Estimating Land Use Effects on Bicycle Ridership

Yuchen Cui
Ph.D. Assistant
National Center for Smart Growth Research and Education
School of Architecture, Planning and Preservation
University of Maryland
College Park, MD 20742
Phone: (301) 405-2373
E-mail: ycui@umd.edu

Sabyasachee Mishra, Ph.D., P.E. (Corresponding Author)
Assistant Professor
Department of Civil Engineering
University of Memphis
Memphis, TN 38152
Phone: (901) 678-5043
Email: smishra3@memphis.edu

Timothy F. Welch, JD, Ph.D.
Assistant Professor
Center for Quality Growth and Regional Development
School of City and Regional Planning
Georgia Institute of Technology
Atlanta, GA 30332
Phone: (404) 385-5114
Email: tim.welch@coa.gatech.edu

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ABSTRACT

State and local agencies are becoming increasingly aware of the need to provide improved bicycle infrastructure as the number of riders has grown over the past several years. However, a lack of bike-specific planning tools makes it difficult for planners to develop ridership estimates and thus accommodate cyclists' needs to provide better infrastructure. This paper proposes a series of empirical models and applies them to the state of Maryland in the United States. A set of spatial lag models are developed to explore land use, built environment, demographic, socio-economic, and travel behavior connections to bicycle ridership. To account for geographical typologies urban, suburban and rural models are proposed. Results show that land use patterns, socioeconomic, demographic, network and travel characteristics are positively correlated with bicycle ridership. Specific types of land use, employment categories, auto ownership, and income levels have inverse relationships with bicycle ridership. The model is also applied to assess two hypothetical future land-use scenarios; in an exercise that shows how this tool may better predict future ridership and infrastructure needs. This proposed approach could be used as a tool to model and forecast bicycle demand, and to assist agencies in preparing and planning for future years.

INTRODUCTION

Active travel modes, such as walking and bicycling, are typical types of physical activity that are believed to increase physical fitness and help lower the risk of chronic conditions such as obesity, high blood pressure, and diabetes *(1–3)*. Also, it has been largely recognized by transportation scholars that, walking and bicycling are environmentally friendly transport modes that do not produce carbon emissions, congestion and traffic noise *(4, 5)*. The bicycle in many cases offers greater mobility, a wide range of health, travel cost and environmental benefits and flexibility to connect with public transportation. However, in a number of cases, existing transportation infrastructure is not well suited for majority of bicyclists. A major issue is a significant lack of safe riding space, particularly dedicated bicycle lanes. From safety standards, this creates a problem for bicyclists and discourages them from traveling by this mode. Planning agencies at the local and state level are starting to focus more attention on the need to provide infrastructure for bicyclists. In an effort to close the gap between bicycle demand as an active travel mode and available facilities, planning agencies are increasingly interested in measuring potential bicycle ridership demand. Past experiences suggest the factors that would explain bicycle ridership are closely related to socio-economics, demographics, public policy, and built environment attributes. Previous literature also shows that urbanization and vehicle ownership are important factors that are correlated with bicycle ridership.

Accordingly, transportation researchers and practitioners have attempted to identify factors that encourage and sustain higher densities of bicycle use, influenced by local land use policy. Such factors include design principles for new subdivisions, accessibility to transit stations, and regional urban form *(6–10)*. Transportation demand, particularly for modes outside of single occupancy vehicle use is highly context sensitive. Land use can be a major contributing factor to this demand. Measures commonly employed in travel behavior studies originate from the concept of the "three Ds" (density, diversity and design). The three factors have since been expanded to incorporate multiple other factors including accessibility, distance to transit, demand management and even demographics *(11)*. Neighborhood type, which represents the interaction of multiple built environment dimensions, has also attracted growing interests in transportation studies *(12)*. At a more localized level, the distribution of access to transportation can have a big impact on its utility *(13)*.

Advocates of active travel modes have promoted and incorporated these ideas in urban plans and ordinances, and in bicycle facility siting decisions. As a result, cities that incorporate a large geographic area and suffer from poor public transit service would be more likely to experience a large shift in bicycle users, should the proper infrastructure be provided. Despite a broad literature focused on the phenomenon of rising bicycle use in the U.S., there is very little research that quantitatively examines the emerging statewide trend from a transportation demand perspective. With an urgent need in many jurisdictions to nurture the growth of bicycle ridership and to facilitate a better understanding of the determinants of bicycle trip generation, further research is needed that examines why and how different factors, including socio-economics, demographics and built environment attributes, influence bicycle-based travel decisions at state level.

This paper is structured as follows. In the next section, we present a thorough review to explore the connections between bicycle ridership and land use patterns to derive and frame the key planning questions. In the following section, we discuss the datasets, the rationale behind the choice of our study area, and the modeling framework for our empirical analysis. In the next section, we present findings of this analysis and discuss implication for planning policy making at state level. In the Section of Planning Application, we apply our model to develop two scenarios for the horizon year and discuss implication for planning decisions at state level. We offer concluding remarks in the end followed by caveats and scope of future research.

LITERATURE REVIEW

With its far-reaching impacts on environment and health, the idea of an active travel mode, including walking and bicycling, has been examined in a substantial amount of the literature. A comprehensive review of transportation and planning literature confirms the relevance of environmental characteristics, including density (of population, housing and employment), street connectivity, and land use patterns for walking and bicycling *(14)*. A study of bicycle-friendly cities in the U.S. identified factors that are significant in influencing bicycling including city size and density, and convenience (availability, cost, and speed) of competing modes *(15)*. Studies conducted in an empirical context consistently showed that well connected streets and smaller city block sizes *(16–18)*, proximity to retail activities *(16)*, higher population density *(19, 20)*, higher housing or residential density *(21)*, and higher retail employment density *(18)* tend to induce non-automobile trips. Active travel was also examined in relation to characteristics of different types of travel mode in several studies. Evidence from these studies showed that traffic volume, highway density, congested travel time, and traffic speeds have negative effects on non-automobile travel frequency *(22–24)*.

In particular, Targa and Clifton *(25)* applied data from the National Household Travel Survey add-on in 2001 for the Baltimore metropolitan region to estimate non-motorized person-level trips; finding neighborhoods with higher densities, better access to bus service and better street connectivity were associated with greater active travel mode shares. In examining non-automobile commuting in 11 Metropolitan Statistical Areas, Cervero *(21)* found that, non-automobile commuting was positively related to household densities of different households types; and the presence of neighborhood shops turned out to be a better predictor of active commuting than residential density. When taking a closer look at land use patterns by land use category, a considerable number of studies consistently show when land use diversity increases, especially near transit stations, grocery stores, and retail stores in neighborhoods, people tend to rely on non-automobile modes more frequently *(26–28)*.

The influence of socio-economic factors including household income, living standards, and vehicle ownership over bicycle mode shares have been examined in a number of studies *(24, 27, 29, 30)*. The evidence on the correlation of bicycling with income and vehicle ownership is confounding. For example, income is inconsistently found to be variably insignificant and significant factor in determining bicycling patterns in U.S. cities *(17, 31, 32)*. While some studies show that higher income is correlated with lower demand of active travel *(24, 27, 33, 34)*, there were contradictory results showing that higher income has a positive influence on non-automobile trip generation *(25*. Vehicle ownership in some cases has been found to be inversely associated with bicycling *(20, 32)*, whereas this relationship was less clear elsewhere *(17)*.

Overall, most of the existing research applies a disaggregate analysis approach, examining non-automobile travel patterns at the household or individual level, controlling for the effects of travelers' characteristics, household attributes, neighborhood built environment attributes, and land use patterns. These disaggregate studies did not account for regional trends (i.e. urban, suburban, and rural) of the travel behavior investigated. This geographic limitation associated with the disaggregate approach can be addressed by an aggregate analysis approach, which relates aggregate travel data to aggregated land-use variables at certain spatial level (zone level or census tract level). Motivated by a need to understand statewide active travel patterns, we develop a series of empirical models for the State of Maryland to examine the predictors of bicycle ridership at the zone level, considering different spatial typologies, land uses, built-environment attributes, socio-economic, and characteristics of transport system. This approach allows us to generate bicycle ridership estimates under different policy scenarios for future years, which can significantly aid policy makers and city planners to effectively promote active bicycle travel at a statewide level.

DATA AND METHOD

To develop a bicycle ridership model for the State of Maryland, we collected data from a number of national, state, and local Metropolitan Planning Organizations (MPOs). The State of Maryland consists of 23 counties and one independent city. Its total population in 2010 was 5.8 million and total employment was 3.4 million *(35, 36)*. To develop our dataset, we subdivided the state into 1,151 Statewide Modeling Zones (SMZs). The main criteria for SMZ delineation was to conform to census geographies, nesting within counties, separating traffic sheds of major roads as well as employment activity centers, and grouping of adjacent traffic analysis zones (TAZs) defined by the MPOs. The study area is displayed in Figure 1.

In developing the bicycle ridership model, we explored a wide range of contributing factors to bicycling as summarized from existing literature - socio-economic, land uses and characteristics of transport system. The data was collected and aggregated at the SMZ level. For MPO regions in the Maryland and Washington metropolitan area, their socio-economic data, including the population, housing, employment, vehicle ownership and school enrollment data, were collected from the cooperative forecast datasets developed by the two state MPOs. For non-MPO designated areas, socio-economic data was collected from the Quarterly Census Employment and Wages (QCEW, formerly known as ES202), which is prepared by the Department of Labor, Licensing and Regulations (DLLR). We divided the MPO and QCEW data into four employment categories by type including retail, office, industrial, and other. Household income data was collected from the MPO datasets and the U.S. Census datasets for both MPO and non-MPO regions. The socio-economic data were normalized by acreage for each SMZ. To define the characteristics of the transport system, we developed a transportation network based on the Census Topologically Integrated Geographic Encoding and Referencing (TIGER) files. Additionally, the Maryland Department of Transportation (MDOT) datasets were referred to define the average freeway distance, average free flow speed, average congested speed, and presence of transit stop. Additionally, the Maryland Department of Planning's (MDP) parcel dataset was used to determine specific land uses, including health care, shopping, retail, office, recreation, dining, warehouse, and other commercial establishments. The descriptive statistics for key variables considered in the empirical analysis section is presented in Table 1. In this study the bicycle ridership model developed was restricted to Maryland SMZs for year 2007. The rationale of using 2007 as the analysis year was that all the input variables collected from different agencies in the State of Maryland were consistent for this specific year.

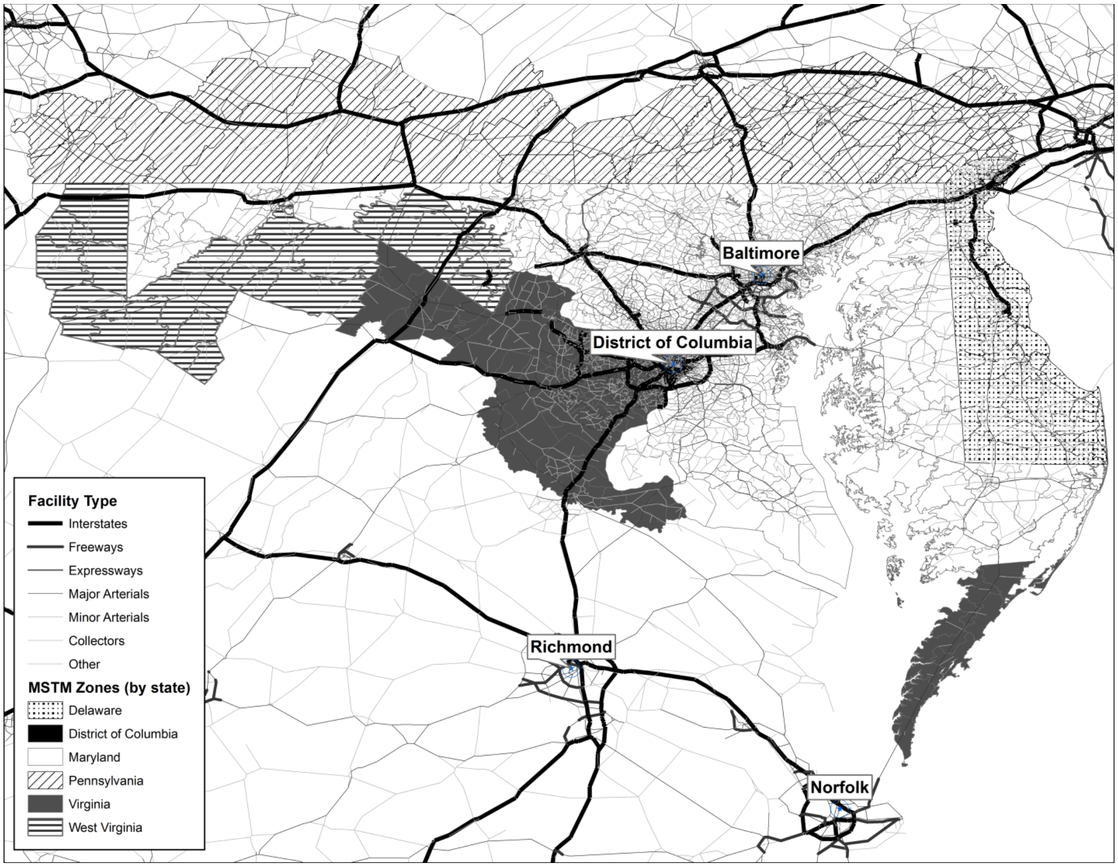

FIGURE 1 Regions used to develop statewide modeling zones (source: Maryland Statewide Transportation Model -MSTM, State Highway Administration).

The dependent variable is defined as the number of bicycle trips generated per zone per day. This data was obtained from a recently conducted Household Travel Survey (HTS)[1] in the Baltimore-Washington region in Maryland, USA. In this paper, bicycle trips are captured from the HTS data. To account for sample versus population data the survey agency has already identified expansion factors considering household and person socio-economic and demographic characteristics. The daily bicycle trips are aggregated at zone level. The zone level daily bicycle trips are the dependent variable in the statistical analysis presented in this paper. To account for variations in the relationship between regional patterns and bicycle ridership across the state, we used a combination of household and employment densities to classify the SMZs into three spatial typologies – urban, suburban, and rural. Details on the spatial classification can be found in the author's previous work *(12)*.

[1] http://www.baltometro.org/regional-data-and-forecasting/household-travel-survey

TABLE 1 Descriptive Statistics

Variables	Mean	S.D.	Min.	Max.
Daily bicycle ridership	1.4424	1.5084	0	8.4784
Population density	4.4222	5.6612	0	42.4043
Household density	1.8761	2.6793	0	21.3794
Household workers density	2.0654	2.6154	0	29.2736
Household with zero workers density	0.0049	0.0210	0	0.5776
Total employment density	3.7840	18.9964	0	476.0905
Retail employment density	0.5707	2.3735	0	62.2317
Office employment density	1.8186	11.4937	0	300.2474
Industrial employment density	0.2817	1.0990	0	29.0244
Other employment density	1.1130	5.4454	0	105.3763
School enrollment density	0.6169	1.2425	0	11.8216
Drive alone density	0.1741	0.2694	0	3.4490
Household with 0 cars	0.1943	0.3616	0	3.0270
Household with income over 60,000	1077.4200	905.1540	0	8737
Average freeway distance (miles)	0.8119	1.8899	0	26.0400
Average free flow speed (mph)	31.6387	6.4007	16.1250	55.8000
Average congested speed	26.7107	5.8400	7.1167	51.1987
Accessibility to transit (dummy)	0.2200	-	0	1
Amtrak presence (dummy)	0.0100	-	0	1
Number of retail locations	32.3400	102.1310	0	950
Number of dinning locations	2.1000	8.4550	0	103
Number of healthcare locations	0.2800	0.7810	0	8
Number of office locations	3.3800	13.3760	0	157
Number of recreation locations	0.4500	1.2620	0	13
Number of shopping locations	8.4500	35.7500	0	462
Number of warehouse locations	1.0800	4.4600	0	59

Note: Unit of density variables was per acre.

We estimated the relationship between explanatory variables and bicycle ridership using a spatial lag model (SLM). SLM provides a robust model where there is a high likelihood of spatial autocorrelation. Spatial autocorrelation analysis includes an assessment and visualization of both global (test for clustering) and local (test for clusters) Moran’s I statistic. The dependent variable (daily bicycle ridership) is visualized by means of a Moran scatter plot. The Moran’s I showed high autocorrelation, for Model I, and Model II-IV. In addition, the significance of autocorrelation is computed using a permutation test by generating random numbers. In this paper 999 random numbers were generated and in all cases the p-value was significant at 95 percent level of confidence. Similar analysis was conducted to test for local clusters. Indication of a cluster at the local level was examined at various statistical confidence levels. If high spatial autocorrelation is detected, the SLM approach is chosen when the Lagrange Multiplier (LM) statistic test is significant for the SLM. The spatial weight matrix of the study area, which contained 1,151 SMZs, was developed by identifying the contiguity (neighboring SMZs) for each SMZ. The spatial matrix is taken as the contiguity weight factor (Lambda) in the SLM. In our study, the SLM assumes that bicycle ridership in an SMZ is influenced by the independent variables in neighboring SMZs. The SLM also assumes the error terms are spatially correlated. The estimation of the spatial regression models is supported by means of the maximum likelihood method *(37)*. The SLM model was developed in software package GeoDa *(38)*.

EMPIRICAL RESULTS

Results of Statistical Analysis

The SLM model was estimated for the entire state and three urban typologies, respectively (Table 3). The estimated coefficient, *t* statistics, statistical significant test, R-square, and the weight factor Lambda are reported. Alternative model specifications (Model II, III and IV) were estimated in order to control as many socio-economic characteristics, demographic attributes, land-use patterns, built environment attributes, and traffic characteristic variables as possible. In the SLM multicollinearity is examined, as it is possible for independent variables to be correlated. The condition number is used as a measure to identify multicollinearity. In the regression process when the condition number is higher than 20, correlated variables are removed from the estimation process. The model development followed a forward selection approach, which decides the addition of each variable based on the improvement of model statistics.

A number of models were developed and is described as follows: Model-I is a SLM estimated at the statewide level; Model-IA, IB, IC, are variants of Model-I estimated at the statewide level, but with additional variables assessed. Overall, Model-I shows the best goodness of fit measure among all statewide models (Model-I, Model-IA, IB, IC), as later explained in the results section. Model-II, III, and IV are three area type models representing varying degree of urban typologies. These three models are estimated with different sample sizes. The purpose of developing the last three models is to examine the effect of specific variables on daily bicycle ridership.

Table 2 presents the estimated results for four model specifications with variables most expected to influence bicycle ridership. Overall, the results were intuitive and robust across all model specifications. As the demographic factors were highly correlated, they were tested by different model specifications. At the state level, bicycle ridership increased with the densities of household, population, household workers, zero-worker households, and school enrollment. The ridership was lower in SMZs with higher household income and higher household vehicle ownership.

TABLE 2 Regression Results for Bicycle Ridership Model at State Level (N = 1144)

Explanatory variables	Spatial Lag Model			
	Model-I	Model-IA	Model-IB	Model-IC
Constant	-0.032	0.034	0.067	0.011
	(-0.45)	*(0.270)*	*(1.011)*	*(0.401)*
Population density	0.033***			
	(6.033)			
Household density		0.062***		
		(7.388)		
Household workers density				0.031***
				(4.667)
Household with zero workers density	0.028		0.114***	
	(2.32)		*(9.154)*	
Industrial employment density	0.036**	0.030*	0.027	0.031***
	(2.953)	*(1.695)*	*(1.982)*	*(3.306)*
Retail employment density		0.006*	0.010	
		(1.963)	*(1.649)*	
Other employment density	0.007	0.007		
	(2.708)	*(2.309)*		
School enrollment density	0.034***	0.038***	0.038***	0.037***
	(4.338)	*(4.789)*	*(4.727)*	*(4.751)*
Household with income over $60,000	-0.000	-0.003	-0.001***	-0.002
	(0.088)	*(0.258)*	*(2.238)*	*(-0.141)*
Drive alone density	-0.200*	-0.110		
	(-2.532)	*(-1.936)*		
Households without cars		0.051		
		(1.266)		
Average freeway distance		-0.047	-0.004	
		(-0.955)	*(-1.852)*	
Transit accessibility	0.087***	0.090***	0.103***	0.094***
	(3.540)	*(3.751)*	*(4.214)*	*(3.843)*
Average congestion speed		-0.001		
		(-0.775)		
Average free flow speed	0.001		-0.003	-0.001
	(0.637)		*(-1.308)*	*(-0.224)*
Amtrak presence	-0.277***	-0.260***	-0.314***	-0.283***
	(-2.600)	*(-2.435)*	*(-2.936)*	*(-2.657)*
Number of Office Locations	0.004***		0.003***	
	(5.046)		*(4.414)*	
Lambda	0.852	0.871	0.884	0.877
	(86.759)	*(88.371)*	*(91.588)*	*(90.144)*
Sample size	1144	1144	1144	1144
R-square	0.9588	0.9586	0.9584	0.9582

Note: Dependent Variable: Total daily bicycle ridership; T-statistics are in parenthesis

*** Significant at 99%; ** Significant at 95%; * Significant at 90%

A variety of employment types uniquely impacted bicycle ridership. Industrial employment and other employment densities had negative effects on bicycle ridership while retail employment density had a positive effect. Bicycle ridership decreased with increasing drive-alone density, average congestion speed, average free flow speed, and average freeway miles in an SMZ. Consistent with our expectations, the presence of Amtrak service was negatively associated with bicycle ridership since the Amtrak stations were typically isolated from residential areas. Transit accessibility was found to be positively associated with bicycle ridership, implying the existence of multi-modal non-automobile trips in the state. Among all the land use categories (i.e. number of retail, dinning, office, recreation, and shopping jobs), only the number of office locations was found to be significantly related to bicycle ridership. Bicycle ridership increased where there was more office land use. Land use related to retail, dinning and recreation were found to be counter-intuitively insignificant factors despite being usually located close to residential and business areas. As a result, these land uses were not included in the statewide models. Our study area has a considerable amount of rural land, which contains a highly homogeneous set of land uses. Therefore, the relationship between bicycle ridership and land use may be obscured by having a large portion of rural lands as part of our study area. This suggested the necessity to estimate the interactions between land-use patterns and bicycling activity by urban typology. The weight factor Lambda was highly significant in all SLMs and the goodness-of-fit results of the SLMs appeared robust across all model specifications. This finding suggests the importance of taking the spatial interactions and bicycle ridership interdependencies into consideration.

Table 3 reports SLM results at the urban, suburban and rural area typology levels. Several important implications emerge from the results. First, the constant was positive and significant for all the models but its magnitude dropped drastically from urban models to rural models. Secondly, the number of high income households was a significant factor inversely associated with bicycle ridership across all models with similar coefficient magnitudes. Comparing the models estimated at state level and at different spatial typology levels, the directionality and magnitude of their estimated coefficients were consistent. However, some significant factors in statewide models became insignificant in the spatial topology models, including population density, school enrollment density, average freeway distance, and number of office locations. Additionally, there were some noticeable differences across the models at each spatial typology level. First, some contributing factors of bicycle ridership were only significant in urban and suburban models. In these models, the population density, school enrollment density, and the number of retail centers were positively associated with bicycle ridership and the average freeway distance was a negative factor. Second, transit accessibility (positive association) and Amtrak presence (negative association) were not significant predictors of bicycle ridership in urban models, but their relationships were significant in suburban and rural models. Third, several relationships between explanatory variables and bicycle ridership were only significant at specific spatial typologies. In urban areas, when average free flow speed or household vehicle ownership became higher, it discouraged bicycle trips all else being equal. When there were more recreation centers in urban areas, the bicycle ridership increased significantly. In suburban areas, the average congestion speed was negatively related to bicycle ridership. In rural areas, the positive influence of household density on bicycle ridership was significant.

TABLE 3 Regression Results for Bicycle Ridership Model for Three Urban Typology Models

Explanatory variables	Spatial Lag Model		
	Model-II (Urban)	Model-III (Sub-Urban)	Model-IV (Rural)
Sample size	465	420	259
Constant	0.452***	0.458***	0.197***
	(2.945)	*(2.886)*	*(3.848)*
Population density	0.060***	0.063***	
	(7.166)	*(6.017)*	
Household density			0.392***
			(10.396)
Industrial employment density	0.106***		0.154***
	(6.386)		*(3.118)*
Other employment density	0.005	0.022**	0.054***
	(1.020)	*(2.285)*	*(3.332)*
School enrollment density	0.056***	0.132***	
	(3.637)	*(6.179)*	
Household with income over $60,000	-0.001**	-0.079**	-0.088***
	(-1.695)	*(-2.084)*	*(-3.099)*
Drive alone density	-0.319		-1.800***
	(-2.110)		*(-7.101)*
Households without cars	0.062	-0.061	
	(2.025)	*(-0.511)*	
Average freeway distance	-0.022*	-0.021**	
	(-2.091)	*(-1.976)*	
Transit accessibility		0.560***	0.215***
		(7.684)	*(3.487)*
Average congestion speed		-0.009	
		(-1.522)	
Average free flow speed	-0.010**		
	(-2.359)		
Amtrak presence		-1.184***	-1.724***
		(-3.851)	*(-4.218)*
Number of Retail Locations	0.001***	0.004***	
	(3.618)	*(5.895)*	
Number of Recreation Locations	0.032		
	(1.521)		
Lambda	0.746	0.7391	0.561
	(40.133)	*(33.815)*	*(14.679)*
Sample size	465	420	259
R-square	0.9497	0.8427	0.8480

Note: Dependent Variable: Total Daily Bicycle Ridership; T-statistics are in parenthesis

*** Significant at 99%; ** Significant at 95%; * Significant at 90%

The difference in the model specifications at different spatial typologies is partly the result of different land use composition in urban, suburban and rural areas. Considering the extent to which the explanatory variables exerted influence on bicycle ridership in different spatial contexts, it justified our decision to examine the bicycle ridership correlates at different spatial levels.

Results of Elasticity Estimation

The model estimations developed in this paper provide an opportunity to examine the individual variables that influence bicycle ridership. The most significant variables from Model-1 were examined in this case. While the coefficients from Table 2 provide a good explanation of the magnitude of each variable that influenced bicycle ridership, elasticity is useful to examine how in a much more real-world context each variable influenced the ridership. Figure 2 provides the elasticities of bicycle ridership with respect to several key variables from the Model-1 (see Table 2 for Model-I details).

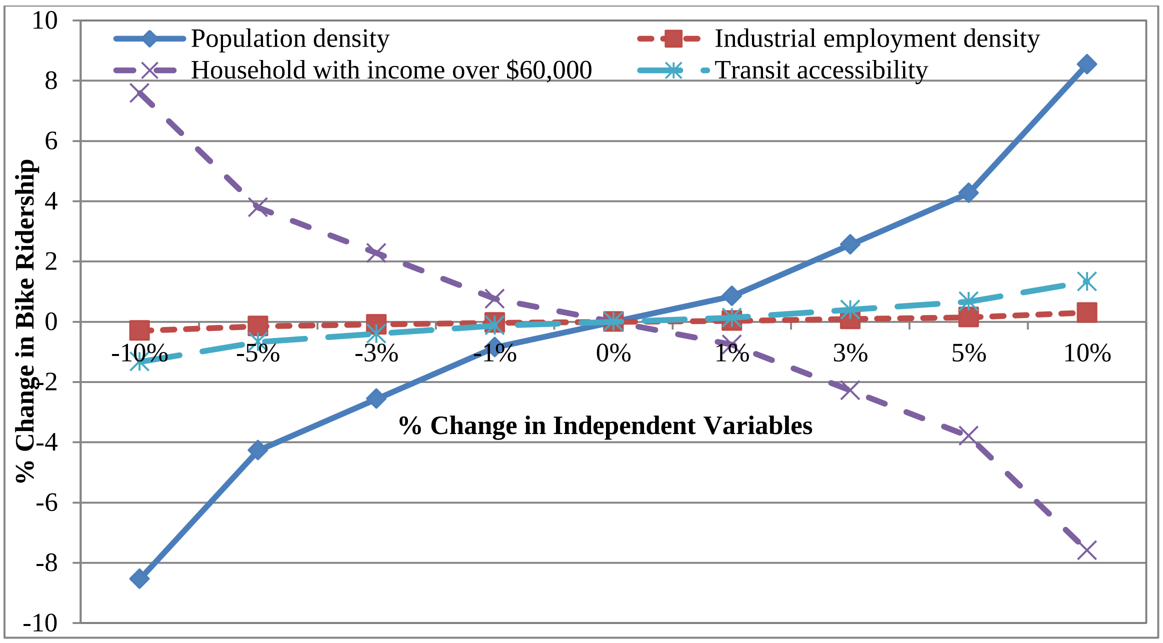

FIGURE 2 Elasticity of bike ridership to key independent variables.

The X-axis of Figure 2 represents percentage change in the independent variable and Y-axis shows the corresponding change in bicycle ridership. For example, a 1 percent change in population density will result in a .85 percent change in bike ridership. Similarly, a 5 percent increase in households with number of households with income over $60,000 will result in a 3.79 percent reduction in bicycle ridership. It appeared that bicycle ridership was very sensitive to population density and number of households with income over $60,000. While population density was positively related to bicycle ridership, it suggested higher population density increased the probability of having higher bicycle ridership; number of households with higher income was inversely related to bicycle ridership, suggesting higher income zones may tend to have lower bicycle ridership and vice versa. Similarly, industrial employment density and transit accessibility were positively related to bicycle ridership. The purpose of elasticity analysis is to enhance policy making and to estimate how bicycle ridership can be influenced by changes in other variables.

PLANNING APPLICATION

In this section, we applied one of the abovementioned empirical models to predict bicycle ridership in two future scenarios. Based on the robustness of our key explanatory variables across different model specifications and the planning objects in the State of Maryland, we found it more appropriate to use the coefficients of the statewide Model I. To be comprehensive on demonstrating the application process, we drew framework of Maryland Scenario Project (MSP), which was conducted by the National Center of Smart Growth (NCSG) at the University of Maryland College Park (refer to 30 for detailed description). Based on this policy-making context, we characterized one set of 2030 future year scenarios as Constrained Long Range Plan (CLRP) and High Energy Price (HEP). CLRP scenario represents the visionary land use and transportation growth used for decision-making of future infrastructure investment by the state DOT. Under HEP scenario, oil prices were presumed to rise at one percent above the projected inflation rate. The data of the future scenarios was developed based on 2030 household and employment projections from the Baltimore and Washington MPOs through a process called cooperative forecasting. For areas outside the MPO regions, household and employment estimates were developed based on projections from the MDP.

In order to predict the bicycle ridership in future scenarios, socioeconomic and demographic data were obtained from the process as mentioned above. Road network related variables, such as average congestion speed and free flow speed, were derived from the 2030 network developed by NCSG for the Maryland Statewide Transportation Model (MSTM). All other variables, including the land-use variables for different land-use categories, transit accessibility, and Amtrak presence were assumed to be the same as they were in 2007 (because these data were not available from public data sources). This assumption can be justified by looking at Table 2 and Table 3, where those variables showed lower magnitude of impact to determining the bicycle ridership compared to other explanatory variables.

Figure 3 shows bicycle ridership at the zonal level under two future scenarios. For 2030 CLRP, both Washington and Baltimore metropolitan areas had higher bicycle ridership referring to larger concentration of population and employment (Figure 3(a)). 2030 HEP scenario suggested that urban areas not only had higher bicycle ridership, but the distribution of bicycle ridership concentrated in the core of urban areas (Figure 3(b)). Due to the assumed higher oil prices in 2030, the 2030 HEP scenario resulted in higher bicycle ridership and most bicycle users were expected to shift to the core of urban areas in order to remain close to both households and jobs.

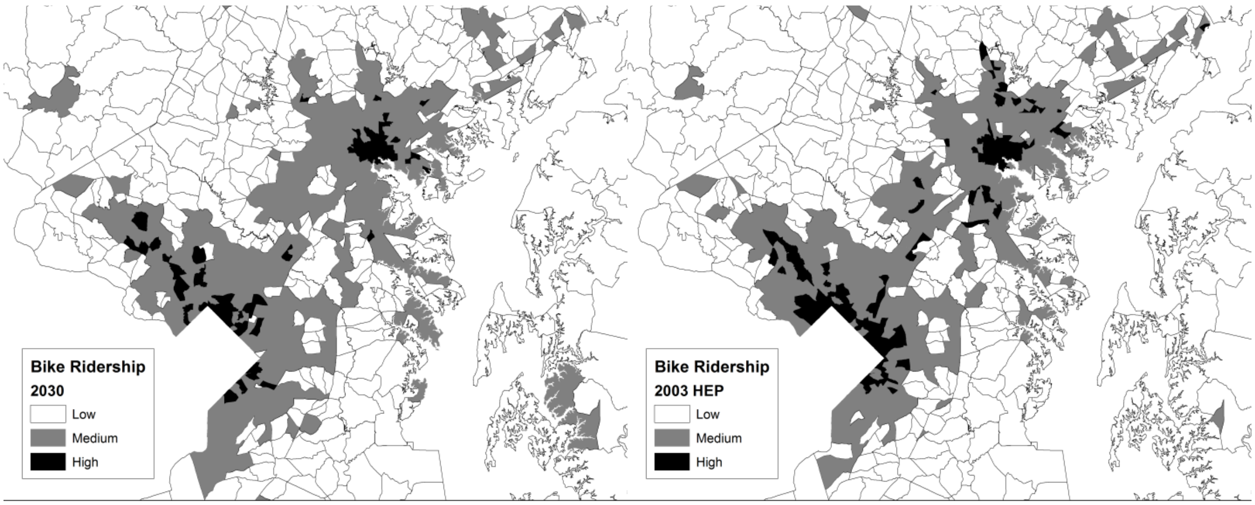

FIGURE 3(a) 2030 bicycle ridership FIGURE 3(b) 2030 HEP bicycle ridership

FIGURE 3 Bike ridership for future year scenarios.

DISCUSSION AND CONCLUSIONS

Despite significant amount of research in the literature where determinants of bicycling were examined, most of the past studies provide an incomplete picture about the impact of explanatory factors on bicycling ridership. In this paper we propose an aggregate framework and an array of models to help policy makers understand higher-level determinants to bicycle ridership generation at the state level. This study is directed toward analyzing the effects of various explanatory variables, including socio-economic and demographic characteristics, built environment attributes, land-use categories, and transport system attributes. The analysis is based on zonal data collected for the State of Maryland. The focus of the analysis is placed on the spatial dependency of bicycle ridership across zones in our study area. Contrary to the standard linear regression method used in a majority of related studies, a unique formulation of a spatial lag model was developed in this study to account for the phenomenon of spatial dependency. The impacts of the land-use, built-environment and transport system factors on the number of bicycle trips in a day was examined, controlling for a range of other explanatory factors including socio-economic and demographic attributes. The same set of explanatory factors was examined at the state level and at three spatial topology levels to provide more accurate forecasts of spatial policy intervention on bicycle use.

The result of the analysis show the urban model had the highest R-square and the rural model had the lowest R-square. The difference in the model statistics may be due to higher bicycle ridership generated in urban areas than in rural areas. The densities of household workers, zero-worker households, and retail employment were significant determinants to bicycle ridership in the statewide model but these factors lost their significance in three urban typology models. The most noteworthy findings of this study are summarized as follows.

The direction of the correlation between bicycle ridership and the demographic data as well as socio-economic factors such as population density, household density, school enrollment density, industrial employment density and other employment density are all positive. This finding is consistent with evidence from previous studies that show as the intensity of demographics and economic activity rises, so does the proportion of bicycle trips *(19, 20)*. However, the significance and strength of these correlations vary at different spatial typologies. Urban and suburban areas are sensitive to a change in population and school enrollment but not to changes in household density, which is a significant predictor of bicycle ridership in rural areas. The impacts of employment on bicycle ridership also vary by spatial topology and by employment type. This result suggests that bicycling is more attractive in densely populated neighborhoods, where limited parking space and stringent speed limits may discourage vehicle trips *(19)*.

The results of the analysis also show that the density of higher income (over $60,000 annually) households and greater levels of vehicle ownership are consistent with decreased bicycle mode shares. This piece of finding illustrates the value of the SLM approach to help decision makers evaluate the possible impact of spatial dependency of travelers' behavior at aggregate levels as a tool to develop more effective intervention policy.

In this analysis, a number of land-use variables such as the number of retail locations and the number of recreational locations had a positive influence on bicycle ridership in the urban and suburban models. This result is a positive indication consistent with the findings of other studies that if urban development provides opportunities for discretionary activities by locating retail stores and recreational centers in residential neighborhoods, it is likely to promote bicycling and improve general public health in these areas. In the context of trip making in suburban and rural areas, transit accessibility has the potential to increase bicycle trip frequency, which is also consistent with findings from past studies. Policy related to these environmental and land use elements should provide bicycling opportunities (e.g. add exclusive bicycle lanes and lower speed limit) to reach different activity destinations such as transit stops, grocery stores, and recreational centers as better access to bus stops and bus lines encourages active "bike-and-ride" travel *(25, 28)*.

The variables representing intensity of the transport system had a negative impact on bicycle ridership in urban and suburban areas, confirming the commonly held view that higher traffic speeds, busier roads and the presence of more freeway right-of-way are linked with fewer bicycle trips *(22–24)*. In suburban and rural areas, the presence of an Amtrak station is associated with lower level of bicycle ridership. This may be more an effect of the typical location of a station on non-automobile trips in non-residential locations, than the effect of the Amtrak itself.

We acknowledge that there are several limitations in this research. Our analysis was developed at the zonal (SMZ) level and did not account for behavioral characteristics and the impact of climate on bicycling. This limitation can be surmounted when additional data resources become available in the future. Research presented in this paper provides a useful tool for state agencies to begin estimating bicycle ridership generation factors and their interdependencies with several exogenous attributes.

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