and emissions, with 8% of global greenhouse gas (GHG) emissions produced via tourism, and 40% of those emissions coming via aviation (Lenzen et al., 2018). Llorca et al. (2018) developed a model for generation, distribution, and mode choice in person trips over 40 km (25 miles, one-way)–but only from Ontario province, in Canada. They observed that land use attributes and trip purpose (or destination activities) are important for destination choice probabilities. For international trip generation, they estimated only the total number of trips (not destination, mode, or timing), due to the lack of data. Prior research on travelers' perception of destinations indicates that factors such as the destination's scenic appeal, cultural sites, and leisure activities, as well as the travelers' attitude towards the location, prior information about the place and personal constraints like time and money, significantly influence destination selection (Um and Crompton 1990; Trembath et al., 2011; Crompton and Ankomah, 1993). However, there is a subset of travellers who are willing to choose a specific destination solely because discounted tickets are available, rather than due to prior intentions to visit that destination (Keshavarzian and Wu 2017).

Transport planning heavily relies on forecasts of travelers' trip decisions, including international travel. Tourism flows and international trade volumes do show up in the literature, especially for specific market pairs. For example, Qu and Lam (1997) used ordinary least squares models to estimate travel demand for mainland Chinese tourists to Hong Kong. They identified income and visa requirements as key predictors. Keum Kiyong (2010) used a gravity model and Linder economic hypothesis to predict trade patterns and tourism flows across Korea. The study confirmed the robustness of the gravity model in estimating international flows. Wu et al. (2012) explored tourism flows between Chinese regions and offered suggestions for tourism improvements. Li et al. (2006) used a time-varying parameter error correction model (TVP-ECM) to predict tourist demand by considering the dynamic changes in demand over time. The model was later compared with other fixed-parameter econometric models and time-series models.

Most studies focus only on international flows between specific places (e.g., like from the US to Canada (Qu and Or, 2006) or all in-coming flows (e.g., Zhang et al., 2009). International business trips are regularly overlooked. Furuichi and Koppelman (1993) used a nested logit model to predict the departure and destination airports of air travelers. They used a survey of international air travelers from Japan and indicated that a joint departure airport and destination choice model better predicts leisure and business international travels than multinomial logit models. They also estimated an integrated model to forecast international air travel demand. This model consists of three major parts: a model for selecting the departure airport, a model for deciding the destination, and one for trip generation. The destination choice model includes a "logsum variable," which combines different levels of service variables associated with access and line-haul travel. The logsum variable quantifies the popularity of a destination by considering many aspects including duration of travel, convenience, and the availability of services. This model considers the cognitive processes of travelers, including their evaluation of different destination characteristics and their tendency to choose certain places over others (Furuichi and Koppelman, 1994).

Many studies in the literature investigated domestic destination choice problems using different statistical models. For example, Woodside and Lysonski (1989) introduced a comprehensive empirical model that aims to forecast the selection of a destination by a traveler. The model was developed based on data collected through a 20-minute survey administered to young adults from New Zealand. These individuals had engaged in overnight travel away from their residence for a duration of seven days or more within the preceding 12 months. The findings of the study suggest that the level of travelers' awareness, past experience, and the range of alternative destination choices have a significant impact on predicting the chosen destination. A study conducted by Mutinda and Mayaka (2012) examined the factors influencing the destination choices of Nairobi residents. The study found that personal safety, destination characteristics, travel arrangements, and party size significantly impact tourists' selection of a location. Clifton et al. (2016) employed the multinomial logit method to forecast the selection of destinations for walking trips within the Portland, Oregon region. Based on the findings, it can be inferred that factors such as employment opportunities, proximity to the location, and the specific attributes of the location significantly influenced the likelihood of selecting it.

Air is a major mode for trips over 500 miles, as well as international travel. Americans made 100 million international trips to other nations in 2019 (including one-way and round trips from US by all modes). BTS (2019) reported that US airlines handled 115 million air passengers in the same year, including both Americans and non-American passengers. Airfare and duration are expected to be important indicators of international travel mode and destination choices. Flight price fluctuates depending on purchase time, number of stops, flight date, and seat class. Recent studies have used machine learning algorithms to predict flight fare using different datasets (e.g., Tziridis et al., 2017). Ratnakanth (2022) analyzed different methods presented in the literature for flight price prediction and indicated that random forest and gradient boosting techniques outperform other machine learning approaches for flight fare prediction. The study stated airline company, travel time, number of stops, and destination as effective factors in the flight price. Flight fare prediction studies are mostly used for defining prices in the future for various airlines. In this study, flight fare and duration are inputs of the trip distribution model and its application. The existing body of research predominantly focuses on either tourist destinations or airfare prediction, leading to a lack of comprehensive analysis of how users make choices regarding foreign travel and the subsequent influence on airfares to their chosen destinations. The present study seeks to tackle this discrepancy by estimating multiple models for airfare prediction to be used inside other international trip destination models, such as the gravity model presented in this paper. International trip demand models presented in this study gives insights to the international trip trends from and into the US, and as a result the insights are helpful in making informed decisions regarding overseas investments, offering guidance and investments in tourism, and efficiently managing embassy activities. In addition, the airfare models and the trip demand model can be used in optimizing aircraft scheduling and pricing of flight tickets, as they estimate the flight tickets as a function of multiple factors, such as time of flight and airline. The research findings on airfare rates and trip time can be leveraged to improve aircraft scheduling and pricing strategies. Airlines can use this study to improve schedules and pricing models, thereby ensuring efficiency and competitiveness in the market. Both governments and businesses can make well-informed decisions regarding investments made abroad. With the help of an insight into the tastes and choices of passengers, they will be in a good position to make strategic decisions on investments in tourism infrastructure and marketing. The study's models can also be employed by tourism boards and industry stakeholders to decide on tourism marketing and infrastructure expansion. The Embassies can optimize their management practices by customizing their operations according to travel patterns. Gaining insight into the preferences of passengers and the level of popularity of specific destinations can enhance the efficiency of preparing events, consular services, and diplomatic engagements. This study employs an integrated approach by combining choice behavior models that take into account demographic characteristics with destination selection behavior that is influenced by different trip attributes. Furthermore, this study investigates the correlation between variations in airfare and factors such as destination, time of year, and ticket type.

The primary objective of this research is to augment the understanding of individuals' global travel patterns, with a specific focus on air transportation originating from the United States. The aim of this study is to utilize travel demand models to forecast airfare rates, travel time, and the distribution of trips among major airports in the United States and worldwide. The research relies on a 10% sample of the 2019 DB1B dataset, which comprises a vast amount of data, encompassing 2.6 million itineraries for roughly 3.9 million travelers. This data is composed of data pertaining to the sale of airline tickets for passengers, which has been gathered by BTS. The study employs Feasible Generalized Least Square (FGLS) models as the methodology to estimate airfares for individual paid itineraries and passengers. Additionally, the FGLS models are utilized to examine the variance in fares for international round trips originating from the US and one-way journeys with US origins. A trip frequency model estimated by Fakhrmoosavi et al. (2023) is first used to estimate the number of long-distance trips among Americans. Then, a binomial logistic regression model is utilized to ascertain the inclinations of Americans towards overseas trips in comparison to domestic long-distance excursions. Ultimately, a gravity model is utilized to approximate the dispersion of journeys originating from diverse locations within the United States to global destinations. The current study expands upon previous studies by presenting demand models for international trips to and from the US. Most prior studies either focus on domestic travel or on limited origin-destination sets. In addition, this study uses an FGLS model to predict airfares, considers heteroskedasticity and autocorrelations. Finally, this study uses multiple data sources, including the DB1B flight ticket data, 2016-17 NHTS, and multiple other tourism data sources to estimate the international trip models considering land trips in addition to air travel.

The remainder of this paper is organized as follows. The subsequent section provides a summary of the datasets employed in this investigation for the purpose of approximating models pertaining to international trip distribution and flight fare explicated. The third section presents the estimated models and is subsequently succeeded by the principal findings derived from models. The final segment provides a summary of the study's conclusions, limitations, and potential future applications.

DATASETS USED

Using international travel datasets, this research examines Americans' overseas destination preferences and models the international travel demand to better prepare for future transportation. This study uses 2019 DB1B flight ticket data, the 2016-17 NHTS as well as publicly available international travel data collected by the National Travel and Tourist Agency (NTTO), Survey of International Air Travelers (SIAT), and Travel and Tourism Satellite Account (TTSA). According to past annual passenger miles recorded by NTTO, international travel accounted for 40% of all revenue passenger miles traveled by US airlines in 2019 wherein US-flagged carriers handled 47% of total international air passengers to and from the United States (APIS/I-92 Monitor, ITA, 2019; BTS, 2019). The SIAT survey on US residents visiting overseas countries revealed that European (19.1%) and Caribbean countries (9.4%) accounted for a large proportion of overseas destinations from US, after Canada and Mexico (54.9%) (SIAT, 2019). Figure 1 shows Americans' rates of travel to different overseas regions in 2019 by air.

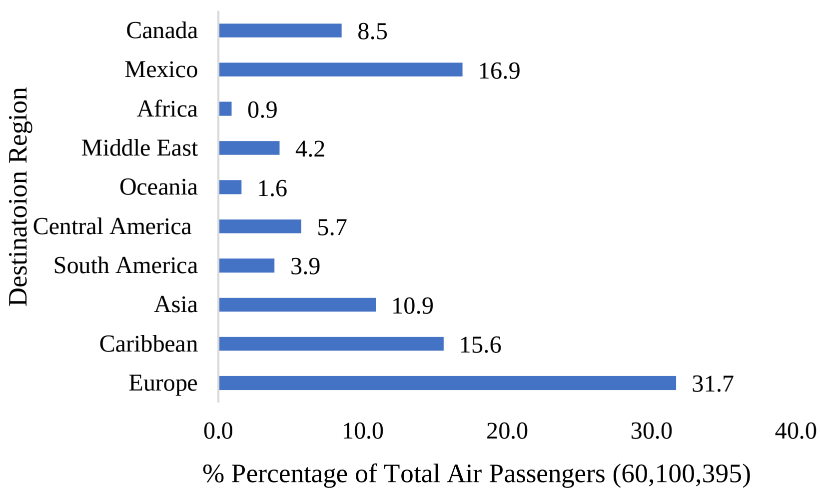

Figure 1 Americans' outbound travel by air in 2019 (SIAT, 2019)

The main data source in this study is the DB1B ticket data collected by the BTS Office of Airline Information. This data is a 10% random sample of US airline passenger ticket itineraries reported by the US flag carriers only. It includes trip origin and destination data, yearly and quarterly indicators, number of passengers, number of legs, and distance and fare information for each itinerary. The dataset producers began publishing records in 1993, providing 28 years of available data. This study uses a 10% sample of the 2019 data (before the COVID-19 pandemic), which contains 2.6 million itineraries for 3.9 million passengers. TABLE 1 and TABLE 2 summarize one-way itineraries to and from the US in the 2019 DB1B data. This includes flight fare and distance flown per itinerary, fare per distance flown, party size (i.e., the number of individuals per flight ticket), and average number of legs (i.e., segments) per trip.

Additionally, the 2016-17 NHTS dataset is used to model Americans' international trip-making choices versus domestic long-distance trips. The trip frequency model for long-distance trips (over 75 miles one-way) is estimated using this NHTS dataset leveraged in the study done by Fakhrmoosavi et al. (2023). With this model, travelers' decisions to make a long-distance international trip will be modeled using the 2016-17 NHTS dataset. The 2016-17 NHTS data includes 923,572 trip records, which sum to 371 billion trips using NHTS expansion factors. In this dataset, 134.46 million expanded trips are reported as international trips, which account for only 1 percent of the total long-distance trips (~7 billion weighted) (Kockelman et al, 2022). The population of 2019 destination nations, as well as information about the languages spoken in the destination countries, were obtained from the United Nations Data (2019). If English is one of the major languages spoken, this study assumes the nation is significantly English-speaking. Additionally, the major tourist attractions in 2019 were obtained from the 2019 edition of Euromonitor International's city tourist arrivals (RabiaYasmeen, 2022) research report that covers over 400 cities worldwide. In the report, a tourist is defined as an international tourist who visits another country for at least 24 hours and resides in a paid or unpaid, group or private lodging for a period not exceeding 12 months. Figure 2 shows a geographical heat map for the number of leisure trips from US airports to popular tourist destinations (destination airports are grouped by country). Furthermore, the study uses the median income of destination nations collected from the International Monetary Fund (IMF) website which provides openly accessible data (IMF, 2019).

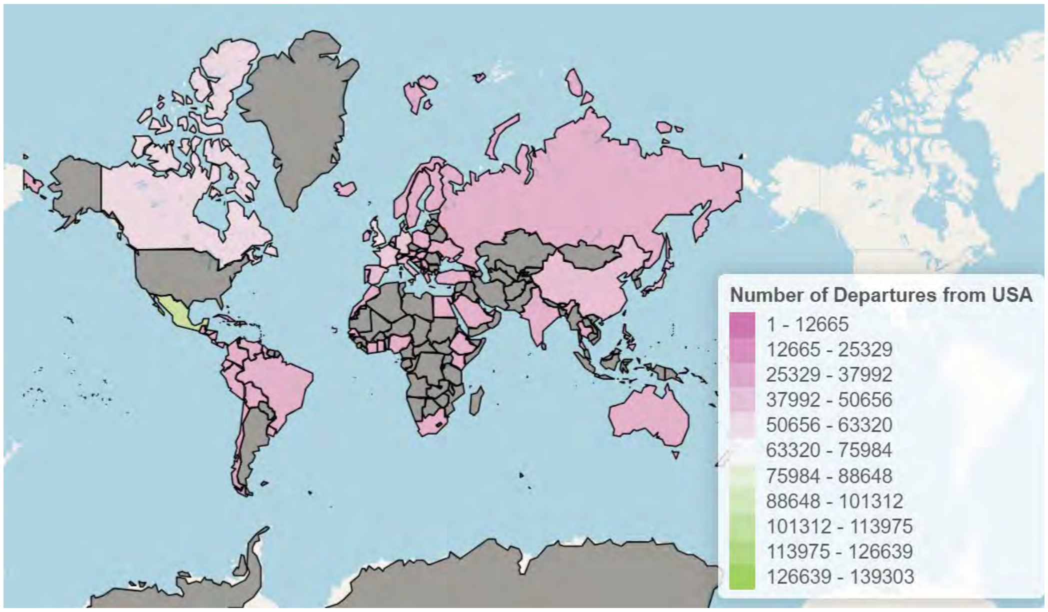

Figure 2 Number of leisure trips from US to popular tourist destinations by air, 2019 (Rabia Yasmeen, 2022)

TABLE 1 Summary statistics for the DB1B round-trip air ticket data - 2019

	Mean	**Median**	**Std dev**	**Max**	**Min**
Quarter 1, *N* = 246,168					
Flight Fare per Itinerary ($)	953	635	1175	16427	0
Distance Flown (miles)	6669	5232	4313	26051	196
Fare per mile ($)	0.171	0.127	0.16	2.918	0
Party Size	1.446	1	2.58	311	1
Segments	3.058	3	0.96	4	2
Quarter 2, *N* = 318,033					
Flight Fare per Itinerary ($)	1022	702	1151	17177	0
Distance Flown (miles)	7150	7298	4244	25870	196
Fare per mile ($)	0.173	0.128	0.16	3.209	0
Party Size	1.414	1	2.57	427	1
Segments	3.041	3	0.96	4	2
Quarter 3, *N* = 309,842					
Flight Fare per Itinerary ($)	1033	733	1100	18491	0
Distance Flown (miles)	7318	7662	4167	26950	196
Fare per mile ($)	0.171	0.128	0.15	2.883	0
Party Size	1.374	1	2.15	229	1
Segments	3.010	3	0.96	4	2
Quarter 4, *N* = 174,532					
Flight Fare per Itinerary ($)	1055	724	1226	17272	0
Distance Flown (miles)	6921	5331	4504	27338	196
Fare per mile ($)	0.186	0.144	0.16	2.617	0
Party Size	1.307	1	2.37	322	1
Segments	3.327	4	0.90	4	2

TABLE 2 Summary statistics for the DB1B one-way trip air ticket data - 2019

	Mean	**Median**	**Min**	**Max**	**Std Dev**
Quarter 1, *N* = 371,334					

Flight Fare per Itinerary ($)	494	304	0	11703	658.5
Distance Flown (miles)	3260	2129	98	21943	2621.6
Fare per mile ($)	0.191	0.138	0	3.795	0.196
Party Size	1.539	2	1	368	3.571
Segments	1.899	2	1	4	0.648
Quarter 2, *N* = 287,751					
Flight Fare per Itinerary ($)	495	316	0	12743	637.7
Distance Flown (miles)	3329	2228	98	22833	2586.1
Fare per mile ($)	0.194	0.143	0	3.867	0.196
Party Size	1.595	2	1	335	4.179
Segments	1.900	2	1	4	0.644
Quarter 3, *N* = 221,507					
Flight Fare per Itinerary ($)	534	342	0	11692	622.9
Distance Flown (miles)	3450	2306	98	20248	2656.4
Fare per mile ($)	0.201	0.153	0	3.5	0.193
Party Size	1.524	2	1	440	3.714
Segments	1.913	2	1	4	0.650
Quarter 4, *N* = 167,983					
Flight Fare per Itinerary ($)	500	318	0	11477	642.4
Distance Flown (miles)	3306	2165	98	20754	2639.1
Fare per mile ($)	0.197	0.144	0	3.469	0.191
Party Size	1.570	2	1	483	4.383
Segments	1.887	2	1	4	0.649

METHODOLOGY

The main goal of this study is to improve the knowledge of the international travel behaviors of individuals, specifically focusing on air travel originating from the United States. The first step of the methodology adopted in this study uses the 2016-17 NHTS data to predict the likelihood of Americans making an international trip as shown in Figure 3. The decision of whether a traveler chooses to make a long-distance international trip as opposed to a domestic long-distance trip exceeding 75 miles is evaluated through the application of a binomial logit model. The trip frequency model for long-distance trips (over 75 miles one-way) is first estimated using the NHTS dataset and a model presented in Fakhrmoosavi et al. (2023) and Kockelman et al. (2022). The study estimated long-distance trips per day at the individual level using a zero-inflated negative binomial (ZINB) model and the 2016-17 NHTS data. The zero-inflated negative binomial model comprises two components: firstly, a logit model that determines the likelihood of an individual undertaking a long-distance trip, and secondly, a negative binomial count model that estimates the count of trips made using demographic factors, temporal factors, and the purpose of the trip.

The population weights are used in order to improve the accuracy of parameter estimates in reflecting the demographics at the household and individual levels in the United States. Then, for each trip inside this trip frequency, the binomial logit model stated earlier is used to estimate the decision between domestic and international long-distance trips. The general logistic regression model with k predictors is given below:

$$log\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k \quad (1)$$

Assuming a binary dependent variable Y, a value of 1 is assigned to indicate that an individual is making an international trip, while a value of 0 is assigned to indicate the opposite. The variable p denotes the conditional probability of Y equating to 1, which signifies the occurrence of an international trip, given the value of X. The model consists of independent variables X_1, X_2, …, X_K, and parameters b_0, b_1, b_2, …, b_k, which are assumed to be independent. Table 3 presents the parameters that are statistically significant in the model for long-distance trip frequency. The table further shows the practical significance of these variables, i.e., the effects of a one standard deviation increase in each covariate on trip frequency. The parameter estimates of the count model indicate that there is an increase of nearly 51% in long-distance trip rates when there is a 1 standard deviation rise in the natural logarithm of household annual income, which is measured in US dollars. The skewing of the population-weighted sample by one standard deviation towards males resulted in a 21.6% increase in the mean frequency of long-distance trips. An addition of one standard deviation in the number of vehicles owned by households resulted in a 66% rise in the frequency of long-distance trips.

The distribution of trips from US origin airports to international airports in other countries is formed using an origin-constrained gravity model and DB1B data. The Gravity Model is a widely utilized method for trip distribution within the four-step travel demand forecast model. The model, named after Newton's law of gravitation, postulates that the correlation between two locations (in this context, the number of trips) is directly proportional to the product of their magnitudes (typically measured by population or employment) and inversely proportional to the travel expenses (distance, time, or monetary cost) incurred in commuting between them. The general formulation of the gravity model is given below.

$$T_{ij} = \alpha \frac{P_i P_j}{D_{ij}^2} \quad (2)$$

The formula presented involves the populations of origin and destination denoted as P_i and P_j, respectively. Additionally, the distance between the two is represented by d_{ij}. The proportionality factor α is expressed in units of trips multiplied by distance squared divided by population squared. This study employs flight duration and fare, an English language country indicator, a tourism attraction country indicator, and the population of the country as its inputs. The DB1B data does not include information regarding the duration of flights. Therefore, the estimate presented here is based on the average speed and delay for each stop. Furthermore, FGLS models are utilized to estimate flight fares and their fluctuations for outbound and roundtrips originating from the United States, with the intention of incorporating these findings into model implementations. There are several advantages of using FGLS over Ordinary Least Squares (OLS). The presence of heteroscedastic errors can lead to the inefficiency of OLS estimators and introduce bias in standard errors; therefore, the FGLS estimator is used when the type of heteroskedasticity needs to be estimated.

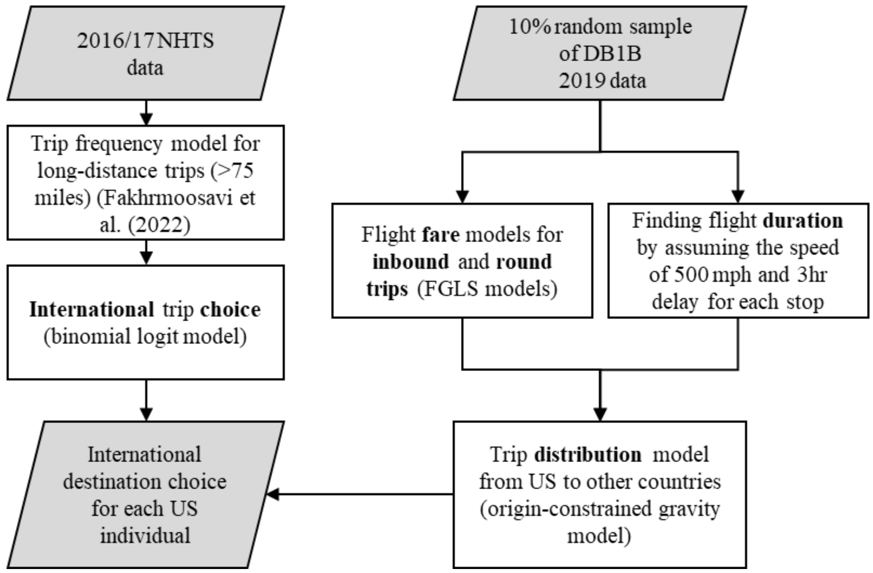

Figure 3 Modeling framework to predict destinations for international trips from the U.S

TABLE 3 ZINB model for long-distance trip frequency as used by Fakhrmoosavi et al (26)

Negative binomial model coefficients variable	**Estimate**	**t-stat**	**P-value**	**Practical Significance**
Intercept	0.799	3.62	0.000	-
Male	0. 172	7.85	0.000	0.216
Age	-0.002	-3.52	0.000	-0.099
Ln (Household Income) ($)	-0.079	-2.72	0.006	0.507
Education associate degree or higher	0. 191	6.84	0.000	0.216
#Adults	-0.228	-4.71	0.000	-0.460
Worker	-0.080	-3.95	0.000	-0.077
HH vehicle count	0. 141	12.40	0.000	0.657
Ln (θ)	15.45	6.44	0.017	
Zero-inflation model coefficients	**Estimate**	**t-stat**	**P-value**	**Practical Significance**
Intercept	7. 125	31.49	0.000	-
ln (Household Income) ($)	-0.043	-4.04	0.000	0.507
Household vehicle count	-0.4 10	-19.80	0.000	0.657

n = 201,820, Pseudo-R1=0.015

RESULTS

This study presents three distinct sets of findings. Firstly, the FGLS models are introduced to predict airfares for individual paid itineraries. Subsequently, the outcomes of the binary choice model used to determine the likelihood of an American embarking on international travel have been explained. The impact of the destination and trip attributes on destination selection is then discussed with the aid of estimated gravity model.

Flight Fare and Duration Models

International Round Trips - US Origin

FGLS models for 2019 round-trip itineraries (TABLE 4) indicate that flight fare decreases whenever 1) an intermediate stop is included in an otherwise uninterrupted trip, and 2) the number of passengers on the itinerary increases. The cost of air travel for coach class passengers rises by

\$0.058 per mile, whereas for business class or higher passengers, the rise is \$0.281 per mile. The cost of air travel to a country with a higher population density is comparatively lower than that of a country with a lower population density. This can be attributed to the increased number of flights to densely populated countries, leading to heightened competition among airlines and a consequent reduction in airfare. It is noteworthy to observe that the cost of a return journey to an English-speaking nation is comparatively lower than that of a trip to a non-English-speaking destination. The cost of travel during the months of October to December is comparatively higher than that of other months throughout the year. Shifting all samples towards business or higher class and towards United Airlines increases the flight fare by 150% and 7.5%, respectively. TABLE 5 presents the model estimates when the log of linear model residuals is regressed on all dependent variables. The table indicates that the coefficients show a significant deviation from zero, thereby implying the existence of heteroskedasticity. A positive coefficient indicates a direct relationship between the independent variable and the variance of the errors, such that a rise in the independent variable is associated with a rise in the variance of the errors. A coefficient with a negative value indicates an inverse relationship. The results show that the flight prices of itineraries with more than 1 stop, travel to non-English speaking destinations, and trips with more than one party size vary significantly in price compared to others.

TABLE 4 FGLS model estimates for international round trips to and from US

Y: Fare (\$) per paid Itinerary per passenger, N = 1,048,268, Adj. R^2: 0.3026			
Variable Name	**Estimate**	**t-stat**	**P-value**
(Intercept)	337.60	105.136	0.000
Distance Flown (miles)	0.058	208.72	0.000
Distance Flown (miles)*Business class or higher	0.281	108.32	0.000
Trip made during April to June	20.41	12.529	0.000
Trip made during July to September	18.54	11.364	0.000
Trip made during October to December	69.04	54.304	0.000
Restricted Coach Class	56.69	35.829	0.000
Business class or higher	-118.2	-5.649	0.000
#Passengers on the Itinerary	-8.388	-63.497	0.000
log (Population of Destination Country)	-8.204	-36.758	0.000
Itinerary with 1 stop	-99.16	-59.481	0.000
Itinerary with 2 stops	-69.97	-67.127	0.000
Outbound Trip	125.0	124.255	0.000
Destination is English-Speaking	-8.798	-5.588	0.000
Median Income of Destination Country	0.002	29.97	0.000
Alaska Airlines	-53.25	-9.542	0.000
JetBlue Airlines	-15.52	-5.375	0.000
Delta Airlines	51.71	23.759	0.000
United Airlines	88.66	63.178	0.000
SkyWest Airlines	76.96	17.412	0.000
Endeavor Air	37.65	8.713	0.000

Canadian Pacific Airlines	14.90	2.92	0.004
Hawaiian Airlines	775.3	26.819	0.000
GoJet Airlines	-41.06	-11.981	0.000
Southwest Airlines	-159.9	-43.468	0.000
Spirit Airlines	143.6	47.993	0.000
Mesa Airlines	-17.45	-4.173	0.000
Republic Airlines	110.3	17.973	0.000
Eva Airlines	39.46	6.438	0.000
PSA (American Eagle) Airlines	148.3	13.788	0.000
Frontier Airlines	-215.3	-10.231	0.000
Sun Country Airlines	-227.8	-3.188	0.001
Horizon Air	-5.249	-0.67	0.503
Distance Flown (miles)*Destination is English Speaking	-0.002	-6.894	0.000
Distance Flown (miles)*Trip made during April to June	0.004	12.322	0.000
Distance Flown (miles)*Trip made during July to September	0.006	18.248	0.000
Business class or higher*Destination is English Speaking	131.2	6.995	0.000
Trip made during April to June*Business class or higher	-83.24	-4.228	0.000
Trip made during July to September*Business class or higher	-157.5	-7.571	0.000
Business class or higher*Alaska Airlines	-209.9	-3.888	0.000
Business class or higher*JetBlue Airlines	-524.0	-3.506	0.000
Business class or higher*Delta Airlines	-858.6	-38.11	0.000
Business class or higher*United Airlines	225.0	9.995	0.000
Business class or higher*SkyWest Airlines	-276.1	-4.241	0.000
Business class or higher*Endeavor Air	-578.5	-6.903	0.000
Business class or higher*Canadian Pacific Airlines	-393.6	-3.367	0.001
Business class or higher*Hawaiian Airlines	-588.2	-7.498	0.000
Business class or higher*Itinerary with 1 stop	-143.9	-4.367	0.000
Business class or higher*Itinerary with 2 stops	-318.5	-17.82	0.000
Distance Flown (miles)*Alaska Airlines	-0.008	-5.609	0.000
Distance Flown (miles)*JetBlue Airlines	0.009	13.158	0.000
Distance Flown (miles)*Delta Airlines	0.014	39.903	0.000
Distance Flown (miles)*Southwest Airlines	-0.011	-10.395	0.000
Distance Flown (miles)*Spirit Airlines	-0.031	-28.813	0.000
Distance Flown (miles)*SkyWest Airlines	0.017	15.968	0.000
Distance Flown (miles)*Republic Airlines	0.027	26.092	0.000
Distance Flown (miles)*Endeavor Air	0.029	25.92	0.000
Distance Flown (miles)*Eva Airlines	0.027	15.114	0.000
Distance Flown (miles)*PSA Airlines	0.013	7.713	0.000

Distance Flown (miles)*Horizon Air	-0.010	-3.433	0.001
Distance Flown (miles)*Hawaiian Airlines	-0.066	-18.948	0.000
Distance Flown (miles)*GoJet Airlines	0.007	2.596	0.009
Distance Flown (miles)*Frontier Airlines	-0.015	-2.116	0.034
Distance Flown (miles)*Sun Country Airlines	0.047	2.255	0.024

TABLE 5 Variance model estimates for international round trips to and from US

Y = log(Residuals^2) , N =1,048,268, Adj. R^2*: 0.2947*

Variable Name	**Estimate**	**t-stat**	**P-value**
(Intercept)	9.371	513.9	0.000
Distance Flown (miles)	0.000	325.3	0.000
Trip made during April to June	-0.018	-2.97	0.003
Trip made during July to September	-0.023	-3.76	0.000
Trip made during October to November	0.253	34.45	0.000
Alaska Airlines	0.073	3.90	0.000
JetBlue Airlines	-1.017	-76.26	0.000
Delta Airlines	0.211	34.25	0.000
Southwest Airlines	-0.609	-48.24	0.000
United Airlines	0.116	17.41	0.000
Spirit Airlines	-0.970	-61.27	0.000
Mesa Airlines	0.110	5.89	0.000
SkyWest Airlines	0.156	9.90	0.000
Republic Airways	-0.081	-4.58	0.000
Endeavor Air	0.187	10.30	0.000
Canadian Pacific Air Lines	0.136	4.46	0.000
Eva Air	0.166	6.50	0.000
PSA (American Eagle) Airlines	-0.056	-2.31	0.021
Horizon Air	0.428	11.37	0.000
Hawaiian Airlines	-0.129	-6.64	0.000
GoJet Airlines	0.262	6.05	0.000
Frontier Airlines	-0.993	-18.90	0.000
Sun Country Airline	1.336	21.93	0.000
Itinerary with 2 stops	-0.207	-23.03	0.000
Itinerary with 3 stops	-0.307	-53.60	0.000
Restricted Coach Class	-0.503	-63.38	0.000
Business class or higher	2.840	270.69	0.000
Outbound Trip	0.351	62.39	0.000
Destination is English Speaking	0.217	41.89	0.000

ln (Population of Destination Country)	0.010	7.06	0.000
#Passengers on the Itinerary	0.006	6.11	0.000

International One-way Trips - to and from US

The FGLS model results for air fares of international one-way trips to and from US are shown in TABLE 6, and the variance model estimates are shown in TABLE 7. The estimated model coefficients reveal that a flight price costs \$0.078 per mile flown for coach class and \$0.163 per mile flown for business class or higher. The flight fare decreases as the number of passengers rises, and the number of stops on the itinerary increases. A trip made from April to June shows high variation as compared to other days of the year. Shifting the sample towards business or higher class increases the flight fare by 125%, while the same shift towards Southwest Airlines decreases the cost by 58.5%. There is a similar trend found in one-way flight fares as found in round trips, which is that the cost of air travel to a country with a higher population density is comparatively lower than that of a country with a lower population density. Additionally, the cost of a return journey to an English-speaking nation is comparatively lower than that of a trip to a non-English speaking destination. Variance model estimates are shown in Table 7. The estimates indicate that the flight prices of the itineraries with more than 1 stop, travel to non-English speaking destinations, and trips with more than one party size vary significantly in price compared to others.

TABLE 6 FGLS model estimates for international one-way trips - to and from US

Y: Fare (\$) per paid Itinerary per passenger, N = 1,048,575, Adj. R^2: 0.2446

Variable Name	**Estimate**	**t-stat**	**P-value**
(Intercept)	320.0	154.7	0.000
Distance Flown (miles)	0.078	179.0	0.000
Distance Flown (miles)*Business class or higher	0.163	61.53	0.000
#Passengers on the Itinerary	-3.602	-70.87	0.000
Outbound Trip?	-34.20	-58.49	0.000
Restricted Coach Class	-7.743	-7.78	0.000
Business class or higher	-66.53	-2.40	0.016
Trip made during April to June	8.645	8.72	0.000
Trip made during July to September	1.907	1.76	0.079
Trip made during October to December	4.992	4.24	0.000
Itinerary with 1 stop	-40.23	-76.41	0.000
Itinerary with 2 stops	-23.69	-21.29	0.000
Itinerary with 3 stops	117.5	24.43	0.000
Destination is English-Speaking	-24.75	-27.51	0.000
Median Income of Dest Country	0.005	63.34	0.000
Ln (Population of Destination Country)	-7.668	-53.18	0.000
Alaska Airlines	-29.55	-13.63	0.000
JetBlue Airlines	-42.76	-24.86	0.000
Delta Airlines	-11.08	-7.54	0.000
United Airlines	-16.53	-11.23	0.000
SkyWest Airlines	24.71	11.15	0.000
Canadian Pacific Airlines	-18.48	-13.53	0.000

Horizon Air	-4.890	-1.98	0.048
Hawaiian Air	253.2	16.08	0.000
SunCountry Airline	-72.60	-12.45	0.000
Southwest Airlines	-7.897	-3.21	0.001
Spirit Airlines	-92.82	-53.99	0.000
Mesa Airlines	56.18	36.24	0.000
Republic Airline	1.783	0.75	0.453
Endeavor Airline	15.17	6.92	0.000
Eva Airline	21.46	6.29	0.000
PSA Airline	23.54	6.84	0.000
GoJet Airline	60.15	12.90	0.000
Frontier Airline	-118.5	-18.18	0.000
Distance Flown (miles)*Trip made during April to June	-0.004	-7.81	0.000
Distance Flown (miles)*Trip made during July to September	0.008	16.50	0.000
Distance Flown (miles)*Trip made during October to December	-0.004	-6.92	0.000
Distance Flown (miles)*Alaska Airlines	-0.008	-8.38	0.000
Distance Flown (miles)*JetBlue	0.014	21.68	0.000
Distance Flown (miles)*Delta Airlines	0.015	24.10	0.000
Distance Flown (miles)*Southwest Airlines	-0.031	-21.67	0.000
Distance Flown (miles)*United Airlines	0.018	35.57	0.000
Distance Flown (miles)*Spirit Airlines	-0.032	-35.40	0.000
Distance Flown (miles)*SkyWest Airlines	0.008	7.46	0.000
Distance Flown (miles)*Republic Airline	0.017	12.07	0.000
Distance Flown (miles)*Endeavor Airline	0.007	5.47	0.000
Distance Flown (miles)*Eva Airline	0.032	15.65	0.000
Distance Flown (miles)*PSA Airline	-0.009	-3.74	0.000
Distance Flown (miles)*Horizon Air	-0.004	-2.54	0.011
Distance Flown (miles)*Hawaiian Air	-0.039	-12.92	0.000
Distance Flown (miles)*GoJet Airline	-0.005	-1.72	0.085
Distance Flown (miles)*Frontier Airline	-0.012	-3.09	0.002
Business class or higher*Alaska Airlines	-123.4	-7.23	0.000
Business class or higher*JetBlue Airlines	505.0	12.18	0.000
Business class or higher*Delta Airlines	53.82	3.13	0.002
Business class or higher*United Airlines	-45.94	-4.17	0.000
Business class or higher*SkyWest Airlines	-43.62	-1.80	0.071
Business class or higher*Canadian Pacific Airlines	-95.83	-3.32	0.001
Business class or higher*Horizon Air	-68.84	-2.46	0.014
Business class or higher*Hawaiian Air	262.1	3.22	0.001
Business class or higher*SunCountry Airline	-360.0	-6.10	0.000
Business class or higher*Itinerary with 1 stop	-105.5	-11.57	0.000
Business class or higher*Itinerary with 2 stops	-353.4	-18.70	0.000
Business class or higher*Itinerary with 3 stops	-520.1	-7.41	0.000

Business class or higher* Destination is English Speaking	52.91	5.56	0.000
Distance Flown (miles)* Destination is English Speaking	-0.010	-25.76	0.000
Business class or higher* Ln (Population of Destination Country)	11.86	4.73	0.000
Trip made during April to June*Business class or higher	-50.15	-4.93	0.000
Trip made during July to September*Business class or higher	-126.1	-9.99	0.000
Trip made during October to December*Business class or higher	-35.60	-2.69	0.007

TABLE 7 Variance model estimates for international one-way trips - to and from US

Y = log(Residuals^2) , N = 1,048,575, Adj. R^2: 0.2896

Variable Name	Estimate	t-stat	P-value
(Intercept)	9.880	628.2	0.000
Distance Flown (miles)	0.000	364.8	0.000
#Passengers on the Itinerary	0.006	9.6	0.000
Itinerary with 2 stops	-0.203	-26.8	0.000
Itinerary with 3 stops	0.088	3.80	0.000
Restricted Coach Class	-1.037	-153.0	0.000
Business class or higher	1.959	192.8	0.000
Destination is English Speaking?	-0.214	-41.1	0.000
Ln (Population of Destination Country)	-0.046	-34.7	0.000
Trip made during April to June	-0.066	-13.0	0.000
Alaska Airlines	-0.174	-12.9	0.000
JetBlue Airlines	-1.324	-124.6	0.000
Delta Airlines	0.113	16.1	0.000
Southwest Airlines	-0.642	-48.4	0.000
United Airlines	-0.126	-18.7	0.000
Spirit Airlines	-1.351	-112.3	0.000
Mesa Airlines	-0.219	-13.4	0.000
SkyWest Airlines	-0.094	-6.9	0.000
Republic Airways	-0.119	-6.8	0.000
Endeavor Air	0.040	2.5	0.014
Canadian Pacific Air Lines	-0.446	-24.7	0.000
PSA Airlines	-0.162	-5.9	0.000
Horizon Air	-0.158	-7.5	0.000
Hawaiian Airlines	-0.228	-8.3	0.000
GoJet Airlines	0.164	5.1	0.000
Frontier Airlines	-1.145	-32.3	0.000

International Trip Choice

A binomial logit model has been employed to determine the preference of American individuals for international travel over domestic travel. The study assesses the likelihood of making an international trip by considering demographic factors, temporal factors, and the purpose of the trip. The specifications of the logistic regression model for estimating international trip choice for Americans are shown in TABLE 8. The findings indicate that males, individuals of Caucasian ethnicity, those with higher incomes, and those who are not employed full-time show a higher inclination to make an international trip. The likelihood of international travel tends to be higher during the summer and spring seasons. Additionally, trip purpose was found to be statistically significant in the model. In order to assess the practical significance of the variables' impact on international trip decision-making, effect sizes are computed. The results show that international trip frequency (per person) rises by about 16% with a 1 standard deviation increase in the respondent's household income (i.e., $62,000). Increasing the summer trip and spring trip indicators by 1 standard deviation also increases the frequency of international trips by 19% and 14%, respectively. International trips fall by 23% when the female indicator increases by 1 standard deviation, and 31% when the full-time employed indicator increases by 1 standard deviation. Religious and personal business trips are also less likely to be international.

TABLE 8 Specifications of the binomial logistic regression model for international versus domestic trips

	Coefficient Estimates	t-Stat	P-Value	Practical Significance
(Intercept)	-5.594	-7.14	0.000	-
Household income (1000$)	0.006	1.63	0.103	0.161
Female	-1.067	-2.42	0.016	-0.228
Hispanic	1.424	2.67	0.008	0.148
White	1.114	2.27	0.023	0.159
Full-time employed	-1.501	-3.65	0.000	-0.315
Summer trip	0.988	1.78	0.075	0.193
Spring trip	0.907	1.68	0.094	0.140
Personal business trip	-1.066	-1.44	0.150	-0.104
Religious community trip	-14.232	-47.88	0.000	-0.869

R-squared: 0.1344, n= 13,966

Trip Distribution Model

An origin-constrained gravity model was used to distribute trips among different origins and destinations. A logarithmic operator was applied to form a log-linear gravity model, and an ordinary-least-squares (OLS) model was estimated to find the number of trips distributed between each origin and destination pair. The friction factor here is a function of impedance incorporating auto and air travel times and costs (i.e., flight fare, highway toll) normalized by the value of time. The value of travel time for air travelers is assumed to be $30 per hour and $20 per hour for auto users. TABLE 9 shows the specifications of this log-linear model as well as the practical significance of different statistically significant variables. This model was estimated using data from multiple sources indicating trip production for 334 major US airports and attractions of country locations for 1028 international airports in countries other than the US. Due to the lack of data about the origins and destinations of land travelers to Canada and Mexico, major airports in most touristic cities in Canadian provinces that are accessible from the US (e.g., Ontario, Quebec, British Columbia, Alberta, Nova Scotia) are considered as destination locations. Origins are also assumed to be the major airport of the closest state in the US. For Mexico, all trips are aggregated into origin and destination pair from Texas to the Sinaloa state in Mexico. The trip distribution model indicated that trips headed to a foreign destination from an American origin fall 41% when the travel start-to-end time increases by 7 hours, or the air ticket increases by $210. Destinations hosting tourist attractions increase origin-destination flow by 48% when this indicator variable goes from 0 to 1. The population and English-speaking indicator (for the destination country) are neither practically nor statistically significant. The modeling framework and results of this paper can be used to craft decarbonizing policies and practices, aircraft scheduling and flight ticket pricing, overseas investment decisions, tourism guidance and investments, and embassy operations.

TABLE 9 Specifications of the log-linear gravity model to estimate the number of trips between US major airports and other countries' airports

	Estimate	t-stat	P-Value	Practical Significance
(Intercept)	9.796	104.65	0.000	
Trip Production in Origin Airport	0.238	81.62	0.000	0.969
Travel Time & Cost	-1.578	124.11	0.000	0.409
Population of Destination Country	0.0013	0.50	0.616	0.0012
Tourism Indicator in Destination Country	0.907	51.60	0.000	0.136
English Speaking Country (Destination)	0.0024	0.17	0.864	0.0004

CONCLUSIONS

This study integrates demographic choice behavior models with destination selection based on several trip variables and evaluates airline price changes by destination, season, and ticket type. It uses 2019 DB1B aircraft ticket data, the 2016-17 NHTS, US outbound passenger travel aggregate estimates of the 2019 NTTO, destination country characteristics from UN world information, and major attraction city data for tourists in 2019 from the Euromonitor international report. The main data source of this study, 2019 DB1B provided by BTS, revealed that the flight fare for international travel falls as the number of passengers on the itinerary rises. Round trips made in October to December are more expensive than those taken during the other months of the year, while one-way trips made during April to June show high variation as compared to other times of the year. A round trip to an English-speaking nation is less expensive than traveling to or from a non-English-speaking country if other variables are kept constant. The international round-trip air fares cost $0.058 per mile flown for coach class and $0.281 per mile flown for business class or higher. Shifting the sample towards business or higher class increases the one-way flight fare by 125% and the round-trip fare by 151%.

It is important to acknowledge that the coefficients of the variance model display notable deviation from zero, indicating the presence of heteroscedasticity. The international trip choice model reveals that the probability of taking international trips rises by 16% when household income is increased by 1 standard deviation (i.e., $62,000). Employment status, race, female indicator, trip season, and trip purpose are other significant variables affecting Americans' international trip choices. A gravity model was used to distribute international trips among various major airports in the US and other countries. The trip distribution model indicated that travel time and cost, as well as tourism attractions in the destination, are the statistically significant variables affecting the number of trips to an international location. This model also suggested that trips headed to a foreign destination from an American airport fall 41% when the friction factor (i.e., travel time and normalized cost by value of time for different modes) rises by 7 hours and increases 48% when all destinations shift to a tourist attraction from not being an attraction.

The study provides valuable insights into the correlation between flight rates and other factors, such as passenger flows, travel season, characteristics of the destination country, and data on popular attractions in the area. These findings can assist airlines in optimizing their scheduling and pricing strategies. Airlines can modify their pricing strategies by analyzing the recognized trends, thereby providing competitive prices and optimizing their schedules to accommodate the preferences of travelers. The identification of statistically significant variables influencing the frequency of trips to an overseas destination can help with focused marketing and promotion of various tourism attractions. The present study also possesses certain limitations that warrant careful consideration, thereby highlighting potential avenues for future research. As per the authors' understanding, there is a lack of publicly available data that comprehensively documents the number of international ground trips originating from cities in the United States to cities in Canada or Mexico. The dataset used in this research consisted of aggregated figures representing the number of border crossings. These figures were subsequently employed to allocate trips to various destinations, taking into account their respective tourist attractions. The dataset utilized in this study is indicative of the period prior to the onset of the pandemic. The emergence of the COVID-19 pandemic resulted in unparalleled limitations and modifications in global travel behaviors. Although many studies show the recovery of air trips from the pandemic effects (25; 6), it is imperative to include post-pandemic data in order to achieve a comprehensive understanding of international travel and accommodate its dynamic nature. This uncovers a prospective avenue for further investigation to enhance the breadth of this research. Moreover, there is a substantial need for comprehensive investigation and improvement in the accounting process for land-based transportation. Enhancing the accuracy and relevance of global travel demand models will strengthen their capacity to forecast and analyze travel patterns in the dynamic international context.

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The authors confirm contribution to the paper as follows: study conception and design: Fakhrmoosavi, F., Kockelman, Paithankar, P., Perrine, K.; data collection: Perrine, K., Kockelman; analysis and interpretation of results: Paithankar, P., Fakhrmoosavi, F., and Kockelman; draft manuscript preparation: Paithankar, P., Fakhrmoosavi, F., Kockelman; All authors reviewed the results and approved the final version of the manuscript.

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