How far are we from transportation equity? Measuring the effect of wheelchair use on daily activity patterns.

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Abstract

This is the abstract

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1. Introduction

In 1990, the United States Congress passed the Americans with Disabilities Act (ADA), seeking to protect individuals with qualifying disabilities from discrimination while using public services including transportation systems (Title II), and in public accommodations (Title III) among other specifics. For transportation service providers, ensuring equal access for wheelchair users is a critical design constraint for vehicles as well as stations and the surrounding areas (Federal Transit Administration, 2015). Buses and trains had to be redesigned with low floors and access ramps; elevators and ramps needed to be installed in stations alongside escalators and stairs. Even today, most traditional automobiles remain inaccessible — at least without substantial modification — to wheelchair users. This last challenge is a particular concern for transportation network companies (TNC's), who often use private vehicles owned by individual operators.

Though the ADA only requires agencies to provide reasonable accommodation on public conveyances and does not try to establish equity in outcomes, the passage of 30 years provides a convenient time to consider what gaps and challenges persist for wheelchair users in accessing and using the transportation system. Specifically, what gap exists in the observed travel behavior outcomes of wheelchair users vis a vis the non wheelchair using population, all else equal? And more importantly, how should this gap be applied within travel forecasting models and related planning activities?

In this paper, we investigate the degree to which daily activity patterns are influenced by an individual's use of a wheelchair. This involves two separate analyses: first, we model daily activity pattern choice using responses to the 2017 National Household Travel Survey (U.S. Department of Transportation and Federal Highway Administration, 2017), incorporating the individual's wheelchair use as an explanatory

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variable. Second, we apply the behavioral estimates obtained from the choice analysis in a modified activity-based model for the Wasatch Front metropolitan region in Utah to estimate the population-level effects of introducing wheelchair status in a regional travel demand model.

The paper proceeds in a typical fashion. A literature review discusses prior attempts to evaluated and quantify the travel behavior of users with disabilities. A section describing the methodology of the choice analysis and model application is followed by a discussion of the results from both analyses. The paper concludes with a discussion of limitations in this analysis and associated avenues for future research and policy intervention.

2. Literature

Recent analysis (Brumbaugh, 2018) of the 2017 NHTS suggests there are 13.4 million individuals individuals in the US with travel-limiting disabilities — as defined by a specific question in the NHTS and encompassing sight, ambulatory, hearing, and other disabilities. Of these individuals, 20 percent (or 2.7 million) use wheelchairs. With the relative aging of the U.S. population, the share of Americans with all disabilities as well as those using wheelchairs is likely to rise substantially [Sweeney (2004); Laplante2003].

The question of how the travel behavior of individuals with travel-limiting disabilities varies from the travel behavior of individuals without these disabilities has been addressed previously in a number of studies. That said, the literature on this topic is relatively fragmented due to the wide variety of specific disabilities people. The literature also has suffered from a relatively fragmented approach; rather than considering how disability manifests at each hierarchical level of the transportation decision-making process, the literature consists largely of ad-hoc studies conducted on a specific, specially collected dataset.

With regards to travel patterns, surveys of the general population and surveys specifically targeted at individuals with disabilities both reveal significant and meaningful differences compared to individuals without disabilities. Specific findings include that individuals with disabilities leave their homes on fewer days if ever (Sweeney, 2004), make fewer daily trips (Brumbaugh, 2018; Schmöcker et al., 2005) make fewer work trips and more healthcare maintenance trips (Ermagun et al., 2016), rely more on others for their travel (Sweeney, 2004) and have considerably restricted mode choices Ruvolo (2020). These differences in mobility and activity patterns have important and observed negative implications for the individual's access to opportunity for employment (Lubin and Deka, 2012; Rosenbloom, 2007) and social interaction (Bascom and Christensen, 2017; Velho et al., 2016). Some recent studies have also looked at the meaningful role of developmental (Wasfi and El-geneidy, 2007) and intellectual (Feeley, 2019) disabilities on travel patterns.

The underlying reasons why wheelchair users and others with disabilities exhibit different travel patterns than other individuals are varied, but are likely to include both technical and attitudinal barriers. Technical barriers include poor access to private vehicles (Van Roosmalen et al., 2010), poorly maintained sidewalk and pedestrian infrastructure (Frackelton et al., 2013), lack of physical access to TNC vehicles (Ruvolo, 2020), bus ramp complication and malfunction (Velho et al., 2016), and numerous other problems across many modes. Attitudinal barriers include feeling shame when safety alarms alert all passengers that a ramp is being deployed or motion sickness when the users are forced to travel backwards in the wheelchair priority area (Velho et al., 2016), or suffering outright discrimination from TNC operators (Bascom and Christensen, 2017).

In spite of this relatively mature literature, however, there has not to date been a rigorous evaluation of the travel behavior of individuals with disabilities within the framework of a travel activity model. As a result, recent attempts to simulate or model services aimed at this population have needed to make simplifying assumptions. In an attempt to model demand for a modern mobility system targeted at wheelchair users in Berlin, Bischoff (2019) simply assumed demand for this service would be similar to current demand for the regional paratransit system, augmented by a mode shift from taxi. In this initial study there was no link between the MaaS trips and the daily activities of the wheelchair users; there was not even a good understanding of likely trip origin, destination, or length distribution.

Including wheelchair users or wheelchair use status in a regularized travel model framework would help to fill two important gaps in the current literature. First, the comparison would help to illuminate the travel behavior characteristics of this important population within a framework that is readily understandable *vis a vis* other population segments. Second, researchers engaged in policy and planning work for this population could replace simplifying assumptions with plausible daily activity patterns rooted in observed behavior.

3. Methods

Activity-based models are a relatively mature construct in travel behavior research and in practical demand forecasting (Rasouli and Timmermans, 2014). Activity-based models attempt to recreate the long- and short-term decision patterns of individuals within a chain of econometric and statistical choice models. The specific sub-models included in this chain can vary between specific implementations, but a recent open-source project — ActivitySim (AMPO, 2020) — implements a popular set of models (Davidson et al., 2010). Specifically, the ActivitySim demonstration model is a implementation of the “Travel Model One” model for the Metropolitan Transportation Commission (MTC, San Francisco Bay) (Erhardt et al., 2012). For simplicity and comparison with other models, we apply the ActivitySim model in this research.

The first step in the ActivitySim model chain is a *daily activity pattern* model of the type described by Bradley and Vovsha (2005). This model allows individuals to choose one of three daily activity patterns:

- Mandatory (M) daily patterns revolve around school and work activities that are typically considered non-discretionary. These activities and the travel to them anchor an individual’s daily schedule, though other tours are possible.

- Non-Mandatory (NM) daily patterns involve only discretionary activities: shopping, maintenance, etc.
- At-Home (H) daily patterns describe the schedule and activities of individuals who never leave the home during the travel day.

The choice between the daily patterns is described with a multinomial logit model (Domencich and McFadden, 1975), where the utility functions for each option are determined by an individual's socioeconomic characteristics and person type segment. The specific innovation of the Bradley and Vovsha (2005) model is that the daily activity patterns are coordinated, or that the choice of one individual in a household influences the choice probability of other household members.

In this research, we first estimate a daily activity pattern model for respondents to the National Household Travel Survey. We then apply the estimated coefficients within an ActivitySim implementation calibrated to the Wasatch Front Region in Utah.

3.1. Choice Model

Data for this study comes from the 2017 NHTS (U.S. Department of Transportation and Federal Highway Administration, 2017). We restrict the data to households where the metropolitan statistical area (MSA) population size is between one and three million people. There are 76,367 individuals in 36,497 households that responded to the NHTS from these areas, though not all of these records are useful due to missing or incomplete data in key variables.

The NHTS releases public data in separate tables for persons, households, trips and vehicles; to determine the daily activity pattern for a given individual it was necessary to transform the trips table into a table of activities. We did this by reconstructing a schedule for each person from the reported trip origin and destination activity codes. We then determined whether each reported tour (a chain of activities away from the individual's home) contained a mandatory school or work activity. If any tour contained a mandatory activity, the person's entire daily activity pattern was classified as "mandatory"; if not, the daily activity pattern was "non-mandatory." By identifying respondents in the persons table without records in the trips table, we can determine individuals with a "home" daily activity pattern.

We do, however, adopt the person type segmentation strategy employed by ActivitySim; segmentation allows for heterogeneity in available alternatives and utility coefficients between individuals with highly divergent expected behaviors. For example, full time workers and pre-driving age school children will have strongly different responses to income, automobile availability, and and other variables in determining their most likely daily pattern. A complete descriptive list of each person type is given in the data section below. ActivitySim classifies persons into seven person segments, though we only consider four types in this study, defined as follows:

- Full-time workers (FW) - reported working “full-time” at their primary job.
- Part-time worker (PW) - reported working “part-time” at their primary job, as well as any person who reported being a “non-worker” or “retired” who nevertheless reported a work or school activity.
- Non-working adults (NW) - reported “unemployed” as their primary activity of the previous week, as well as individuals over 18 who were not classified elsewhere.
- Retired (RT) - reported “retired” as their primary activity of the previous week, or who are over the age of 65 and reported that they were not workers.

The other three person types are university students, schoolchildren under driving age, and driving-age schoolchildren. A limited number of individuals who could plausibly be considered university students responded to the NHTS, so we cannot estimate reliable choice models. Among schoolchildren of any age, too few report using wheelchairs to justify including these segments in this study.

The NHTS has a number of questions where respondents can indicate a disability for themselves or other household members. Each respondent is asked “Do you have a condition or handicap that makes it difficult to travel outside of the home?” If the answer is yes, several follow-up questions are asked, including “Do you use any of the following medical devices? Select all that apply.” The list of medical devices respondents can indicated includes canes, walkers, seeing-eye dogs, crutches, motorized scooters, manual wheelchairs, motorized wheelchairs, or something else (other). For this study, we identify wheelchair users as respondents who report using a manual wheelchair, mechanical wheelchair, or motorized scooter.

The specific variables included in the daily activity pattern choice models are based initially on the variables used in the ActivitySim example model (which are those used in MTC Travel Model One. The variables available include the age of the person and the household income treated as categorical ranges; gender, work, and college degree status are treated as binary values. Automobile availability is included via a binary “sufficiency” variable where a household with at least as many vehicles as adults is considered “auto sufficient.” Descriptive statistics of the model variable within each person segment are given in Table 1

Table 1: Model Estimation Data: Descriptive Statistics

		Full-time worker (N=16188)		Non-worker (N=3723)		Part-time worker (N=4028)		Retired (N=10060)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Bachelors or more		0.6	0.5	0.4	0.5	0.5	0.5	0.4	0.5
		N	Pct.	N	Pct.	N	Pct.	N	Pct.
Age	05-39	5762	35.6	1450	38.9	1356	33.7	8	0.1
	40-64	9570	59.1	2239	60.1	1705	42.3	1833	18.2
	65-79	836	5.2	33	0.9	903	22.4	6321	62.8
	80+	20	0.1	1	0.0	64	1.6	1898	18.9
Wheelchair	FALSE	16161	99.8	3609	96.9	4010	99.6	9619	95.6
	TRUE	27	0.2	114	3.1	18	0.4	441	4.4
Income	< $25,000	872	5.4	961	25.8	663	16.5	1825	18.1
	$25,000 - $50,000	2235	13.8	632	17.0	713	17.7	2437	24.2
	$50,000 - $100,000	5312	32.8	953	25.6	1203	29.9	3245	32.3
	> $100,000	7476	46.2	1102	29.6	1333	33.1	1975	19.6
Sex	Male	8820	54.5	1192	32.0	1487	36.9	4488	44.6
	Female	7368	45.5	2531	68.0	2541	63.1	5572	55.4
	I prefer not to answer	0	0.0	0	0.0	0	0.0	0	0.0
	I don't know	0	0.0	0	0.0	0	0.0	0	0.0
Works from Home	-1	0	0.0	3721	99.9	267	6.6	10060	100.0
	-7	2	0.0	0	0.0	1	0.0	0	0.0
	-8	1	0.0	0	0.0	1	0.0	0	0.0
	-9	728	4.5	0	0.0	0	0.0	0	0.0
	01	1718	10.6	0	0.0	940	23.3	0	0.0
	02	13739	84.9	2	0.1	2819	70.0	0	0.0

3.2. ActivitySim Implementation

4. Results

4.1. Choice Analysis

We estimated the models using mlogit for R Croissant (2020). As described above, the alternatives for daily activity pattern choice are a Mandatory pattern where the individual's day involves a work or school tour, a Non-Mandatory pattern where only discretionary trips are taken, and a Home pattern where the individual does not leave home. In the models estimated for this study, the Home pattern serves as the reference alternative with a utility of zero. Retired and otherwise non-working individuals choose only between Non-Mandatory and Home daily activity patterns.

The model estimates are presented in Table 2. The estimated coefficients are of the expected sign, though not all are significant. Some predictors that proved to be insignificant, such as automobile availability for full-time workers, were excluded from the estimated models. The overall model fit — as indicated by the McFadden ρ^2 with respect to a market shares (constants only) model — is not strikingly high. Were the purpose of this research to identify the best fit model of activity pattern choice for each person segment we would undertake an exercise to include, exclude, and identify potential transformations for different sets of variables. In this case, however, the goal of these models is simply to provide a plausible comparison point for the behavior of individuals using wheelchairs against the behavior of individuals in other person type segments.

In this regard, the model results show strong divergence of the utility preferences of individuals who use wheelchairs. For instance, full-time workers in the middle income groups are modestly less likely to choose non-mandatory patterns, and part-time workers of higher income are less like to choose mandatory patterns. Income appears to have no discernible effect on the choices of non-working and retired individuals. We see a negative utility score for all person types with a wheelchair variable, and "mandatory" is even more negative. This is expected as individuals with wheelchairs are less likely to take a work or school trip compared to a shopping or a recreational trip. Non-workers and retired person types do not have a coefficient for "mandatory" DAP because those users by definition do not take "mandatory" DAP. Indeed, wheelchair use is among the strongest predictors of daily activity pattern choice across population segments.

4.2. Activity-based Model

As a secondary example, the research measures the impact of wheelchair status on ActivitySim's selection of daily plans for our given synthetic population. Given a "Before" scenario in ActivitySim of the Salt Lake Area and ignoring the newly added wheelchair status in the synthetic population, ActivitySim predicted a DAP for each individual. In a second, "After" scenario, ActivitySim again predicted a DAP for each person, this time considering the wheelchair use status of each individual in the population. We

Table 2: Daily Activity Pattern Model Estimates

		Full-time worker	Non-worker	Part-time worker	Retired
(Intercept)	M	2.083 (15.207)**		1.545 (10.300)**	
	NM	1.137 (7.854)**	0.591 (6.359)**	0.338 (2.088)	−1.169 (−1.506)
wheelchairTRUE	M	−1.851 (−3.328)**		−3.315 (−3.906)**	
	NM	−0.625 (−1.315)	−0.721 (−3.647)**	−1.866 (−3.560)**	−1.258 (−11.924)**
male	M	0.008 (0.140)		−0.040 (−0.347)	
	NM	−0.148 (−2.378)	−0.271 (−3.477)**	−0.219 (−1.828)	0.235 (4.798)**
bach_degree	M	0.353 (5.716)**		0.360 (3.033)**	
	NM	0.648 (9.834)**	0.501 (6.028)**	0.584 (4.815)**	0.349 (6.521)**
income$25,000 - $50,000	M	−0.055 (−0.373)		0.169 (0.876)	
	NM	−0.371 (−2.344)	−0.167 (−1.506)	0.444 (2.196)	−0.095 (−1.358)
income$50,000 - $100,000	M	−0.175 (−1.272)		−0.160 (−0.971)	
	NM	−0.312 (−2.146)	−0.052 (−0.506)	0.190 (1.096)	0.115 (1.643)
income> $100,000	M	−0.206 (−1.495)		−0.326 (−1.994)	
	NM	−0.233 (−1.610)	−0.088 (−0.844)	0.127 (0.737)	0.036 (0.444)
age_bin40-64	M	−0.006 (−0.104)		0.669 (5.094)**	
	NM	0.026 (0.386)	0.433 (5.788)**	1.055 (7.805)**	2.241 (2.886)**
age_bin65-79	M	0.179 (1.147)		0.395 (2.614)**	
	NM	0.801 (5.081)**	1.690 (2.998)**	0.721 (4.647)**	2.132 (2.752)**
age_bin80+	M	17.592 (0.004)		2.067 (2.293)	
	NM	17.247 (0.004)	14.648 (0.008)	2.154 (2.391)	1.536 (1.980)
works_home	M	−1.542 (−18.502)**		−1.340 (−9.830)**	
	NM	−0.044 (−0.558)		0.112 (0.869)	
	N	15 895	3648	3912	9482
	AIC	26 550.18	4470.948	6965.196	10 689.72
	Log likelihood	−13 253.09	−2225.474	−3460.598	−5334.858
	ρ^2	0.031	0.019	0.055	0.026

Coefficients represent utility change relative to H: stay at home pattern.

t-statistics in parentheses, * $p < 0.5$, ** $p < 0.01$

Table 3: Daily Activity Pattern Change

		DAP with Wheelchair Use		
Group	DAP without Wheelchair Use	H	M	N
Wheelchair Users	H	3369	20	459
	M	932	1642	308
	N	3584	23	10261
Household Members	H	4511	213	631
	M	759	15409	301
	N	1235	415	13119
Not Affected	H	309965	2	
	M	2	1460582	
	N		2	659258

hypothesized that those with wheelchairs and those in the same households as individuals with wheelchairs would change their DAP because of the negative utility scores applied to the "mandatory" and "nonmandatory" DAP alternatives, and the rest of the population would be unaffected. The DAP of those within the same household of a wheelchair user may change because of the coordinated nature of household DAP in ActivitySim. Table 3 shows the change in DAP among those with wheelchairs, in the same household as one with a wheelchair, and with neither a wheelchair nor in the same household. The table contains both total volumes and percentages; the value of percent is by total volume in the group, for example, 16.4 percent of Wheelchair Users chose a "home" pattern in both the "Before" scenario and the "After" scenario. The latter group is rightly unaffected by the wheelchair implementation in the simulation (with the exception of a few changes attributable to randomness) and does not include a percentage breakdown. Primarily, DAP remain the same for most individuals, as shown in the diagonal. However, there is a large volume of wheelchair users and their household members that stay home, particularly from "nonmandatory" DAP. This finding is consistent with our hypothesis.

5. Discussion

We have finished a nice book.

6. Conclusion

This is the end of the paper.

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