Land Use Effects on Bicycle Ridership: A Framework for State Planning Agencies

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ABSTRACT

State and local agencies are more aware to provide infrastructure needs as bicycle riders are increasing over period of time. Because of the lack of planning tools, it is difficult to determine bicycle ridership estimates and the corresponding needs to provide infrastructure for bicyclists. This paper proposes a series of empirical models and applied them to the State of Maryland in the United States, using ordinary least squares and spatial lag approaches to explore land use, built environment, demographics, socio-economic, and travel behavior connections to bicycle ridership. A set of separate models are proposed for three urban typologies: urban, suburban and rural. Results show that some 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 high income have negative relationships with bicycle ridership. The model is also used for future year application under two suggested land-use scenarios. Future year results seem reasonable and follow expected trend. This proposed approach can be used as a tool to model and forecast bicycle demand, and to assist planning agencies in preparing and planning ahead for future events.

Keywords: bicycle ridership; land use; ordinary least squares; spatial lag; urban typologies

INTRODUCTION

Bicycle use is getting more popular for commuting, shopping and other trip purposes because of its higher mobility, wide range of benefits and flexibility to connect with public transportation. However, for number of cases, existing transportation infrastructure is not ready to accommodate as many bicycles as possible because there are not enough dedicated bicycle lanes. From safety standards, this creates a problem to bicyclists and discourages them to travel under unsafe conditions. Planning agencies at local and state level are paying more attention to provide infrastructure for bicyclists if there is a need. In their effort to close this gap, the use of bicycle is encouraged as an active travel mode, which has great potential to reduce vehicular congestion and lead to environmental benefits. Therefore, for planning agencies, their key task is to determine the bicycle ridership demand so that they can make decisions to provide adequate infrastructure for bicyclists. Past experiences suggest the factors that would explain bicycle ridership are closely related to socioeconomics, demographics, public policy, and built environment attributes. Previous literature also shows that income, urbanization, and vehicle ownership are important factors that are correlated to bicycle ridership.

Accordingly, transportation researchers and practitioners have attempted to identify factors that encourage and sustain higher densities of bicycle use under the influence of local land use policy. Such factors include design principles for new subdivisions, accessibility to stations, and regional urban form (*1*–*5*). Advocates of active travel mode have promoted and incorporated these ideas in urban plans and ordinances, and in bicycle siting decisions. As a result, cities with large geographic area and poor public transit service would be more likely to experience a large shift of bicycle users. Despite the literature focusing on the bicycle phenomenon in the U.S., there is little research that quantitatively examined the emerging trend in greater detail from a transportation perspective. With the urgent need to facilitate the understanding of determinants to bicycle ridership generation, further research needs to be conducted on why and how different factors, including socioeconomics, demographics and built environment attributes, would impact the travel decisions on bicycle use at both household and state levels. These decisions have profound influence towards planning agencies on how to provide adequate infrastructure needs to bicycle users.

The land use measures employed in travel behavior studies originated from the concept of “three Ds” (density, diversity and design) and was followed by accessibility, distance to transit, demand management and even demographics (*6*). Neighborhood type, which represents the interaction of multiple built environment dimensions, has also attracted growing interests in transportation studies (*7*). Over the past two decades, there was increasing volume of literature trying to evaluate preferences and choices of owning a bicycle. To date, there is limited literature that could provide policy implications to planning agencies so as to determine the demand of bicycle use, identify contributing variables of bicycle ridership, and plan ahead for future events.

In this paper, we proposed a framework using bicycle ridership as the key measure. We examined how different outcomes in different futures may present the state agency with specific planning choices. We chose the State of Maryland in the United States as our study area. Using a number of criteria, we subdivided the state into 1151 statewide modeling zones (SMZs). In base year (2007), we estimated effects of a range of explanatory variables at state level, including developed land under different uses, population and employment densities, developed land densities by industry category, auto ownership, household income density, workers per household, free flow speed and congested speed of existing transportation infrastructure, current transport capacities, and accessibility to different transport modes. In spite of developing the statewide models, we also estimated a set of econometric models for urban, suburban and rural typologies. We found that characteristics of land uses, transit accessibility, household income, and density variables were strongly significant and robust predictors of bicycle ridership for the statewide and urban areas datasets.

The 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; and in the next two sections, we present findings of this analysis and apply our model to develop scenarios for the horizon year and discuss implication for planning decisions at state level, respectively. We offer concluding remarks in the final section followed by caveats and scope of future research.

LITERATURE REVIEW

Regular physical activity is believed to increase physical fitness and help lower the risk for chronic conditions such as obesity, high blood pressure, and diabetes (*8–10*). Organized sports, free play, leisure time exercise, strength training, and active travel modes, such as walking and bicycling, are the typical types of physical activity (*11*). Meanwhile, it has been largely recognized by the transportation scholars that, walking and bicycling are environmental friendly transport modes which do not produce carbon emissions, congestion and traffic noise (*12*, *13*).

With its far-reaching impacts on environmental and health, active travel mode has been examined by a substantial amount of literature (see *1* and *14* for detailed reviews of those studies). Generally, most disaggregated and controlled studies showed that trip generation rates of non-motorized travel mainly depended on household vehicle ownership, employment status of household members, and education level of household members (*15–18*). Particularly, the influence of household income on active travel demand is confounding. While some researchers indicated that, higher income was found to be correlated with lower demand of active travel (*16*, *17*, *19*, *20*), there were contradictory results showing that higher income had positive influence on walking or bicycling trips (*21*).

Likewise, studies that focused on non-motorized travel behavior presented that mode choices depended as much on built environment attributes as on socioeconomic and demographics characteristics. Using household survey data on 11 Metropolitan Statistical Areas, Cervero (*22*) examined how mixed land-use patterns influenced non-automobile commuting, giving special attention to retail activities in neighborhoods. Having controlled built environment attributes and household characteristics, Cervero concluded that, non-automobile commuting was positively related to neighborhood densities and the presence of neighborhood shops was found to be a better predictor of commuting by bicycle or walking than residential density. Targa and Clifton (*21*) applied 2001 National Household Travel Survey add-on for the Baltimore metropolitan region to estimate the person-level walking trips. Finding from their study showed that, neighborhood with higher densities, better access to bus transit lines, better street connectivity, and mixed land-uses were associated with number of trips made by active travel mode. Consistently, Guo et al. (*19*) and Sehatzaden et al. (*17*) pointed out in their studies that higher population density was related to lower active travel frequency and higher retail employment density had a positive association with it. One common finding that can be derived from those studies is that neighborhood built environment has considerable impact on people's choices of active travel mode.

Moreover, some studies suggested the need to take closer look to land-use patterns and incorporate particular land-use categories in order to understand the determinants to different active travel mode choices (*16, 20, 23, 24*). Those studies consistently revealed that, when land-use diversity increased, especially for the intensities of transit station, grocery stores, and retail stores in neighborhoods, people tended to rely on non-motorized modes more frequently. Transportation scholars argued that the road traffic characteristics also had great impact on people's choices of travel modes. Traffic volume, highway density, congested time, and traffic speed were shown to have negative effects on non-motorized travel frequency (*17, 25, 26*).

Overall, most of existing research has focused on examining the non-motorized travel patterns at household or individual level, controlling the effects of traveler's characteristics, household attributes, neighborhood built environment attributes, and land use patterns. However, there is geographic limitation in existing disaggregated studies as they did not encompass their studies area at state level. Those studies also failed to account for spatial typologies (i.e. urban, suburban, and rural) in their analysis. With the need to understand statewide active travel patterns, we developed a series of empirical models for the State of Maryland to examine the predictors of bicycle ridership, considering different spatial typologies, land-uses attributes, built environment attributes, socioeconomic, demographics, and road traffic characteristics. This approach would allow us to generate bicycle ridership under different policy scenarios in future year, which would further help policy makers and city planners to effectively promote active bicycle travel at state 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 agencies. Basically, the State of Maryland consists of 23 counties and one independent city. Its total population was 5.8 million and total employment was 3.4 million in 2010 (*27*). There were seventeen types of public transportation systems identified, such as metro rail, commuter rail, local bus and long distance buses. To develop our dataset, we subdivided the state into 1,151 Statewide Modeling Zones (SMZs). The main criteria for SMZ delineation was to conforming 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). The development of SMZs also delineated areas with good accessibility to Metro stations and distinguished rural from urban/suburban development and zoning boundaries as much as possible. This SMZ development went through several iterations and reviews with the State Highway Administration (SHA) as part of a larger modeling project.

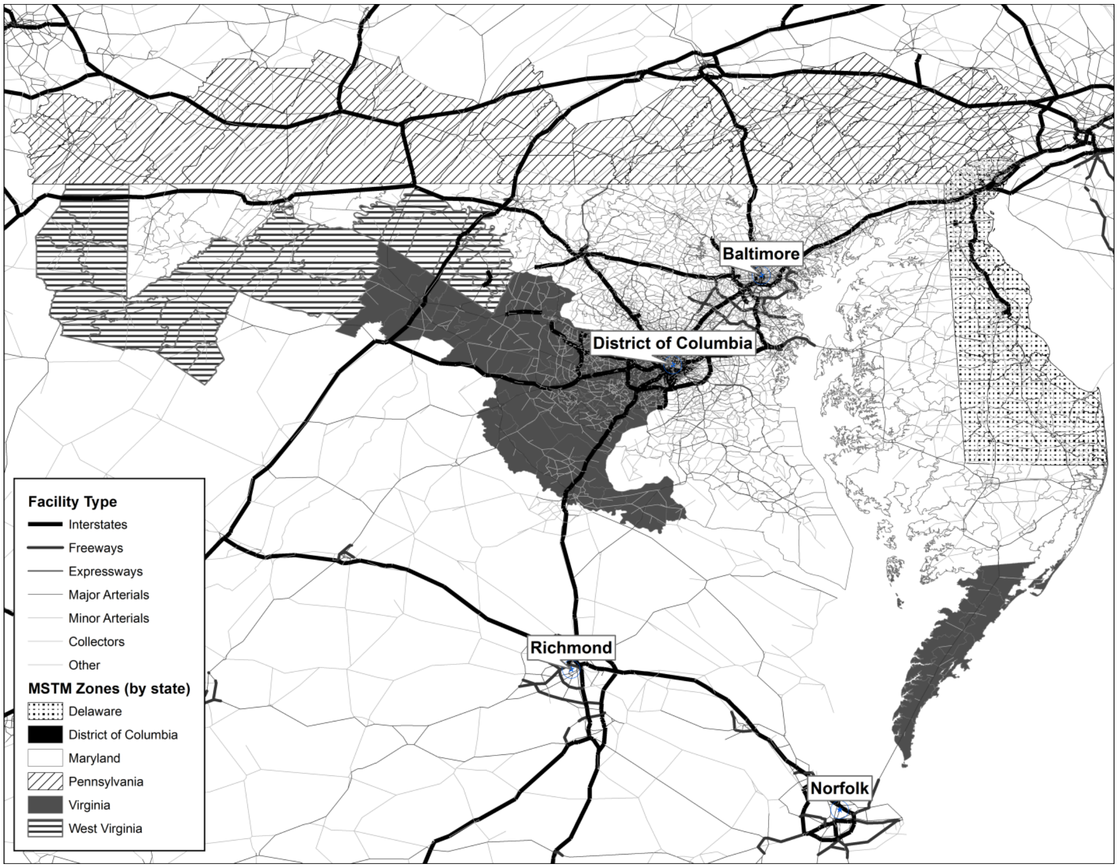

FIGURE 1 Regions used to develop statewide modeling zones (source: Maryland Statewide Transportation Model, State Highway Administration).

For MPO regions in the Maryland and Washington metropolitan area, their socio-economic data were collected from the cooperative forecast datasets that belonged to Baltimore Metropolitan Council (BMC) and Metropolitan Washington Council of Governments (MWCOG). For non-MPO covered areas, their socio-economic data were collected from Quarterly Census Employment and Wages (QCEW, formerly known as ES202), which was prepared by the Department of Labor, Licensing and Regulations (DLLR). The MPO and QCEW data were then aggregated to determine the employment by categories, such as retail, office, industrial, and other. Household income data was collected from MPO datasets and U.S. Census datasets for both MPO and non-MPO regions. We also developed a number of land use and network characteristics from a variety of datasets as well as through the GIS analysis. Transportation network was developed from Census TIGER files. Particularly, the Maryland Department of Transportation (MDOT) datasets were used to determine the total freeway distance, average free flow speed, average congested speed, and presence of bus stop. Additionally, the Maryland Department of Planning's (MDP) Property View dataset was used to determine specific land uses, including health care, housing, shopping, industry, office, recreation, dining, warehouse, and other commercial establishments. The descriptive statistics for key variables discussed in the empirical analysis section are presented in Table 1.

In this study the bicycle ridership model developed was restricted to the SMZs within Maryland for year 2007. The rational of using 2007 as base year was that all the input variables collected from different agencies in the State of Maryland were only consistent for this specific year. The socioeconomic data were classified by densities and were further classified by the number of workers, household size, and household income. To account for variations in relationship between land use patterns and ridership across the state, we used a combination of household and employment densities to classify SMZs under three spatial typologies – Urban, Suburban, and Rural. Details of the spatial classification can be found in the literature (*7*). The dependent variable was bicycle ridership and it was the ridership data provided by local MPOs and SHA. We also developed two land use scenarios for future year 2030 and they were constrained long range plan (2030-CLRP) and 2030 high energy price (2030-HEP).

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
Retail count	32.3400	102.1310	0	950
Dinning count	2.1000	8.4550	0	103
Healthcare count	0.2800	0.7810	0	8
Housing count	4.5200	20.1120	0	267
Office count	3.3800	13.3760	0	157
Recreation count	0.4500	1.2620	0	13
Shopping count	8.4500	35.7500	0	462
Warehouse count	1.0800	4.4600	0	59
Transportation count	0.0100	0.1020	0	2

Note: Unit of density variables was per acre.

There were two methodological approaches applied in this study. The first step was to specify and estimate a linear regression model by means of the ordinary least squares (OLS) for entire state. OLS is a simple but validate modeling approach that would assist us in scenario analysis and model application as presented later in this paper. R square value adjusted for the number of parameters (Adjusted R-square) was used as scalar measures of fit for the OLS models. The second step was to estimate the relationship between explanatory variables and bicycle ridership using a spatial regression model – spatial lag model (SLM). The SLM is a modeling technique that has been applied when high likelihood of spatial autocorrelation exists and when there are variations of a specific variable across space. The rationale of the spatial regression method was discussed by Anselin et al (*28*). Estimation of the spatial regression models is supported by means of the maximum likelihood (ML) method (*29*). Specifically, the SLM includes a contiguity weight factor (Lambda) that accounts for the effects due to the characteristics of surrounding SMZs. These two methods (OLS and SLM) were then repeated on a dataset which consisted of SMZs for three different urban typologies.

EMPIRICAL RESULTS

The OLS model was estimated for entire state and three urban typologies, respectively. The estimated coefficient, *t* statistics, statistical significant test, R-square, adjusted R-square for OLS, and spatial weight matrix (Lambda) for SLM were reported. Alternative model specifications were estimated in order to control as many socioeconomic characteristics, land-use patterns, built environment attributes, and traffic characteristics variables as possible. Appropriate measures were considered to avoid multicollinearities among those variables for both OLS and SLM.

Table 2 presents the OLS and SLM estimated results for four model specifications with proposed explanatory variables. Overall, the results were intuitive and robust across all model specifications. At state level, bicycle ridership increased with household, population, household workers, zero-worker household, and school enrollment densities and the ridership was higher in lower income and lower car ownership households. A variety of employment types impacted bicycle ridership differently. Industrial employment and other employment densities had negative effects on bicycle ridership while retail employment had positive effect on it. The 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, Amtrak presence was negatively associated with bicycle ridership since the Amtrak stations were not usually built very closely to residential areas. Transit accessibility was found to be positively associated with bicycle ridership, implying the multi-modal non-automobile trips in the state.

The effects of a number of land-use categories (i.e. number of retail, dinning, office, recreation, and shopping), were also found to be significantly related to statewide bicycle ridership and the results were consistent with our expectations. Particularly, bicycle ridership increased where there was more retail, office, or recreation centers but it declined when number of shopping or dining centers increased. These results reflected the facts that shopping centers and dining restaurants were usually concentrated in non-residential areas, where could not be conveniently reached by bicycle. On the contrary, the retail stores and recreational centers could possibly be concentrated around residential areas in order to attract more customers and the relatively shorter travel distance would encourage people to travel on bicycle more frequently.

The SLMs estimated on statewide dataset showed similar results for most of the variables compared to the OLS models. Some of the OLS estimated coefficients became statistically insignificant in the SLMs, and the weight matrix variable (Lambda) was strongly significant in all four models. These results indicated that the spatial interactions and bicycle ridership interdependencies should not be neglected. The goodness-of-fit results of SLMs appeared to outweigh OLS models for each model specification analyzed at state level.

TABLE 2 Regression Results for Bicycle Ridership Model at State Level

Explanatory variables	Ordinary Least Squares				Spatial Lag Model			
	Model-I	Model-IA	Model-IB	Model-IC	Model-II	Model-IIA	Model-IIB	Model-IIC
Constant	1.426***	1.805***	2.187***	1.858***	-0.031	0.031	0.096	0.027
	(8.922)	*(11.768)*	*(13.819)*	*(11.093)*	*(-0.440)*	*(0.461)*	*(1.473)*	*(0.401)*
Population density	0.175***				0.033***			
	(14.293)				*(6.104)*			
Household density		0.358***				0.056***		
		(15.328)				*(5.420)*		
Household workers density				0.226***				0.048***
				(16.478)				*(8.471)*
Household with zero workers density	0.115*		0.563***		-0.006		0.091***	
	(2.051)		*(16.098)*		*(-0.259)*		*(6.220)*	
Industrial employment density	0.095**	0.184***	0.166***		0.027**	0.007	0.010	0.007
	(3.218)	*(4.717)*	*(4.440)*		*(2.135)*	*(0.449)*	*(0.696)*	*(0.659)*
Retail employment density		-0.058***	-0.055***			0.013*	0.011	
		(-3.643)	*(-3.347)*			*(1.863)*	*(1.609)*	
Other employment density	0.031***	0.018**			0.004	0.003		
	(4.846)	*(2.928)*			*(1.387)*	*(1.185)*		
School enrollment density	0.159***	0.188***	0.200***	0.207***	0.036***	0.040***	0.039***	0.042***
	(8.470)	*(9.961)*	*(10.079)*	*(10.344)*	*(4.446)*	*(4.889)*	*(4.916)*	*(5.253)*
Household with income over $60,000	-0.175**	-0.200***	-0.064*	-0.191***	0.000	0.003	0.026***	-0.002
	(-6.710)	*(-7.609)*	*(-2.409)*	*(-6.730)*	*(0.042)*	*(0.258)*	*(2.471)*	*(-0.141)*
Drive alone density	-1.427***	-1.443***			-0.149*	-0.098		
	(-7.633)	*(-7.151)*			*(-1.835)*	*(-1.131)*		
Households without cars		0.469***				0.051		
		(4.923)				*(1.266)*		
Average freeway distance		-0.048***	-0.055***			-0.005	-0.004	
		(-3.909)	*(-4.348)*			*(-0.955)*	*(-0.852)*	
Transit accessibility	0.454***	0.479***	0.602***	0.522***	0.099***	0.110***	0.112***	0.101***
	(8.087)	*(8.453)*	*(10.167)*	*(8.773)*	*(3.964)*	*(4.373)*	*(4.506)*	*(4.083)*
Average congestion speed		-0.036***				0.000		
		(-7.220)				*(-0.084)*		
Average free flow speed	-0.024***		-0.043***	-0.035***	0.001		-0.002	-0.0004
	(-5.462)		*(-9.585)*	*(-7.499)*	*(0.637)*		*(-1.308)*	*(-0.224)*
Amtrak presence	-0.889***	-1.007***	-1.315	-0.899***	-0.307***	-0.226***	-0.328***	-0.205***
	(-3.551)	*(-3.987)*	*(-4.896)*	*(-3.381)*	*(-2.869)*	*(-2.108)*	*(-3.060)*	*(-1.941)*
Number of Retail Locations	0.004***	0.004***	0.004***	0.007***	0.001***	0.001***	0.001***	0.001***

	(9.199)	*(9.335)*	*(10.653)*	*(16.758)*	*(2.775)*	*(3.559)*	*(3.171)*	*(4.479)*
Number of Dinning Locations		-0.018***				-0.004***		
		(-3.805)				*(-1.902)*		
Number of Office Locations	0.006***		0.005**		0.004***		0.003***	
	(3.365)		*(2.648)*		*(4.705)*		*(4.172)*	
Number of Recreation Locations	0.063**				0.011			
	(2.577)				*(1.042)*			
Number of Shopping Locations	-0.005***			-0.004***	-0.001			-0.00002
	(-3.968)			*(-3.622)*	*(-0.911)*			*(-0.038)*
Lambda					0.852	0.861	0.874	0.868
					(74.418)	*(76.454)*	*(82.041)*	*(78.252)*
Sample size	1144	1144	1144	1144	1144	1144	1144	1144
R-square	0.7753	0.7692	0.7389	0.7353	0.9589	0.9583	0.9584	0.9582
Adjusted R-square	0.7727	0.7663	0.7364	0.7332				

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

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

Table 3 presents OLS and SLM results at typology level for urban, suburban and rural areas, respectively. The directionality and magnitudes were consistent with models estimated on statewide dataset. Several highlights can be derived from the results. First, the constant was positive and significant for all the OLS and spatial lag models. The magnitude of the constant decreased from models for urban area to models for rural areas, implying that the overall bicycle ridership difference between urban to rural areas was smaller. Secondly, there tended to have more bicycle ridership where employment density was higher or in lower income households across all models.

Additionally, there were some noticeable differences across the models at typology level. First, in urban and suburban areas, population density, school enrollment density, and number of retail centers were positively related to bicycle ridership while average freeway miles was negatively correlated with it. However, those relationships became insignificant in rural area. Secondly, while transit accessibility (positive association) and Amtrak presence (negative association) were significant predictors to bicycle ridership in suburban and rural areas but their relationships were not significant in urban area. Thirdly, several relationships between explanatory variables and bicycle ridership were only significant in certain typology model. In urban area, bicycle ridership was higher where average free flow speed decreased, number of shopping centers was lower, or number of recreational centers was greater. In suburban area, number of dining restaurants and average congestion speed were negatively related to bicycle ridership while number of health centers and number of office centers were positively correlated with it. Fourthly, it is worth noting that, number of households without cars had positive impact on bicycle ridership in urban area but this association became negative in suburban area. This spatial disparity implied that it was necessary to estimate the dataset at spatial typology level, considering the different influence that explanatory variables would have on bicycle ridership in different areas.

Generally, urban typology model had the highest R-square while rural typology model had the lowest R-square. It may be due to the higher bicycle ridership generated in urban areas than that in rural areas. Comparing the models estimated at state level and typology level, several differences can be perceived. First, in typology models, population density and school enrollment showed smaller magnitude while household density, transit accessibility, Amtrak presence, and health count showed greater magnitude. Secondly, household workers, zero-worker household, and retail employment densities were stronger determinants to bicycle ridership in statewide model but they lost their significance in typology models. Their relationships with the bicycle ridership may not be clear due to the relative similarity of land-use patterns in urban area, which led to lower variance among the explanatory variables in urban SMZs. Thirdly, the magnitude of the land-use effects was relatively smaller than other explanatory variables at both state level and typology level.

Specifically, there was an interesting finding that, number of healthcare centers was found to be positively related to bicycle ridership in suburban area. It indicated higher equality in healthcare service to those who did not own automobile and mainly relied on bicycles. Generally, land-use variables were mainly significant in urban and suburban areas, but not in rural area. This is understandable since the commercial land uses were generally planned where people resided.

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

Explanatory variables	Ordinary Least Squares			Spatial Lag Model		
	Model-III (Urban)	Model-III (Sub-Urban)	Model-III (Rural)	Model-IV (Urban)	Model-IV (Sub-Urban)	Model-IV (Rural)
Constant	1.730***	1.218***	0.521***	0.522***	0.602***	0.197***
	(6.234)	*(5.060)*	*(8.741)*	*(3.437)*	*(3.077)*	*(3.848)*
Population density	0.160***	0.110***		0.052***	0.063***	
	(9.557)	*(8.621)*		*(5.571)*	*(6.017)*	
Household density			0.676***			0.392***
			(14.531)			*(10.396)*
Industrial employment density	0.095*		0.251***	0.056***		0.154***
	(2.311)		*(3.722)*	*(2.596)*		*(3.118)*
Other employment density	0.020*	0.028*	0.096***	0.005	0.022**	0.054***
	(2.176)	*(2.273)*	*(4.348)*	*(1.020)*	*(2.285)*	*(3.332)*
School enrollment density	0.180***	0.143***		0.061***	0.132***	
	(5.798)	*(5.276)*		*(3.637)*	*(6.179)*	
Household with income over $60,000	-0.194***	-0.150***	-0.169***	-0.025	-0.079**	-0.088***
	(-4.638)	*(-3.149)*	*(-4.472)*	*(-1.086)*	*(-2.084)*	*(-3.099)*
Drive alone density	-1.168***		-2.658***	-0.202		-1.800***
	(-4.014)		*(-7.776)*	*(-1.292)*		*(-7.101)*
Households without cars	0.323*	-0.317*		0.002	-0.066	
	(2.435)	*(-1.941)*		*(0.025)*	*(-0.511)*	
Average freeway distance	-0.094**	-0.037**		-0.030*	-0.021**	
	(-2.800)	*(-2.845)*		*(-1.658)*	*(-1.976)*	
Transit accessibility		0.993***	0.582***		0.560***	0.215***
		(11.625)	*(7.605)*		*(7.684)*	*(3.487)*
Average congestion speed		-0.020**			-0.009	
		(-2.629)			*(-1.522)*	
Average free flow speed	-0.029***			-0.010**		
	(-3.621)			*(-2.359)*		
Amtrak presence		-1.683***	-2.181***		-1.184***	-1.724***
		(-4.341)	*(-3.892)*		*(-3.851)*	*(-4.218)*
Number of Retail Locations	0.004***	0.006***		0.001***	0.004***	
	(7.689)	*(7.186)*		*(3.618)*	*(5.895)*	
Number of Dinning Locations		-0.035***			-0.014**	
		(-3.939)			*(-2.028)*	
Number of Health Care Locations		0.108*			0.118***	

		(1.906)			*(2.629)*	
Number of Office Locations		0.010**			0.006*	
		(2.477)			*(1.804)*	
Number of Recreation Locations	0.104**			0.032		
	(2.640)			*(1.521)*		
Number of Shopping Locations	-0.004*			-0.001		
	(-2.413)			*(-1.497)*		
Lambda				0.701	0.421	0.561
				(31.138)	*(14.930)*	*(14.679)*
Sample size	465	421	259	465	421	259
R-square	0.8280	0.7570	0.7212	0.9504	0.8427	0.8480
Adjusted R-square	0.8230	0.7490	0.7134			

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

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

PLANNING APPLICATION

Ridership Scenarios

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 OLS 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. Specifically, three main parameters were taken into consideration in HEP scenario, and they were increase in federal defense spending, increase in employment in professional service, and increase in agriculture commodity price. The rationale on this parameter-selection was that, without changing major government policy, to identify the clustered urban development, reduced development on green infrastructure, and fewer vehicle miles travelled (VMT).

The CLRP scenario 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 Maryland Department of Planning. The CLRP scenario represented the allocation of jobs and households that most closely reflected official forecasts adopted by state, regional, and local governments. The HEP scenario was created to explore the effects of high energy prices on development patterns and travel behavior. This scenario derived population and employment from national forecasts of economic activity provided by the Inforum Longterm Interindustry Forecasting Tool (LIFT) model. The outcomes of this model influenced the regional and local demographic change and determined household and employment distributions in the SMZs (refer to *31*for detailed description).

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. However, when these data become available in the future, this assumption can be relaxed and predicted values can be used in the model.

Figure 2 shows bicycle ridership at the SMZ 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 2(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 2(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.

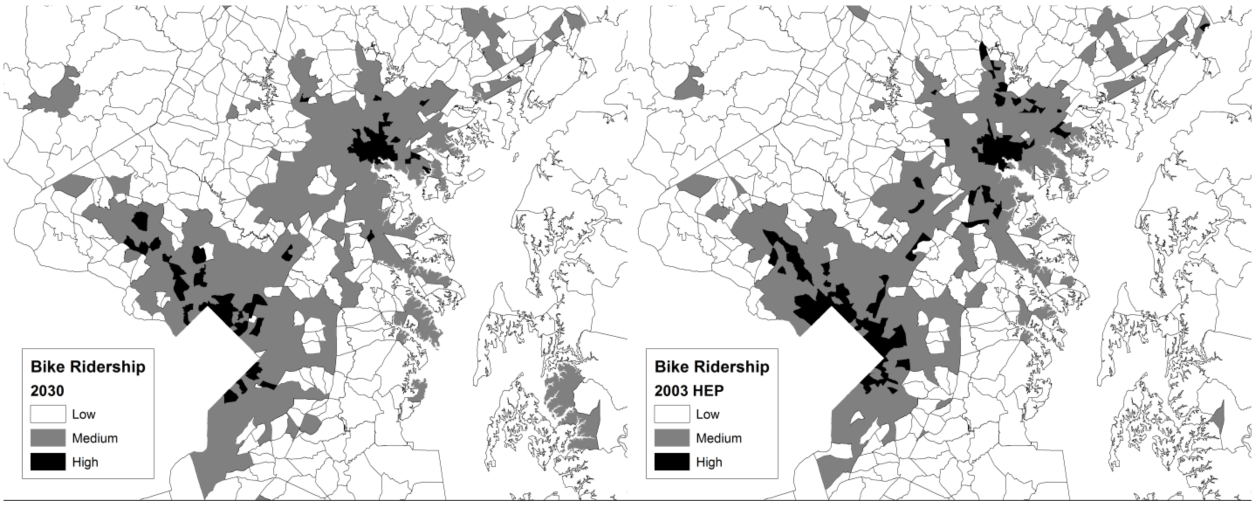

FIGURE 2(a) 2030 bicycle ridership FIGURE 2(b) 2030 HEP bicycle ridership

FIGURE 2 Bike ridership for future year scenarios.

Elasticity Estimation

The model estimations developed in this paper provides 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 3 provides the elasticities of bicycle ridership with respect to several key variables from the Model-1 (see Table 2 for Model-I details).

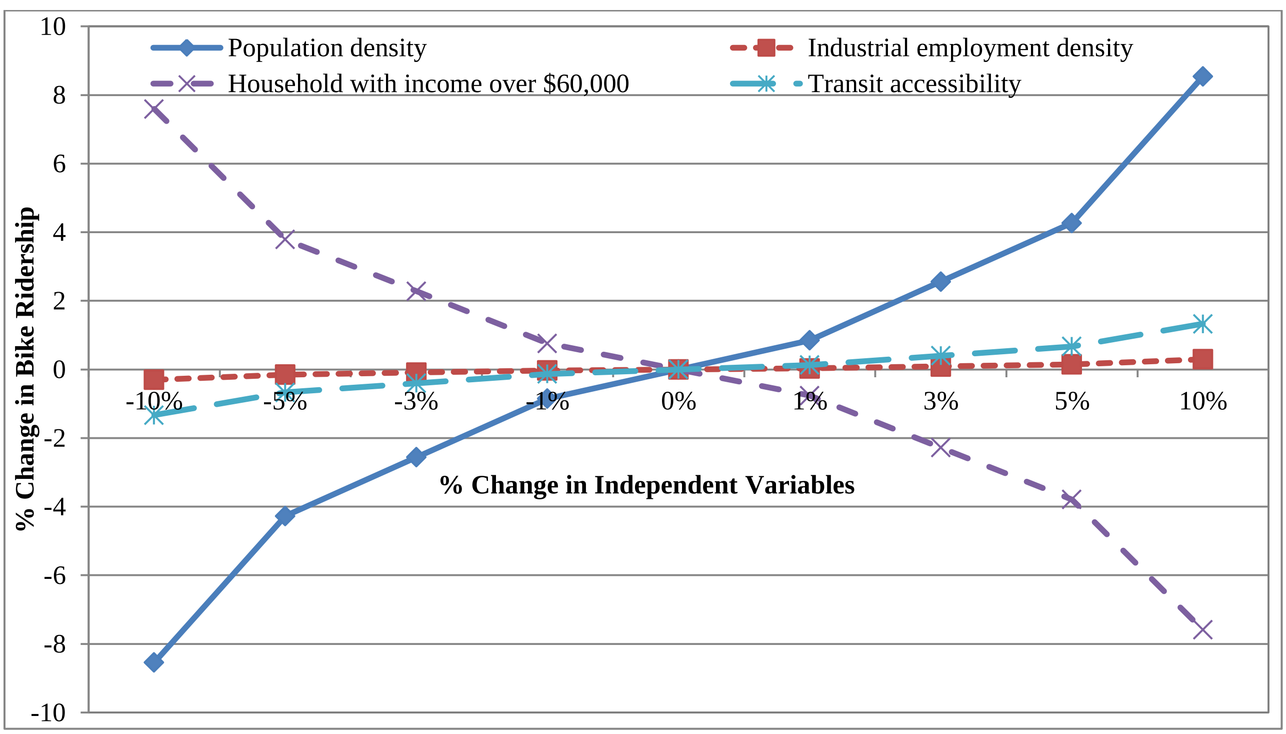

FIGURE 3 Elasticity of bike ridership to key independent variables.

X-axis of Figure 3 represents percentage change in 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.

CONCLUSIONS

In this paper we proposed a framework and set of models to help policy makers understand higher level determinants to generating bicycle ridership in the State of Maryland. We developed a number of OLS and SLM models in order to control several sets of exogenous variables, including socioeconomic and demographics characteristics, built environment attributes, land-use categories, and road traffic variables. Irrespective of the statewide and typological differences, the results were consistent with our expectation. Overall, our analysis showed that, (1) the land use and built environment attributes are strong predictors of bicycle ridership at state level; (2) different employment types predicted bicycle ridership differently. Urban and suburban areas with more retail and recreation centers tended to produce more bicycle trips than their counterparts; (3) road traffic related variables significantly predicted bicycle ridership, which implied potential impact of infrastructure investment on active travel mode; (4) the magnitude and significance of explanatory variables varied by subarea typologies, suggesting the need to present prospective policy-making within a finer spatial framework; (5) the differences of relationships between explanatory variables and bicycle ridership estimated by OLS and SLM confirmed the existence of spatial interdependency among the SMZs, as we expected.

For model application we used two future year scenarios – 2030 constrained long range plan and 2030 high energy prices. The primary purpose of model application was to demonstrate how such analysis could lead to multiple choices that planning agency can possible consider when making future plans. Multiple scenarios showed how bicycle ridership could vary by parts of the state and demonstrated the model's value in assessing interdependencies of land use planning decisions and bicycle ridership. State agencies can use such planning tool to predict bicycle ridership and adjust roadway investments to encourage active travel model.

We acknowledge that there are several limitations in this research. Our analysis was developed at the SMZ level only and did not take individual characteristics into account. This limitation can be avoided when additional data resources become available in the future. Model application shown in the paper was to justify the model estimation process for prediction purposes but not recommended for the use of policy making. With more available land use and transportation data, realistic model application can be developed in order to reflect policy scenarios. However, research presented in this paper already provided a useful tool for state agencies to analyze hypothesis on bicycle ridership generation and its interdependencies with several exogenous attributes.

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REFERENCES

1. Ewing, R., and R. Cervero. Travel and the Built Environment: A Synthesis. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1780, No. -1, 2001, pp. 87-114.

2. Krizek, K. J. Residential Relocation and Changes in Urban Travel: Does Neighborhood-Scale Urban Form Matter? Journal of the American Planning Association, Vol. 69, No. 3, 2003, pp. 265-281.

3. Meijers, E., J. Hoekstra, M. Leijten, E. Louw, and M. Spaans. Connecting the Periphery: Distributive Effects of New Infrastructure. Journal of Transport Geography, Vol. 22, No. 0, 2012, pp. 187-198.

4. Miller, E. J., D. S. Krieger, and J. D. Hunt. Integrated Urban Models for Simulation of Transit and Land use Policies: Guidelines for Implementation and use. Transportation Research Board, 1999.

5. Heath, G. W., R. C. Brownson, J. Kruger, R. Miles, K. E. Powell, and L. T. Ramsey. The Effectiveness of Urban Design and Land use and Transport Policies and Practices to Increase Physical Activity: A Systematic Review. Journal of Physical Activity & Health, Vol. 3, 2006, pp. S55.

6. Cervero, R., and K. Kockelman. Travel Demand and the 3Ds: Density, Diversity, and Design. Transportation Research Part D: Transport and Environment, Vol. 2, No. 3, 1997, pp. 199-219.

7. Mishra, S., T. Welch, and A. Chakraborty. An Experiment in Mega-Regional Road Pricing using Advanced Commuter Behavior Analysis (Forthcoming). Journal of Urban Planning and Development, 2013.

8. United States. Public Health Service. Office of the Surgeon General, National Center for Chronic Disease Prevention, Health Promotion (US), President's Council on Physical Fitness, and Sports (US). Physical Activity and Health: A Report of the Surgeon. Jones & Bartlett Learning, 1996.

9. Fletcher, G. F., G. Balady, S. N. Blair, J. Blumenthal, C. Caspersen, B. Chaitman, S. Epstein, E. S. Sivarajan Froelicher, V. F. Froelicher, I. L. Pina, and M. L. Pollock. Statement on Exercise: Benefits and Recommendations for Physical Activity Programs for all Americans. A Statement for Health Professionals by the Committee on Exercise and Cardiac Rehabilitation of the Council on Clinical Cardiology, American Heart Association. Circulation, Vol. 94, No. 4, 1996, pp. 857-862.

10. Bassett, D. R.,Jr, J. Pucher, R. Buehler, D. L. Thompson, and S. E. Crouter. Walking, Cycling, and Obesity Rates in Europe, North America, and Australia. Journal of Physical Activity & Health, Vol. 5, No. 6, 2008, pp. 795-814.

11. Caspersen, C. J., K. E. Powell, and G. M. Christenson. Physical Activity, Exercise, and Physical Fitness: Definitions and Distinctions for Health-Related Research. Public Health Reports (Washington, D.C.: 1974), Vol. 100, No. 2, 1985, pp. 126-131.

12. Koplan JP, D.,W.H. Caloric Imbalance and Publichealth Policy. The Journal of American Medical Association, Vol. 282, No. 16, 1999, pp. 1579-1581.

13. USDOT. The National Walking and Bicycling Study: 15-Year Status Report. U.S.Department of Transportation, Federal Highway Administration, Washington, DC, 2010.

14. Badoe, D. A., and E. J. Miller. Transportation–land-use Interaction: Empirical Findings in North America, and their Implications for Modeling. Transportation Research Part D: Transport and Environment, Vol. 5, No. 4, 2000, pp. 235-263.

15. Ferdous, N., R. M. Pendyala, C. R. Bhat, and K. C. Konduri. Modeling the Influence of Family, Social Context, and Spatial Proximity on use of Nonmotorized Transport Mode. Transportation Research Record, No. 2230, 2011, pp. 111-120.

16. Handy, S., and K. Clifton. Local Shopping as a Strategy for Reducing Automobile Travel. Transportation, Vol. 28, No. 4, 2001, pp. 317-346.

17. Sehatzadeh, B., R. B. Noland, and M. D. Weiner. Walking Frequency, Cars, Dogs, and the Built Environment. Transportation Research Part A: Policy and Practice, Vol. 45, No. 8, 2011, pp. 741-754.

18. Rodríguez, D. A., and J. Joo. The Relationship between Non-Motorized Mode Choice and the Local Physical Environment. Transportation Research Part D: Transport and Environment, Vol. 9, No. 2, 2004, pp. 151-173.

19. Guo, J. Y., C. R. Bhat, and R. B. Copperman. Effect of the Built Environment on Motorized and Nonmotorized Trip Making: Substitutive, Complementary, Or Synergistic? Transportation Research Record, No. 2010, 2007, pp. 1-11.

20. Ortúzar, J. d. D., A. Iacobelli, and C. Valeze. Estimating Demand for a Cycle-Way Network. Transportation Research Part A: Policy and Practice, Vol. 34, No. 5, 2000, pp. 353-373.

21. Targa, F., and K. Clifton. Built Environment and Nonmotorized Travel: Evidence from Baltimore City using the NHTS. Journal of Transportation and Statistics, Vol. 8, No. 3, 2005, pp. 55-70.

22. Cervero, R. Mixed Land-Uses and Commuting: Evidence from the American Housing Survey. Transportation Research Part A: Policy and Practice, Vol. 30, No. 5, 1996, pp. 361-377.

23. McConville, M. E., D. A. Rodríguez, K. Clifton, G. Cho, and S. Fleischhacker. Disaggregate Land Uses and Walking. American Journal of Preventive Medicine, Vol. 40, No. 1, 2011, pp. 25-32.

24. Giles-Corti, B., and R. J. Donovan. Relative Influences of Individual, Social Environmental, and Physical Environmental Correlates of Walking. Am J Public Health, Vol. 93, No. 9, 2003, pp. 1583-1589.

25. Hunt, J. D., and J. E. Abraham. Influences on Bicycle use. Transportation, Vol. 34, No. 4, 2007, pp. 453-470.

26. Antonakos, C. L. Environmental and Travel Preferences of Cyclists. University of Michigan., 1993.

27. DeNavas-Walt, C., B. D. Proctor, and J. C. Smith. US Census Bureau, Current Population Reports, P60-238. Income, Poverty, and Health Insurance Coverage in the United States: 2009, 2010.

28. Anselin, L., I. Syabri, and Y. Kho. GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis, Vol. 38, No. 1, 2006, pp. 5-22.

29. Anselin, L., and A. K. Bera. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. Statistics Textbooks and Monographs, Vol. 155, 1998, pp. 237-290.

30. Chakraborty, A., N. Kaza, G. Knaap, and B. Deal. Robust Plans and Contingent Plans: Scenario Planning for an Uncertain World. Journal of the American Planning Association, Vol. 77, No. 3, 2011, pp. 251-266.

31. Mishra, S., X. Ye, F. Ducca, and G. Knaap. A Functional Integrated Land use-Transportation Model for Analyzing Transportation Impacts in the Maryland-Washington, DC Region. Sustainability: Science, Practice, & Policy, Vol. 7, No. 2, 2011, pp. 60-69.