Tour Generation of Interregional Travel in the United States: Insights from the 2017 National Household Travel Survey (NHTS)

Ming Zhang (PI)

Yang Li (GRA)

March 2024

A publication of the USDOT Tier 1 Center:

Cooperative Mobility for Competitive Megaregions

At The University of Texas at Austin

Technical Report Documentation Page

1. Report No. CM2-76	2. Government Accession No.	3. Recipient's Catalog No. ORCID: 0000-0002-4827-1323
4. Title and Subtitle Tour Generation of Interregional Travel in the United States: Insights from the 2017 National Household Travel Survey (NHTS)		5. Report Date March, 2024
		6. Performing Organization Code
7. Author(s) Qisheng Pan, Bumseok Chun, Subham Kharel, Mansha Swami		8. Performing Organization Report No. CM2-2022-1
9. Performing Organization Name and Address he University of Texas at Austin School of Architecture 310 Inner Campus Drive, B7500 Austin, TX 78712		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. USDOT/69A3551747135
12. Sponsoring Agency Name and Address Center for Cooperative Mobility for Competitive Megaregions The University of Texas at Austin 310 Inner Campus Drive, Goldsmith Hall, 2.308 Austin, TX 78712		13. Type of Report and Period Covered Technical Report conducted May 2021-March 2024
		14. Sponsoring Agency Code
15. Supplementary Notes Project performed in cooperation with the United States Department of Transportation		

16. Abstract

This study focuses on interregional travel, a submarket of long-distance travel (LDT) with one-way distance in the range of 50–600 miles. Interregional travel warrants focal attention for two reasons. First, despite its modest share (less than 4%) in the US domestic travel market, interregional travel contributes over 20% of total vehicle miles traveled and a commensurate amount of transportation emissions. Second, interregional travel covers a distance range with the greatest potential to achieve multimodality. Better understanding interregional travel can help inform statewide and nationwide transportation planning, for instance, the ongoing Federal Rail Administration's Regional Rail Planning. However, existing studies on interregional travel are scarce due to data limitations. This study taps into the data from National Household Travel Surveys (NHTS) and analyzes the characteristics of interregional tours, with a tour consisting of multiple connected trips. To address the issue of excessive zero observations for interregional travel in the cross-sectional NHTS dataset, the study estimates zero-inflated models and contrasts tour generation characteristics for interregional travel with those for intraregional and the long-haul component of LDT. Elasticities of interregional tour frequencies are calculated with respect to five planning or policy variables, including age, gasoline price-adjusted income, vehicle ownership, household size, and tour complexity. The study demonstrates the potential of utilizing the existing NHTS data for interregional travel analysis. The study's findings help inform multiregional and national transportation investment decisions and policy deliberations.

17. Key Words Interregional travel; Trip generation; Zero-inflated model; Trip chain analysis; National Household Travel Survey (NHTS)		18. Distribution Statement No restrictions	
19. Security Classif. (of report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of pages 42	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized.

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Executive Summary

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Chapter 1. Introduction

People's travel behavior evolves along with technological advances, societal transformation, and the changing conditions of the built and natural environment. This paper examines a growingly important, but not yet well-understood travel behavior, interregional travel. As the term self-explains, interregional travel denotes trip-making that originates in one region and ends in another. This geography-based trip categorization is closely related to distance-based travel market segmentation. Trips happening between regions tend to be longer in distance or duration than those within a region and therefore have been conventionally categorized as part of long-distance travel (LDT). Interregional trips in this U.S.-based study refer to the short-haul component of LDT occurring between metropolitan areas with a one-way distance range of 50-600 miles (see the literature review section for a detailed explanation).

Interregional travel has begun to gain attention from transportation researchers and policymakers for several reasons. First, interregional travel contributes to more than 20% of total vehicle miles traveled (VMT) in the United States, although it only accounts for less than 4% of total trips (Federal Highway Administration [FHWA], 1969–2017). Second, interregional travel dominates the LDT market. The most comprehensive LDT survey in the United States, conducted in 1995, showed that interregional travel (with a one-way distance of 100–500 miles) took up over three-quarters of LDT nationwide (Federal Highway Administration [FHWA], 2015; McGuckin, 2013). Interregional travel is also one of the fastest-growing travel market segments. Between 1980 and 2000, inter-metropolitan passenger flows increased by more than 28%, compared to the 11.5% growth of overall commuting in the United States (Pisarski, 2006). Third, interregional travel spans a distance range corresponding to the territory of megaregions (termed mega-city regions or city-cluster regions in different country contexts) in which different modes, including cars, airplanes, trains, and intercity buses, can offer competitive services. It is a market segment with the greatest potential to achieve multimodality and minimize transportation emissions (Steer Davies Gleave, 2004; (National Academies of Sciences, Engineering, and Medicine (NASEM), 2016).

Nevertheless, the current knowledge about interregional travel is very limited. From 2012–2015, the Executive Committee of the U.S. Transportation Research Board (TRB) delegated a 15-member special committee, chaired by the late Professor Martin Wachs, to study interregional passenger travel issues and opportunities in the short-haul LDT market. One central finding of the study is that “appropriate analytical tools and up-to-date data on LDT in the United States are lacking” (National Academies of Sciences, Engineering, and Medicine (NASEM), 2016, p. 1). The committee also identified institutional constraints as being a major challenge to transportation planning for interregional travel. Interregional travel often traverses multiple metropolitan regions, going beyond the jurisdictions of individual metropolitan planning organizations (MPOs) that focus on daily travel and operate only within their financial and jurisdictional provisions. The report released by the special committee along with several other studies urged for new research and data collection to better understand interregional travel (Aultman-Hall et al., 2018; LaMondia et al., 2014; National Academies of Sciences, Engineering, and Medicine (NASEM), 2016).

This study echoes the call from the TRB Special Committee to improve understanding of interregional travel. The central questions of interest are: What are the unique characteristics of interregional travel relative to the long-haul component of LDT and intraregional travel? Who makes interregional trips (or what are the sociodemographic characteristics of interregional trip makers)? What are the underlying factors influencing interregional trip-making decisions? While lack of data has been a major constraint hindering the current interregional travel research, this study taps into the potential of the existing U.S. National Household Travel Surveys (NHTS). Insights gained from the study will inform strategic transportation investment decisions and policymaking targeting the interregional travel market. Lessons learned from working with NHTS data also help improve future NHTS design to capture emerging travel market trends.

The paper is organized as follows. The next section reviews the related literature. It is then followed by the description of data and analysis methods used in the study. Analysis results are presented and interpreted in the Results section. Lastly, the paper summarizes the study findings and draws conclusions.

Chapter 2. Literature review

The first challenge facing interregional travel research is how an interregional trip should be defined and identified for transportation planning and policymaking purposes. Conventionally, metropolitan travel and LDT have been treated as distinct travel markets. Metropolitan travel demand analysis focuses on the trips that recur daily and take place within the metropolitan boundary (Davidson et al., 2007). In contrast, LDT refers to trips that are long in travel distance or time duration but do not recur daily. Traveler's decision timeframe considered for LDT analysis varies across agencies or studies. Some use a two-week (14-day) frame (Bricka, 2001; Bricka & Sabina, 2012; Erhardt et al., 2007). Others use a 4-week (28-day) period (Janzen et al., 2018; Moeckel & Donnelly, 2011). Still others analyze LDT on a seasonal or annual basis (Bacon & LaMondia, 2016; Dowds et al., 2020; Lin et al., 2018).

Existing LDT studies have used various distance or time thresholds to identify LDT trips. In the U.S., the latest, most comprehensive nationwide LDT data survey is the 1995 American Travel Survey (ATS). The survey defined long-distance trips as those of 100 miles or farther away from home (BTS, 1997). The Nationwide Personal Transportation Surveys (NPTS) conducted between 1977 and 1995 used a distance threshold of 75 miles to define trips as LDT. However, the LDT distance threshold changed to 50 miles one-way in the 2001 National Household Travel Survey (NHTS) (FHWA, 2001). Several states have conducted their own LDT surveys, each employing its state-specific definition. The 2009 Colorado Front Range Household Survey defined long-distance trips as travel to destinations outside a 50-mile radius of the home location (Bricka & Sabina, 2012). The three Michigan Statewide Travel Counts Surveys conducted in 2005, 2009, and 2015 defined LDT as trips with a destination more than 100 miles from home (McGuckin et al., 2016; Michigan DOT, 2006). The 2012 California Household Travel Survey applied a 50-mile threshold, the same as in the 2001 NHTS, to define LDT (Kunzmann & Masterman, 2013).

While existing studies have specified varying distance thresholds to define the lower end of LDT, they have left open the upper end of LDT. For interregional travel (i.e., the short-haul of LDP) analysis, an upper end should also be specified. The TRB Special Committee used a distance range of 100-500 miles for their study purposes. Our study follows the 2001 NHTS convention to define the lower end of interregional travel at the threshold of 50 miles one-way. For the upper end, we expand the threshold used by the TRB Special Committee to 600 miles one-way. It should be noted that this distance range of 50-600 miles one-way presents our working definition of interregional travel. The distance thresholds may vary depending on study purposes or data availability. Applying this rather wide range of distance thresholds (relative to that in the TRB Special Committee report and other studies), we take into consideration of growing fuzzy boundaries between metropolitan travel and LDT - Trip distances and times for metropolitan travel have become longer (e Silva & Melo, 2018; Melo & e Silva, 2017; Ravalet & Rérat, 2019), whereas LDT has become growingly frequent (Frick & Grimm, 2014; Garden, 2012; Moss & Qing, 2012). The convergence of metropolitan travel and LDT leads to the rise of interregional travel.

The widespread applications of information and communication technologies (ICTs), such as online shopping and working from home via telecommuting, teleconferencing, and teleservices, are among the major drivers of growing LDT, including interregional travel (Keseru & Macharis, 2018; Lyons, 2019; B. Wang & Loo, 2019). ICTs enable productive use of onboard time for work or other activities Consequently, people are engaging in activities involving LDT trips more frequently than before, and daily travel is becoming longer (e Silva & Melo, 2018; Melo & e Silva, 2017; Öhman & Lindgren, 2003). Aside from technological effects, demographic shifts also shape the future of the interregional travel and LDT market. A California-based study reports that Millennials (or Generation Y, referring to those born in the last two decades of the 20th century) make more long-distance travel than Generation X (Berliner et al., 2018). Wang and Akar (2020) found that the average distance traveled by Millennials was longer for social activities than that by Generation X.

The increasing interregional travel coincides with the growth of megaregions. A megaregion consists of two or more metropolitan areas and their integrated hinterland (Yaro et al., 2022). Megaregions are anticipated to comprise 75% of the U.S. population by 2050 (Martin et al., 2016; RPA, 2006). Megaregion planning and policymaking involve multiple metropolitan areas beyond their jurisdictional boundaries. The rapid growth of megaregions poses challenges to interregional transportation systems and underscores the need for future investment in transportation infrastructure (Ross & Woo, 2011), thereby motivating research interests in interregional travel.

The second challenge facing interregional travel analysis pertains to methodological and data constraints. Compared to travel within metropolitan areas, interregional travel has received limited attention from academia and practice (Berliner et al., 2018). For metropolitan transportation planning, interregional travel is commonly treated as external. Some travel demand models built for intercity, statewide, and nationwide applications contain interregional travel implicitly. Intercity travel often involves trip origins and/or destinations in large cities or metropolitan areas. Accordingly, intercity travel models have been widely used to assess the demand changes from introducing new intercity travel modes, for example, the evaluation of high-speed rail projects in Texas, California, and Northeast Corridor (Cambridge Systematics, Inc., 2016; Liu & Li, 2012; Sperry, 2012). In Europe where geographies are relatively small compared with the United States, LDT models or interregional models are mainly developed at the national or international level. In the United States, LDT models are built largely on a statewide scale. As of 2017, 15 states have developed LDT demand models (Donnelly & Moeckel, 2017). One noteworthy LDT modeling effort developed a series of models constructed at the US national level (Outwater, et al., 2015; Bradley, et al., 2016). The modeling framework consists of four sub-models, including macroeconomic and land-use models, population and long-term mobility models, LDT demand models, and traffic assignment models. This national model used a simulation approach to predict the nationwide LDT tours each household made in each month of the year. Research has pointed out that people's LDT behavior is influenced by some factors distinct from those influencing short-distance travel. Nevertheless, only a limited number of studies have explored these factors (Mitra & Saphores, 2019).

The limited research on interregional travel is largely due to the deficiency of LDT data (National Academies of Sciences, Engineering, and Medicine (NASEM), 2016). Several studies have made efforts to collect LDT data focusing on specific regions (Aultman-Hall, 2018; Aultman-Hall et al., 2018; LaMondia et al., 2014). At the national level, the most comprehensive dataset on LDT is available from the 1995 ATS. Four quarterly interviews were conducted between April 1995 and March 1996, involving approximately 80,000 U.S. households. The survey collected data on various characteristics of LDT (trips over 100 miles), including origin, destination, mode, volume, purpose, intermediate stops, travel date, trip duration, number of nights away, and type of lodging used. However, the survey excluded LDT for commuting purposes and did not include daily travel information. While the LDT-specific survey discontinued, five of the eight waves of NPTS/NHTS included LDT attributes, although limited. There exists considerable untapped potential in the NPTS/NHTS database for interregional travel analysis.

Interregional trip-making often involves multiple purposes, origins, and destinations. Trip makers tend to combine/connect their multi-purpose trips to minimize the overall travel cost or maximize the overall benefits of travel across multiple destinations and regions (Anas, 2007; Krizek, 2003). The mechanisms underlying the mixed purposes of interregional travel are understudied and call for a modeling framework that is different from the trip-based models developed for daily short-distance travel within metropolitan areas (Aultman-Hall, 2018). As people increasingly incorporate non-work activities into the work commute or the chained non-work activities within daily activity scheduling, a trip-chain perspective would be more suitable than a trip-based approach for interregional travel analysis (Bricka, 2008). An empirical study using the US Longitudinal Survey of Overnight Travel (2013-2014) dataset demonstrates that the trip-chain framework better captures the complexity of interregional travel than the conventional trip-based approach (Aultman-Hall, 2018).

Interregional travel, as a portion of LDT, occurs not in a daily routine but takes place as a rare event (Alizadeh et al., 2022). Observations from cross-sectional travel survey days may exhibit many zeros, namely excess zeros. Zero values reported from the surveyed individuals include two types. One denotes structural zeros, presented by people who never make interregional travel. The other is incidental or sampling zeros, indicating that the surveyed individuals happened to make no interregional trips on the surveyed travel day. Ignoring excess zeros can cause biased estimates and overdispersion. Several studies have applied a zero-inflated modeling approach to address the sampling issue of excess zeros (Kim & Mokhtarian, 2021). Zero-inflated model is conceptualized as a latent variable model featuring an unobserved Bernoulli random variable (Lambert, 1992). The modeling technique has been increasingly applied in recent transportation research. Kim and Mokhtarian (2021) modeled LDT trips for leisure/recreational/social purposes with LDT data collected from the State of Georgia. The study estimated trip-based choice models considering the mode used by cars and airplanes. Alemi et al. (2019) adopted a zero-inflated model to investigate the determinants of ride-hailing in California. Chen et al. (2023) explored the impacts of determinants on mode choices. Semple et al. (2023) focused on the frequency of work trips during the pandemic. Dong (2022) explored the determinants of TNC usage. Other applications include freight demand analysis and crash/accident analysis (Luo et al., 2022; Mathew & Benekohal, 2021; Middela & Ramadurai, 2021).

This study aims to improve understanding of interregional travel. The study applies the trip-chain analysis framework and explores the data potential from the latest NHTS.

Chapter 3. Methods

3.1. Data

The study uses the 2017 NHTS data. The survey collected demographic information of the sampled individuals and households. People responded to the survey by completing their travel diaries, reporting all trips made on an assigned day. After excluding the records with missing values, the final sample contains 254,367 individuals. Error! Reference source not found. 51,362 of them recorded zero trips on the survey day. The remaining 203,005 individuals made one or more trips. Among those who made trips, 189,327 individuals traveled with one-way distance less than 50 miles, i.e., intraregional travel. 17,019 individuals made interregional travel with one-way distance, the sum of all chained trip segments in the one-way tour, between 50 and 600 miles. 1,088 individuals made trips longer than six hundred miles, i.e., the long-haul component of LDT.

Table 1 below shows sample summary statistics.

Table 1 Sample Summary Statistics

Variables		Min.	Max.	Mean.	Std. dev
Number of trips on the survey day (Average across 203,005 individuals)		1	50	4.22	2.38
Number of within intraregional travel tours on the survey day (Average across 189,327 individuals)		1	39	4.14	2.33
Number of trips within interregional travel tours on the survey day (Average across 17,019 individuals)		1	47	4.04	2.49
Number of trips within long-haul component of LDT tours on the survey day (Average across 1,088 individuals)		1	13	4.07	1.85
Person attributes	Age (years)	5	92	48.43	21.79
	Gender: 1: Male; 0: Otherwise	0	1	0.47	0.50
	Employment status: 1: Employed; 0: Otherwise	0	1	0.49	0.50
	Edu.1: <= high school	0	1	0.34	0.47
	Edu.2: some college or associate degree	0	1	0.26	0.44

	Edu.3: bachelor's degree	0	1	0.21	0.41
	Edu.4: graduate or professional degree	0	1	0.19	0.39
Household attributes	Live in MSA: 1: Yes; 0: No	0	1	0.85	0.36
	Live in urban area: 1: Yes; 0: No	0	1	0.77	0.42
	Live in megaregion: 1: Yes; 0: No	0	1	0.44	0.50
	Household income ($1,000s)	5	225	84.12	59.95
	Adjusted household income (Adjusted using state-level gasoline price by calculating income/100/gasoline price)	15.48	1008.97	342.45	245.17
	Household size	1	13	2.71	1.41
	Vehicles per person in household	0	12	0.94	0.57
	State population from 2017 American Community Survey 5-Year Data (million persons)	0.583	38.98	19.21	12.93
Number of individuals		254,367			

3.2. Analytical Methods

Consumer behavior theory suggests that travel demand is derived from the need to move from one place to another to participate in various activities (Oi & Shuldiner, 1962, p. 10). Activities located in destinations attract or produce trips. Some of the destinations are primary, serving the main purposes of making trips, whereas others are secondary or tertiary. People often avoid making separate round trips for multiple purposes but instead chain their trips and activities to save on total travel costs (Anas, 2007; Krizek, 2003; Nishii et al., 1988). A trip tour is a commonly used unit of analysis for analyzing trip-chaining behavior. A tour is defined as connected, chained trip segments. Tours may be simple or complex depending on the tour composition of purposes, travel modes, distances, along other attributes (Çolak et al., 2015; Schneider et al., 2013). This study focuses on tour generation measured by tour frequencies for interregional travel. An interregional travel unit for the study denotes a one-way tour with a total distance in the range of 50–600 miles with either end at home locations.

This study applies Zero-Inflated Negative Binomial (ZINB) regression to analyze interregional travel tour generation. The base model starts with a negative binomial regression without tour complexity measurement, then a negative binomial regression with tour complexity measurement, and a ZINB regression with tour complexity measurement. Equations (1)~(4) below give the ZINB regression function for a response y_i making j trips:

$$Pr(y_i = j) = \begin{cases} \pi_i + (1 - \pi_i)g(y_i = 0), \ j = 0 \\ (1 - \pi_i)g(y_i), \ j > 0 \end{cases} \tag{1}$$

$$g(y_i) = Pr(Y = y_i|\mu_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i} \tag{2}$$

$$log(\mu_i) = \boldsymbol{X\beta} \tag{3}$$

$$log\left(\frac{\pi_i}{1 - \pi_i}\right) = \boldsymbol{Z\gamma} \tag{4}$$

The ZINB model conflates tour adoption and tour frequency processes. The π_i refers to the probability of never making interregional travel by individual i. The underlying factors associated with π_i are estimated by logistic regression (Equation (4)). The underlying factors associated with the number of interregional travel tours are estimated using Negative Binomial regression (Equation (3)).

β and γ are coefficients to be estimated capturing the influence of personal and household socioeconomic factors, spatial factors, and tour characteristics on the generation of interregional travel tours. Based on the literature and data availability, selected factors include age, gender, income, educational attainments, employment status, presence of children, vehicle ownership, tour characteristics, and geographical locations (Berliner et al., 2018; Llorca et al., 2018). Conceptually, the structural zero regime captures those who do not make interregional travel due to structural constraints, including employment status, income, gender, vehicle ownership, and geographical locations. By contrast, zero tours in the tour-making regime are largely accounted for by broader factors (Chen et al., 2023; Kim & Mokhtarian, 2021).

Chapter 4. Results

This section presents analysis results organized around the three central questions of interest concerning (1) the characteristics of interregional travel relative to intraregional and the long-haul component of LDT, (2) the sociodemographic characteristics of interregional tour makers, and (3) the underlying factors influencing interregional tour-making decisions.

4.1. Tour characteristics of interregional travel

Figure 1 shows that interregional travel, with a one-way travel distance of 50–600 miles¬¬, took a large portion (94%) of the long-distance travel market. Figure 2 illustrates that the duration distribution of intraregional travel was severely right skewed. Most intraregional tours had relatively short tours within 60 minutes. The duration distribution of interregional travel was in the middle of three travel markets, where most interregional tours had a duration in the range of 120-210 minutes. The long-haul component of LDT spanned in a wide range with most locating in the range of 270-360 minutes. Figure 3 shows the main mode distribution of tours. Intraregional and interregional travel primarily used vehicles as the main mode, while the air mode dominated the long-haul component of LDT. For interregional travel tours, the shares of bus, rail, and airplanes are close. For the travel tours using rail, interregional travel outnumbered intraregional and the long-haul component of LDT.

4.1.1. Distance/duration/main mode distribution

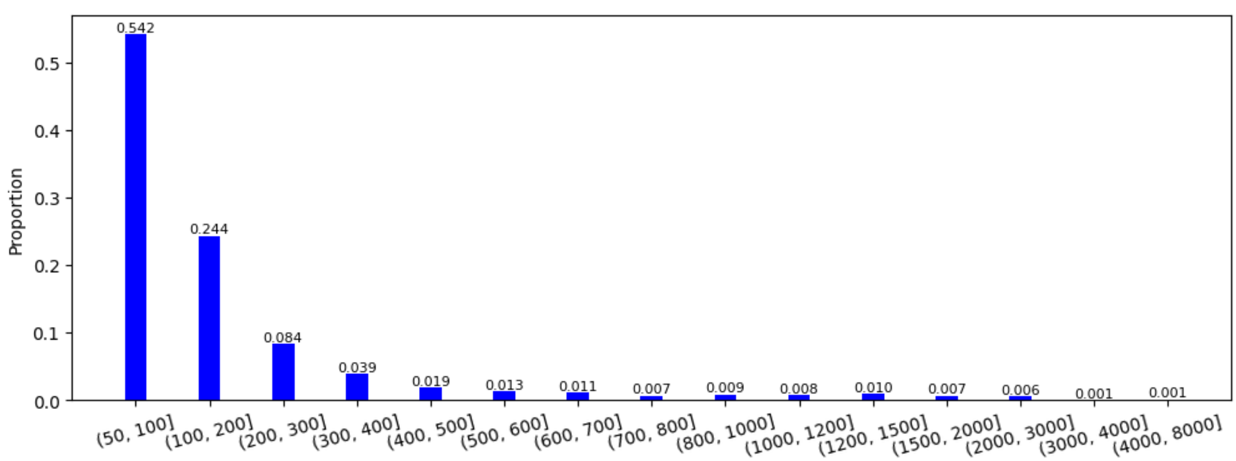


Figure 1 Proportion of Trips by One-way Tour Distance (50 Miles or More)

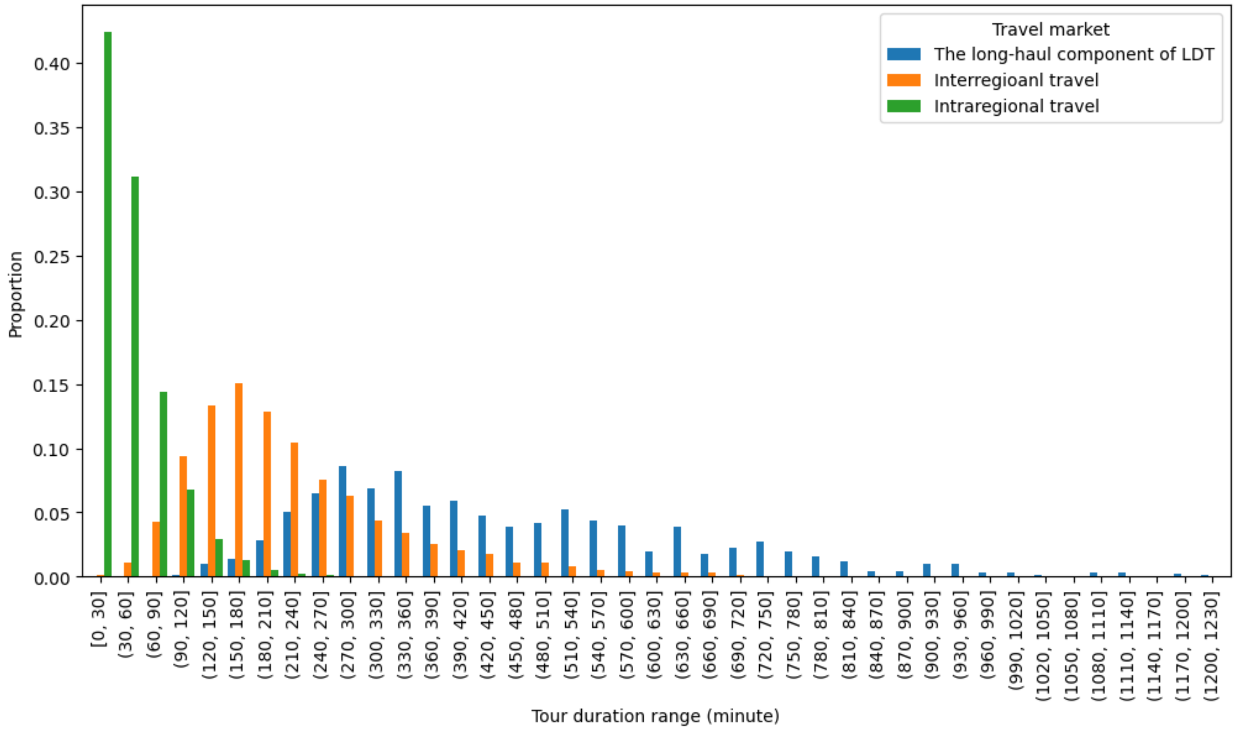


Figure 2 Proportion of Trips by Tour Duration (minute)of the Three Travel Market Segments

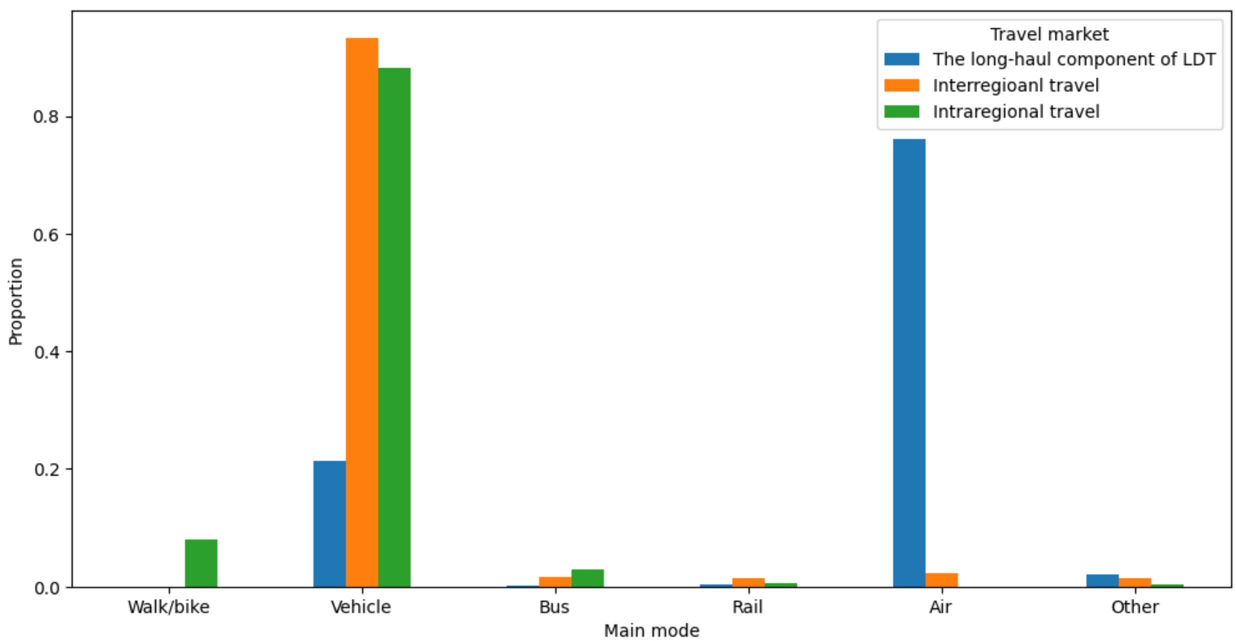


Figure 3 Share of the Main Modes in Trip Tours of the Three Travel Market Segments

4.1.2. Tour complexity

Tour complexity is a key attribute of trip-chaining behavior. Common measures of tour complexity include the number of stops or trip segments in each tour, the sequence of trip segment purposes, the combination of trip segment purposes, and tour duration (Currie & Delbosc, 2011; Grue et al., 2020; Ho & Mulley, 2013; Ma et al., 2014; Noland & Thomas, 2007; Pettersson & Schmöcker, 2010; Ye et al., 2007).

Table 2 reports the analysis results of tour complexity indicated by the number of non-home stops for intraregional, interregional travel, and the long-haul component of LDT. On average, interregional travel had 3.32 non-home stops, slightly less than the number of stops within the long-haul component of LDT tours (3.85) but much more than that within intraregional travel tours (1.90). The differences in tour complexity among the three market segments are statistically significant.

Table 2 Average number of non-home stops of Three Travel Market Segments

Travel market	Average number of non-home stops (std.dev)	Tour sample size
(1) Intraregional Travel	1.90 (1.42)	273,911
(2) Interregional Travel	3.32 (2.38)	17,149
(3) The long-haul Component of LDT	3.85 (1.81)	1,088
(2)-(1)	1.42***	
(2)-(3)	-0.53***	

Significance: *p<0.1; **p<0.05; ***p<0.01. F-Statistic=8109.399, p=0.000.

Table 3 and Figure 4 present the purpose complexity of travel tours for the three market segments. Following the conventional definition, this study identifies the main purpose of a tour based on the activity for which the longest time was spent (Cirillo & Axhausen, 2002). From Table 3 and Figure 4 we observe different tour complexity patterns between interregional travel and other two market segments. In the intraregional travel market, single purpose tours account for 68.41%, more than two thirds of all tours. Interregional travel exhibits the opposite distribution, with multipurpose tours accounting for 62.85%. The share of multipurpose tours is even larger for the long-haul segment of LDT at 71.32%. This purpose complexity pattern makes intuitive sense: when travel distance increases from intraregional travel to interregional and long-haul travel, people are more likely to combine multipurpose activities into a single tour.

The distribution of specific purposes displays interesting, varying patterns across the three market segments. For single-purpose tours, social and recreational travel accounts for 36.02 percent of all interregional travel, followed by work-related travel (30.17%). For intraregional travel, however, travel for shopping and errands has the largest share of 36.59%. The shares of intraregional travel for work-related and social and recreational purposes are about the same at 20.87% and 20.2%, respectively. In the long-haul segment of LDT, the purpose "Change type of transportation" dominates (48.08%), while work-related travel accounts for 25.64%. For multipurpose tours, work-related intraregional travel has the largest share (37.53%). Two main purposes, Social and recreational (30.19%) and Work-related (29.83%), have the highest shares for interregional travel. More than half of the long-haul multipurpose tours are for the purpose of "Change type of transportation," for instance, connecting flights.

The varying patterns of purpose complexity across intraregional, interregional, and the long-haul LDT as shown in Table 3 and Figure 4 suggest the necessity of distinguishing the three market segments for transportation planning and policy deliberation.

Table 3 Purpose composition of three travel markets

Purpose	**Intraregional Travel**	**Interregional Travel**	**Long-haul Component of LDT**
Tour sample size	273,911 (100.00)	17,149 (100.00)	1,088 (100.00)
Single purpose (%)	187,392 (68.41)	6,371 (37.15)	312 (28.68)
Work-related (%)	39,111 (20.87)	1,922 (30.17)	80 (25.64)
School/Church (%)	22,039 (11.76)	205 (3.22)	0 (0.00)
Shopping and Errands (%)	68,563 (36.59)	1,377 (21.61)	9 (2.88)
Social and Recreational (%)	37,853 (20.20)	2,295 (36.02)	69 (22.12)
Health care visit (%)	4,503 (2.40)	184 (2.89)	0 (0.00)

Volunteer activities (%)	2,580 (1.38)	43 (0.67)	0 (0.00)
Pick up/drop off someone (%)	11,731 (6.26)	165 (2.59)	2 (0.64)
Change type of transportation (%)	282 (0.15)	107 (1.68)	150 (48.08)
Other (%)	730 (0.39)	73 (1.15)	2 (0.64)
Single Purpose Subtotal (%)	187,392 (100.00)	6,371 (100.00)	312 (100.00)
Multiple purposes (%)	86,519 (31.59)	10,778 (62.85)	776 (71.32)
Work-related (%)	32,473 (37.53)	3,215 (29.83)	104 (13.40)
School/Church (%)	10,978 (12.69)	532 (4.94)	2 (0.26)
Shopping and Errands (%)	14,241 (16.46)	2,571 (23.85)	144 (18.56)
Social and Recreational (%)	19,556 (22.60)	3,254 (30.19)	97 (12.50)
Health care visit (%)	4,654 (5.38)	492 (4.56)	3 (0.39)
Volunteer activities (%)	2,130 (2.46)	107 (0.99)	1 (0.13)
Pick up/drop off someone (%)	1,809 (2.09)	322 (2.99)	24 (3.09)
Change type of transportation (%)	175 (0.20)	187 (1.74)	392 (50.52)
Other (%)	503 (0.58)	98 (0.91)	9 (1.16)
Multiple Purpose Subtotal (%)	86,519 (100.00)	10,778 (100.00)	776 (100.00)

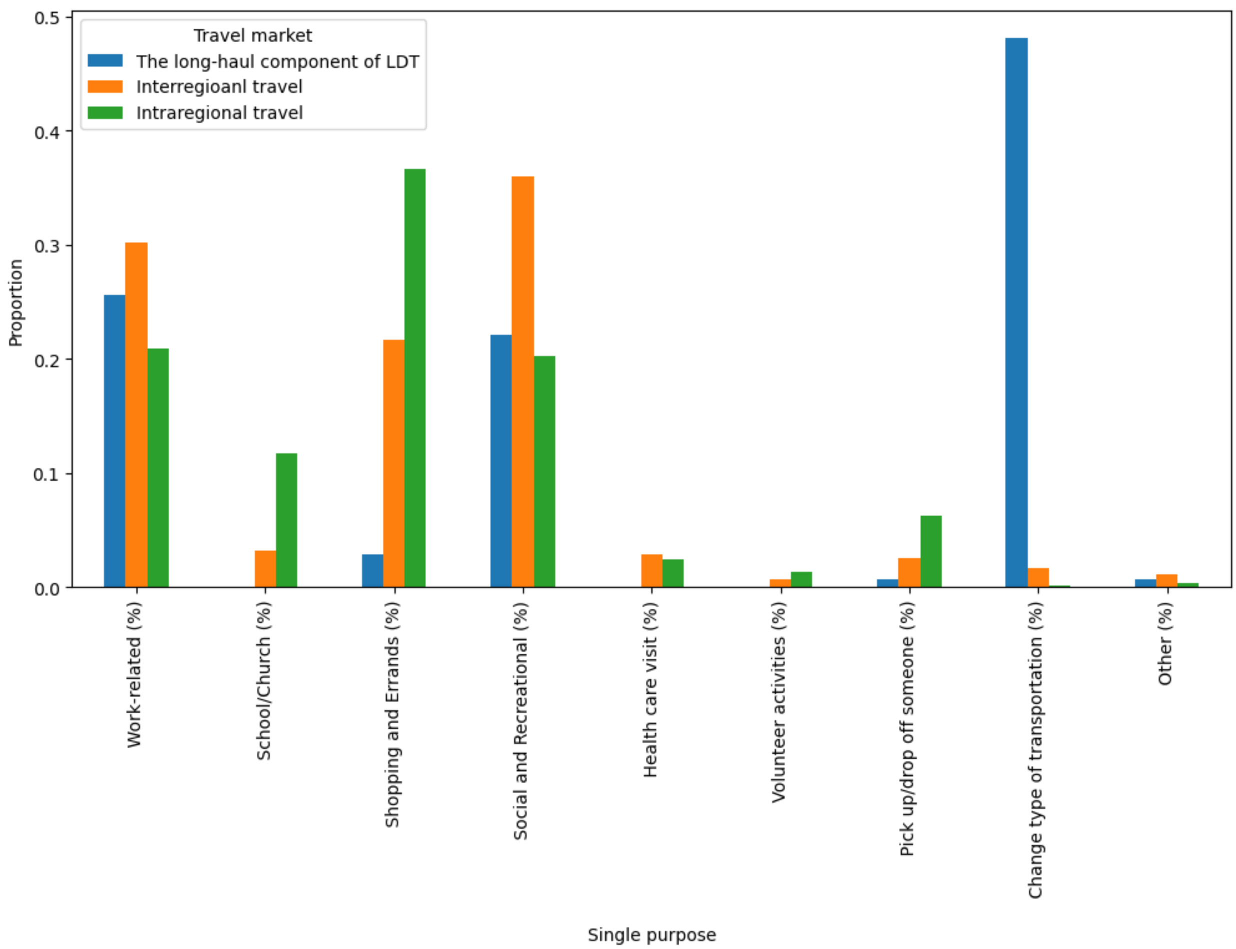
Note:

For multi-purpose travel, the main purpose of a tour was decided by activity type on which the longest time was spent along the whole tour.

‘Shopping and Errands’ purpose includes shopping and general errands (post office, library).

‘Social and recreational’ purpose includes attending adult care, recreational activities, exercise, and visiting friends.

‘Other’ purpose includes other unknown purposes.



Travel market
The long-haul component of LDT
Interregioanl travel
Intraregional travel
Proportion
0.0
0.1
0.2
0.3
0.4
0.5
Work-related (%)
School/Church (%)
Shopping and Errands (%)
Social and Recreational (%)
Health care visit (%)
Volunteer activities (%)
Pick up/drop off someone (%)
Change type of transportation (%)
Other (%)
Single purpose

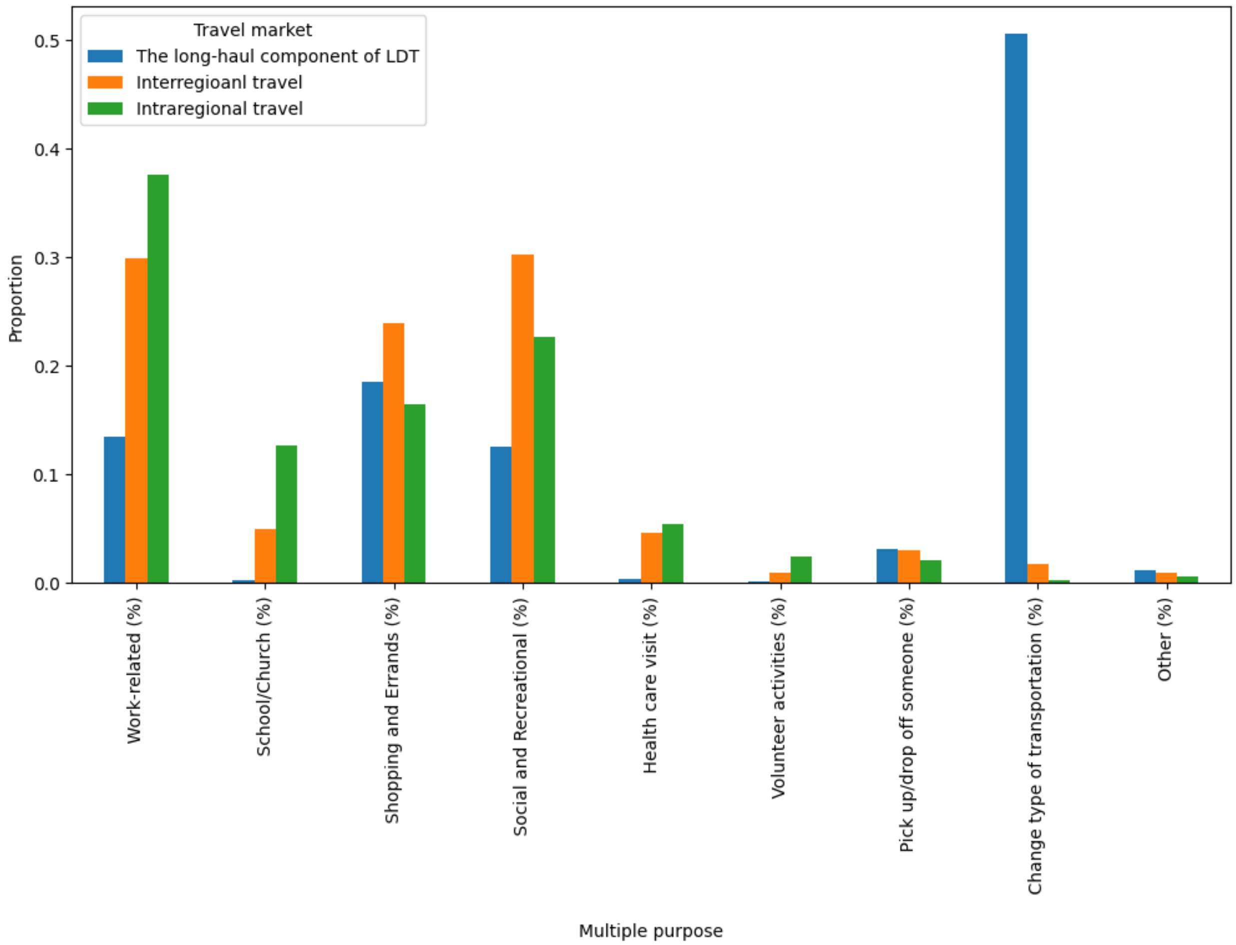


Figure 4 Tour purpose distribution of three travel markets

4.2. The sociodemographic characteristics of interregional trip makers

To shed light on who makes interregional travel, this study distinguishes between two groups of tour-making travelers, the structural zero-tour group and the tour-making group, using the results from the zero-inflated modeling. The structural zero-tour group refers to those who, in statistical terms, never make interregional travel. The tour-making group consists of people who do make interregional travel. Some of them may report zero interregional travel tours. These are sampling or incidental zeros – the sampled individuals happened to make no interregional travel tours on the survey day.

Table 5 shows the distribution of traveler groupsError! Reference source not found.. The share of structural zero group is 1.66%, and the share of tour-making group was 98.34%. As mentioned before, interregional travel was mainly made by car, the share of tour-making group (98.34%) was comparable to the share of the trip-making group for leisure travel obtained by Kim and Mokhtarian (2021) (air: 59%, vehicle: 90%). The share was higher because this study used a one-day survey that only collected interregional travel within the 24-hour frame, while Kim and Mokhtarian (2021) used the year-long survey data that collected LDT for the past 12 months. The short data-collection period might lead to an overestimation of accidental zero tours in the tour-making regime. Thus, it is more appropriate to use longer-time-frame survey data.

Conceptually, people who never make any interregional travel are restrained by structural constraints, including income, gender, household size, vehicle ownership, and living locations (Kim & Mokhtarian, 2021). Table 4 presents the profiles of two traveler groups, distinguishing between travel regimes (structural zeros and tour making).

People from both groups were mainly female, but the share of male in tour-making group was less than that in structural zero group. Tour-making group had averagely higher household income and larger household size than those from structural zero group. Among people who belonged to the tour-making group, they had averagely more vehicles than people from structural zero group. People from tour-making group had lower share of urbanists than that from structural zero group.

Note that Table 4 presents aggregated characteristics of traveler groups for work and nonwork travel, the specific impacts of structural factors will be shown in the next section.

Table 4 Profiles of two interregional traveler groups

Characteristics	**Traveler Groups**								**Mean difference**
	(1) Structural zeros N=4,233 (1.66%)				**(2) Tour making N=250,134 (98.34%)**				**(2)-(1)**
	Min	**Max**	**Mean**	**Std. dev**	**Min**	**Max**	**Mean**	**Std. dev**	
Male	0	1	0.49	0.50	0	1	0.47	0.50	-0.02**
Household income (1,000)	5	225	20.31	29.41	5	225	85.20	59.75	64.90***

Household size	1	10	2.54	1.93	1	13	2.71	1.40	0.17***
Vehicles per person	0	0.67	0.02	0.07	0	12	0.96	0.56	0.94***
Live in urban area	0	1	0.94	0.23	0	1	0.77	0.42	-0.18***

Significance: *p<0.1; **p<0.05; ***p<0.01.

4.3. The underlying factors influencing interregional trip-making decisions

This section presents empirical results from two zero-inflated models with varied specifications, i.e., Model 2 incorporates a complexity measurement, while Model 1 does not. Model estimates are presented in Table 5. The estimated coefficients in models provided information on the changes in the expected tour frequency given the changes in explanatory variables, shown as values in parenthesis under coefficient estimates in Table 5. For the count portions of two models, a unit change in the regressor x_i implies a percentage change in the frequency of tours by $100 \times [\exp(\beta_i) - 1]$ (Jang, 2005). For the zero-inflation portion of two models, the change refers to odds ratio change, indicating the change in the ratio of the probability of choosing to belong to the structural zero groups over the probability of choosing to belong to the tour-making group. The Vuong tests demonstrates that the ZINB models were better than the negative binomial models.

The effects of explanatory variables differ between Model 1 and Model 2, suggesting that the inclusion of complexity measurement has impacts on the tour frequency. The goodness-of-fit statistics, including Bayesian information criterion (BIC), Akaike information criterion (AIC), log-likelihood, and McFadden Pseudo-R^2, show that Model 2 has a better fit. The test between these two nested models suggests a significantly better fit of Model 2 than Model 1 (p-value of Chi-square test < 0.01); thus, the inclusion of complexity measurement is preferred. Similarly, (p-value < 0.01). The results of Model 2 are discussed in detail in this section. As few studies focus on interregional travel, the results are discussed with a comparison to LDT-related research.

4.3.1. Never making interregional travel

The positive coefficients in the logistic regression of ZINB indicate higher propensities of belonging to the structural zero regime and thus decrease the likelihood of making interregional travel. The model estimates are shown in the zero-inflation portion of the zero-inflated model (**Table 5**).

Gender, income, household size, vehicle ownership, and living location were seen as structural constraints for the interregional travel adoption process. Being male was more likely to never make any interregional travel. Not surprisingly, higher-income people were more likely to belong to the tour-making regime (Kim and Mokhtarian, 2021). Having a large household size was not associated with belonging to the structural zero group. Having more vehicles in the household was more likely to make interregional travel. The impacts were sizable, which reflected substantial impacts of vehicle ownership on promoting interregional travel. Living in urban areas discouraged residents from making any interregional travel (Pukhova et al., 2021).

4.3.2. Travel making

The model estimates for the trip-making regime are shown in the count model portion of the zero-inflated model (Table 5). Age had positive impacts on work interregional travel but negative impacts for interregional travel (LaMondia et al., 2014; Outwater, Bradley, Ferdous, Bhat, et al., 2015). Males generally made more interregional work travel than females (Aultman-Hall et al., 2018; Erhardt et al., 2007; Kim & Mokhtarian, 2021; Pukhova et al., 2021). Male made more than female by 9.5%, comparable to 16% obtained in existing research (Mitra & Saphores, 2019). Higher education was positively associated with interregional travel (Aultman-Hall et al., 2018; Erhardt et al., 2007; LaMondia et al., 2014). Employed people made more interregional travel. People with higher income was likely to make more interregional travel (Davis et al., 2018; Kim & Mokhtarian, 2021; LaMondia et al., 2014; Lu et al., 2014; Mitra & Saphores, 2019; Outwater et al., 2010; Pukhova et al., 2021). Household size presents significant negative impacts frequency (Cambridge Systematics, Inc., 2016; Erhardt et al., 2007; Outwater et al., 2010). Higher vehicle ownership would lead to more interregional travel (LaMondia et al., 2014). Living in MSAs, urban areas, or megaregions was associated with less work or nonwork interregional travel (Pukhova et al., 2021). State-level population showed positive impacts on interregional travel, suggesting more interregional tours in states with large populations. The proportions of single-purpose tours had positive impacts on tour frequency. It is reasonable, as the tendency of making single-purpose tours promotes more tours (Daisy et al., 2020).

Table 5 Model Estimates

Variable	Model 1		Model 2	
	Estimates (Change)	95% Confidence interval	Estimates (Change)	95% Confidence interval
Count portion				
(Intercept)	-3.876*** (-97.9)	[-4.039, -3.714] ([-98.2, -97.6])	-3.795*** (-97.8)	[-3.953, -3.636] ([-98.1, -97.4])
log(age)	0.048*** (4.9)	[0.015, 0.080] ([1.5, 8.4])	0.029* (2.9)	[-0.004, 0.061] ([-0.4, 6.3])
Male	0.221*** (24.7)	[0.187, 0.255] ([20.6, 29.0])	0.095*** (9.9)	[0.061, 0.128] ([6.3, 13.6])
Edu. 2	0.153*** (16.5)	[0.107, 0.199] ([11.3, 22.1])	0.115*** (12.2)	[0.069, 0.161] ([7.2, 17.5])
Edu. 3	0.272*** (31.2)	[0.222, 0.321] ([24.8, 37.9])	0.277*** (31.9)	[0.227, 0.326] ([25.5, 38.5])
Edu. 4	0.205*** (22.8)	[0.150, 0.261] ([16.2, 29.8])	0.254*** (29.0)	[0.200, 0.309] ([22.1, 36.2])
Employed	0.399*** (49.0)	[0.362, 0.436] ([43.6, 54.7])	0.285*** (32.9)	[0.247, 0.322] ([28.1, 38.0])
log(adjusted household income)	0.257*** (29.3)	[0.232, 0.282] ([26.1, 32.5])	0.171*** (18.7)	[0.148, 0.195] ([15.9, 21.5])
log(household size)	-0.080*** (-7.7)	[-0.125, -0.035] ([-11.8, -3.4])	-0.130*** (-12.2)	[-0.172, -0.088] ([-15.8, -8.4])
Vehicles per person	0.123*** (13.1)	[0.090, 0.156] ([9.4, 16.9])	0.052*** (5.3)	[0.019, 0.085] ([1.9, 8.9])
Live in MSA	-0.310*** (-26.7)	[-0.359, -0.262] ([-30.2, -23.0])	-0.183*** (-16.7)	[-0.231, -0.135] ([-20.7, -12.6])
Live in urban	-0.326*** (-27.8)	[-0.369, -0.283] ([-30.9, -24.6])	-0.309*** (-26.6)	[-0.351, -0.268] ([-29.6, -23.5])
Live in megaregion	-0.194*** (-17.6)	[-0.233, -0.154] ([-20.8, -14.3])	-0.118*** (-11.2)	[-0.158, -0.079] ([-14.6, -7.6])

log(state population)	0.085*** (8.9)	[0.066, 0.104] ([6.8, 10.9])	0.044*** (4.5)	[0.025, 0.063] ([2.6, 6.5])
Prop. of single-purpose tours	\	\	3.110*** (2143.0)	[3.076, 3.144] ([2068.2, 2220.4])
Log(theta)	23.470***	\	15.692***	\
Zero-inflation portion				
(Intercept)	-1.139* (-68.0)	[-2.365, 0.087] ([-90.6, 9.1])	-0.693 (-50.0)	[-2.424, 1.038] ([-91.1, 182.5])
Male	0.285 (33.0)	[-0.156, 0.727] ([-14.4, 106.9])	0.584* (79.3)	[-0.100, 1.267] ([-9.5, 255.2])
log(adjusted household income)	-0.326*** (-27.8)	[-0.503, -0.148] ([-39.5, -13.8])	-0.580*** (-44.0)	[-0.851, -0.309] ([-57.3, -26.6])
log(household size)	1.375*** (295.4)	[0.868, 1.881] ([138.3, 555.9])	0.699** (101.2)	[0.070, 1.328] ([7.2, 277.4])
Vehicles per person	-9.827*** (-100.0)	[-11.725, -7.929] ([-100.0, -100.0])	-15.741*** (-100.0)	[-20.558, -10.925] ([-100.0, -100.0])
Live in urban area	1.199*** (231.5)	[0.370, 2.027] ([44.8, 659.0])	1.129* (209.1)	[-0.182, 2.439] ([-16.6, 1045.9])
Model summary				
AIC	111,080.1		89,552.35	
BIC	111,299.5		89,782.17	
Log-Likelihood	-55,519.05 (df=21)		-44,754.17 (df=22)	
McFadden Pseudo-R^2	0.04 (df=21)		0.23 (df=22)	
Vuong statistic	5.51***		4.52***	
Observations	254,367		254,367	

Significance: *p<0.1; **p<0.05; ***p<0.01.

Note: McFadden Pseudo-R^2 is calculated as $1-\frac{LL_{mod}}{LL_c}$ (LL_c means the constant-only Negative Binomial model). Change is calculated as $100 \times [\exp(\beta_i) - 1]$.

4.4. Marginal effect analysis of interregional travel generation

Table 5 gave information on the changes (marginal effects/elasticities) in the expected tour frequency given the changes in explanatory variables. To illustrate the trend of tour frequency, this section examines the influence of specific variables on the tour frequency by displaying frequency patterns for covariate-adjusted model results predicted from Model 1 and Model 2 (Figure 5). This section estimates the interregional tour frequency for a covariate-adjusted individual with assumed sociodemographic or tour characteristics, including age, adjusted household income, vehicle ownership, household size, and proportions of single-purpose tours. The other control variables not used as the interested factors are set at their mean values. Generally, the trend line representing Model 21 located above that of Model 2, indicating that the inclusion of the complexity measurement had significant impact on the model estimates and the exclusion of the complexity measurement may overestimate the marginal effects of sociodemographic factors.

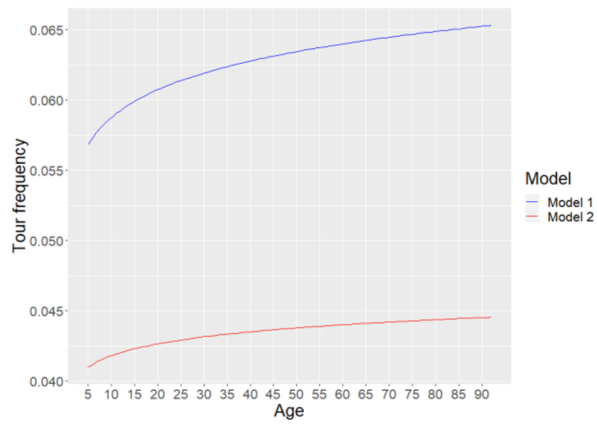
The age was log-transformed in this study. The elasticity for nonwork travel (0.029 in Table 5) means 1% increase in age led to 0.029% increase in interregional tour frequency. At the mean age (48 years old in **Table 1**), 1 year-old change was associated with 0.060% ($1/48 * 100 * 0.029\%$) change in tour frequency. The impact of age on leisure LDT frequency in the California case (Berliner et al., 2018) was that 1 year-old change in age led to 1% change in tour frequency, which was much more than the results obtained in this study. The existing research used data collected specifically from California residents between 18-50 years old. It indicated that the average nationwide interregional trip making was less than those made by young people from California. What is more, the slope of the impacts of age on the tour frequency decreased as age increased (Figure 5). It indicates that as people grow older, their travel habits become stable with fewer changes.

At the average adjusted household income (34.24 in **Table 1**), 1 unit change in the adjusted household income led to 0.499% ($1/34.24 * 100 * 0.171\%$) change in tour frequency on average (Table 5), which was higher than that obtained in existing research where the marginal effect for work travel was 8.8% with a respective $10k change in individual income (Berliner et al., 2018). It might be because the existing research focuses on the travel behavior of California residents whose average income is higher than those on average in the nation. Higher-income people might have less travel sensitivity to income change. It is supported by the pattern shown in Figure 5. The slope of the impact of adjusted income on the tour frequency decreased as adjusted income increased. As household income became high, the cost of interregional travel might be less burdensome for individuals to make interregional travel; thus, tour-making sensitivity to changes in adjusted income became smaller.

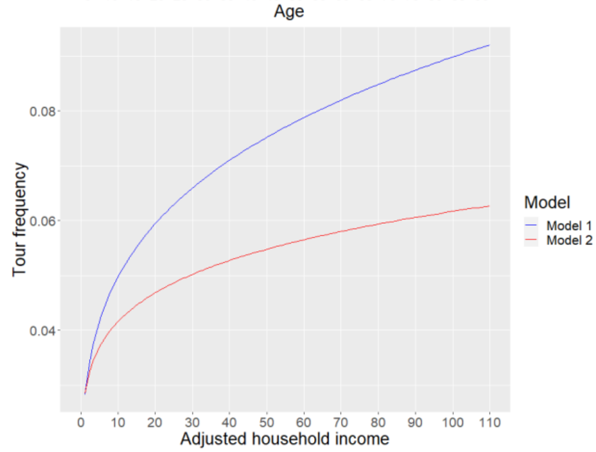
The impacts of vehicle ownership consisted of two parts. More vehicles per person contributed to increasing the probability of belonging to the tour-making group by a large extent. For people making interregional travel, vehicle ownership increased the tour frequency by 5.2% (Table 5). Furthermore, the impacts of vehicle ownership on tour frequency increased as the number of vehicles per person increased (Figure 5).

Household size had negative impacts on tour frequency. Specifically, 1 person increase in the household was associated with 0.13% decrease in tour frequency (Table 5). As shown in the travel pattern (Figure 5), the slope of the impact of household size decreased as household size increased.

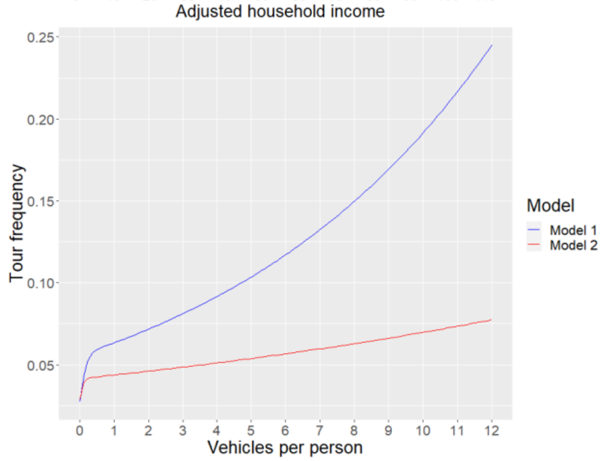
The proportions of single-purpose tours presented a massive influence on tour frequency. Moreover, impacts increased as proportions increased. The result implies that, when people tend to make single-purpose tours, their tour frequency increases. In addition, as the proportion becomes larger, people make many more tours.



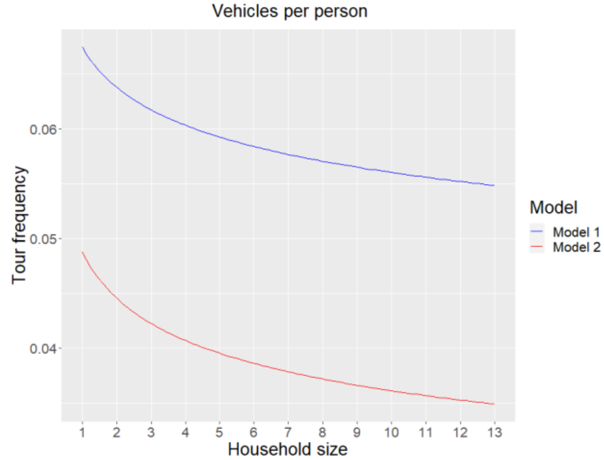
Tour frequency
0.040
0.045
0.050
0.055
0.060
0.065
5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90
Age
Model
Model 1
Model 2



Tour frequency
0.04
0.06
0.08
0 10 20 30 40 50 60 70 80 90 100 110
Adjusted household income
Model
Model 1
Model 2



Tour frequency
0.05
0.10
0.15
0.20
0.25
0 1 2 3 4 5 6 7 8 9 10 11 12
Vehicles per person
Model
Model 1
Model 2



Tour frequency
0.04
0.05
0.06
1 2 3 4 5 6 7 8 9 10 11 12 13
Household size
Model
Model 1
Model 2

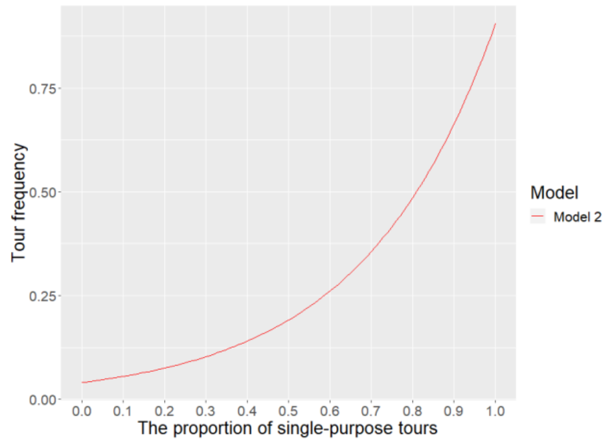


Figure 5 Estimated tour frequency for a covariate-adjusted individual

4.5. Interregional travel tour rates

Based on model results, Table 6 shows derived tour rates for interregional travel. The recommended cross-classification is household income and household size. The household income is stratified into four categories, and household size is stratified into five categories. Compared to the recommended long-distance trip production rates in existing report (Schiffer, 2012), the recommended daily interregional person tour rates are higher. It is reasonable, as existing report made recommendation based on 1995 ATS that defined long-distance travel as round-way tours with furthest destination 75 miles away and excluded one-way tours and tours with distance between 50 and 75 miles. Another reason might be due to the increasing trend of LDT in recent decades.

Table 6 Daily interregional person tour rates

Urban area						
Income by household size	1	2	3	4	5+	Total
0-24,999	0.033	0.032	0.028	0.024	0.021	0.030
25,000-49,999	0.053	0.049	0.044	0.040	0.035	0.047
50,000-99,999	0.072	0.066	0.059	0.051	0.043	0.061
100,000+	0.096	0.084	0.078	0.067	0.055	0.076
Total	0.056	0.065	0.060	0.055	0.044	0.059
Rural area						

0-24,999	0.056	0.059	0.051	0.059	0.048	0.056
25,000-49,999	0.098	0.079	0.085	0.080	0.056	0.081
50,000-99,999	0.143	0.119	0.099	0.095	0.072	0.109
100,000+	0.165	0.154	0.121	0.115	0.096	0.133
Total	0.094	0.111	0.096	0.098	0.073	0.101
Total						
Income by household size	1	2	3	4	5+	Total
0-24,999	0.038	0.040	0.033	0.031	0.027	0.036
25,000-49,999	0.062	0.058	0.054	0.051	0.040	0.056
50,000-99,999	0.083	0.080	0.068	0.062	0.051	0.073
100,000+	0.105	0.099	0.086	0.075	0.063	0.087
Total	0.063	0.077	0.068	0.064	0.050	0.068

Chapter 5. Discussions

Interregional travel is gaining increasing attention from transportation planners and policy-makers because of its close relationship with society. Yet there has been limited understanding of interregional travel behavior due to a lack of data about the specific market segment (NASEM, 2016). This study explores the potential of utilizing the existing US national travel surveys to fill the knowledge gap. The study estimated travel tour generation models for interregional travel using the 2017 US NHTS. Given that NHTS reports travel characteristics on assigned travel days but interregional travel does not take place on a daily basis, the survey data presents “excess zero” observations for international travel tours. A Zero-Inflated Negative Binomial modeling approach was taken to overcome the data limitation.

The study presented unique characteristics of interregional travel as relative to intraregional travel and the long-haul component of LDT. Interregional travel took up a major portion of LDT. It displayed similar characteristics to both the intraregional travel market and the long-haul component of LDT market. For example, the tour duration distribution of interregional travel located in the middle of intraregional travel and the long-haul component of LDT markets. Most interregional tours had a duration in the range of 120-210 minutes. Interregional tours might be a trade-off between travel cost and living cost (Alonso, 1964). For example, people might choose to live far away from their work locations to have low housing prices and well-paid jobs. In such cases, longer-distance commutes are the outcome of a job search process where the longer-distance commutes are typically compensated by higher wage rates (Plaut, 2006; Sandow & Westin, 2010). In addition, the interregional travel market resembles the intraregional travel market in having vehicles as the main mode and demonstrates the potential to offer competitive service (National Academies of Sciences, Engineering, and Medicine (NASEM), 2016). Note that rail mainly serves the interregional travel market and merits special consideration in future research. Interregional travel was composed of multiple trip segments and had a large portion of multiple-purpose travel, which was much more than intraregional travel but resembled the long-haul component of LDT. What is more, a large portion of interregional travel tours were for multiple purposes, similar to the long-haul component of LDT. For multiple-purpose interregional travel, it largely comprised shopping/errands and social/recreational trip segments, similar to intraregional travel.

This study separated travelers into two groups, including the structural zero group and the tour-making group, according to the structural factors (gender, household income, household size, vehicle ownership, and living location). The profiles of these two groups were presented by showing the aggregated sociodemographic characteristics. It showed that the shares of two groups were comparable to the results in the existing study (Kim & Mokhtarian, 2021). However, due to the data being collected within 24 hours, the model in this study overestimated shares in the tour-making regime interregional travel. Generally, people belonging to the tour-making group had higher income, more vehicles per person, and larger household size. Their shares of males and residents living in urban areas were less than structural zero group.

For transportation planning and policymaking, the underlying factors influencing interregional travel were examined. The impact tour complexity, measured by the proportion of single-purpose tours, was tested by comparing models. The results demonstrated the legitimate inclusion of complexity measurement in the model. Additionally, ZINB models outperformed negative binomial models.

The results demonstrated the significant impacts of structural constraints (including gender, income, household size, vehicle ownership, and living location) for travelers on the interregional tour adoption process and examined the impacts of factors (age, gender, education, employment status, income, household size, vehicle ownership, living location, and tour complexity measurement) contributing to the tour frequency for the tour-making group. The living locations were represented by multiple variables, including living in MSA, living in urban areas, living in megaregion, and state-level population. As shown in previous studies, LDT was largely affected by census region (Dargay & Clark, 2012; Fisher et al., 2022). Census region factors have been tested in the model building but did not produce legitimate parameter estimates. Instead, the state-level impacts represented by state population generate reasonable estimates, demonstrating that interregional travel behavior varies across states (Kim & Mokhtarian, 2021). Living in rural areas favors conducting interregional travel. The limited access to the railway network in rural areas might contribute to the intense use of vehicles for interregional travel.

This study looked at the influence of key planning and policy variables (age, income, vehicle ownership, household size, and tour complexity measurement) on the tour frequency patterns by investigating both their marginal effect/elasticity and their relationship with frequency. Income and vehicle ownership facilitate interregional tour-making via two processes, encouraging people to make interregional travel and increase the frequency. The sensitivity of tour frequency to income decreased as income increased and the sensitivity to vehicle ownership increased as vehicle ownership increased. Older people made more interregional travel. The increasing in household size discouraged interregional travel by both decreasing the probability and frequency of interregional tour making. The sensitivity of tour frequency to age and household size dropped as these two factors become larger. The complexity measurement presented a significant and substantial impact on the tour-making regime. As the proportion glowed, the sensitivity of tour frequency increased.

This study gave the recommended daily interregional person tour rates. The interregional tour rates are higher than the existing recommended LDT tour rates derived using 1995 data to support the up-to-date transportation planning practice.

Chapter 6. Conclusions

As the daily travel distance becomes longer and long-distance travel becomes more frequent, interregional travel emerges as a critical travel market that merits investigation. This study echoes the call of the TRB committee to obtain empirical findings by using appropriate analytical tools and datasets (NASEM, 2016). Several contributions are summarized below.

First, this study utilizing the 2017 NHTS demonstrated untapped potential in the existing national travel surveys to overcome data limitations facing interregional travel research. At the same time, the study revealed shortcomings of the daily travel-based travel surveys for understanding interregional travel decisions that households make primarily on a weekly-, monthly-, or seasonal basis. Design for future national travel surveys should expand the timeframe for travel decisions to capture better future trends, including the trends of interregional travel. In addition, the impacts of employment status on interregional tour-making are obtained using data in 2017 under the assumption that employed individuals work on-site. However, flexible work policies, e.g., remote working and flexible working time, have been widely enforced during the time of COVID and might change work habits. People who have alternatives to work from home or have flexible working time might reduce interregional work travel (Iacus et al., 2020; Truong & Truong, 2021). During the transition to the post-COVID situation, whether the changes in people's habits and preferences regarding working from home persist and what their impacts are yet to be thoroughly examined. In order to investigate the impacts of flexible work policies, the relevant factors should be considered in the future data collection design.

Second, this study analyzed interregional travel generation behavior, focusing specifically on the tour as the primary unit of analysis. The study revealed that tour complexity in terms of travel purposes had significant impacts on tour-making. It reinforced the need, as previously articulated in research, for an analysis based on tours when examining long-distance travel (Aultman-Hall, 2018; Bricka, 2008). However, current tour-based travel demand modeling practice lacks the consideration of the complexity of tours on the tour making. For example, e.g., the San Francisco County Chained Activity Modeling Process (SF-CHAMP) and the Atlanta model consider tour frequency and stop frequency independently (Atlanta Regional Commission (ARC), 2019; Cambridge Systematics, Inc., 2002). The substantial impacts of tour complexity suggest their potential in increasing the accuracy of predicting the tour frequency. This study shed light on the necessity and potential of the consideration of tour complexity in the tour-based demand modeling practice.

Third, several implications for future policymaking can be drawn from the insights gained in this study. It is critical to understand factors associated with two types of travel regimes, i.e., structural zero regime and tour-making regime, for understanding future travel trends. For example, gender, income, household size, vehicle ownership, living in urban areas impact both tour adoption and tour frequency. Age and tour complexity affect tour frequency. The diversity of driving forces found in individual structural constraints suggests different mobility strategies for interregional travel-making decisions. Structural constraints have impacts on individuals' decision on never making any interregional travel. The impacts of structural constraints on whether making interregional gave insights on policy measurements. The structural zero group merits further investigation into the cause of constraints, and it might be associated with the social equity issue.

Fourth, insights could be drawn for future interregional travel planning practice. Policies to reduce vehicle ownership have a great impact on interregional travel as the vehicle is the main mode adopted for interregional travel. However, interregional travel is the main travel market served by rail system. The finding coincides with the argument found in the Milan case where high-speed rail plays an important role for long-distance commuters (Pucci et al., 2022). The growing interest in developing and improving the rail system in the U.S. and enforcing affiliated regulatory measures favor interregional travel. The understanding of the characteristics of travelers and determinants of interregional travel contributes to the strategy-making to develop and improve services of the rail system. Aside from acknowledging the impacts of demographic factors, this study tested and confirmed the impacts of geographic locations represented by state-level populations (Kim & Mokhtarian, 2021). It might support the unbalanced development of the transportation system in the U.S., revealing the need to create a well-distributed and accessible interregional transportation network.

Chapter 7. Acknowledgments

This research was supported by the Cooperative Mobility for Competitive Megaregions (CM2) center at The University of Texas at Austin.

Chapter 8. References

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