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Do Your Neighbors Affect Your Mode Choice?
A Spatial Probit Model for Commuting to The Ohio State University

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ABSTRACT

Neighborhood effects have recently become a focus of interest in transportation research, whereby transportation mode choice is not only affected by an individual's characteristics and the physical conditions of the transportation system, but also by the mode choices of that individual's neighbors. This study supports the neighborhood effects argument, using a spatial econometrics approach and data from The Ohio State University's 2011 Campus Transportation Survey. A spatial probit model of commuters' mode choices (auto versus non-auto) is estimated, accounting for spatial autocorrelation. The results reveal that the more non-auto (walking, bicycling, and transit) users are residing around an individual, the more attractive these modes become for this individual. In addition to these spatial effects, the results indicate that students are more likely to commute to campus by non-auto modes, as compared to faculty and staff, and that the probability of choosing non-auto modes decreases with distance from campus. Feeling of safety, duration of travel, flexibility of departure time, ability to make stops on the way to/from campus, and attitudes towards auto use (being a car patron or a captive user), also affect an individual's mode choice. These findings provide campus transportation planners new insights on the factors influencing travel mode choices.

1. **INTRODUCTION**

Interest in reducing car use for commuting is increasing across the country. Several universities are encouraging alternative modes (e.g. walking, bicycling, ridesharing, and transit) because of their social and environmental benefits *(1-4)*. Discrete choice models have been used to analyze individual decision-making in transportation, whereby individuals maximize their utility based on their own socioeconomic characteristics. However, the interactions between the decision makers in a neighborhood or social network are generally ignored in such models. These neighborhood effects (social network or spill-over effects) have been shown to explain a range of individual behaviors *(5-8)*. The term "neighborhood effects" is used here, because the spatial interactions of decision makers are defined by geography rather than personal social networks (i.e. an individual's mode choice is affected by neighbors living within a certain distance). The basic transportation assumption is that the more a commuting mode is used within a neighborhood, the more attractive it becomes to all commuters *(9-11)*. Therefore, policies to enhance non-auto mode choice should focus not only on improving related infrastructures but also on promoting a non-auto-use culture if these neighborhood effects are significant *(10, 12)*.

The study area of this research is The Ohio State University (OSU) main campus, located in Columbus, Ohio, with an area of about 7 km^2 and over 80,000 people commuting to campus. The Columbus metropolitan area has long been dominated by cars because of low population density and a well-connected highway system. The transportation infrastructure on and around campus is car oriented, encouraging people to drive cars even within distances suitable for walking, bicycling, and transit *(1)*. To reduce car travel on/to campus, the OSU Transportation and Parking Services (T&P) office has attempted to improve conditions for non-auto modes. To be able to change individuals' mode choices, it is important to assess the propensity of choosing non-auto modes across faculty, students and staff, whether current non-auto infrastructures help decrease auto use and finally whether neighborhood effects impact people's mode choices, asides from ordinary socioeconomic factors

This study analyzes neighborhood effects, using data from the 2011 OSU Campus Transportation Survey. Questions cover respondents' travel modes, socioeconomic features, attitudes toward mode choices, and proximity to non-auto facilities. The survey also records respondents' residential locations, providing the basis for defining spatial relationships. Spatial probit models are estimated to account for spatial autocorrelation. The results can be used to analyze the direct effects that increase one's probability of choosing non-auto modes and indirect effects that increase such probability for this individual's neighbors.

2. **BACKGROUND**

Over the last couple of decades, decision makers in several metropolitan regions have been trying to reduce solo driving and promote alternative modes of transportation to reduce traffic congestion, noise, and air pollution. Numerous studies have been conducted on the links between land-use and built environment features, the impacts of various TDM (Transportation Demand Management) strategies, and the resulting travel patterns *(13-17)*.

The effects of personal characteristics and attitudes towards transportation have also been studied by several researchers. For instance, Cao and Mokhtarian *(18)* state that not only the amount of travel but also the individuals' specific characteristics (attitudes, personality, and lifestyle) influence individuals' travel choices. Schwanen and Mokhtarian *(15)* conclude that neighborhood characteristics interact with commuters' beliefs about auto use, and these two factors should be considered simultaneously while analyzing commuting modes and residential locations. Zhao *(19)* examines car dependence and reports that higher income, having children, and living in the suburbs increase subjective car dependence, whereas higher population density decreases this dependence.

Some studies focus specifically on personal attitudes and auto use. For instance, Graham-Rowe et al. *(20)* present a review of the evidence regarding several interventions carried out to reduce car use, and conclude that driving habit is one of the most important factors affecting future auto use. They find that interventions may be more effective if they target drivers who have both a strong driving habit and a strong motivation to reduce car use, or target people who have just changed residence and have not established travel habits yet. Eriksson et al. *(21)* state that personal norms, general intentions, and the perceived impacts of different TDM measures are important determinants of the resulting car use reductions.

In addition to studies based on focus groups and general populations, there is a growing literature examining travel patterns on college campuses, as the adverse effects of driving (congestion, increased parking demand, reduced physical activity) have spread to these campuses. As first stated by Balsas *(4)*, campuses differ from other urban areas, with their unique population of younger and more active individuals, a continuous movement of people throughout the day, and irregular schedules. He argues that the travel behavior and environmental awareness adopted by students may spread to the whole nation over time. Thus, campuses may have a unique opportunity to reduce overall auto use.

In addition to the early work of Balsas, Akar and Clifton *(3)* and Akar et al. *(22)* examine the factors associated with bicycling choice at the University of Maryland and OSU campuses, respectively. Zheng et al. *(2)* examine the potential demand for car-sharing at the University of Wisconsin-Madison. Barata et al. *(23)* analyze the willingness to pay for reserved parking at the University of Coimbra campus. Dorsey *(24)* studies the impacts of a public transit pass incentive program, using case studies from universities in Utah to demonstrate the potential to increase transit ridership. Akar et al. *(1)* conduct an analysis of the travel patterns of the OSU campus community. They use the 2011 Campus Transportation Survey data, which is the source of information for the current study as well. Using a multinomial choice model, they report that individuals prefer driving alone because of their concern for safety, travel time, flexibility of departure time, and the ability to make stops on the way, and suggest that the same level of service must be provided by alternative modes to be competitive with car use. However, this study does not consider neighborhood effects. In contrast, the present study analyzes the commute mode choice while considering these effects and focuses on auto versus non-auto choice because increasing the share of alternative modes (walking, bicycle, and transit) are the targets of TDM policies on campus.

Borrowing from a well-established perspective in sociology, recent economic research has started focusing on the role of social interactions in economic behavior and decision-making, particularly the effect of social interactions taking place within a neighborhood. Brock and Durlauf *(5, 7)* are among the first researchers to focus on these effects within the context of discrete choices. They formulate a multinomial logit model based on an individual utility function that includes a private utility component (individual characteristics), a social utility component depending on the decisions of other individuals in the neighborhood (social interactions), and a random utility term. They analyze the properties of the multiple equilibria that would result from the solution of this model under non-cooperative decision making, compare these equilibria to the solution that would be obtained if a social planner would set choices, and discuss the econometric estimation of the model. However, this work is essentially theoretical, as these logit models are not estimated with real-world data. Likewise, Paez and Scott *(6)* and Paez et al. *(8)* also use a multinomial logit model to address the effects of social interactions on the discrete decisions of telecommuting adopters and residential location seekers. In contrast to *(5, 7)*, this model involves some dynamics, whereby an individual's decision today is a function of her characteristics, her decision in the previous period, and the decisions of the other members of the social network in the previous period. Using hypothetical values for the model parameters, the model is numerically solved via Monte Carlo simulation. While conclusions are drawn from the simulation results under different hypotheses, this work remains theoretical because the model is "assumed" and not estimated with real-world data.

Goetzke *(9)* and Goetzke et al. *(10, 11)* appear to be the first to empirically estimate such models. They analyze social network effects in transport mode choice, with a focus on walking, bicycle, and public transit. The spatial lag term of the dependent variable is estimated with an instrumental variable approach to account for the binary mode choices. The more people use a particular mode, the more attractive this mode becomes to all other people in a neighborhood. The results confirm that increased use of one specific mode in a neighborhood increases the likelihood of this mode being chosen by others in the same neighborhood. While a given individual may have her own preference for mode choices (own effects), she is also affected by her neighbors' mode choices (neighborhood effects).

Goetzke and collaborators use a 2SLS (2-stage least squares) instrumental variable method to account for spatial autocorrelation. This method is problematic due to endogeneity, since the transportation mode share of neighbors is correlated with the unobserved utility of the given individual. Also, their neighborhood structure is defined by a given number of nearest neighbors. Although this approach is acceptable when the population distribution is homogenous, problems may arise when it is not. For instance, the average distance from an individual to her 30 nearest neighbors will be smaller in a dense central city neighborhood than in a suburban area. In addition, these distances vary, and so do the effects of next door neighbors versus neighbors living three blocks away. In some cases, some of these nearest neighbors may be quite far away, and therefore their impacts may be very small to non-existent, and treating all these 30 neighbors equally is not realistic. The present study adds to the existing literature by defining a distance-based neighborhood structure, and examining the neighborhood effects using a spatial probit model. The spatial weight matrix is based on this neighborhood structure.

3. DATA

3.1. OSU Campus Transportation Survey

The 2011 OSU Campus Transportation Survey was designed and administered online because of the ease of data entry and cost. The email addresses of 20 percent of the campus population were acquired from the University's Human Resources and Registrar offices. In addition, the survey link was made available through the T&P website, and was included in university newsletters.

Detailed information on the survey procedure can be found in Akar et al. *(1)*. Around 3,000 individuals participated in the survey, with 2,300 complete responses.

Table 1 presents descriptive statistics for the off-campus residents' mode choices. Most of the respondents (72 %) commute to campus by car (carpool and drive alone). Students are more likely to use non-auto modes as compared to faculty and staff. Most respondents living less than 1.6 km (1 mile) from campus choose non-auto modes (87%). More than half of the respondents living between 1.6 to 8 kilometers (1 to 5 miles) from campus commute by car. The percentage of respondents who choose driving increases with distance.

Figure 1 presents the spatial distribution of the respondents. Most of the respondents who walk, bike or take transit are located within a 20 km buffer from the center of the university campus. Moreover, both non-auto users and auto users display several spatial clusters, which points to possible spatial autocorrelation.

Table 1 Off-Campus Residents

	Non-auto users (%)	Auto users (%)	N
Status			
Faculty	12.9	87.1	223
Staff	9.0	91.0	1184
Graduate	40.4	59.6	463
Undergraduate	64.5	35.5	578
Gender			
Female	23.2	76.8	1417
Male	36.0	64.0	1027
Location			
Less than a mile	87.4	12.6	381
1 to 5 miles (1.6 to 8 km)	41.4	58.6	760
5 to 10 miles (8 to 16 km)	10.4	89.6	451
Over 10 miles (16 km +)	10.3	89.7	1012
Total	28.4	71.6	2604

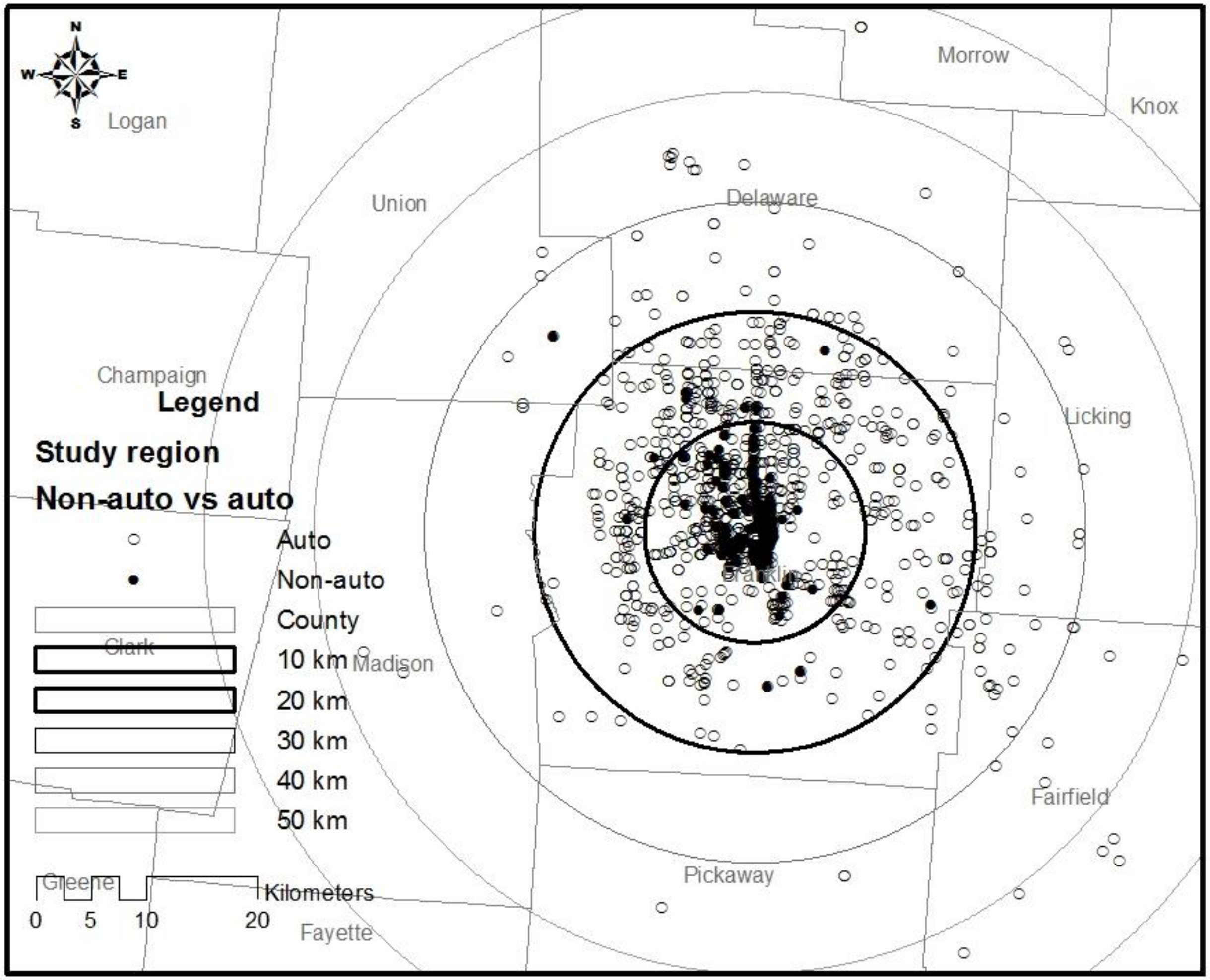

Figure 1 The Study Region

3.2. Attitudes Towards Travel Modes and Principal Component Analysis

The survey asks respondents about their attitudes towards auto use and the most important factors in making commuting mode choices. Table 2 summarizes these responses. Travel time, weather, and departure time flexibility are the three most important factors. About 78% of the respondents agree with the statement "my lifestyle is dependent on having a car", 60% actively try to reduce their car uses, and 32% have no interest in reducing it. Around 53% of the respondents have no other options but to drive to campus, and 42% do not consider other travel options.

Table 2 Attitudes Towards Mode Choices

General attitudes towards mode uses					
	Not important %	Somewhat important %	Important %	Very important %	N
Travel time	8.1	14.0	29.0	48.9	2570
More flexible departure time	12.1	15.8	29.6	42.5	2570
Ability to stop on my way to/from campus	23.7	24.5	25.1	26.7	2549
Safety from crime	19.1	20.9	26.5	33.5	2557
Safety from traffic	15.9	19.8	30.0	34.3	2564
Weather	9.9	12.8	29.6	47.8	2578
Cost	12.4	19.4	31.3	36.9	2571
Concern for the environment	22.4	34.6	28.6	14.4	2548
Attitudes toward auto use					
	Strongly disagree %	Disagree %	Agree %	Strongly agree %	N
My lifestyle is dependent on having a car	8.55	13.30	35.18	42.97	2504
I don't think about my travel options	21.13	36.61	26.61	15.65	2409
I am actively trying to use my car less often	10.87	30.43	39.32	19.38	2373
I have no interest in reducing my car use	24.40	43.79	20.63	11.18	2414
I have no other option but to drive to campus	25.25	23.15	19.28	32.32	2432

Source: Akar et al. *(1)*.

In order to incorporate these attitudes in mode choice models, Akar et al. *(1)* have conducted a principal components analysis (PCA) of these highly correlated attitudes, resulting in four principal components. Individuals are then scored on each of these components. For instance, the first component is defined as *"concerned for safety and weather"*, and individuals who are concerned about crime- and traffic-related safety and weather conditions score high on this component. The second component is defined as "*cost and environment conscious"*. People concerned about travel time score high on the third component. Flexibility of departure time and the ability to make stops on the way to/from campus characterize the fourth component. Details regarding these principal components can be found in Akar et al. *(1)*.

In the present study, we conduct an additional PCA and create two more components explaining respondents' attitudes towards auto use. The first component is characterized by not thinking about travel options, having no interest in reducing car use, and not trying to reduce auto use. Individuals who score high on this component are referred to as *"auto patron"*. Individuals who would like to reduce their auto use but think they do not have alternatives score high on the second component, referred to as *"captive user"*. The results, including the percentage of explained variance and the loading values for each component, are reported in Table 3.

Table 3 Principal Component Analysis – Attitudes towards Auto Use

Components	Auto patron	Captive uses
My lifestyle is dependent on having a car	**0.452**	**0.457**
I don't think about my travel options	**0.487**	-0.093
I am actively trying to use my car less often	-0.435	**0.486**
I have no interest in reducing my car use	**0.458**	-0.420
I have no other option but to drive to campus	0.401	**0.608**
Eigenvalues	2.604	1.007
% of variance	52	20

4. METHODOLOGY

4.1. Spatial Probit Model for Non-auto Use

Discrete choice models are used to explain the effects of socio-demographics, travel characteristics, and personal attitudes on observed mode choices. It has, however, been argued that the more individuals use one specific mode, the more likely this mode is to also be used by others in the same geographic location *(25, 26)*. This neighborhood effect can be captured by a spatial probit model based on random utility theory. If Alternative 1 is chosen, then this alternative (i.e., y = 1) is assumed to carry the highest positive net utility (i.e., $U_1 > U_0$). The probability of such selection from a choice set is *(25)*:

$$P(y = 1|x_k) = P(U_1 \geq U_0) = P(y^* \geq 0) = F((I - \rho W)^{-1}\beta_k x_k) \quad (1)$$

where y^* is the latent or unobserved utility. It underlies the observed choice outcome (y), which follows a truncated multivariate normal distribution (TMVN), with a mean vector and variance-covariance matrix presented in Eq. (2), where the original variance is set equal to 1 (i.e., $\sigma_\varepsilon^2=1$) *(25)*. W is the spatial weight matrix used to capture the spatial autocorrelation.

$$y^* \sim TMVN\{(I - \rho W)^{-1}\beta X, [(I - \rho W)'(I - \rho W)]^{-1}\} \quad (2)$$

The latent dependent variable is a function of a set of explanatory factors, x_k, together with a spatial lag term, Wy^*, and β_k and ρ (spatial scale) are parameters (Eq. (3)). The error term follows a TMVN distribution. The choice set includes non-auto (walking, biking, taking transit), and auto (carpool and drive alone) choices.

$$y^* = \rho W y^* + \beta_k x_k + \varepsilon = (I - \rho W)^{-1} \beta_k x_k + (I - \rho W)^{-1} \varepsilon \tag{3}$$

The explanatory variables are:

1. Status (faculty, staff, graduate, undergraduate);
2. Gender (1: female; 0: male);
3. Proximity to bicycle infrastructure and bus stops (1: there is a bike trail/path/lane or a bus stop within 0.8 km (0.5 mile) of the residence location; 0: otherwise);
4. Departure time flexibility (1: flexible; 0: not flexible);
5. Distance from residence to campus (unit: km);
6. Attitudes towards general mode choice (Component 1: safety and weather; Component 2: environment and cost; Component 3: time concern; Component 4: flexibility);
7. Attitudes toward auto use (Component 1: auto patron; Component 2: captive user).

Equation (3) indicates that the utility of choosing non-auto modes is not only affected by the above-mentioned variables but also by the neighborhood effects represented by the spatial lag term, Wy^*, which measures the mode choices of the respondent’s neighbors. It is assumed that there is a positive relationship between the mode choice of a given individual and those of her neighbors, measured by the spatial scale ρ. The larger the ρ, the stronger the spatial autocorrelation.

4.2.Estimation of the Spatial Probit Model

The Bayesian approach developed by LeSage and Pace *(25)* is used to estimate the spatial probit model. Instead of using the maximum likelihood method, the Bayesian approach estimates the parameters from a posterior density function that is the product of the prior distribution of the parameters and the likelihood function. When the posterior density function is mathematically too complicated to be integrated, a Markov Chain Monte Carlo (MCMC) simulation method is used to estimate the parameters, by examining a large random sample from the posterior distribution *(25)*. As the parameters β, ρ, y^* must be estimated, Gibbs sampler, one of the MCMC methods, is used *(26)*. The algorithm begins by drawing from the conditional distribution associated with the first parameter, and proceeds sequentially with each parameter until all parameters have been drawn. The advantage of this method is that it simulates the continuous latent variable, y^*, and then treats the data like a regular linear regression *(26)*.

4.3.Spatial Weight Matrix (W)

The spatial lag term, Wy^*, represents the neighborhood effects on each respondent's choice. The spatial weight matrix, W, must be based on a selected neighborhood structure. There are several methods for defining this structure, including adjacency, k-nearest neighbors, and distance-based *(27)*. The last method is selected here, because adjacency is generally used for lattice data defined by shared borders (e.g., Census tracts) *(28)*, and the k-nearest neighbors method is not suitable because of the spatial heterogeneity of respondents' distribution.

Once a neighborhood structure is defined, it can be converted into a spatial weight matrix. The standard spatial weight (SSW) has been most often used *(27)*, whereby each entry is defined as 1 over the number of neighbors within the row. For instance, if an individual has 5 neighbors, the entry for each neighbor is 0.2. This method treats every neighbor's effect equally. However, it may be necessary to treat these effects as decreasing with distance. In this case, the 1 entry in the SSW matrix is divided by distance, or inverse distance weight (IDW). Note that a zero entry in the matrix implies lack of neighbors for a given individual. Each non-zero spatial weight is then defined as:

1. Standard spatial weight (SSW): 1/n;
2. Inverse distance weight (IDW): 1/(n*distance),

where n is the number of actual neighbors in a given row of the matrix.

4.4. Summary of Spatial Weight Matrices

Respondents' locations are points distributed across the region (Figure 1). Individuals within 1 km around each respondent are considered her neighbors. Table 4 indicates that each respondent has an average of 35 neighbors, and the average distance between any pair of neighbors is about 0.5 kilometers. This neighborhood structure matrix is first converted into a SSW matrix, and then into an IDW matrix.

Table 4 Descriptive Statistics for Neighborhood Structure and Spatial Weights

	Minimum	Median	Mean	Maximum
Neighborhood structure				
Number of neighbors	0	9	35	182
Distance between neighbors (meters)	7	651	464	1000
Spatial weight matrix				
Standard spatial weight (SSW)	0.005	0.009	0.025	1
Inverse-distance weight (IDW)	0.001	0.008	0.024	1

4.5.Marginal Effects

LeSage *et al. (25, 29)* propose a method to interpret marginal effects with respect to the independent variables in the spatial probit model. They show that these effects can be calculated by using the inverse matrix $(I\text{-}\rho W)^{-1}$ in the following equation:

$$\partial E[y|x_r]/\partial\, x_r' = \Phi((I-\rho W)^{-1}\beta_r\overline{x_r}) \odot (I-\rho W)^{-1}\beta_r \tag{4}$$

where $\overline{x_r}$ is the mean of the r^{th} variable, Φ is a standard normal distribution, and $\odot$ is element-by-element multiplication. Equation (4) can be separated into two parts: direct effects (DE) and neighborhood effects (NE). The diagonal elements in Eq. (4) are used for DE, while the others are for NE *(25)*. For instance, if respondent *i* lives farther away from campus, this generates a direct impact (DE) on the probability that she chooses a non-auto mode, as well as a neighborhood impact (NE) on the choice of neighboring respondent j.

5. RESULTS

5.1. Spatial Probit Model for Choosing Auto versus Non-Auto

Table 5 presents the descriptive statistics for the variables used for the estimation of the mode choice model. Non-auto modes are used by (26%) of the respondents. Staff makes up the largest share of respondents (49%). Most respondents are female (59%), reside within 0.8 km from bicycle facilities or transit stops (66% and 79%) and have departure time flexibility (64%). The average distance between campus and a respondent's residence is about 10 km. Statistics for the principal components characterizing most important factors affecting individuals' mode choices and attitudes towards auto use are also provided.

Table 5 Descriptive Statistics of Variables (N=1584)

Dummy variables				
Percent commuting by walking, bicycling and transit				26%
Status and gender				
Faculty				9%
Staff				49%
Graduate				19%
Undergraduate				23%
Female				59%
Proximity to infrastructure and departure flexibility				
Bus stop (within 0.5 miles of a bus stop)				79%
Bike trail/path (within 0.5 miles of a bicycle trail/path)				66%
Departure flexibility				64%
Continuous variables				
	Mean	Minimum	Maximum	Std. Dev.
Distance (km)	9.83	0.19	46.80	8.42
General attitudes toward mode choices (PCA)				
Safety and weather	-0.017	-3.282	2.084	1.352
Environment and cost	-0.028	-2.573	2.361	1.156
Time	0.046	-3.381	1.889	1.100
Flexibility	0.062	-2.684	2.451	1.096
Attitudes toward auto use (PCA)				
Auto patron	-0.100	-3.571	3.433	1.607
Captive users	-0.063	-3.849	2.544	0.993

Table 6 presents the results of (1) a non-spatial logit model and (2) a spatial probit model with the IDW matrix. Auto choice is set up as the base case. In the logit model, undergraduate students are more likely to choose non-auto modes than graduate students, faculty and staff. The coefficient for faculty is not significant, indicating that faculty members' choices are not different from those of staff members (base case). Overall, there is no significant difference between the choices of males and females. Surprisingly, proximity to bus stops, bicycle trails and having departure time flexibility are not significant. However, the distance from residence to campus (positive sign) and the squared distance (negative sign) are significant, indicating that the probability of choosing a non-auto modes decreases with distance from campus, although at a decreasing rate.

Regarding general attitudes toward mode choices, the higher the concern for safety, travel time, and the ability of making stops on the way to/from campus, the smaller the probability of choosing non-auto modes. However, the concern for travel time is not significant. Note that safety is not significant in the logit model but significant in the spatial probit model. In contrast, the higher the concern for the environment and cost, the higher the probability of choosing non-auto modes.

It is not surprising that the principal component variables representing auto patrons and captive drivers have both negative signs. Auto patrons (individuals who think their lifestyles are dependent on their cars, and have no interest in reducing their car use) and captive users (individuals who would like to reduce their car use, but have no other options) are less likely to choose non-auto modes. As expected, the 'captive user' coefficient is smaller than the 'car patron' coefficient in magnitude.

In the spatial probit model, the coefficients of the above-discussed variables display generally smaller values as compared to the logit model, but have the same signs. This is as expected, as neighborhood effects are clearly separated from direct effects. The spatial scale ρ is significant with a value of 0.24, and therefore supports the assumption of significant neighborhood effects.

Table 6 Results for Auto versus Non-auto Choice Models (N=1584)

	Non-Spatial Logit		Spatial probit (IDW)	
Variable	Coef.	Std. Dev.	Coef.	Std. Dev.
Cons.	**-1.776**	**0.817**	**-1.171**	**0.452**
Status (staff is the base case) and gender (male is the base case)				
Faculty	0.170	0.372	0.043	0.206
Graduate	**1.141**	**0.255**	**0.529**	**0.145**
Undergraduate	**2.445**	**0.257**	**1.227**	**0.142**
Female	-0.224	0.197	-0.122	0.116
Proximity to non-auto infrastructure, departure flexibility and distance from campus				
Bus stop	0.111	0.624	0.191	0.330
Bike trail	-0.020	0.257	-0.075	0.142
Departure flexibility	0.240	0.210	0.137	0.114
Distance	**-0.308**	**0.045**	**-0.096**	**0.027**
$Distance^2$	**0.007**	**0.001**	**0.002**	**0.001**
General attitudes toward mode choices (PCA)				
Safety and weather	-0.164	0.090	**-0.107**	**0.051**
Environment and cost	**0.284**	**0.103**	**0.169**	**0.061**
Time	-0.096	0.095	-0.047	0.054
Flexibility/making stops	**-0.293**	**0.101**	**-0.179**	**0.055**
Attitudes toward auto use (PCA)				
Auto patron	**-0.955**	**0.085**	**-0.519**	**0.048**
Captive users	**-0.693**	**0.112**	**-0.356**	**0.060**
Spatial scale (ρ)			**0.239**	**0.058**

Note: Bolded coefficients are significant at the 95% level

5.2. Marginal Effects Analysis

Table 7 presents the average direct (DE), neighborhood (NE), and total (TE) effects resulting from changes in several independent variables. The IDW matrix implies distance-attenuated neighborhood effects. A 1 km increase in a respondent's residence location away from campus will directly reduce her probability of choosing a non-auto mode by 0.66% (own effect), and the indirect effect on her neighbors would be a probability decline of 0.2%. A respondent's probability of choosing a non-auto mode will directly decrease as she is more concerned about safety and weather (0.01%) and flexibility (0.02%), but will directly increase with more concern about environment and cost (0.02%). These changes in travel concerns will also indirectly affect her neighbors' mode choices as well. Similar negative effects can be observed for being auto patron and captive user. The own effect (DE) magnitudes are about three times as the neighborhood effects (NE). This is evidence that respondents' mode choices are certainly affected by their neighbors' mode choices. However, the result also indicates that this choice depends more on an individual's own characteristics than on her neighbors' choices.

Table 7 Average Marginal Effects

Variable	Direct effect (DE)	Neighborhood effect (NE)	Total effect (TE)
Distance (km)	-0.663	-0.202	-0.865
Safety and weather	-0.014	-0.004	-0.018
Environment and cost	0.022	0.007	0.029
Flexibility	-0.023	-0.007	-0.030
Auto patron	-0.066	-0.021	-0.087
Captive users	-0.045	-0.014	-0.059

6. CONCLUSIONS

Choosing alternative modes of transportation can certainly reduce transportation expenditures, and congestion for the campus community. The estimation of the spatial probit model for auto versus non-auto choices shows that spatial autocorrelation exists in commuting mode choices. The more non-auto users, the more attractive the non-auto modes become to all commuters. Students are more likely to choose these modes as compared to faculty and staff. Surprisingly, proximity to non-auto infrastructure does not seem to influence non-auto mode choices. However, distance between residence and campus turns out to be a major factor for choosing alternative modes. The principal component analyses and model results reveal that safety, travel cost and ability to make stops on the way to/from campus significantly affect individuals' mode choices. It is also interesting that most respondents (captive users) have an interest in reducing car use but have no available alternative modes. Therefore, promoting non-auto modes can be achieved by reducing travel time and cost, improving safety and ability of making stops, and encouraging a non-auto-user culture based on neighborhood effects.

Most transportation mode choice models fail to account for neighborhood effects or how an individual's behavior may be affected by her neighbors' choices. When such models are used in forecasting for new transit projects and in providing planning information to decision makers, the results may be biased because of the non-inclusion of these effects in the model *(9)*. This is also true for planning for bicycling and pedestrian infrastructure.

A large share of the university population lives within a couple of miles from campus, and the results suggest that students should be the targets for promoting alternative modes, much more so than faculty and staff, as they are more likely to choose alternative modes of transportation to begin with. While proximity to bicycle infrastructure and bus stops appear to have no significant effect on mode choice, further efforts in providing safe, flexible and convenient conditions might have such effect. The results also reveal that more research is needed to understand the needs of auto patrons and captive auto users. As car orientation is deeply embedded in the American culture, understanding and being able to shape neighborhood effects may become an extremely helpful lever to change people's behavior and increase the use of alternative modes.

REFERENCES

1. Akar, G., C. Flynn, and M. Namgung., *Understanding travel choices and links to TDM: A case study of The Ohio State University.* Transportation Research Record (TRR), Journal of the Transportation Research Board, 2012. **Forthcoming**.
2. Zeng, J., et al., *Carsharing in a university community: Assessing potential demand and distant market characteristics.* Transportation Research Record (TRR), Journal of the Transportation Research Board, 2009. **2110**: p. 18-26.
3. Akar, G. and K.J. Clifton, *The influence of individual perceptions and bicycle infrastructure on the decision to bike* Transportation Research Record (TRR), 2009. **2140**: p. 165-172.
4. Balsas, C.J.L., *Sustainable transportation planning on college campuses.* Transport Policy 2003. **10** p. 35–49.
5. Brock, W. and S. Durlauf, *Discrete choice with socal interactions.* Review of Economic Studies, 2001. **68**: p. 235-260.
6. Paez, A., D.M. Scott, and E. Volz, *A discrete-choice approach to modeling social influence on individual decision making.* Environment and Planning B: Planning and Design, 2008. **35**(6): p. 1055-1069.
7. Brock, W. and S. Durlauf, *A multinomial-choice model of neighborhood effects.* American Economic Review, 2002. **92**: p. 298-303.
8. Paez, A. and D.M. Scott, *Social influence on travel behavior: a simulation example of the decision to telecommute.* Environment and Planning A, 2007. **39**(3): p. 647-665.
9. Goetzke, F., *Network Effects in Public Transit Use: Evidence from a Spatially Autoregressive Mode Choice Model for New York.* Urban Studies, 2008. **45**(2): p. 407-417.
10. Goetzke, F. and T. Rave, *Bicycle Use in Germany: Explaining Differences between Municipalities with Social Network Effects* Urban Studies, 2011. **48**: p. 427-437
11. Goetzke, F. and P.M. Andrade, *Walkability as a Summary Measure in a Spatially Autoregressive Mode Choice Model: An Instrumental Variable Approach*, in *Progress in Spatial Analysis, Advances in Spatial Science*, A. Páez, et al., Editors. 2010, Springer Berlin Heidelberg. p. 217-229.

12. Nelson, A.C. and D. Allen, *If You Build Them, Commuters Will Use Them: Association Between Bicycle Facilities and Bicycle Commuting.* Transportation Research Record, 1997. **1578**: p. 79–83.
13. Handy, S., *Smart Growth and The Transportation-Land Use Connection: What Does The Research Tell Us?* International Regional Science Review, 2005. **28**(2): p. 146-167.
14. Cervero, R., *Built environments and mode choice: toward a normative framework.* Transportation Research Part D: Transport and Environment, 2002. **7**(4): p. 265-284.
15. Schwanen, T. and P.L. Mokhtarian, *What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?* Journal of Transport Geography, 2005. **13**(1): p. 83-99.
16. Cervero, R. and C. Radisch, *Travel choices in pedestrian versus automobile oriented neighborhoods.* Transport Policy, 1996. **3**(3): p. 127-141.
17. Boarnet, M. and R. Crane, *The influence of land use on travel behavior: specification and estimation strategies.* Transportation Research Part A: Policy and Practice, 2001. **35**(9): p. 823-845.
18. Cao, X. and P.L. Mokhtarian, *How do individuals adapt their personal travel? Objective and subjective influences on the consideration of travel-related strategies for San Francisco Bay Area commuters.* . Transport Policy, 2005. **12**(4): p. 291-302.
19. Zhao, J. *A subjective measure of car dependence*. in *TRB, Transportation Research Board, 90th Annual Meeting*. 2011. Washington, DC.
20. Graham-Rowe, E., et al., *Can we reduce car use and, if so, how? A review of available evidence.* Transportation Research Part A: Policy and Practice, 2011. **45**(5): p. 401-418.
21. Eriksson, L., A.M. Nordlund, and J. Garvill, *Expected car use reduction in response to structural travel demand management measures.* Transportation Research Part F: Traffic Psychology and Behaviour, 2010. **13**(5): p. 329-342.
22. Akar, G., N. Fischer, and M. Namgung, *Bicycling Choice and Gender, Case study: The Ohio State University.* International Journal of Sustainable Transportation, 2012. **forthcoming**.
23. Barata, E., L. Cruz, and J.-P. Ferreira, *Parking at the UC campus: Problems and solutions.* Cities, 2011. **In Press**.
24. Dorsey, B., *Mass transit trends and the role of unlimited access in transportation demand management.* Journal of Transport Geography, 2005. **13**(3): p. 235-246.
25. LeSage, J. and R.K. Pace, *Introduction to Spatial Econometrics*2009: Chapman and Hall.
26. Thomas, T.S. *A Primer for Bayesian Spatial Probits with an Application to Deforestation in Madagascar. Companion paper for the policy research report on forests, environment and livelihoods. The World Bank, Washington, D.C.* 2007.
27. Bivand, R.S., E.J. Pebesma, and V. Gomez-Rubio, *Applied spatial data analysis with R*, ed. Springer2008.
28. Cressie, N., *Statistics for Spatial Data (Revised Edition)*1993: NJ: Wiley Press.
29. LeSage, J. and M.M. Fischer, *Spatial growth regressions: Model Specification, Estimation and Interpretation.* Spatial Economic Analysis, 2008. **3**(3): p. 275-304.