Travel Mode Choice and Social and Spatial Reference Groups

Comparison of Two Formulations

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This paper investigates social influence on mode choice by using two methods for defining reference groups: the ego networks of respondents' social contacts and respondents' spatial or geographic neighbors. The use of social network analysis builds on traditional models of travel behavior that rely on individualistic assumptions about decision making rather than the social context in which travel behavior takes place. First, mode choice is explored with traditional socioeconomic, attitudinal, and trip characteristic variables; in addition, to address social influence, egocentric social network factors consisting of the behaviors of social contacts are incorporated into models to investigate whether the choice of transportation mode made by "egos" (the individuals sampled) was influenced by the behaviors of "alters" (the egos' personal network of contacts). Second, with the use of spatially defined reference groups, neighborhood mode use variables are considered for their potential influence on mode choice. Models are compared, and findings show that, for some modes, the choices of ego network and spatial neighborhood have similar effects while, for other modes, the effects on mode choice are different. Findings suggest that ego network processes related to mode choice are dissimilar from those of spatial neighborhoods.

This paper investigates two methods for defining reference groups: the ego networks consisting of respondents' social contacts and the networks of respondents' spatial or geographic neighbors. Both the ego network and the spatial reference have the potential to influence mode choice. The results presented here highlight the differences between socially defined and spatially defined reference group effects. A growing body of research addresses social influences and social networks in transportation (*1–3*). The ways of defining both the social effects and the groups within which social influence occurs are important issues for consideration.

Recent research in the field of network science has demonstrated that social networks profoundly influence individual behavior ranging from political decisions (*4*) to diet and exercise (*5*). Social networks also provide pathways for social influence, in which the travel choices of one person affect the choices of individuals to whom they are socially connected. As in other behavioral research, in transportation research how social network processes affect travel behavior is becoming a central topic. Understanding social influences in travel behavior informs broader questions related to how social network–based policies and programs may be used to affect behavior changes for congestion relief and transportation demand management.

Social networks act as avenues for the diffusion of information. For example, social groups may discuss alternative modes, changes or improvements to transit service, or new infrastructure. Social influence may also occur through normalization of behaviors, such as the use of a particular mode of transportation or the reinforcement and reaffirmation of behaviors. To find new and innovative solutions for reducing transportation emissions and supporting alternative modes, transportation professionals must improve their understanding of the mechanisms that influence individual travel behavior. Social influences may be a powerful tool that could be incorporated into campuswide, local, or regional policies to promote the use of sustainable methods of transportation. By exploring the means by which social influence may be identified and the ways in which social reference is defined, this paper contributes to the understanding of how to study these processes and of how they may be incorporated into policy.

SOCIAL NETWORKS AND TRAVEL BEHAVIOR

Background

Travel behavior research has developed a strong understanding of factors that contribute to individual transportation choices; however, these models have left a portion of the influences unexplained and generally looked at individual travel behavior as an atomized choice made without respect to the influences of social relationships. Travel behavior research typically uses a utility maximization framework and predominantly relies on trip characteristics and individual sociodemographics to understand and predict travel behavior. Social network theory recognizes that decisions are made in a social context, and social relationships may directly affect the costs and benefits of different choices, such as transportation mode, for example, by making the finding of information easier or through establishment of behavioral norms. Thus, transportation research that ignores social networks is likely to miss a number of important variables; the nature of and the extent to which social network variables affect transportation behavior is a matter for empirical research like that presented here.

Social networks are involved in many aspects of transportation, including trip generation: individuals make trips to spend time with others in their social networks. Thus, social networks influence daily activity patterns in ways that may be used to predict travel behavior and trip generation (*6*). Simultaneously, the frequency

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of social interactions, and the associated amount of travel, may depend on network structure and composition as well as with whom activities take place (*7*). Information and communication technologies (ICT) coupled with increased mobility influence social travel through the continual coordination of and last-minute changes to plans (*1*). ICT could also reduce social travel in some cases in which social interactions are sometimes replaced by communication over the Internet (*8*).

In addition to affecting trip generation, social networks also provide transportation resources. In some elderly populations, those with active social networks, and to some extent those living in retirement homes, may be more likely to use ridesharing (*9*). Other populations, such as some immigrants, depend on each other for transportation resources, and although the type of social ties matters, geographical and temporal factors are also relevant, as is having either a car or the ability to drive (*10*). Expanded networks (beyond close personal networks) may provide more resources (*10*), highlighting the importance of weak ties (*11*). Evidence also exists that transportation mode choices affect social interactions and that high levels of automobile use can limit social interactions (*12*).

Reference Groups and Mode Choice

In relation to social influence on mode choice, recent work may be categorized by the type of reference group used in analysis. In some cases, researchers consider an explicit social reference group: a network consisting of individuals and their reported social connections. The connections in these networks are self-defined (by network members). In other cases, a general or spatial reference group, such as neighbors or peers (with respect to sociodemographics), has been used to estimate social influence on mode choice. The connections in these assumed networks are exogenously defined (by the researcher). The aim of this paper is to further the understanding of how the definition of "reference group" affects outcomes.

Looking at explicit social reference groups, or social networks, Wilton et al. (*2*) find factors such as learning and validation from peers and coworkers about experiences have an effect on the choice to telecommute. Social factors also include interactions with coworkers at work (that can be either be beneficial or distracting) and a culture around telecommuting in some instances (*2*). Scott et al. also find that social effects may play an important role in the decision to telecommute, and the characteristics of relationships affect the relevance of social influence (*13*). Páez and Scott simulate a panel study and show the first-wave behaviors within social networks affect the behaviors of individuals in the second wave (*14*). In all these cases, the "social reference group" is defined as a group of networked individuals; observed, reported, or simulated ties are present between individuals.

Spatial reference groups are also likely to have an influence on mode choice. In a spatially autoregressive logit mode choice model (one that uses 40 nearest neighbors) in New York City, Goetzke finds that neighborhood network effects influence the use of transit (*15*). Dugundji and Walker consider residential district, socioeconomic group, and postal code in discrete choice models with social interdependence on decision making and find that social influence occurs to some extent (*16*). Further, differences in the mode share of bicycling from one German city to another can be attributed to a city-level cultural component characterized as a social network effect, though it is broadly defined (*17*). In addition, evidence shows that attitudes are spatially distributed with nonrandom patterns, though unclear is whether this nonrandomness is a result of self-selection or localized changes in attitude that are based on physical attributes of neighborhoods (*18*).

DATA AND METHODS

Surveys

In coordination with an annual campus travel survey (CTS) at the University of California, Davis, in the 2012–2013 academic year, a social networks and travel survey (SNTS) was administered to a sample of students. The CTS was sent to 28,838 members of the Davis campus in October 2012 and resulted in 3,982 usable responses, a response rate of 13.8% (*19*). At the end of the survey, students were presented with an option to participate in the SNTS at a later date and were asked to provide an e-mail address to which the survey invitation could be sent. Of the 3,171 students who participated in the CTS, 56% (1,789) indicated interest in the SNTS. Because of a conflict with another survey, in March 2013, a subset consisting of 1,642 of these students were sent invitations to participate. Ultimately, 962 students completed the survey (an initial response rate of 59%). Of these, 692 provided enough information to be included in analysis (22% of the initial 3,171 students who participated in the CTS).

The survey aimed to capture both the key variables of interest to this research as well as variables known to be important factors in travel behavior, such as sociodemographics, trip and mode characteristics, and the built environment (*20, 21*), and attitudes (*22*). Some of this information was collected in the CTS and linked to respondents in the SNTS. In the SNTS, respondents were first asked what transportation modes were available to them, what mode of transportation they usually used for travel to campus, and why they considered some modes unavailable. Next, the survey asked about the importance (on a five-point scale) of 18 factors, including some social factors, in the choice of their usual mode.

Reference Groups

In the survey's name generator, respondents were asked to identify contacts within their social networks. While social networks may be studied in numerous ways [see Wasserman and Faust (*23*)], the primary method used here is ego network analysis. In this approach, a sample of individuals is selected. The sampled individuals are the "egos," who are connected to their own personal network (which may be defined in multiple ways) of contacts or "alters." The name generator asked respondents to think about their social circle, including "people with whom you live, work or attend class, socialize or participate in activities, etc., or people you speak with over the phone or internet." Spaces were provided for the ego to name up to five alters with whom they had different types of interactions over the past 6 months.

Three versions of the name generator were included in the survey, with one version randomly assigned to each respondent. In all three versions, the social circle was defined in the same way, but respondents were asked to list the names of different types of contacts so as to investigate the effects of name generator wording on ego network characteristics. [For a discussion of possible effects, see Campbell and Lee (*24*), Bernard et al. (*25*), and Klofstad et al. (*4*).] The first name generator requested the names of "any five people who have been in your social circle over the past six months" (any-five-contacts name generator). The second version requested the names of "the five contacts you have had the most frequent regular interaction with over the past six months" (frequent-interactions name generator). The third asked for "five people in your social circle, with whom you spoke about transportation in the past six months" (transportation-discussion name generator).

Once alters were named, respondents were asked about their relationships with each alter, including the length of time that they had known each other and their level of closeness. They were also asked the usual commute mode of transportation for each alter and the location of the alter's residence in relation to the ego's. The egos provided all information about alters and their ego network. Ninety alters participated either in the CTS or in a snowball survey administered as a follow-up to the SNTS and reported their own usual mode of transportation. These reports were compared with the ego-reported usual mode for these alters. Egos correctly identified an alter's mode about 80% of the time. For this reason—as well as for the idea that the ego may be as influenced by what he or she thinks that alters are doing as much as by what the alters are actually doing—ego accounts of alter behaviors are presumed to be correct. Egos also provided information about relationships among their alters. This information was used to calculate ego network density: the number of observed–reported ties divided by the possible number of ties. A network of n individuals has $2(n - 1)$ possible ties. In this study, most ego networks include six individuals and have 10 possible ties.

For each respondent, spatial reference groups were also identified. Respondents gave the cross streets for an intersection near their home address, and these intersections were geocoded. As with the name generator—and in alignment with the overall theme of identifying a suitable means to define reference groups—an exploratory approach was used to determine the appropriate geographic scale for a spatial reference group. Selecting neighbors by using an arbitrary distance may not identify spatial patterns that are scale dependent. If the geographic neighborhoods are too small, they may include too few individuals and poorly represent the spatial context. If the neighborhoods are too large, each individual's neighborhood will be equal to (or quite similar to) that of every other person, and at the extreme, would include the entire sample. To address these issues related to neighborhood definition, 100 distinct neighborhood sizes were considered.

Each neighborhood was generated by using a circle with radius = d with the respondent's residential cross streets at the center. The radii lengths, or distances from the respondent's cross streets, ranged from 250 ft (2 to 3 houses in each direction) to 25,000 ft (about 5 mi). For each neighborhood size, neighborhood networks were exogenously defined by using all CTS participants within the given distance of the respondent as neighborhood–network members. Mode choices for neighbors were identified, and the percentage of neighbors using each mode of transportation was computed. As the distance was increased, the percentage of neighbors using each mode became level and was roughly equivalent to the population share of those using that mode. A clearly best solution to this problem was not found. Models were estimated by using each neighborhood size, though only two are presented here: one small and one medium sized.

ANALYSIS AND OUTCOMES

The "ego network" is defined as the set of alters that the ego names in the survey and the relationships between them. To analyze whether social influence affects mode choice even when one controls for factors typically used in travel behavior research, the behaviors of the alters are used as explanatory variables in model estimation of the mode choice of the ego. Because the name generators could affect characteristics of the ego networks, network properties are first compared in relation to the name generator questions (Table 1).

TABLE 1 Ego Network Characteristics by Name Generator

	Mean of Contacts (%)		
Ego Network Characteristic	Any Five Contacts	Frequent Interactions	Discuss Transportation
Geographic nearness			
Roommates (p = .105)	35	34	30
In same neighborhood (p = .311)	19	16	19
In same town (p = .341)	29	26	26
In nearby town (p = .005)	6	12	10
In same state (p = .129)	6	8	9
In another state (p = .301)	1	2	3
In another country (p = .201)	0	1	0
Closeness in relationship			
Not close (p = .137)	2	4	2
Somewhat close (p = .287)	8	10	11
Moderately close (p = .798)	22	21	21
Considerably close (p = .086)	29	23	28
Very close (p = .252)	37	41	36
Duration of relationship			
Less than 1 month (p = .617)	1	0	1
1 to 6 months (p = .765)	10	10	11
6 months to 1 year (p = .550)	17	16	18
1 to 2 years (p = .682)	22	22	20
2 to 5 years (p = .015)	32	30	24
More than 5 years (p = .040)	16	21	22

NOTE: P-values are shown for ANOVA in comparisons of means and for chi-squared test for categorical variables. Mean of number of contacts named, sample size, mean of ego network density, respectively: any five contacts = 4.73, 231, .440; frequent interactions = 4.87, 245, .427; discuss transportation = 4.45, 222, .432.

The names of one or more contacts were reported by 692 respondents. Roughly equal numbers of respondents saw each of the three name generator questions. All the statistics about the contacts were given as percentages. The alternative was to use counts; however, both methods can distort lower numbers because one of one would yield 100%, just as five of five would yield 100%, but as straight counts, one and five are quite different. As most (613 of 692, or 88%) respondents had five contacts and because percentages reflect the overall makeup of the ego networks and are more directly comparable with the spatial neighborhoods, for which percentages are also used, percentages were selected for the statistics about the contacts.

Few network characteristics differed by name generator. Namely, the transportation-discussion generator yielded lower numbers of contacts than the other two. Those who saw the any-five-contacts generator listed more roommates and fewer contacts in a nearby town than those who saw the other two name generators. Those who saw the frequent-interactions generator had the most considerably close contacts. The transportation-discussion name generator produced the fewest contacts known for 2 to 5 years but the most contacts known for 5 years or more, while the any-five-contacts name generator had the most contacts known for 2 to 5 years.

Other characteristics of the ego networks were examined, but no other properties exhibited significant differences with respect to the name generator. The only exception was the frequency of interactions with alters. Those who saw the frequent-interactions generator had the most contacts with whom they interacted every day (about 50%, on average) and the fewest contacts with whom they interacted less than once a month (about 0.2% on average). This result is not surprising, as the formulation of the question addressed frequency of interactions. While some variation existed in ego network properties in relation to name generator, it was not considered sufficiently comprehensive to require or to warrant separate analysis for each group. Future work on this project will explore existing differences in ego network properties and the ways in which these properties relate to mode use of the ego network.

Both the CTS and the SNTS surveys presented mode choice with nine alternative modes of transportation. Because extremely few students commuted by modes other than bike, bus, or driving alone, the analysis presented here focused on the respondents who used these three modes. Those modes accounted for 633, or 91%, of the respondents who named at least one contact in the SNTS. The data set was also reduced to include only those respondents who lived in Davis because information was limited about neighbors for those respondents who lived outside Davis. Table 2 presents the mode use of the remaining 576 respondents and summarizes the mean percentage of ego network and neighborhood use for each mode.

Respondents tended to use the mode that was used by the highest percentage of their reference group, whether the reference group was the ego network or the neighborhood (highlighted cells, on the diagonals, in Table 2). Mode use within ego networks was somewhat more diverse among the three modes than it was in neighborhoods, but overall percentages of the ego network and the neighborhoods were fairly similar, with a few exceptions. Notably, the percentage of neighborhoods that drove was less than 10% for those who chose either bike or bus as their mode of transportation, but the ego network percentage of drivers was roughly 20%. These figures indicate slightly less correlation in behavior within ego networks than within neighborhoods. Bikers had fewer bikers in their ego networks relative to their neighborhoods, but for both driving and bus, the ego network proportions of bikes were higher than the proportions in the neighborhood. Two potential explanations for this finding are that the neighborhood values reflected the behaviors for individuals in the city of Davis, and although spatial variation occurred, more variation occurred between Davis and other locations than between neighborhoods within Davis.

The remainder of this paper investigates the ways that these two reference groups relate to mode choice when it is considered beside other factors typically important in travel behavior, such as trip and individual characteristics. Table 3 shows a selection of variables considered or included in model estimations. Respondent age differed with mode choice, as did the mean distance traveled to campus. Both males and females tended to choose bike as their usual mode more than bus or drive; however, more males biked than females, and almost 30% of females chose to ride the bus. Extremely few of those who drove alone reported that the "cost of owning a car or other vehicle" was more than moderately important in their decision to drive alone. This factor was more important for those who biked or rode the bus.

In the next section, models for mode choice are presented. Reference group variables are incorporated into models while the model controls for variables typically considered in mode choice analysis. Analysis such as that presented here is faced with the challenge of multiple explanations for correlations in behavior within neighborhoods and within ego networks. Social influence is likely within ego networks, within neighborhoods, or both. At the same time, individuals within the same neighborhood face a similar choice context, for example, similar commute distance. This factor is also true for some individuals within the same ego network, though to a lesser extent, because those networks consist of individuals from varying neighborhoods, different towns, and the like. The possibility also exists that neighbors or members of the same ego network share characteristics that drew them toward their neighborhood or their

TABLE 2 Mean Percentage of Reference Group Mode Use and Respondent Mode Choice

	Mean Percentage of Ego Network Alters Using Each Mode			Mean Percentage of Neighbors Using Each Mode, $d = 1,250$ ft			Mean Percentage of Neighbors Using Each Mode, $d = 2,250$ ft		
Ego Mode	Bike ($p < .001$)	Drive ($p = .699$)	Bus ($p < .001$)	Bike ($p < .001$)	Drive ($p = .122$)	Bus ($p < .001$)	Bike ($p < .001$)	Drive ($p = .003$)	Bus ($p < .001$)
Bike ($N = 390$) 52.2%	47	21	16	63	7	22	63	7	23
Drive ($N = 37$) 13.7%	23	40	16	44	14	32	50	13	31
Bus ($N = 149$) 25.8%	24	20	45	46	9	36	52	8	32

NOTE: Each column represents the comparison between average mode use for each mode, according to the ego's mode. P-values are shown for ANOVA in comparisons of means. Mode use by ego network–neighbors does not add up to 100% across rows because only relevant modes are shown.

TABLE 3 Respondent Characteristics with Respect to Mode Choice

	Bike		Drive Alone		Bus	
Characteristic	Count	Percentage	Count	Percentage	Count	Percentage
Gender (p = .001)						
Females N = 398	248	63	31	8	117	30
Males N = 169	126	79	6	4	28	18
Importance of "the cost of owning a car or other vehicle" in mode choice (p < .001)						
Not important	66	17	11	31	20	14
Slightly important	37	10	9	25	17	11
Moderately important	76	20	9	25	25	17
Considerably important	83	22	6	17	48	32
Extremely important	120	31	1	3	38	26
Importance of "commuting at the times I prefer" in mode choice (p = .521)						
Not important	12	3	0	0	1	1
Slightly important	10	3	1	3	8	5
Moderately important	39	10	3	8	16	11
Considerably important	107	28	9	24	39	26
Extremely important	215	56	24	65	85	57
Familiarity with UC-Davis Transportation and Parking Services GoClub Program (p = .196)						
It's new to me	177	46	16	43	60	42
I've heard of it, but never used it	138	36	15	41	66	46
I've used it	68	18	6	16	16	11

NOTE: UC = University of California. P-values are shown for ANOVA in comparisons of means and for chi-squared tests for categorical variables. Mean age (sample size) and mean distance to campus (sample size): bike = 22.11 (390) and 1.72 (379); drive alone = 24.27 (37) and 2.43 (28); bus = 20.92 (148) and 2.11 (142).

social circle. These same characteristics may also predispose them to make similar transportation choices.

This paper focuses on methods for defining reference groups, either by ego network or by neighborhood. Related work that aims to address the challenges outlined above includes discrete choice models (*26*), the linear-in-means model (*27*), and the spatial autoregressive model (*28*). Lee (*29*) and Bramoullé et al. (*30*) provide some discussion of how the last two of these models are used in social contexts as well as how they are functionally related. The linear-in-means model has been used in linear (*30, 31*) and discrete applications (*26*). Lee provides a detailed example of the estimation of peer effects, addressing endogeneity, by using the spatial autoregressive model (*29*).

Model 1 employs the use of the ego network mode, among other factors, to predict mode choice. Model 2 employs mode use in a small (1,250-ft radius) neighborhood and Model 3 in a medium-sized (2,250-ft radius) neighborhood. The base alternative in each model is bike, with coefficients estimated for the alternatives bus and drive. All three models perform fairly well, when adjusted ρ^2 is considered; however, the Akaike information criterion for Model 1, which employs the ego network, is somewhat better than for either model that uses neighborhoods (Table 4).

Sociodemographic and trip characteristics generally exhibit expected effects: gender and distance to campus are both important factors, with males more likely to bike than to use either of the other modes and individuals living farther from campus more likely to drive or take the bus than to bike. The less important the cost of owning a car or other vehicle is, the more likely individuals are to drive to campus; because the cost is less relevant to these individuals, they are more willing to pay to drive. Further, the importance of going to other places before, during, or after work–school increases the likelihood of driving, and the importance of using the same means of transportation every day increases the likelihood of taking the bus. Other variables in model estimations include the familiarity with transportation resources on campus, level of information about parking, and feeling of safety with respect to biking, and these have expected effects on mode choice.

For the variables related to the reference groups, both formulations—ego network and neighborhood—are relevant in mode choice; however, as noted earlier, choices within neighborhoods and within ego networks may be similar because of mechanisms other than strict social influence. Neither the percentage of the ego network nor that of neighbors who drive has a significant effect on the likelihood that the ego chooses to drive. Those with higher percentages of their ego network biking are more likely to bike than to drive but not necessarily more likely to bike than to take the bus. In contrast, a higher percentage of an ego network taking the bus increases the likelihood that the ego takes the bus.

In the neighborhood models, the results are somewhat different. Higher percentages of bikers in both sizes of neighborhood increase the likelihood of biking compared with both driving and taking the bus. In the small neighborhood, higher percentages of neighbors taking the bus increase the likelihood of taking the bus, but this likelihood is not a significant effect in the medium-sized neighborhood. The coefficient values are larger for the percentage of neighbors biking in the medium neighborhood, likely because the medium-sized neighborhood has some feature (such as more people living farther from bus lines or more people living closer to bike paths) that improves biking as an option relative to taking the bus and driving. Such a feature would increase the neighborhood percentage of bikers and increase the likelihood that any single neighborhood resident (i.e., the respondent) bikes.

TABLE 4 Multinomial Logit Models of Mode Choice with Reference Group Variables

	Model 1		Model 2 d = 1,250 ft		Model 3 d = 2,250 ft	
Variable in Model Estimation	Drive	Bus	Drive	Bus	Drive	Bus
Constant	–5.66**	–2.89**	–5.94***	–1.86*	–3.71	–0.16
Male	–1.28*	–0.78**	–1.19*	–0.94***	–1.15*	–0.94***
Distance to campus	0.67**	0.29*	0.72**	0.36**	0.70**	0.38**
Importance of "Cost of owning a car or other vehicle"	–0.52***	0.01	–0.58***	0.02	–0.56***	0.07
Importance of "Going other places before, during, or after work"	0.85***	–0.10	0.86***	–0.22**	0.80***	–0.23**
Importance of "Using the same means of transportation every day"	0.13	0.30***	0.24	0.40***	0.22	0.43***
Agreement with "Feel safe biking" (reverse scale)	0.47**	0.53***	0.61***	0.54***	0.63***	0.54***
Number of sources of information about parking	–0.02	0.24**	–0.01	0.21**	0.00	0.23**
Familiarity with campus tire air repair stations (reverse scale)	–0.78*	–0.75***	–0.49	–0.48**	–0.45	–0.51**
Familiarity with in-vehicle parking meter (reverse scale)	0.46	0.79***	0.42	0.73***	0.40	0.69***
Familiarity with UC-Davis GoClub (reverse scale)	–0.20	–0.39*	0.17	–0.42**	0.21	–0.41**
Percent alters biking	–2.40**	–0.94	NA	NA	NA	NA
Percent alters taking the bus	0.38	3.66***	NA	NA	NA	NA
Percent alters driving	1.70	1.12	NA	NA	NA	NA
Percent neighborhood biking	NA	NA	–2.14**	–1.99***	–4.80*	–4.29***
Percent neighborhood taking the bus	NA	NA	–0.79	2.08***	–2.31	0.65
Percent neighborhood driving	NA	NA	–0.56	–0.55	–2.25	–2.03

NOTE: $*p < .1$; $**p < .05$; $***\ p < .01$. Adjusted rho-squared indicates the proportion of variance explained by the model. In final model estimations total sample is 483; 340 bike, 25 drive, and 118 bus as usual mode of transportation. NA = not available. Log likelihood of full model estimation, adjusted rho-squared (pseudo), Akaike information criterion, respectively: Model 1 = –237.98, .499, 531.96; Model 2 = –266.12, .446, 588.23; Model 3 = –268.12, .442, 592.24.

Although results are similar across all three models, these similarities are not considered to be attributable to the same processes. In the neighborhood models, shared environment (spatial, geographic, or neighborhood factors) conceivably accounts for the greatest portion of the correlation in mode choice between the respondent and neighbors. In the ego network model, shared environment certainly accounts for some portion of the correlation in behaviors but not as completely as in the neighborhood models. Social processes, including social influence, or even endogenous processes, such as homophily and self-selection, are surely reflected in these results as well. If spatial autocorrelation were driving the results in the ego network model, the coefficients would be more similar to those in the spatial models, and the same effects on likelihood would be significant. They are not; the coefficient for the percentage of the ego network that takes the bus is not significant in the ego network model (though it is in both neighborhood models), suggesting that some processes occur in ego networks that do not occur in neighborhoods.

DISCUSSION AND CONCLUSIONS

The research presented here investigated relationships within social influence and travel behavior by considering the importance of ego networks and neighborhoods. Social influence in transportation is becoming a topic of increasing coverage, and exploring various means of defining reference groups grows in importance as techniques and methods are refined. The focus of this analysis was how socially defined reference groups (ego networks) and spatially defined reference groups (neighborhoods) differ both conceptually and in measured effects. Each of these definitions possesses certain subtleties; in this case, to identify ego networks, three versions of a name generator were used, though few significant differences were found between them. Alternative means of defining ego networks, however, may result in finding additional differences.

Further, spatial reference groups may be defined in many ways. Here, neighbors within a given distance of the respondent were counted for 100 distances ranging from 250 ft to about 5 mi. Although models were estimated for every distance, two were selected for presentation here: neighborhoods with a radius of 1,250 ft and of 2,250 ft. Another approach to defining neighborhoods in which social influence may be relevant is with t-communities (tertiary-street communities) (*32*). Though potential ways to define both social and spatial reference groups are many, the primary interest here was to compare social reference group with spatial reference group.

Much work remains to identify the most satisfactory means for defining reference groups (and the best means surely differs between analytic contexts); however, conclusions of interest are drawn from the analysis presented here. First, whether defined socially or spatially, reference groups have relevance in transportation mode choice. Although both types of reference group are relevant, and although within-group behaviors tend to be correlated in both cases, the mechanisms operating in neighborhoods are not the same as those operating within ego networks. For example, the percentage of ego network biking is important for the choice between biking and driving, whereas the percentage of spatial neighbors biking is important for both the choice between biking and taking the bus and the choice between biking and driving.

The results presented here are part of ongoing research exploring social influence in travel behavior. Future steps in this project include taking into account sources of endogeneity in the relationship between reference group and mode use. Future work will also identify how properties of ego networks relate to ego and alter mode choices, as well as whether certain types of relationships are more influential than others. The way in which "reference group" is defined is a key question for research aiming to understand social and spatial influences on travel behavior. As work in this area advances, policies seeking to improve the use of alternative modes can capitalize on this type of knowledge to implement socially relevant programs.

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