LONG-DISTANCE TRIP GENERATION AND PARTY SIZE BEFORE AND AFTER PANDEMIC

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ABSTRACT

Long-distance (LD) travel, although infrequent, accounts for a disproportionately large share of person-miles, and its key determinants have shifted profoundly since the COVID-19 pandemic. Most existing studies on LD trips rely on pre-pandemic data and do not account for these changes. This study fills this gap by examining changes in Americans' passenger travel, combining household-level trip records from the 2017 and 2022 National Household Travel Surveys (NHTS). Results show that LD trip rates remained low in both years, and the number of trips declined after the pandemic. In 2017, rural residence, greater household vehicle ownership, and a higher number of workers in the household increased the likelihood of LD travel, especially on weekends, indicated by the Hurdle models' estimation for LD trip generation. However, in 2022, vehicle access and the presence of worker-rich and rural white households had become even more influential, while child-free adult households were less likely to travel on weekends. Temporal and spatial patterns also shifted, with August and urban renters seeing higher trip rates in 2022. Party size remained stable, with pairs accounting for half of LD trips, and there was only a slight increase in mean size. Ordered logit models show that larger groups preferred weekend trips, whereas business travel was mainly done by smaller parties. Before the pandemic, pickup-truck use and white households were associated with a higher likelihood of traveling in larger groups. After the pandemic, car use became linked to smaller group sizes, and white households showed an even stronger tendency to travel in larger groups compared to before.

Keywords: Long-distance travel, Travel demand modeling, Trip generation, Travel party size, Ordered logit model, Hurdle model.

BACKGROUND

Long-distance (LD) trips (usually defined as one-way trips of 50 miles or more) comprise just 2.5% of person-trips yet generated 43.3% of person-miles traveled (PMT) in 2017, rising to 34% when using a 100-mile threshold (McGuckin, 2018; Perrine et al., 2020). Such travel drives traffic volumes, congestion, emissions, crashes, pavement wear and travel costs. Limtanakool et al. (2006) and Aamaas et al. (2013) showed that LD travel, while infrequent, accounts for the majority of climate impacts from passenger transport. They argued that infrastructure investments surrounding high-speed rail can alter these modal shares and reduce emissions (Kristoffersson & Liu, 2023; Gutierrez, 2001). Due to pandemic, passenger trips of 25–100 miles in April 2020 fell by 47% relative to April 2019 (BTS, 2020), only to rebound as telecommuting and e-shopping became entrenched (Perrine et al., 2020). Moreover, LD mobility enhances access to specialized services such as health care, retail outlets and social events, especially in rural areas, and sustains spatially extended social networks (Urry, 2003). The 2001 National Household Travel Survey (NHTS) was the first U.S. survey to collect detailed LD data prior to 2020 (Hu and Reuscher, 2004). Its 2017 data release focuses on one-day, one-way trips that contributed over 1,500 trillion annual LD PMT, with private vehicles accounting for 90% of trips but just 8% from public modes (e.g., air, bus, train) (BTS, 2017; McGuckin, 2018). By the late 2000s, over 35 state agencies, often with federal partners, had established inter-regional and statewide models (Souleyrette et al., 1998; Giaimo & Schiffer, 2005; Horowitz, 2006, 2008; Cohen et al., 2008).

Despite these advances, LD trip-making has remained relatively under-served in both data collection and methodological improvements compared to urban travel systems. Sustained economic expansion, rising car ownership, and infrastructure improvements in highways, rail, and air transport have lowered both monetary and time costs while enhancing safety and enabling travelers to maintain a roughly constant time budget even as trip distances increase (Arbues et al., 2016; Schafer, 1998). At the same time, higher disposable incomes and more affordable vehicle access have driven both business and personal LD trips, promoting inter-regional economic integration, improving access to services, and expanding tourism markets (Limtanakool et al., 2006). The COVID-19 pandemic, however, has disrupted these patterns, with social-distancing mandates and stay-at-home orders leading to the closure of businesses, recreational venues, workplaces, and schools, and imposing domestic and international travel restrictions (Engle et al., 2020; Beigi et al., 2022), developments that pre-2022 data and models cannot capture (for instance, sharp decline in commute trips, changes in departure times). As a result, individuals substituted or supplemented out-of-home activities with home-based alternatives (Fatmi et al., 2021). The rapid shift to flexible work arrangements and widespread work-from-home significantly reduced commute trips and influenced daily travel patterns (Elldér, 2020). In the United States, county-level commuting volumes declined by approximately 65% compared to typical daily levels (Klein et al., 2020). In the United Kingdom, nearly half of former transit commuters planned to switch modes post-pandemic, while over 80% of car commuters intended to continue driving once restrictions eased (Harrington and Hadjiconstantinou, 2020). Beyond daily trips, remote work and distance learning effectively eliminated commutes as physical workplaces and schools closed (Leger, 2020). At the same time, online shopping emerged as a primary means of avoiding in-store purchases (The Globe and Mail, 2020), and global border closures severely curtailed LD travel (The New York Times, 2020).

Determinants of LD Trip Generation

LD travel decisions hinge on both cost–time trade-offs and choices about overnight stays with an average occupancy exceed two persons per LD trip, which is far above the 1.1 persons for work or 1.3 for other urban trips showing the importance of schedule coordination and larger-vehicle use (LaMondia et al., 2016b). Frequency, distance, mode, destination, household income, traveler age, education, and the presence of children all significantly influence LD trip rates (Sandow and Westin, 2010; Collia et al., 2003; Holz-Rau et al., 2014; Cho, 2013). Event-specific purposes such as, conferences, weddings, funerals, sports tournaments, music concerts regularly raise LD travel (Yang et al., 2016; Burke and Woolcock, 2013; McKercher et al., 2008; Aguilera, 2008). Business travelers, especially with employer reimbursements, often choose faster modes (air + TNC) for trips over 750 miles and prioritize schedule flexibility and travel time over cost (Cai et al., 2011; Gustafson, 2012). Leisure and tourism trips cluster around holiday periods, shaping seasonal demand for these LD trips (Große et al., 2019). Several studies have quantified the effects of socioeconomic variables on LD travel, such as Orfeuil and Soleyret (2002) who showed that middle-aged, higher-income, centrally located French travelers travel farther, with urban residents using cars less. Limtanakool et al. (2006) found in the U.K. and Netherlands that higher income raises LD-trip likelihood, while female gender and complex households reduce it, and that women and urban residents showed higher train use. In the U.S., Mallett (1999a and 1999b) and Georggi and Pendyala (1999) showed that high-income, car-owning, educated households make more LD trips, whereas minorities and single parents are less mobile. Mokhtarian et al. (2001) further revealed that attitudes, personality, and lifestyle can yield superior explanatory power over demographics alone.

LD Trip Generation and Mode-Choice Modeling

Past research on LD trip-generation modeling have used ordered probit (LaMondia, 2014), negative-binomial regression (Aultman-Hall, 2018; Berliner, 2018; Czepkiewicz et al., 2018), nested and multinomial logit models (Koppelman and Hirsh, 1986; Forinash & Koppelman, 1993; Bhat, 1995; Lee et al., 2010), and joint-estimation frameworks (FHWA, 2015; Erhardt et al., 2007; Rohr et al., 2013; Bernardin et al., 2017; Perrine et al., 2020; Outwater et al., 2010; Moeckel et al., 2015). Some modeling efforts include Europe's TRANS-TOOLS project; statewide LD models in Ohio and California (Erhardt et al., 2007; Rohr et al., 2013; Perrine et al., 2020); and the FHWA's national rJourney model, which jointly estimated trip generation, duration, party size, and mode choice (FHWA, 2015). Beyond traditional cost–time considerations, recent work has examined the psychological and experiential dimensions of LD travel. Lyons et al. (2007), Wardman and

Lyons (2016), and Cornet et al. (2021) found that in-transit productivity or leisure enhances the perceived value of travel time in LD trips, especially for rail. Wang and Loo (2019) documented increased "e-activity" satisfaction on high-speed trains enabled by ICT, while Price and Matthews (2013) highlighted LD leisure travel's restorative benefits for parents and children. At the mode-choice level, multilevel multinomial-logit analyses showed that socioeconomic characteristics, trip attributes, specially, overnight stays and the geographic context of trip origins jointly influence utilities for car, bus, and train alternatives (Arbues et al., 2016). Longer trip durations increase rail demand, with women and urban residents particularly responsive to service improvements (Bhat, 1997; Limtanakool et al., 2006; Georggi & Pendyala, 2001), while seniors favor cars and lower-income or minority groups rely more on buses and trains (Kuhnimhof et al., 2012; Mallett, 2001). Land-use factors like population density, mixed development, proximity to high-speed stations further modulate mode shares (Limtanakool et al., 2006; Garmendia et al., 2011), although lifestyles and preferences (subjective factors) also influence LD choices (van Acker et al., 2007).

Although urban studies have examined rule-based heuristics (Wolf et al., 2001; Stopher et al., 2005, 2008a), clustering and validation techniques (Stopher et al., 2008b; Chen et al., 2010; Gong and Chen, 2012; Bohte and Maat, 2009) and machine-learning methodologies (Griffin et al., 2005; Deng & Ji, 2010; Liu et al., 2013; Wang and Sun, 2015; Lu et al., 2013), these methods have seen little extension to LD travels, where trip purpose diversity and party size critically influence decisions (Lu et al., 2015). Addressing this gap, the present study systematically analyzes LD trip behavior using the 2017 and 2022 NHTS datasets, thereby capturing both pre- and post-COVID-19 shifts in travel. It then models LD (trips greater than 50 miles) trip generation and travel party sizes, taking into account trip purposes and other household demographic characteristics.

DATA ANALYSIS

This study uses two primary datasets, 2017 and 2022 NHTS (Table 1), to examine LD travel patterns and their trends over time. The 2017 NHTS provides a nationally representative snapshot of travel behavior in the pre-pandemic era, while the 2022 NHTS offers comparable data reflecting the profound changes in mobility following the COVID-19 pandemic. The 2017 NHTS provides the U.S. Department of Transportation's comprehensive, nationally representative portrait of daily travel by American residents in all 50 states and the District of Columbia. After a pilot phase in mid-2015, the main survey ran from March 2016 through May 2017, with assigned travel days spanning April 19, 2016, to April 25, 2017. Each sampled household reported every trip taken over a 24-hour "travel day" (4 AM local time to 3:59 AM the next calendar day) by all five and older members. For each trip, respondents recorded purpose (e.g., work, school, shopping, recreation), mode of travel (private vehicle, transit, walking, cycling, etc.), time of day, day of week, and vehicle occupancy. These trip records were then linked to detailed household and person files, capturing vehicle attributes (make, model, year), demographic characteristics (age, gender, driver status), and socioeconomic measures (income, number of workers, housing type).

Shifts in LD Travel Volumes and Demographics: Before and After Pandemic

Total US passenger trips fell from about 371 billion in 2017 to roughly 253 billion in 2022 (Table 1). LD trips (one-way, 50 miles or more) declined from approximately 9 billion in 2017 to 7.5 billion after the pandemic (2022), with a drop of 17%. Yet because short trips shrank even more, the share of LD travel rose from 2.4% to 3% of all trips, despite an overall 32% decline in total trip volume in 2022. The demographic composition of the NHTS samples reveals subtle shifts before and after the pandemic (Table 2). The proportion of individuals with less than a high school education increased from 12% to 15%, while the share of respondents with a bachelor's degree or higher declined: bachelor's degree holders dropped from 21% to 17%. In July 2017, the highest volume was registered at roughly 1.02 billion trips, with August and June close behind at around 0.8 billion (Figure 1). In contrast, 2022's peak moves to August at about 1.07 billion, followed by February, a mid-winter surge of 0.91 billion that far exceeds 2017's February total (0.52 billion). The February spike likely reflects a post-pandemic rebound during winter travel (e.g. mid-winter school breaks or delayed holiday trips), while the later shift of the peak from July to August suggests households postponed peak-season LD travel into late summer. Weekday LD volumes shows a U-shape (see Figure 2): Saturday fell from 1.86 billion to 1.60 billion, Sunday and Friday to around 1.30 billion (15–22%).

Table 1 Comparison of NHTS Survey Data: 2017 vs. 2022

Level	Survey Records 2017	Weighted Observations 2017	Survey Records 2022	Weighted Observations 2022	% Change
Household	129,696	118,208,251	7,893	127,544,707	7.90%
Person	264,234	301,599,169	16,997	305,560,925	1.31%
Trip Seg (one-way)	923,572	371,151,971,524	31,074	253,754,536,507	-31.6%
Vehicle	256,115	222,578,947	14,684	232,837,104	4.61%

Table 2 Demographic Distributions of the 2017 and 2022 NHTS Datasets

Variable	Category	2016/2017 NHTS (%)	2022 NHTS (%)
PERSON			
Sex	Male	49.01	48.53
	Female	50.92	50.88
Race	White	71.96	71.37
	Black or African American	12.62	12.41
	Asian	5.29	5.69
	American Indian or Alaska Native	0.86	1.17
	Native Hawaiian/Pacific Islander	0.28	0.45
	Multiple responses selected	3.93	4.25
	Some other race	4.34	4.67
Education	Less than high school	11.93	14.79
	High school graduate or GED	21.58	26.59
	Some college or associate degree	28.56	27.44
	Bachelor's degree	21.03	17.24
	Graduate or professional degree	16.90	13.93
	Younger than 10 years old	6.73	6.17
	11–17 years old	9.87	10.20
	18–24 years old	10.04	9.02
	25–34 years old	14.20	13.96
	35–44 years old	14.12	14.30
	45–54 years old	13.31	13.24
	55–64 years old	14.51	14.01
	65–74 years old	10.78	11.39
	75 years or older	6.44	7.70
HOUSEHOLD			
	1 person HH	12.32	12.48

Household Size	2 people in HH	29.30	30.55
	3 people in HH	19.05	18.34
	4 people in HH	22.13	18.81
	5 people in HH	10.39	11.30
	6 people in HH	4.42	4.71
	7 or more people in HH	2.59	3.80
Annual Household Income	Less than $10,000	6.01	5.00
	$10,000–$14,999	4.57	3.14
	$15,000–$24,999	8.07	5.66
	$25,000–$34,999	8.87	7.48
	$35,000–$49,999	11.07	9.83
	$50,000–$74,999	16.31	16.48
	$75,000–$99,999	12.93	13.18
	$100,000–$124,999	10.56	10.41
	$125,000–$149,999	6.19	7.78
	$150,000–$199,999	6.10	9.29
	$200,000 or more	6.60	11.76
#Children	0 children	75.77	76.13
	1 child	12.19	11.44
	2 children	8.86	8.47
	3 children	2.31	2.78
	4 children	0.63	0.93
	5 or more children	0.24	0.25

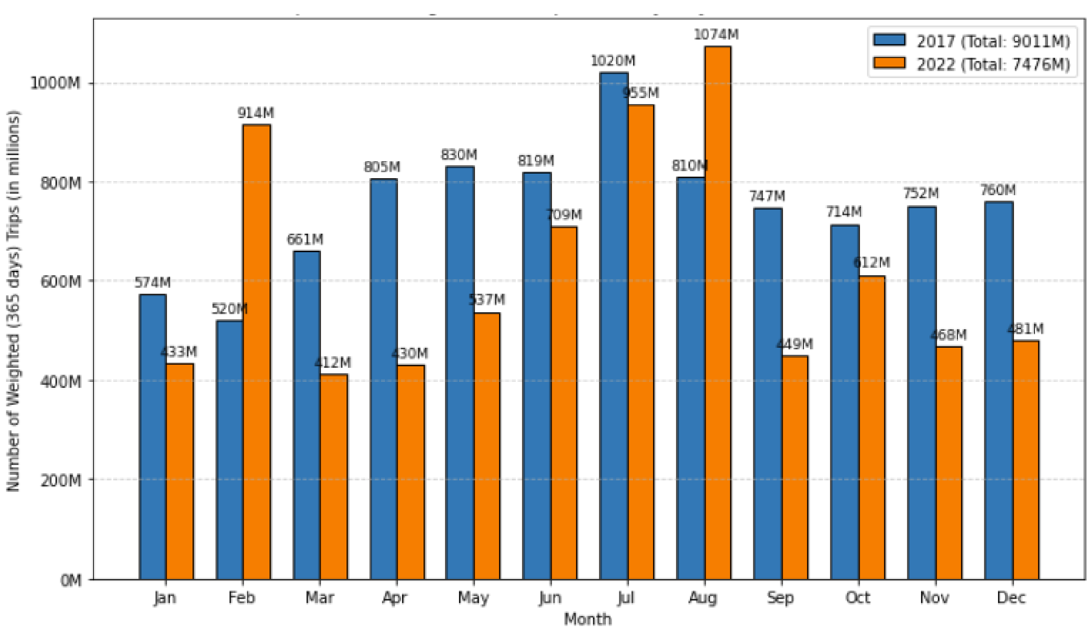

Figure 1 Comparison of Annual Weighted LD Trips by Month (50+ miles and 75+ miles):2017 vs. 2022

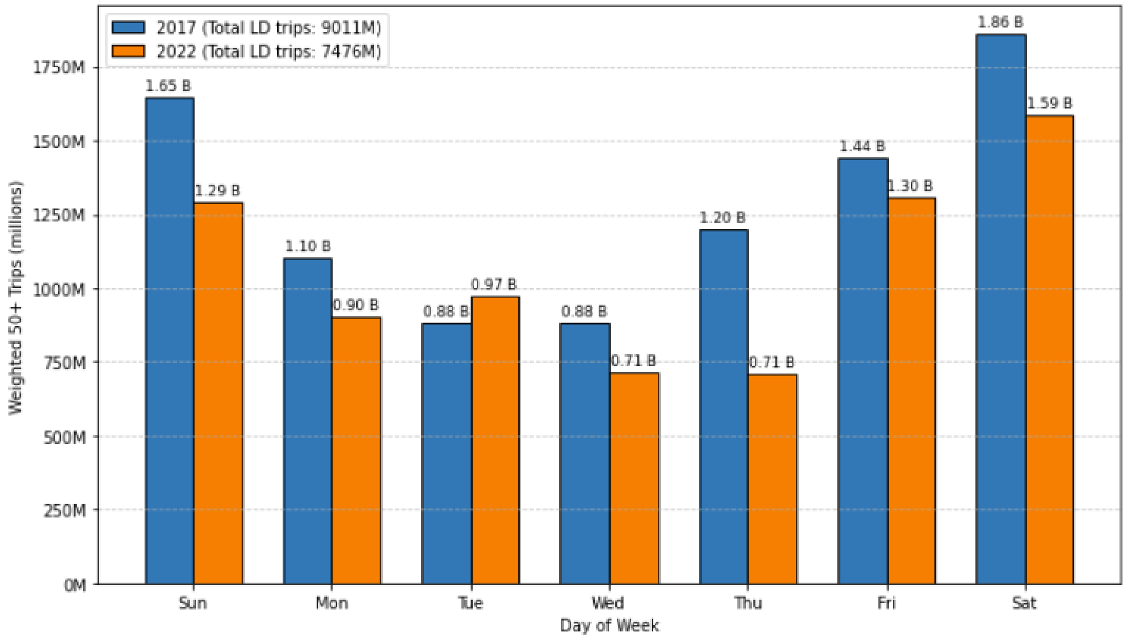

Figure 2 Comparison of Annual Weighted LD Trips by Day of the Week (50+ miles and 75+ miles): 2017 vs. 2022

Both years show two clear "rush" periods for LD trips (Figure 3): a morning wave of departures and an evening wave of returns. In 2017, trip departures began climbing rapidly after 4 AM, peaking sharply at about 760 million at 10 AM, and then forming a second, slightly lower peak of roughly 700 million around 4 PM. In 2022, these peaks are both smaller and occur a bit earlier: the morning high falls to about 650 million at 7–8 AM, and the evening high drops to around 560 million at 4 PM. Nighttime travel remains low in both years, but 2022 shows a slight uptick in arrivals around 11 PM, a trend that does not appear in 2017. Figure 4 shows a dramatic increase in LD trips in February 2022, with the average number of trips per household rising to 25, compared to 8 in February 2017. In July and August, 50+ mile trips doubled, July rising from 13 to 25 and August from 10 to 26 trips per household. The 75+ mile pattern is similar (July 8 to 18; August 6 to13). Only April and December saw 50+ mile values in 2022 that were near or below 2017 levels; for 75+ mile trips, April, May, November and December changed little, and September declined slightly.

Between 2017 and 2022, LD VMT (Figure 5) in the U.S. fell modestly from 577 billion to 539 billion miles (6.6% drop), while LD PMT plunged 31% (Table 3). VMT by vehicle-type shares shifted significantly: standard cars declined from 51% to 37% of LD VMT, SUVs/crossovers rose from 26% to 32%, pickups increased from 14.4% to 21%, and vans rose from 6.9% to 10.7%. Rental cars, motorcycles/mopeds, and RVs (each 0.3–1.5 % in 2017) were not captured in 2022. These VMT changes mirror PMT redistribution (Table 3): ground modes expanded from under 50% to nearly 66 % of LD PMT, while air travel fell from 39% to 32.5%. Within ground travel, SUVs grew from 15% to 24% of PMT, cars held around 23 % (down from 27%), pickups climbed from 7.2% to 12%, and vans from around 5% to 7%; all other modes (rail, bus, taxi, bicycle, etc.) contracted from ~11% to under 3%. Mode shares in the LD Survey (Figure 6) revealed a post-pandemic shift toward private vehicles. Cars accounted for 46.7% of LD person-trips, higher than the shares in the 2017 (41%) and 2022 (37%) NHTS datasets, while SUVs/crossovers and pickups each registered lower shares (25% vs. 31% and 9.5% vs. 15.8%, respectively). Public/commuter buses, commuter rail, and RVs remain under 2% in all surveys, indicating a sustained reluctance to shared modes and a rebound in air travel to meet pent-up leisure demand.

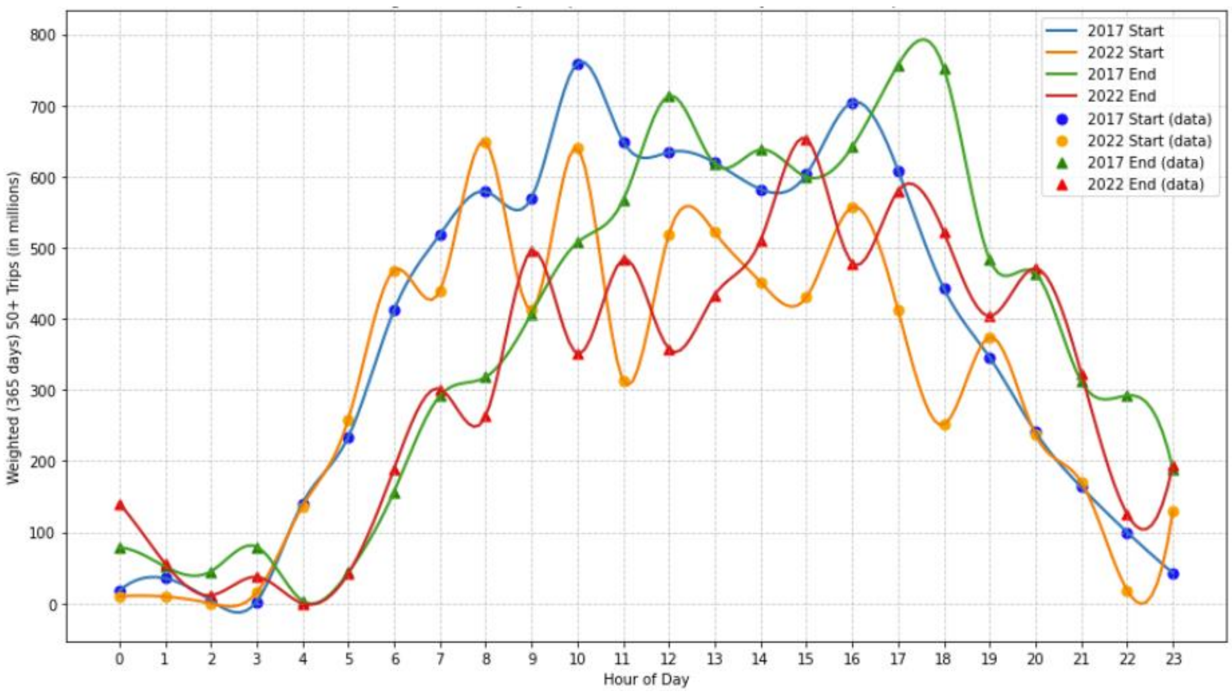

Figure 3 Hourly Distribution of Weighted 50+ Mile Trip Departure and Arrival Counts (2017 vs. 2022)

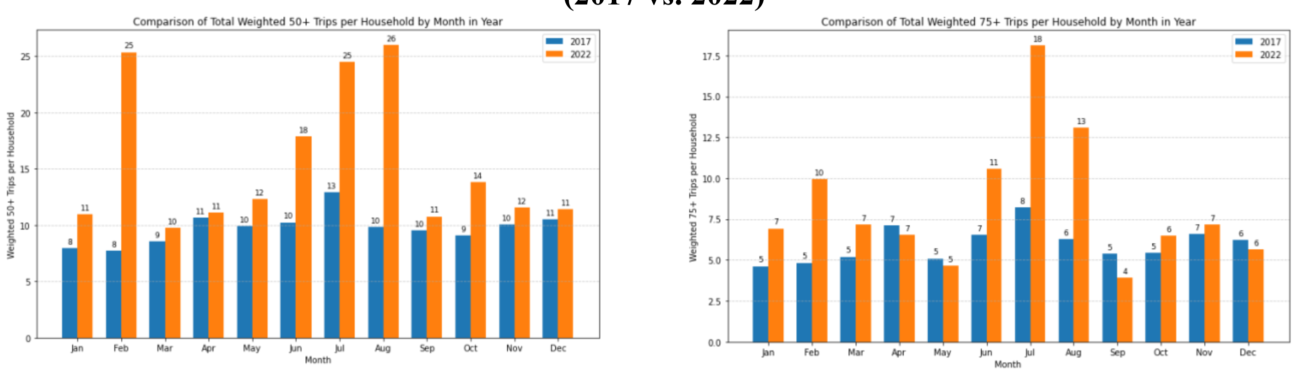

Figure 4 Comparison of Daily Weighted LD trips (50+ miles and 75+ miles): 2017 vs. 2022

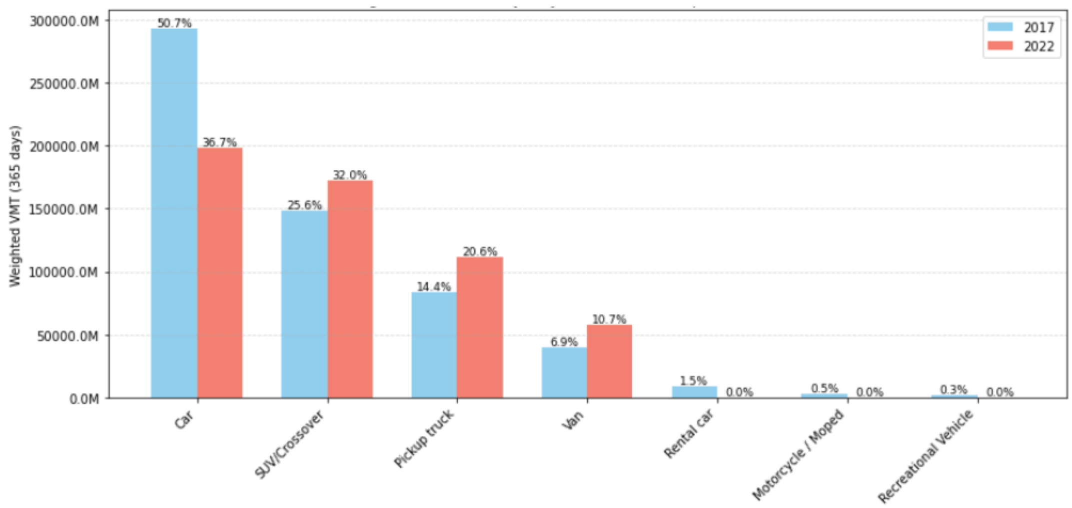

Figure 5 Changes in Weighted VMT for LD Trips by Vehicle Type (2017 vs. 2022)

Table 3 LD Person-Miles Traveled by Mode: Before and After Pandemic

	2017		2022	
Mode	**PMT (In billion person-miles)**	**Percentage Share**	**PMT (billion person-miles)**	**Percentage Share**
Airplane	1.83	38.9	1.05	32.5
Car	1.28	27.2	0.74	22.7
SUV	0.71	15.1	0.78	24.0
Pickup truck	0.34	7.2	0.39	12.0
Van	0.23	4.9	0.23	7.1
Amtrak/Commuter rail	0.06	1.2	0.01	0.4
Recreational Vehicle	0.01	0.2	0.01	0.4
School bus	0.02	0.3	0.01	0.2

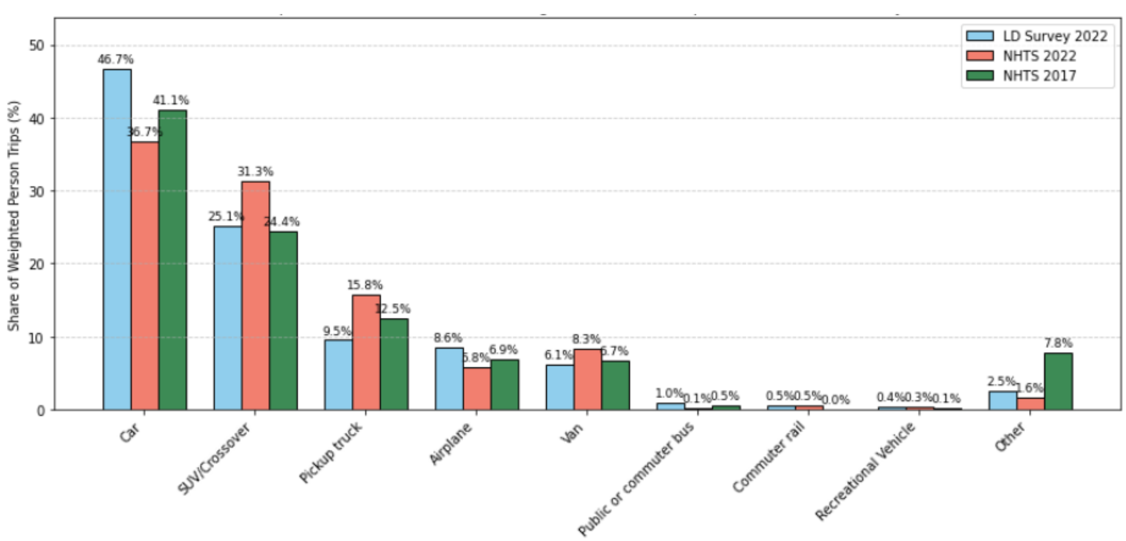

Figure 6 Mode Share of Weighted LD Person Trips: LD Survey 2022 vs. NHTS 2022 vs. NHTS 2017

LONG-DISTANCE TRIP MAKING

The trip frequency of daily LD at the household level was exceedingly rare: in both years, over 90% of the weighted household population reported zero such trips on a given day (92% in 2017 vs. 95% in 2022). Among the small fraction with at least one LD trip, solo trips per day account for 2.5% of households in 2017 and fall to 1.3% in 2022, and two-trips days decline from 3.4% to 1.9%. Beyond three trips per day, frequencies rapidly approach zero in both survey years, showing an extremely skewed distribution. Because traditional Poisson or linear models struggle with these excess zeros and the observed overdispersion (variance greatly exceeding- the mean), the study used a hurdle modeling approach. It separates the process into two stages: first, a binary logit model predicts the likelihood of a household making any LD trip (π_i); second, a truncated negative binomial (NB) model that estimates the number of trips among those households that do travel (μ_i). This two-part structure allows for estimation of both the probability and intensity of LD travel.

Let Y_i be the daily trip counts of 50-mile or more for household i. Then the probability mass function (PMF) is defined in the equation below.

$$P\left(Y_i = 1 \mid X_i^{(\text{infl})}\right) = \pi_i$$

$$P\left(Y_i = y \mid X_i^{(\text{infl})}, X_i^{(\text{count})}\right) = (\pi_i)\frac{f_{\text{NB}}(y \mid \mu_i, \alpha)}{1 - f_{\text{NB}}(0 \mid \mu_i, \alpha)}, y > 1, \ldots$$

and

$$f_{\text{NB}}(y \mid \mu_i, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(\alpha^{-1})y!}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y}$$

Where f_{NB} is the PMF of $\text{NB}(\mu_i, \alpha)$. The denominator $1 - f_{\text{NB}}(0 \mid \mu_i, \alpha)$ ensures the zero count is "hurdled" out of the NB distribution. Table 4 presents the two-part hurdle-model estimates for the 2022 NHTS sample (N = 7,893), while Table 5 shows the corresponding results for 2017 (N= 125,310). Both models decompose LD trip generation into a zero-inflation logit and a truncated negative binomial count stage, but key drivers vary across survey years. "Practical Significance" values in these tables report the percent change in the average predicted dependent variable associated with a one-standard-deviation increase in a continuous covariate or a shift from 0 to 1 for a binary factor. In 2022, the zero-inflation stage confirms that greater vehicle availability and demographic–spatial interactions significantly raise the odds of reporting LD trips. A standard deviation increases in household vehicles raise the odds of zero trips by 23%. Similar increases in white households with more workers exhibit a 25% rise in LD trip making, and rural white households show a 28.5% increase. The weekend composition also matters: households of two or more adults without children are 51.5% more likely to forgo a LD trip, reflecting strong recreational travel propensity among child-free weekend groups. Once the initial hurdle is crossed, the 2022 count stage revealed that income, licensure, workforce structure, seasonality, and built-environment interactions jointly determined trip frequency. A standard deviation increase in household income (in \$1000) corresponds to a 9.2% decline in expected daily trips, whereas the same rise in licensed driver boosts frequency by 44%. Labor-force composition shows opposing effects: a standard deviation rise in the workers-to-household-size ratio reduces trips by 42%, while a similar rise in the ratio of workers to adults increases them by 112%. Seasonally, August trips peak with a 12% uplift, the interaction between white households and worker count yields a 21% decrease per standard deviation rise in worker, urban renters take 15.2% more trips, and similar rise in worker on Saturdays raises trip counts by 9.5%.

Table 4 Hurdle-Model Estimation Results for 2022 NHTS (N = 7,893)

Zero Inflation Model (Pseudo R^2=0.05)		
Variable	**Coefficient**	**Practical Significance (%)**
Intercept	3.785	-
Household vehicle count	0.262	23
Workers × White race	0.290	25.2
Rural location × White race	0.335	28.5
Weekend (≥2 adults, no children)	0.724	51.5
Count Model (Pseudo R^2=0.19)		
Variable	**Coefficient**	**Practical Significance (%)**
Intercept	9.670	-
Household income ($1000)	-1.391	-9.2
Number of licensed drivers	0.461	44.2
Workers per household member	-1.336	-41.9
Workers per adult	1.676	111.8
August (month indicator)	0.477	11.9
Workers × White race	-0.263	-21.2
Urban location × rented dwelling	0.337	15.2
Workers × Saturday	0.200	9.5

Note: All coefficient estimates are statistically significant at $p < 0.05$

By contrast, the 2017 zero-inflation results (see Table 5) shows that household location, resources, and weekend timing increase the odds of making LD trips. A one-standard-deviation (one-SD) shift toward rural residence increases the odds of taking any 50+ mile trip by 23.6%, indicating that non-urban households were more inclined to undertake at least one LD outing. Similarly, a one-SD rise in household vehicle count raises trip making odds by 25.4%, and the same increase in household workers boosts those odds by 25.9%, suggesting that both additional vehicles and greater workforce commitments make at least one trip more likely. Non-workday timing also promotes LD trip making: relative to weekdays, Fridays, Saturdays, and Sundays see 40.9%, 33.8%, and 33.5% higher odds, respectively, of taking a LD trip. In the 2017 count stage, income exerts a mild adverse effect; with one-SD increase in household income reduces trip counts by 2.3%—while driver availability continues to facilitate travel (+13.6%). Workforce composition again diverges, with workers per household member reducing counts by 24.6% and workers per adult boosting them by 24.4%. Demographic–spatial interactions play a more minor role: rural white households take 4.2% fewer trips, and urban mortgaged households 3.2% fewer. Weekend interactions remain positive but modest: one-SD rise in worker on Saturday and Sunday raises trip counts by 6.8% percent and 5.7%, respectively.

Table 5 Hurdle-Model Estimation Results for 2017 NHTS (Y: Number of LD Trips, N:125,310)

Zero Inflation Model (Pseudo R^2=0.03)		
Variable	**Coefficient**	**Practical Significance (%)**
Intercept	-3.311	-
Rural household location	0.212	23.6
Number of vehicles in household	0.226	25.4
Number of workers in household	0.230	25.9
Saturday indicator	0.291	33.8
Sunday indicator	0.290	33.5
Friday indicator	0.343	40.9
Count Model (Pseudo R^2=0.33)		
Variable	**Coefficient**	**Practical Significance (%)**
Intercept	0.652	-
Household income ($1000)	-0.0003	-2.3
Number of licensed drivers	0.163	13.6
Workers per household member	-0.734	-24.6
Workers per adult	0.530	24.4
Rural × White-race interaction	-0.097	-4.2
Urban × Mortgaged home interaction	-0.065	-3.2
Workers × Saturday interaction	0.120	6.8
Workers × Sunday interaction	0.098	5.7

Note: All coefficient estimates are statistically significant at $p < 0.05$

PARTY SIZE FOR LONG-DISTANCE TRIPS

The party-size LD trips reveal stable household travel groupings between 2017 and 2022. In both survey years, the median party size is exactly two, indicating pairs took half of all LD trips. The weighted mean party size rises only slightly from 2.6 in 2017 to 2.8 in 2022, reflecting a modest uptick in larger groups. At the lower bound, solo travelers account for the smallest parties in both datasets, while the extreme upper tail is driven by a few very large groups (a maximum of 333 in 2017 versus 99 in 2022), which inflate the standard deviations to roughly 6.67 in each year. On average, the mean party size in the LD data is 2.85 persons, versus 2.67 in the one-day dataset. Table 6 presents ordered-logit estimates of party-size category (1, 2 or 3+ travelers) among households taking at least one LD trip in 2017 and 2022. In both survey years the number of adults on the trip reduces the odds of a larger party: a one-SD rise in adults cuts those odds by 32% in 2017 and 36% in 2022. In contrast, binary indicators for household size (relative to single-adult trips) strongly boost the odds of traveling in groups of 2+ and 3+ people. For example, two-person households are associated with 85% higher odds of larger party size in 2017 and 27.5% in 2022; the effect grows with household size, e.g., the five-person household indicator raises odds by approximately 72% in 2017 and 50.4% in 2022. More household vehicles were seen to dampen party size.

In 2017, having two vehicles (vs. one) raised the odds of a larger party by only 10.5%, whereas in 2022 it reduced the odds by 40%, and the adverse effect intensified for three or more vehicles (–17.4% and –61.9% in 2022). Weekend trips (Saturday or Sunday) strongly favor larger parties in both years, the weekend indicator raises odds by 89.4% in 2017 and 85.0% in 2022, whereas business-purpose trips overwhelmingly reduce party size (–96.9% practical significance both years), consistent with solo or small-group business travel. In 2017, pickup-truck mode increases the odds of larger parties by 53.8%, while the black-household indicator reduces the odds by 31.4%. In 2022, car trips reduced party-size odds by 59%, while the white-household indicator increased them by 95%. Thus, party composition is driven first by basic household size and adult count (substantial and monotonic effects), then by how many vehicles are available (with a pronounced change between 2017 and 2022), while timing (weekend vs. weekday), purpose (business vs. non-business), and mode and race influence modulate these party size shifts.

Table 6 Ordered Logit Model Estimation Results for 2017 and 2022 NHTS (Y: Number of HH People Travelling Together on LD Trips)

	2017 NHTS (N=25,461)		2022 NHTS (N=958)	
Variable	**Coeff**	**Pract Sig (%)**	**Coeff**	**Pract Sig (%)**
Number of adults in HH	-0.519	-31.9	-0.676	-36.2
Two-person HH	4.459	85.0	3.350	27.5
Three-person HH	5.462	123	4.569	95.4
Four-person HH	6.209	49.6	5.272	19.38
Five-person HH	6.575	71.5	6.225	50.4
Six-person HH	6.952	10.4	4.321	74.3
Seven-person HH	7.528	18.5	4.909	13.5
Two vehicles in HH	0.100	10.5	-0.512	-40.1
Three vehicles in HH	-0.191	-17.4	-0.965	-61.9
Four vehicles in HH	-0.434	-35.0	-1.040	-64.7
Weekend trip indicator	0.639	89.4	0.615	85
Business-purpose trip	-3.488	-96.9	-3.464	-96.9
Home owned with mortgage	0.088	9.20	-	-
Black HH indicator	-0.377	-31.4	-	-
Pickup-truck mode	0.431	53.8	-	-
Car mode	-	-	-0.891	-59.0
White HH indicator	-	-	0.668	95
Threshold between party size categories 1 and 2	3.453		1.905	
Threshold between party size categories 2 and 3	5.826		4.216	

Note: All coefficient estimates are statistically significant at $p < 0.05$

CONCLUSION

Long-distance travel, though it constitutes a small share of all person-trips, drives a disproportionately large share of person-miles, congestion, emissions, and infrastructure wear, and that its determinants shifted significantly between pre- and post-pandemic periods. This paper fills critical gaps in LD trip modeling by quantifying how household composition, socioeconomic status, and trip purpose jointly influence both the probability and frequency of Americans' LD trip making before and after the pandemic. By applying a two-part hurdle model to the 2017 and 2022 National Household Travel Surveys (NHTS), the study first presents how household resources, demographic interactions, and temporal factors influence the decision to undertake a trip of 50 miles or more, and then how those same factors shape trip frequency once this hurdle is crossed. Results reveal that LD trips were extremely rare in both 2017 and 2022, with over 90% of households reporting no LD trips on a given day, and the proportion of trip-making households declining after the pandemic. In pre-pandemic year, rural households with more vehicles and workers were most likely to undertake LD travel, especially on Fridays and weekends. The influence of vehicle access, as well as the presence of white households with more workers and rural white households, had become even more pronounced after the pandemic.

In contrast, households with two or more adults and no children were less likely to travel on weekends. Among trip-making households, higher income consistently reduced the number of LD trips, whereas having more licensed drivers and a higher ratio of workers to adults substantially increased trip frequency, with these effects intensifying after the pandemic. Temporal and spatial patterns also shifted: in 2017, rural white and urban mortgaged households took fewer trips, and weekends modestly raised counts; after the pandemic, August saw the highest trip rates, urban renters traveled more, and the impact of worker presence on Saturdays increased, while white households with more workers took fewer trips. Ordered-logit models were employed to predict party size for LD, and the results show that pairs accounted for half of all LD trips in both years, and only a slight increase in average party size from 2.6 to 2.8. Solo travelers were consistently the smallest groups, while very rare, very large parties inflated the average. A larger household size significantly increased the likelihood of traveling in groups of two or more, with this effect becoming more pronounced with each additional household member.

However, the presence of more adults on the trip actually reduced the odds of larger parties. The impact of vehicle ownership shifted: while having two vehicles slightly increased the odds of a party in 2017, by 2022, having two or more vehicles significantly reduced the likelihood of larger parties. Larger groups consistently favored weekend travel, while business trips were overwhelmingly associated with smaller parties. Mode and race also mattered: in 2017, pickup-truck trips and white households increased the odds of party size, while black households reduced them; by 2022, car trips reduced the odds of party size, and white households were even more likely to travel in larger groups. Thus, household size and adult composition were the primary drivers of LD party size, with vehicle availability, trip timing, purpose, mode, and race shaping these patterns in distinct ways across the two survey years. This study aids transport planners and policymakers in anticipating, managing, and mitigating the impacts of this vital yet understudied LD travel segment, for example, tailoring seasonal capacity management, calibrating high-speed rail subsidies, or designing rural mobility services that reflect new work-and-leisure balances.

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AUTHOR CONTRIBUTIONS

The authors confirm the contribution to the paper as follows: Conceptualization, data curation, formal analysis, investigation and methodology: Priyanka, P.; Huang, Y.; Khan, N. and Kockelman, K.; Resources and Software: Priyanka, P.; Kockelman, K.; Project administration and Supervision: Kockelman, K. Huang, Y. and Khan, N.; Visualization and Writing – original draft: Priyanka, P., Huang, Y.; Writing – review & editing: Huang, Y.; The authors confirm their respective contributions to this manuscript as outlined above.

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