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The Association of Trip Distance With Walking To Reach Public Transit: Data from the California Household Travel Survey

Casey P. Durand, PhD[1,2], **Xiaohui Tang, MS**[1,2], **Kelley P. Gabriel, PhD**[2,3], **Ipek N. Sener, PhD**[4], **Abiodun O. Oluyomi, PhD**[2,3], **Gregory Knell, MS**[2,3], **Anna K. Porter, MPH**[2,3], **Deanna M. oelscher, PhD**[2,3], and **Harold W. Kohl III, PhD**[2,3,5]

[1]University of Texas School of Public Health, Houston, TX

[2]Michael and Susan Dell Center for Healthy Living, University of Texas School of Public Health

[3]University of Texas School of Public Health, Austin, TX

[4]Texas A&M Transportation Institute, Austin, TX

[5]University of Texas at Austin, Austin, TX

Abstract

Introduction—Use of public transit is cited as a way to help individuals incorporate regular physical activity into their day. As a novel research topic, however, there is much we do not know. The aim of this analysis was to identify the correlation between distance to a transit stop and the probability it will be accessed by walking. We also sought to understand if this relation was moderated by trip, personal or household factors.

Methods—Data from the 2012 California Household Travel Survey was used for this cross-sectional analysis. 2,573 individuals were included, representing 6,949 transit trips. Generalized estimating equations modeled the probability of actively accessing public transit as a function of distance from origin to transit stop, and multiple trip, personal and household variables. Analyses were conducted in 2014 and 2015.

Results—For each mile increase in distance from the point of origin to the transit stop, the probability of active access decreased by 12%. With other factors held equal, at two miles from a transit stop there is a 50% chance someone will walk to a stop versus non-active means. The distance-walking relation was modified by month the trips were taken.

Conclusions—Individuals appear to be willing to walk further to reach transit than existing guidelines indicate. This implies that for any given transit stop, the zone of potential riders who will walk to reach transit is relatively large. Future research should clarify who transit-related walkers are, and why some are more willing to walk longer distances to transit than others.

Corresponding Author: Casey P. Durand, PhD MPH, University of Texas School of Public Health, 7000 Fannin, #2532, Houston, TX 77030, T: 713-500-9685, F: 713-500-9750, Casey.P.Durand@uth.tmc.edu.

Keywords

Public transit; physical activity; built environment; planning; transportation

1. Introduction

Public transit (e.g. buses, trains, light rail) use is a way to incorporate regular physical activity into daily life. Public transit is generally not a point-to-point mode of travel; it requires another form of travel to reach a pick up point and to get from a drop off point to the traveler's final destination.[1-3] To the extent that these additional trip components involve physical activity, such as walking or biking, transit riders can achieve upwards of 30 minutes per day of walking, an amount sufficient to meet current guidelines for 150 minutes per week of moderate-intensity physical activity.[3,4]

Despite this possibility, there is a great deal still unknown about the correlation between public transit use and physical activity. One of biggest gaps is how exactly distance to transit stops may affect the choice of modes to arrive at (access) and depart from (egress) transit stops. This is an important question because distance to destinations is widely thought to be an important predictor of active travel. For example, among children, there is a clear inverse association between distance from home to school and the odds of active travel by walking or biking versus a non-active mode. [5,6] Among adults, both leisure and work trips are less likely to be made by walking and biking the further the trip distance, although leisure trips seem to be affected to a greater degree by trip distance.[7]

Public transit planners typically assume that most users will arrive and depart from transit stops via walking. As a result, they often define a catchment zone, (the geographic area encompassing all possible riders) as between 0.25 and 0.5 miles from a stop.[8-12] However, the type of transit may influence this catchment zone. There is some evidence that users are willing to walk a further distance to reach a rail stop versus a bus stop.[9,12] The problem is that these are rough rules of thumb, and there is little scientific evidence to support any standard catchment zone definition. In fact, prior research in this area shows, with some consistency, that the catchment zone could be significantly larger than thought.[9,13,14] The existing literature, however, is limited because the studies generally restrict the analysis sample to only those who walked to transit. This precludes any understanding of how individual or contextual factors, including distance, affect the basic decision to use an active or non-active mode of transport to reach transit. Ultimately, this leads to an inability to understand whether any of those who currently reach transit via motorized means could potentially be the targets of interventions to encourage active transportation decisions.

More precise knowledge of how distance affects mode choice will enable planners to make more informed decisions about transit stop placement. Perhaps more importantly, it may help guide decisions about infrastructure improvements (e.g. sidewalks, street lighting, street-crossing aids, etc.) that may be necessary to facilitate use of transit, especially among those who would be transit users by choice rather than necessity. Directing improvements to areas with the highest proportion of likely transit walkers may promote transit use and physical activity in the process.

The purpose of this paper is to determine the association between distance to a transit stop and transit access mode. Specifically, we are interested in whether this mode is active or not (i.e., walking). Also, because it is likely that the association between distance and transit access mode will not be universal, we aimed to determine whether this association is moderated by household-, individual-, or trip-level factors.

2. Methods

2.1 Data

Data for these analyses were collected as part of the California Household Travel Survey (CHTS). This statewide travel survey was conducted in 2012, ultimately enrolling over 42,000 households. An address-based sampling frame was used to recruit households via computer-assisted telephone interviewing and a CHTS website. Data collected included a questionnaire, a single-day travel diary, and, for some households, global positioning system (GPS) data. All people within a recruited household were asked to complete the individual-level questionnaire and travel diary, while one person also completed the household-level questionnaire. This analysis was restricted to adults aged 18 years and older. The complete dataset was downloaded from the Transportation Secure Data Center maintained by the National Renewable Energy Laboratory in September 2014.Further description of the survey sampling plan and methodology is available elsewhere.[15] The protocol for this analysis was granted exempt status by the university's institutional review board, due to the publicly available, de-identified nature of the data set.

2.2 Measures

Relevant measures were obtained from the individual and household-level questionnaires and the single-day travel diary, both of which were retrieved via computer-assisted telephone interviewing, online survey, or mailed survey. The dependent variable was a binary indicator of whether, for a given trip using public transit, the individual accessed or departed from the transit stop via either active (walking) or inactive (all other travel modes) means. Trips to transit made by wheelchair, plane or “other non-motorized” modes were excluded, because of a lack of definition of the “other category”, and the fact that these different forms of non-motorized travel potentially have very different metabolic costs, resulting in an overly heterogeneous category. Trips to transit made by bicycle were also excluded. Although bicycling is an active form of travel, very few trips to reach transit were made via bike in this sample (<2%). This, plus the fact that combining walking and biking into a single active travel variable could mask significant differences between the two, led us to exclude biking trips to reach transit.

The focal independent variable was the distance of the trip to reach or depart a transit stop. This was done by the primary data collection contractor using their proprietary Trip Builder program.[15] The program works by using Google Maps to determine a route between the origin and destination. The distance of that route is then processed using PostGIS 2.0's ST_Length function, which computes geography lengths by adding up the distances between the line's vertices using the Haversine formula. Independent variables were selected on the basis of prior research examining the correlates of transit access, as well as variables known to correlate with physical activity.[10,13,16-19] Broadly, these variables represent factors at the household level, individual level, and the trip level. Household variables included income assessed via 10 response options, number of individuals in the household, number of household vehicles, and residence type (e.g. single family detached, small apartment building, large apartment building, etc.). We also included an indicator of the month and day of week the household participated in the study. Individual level demographic variables included age, sex, education (coded in six categories), and binary variables indicating homeowner or renter, employment, disability, foreign-born, driver's license, and Hispanic ethnicity status. Trip level variables included mode of transit they were either accessing or departing from, the origin or destination of the transit access/egress trip (home, or non-home), and the trip number (out of the total trips, transit and non-transit, taken that day).

2.3 Analysis

The unit of analysis was at the level of the trip derived from the travel diary. Due to the nature of the sampling strategy employed by the CHTS, trips each day are nested within individuals, who are nested within households. Conceptually, this resulted in a three-level analysis. However, preliminary analysis of the null or independence three-level probit model, in which the binary active access variable was predicted as a function of only the person and household grouping variables, indicated that after accounting for clustering of trips at the household level, virtually no variance was left at the individual level. Therefore, we only accounted for clustering of trips at the household level. To accomplish this, we utilized generalized estimating equations (GEE), clustering at the household level and specifying a probit link, an exchangeable working correlation structure, and robust standard errors. All independent variables were entered simultaneously. To assess the moderating or interaction effects between the focal predictor of trip distance and the remaining independent variables, separate models were specified in which the independent variables were individually interacted with trip distance. Model parameter estimates are presented as probit coefficients and standard errors. Probit coefficients refer to the change in the probability index function per unit increase in the independent variable. For ease of interpretation, average marginal effects (AME) in the probability metric are also provided. AMEs are interpreted as the change in the probability of the limited dependent variable per unit increase in the independent variable. Alpha level was set at 0.05. Data management and statistical analyses were completed using Stata SE 13.1 (StataCorp, College Station, TX).

Analyses were conducted in 2014 and 2015. Complete Stata syntax to replicate the analyses is available at <masked for peer review>

One difficulty in analyzing travel survey data in this context is that a trip to reach a transit stop could simultaneously be a trip to depart from a prior stop. For example, this would be true if an individual got off bus A at a stop, and then walked four blocks to another transit stop, whereby they stepped onto bus B. If only a single analysis were conducted, it would be unclear whether to code this as an access or egress trip. Therefore, we elected to conduct separate analyses for access and egress trips, which also allowed us to model the factors unique to each trip, such as the mode of transit they were reaching or departing from, even in situations such as the prior example. However, because the parameter estimates and confidence intervals were generally similar across the access and egress models, we only present the access results here.

3. Results

The original dataset consisted of 460,858 trips, nested within 109,113 persons and 42,431 households. After removing all trips not taken by an adult (18 years and older), those that did not precede a transit trip (i.e., those that were not transit access trips) and access trips taken by bike or other non-motorized means, there were 8,325 trips, nested in 3,069 persons and 2,600 households. Due to missing data, approximately 17% of the otherwise eligible sample was case-wise deleted from subsequent analyses, leaving an analysis sample of 6,949 trips, 2,573 persons and 2,210 households. Sample characteristics can be found in Table 1. No significant differences on any variables in Table 1 were noted between those included in the analytic sample and those excluded due to missing data. The sample is generally similar to the larger population of California, except the analytic sample included a higher percentage of households with no vehicles and incomes less than $25,000 a year, as well as a higher percentage of individuals who report being employed.

3.1 Base models

Results of the initial model, which included all independent variables but no interaction terms, are presented in Table 2. The focal predictor of trip distance exhibited a significant inverse association with the probability of walking to a transit stop versus a non-active mode. For each mile increase in distance from the point of origin to the transit stop, the probability of active access decreases by 12%. Figure 1 shows the probability of active access as a function of trip distance. A clearly lower probability of active access was seen at longer trip distances. An inverse association was also observed with age; at higher ages, the probability of active access was lower. This inverse association was also true for those with a disability relative to those without a disability.

Some variables were found to positively correlate with active access. The probability of active access increased by 8% when trips were home-based, as compared to transit access trips which began someplace other than home. Likewise, an increasing trip number was correlated with greater probability of active access.

Finally, the parameters of the destination mode variable were jointly significant. In order to identify which transit modes were associated with greater probability of active access, post-hoc pairwise comparisons are shown in Table 3. Trips to reach local bus service were more likely to be active than those to reach heavy rail. Also, compared to public transit shuttle, trips to reach express bus service, heavy rail, light rail, and street car were less likely to be active.

3.2 Interaction models

An interaction was found between trip distance and month. Month was parameterized using dummy variables, with January as the reference group; the parameters of the trip distance-month interaction were jointly significant. Under this parameterization, only the contrast between January and June (interaction probit coefficient: -1.05; 95% CI (-1.87, -0.23)) and

January and October (interaction probit coefficient: -.77; 95% CI (-1.43, -0.11))were significant, indicating that for each mile increase in distance, the probability of active access decreased at a more negative rate in June and October compared to January. All other interaction terms were non-significant.

4. Discussion

The results of these analyses make clear that a correlation exists between distance to transit and the mode of access. It is interesting to note the relatively small magnitude of this correlation, however. As shown in Figure 1, even at two miles from a transit stop, there is still about a 50% chance an individual will walk to the transit stop versus using a motorized mode. Therefore, the distance individuals are willing to walk to transit appears to be much higher than the frequently cited rules of thumb of 0.25 to 0.5 miles.[8-12] Our findings are, however, consistent with recent studies examining the association between real estate property values and proximity to light rail stations.[20] This research has shown that the price premium attributable to access to light rail extends up to about a mile from a station. This is of course a rather different research question than we examine here, but it does provide some additional evidence that a transit stop's “sphere of influence” likely does extend well beyond current catchment zone definitions.

There are several important implications from these findings. First, to the extent that neighborhood built environment features impact the decision of how to access transit, policy makers should consider directing improvements to larger areas surrounding transit stops in order to make these pathways more conducive to active access. Second, the results suggest it may be possible to space transit stops further apart than typically thought. This would have the dual advantage of requiring fewer resources from a transit agency and potentially inducing greater amounts of regular physical activity in those accessing the stops. Third, there appears to be a relatively large population of transit riders who would be candidates for efforts to convert their access trips from a motorized mode to an active one. Although riders beyond about a half-mile from a stop may previously have been thought to be almost certain to use a motorized mode to reach a transit stop, we can see that even at two miles, the odds are even that an individual will use an active mode versus a non-active one. It remains unclear what factors would cause one person to walk to a transit stop two miles away, while another at a similar distance would drive, get dropped off, etc. Although we began this effort with our interaction models, future research will be needed to better understand the factors associated with walking trips to transit at longer distances. This would include an emphasis on rigorously designed, controlled, longitudinal research studies. This would provide the necessary framework for developing behavioral interventions in the future.[21]

In our interaction analyses, we found that the association between transit distance and active access varied by month; however, it is unclear what conclusions to draw from this interaction, especially since this was significant only when comparing June and October to January. It could be weather-related, such that temperatures or precipitation in June and October dissuade some from walking who might otherwise do so in January. However, we would caution against over-interpretation of this finding at this point. Month may be a proxy indicator for many factors, including weather, school, and employment or other economic patterns. Additionally, this finding could simply represent a statistical artifact resulting from the multiple tests associated with this interaction analysis. As such, future research is needed to understand in more detail how seasonal factors affect transit access mode.

Interestingly, the correlation between distance and active access does not appear to differ on the basis of certain factors that might be thought to affect proclivity to walk to transit. For example, related prior research has found that individuals walk further to light rail stations than to bus stops.[9,12] In contrast, we found no evidence to suggest that the correlation between active access and trip distance depends on which transit mode is being reached. This is true not just for light rail and bus, but also the five other modes included in this analysis. It is not clear why our results differed from prior studies in this regard, though it seems likely that it could be related to our inclusion of more transit types, a more diverse population, or other model specification differences. In any event, this finding is positive, as it means policies and behavior-change strategies can be deployed across transit types. Also, prior research has found that women are less likely to walk to a light rail transit stop when compared to other options, such as taking a bus or getting dropped off, perhaps because of safety concerns.[16] In the present study, however, not only did gender not correlate with active access to transit, it did not interact with distance either. The reason for the disagreement may be that fear of criminal victimization may be a highly localized phenomena. The prior study was conducted among transit riders in St. Louis, while the present study sampled individuals over the whole state of California. City-specific analyses might be needed to understand whether these possible gender differences exist.

4.1 Strengths and limitations

This analysis is characterized by several strengths. First, we have utilized data from a large, complex survey, covering a diverse population and set of transit systems. This variation allowed us to develop a relatively complex statistical model of the distance-access mode association. Second, we went beyond a simple question of the correlation between distance and transit access mode, to also consider potential interaction effects. Although we found only one moderator, it is equally valuable to know that this relation was constant over some factors.

Limitations to our study include potential difficulties in generalizing from the dataset. Although the California climate is fairly diverse, areas that experience significantly different weather patterns, such as more extreme heat, cold or precipitation, may find these results less useful. Also, as with any self-report instrument, the accuracy of the trip data as reported by participants is unknown. Finally, as the data were collected from across the entire state of California, there was potentially significant variation in the built environment across locations. Lacking detailed local-level data, we were unable to account for the effect of these environmental factors on active access to transit. We were further unable to account for other possibly influential factors, such as attitudes and norms about transportation, transit use and physical activity, or measures of personal health beyond disability.

4.2 Conclusion

Longer distance is clearly correlated with a lower probability of walking to public transit. However, it appears that the distance individuals are willing to walk to transit is greater than previously thought. Advocates of public transit as a means to increase persistently low levels of physical activity should take a more expansive view of the population that could benefit from policy and programmatic interventions to encourage transit use.

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- Use of public transit is correlated with greater physical activity
- The distance individuals are willing to walk to reach transit is uncertain
- We found increasing distance is correlated with lower chance of walking to transit
- However, Individuals appear willing to walk further to transit than previously thought
- This relation generally did not vary over key demographic or economic factors

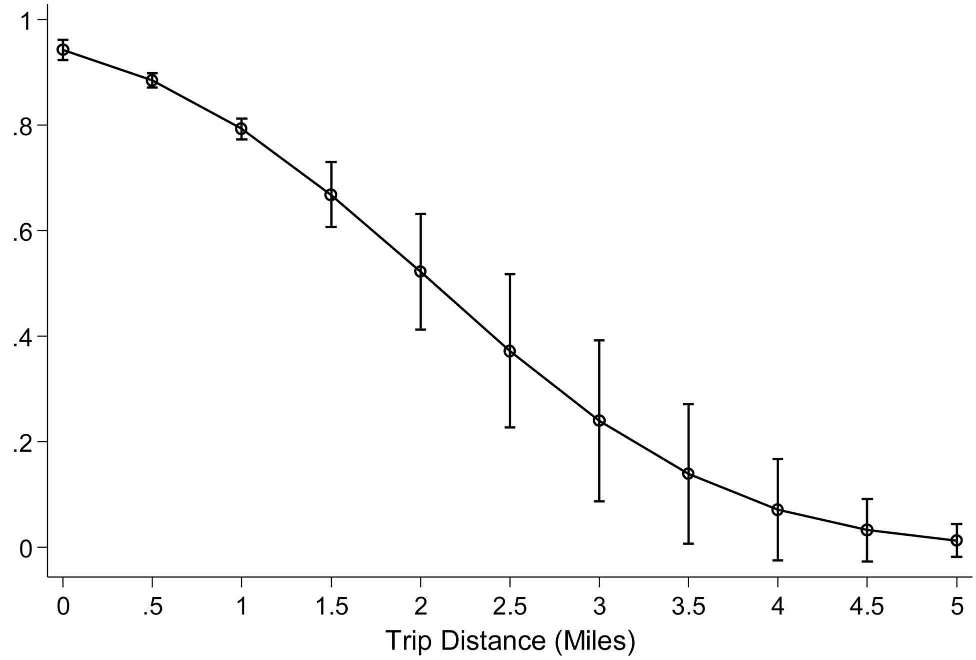

Figure 1. Predicted Probability of Active Access

Table 1

Sample Characteristics

Characteristic	Median (Interquartile range) or percentage
Individual and household characteristics	
Age (years)	49 (35-58)
Household vehicles	1 (0-2)
Household size	3 (2-4)
Household income (categorical)	$35,000-$49,999 ($10,000-$24,999 to $100,000-$149,999)
Renter	53%
Female	53%
Hispanic or Latino	35%
Employed	62%
Disabled	12%
Trip characteristics	
Local or rapid bus	64%
Heavy rail	18%
Light rail	10%
Express or commuter bus	4%
Transit access trip distance (miles)	0.32 (0.13-1.35)
Active access (i.e. walking)	72%
Trip originated at home	31%

Table 2

Regression model coefficients and average marginal effects

Variables	Probit Coefficient	95% Confidence Interval	Average Marginal Effect
Access trip distance (miles)	**-0.80**	-1.02, -.58	-0.12
Trip origin (1=home; 0=non-home)	**0.55**	.41, .68	0.08
Month (ref.=January)			
February	0.10	-.13, .32	0.01
March	0.13	-.07, .33	0.02
April	0.21	-.19, .62	0.03
May	-0.10	-.33, .13	-0.02
June	-0.10	-.35, .14	-0.02
July	0.10	-.15, .35	0.01
August	-0.04	-.25, .17	-0.01
September	-0.05	-.28, .18	-0.01
October	-0.12	-.32, .07	-0.02
November	0.05	-.19, .29	0.01
December	-0.08	-.31, .15	-0.01
Income	0.02	-.02, .05	0.002
Household size	0.03	-.01, .07	0.004
Homeowner (1=yes; 0=no)	0.09	-.04, .23	0.01
Sex (1=male; 0=female)	0.05	-.04, .15	0.01
Hispanic (1=yes; 0=no)	0.06	-.07, .20	0.01
Born in USA (1=yes; 0=no)	0.06	-.06, .17	0.01
Possess driver's license (1=yes; 0=no)	-0.01	-.14, .13	-0.001
Currently employed (1=yes; 0=no)	-0.05	-.16, .06	-0.01
Disability (1=yes; 0=no)	**-0.20**	-.35, -.04	-0.03
Education (ref.=not high school grad)			
High school graduate	-0.08	-.24, .08	-0.01
Some college credit	-0.06	-.27, .14	-0.01
Associate or technical school degree	0.06	-.20, .33	0.01
Undergraduate degree	-0.07	-.28, .13	-0.01
Graduate/professional degree	-0.11	-.32, .10	-0.02
Age (years)	**-0.004**	-.01, -.001	-0.001
Residence type (ref.=Single family detached)			
Single family attached	0.01	-.16, .17	0.001
Mobile home	0.04	-.42, .51	0.01
Building with 2-4 units	0.03	-.13, .20	0.01
Building with 5-19 units	0.16	-.04, .36	0.02
Building with ≥ 20 units	0.17	-.004, .35	0.03
Day of week (ref.=Sunday)			

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Variables	Probit Coefficient	95% Confidence Interval	Average Marginal Effect
Monday	-0.04	-.21, .12	-0.01
Tuesday	-0.10	-.27, .07	-0.02
Wednesday	-0.12	-.29, .05	-0.02
Thursday	-0.05	-.23, .14	-0.01
Friday	0.10	-.12, .33	0.01
Saturday	0.04	-.21, .28	0.01
Number of vehicles at household	-0.05	-.12, .01	-0.01
Destination mode (ref.=local bus)			
Express bus	-0.13	-.34, .08	-0.02
Premium bus	-0.20	-.87, .47	-0.03
Public transit shuttle	0.66	-.035, 1.36	0.07
Heavy rail	**-0.24**	-.38, -.10	-0.04
Light rail	-0.08	-.25, .08	-0.01
Street car	-0.25	-.59, .09	-0.04
Trip number	**0.03**	.01, .05	0.004
Intercept	**1.51**	1.11, 1.90	

Boldface text indicates significant parameter estimates (p≤0.05)

Table 3
Pairwise comparisons of marginal linear predictions

Destination mode	Linear prediction (probit)	Standard error	Pairwise comparisons*
Local bus	1.80	0.17	BC
Express bus	1.67	0.21	AB
Premium bus	1.59	0.39	ABC
Public transit shuttle	2.46	0.38	C
Heavy rail	1.56	0.20	A
Light rail	1.71	0.20	AB
Street car	1.55	0.24	AB

*Linear predictions sharing a letter in the group label are not significantly different at the 5% level.