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Space–time mismatch between transit service and observed travel patterns in the Wasatch Front, Utah: A social equity perspective

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ABSTRACT

In the absence of other alternatives, people who rely on public transportation to conduct their daily activities have travel patterns that differ from discretionary transit users, especially those who choose to use transit for work trips. At the same time, in many regions around the world, public transportation is primarily designed to accommodate peak-hour travel demands in order to reduce congestion and its impacts. It is theorized that this results in a mismatch between the demand and supply of public transportation among populations at risk of social exclusion. In this research, we characterize and compare the spatiotemporal patterns of travel demand and transit supply. Our analysis consists of a comparison between observed travel patterns and a new temporal measure of transit supply based on travel times. We measure travel demand with the observed trip-making characteristics (i.e. origin, destination, time-of-day) of the respondents to two transportation surveys conducted in Utah. Transit supply is characterized using a transit travel time cube, a three-dimensional array of origin–destination transit travel times computed for all origins, destinations and times of day. Mismatch is examined by descriptive and multivariate comparisons of observed trips and computed levels of transit provision. Our results confirm theory: more marginalized groups demand travel between locations at times of the day that are poorly served by transit. However, when controlling for all variables simultaneously in a multivariate regression, few socioeconomic factors remain significant, indicating the overall importance of employment status, making work trips, and traveling during peak times, in explaining mismatch.

1. Introduction

In an urban context, a just society includes equitable access to public transportation (Golub and Martens, 2014; Martens, 2009; Martens et al., 2012). One way to achieve equity, vertical equity in particular, is to provide transit service to those people who need it most, where need is most often assessed using considerations of socioeconomic status (Bullard et al., 2004; Litman, 2002; Litman and Brenman, 2011). Of course, transportation planning incorporates a complex set of technical and political processes, and social equity is but one consideration in a multi-objective agenda that has often favoured more readily measurable, predictable, and pecuniarily expressible outcomes of transport models like travel-time savings, congestion and throughput (Deka, 2004). As according to the adage, "we build what we measure", transport planning has focussed on achieving increased mobility rather than explicitly increasing accessibility or the equitable distribution of the accessibility benefit between modes (Benenson et al., 2011; Golub and Martens, 2014; Kaplan et al., 2014; Martens et al., 2012), across space (Martens et al., 2012; Welch and Mishra, 2013), and between population groups (Delbosc and Currie, 2011; Welch, 2013). As a result, some public transportation systems fall short of meeting the needs of those who depend on transit to participate in daily activities, putting people at risk of transport related social exclusion (Church et al., 2000; Hine, 2003; Kenyon, 2003, 2006; Lucas, 2012; Lucas et al., 2001; Páez et al., 2009; Preston and Rajé, 2007; Raje, 2004).

Most studies of social equity and public transit accessibility entail an aggregate comparison between transit need and transit supply. In these studies, transit need is often established over space as a measure of socioeconomic status in neighborhood units while transit supply is typically measured at the neighborhood level as the ease of reaching transit facilities (Moniruzzaman and Páez, 2012; Murray et al., 1998; O'Neill et al., 1992), reaching transit facilities weighted by level of service (LOS) (Al Mamun and Lownes, 2011; Currie, 2010; Drew and Rowe, 2010; Henk and Hubbard, 1996; Kittelson et al., 2003; Rood and Sprowls, 1998;

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Ryus et al., 2000), or reaching actual destinations with transit (Farber et al., 2014b; Foth et al., 2013; Lei and Church, 2010; O'Sullivan et al., 2000). One drawback of these studies is that transit need is poorly characterized by zonal population characteristics since different population groups demand travel to different types of destinations at different times of the day. Similarly, accessibility is poorly characterized by generalized measures of station access or destination access since travel times to destinations can be highly variable depending on time of day variations in schedules. Ignoring the temporal fluctuations in activity patterns and travel times makes it difficult to know whether the transit services that are "provided" are actually what is "needed" by different population groups at different times of day. In an effort to address temporal variations in transit access, Polzin et al. (2002) conduct a time-of-day mismatch study of aggregate travel demand by computing the percentage of origin–destination flows in a region that could be feasibly met by the current provision of public transit. They consider feasibility as a threshold of acceptable wait time at the origin, and frequency of service at the destination. Although their approach measures temporal mismatch in terms of total travel demand in a region, they make no attempt to further explore the distributional aspects of this mismatch between social groups. In fact, few equity studies have considered the unique spatiotemporal signatures of transit supply and travel demand for different population groups, yet, doing so greatly increases the validity of the analysis and could lead to policies that more effectively increase equity in transit provision (Farber et al., 2014b; Owen and Levinson, 2014; Ritter, 2014). The purpose of this study is to investigate how well public transit matches the spatiotemporal travel patterns for different population groups in the Wasatch Front, Utah. To accomplish this task, we: (a) characterize travel patterns using observed trips from household travel and onboard passenger survey data, (b) put forward a measure of spatiotemporal transit service based on origin-to-destination travel times, and (c) determine whether socioeconomic status is associated with travel demands that are spatiotemporally mismatched with transit supply in the region.

The rest of the paper is organized as follows. In the next section we describe the travel time cube and how we use it to create a temporally dynamic measure of transit service. We also put forward our empirical analysis plan, and provide a description of our study area and datasets. In the third section we present and discuss the results of our descriptive and multivariate analysis of transit mismatch. We conclude the paper in Section 4 with a brief summary of results, a discussion about policy implications, and we propose several avenues for future research.

2. Methods

2.1. The public transit travel time cube

We propose a new data object, the public transit travel time cube, which can be used to establish spatiotemporal signatures of transit service in a region. The travel time cube is a three dimensional array $T = [t_{i,j,m}]$ where $t_{i,j,m}$ is the shortest public transit travel time from location i to location j at time m. In this case, i and j index population weighted block group centroids in the region, and m[1] is used to index the minutes in a day. So, for example, $t_{4,10,480}$ is the travel time from block group 4, to block group 10 with a departure time of 8 am (the 480th minute in the day).

[1] The travel time recorded is the shortest path found in the multimodal network at a particular time of departure. It includes ingress, egress, waiting and transfer time associated with the fastest trip. If the shortest travel time is found by walking only, then the walking only trip time is recorded in the cube.

In practice, the cube is computed in a GIS making use of a pedestrian network file (to model ingress and egress times) and a transit network and schedule stored as a general transit feed specification (GTFS) package[2]. An *Esri ArcMap* plugin named *Add GTFS to Network Analyst* is used to create a routable multi-modal *Network Dataset* and custom travel time evaluators which enable the use of many Esri *ArcMap Network Analyst* functions. We use the *Esri OD Cost Matrix* tool to compute shortest path travel times from centroid to centroid in the region, and custom Python scripts are employed to process the computational workflow of iterating cost matrix computations over every start-time minute of the day. Similar data objects built with tools from Esri and other developers have been used elsewhere in the literature (Farber et al., 2014b; Lei et al., 2012; Owen and Levinson, 2014).

For our case study, we used the Utah Transit Authority (UTA) GTFS data to create travel time cubes for a typical weekday, Saturday and Sunday. The particular GTFS package used for this research consisted of service dates ranging from August 19th to December 7th, 2013 and included 122 transit routes, 6202 transit stops, and 7472 transit trips. Our study area contains 1326 block groups, resulting in $1326 \times 1326 \times 1440 \approx 2.5$ billion uniquely computed shortest path travel times per cube. Given the volume of computations and the ensuing data storage demands, we employed distributed processing in a windows ArcGIS environment to speed up the runtime of our computations. The study area, seen in Fig. 1, was trimmed by excluding some peripheral block groups that either had no transit service, or only very specialized services for accessing ski resorts and distant urban settlements. Also, the use of population weighted centroids ameliorates the effects of varying block group sizes, especially at the periphery of the study area.

2.2. Spatiotemporal measures of transit service

The individual trip records from the two surveys (see Section 2.4) were combined with the travel time cube in order to construct service measures for each observed trip. First, the origin and destination (OD) of each recorded trip was associated with an OD pair in the travel time cube based on a point-in-polygon assignment. Next, an average transit travel time for an hour-long period straddling the observed trip departure time was extracted from the travel time cube. The average travel time within a one-hour period is assumed to be representative of the transit service provided at the time of each recorded trip; this moving average is less sensitive to errors in trip time recording that may significantly impact the travel time extracted from the cube. The selection of a one hour buffer (30 min before and after the observed trip) smoothes the travel time quite substantially (as seen in Fig. 2). A sensitivity analysis found that a 15 min buffer on each side obtained nearly identical travel time results (RMSE = 1.13 min) and a 5 min buffer on each side obtained a RMSE of 4.90 min. The degree of "smoothing" error for a given buffer is associated with the frequency of service and how rapidly frequencies of service change over the course of the day. While the size of the smoothing window we choose may impact the results slightly, we are more comfortable with a higher degree of smoothing than the potential for gross over or under representation of travel times associated with a buffer too small. A full sensitivity analysis of the use of different window thresholds is recommended for future research.

Next, we compare the local average travel time (i.e. within 1 h) of the observed trip to the global average (i.e. across the entire day)

[2] Because of this, our transit travel time cube is based on scheduled travel times, and are not sensitive to real world service disruptions or congestion. Future work investigating real-time or historical vehicle location data is one possible extension of the travel time cube research thread.

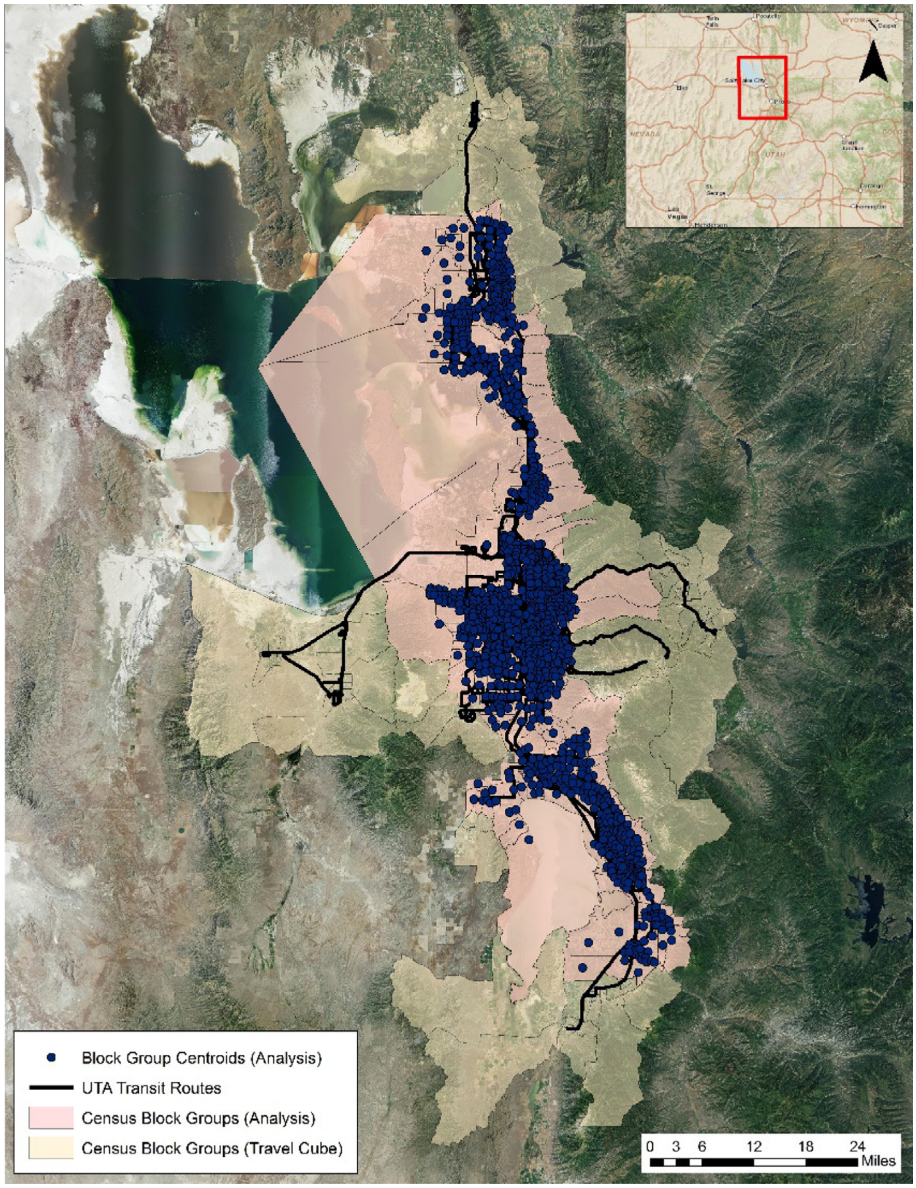

Fig. 1. Wasatch front study area block group centroids.

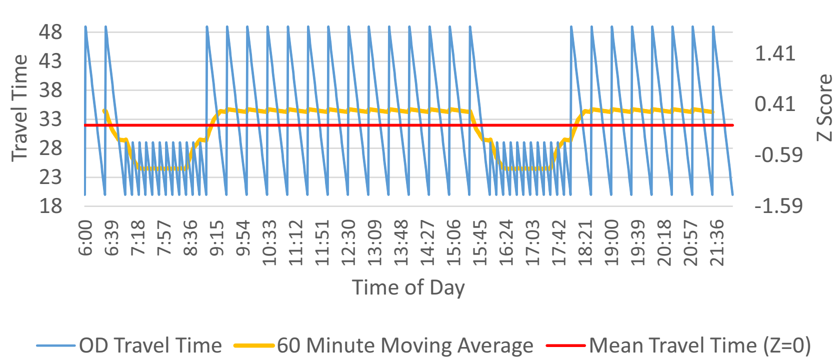

Fig. 2. Illustration and interpretation of level of service *Z*-scores.

to determine whether trips took place during periods of relatively high or low travel times. The one-hour period is centered around each trip's observed departure time. Since travel times for OD pairs are subject to vastly different magnitudes and scales of variation, the service measure associated with each observed trip is standardized into a *Z*-score as follows:

$$Z_q = \frac{X_q - \mu_q}{\sigma_q}$$

where X_q is the local average travel time for trip record q, μ_q is the global average trip time across the entire day for that OD pair, and σ_q is the standard deviation of trip times across the day for that OD pair. Thus, Z_q is an indicator of whether a trip is taken during a time period in which service frequencies are relatively higher or lower for that OD pair. Positive Z-scores indicate higher travel times at the time that an observed trip was made, while negative Z-scores indicate below average travel times. In addition to this measure, we similarly compute Z-scores based on travel speed by dividing the travel times in the travel time cube by the Euclidean distance between origins and destinations. Travel speed, calculated in this manner, is a measure of how well the transit network services the particular OD pair, regardless of distance traveled.

Fig. 2 illustrates how the Z-scores are computed and interpreted. In this example, a pair of bus stops is connected by a single bus route. The in-vehicle journey time is fixed at 20 min. Further assume that the walking time between origin and destination is fixed at some duration greater than 49 min. During peak hours (7–9 am and 4–6 pm) a bus departs every 10 min, and every 30 min at all other times. The blue time series depicts the estimated travel time (waiting time plus in-vehicle time) for the OD pair over the course of the day, from 6 am to 10 pm. The best case travel time is 20 min, when a journey begins at the exact moment of an arriving bus. The worst case occurs during the off-peak times when a journey begins immediately following the departure of a bus. In this case, the maximum estimated travel time is 49 min (29 min of waiting plus 20 min of in-vehicle time). The mean travel time, $\mu_q = 32$ min, is depicted by the red horizontal bar, and the standard deviation of travel times, σ_q, not depicted graphically, is just less than 9 min. The yellow curve depicts the 60 min moving average travel time, X_q from the equation above. The Z-scores for different times of the day are similarly depicted by the yellow curve, with their values appearing on the secondary vertical axis. As can easily be seen, when an individual makes a trip when service frequency is higher, the associated Z-score for travel time will be more negative. Similarly, during periods of relative poorer levels of service, Z-cores will be more positive. In reality, OD travel times, especially those connected via multiple routes or involving transfers, will not vary as regularly as the example provided. Using our methodology, we are able to discriminate between irregular fluctuations in travel times, not just those simply captured in a peak/off-peak dichotomy.

One additional note about the creation of Z-scores must be made. The travel time standard deviation, σ_q, equals 0 for a small number of observed trips that rely on walking only. These trips were excluded from the analysis since they have undefined Z-scores.

2.3. Comparing travel patterns to transit service

Two methods are used to determine whether there are systematic relationships between trip-maker characteristics and the sup-

Table 1
Utah household travel survey (UHTS) ANOVA tests for travel time and trip speed.

Factor	Level	Mean time Z	Mean speed Z	Factor	Level	Mean time Z	Mean speed Z
Res. type	Single family	−0.091	0.109	Mobility	Limited mob.	−0.128	0.124
***	Townhouse	−0.106	0.131	**	No. limited mob.	−0.079	0.096
++	Multi-family	−0.053	0.015		N/A	0.181	−0.1
	<3 Apts.	−0.209	0.204	Gender	Male	−0.099	0.122
	>4 Apts.	0.03	−0.009	**/++	Female	−0.06	0.073
	Mobile	−0.082	0.187	Hispanic	Not-hispanic	−0.083	0.1
	Dorm	−0.067	−0.018	*	Hispanic	0.002	−0.015
	Other	−0.666	0.573		N/A	0.013	0.077
Years at res.	>20	−0.271	0.156	Income	Over 250 K	−0.124	0.156
***	16–20	−0.168	0.157	**	200–50 K	−0.122	0.232
+	11–15	−0.089	0.115		150–200 K	−0.1	0.123
	6–10	−0.06	0.072		100–150 K	−0.088	0.102
	1–5	−0.069	0.093		75–100 K	−0.117	0.141
	<1	0.028	−0.019		50–75 K	−0.085	0.101
Place type	City downtown	0.028	−0.019		35–50 K	−0.054	0.062
***	City residential	−0.069	0.093		25–35 K	−0.03	0.069
+	Suburbs (Mix)	−0.06	0.072		10–25 K	−0.014	0.035
	Suburbs (House)	−0.089	0.115		Under 10 K	0.034	−0.056
	Small town	−0.168	0.157	Education	Grad. degree	−0.124	0.173
	Other	−0.271	0.156	***	Bachelors	−0.098	0.114
Age	85+	−0.158	0.28	+++	Technical	−0.09	0.116
***	75–84	−0.169	0.253		Some college	−0.045	0.032
+++	65–74	−0.133	0.19		Associates	−0.033	0.05
	55–64	−0.097	0.128		HS diploma	−0.027	0.046
	45–54	−0.108	0.127		Less than HS	−0.021	0.051
	35–44	−0.089	0.094	Trip purpose†	HBW	−0.277	0.331
	25–34	−0.068	0.069	***	HBSch	−0.144	0.222
	18–24	0.092	−0.098	+++	HBShp	−0.016	−0.016
Employment status	Full-time	−0.115	0.12		HBPb	−0.173	0.212
***	Part-time	−0.014	0.007		HBO	0.151	−0.17
+++	Self-employed	−0.03	0.052		NHBW	−0.254	0.289
	Student (>25)	0.086	−0.105		NHBNW	−0.044	0.067
	Student (<25)	0.042	−0.039	Travel time††	Peak	−0.505	0.639
	Homemaker	−0.056	0.089	***/+++	Off-peak	0.224	−0.289
	Not-employed	−0.046	0.09				
	Retired	−0.137	0.211				

*, **, *** indicate significance of the ANOVA test for travel time at 0.05, 0.01 and 0.001, respectively.
+, ++, +++ indicate significance of the ANOVA test for travel speed at 0.05, 0.01 and 0.001, respectively.
† HBO: home-based other; HBPb: home-based personal business; HBSch: home-based school; HBShp: home-based shopping; HBW: home-based work; NHBW: non-home-based work; NHWNW: non-home-based non-work.
†† Peak: 6–9 am or 3–6 pm; off-peak: all other times.

Table 2
Utah Onboard Survey (UOBS) ANOVA tests for travel time and trip speed.

Factor	Level	Mean time Z	Mean speed Z	Factor	Level	Mean time Z	Mean speed Z
Age	65+	−0.439	0.986	Mode	FrontRunner	−0.537	1.295
***	45–64	−0.493	1.154	***	TRAX	−0.277	0.692
+++	25–4	−0.413	0.979	+++	Bus	−0.527	1.125
	18–24	−0.301	0.636		N/A	−0.524	0.979
Income	Over 75 K	−0.549	1.239	Trip type†	HBW	−0.534	1.272
***	50–75 K	−0.451	1.033	***	HBC	−0.341	0.746
+++	35–50 K	−0.391	0.959	+++	HBO	−0.177	0.420
	25–35 K	−0.339	0.738		NHB	−0.303	0.638
	15–25 K	−0.306	0.706	Fare type	Cash	−0.275	0.579
	<15 K	−0.276	0.660	***	One-way	−0.326	0.880
No. of vehicles	4+	−0.485	1.082	+++	Reduced fare	−0.257	0.404
***	3	−0.485	1.020		Day/Group	−0.187	0.406
+++	2	−0.468	1.074		Discounted	−0.333	0.741
	1	−0.351	0.854		Adult	−0.481	1.170
	None	−0.221	0.587		Ed/Eco/Annual	−0.532	1.214
Licensed	Licensed	−0.425	0.985		Senior	−0.534	1.046
***/+++	Not Licensed	−0.271	0.592		Student	−0.33	0.761
Frequency	7 Days	−0.172	0.470		Medicaid	−0.27	0.709
***	6 Days	−0.295	0.726		Free fare	−0.132	0.419
+++	5 Days	−0.464	1.096	Egress mode	Drove	−0.496	1.082
	4 Days	−0.457	1.095	***	Walk	−0.394	0.926
	3 Days	−0.437	0.927	++	Bike	−0.265	0.635
	2 Days	−0.356	0.830	Ingress mode	Drove	−0.462	1.062
	1 Day	−0.370	0.788	***	Walk	−0.389	0.900
	Less than 1/week	−0.207	0.273	++	Bike	−0.273	0.655
	First time	−0.315	0.879				

*, **, *** indicate significance of the ANOVA test for travel time at 0.05, 0.01 and 0.001, respectively.
+, ++, +++ indicate significance of the ANOVA test for travel speed at 0.05, 0.01 and 0.001, respectively.
† HBW: home-based work; HBC: home-based college/university/technical school as student; HBO: home-based other; NHB: non-home based.

plied transit service at the time of their trips: ANOVA and multivariate ordinary least squares (OLS) regression. All available factors from the travel surveys were used in our analysis. These include person, household and trip-level characteristics (see Tables 1 and 2 for a complete list of variables). In an effort to study service disparities by socioeconomic status, if socioeconomic status is found to have a significant and positive (negative) relationship with the standardized travel time (travel speed) Z-scores, our hypothesis that transit supply is less likely to meet the needs of those in need is supported. Conversely, if transit provision does not occur in synch with when less affluent people travel, then we could conclude that transit is less likely to meet their needs compared to meeting the needs of the affluent.

2.4. Data used to indicate travel patterns

The Utah household travel survey (UHTS) and the UTA Onboard Survey (UOBS) were used to indicate the spatiotemporal travel patterns for different social groups. These surveys are quite different in scope and sampling method. The UHTS is a state-wide household travel survey typical of those collected for US metropolitan regions. The one-day trip survey recorded 101,404 trips taken by 27,046 individuals living in 9155 randomly selected households across the state of Utah. The survey, being partially funded by Metropolitan Planning Organizations along the Wasatch Front, oversampled the urbanized regions of the state in which UTA operates. This provides a spatially dense sample of households considered to be within the operating district of the transit authority. The UHTS collected information about individual trips, the trip-makers, and their households, and has been used as a data source in a number of peer reviewed articles appearing in the literature (Burbidge, 2012; Farber et al., 2014a; Liao et al., 2015; Tian et al., 2014). Further details on the survey are available in a report published by the data collection consultants, Resource Systems Group, Inc. (Resource Systems Group, 2013). Importantly, the observed trips include those made by all modes. This is in contrast to the trips observed in the UOBS, which only include those done by transit.

The UOBS was collected in 2011 with the goal of describing transit riders as well as calculating overall ridership levels on transit services offered by UTA. Respondents were intercepted randomly at transit stations and aboard transit vehicles. In total, 7123 passengers provided usable responses which included some basic sociodemographic information, and detailed information on the particular trip being made when intercepted. Each respondent indicated whether or not a return trip was planned, and what the planned departure time of the return would likely be. Z-scores were created for these return trips and added to the analysis dataset despite not being observed directly.

The perspective taken in this paper is that the observed activity patterns, especially the timing of activities, represents an inherent desire to participate in activities at different times of the day, depending on the socioeconomic characteristics of the respondents. Among transit users, the above assumption is somewhat flawed, as a person will time the departure from their house with the scheduled arrival of a bus, but this type of timing adjustment occurs at a micro-scale, within the constraints of the route headway. The type of mismatch that we are investigating has to do with larger scale differences in the timing of activities (e.g. peak vs. off-peak, not 8:00 am vs. 8:15 am).

3. Results and discussion

3.1. ANOVA

The ANOVA results for the UHTS and UOBS datasets are presented in Tables 1 and 2, respectively. The tables show the relationships between a host of independent factors and two measures of standardized transit service: transit travel time and transit travel speed. Speed is computed as the travel time divided by the Euclidean distance from origin to destination. In both cases, the measures are standardized temporally against the mean travel times and speeds for each trip across the entire day. For example, in Table 1, observe that travelers from households earning over

Table 3
Summary of ordinary least squares regression analysis for variables predicting travel time *Z*-scores using the UHTS data (*N* = 34,409).

Variable	Model 1		Model 2		Model 3	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Intercept	−0.024	0.019	−0.179	0.019***	−0.166	0.016***
Trip factors						
Trip purpose (HBW)[†]						
HBSch	0.153	0.022***	–	–	–	–
HBShp	0.251	0.014***	–	–	–	–
HBPb	0.105	0.016***	–	–	–	–
HBO	0.304	0.011***	–	–	–	–
NHBW	0.005	0.012	–	–	–	–
NHBNW	0.193	0.012***	–	–	–	–
Peak travel (Off Peak)[††]						
Peak	−0.482	0.007***	–	–	–	–
Individual factors						
Age (35–44)						
18–24	0.066	0.016***	0.079	0.0***	0.081	0.017***
25–34	0.008	0.011	0.011	0.011	0.009	0.011
45–54	−0.017	0.012	−0.015	0.013	−0.014	0.013
55–64	−0.033	0.013**	−0.028	0.014*	−0.029	0.014*
65–74	−0.063	0.018***	−0.053	0.019**	−0.055	0.019**
75–84	−0.090	0.025***	−0.07	0.027**	−0.071	0.027**
85+	−0.098	0.053·	−0.113	0.058*	−0.113	0.057*
Gender (Male)						
Female	−0.001	0.008	0.016	0.008·	0.017	0.008*
Employment status (Full-time)						
Part-time	−0.014	0.012	0.096	0.013***	0.097	0.013***
Self-employed	−0.034	0.015*	0.094	0.016***	0.095	0.016***
Student (>25)	0.015	0.024	0.084	0.026**	0.095	0.026***
Student (<25)	−0.079	0.019***	0.053	0.020**	0.060	0.020**
Homemaker	−0.078	0.013***	0.126	0.013***	0.126	0.013***
Not employed	−0.134	0.022***	0.063	0.023**	0.070	0.022**
Retired	−0.137	0.016***	0.066	0.017***	0.067	0.017***
Education (Bachelors)						
Grad. degree	0.008	0.010	0.005	0.011	–	–
Technical	0.029	0.020	0.026	0.022	–	–
Some college	0.004	0.010	0.007	0.010	–	–
Associates	0.015	0.013	0.024	0.014·	–	–
HS diploma	0.008	0.013	0.012	0.014	–	–
Less than HS	0.033	0.031	0.015	0.034	–	–
Hispanic (No)						
Yes	0.018	0.019	0.021	0.021	–	–
N/A	0.004	0.036	−0.002	0.039	–	–
Race (White)						
Other	−0.008	0.016	−0.029	0.018	−0.021	0.017
N/A	−0.042	0.030	−0.049	0.033	−0.044	0.023·
Licensed (No)						
Yes	−0.027	0.026	−0.048	0.028·	–	–
Limited mobility (No)						
Yes	0.025	0.027	0.033	0.029	–	–
N/A	0.039	0.048	0.055	0.052	–	–
Household factors						
Household size	−0.012	0.003***	−0.013	0.003***	−0.014	0.003***
Household income (50–75 K)						
Under 10 K	0.034	0.029	0.037	0.031	–	–
10–25 K	0.006	0.017	0.022	0.018	–	–
25–35 K	0.013	0.015	0.009	0.017	–	–
35–50 K	−0.008	0.012	0.001	0.013	–	–
75–100 K	−0.025	0.011*	−0.010	0.012	–	–
100–150 K	0.005	0.011	0.007	0.012	–	–
150–200 K	−0.007	0.018	−0.002	0.020	–	–
200–250 K	0.042	0.029	0.082	0.031**	–	–
Over 250 K	−0.024	0.028	−0.006	0.031	–	–
N/A	−0.004	0.013	0.001	0.014	–	–
Place type (Suburbs w/Houses)						
City downtown	0.033	0.019·	0.048	0.021*	–	–
City residential	−0.005	0.009	0.006	0.009	–	–
Suburbs (Mixed)	−0.008	0.009	0.005	0.010	–	–
Small town	−0.027	0.017	−0.022	0.018	–	–
Other	−0.017	0.028	−0.013	0.030	–	–
Residential type (Single family)						
Townhouse	−0.013	0.015	−0.030	0.016·	−0.027	0.016·
Multi-family	−0.021	0.023	−0.013	0.025	−0.004	0.024
<3 Apts.	−0.077	0.038*	−0.082	0.041*	−0.081	0.041*

(*continued on next page*)

Table 3 (*continued*)

Variable	Model 1		Model 2		Model 3	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
>4 Apts.	0.034	0.013**	0.028	0.014'	0.044	0.013***
Mobile	−0.008	0.039	−0.035	0.042	−0.024	0.042
Dorm	0.008	0.057	−0.003	0.063	0.009	0.062
Other	−0.342	0.198'	−0.473	0.216*	−0.465	0.216*
Adjusted R^2	0.170		0.009		0.009	
F for model fit	122.5 (58, 34350)***		7.0 (51, 34357)***		13.1 (25, 34383)***	

', *, **, *** indicate significance at 0.1, 0.05, 0.01 and 0.001, respectively.
The reference category for each factor appears in parentheses.
† HBO: home-based other; HBPb: home-based personal business; HBSch: home-based school; HBShp: home-based shopping; HBW: home-based work; NHBW: non-home-based work; NHWNW: non-home-based non-work.
†† Peak: 6–9 am or 3–6 pm; off-peak: all other times.

$250,000 per year have a mean travel time *Z*-score of −0.124 while those earning less than $10,000 have a mean travel time *Z*-score of 0.034. This indicates that those from high income households typically have spatiotemporal travel demands during periods of more frequent transit service than those in the low income bracket. Similarly, for the same income categories, we see that travel speeds for high income travelers have a *Z*-score of 0.156 compared to −0.056 for the low income group. Thus, transit travel speeds for high-income travelers tend to be higher relative to the low income riders. The significance of these group-wise differences are tested using one-way ANOVA *F*-tests and are indicated with asterisks and plus signs for travel times and travel speeds, respectively.

The results indicate a large number of disparities in transit service by individual, household and trip-type characteristics. In terms of travel time, all variables are significant at least to the 0.05 level. For travel speed, all variables are significant except mobility status, Hispanic status, and household income. We opt to further interpret the nature of these disparities based on the OLS regression results, where confounding factors can be suitably controlled. However, the reader can confirm that for most factors, socioeconomic disadvantage (e.g. lower income, Hispanic, only partial employment, higher rates of residential mobility, etc.) is associated with poorer levels of transit provision in terms of travel time and travel speed. Interestingly, the *Z*-scores for the on-board survey convey that transit trips are taking place during higher service periods as compared to the full set of trips observed in the UHTS. This is likely due to the rational decision by transit riders to travel during periods of better service. Be that as it may, there are still large transit service disparities between socioeconomic groups within the UOBS results. And, the fact that transit service provision is poorer for needier socioeconomic groups who are traveling by car (as observed in the UHTS data), may indicate that their temporal demands for activity participation are not being met by the temporally dynamic supply of transit services.

3.2. Multivariate regression results

Next we present results for 3 models predicting the *Z*-score for travel time based on the Utah household travel survey data (*N* = 34,409). The first model is a full model that controls for all trip-level, individual, and household-level factors in the survey. In the second model, trip-level characteristics are removed. Finally, in the third model, a backwards stepwise regression using the Akaike information criterion is calibrated using model 2 as the starting point.

The purpose for estimating these regression models is to discover which of the correlated socioeconomic factors remain statistically significant while controlling for them simultaneously. This analysis is strictly exploratory, with the major emphasis on understanding the direction, magnitude, and significance of the regression coefficients. Thus, the small but significant values of R^2 for the models is not a large cause for concern (see Table 3). It should be noted that records with ($|Z - \text{scores}| > 3$) were filtered before the regression so that undue influence from extreme values could be mitigated (2.2% of records were removed).

Since the variables are all categorically measured, the regression coefficients represent direct adjustments to the estimated *Z*-scores. We make several findings through a comparison of model results found in Table 3:

- The trip-level characteristics of trip purpose and peak travel are the most explanatory variables in the model. This makes sense, as we know that (a) work trips are more likely to be made during peak hours, and (b) service frequencies is likely to be higher during peak hours.
- *Age:* Compared to the middle aged, youth are more likely to travel during lower periods of service and the older one gets, the more likely they are to travel during periods of higher service, even for those older than 65 years. These relationships hold even while controlling for trip-level characteristics, suggesting a strong mismatch between demand and supply for younger adults, and a better than average match for older adults.
- *Gender:* There is a slight gender effect with females being associated with modest levels of mismatch. This effect diminishes when controlling for trip characteristics.
- *Employment status:* This factor seems to be highly correlated with the trip-level characteristics. When trip characteristics are left uncontrolled, all employment statuses compared to full-time employed are associated with higher degrees of mismatch. When trip characteristics are controlled, being full-time employed is associated with more mismatch than the other statuses. This is most likely a result of the high degree of association between employment status and the timing, purposes and destinations of trips that are made (e.g. more work trips to highly served downtown during peak periods).
- *Insignificant individual level factors:* When controlling for other factors, there is no relationship between mismatch and education status, Hispanic status, race, having a driver's license, or having limited mobility.
- *Household factors:* People living alone are more likely associated with transit mismatch than those living in larger household arrangements. Also, self-reported housing type is consistently significant on several factors. Interestingly, those living in small apartment buildings (3 or less units) have less mismatch than those in single detached housing, while those in larger apartment complexes (4 or more units) are associated with more mismatch. This is true whether or not controls for trip characteristics are in place and is perhaps an artifact of the spatial

distributions of large and small apartment buildings with respect to the transit network. More spatial analysis is required for this relationship to be better understood.

- *Insignificant household level factors:* Once controlling for other factors, there is no consistent relationship between mismatch and household income or self-reported place of residence type. There are several factor levels that obtain significance in models 1 and 2 for these variables, but none that lend much interpretive value to the question at hand.

4. Conclusions

A comparison of the descriptive statistics, ANOVA and multivariate results leads to some interesting interpretation and meaningful findings. On the one hand, the descriptive statistics of mean service Z-scores for different socioeconomic groups tell a very clear story of transit mismatch: those who are most socioeconomically disadvantaged tend to have travel demand patterns that are out of synch with the provision of transit services in the region. The vast majority of the ANOVA F-tests confirm that the differences between socioeconomic groups are statistically significant. The regression results, however, challenge these descriptive findings in two ways. First, it appears that trip purpose and peak-period trip making are the most meaningful explainers of mismatch. Those who travel for work during peak periods are far more likely to travel during periods of higher service provision. Second, many of the factors found to have differences in the descriptive analysis lose importance when controlling for simultaneous effects. Those that remain significantly related to service level include: age, gender, employment status, household size and housing type. Importantly, from a civil rights and environmental justice policy perspective in the United States, race and income effects fall out of significance, indicating that the system isn't specifically discriminating along these lines. Nonetheless, due to the correlations between employment status, housing type, and income, the fact remains that low income individuals in the region experience more transit mismatch than those who earn more, it is just that the cause is more likely to be the trip making patterns associated with un(der)employment, rather than income itself.

The importance of trip purpose and time-of-day in explaining transit mismatch hearkens to the long tradition of predicting these two outcomes using activity-based approaches to travel behavior modeling. Models relating socioeconomic factors of trip-makers to activity purposes and timing have been used to better understand behavior and to populate microsimulation transportation models, but seldom have they been viewed through a social equity lens. The present papers suggest that this literature should be reviewed from the perspective of mismatch between travel demand and transit supply.

The methods developed in this research can be improved in a number ways for future research. First, the creation of the Z-score, while necessary to control for heterogeneity in differences between local and global-average trip times across individuals and space, also somewhat obfuscates the interpretation of the regression coefficients. Marginal impacts on standardized Z-scores are hardly relatable to policy makers or indeed very meaningful in terms of valuing the absolute level of mismatch for an individual's trips or an entire social group's trips. In the future, more sophisticated modeling techniques that can account for size-effect heterogeneity across OD pairs could be employed so that the raw travel times or travel speeds can be used as dependent variables. This will allow for a more practical application of this research in terms of quantifying the experiences of individual trip makers and socioeconomic groups.

Besides these technical refinements, there are clearly extensions of the research that should bear interest to the transportation research community. First, this research has identified a need for a spatial analysis of transit mismatch, with a particular emphasis on locating hotspots of mismatch at the origins or destinations of trips, and determining how these relate to current levels of transit provision. In particular, it will be important to determine whether mismatch can be better reduced through temporal policies (e.g. decreasing headways or shifting time-use behavior) or through spatial policies (e.g. expanding network coverage or decreasing the need for long-distance trips through land use policies). Second, it seems obvious that transit mismatch may be a root determinant of mode choice, and incorporating the degree of mismatch associated with a person's daily activity routine may yield interesting results in a mode choice model.

This paper has focussed specifically on the equity considerations of a new type of transit mismatch, one that incorporates both spatial and temporal patterns of travel demand and public transit supply. It is important to recognize that the research was made possible through the development and use of the travel time cube, a new data object that embodies the spatiotemporal structure of transit connectivity in a region. Besides using the travel time cube to study transit mismatch, work is underway to investigate temporal variations in accessibility, new methods to quantify the effects of transit network modifications, and the impact of the bicycle in conquering the *last mile* problem in transit service provision. Indeed, the travel time cube is proving to be a useful tool that facilities the study of the role of public transit in society.

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