**Social Networks and Transportation Mode Choice**

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**Abstract**

This paper investigates the influence of social networks on the transportation mode choice of students and proposes potential avenues for utilizing social networks as a means for addressing traffic and related problems. Construction of new roadways or widening of existing roadways as a means to reduce congestion is increasingly replaced with Transportation Demand Management (TDM). TDM emphasizes the promotion of alternative modes of transportation through the use of incentives and other programs such as carpool lanes or increased parking costs, in order to reduce congestion and related emissions. One means of promoting alternative modes which has the potential to affect transportation outcomes is the use of social incentives, or social influence. The research findings discussed here indicate a positive relationship between the transportation mode decisions made by an individual’s close social contacts and the individual’s own such decisions and may provide an opportunity to further transportation demand management.

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. Transportation mode choice is explored using traditional socio-economic, attitudinal and trip characteristic variables. Ego-centric social network factors including behaviors of close contacts are incorporated into these models to investigate whether alter behaviors influence ego transportation mode choice. This relationship holds, even when other factors known to be important in mode choice are considered, such as socio-demographics and neighborhood mode use. These findings indicate that social network strategies may be useful tools to motivate the use of alternative means of transportation.

Through analysis of changes in transportation, and actions taken in response to new information about transportation infrastructure or programs, support for potential policy strategies is examined. Potential strategies include social reporting where individuals learn what others around them doing thereby providing a social norm which may influence behavior. Another potential use includes referrals where incentives are provided to those who share information or enlist participation in transportation programs within their social networks. A third strategy may be to introduce buddy programs; providing reduced fares for individuals travelling together. These and other programs may capitalize on social networks as an inexpensive and flexible means for the promotion of alternative modes. This research finds social influence is a relevant factor in transportation decision making, and explores how to use this relationship in transportation policies.

**Introduction**

This paper investigates how social influence plays a role in student mode choice. Recent research in the field of network science has demonstrated that social networks profoundly influence individual behavior ranging from political decisions (Klofstad, McClurg, and Rolfe 2009) to diet and exercise (Fowler and Christakis 2008). Social networks also provide pathways for social influence, where the travel choices of friends and colleagues affect the choices of individuals to whom they are socially connected. As in other behavioral research, how social network processes affect transportation behavior is becoming a central topic in transportation research, and has important implications for the overall design of sustainable transportation policies. Understanding social influences in travel behavior informs broader questions related to how social network-based policies and programs may be utilized 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 their use of alternative modes, changes or improvements to transit routes or schedules, or new bicycle infrastructure. Social influence may also occur through normalization of behaviors, such as the use of a particular mode of transportation. Network influences may also act to reinforce and reaffirm behaviors. In order to find new and innovative solutions to further reduce transportation emissions and support the use of alternative modes it is essential to better understand the mechanisms that influence individual travel behavior. The influence of social networks may be a powerful tool which could be incorporated into campus-wide, local or regional policies in order to reduce the use of single occupancy vehicles and to promote the use of sustainable means of transportation. By exploring the means by which social influence may best be identified, and how social influence may best be defined, this paper contributes to our understanding of how these mechanisms should be studied, as well as potentially how they may be incorporated into policy.

**Background**

Travel behavior research has developed a strong understanding of factors which contribute to individual transportation choices, however, these models have left a portion of the influences unexplained and have generally looked at individual travel behavior as an atomized choice made without respect to the influences of social relationships. 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 it easier to find information, or through the 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 impact transportation behavior is a matter for empirical research like that presented here.

Research in network analysis aims to define the structure of networks, identify relationships among members and to determine the effects of networks on behavior and other outcomes (Wasserman and Faust 1994). While there are numerous ways to study social networks, 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*. Information is gathered about both the ego, and the alters. Ego-networks are constructed, and various network properties are measured at the individual and ego-network level. Behavior and other outcomes are explored with respect to relationships among network members and properties of the network, as well as characteristics of the individuals.

Social networks are involved in many aspects of transportation decision making. Considering information and communication technologies, increased mobility influences social travel through the continual coordination of and last-minute changes to plans (Larsen, Urry and Axhausen 2008). Social networks also act as travel generators with the types of social ties affecting travel behavior when social interactions are sometimes replaced by communication over the internet (Mok, Wellman, and Carrasco 2010). The influence of social networks on daily activity patterns, may also be used to predict travel behavior and trip generation (Han et al. 2011) while the frequency of social interactions may be dependent on network structure and composition as well as with whom activities take place (Carrasco et al. 2008). Further, participation in social activities, may be moderated by automobile use such that high levels of automobile use limit social interactions (Farber and Páez 2009).

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 ride-sharing (Silvis and Niemeier 2009). Other populations, such as immigrants depend on each other for transportation resources although the type of social ties mattered, geographical and temporal factors are also relevant, as well as having either a car or ability to drive (Lovejoy and Handy 2011). Expanded networks (beyond close personal networks) may provide more resources (Lovejoy and Handy 2011).

Of interest to the research presented here, is social influence on mode choice. Wilton, Páez, and Scott (2011) find factors such as learning and *validation* from peers and co-workers about the experience of telecommuting have an effect on the choice to telecommute. Social factors also included interactions with co-workers at work (which could be beneficial *or* annoying/distracting) and a culture around telecommuting which existed in some instances (Wilton, Páez, and Scott 2011). To further study peer effects, Páez and Scott (2007) simulate a panel study and show the first-wave behaviors of contacts affects the behaviors of individuals in the second wave.

Spatial reference groups are also likely to have an influence, shown in a spatially autoregressive (uses 40 nearest neighbors) logit mode choice model in New York City, Goetzke (2008) finds neighborhood network effects influence the use of transit (Goetzke 2008). Dugundji and Walker (2005) consider residential district, socioeconomic group and postal code, in discrete choice models with social interdependence of decision making and find some social influence occurs (Dugundji and Walker 2005). Further, differences in the mode share of bicycling among German cities can be attributed to a city-level cultural component which is characterized as a social network affect, though it is broadly defined (Goetzke and Rave 2010). There is also evidence that attitudes are spatially distributed with non-random patterns, though it is not clear if this is a result of self-selection, or localized changes in attitude based on physical attributes of neighborhoods (Páez 2013). Scott et al. (2012) 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.

In most work related to transportation and social network influence, neighborhoods and other reference groups are utilized in the mode choice models, while those projects which include explicit social networks explore different questions, such as trip generation and transportation resource acquisition. Projects like that of Wilton, Páez, and Scott (2011) and Páez and Scott (2005) use social networks to identify peer effects in telecommuting, but neither utilize explicit social networks in a data driven analysis. This paper builds on work combining network analysis and discrete choice models (Walker et al. 2011, Páez and Scott 2005) by estimating *ego-network effects* on travel behaviors, and comparing results between analytic methods.

**Data Collection and Methods**

For two consecutive years, in coordination with an annual Campus Travel Survey (CTS) at the University of California, Davis, a Social Networks and Travel Survey (SNTS) was administered to a sample of undergraduate and graduate students. Each year in the fall, the CTS is sent out to a random sample of each portion of the campus community (undergraduate and graduate students, faculty and staff). A selection of questions from the CTS are of interest in the present study; these include the usual mode of transportation and the residential location of respondents.

In the fall of 2011, in addition to the questions of the CTS a short section of questions related to social networks and travel was incorporated into the end of the survey. In the fall of 2012, students were presented with an option to participate in the SNTS at a later point in time, and were asked to provide an email address to which the survey invitation could be sent. If students answered “Yes, I would like to receive more information about the Social Network Survey”, in March 2013, they were invited to participate in the SNTS. A total of 1,789 individuals indicated an interest in the SNTS. Due to a conflict with another campus survey, a subset consisting of 1,642 of these students were sent invitations to participate, with 962 respondents ultimately participating in the survey (an initial response rate of 59%). Only 692 named at least one alter and the analysis presented here is for these egos who named at least one alter. Although data was collected for two consecutive years, it was not collected as a panel study, and analysis presented here covers only the second year.

The survey aimed to capture both the variables of interest to this research, as well as variables known to be important factors in travel behavior such as socio-demographics, trip and mode characteristics, the built environment (Ewing and Cervero 2010, Mokhtarian and Cao 2008) and attitudes (Mokhtarian and Salomon 1997). Some of this information was collected in the CTS, and linked to respondents in the SNTS.

In the Social Networks and Transportation Survey, respondents were first asked which modes are available to them, what mode of transportation they usually use for travel to campus, and why they consider some modes unavailable. When asked about modes that are not available, respondents were given options related to physical restrictions on the modes such as bus stop and train station locations, trip distance, physical ability, vehicle ownership and schedule constraints (both for public transpiration modes and carpooling). Next, the survey asked about the usual mode of transportation and the importance (on a 5 point scale) of 18 factors in the choice of their usual mode. Questions related to different types of factors were mixed, in no particular order, to draw attention away from the social factors. In addition to 12 other factors related to costs, environmental impacts, safety and schedule/convenience, six social factors were mixed in:

* The opinions of people I know.
* Things I learn from the news or other sources.
* Using the same means of transportation as other people I know.
* Information about transportation I learn from people I know.
* Getting to school or work with others (by any means of transportation).
* Using a means of transportation that is socially acceptable.

Another section asked respondents about whether they had learned about various transportation programs and resources from a set of possible sources. These questions were followed-up with a set of questions asking about whether they had taken particular actions as a result of receiving that information. The social networks portion of the survey included a “name generator” that asked to identify contacts within their social network. 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 six months. Three versions of the name generator were included in the survey with one version randomly assigned to each respondent in order to investigate the effects of name-generator wording on the characteristics and the structure of the ego-networks. (For a discussion of possible effects see Campbell and Lee 1991, Bernard et al. 1990, and Klofstad, McClurg, and Rolfe 2009.) In its most general form, the name generator requested the names of “any five people who have been in your social circle over the past six months.” The second version requested the names of “the five contacts you have had the most frequent regular interaction with over the past six months.” The third asked for “five people in your social circle, with whom you spoke about transportation in the past six months.”

In all three versions, the social circle is defined in the same way, and over the same time frame, but respondents were asked to list the names of different members of their social network. Once these alters were named, respondents were asked about their relationships with each alter; how long they have known each other, the closeness of their relationship and how close the alters are with each other (if at all). They were also asked to report the usual commute mode of transportation for each of the alters and where each alter lives, in relation to the respondent.

**Analysis and Outcomes**

The ego-network is defined as the set of alters the ego names in the survey and the relationships identified between alters. To analyze whether social influence affects mode choice even when controlling 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. Others have used a neighborhood, or social class as the social reference group (see Goetzke 2008, Dugundji and Walker 2005, and Walker et al. 2011). Since the name generators could affect network properties, I first examine the properties of the networks, with respect to the name generator questions (Table 1).

In the current year, there are 692 respondents who reported the name(s) of at least one contact. Roughly equal numbers of respondents saw each of the three questions. All of the statistics about the contacts are given as percentages, since most (613 out of 692, or 88%) respondents have five contacts. The alternative is to use counts, however both methods can distort lower numbers since 1 out of 1 would yield 100%, just as 5 out of 5 would yield 100%. Similarly, a straight count of 1 is quite different than a count of 5. Here percentages of alters using each mode are used since percentage reflects the overall make-up of the ego networks.

Few characteristics are significantly different between the name generators. Namely, the transportation discussion name generator yielded lower numbers of contacts than either of the other two name generators. Those who were asked to list “any five contacts” had higher percentages of roommates and lower percentages of contacts in a nearby town than either of the other name generators. The only difference in the closeness of relationships was for “considerably close relationships.” Those who were asked to name the contacts with whom they interact most frequently had higher percentages of contacts with this degree of closeness than either of the other two name generator groups.

**Table 1: Ego-network Characteristics by Name Generator1**

|  |  |  |  |
| --- | --- | --- | --- |
| **Ego Network Characteristic** | **Any Five Contacts** | **Frequent Interactions** | **Discuss Transportation** |
| **Number of contacts named** (p < 0.000) | 4.73 (N = 231) | 4.87 (N = 245) | 4.45 (N = 222) |
| **Ego-network Density** (p = 0.306) | 0.440 (N = 231) | 0.427 (N = 245) | 0.432 (N = 222) |
| **Geographic Nearness**  Roommates (p = 0.105)  In Same Neighborhood (p = 0.311)  In Same Town (p = 0.341)  In Nearby Town (p = 0.005  In Same State (p = 0.129)  In Another State (p = 0.301)  In Another Country (p = 0.201) | (N = 231)  35%  19%  29%  6%  6% 1% 0% | (N = 245)  34%  16% 26%  12%  8%  2% 1% | (N =222)  30%  19% 26% 10%  9%  3% 0% |
| **Closeness in Relationship** (as percentage)  Not Close (p = 0.137)  Somewhat Close (p = 0.287)  Moderately Close (p = 0.798)  Considerably Close (p = 0.086)  Very Close (p = 0.252) | (N = 231)  2%  8%  22%  29%  37% | (N= 245)  4%  10%  21% 23% 41% | (N = 222)  2%  11% 21% 28% 36% |
| **Duration of Relationship** (as percentage)  Less than one Month (p = 0.617)  One to Six Months (p = 0.765)  Six Months to One Year (p = 0.550)  One to Two Years (p = 0.682)  Two to Five Years (p = 0.015)  More than Five Years (p = 0.040) | (N = 231)  1%  10% 17% 22% 32% 16% | (N = 245)  0%  10% 16% 22% 30% 21% | (N = 222)  1%  11% 18% 20% 24% 22% |

1p-values are shown for ANOVA in comparisons of means and for chi-squared tests for categorical variables

Lastly, the length of relationships were significantly different for the longest two lengths of relationship; those with the transportation based name generator had the lowest percentage of contacts they had known for two to five years but the highest number of contacts they had known for five years or more. On the other hand, those who were asked to name any five contacts had higher percentages of contacts they had known for two to five years, but lower percentages of contacts they had known for five or more years than either of the other two name generator groups.

Other characteristics of the ego-networks were explored, but no additional ego-network properties exhibited significant differences with respect to the name generator question. The only exception is the frequency of interactions with alters. Those asked the frequent interactions name generator have highest percentages of contacts they interact with every day (about 50%, on average), and lowest percentages contacts they interact with less than once a month (about 0.2% on average). This result is not surprising, as the formulation of the question asked about the frequency of interactions. While there is some variation in the properties of the ego-networks based on which name generator was presented, it is not considered comprehensive enough to require nor even to warrant separate analysis for each group. In the analysis presented here, the mode choice of the ego is considered with respect to ego-network mode use. Table 2 shows the mean percentage of ego-networks using each mode of transportation according to the mode used by the alter. Each column shows the percentage of alters using a particular mode; thus columns do not add up to 100%, since they are mean percentages, according to mode choice of ego. Likewise, the row percentages do not add to 100 since there are small levels of alters using modes not shown (walking, carpooling etc.).

**Table 2: Mean percentage of ego-network mode use with respect to mode choice1, 2, 3**

|  | **Mean percentage of ego-network alters using each mode** | | |
| --- | --- | --- | --- |
| **Ego Mode** | Bike (p < .001) | Drive (p = .699) | Bus (p < .001) |
| **Bike (N = 390) 52.2%** | 47% | 21% | 16% |
| **Drive (N = 37) 13.7%** | 23% | 40% | 16% |
| **Bus (N = 149) 25.8%** | 24% | 20% | 45% |

1 Each column represents the comparison between average mode use for each mode, according to the ego’s mode

2 p-values are shown for ANOVA in comparisons of means

3 Mode use by alters/spatial reference group does not add up to 100% across rows because not all modes are shown

The results in Table 2 are expected; respondents tend to use the mode of transportation used by the highest percentage of their ego-network. It is also possible that information-sharing among social contacts may influence behavior. The next set of figures present information about respondents who made changes to their transportation patterns, or their participation in transportation programs. Respondents were asked whether they had received or obtained information related to various transportation programs and resources. Those who had were then asked if that information had resulted in any related actions. Although respondents could check multiple information sources (and therefore could be double-counted) related to a given program or action, figures 1-5 highlight which information sources are more relevant for which actions and provide insight into when information sharing may be relevant.

**Figure 1: Started Riding Bike after Learning about BEEP**

Figure 1 shows that information about the Bicycle Education and Enforcement Program (BEEP) obtained from talking to people and from the TAPS website were more linked to respondents starting to ride a bike than information from other sources. Overall, 31 respondents reported they started riding a bike, or 11% of the 289 who heard about BEEP from any source. In Figure 2, these same sources of information, but now related to the UC Davis goClub - a commuter club that provides benefits to campus community members who commit to using alternative modes of transportation - are likely most influential in respondents joining the goClub. After hearing about goClub from any source, 89 people joined, or 17% of the 538 that heard about goClub from any source.

**Figure 2: Joined goClub after Learning about goClub**

Figure 3 is also related to the goClub, however in this case, the action is whether resondents reduced the number of days they drive to campus. Though low numbers of respondents took this action overall, most who had heard about the goClub, again from TAPS’ website, or from campus events. In this case, the 12 respondents who reduced driving is only 2% of those who heard about it from any source.

**Figure 3: Reduced Days Driving to Campus after Learning About goClub**

Figure 4 presents those respondents who reported they started taking the bus, with somewhat different sources of information more likely to lead to someone taking the bus; namely pamphlets and welcome materials. This suggests that the UC Davis bus system is doing a good job of outreach to new students; with nearly 20% of the 520 respondents who heard about bus routes starting to take the bus.

**Figure 4: Started Taking the Bus after Learning about Bus Routes and Schedules**

Figure 5 looks again at whether respondents reported decreasing the number of days they drive to campus, however here, with respect to hearing information about parking lot rates. Here, 17% of the 351 who heard about parking lot rates decreased the number of days they drive to campus. The TAPS website and talking to people are again the main information sources for this action, and more individuals took this action overall than individuals who heard about the goClub.

**Figure 5: Decreased Days Driving to Campus after Learning about Parking Lot Rates**

The remainder of this paper investigates this relationship when considered alongside other factors which are typically important in travel behavior, such as trip and individual characteristics. Table 3 shows some of the other variables considered and/or included in model estimations with respect to respondent mode choice. Respondent age appears to be quite different across categories, but is not found to be significantly different, however, the mean distance travelled to campus is very different with respect to mode choice. Both males and females tend to choose bike as their usual mode more than either of the other modes, however, more males than females bike, and 30% of females choose to ride the bus. Those who drive alone have the lowest percentage of respondents who feel that “The cost of owning a car or other vehicle” is more than moderately important in their decision to drive alone, while lower numbers of those using the other two modes report lower levels of importance of this factor.

The descriptive statistics shown here present a small portion of the variables collected in project surveys, and demonstrate the potential relationships different factors have with mode choice. Taking many variables into account while exploring the primary questions of interest here, related to social influence and mode choice, will improve analysis and control for many factors that affect mode choice outside of social or spatial influences.

**Table 3: Respondent Characteristics with respect to Mode Choice1**

| **Characteristic** | **Bike** | | **Drive Alone** | | **Bus** | |
| --- | --- | --- | --- | --- | --- | --- |
| **Mean age** (p = 0.011) N = 575 | 22.11 | N = 390 | 24.27 | N = 37 | 20.92 | N = 148 |
| **Mean Distance to Campus (miles)** (p < .001) N = 549 | 1.72 | N = 359 | 2.43 | N = 28 | 2.11 | N = 142 |
| **Gender** (p = 0.001) |  |  |  |  |  |  |
| 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 “Going other places before, during or after school/work” in mode choice** (p = .051) | | | | | | |
| Not Important | 34 | 9% | 0 | 0% | 11 | 7% |
| Slightly Important | 40 | 10% | 3 | 7% | 23 | 15% |
| Moderately Important | 81 | 21% | 4 | 10% | 38 | 25% |
| Considerably Important | 125 | 33% | 15 | 36% | 44 | 29% |
| Extremely Important | 103 | 27% | 15 | 36% | 30 | 19% |
| **Importance of “Commuting at the times I prefer” in mode choice** (p = 0.521) | | | | | | |
| 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 = 0.196) | | | | | | |
| 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% |

1p-values are shown for ANOVA in comparisons of means and for chi-squared tests for categorical variables

In the next section models for mode choice are presented and social reference group variables are incorporated. Analyses such as that presented here are faced with the challenge that there are multiple explanations for why the ego makes the same mode choice as alters in their ego-network. The ego could be influenced by others in the network. Alternatively, it could be that the ego and alters have a similar choice context, for example, similar commute distance or similar costs associated with each mode could result in the same mode choice among ego-network members. It is also possible that ego and alters are all predisposed to make the same choice because of shared attitudes about transportation or related factors. The present paper is focused on the methods for defining the social reference group; either by the ego-network or a spatial reference group. Future work in this and related areas should aim to address the endogeneity issues outlined here through the use of additional statistical controls, (quasi-)experimental design and other approaches.

Model estimations do not provide an exhaustive look into factors which might affect travel behavior, instead, factors thought to be relevant such as socio-demographic variables, trip characteristics and attitudes are included as control variables, and social network and spatial variables are evaluated for their relevance. The base alternative for each model is Bike, with coefficients estimated for the alternatives Bus and Drive Alone. Variables which have been found to be significant factors for one or more alternatives are retained in model estimations. All variables representing mode use in both types of social reference group are retained regardless of significance, in order to compare effects across model estimations.

**Table 4: Multinomial Logit Model Estimations of Mode Choice (N = 483)1, 2, 3**

| **Variables in Model Estimation** | **Model 1** | | **Model 2** | |
| --- | --- | --- | --- | --- |
| Drive | Bus | Drive | Bus |
| Constant | -5.00\*\*\* | -3.35\*\*\* | -4.40\*\* | -3.38\*\*\* |
| Distance to Campus | 0.83\*\*\* | 0.53\*\*\* | 0.63\*\* | 0.27 |
| Importance of “Going other places before, during or after work” | 0.69\*\* | -0.08 | 0.71\*\* | -0.07 |
| Importance of “Using the same means of transportation every day” | 0.31 | 0.34\*\*\* | 0.21 | 0.25\*\* |
| Importance of “Cost to take bus, train or light rail” | -0.51\*\*\* | 0.40\*\*\* | -0.40\*\* | 0.33\*\*\* |
| Importance of “Getting physical exercise during my commute | -0.88\*\*\* | -0.74\*\*\* | -0.74\*\*\* | -0.62\*\*\* |
| Agreement with “Feel safe biking” (reverse scale) | 0.46\*\* | 0.52\*\*\* | 0.42\* | 0.55\*\*\* |
| Agreement with “Travel Time is Wasted Time” (reverse scale) | -0.65\*\*\* | -0.33\*\* | -0.56\*\* | -0.28\*\* |
| Received information about parking from any source | 1.26\* | 0.35 | 1.22\* | 0.33 |
| Familiarity with in vehicle parking meter (reverse scale) | 0.28 | 0.58\*\* | 0.29 | 0.55\*\* |
| **Percent alters biking** | **---** | **---** | **-2.23\*** | **-1.08** |
| **Percent alters taking the bus** | **---** | **---** | **0.78** | **0.68** |
| **Percent alters driving** | **---** | **---** | **-1.35** | **2.22\*\*\*** |
| **Model Diagnostics** | | | | |
|  | **Model 1** | | **Model 2** | |
| Log-likelihood of full model estimation | -239.55 | | -218.49 | |
| Adjusted rho-squared (pseudo r-squared) | 0.52 | | 0.55 | |
| Akaike Information Criterion | 519.11 | | 488.98 | |

1 \*, \*\* and \*\*\* indicate significance of parameter estimates to the .1, .05 and .01 levels

2Adjusted rho-squared (*adj-ρ2*) indicates the proportion of variance explained by the model

3 In final model estimations 354 bike, 27 drive and 117 take the bus as usual mode of transportation

Model 1 shows the best model for mode choice, using the available variables. Primarily, attitudes were found to be relevant in mode choice in this population, with distance to campus also playing a role in mode choice. Those for who it is important to be able to go other places before or after work are more likely to drive, while those who like to get physical exercise in their commute are more likely to bike than either of the other modes. Feeling safe biking also contributes to the likelihood of biking. In Model 2, the ego-network variables are also included in the model, without having much effect on the other variables in the estimation, these variables improve the overall model fit. Though they are not important for all choices, the percentage of contacts who bike does increase the likelihood that the ego bikes, and those egos with higher percentages of their ego-network that take the bus are more likely to take the bus.

**Discussion and Conclusions**

The research presented here explores the role of social networks in transportation decision making. Two inter-related avenues of social influence are explored; information-sharing and social norms. In some cases talking to people about a program or resource led to action more than other sources of information; namely with respect to the BEEP program and participation in the goClub. For other programs, talking to people did not lead to action as much as other sources of information, however social information sharing is still likely a good means to distribute information with the potential to lead to increases in the use of alternative modes of transportation.

Multinomial logit models were used to estimate the effect of ego-network mode use on respondent mode choice, and show that when more members of a respondent’s ego-network use a particular mode of transportation, I tis more likely that the respondent uses that mode as well. Social influence in transportation is becoming a topic of increasing coverage, and it is important to explore various avenues of social influence as this area of research becomes more refined. There are also subtleties within the definition of social influence. In this case, three versions of a name generator were utilized and it was found that there were few significant differences between the name generators used, in terms of the number of alters, the types of relationships and other characteristics of the networks elicited. Alternative means of defining the social reference group, however, may result in quite different networks.

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 ego mode choice and reference group mode use. Future work will also aim to identify how properties of the ego network relate to ego and alter mode choices, as well as whether certain types of relationships are more important than others.

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