Multi-level Urban Form and Bikesharing; Insights from Five Bikeshare Programs Across the United States

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ABSTRACT

Bikesharing programs in their current form have been in place for several years in many cities across the United States. Encouraging people to use bikesharing for their daily routine travels has numerous social, economic, environmental, and health benefits. Therefore, it is important to understand factors influencing bikesharing usage in different urban areas in order to improve the system and encourage more use. This paper investigates how built environment at both local and regional scales influences bikesharing usage in five large metropolitan U.S. areas in the U.S. The study areas include Boston, Chicago, Philadelphia, Minneapolis, and Washington, D.C. and the data consists of around 9 million bike trips in over 1,500 stations over a one-year period. Multi-level mixed effect regression model is built to predict the number of trips originated from each station with respect to the station's built environment pattern, as well as the overall urban form in the entire city. The results are consistent with previous research on the effect of land use at the local level on bikesharing demand. At the regional level, results suggest that the overall walkability and job accessibility via bikesharing networks are significant factors influencing bikesharing activities and demand. Models developed in this study could be applied to other communities that are seeking to improve and/or expand their bikesharing systems, as well as cities planning to launch new bikesharing programs.

Keywords: Bikesharing, Urban Form, Multi-level Built Environment, Demand Analysis, Travel Behavior.

1. INTRODUCTION

According to NHTS, Bicycle use has slightly increased from 0.7% of all trips in 1977 to about 1% in 2009. Although this is not a large increase, it reflects the potential of biking to be part of people's daily travel pattern as a more sustainable mode of transportation. Mode choice decision is often influenced by the distance to be traveled (and the time limitations). According to NHTS, the average trip distance is 0.7 miles for walk trips and 2.3 miles for bike trips. Therefore, biking could, in most cases, replace the walking trips as well as short auto trips.

Promoting biking as an active mode of transportation with many social, environmental, and health benefits has become a popular strategy for planners and policy-makers to promote sustainable cities. After successful implementation in a few European cities, the bikesharing program was launched in many U.S. cities to encourage biking to ultimately improve traffic conditions, environmental air quality, and people's health conditions through increasing the level of physical activity. It is cheaper than auto and transit, and also could complement transit use if it is used as an access/egress mode. By December 2016, there were over 70 bikesharing systems offering more than 27,000 public bikes in the U.S. metropolitan areas. The demand for bikesharing has been growing rapidly over the past few years, creating a need for advanced bikesharing demand models.

Many factors contribute to the choice of bikeshare as a travel mode, including the trip purpose, activity to be reached at destination, the characteristics of the origin-destination travel path (or road network), the travel path's topography (presence of hills, etc.), road safety, and weather conditions. Other important factors include the socio-demographic characteristics of the trip-maker, accessibility to other modes, system characteristics such as the location and spatial distribution of docking stations, and the system's capacity. The built environment in the areas surrounding the stations as well as in the entire region is another significant factor influencing a person's decision to use a bikesharing system, both as a primary travel mode for short trips or as a complementary mode for longer transit trips. Once the choice is made, the built environment also influences the distance traveled by bike and the stations to choose as pick-up and drop-off locations. At the local level, factors such as the concentration of jobs and retail/shopping opportunities around stations (Wang *et al., 2015*), population living within walking distance, existence and quality of sidewalks and/or bike lanes (Buck and Buehler, 2012), and the level of street connectivity all could influence the extent to which a particular station is attracting bikeshare users.

At the regional level, the distribution of stations in the entire region, employment accessibility within the bikesharing system network, and the overall distribution of various destinations in the entire region could potentially influence the quality and frequency of using the bikesharing system for a particular trip or as a routine daily commute mode by an individual. Accessibility to docking stations (i.e., greater number of docking stations near home and work locations) and an efficient spatial distribution of stations (a well-connected bikesharing network) throughout the metropolitan area play major roles in increasing a system's use.

However, the effect of built environment on the demand for bikesharing was not studied adequately until very recently and there are relatively few studies focusing on the effect of urban form around docking stations and its influence on bikeshare use. Recently, a number of researchers developed models to estimate the bikesharing demand and activity of the docking stations relative to the built environment characteristics. For instance, Wang et al. (2012) investigated the effect of job density and businesses near stations on annual usage in Minneapolis and found that the number of trips to and from bikeshare stations is significantly associated with neighborhood socio-demographics, proximity to the city center and economic activities, accessibility to trails, and distance to other bike share stations. Hampshire and Marla (2012) also found that population and employment densities are highly correlated with a higher system use in Barcelona, Spain (Hampshire and Marla, 2012). Buck and Buehler (2012) performed a similar analysis for the Washington, D.C. bikeshare system and suggested that there is a statistically significant relationship between the bike lane supply and the number of bikesharing trips, after controlling for population, retail densities and car ownership. Rixey (2013) did a comparative analysis for the effects of land use on a bikeshare stations' activity in three U.S. cities and found that population and job densities significantly affect bikesharing usage. Faghih Imani et al. (2014) focused on the effects of land-use on bicycle flows in Montreal, Canada, and suggested that station proximity to major roads negatively influenced the ridership. Also, a higher number of stations close to each other would increase the usage in the system. Mateo-Babiano et al. (2016) investigated the joint effects of built environment, biking infrastructure, and topography on bikesharing demand in Brisbane, Australia and found that bikesharing usage is significantly correlated with the length of *off-road* bikeways near each station and in general, the stations located in the city center are more active than the rest of the stations.

Despite very interesting findings and useful policy recommendations made by these papers, they have limitations. First, their built environment measures are mostly limited to population and job densities, number and length of bike lanes, and some approximate measures for accessibility and level of mixed use development (Buck and Buehler, 2012; Martin and Shaheen, 2014). Second, in many of these past studies, the time period for the analysis was narrowed down to one day or one month—typically in summer—or a short period of time (Buck and Buehler, 2012; Jäppinen et al., 2013; Muarer, 2011).

The main objective of the current analysis is to explore and quantify the influence of various built environment factors on bike sharing usage in five U.S. metropolitan areas using a spatial-statistical approach to measure the built environment at multiple scales. To capture both local and regional effects, we used measures such as residential and employment densities, level of mixed use, job accessibility within a certain travel time (distance), road network density, and intersection density to account for these effects at the station level. We also provided measures of walkability and employment accessibility through the bikesharing system, as well as aggregate measures of residential and employment densities throughout each entire metropolitan area to address the regional effects. This paper contributes to the literature by exploring the associations between built environment at multiple scales and bikesharing usage in five U.S. metropolitan areas with relatively large bikesharing systems.

2. DATA AND VARIABLES

The built environment data is obtained from the EPA's Smart Location Database (SLD). The SLD provides a wide range of land use measures at the census block group (CBG) level and a number of aggregated socioeconomic and demographic measures for the entire nation. The availability of SLD for all metropolitan areas across the country eliminates the data consistency issue faced in many previous multi-city studies. Other data sources, such as Census/TIGER data and the walk score data, were also used to calculate variables such as average block size and walkability scores.

Table 1 presents definitions of all variables considered for the analysis along with their data sources. The independent variables are measured at two levels: the census block group where the station is located, and the metropolitan area where the station is located. In addition to the built environment variables, some aggregated measures of socioeconomic and demographic characteristics of the CBG or the entire metro area are used in our models.

Table 1 Variables and Data Sources

Variables	Description	Data Source
Dependent Variable		
Number of Trips Originated From Each Station in 2016 (1000)		CityBikeshare
Variables Measured at the Census Block Group (CBG) Level		
P_autoown2+	Percentage of CBG population with 2+ cars	SLD
BG_Popdens	Gross population density (people/acre)	SLD
BG_Empdens	Gross employment density (jobs/acre)	SLD
BG_entropy	Level of employment type mixture[1]	SLD
BG_Rdntwrk_Ped	Facility miles for pedestrian-oriented links per sq. mile	SLD
BG_intrsctdens_auto	Intersection density for auto-oriented intersections	SLD
BG_45Transit	Jobs within 45-minute transit commute	SLD
BG_45Auto	Jobs within 45-minute auto commute	SLD
BG_TransitEmp	Proportion of CBG employment within ½ mile of transit	SLD

[1] Entropy measures how equally different types of land use are mixed within a geographic unit (such as TAZ or census block). The formula we used to calculate this measure has been used previously in several land-use and transportation related articles (Nasri and Zhang, 2012; Zhang et al. 2012; Frank et al. 2005). It is *Entropy* = -jPjln(Pj)ln(J) where Pj is the proportion of land use in the jth land use category and J is the number of different land use types in the area.

BG_rail050	Number of rail transit stops within ½ mile	Walk Score Inc.
Variables Measured at the Metropolitan Level		
Emp_bikeshare	% employment with access to bikeshare system	SLD
M_WalkScore	Walk score rating of the entire metro area	Walk Score Inc.

The dependent variable used in our model is the number of total trips originated from each bikeshare station during the entire year of 2016[2]. We used log transformation of the dependent variable in the model to make sure about normal distribution. The trip records for each case study area are obtained from their bikeshare system's website. These datasets are publicly available for multiple years (for the entire operation period for each city). For the current study, we used the 2016 data for all cities for the sake of consistency, even though in some cities, data was available for part of 2017 as well. Data for each trip record includes the trip origin and destination station location, start/end date and time, and the user type (subscriber vs. casual user). Trips starting and ending at the same station that lasted less than three minutes were considered invalid trips and were removed from the dataset (These are most likely the result of someone unlocking a bike and then changing their mind and return it without actually taking a bike trip). After removing the invalid trips and the observations with missing values, the dataset includes 1,514 observations (bikeshare stations) located in five metropolitan areas. In the following section, the case study areas and their bikeshare system's characteristics are reviewed in terms of the current state of the bikesharing usage in each city and how they are similar and/or different.

2.1. Case Studies

In total, there are 1,514 stations in our sample. Table 2 below summarizes the stations' characteristics and bikesharing activities in all five case study areas. As the table indicates, Chicago has the largest bikesharing system among all five areas, with over 500 stations and close to 6,000 bikes. All five cities are among the ten cities with the largest bikesharing systems in the U.S., and they have different urban form patterns in terms of population and employment densities, accessibility measures, and connectivity, as well as their different geographical location and climate conditions.

Table 2 Bikesharing Systems' Characteristics and Summary*

System	**Boston**	**Chicago**	**Minneapolis**	**Philadelphia**	**Washington, DC**
# of stations	187	581	198	108	440
Total # of bikes	1,800	5,800	1,800	1,000+	3,700
# of trips (2016)*	1,175,177	3,477,131	417,055	636,360	3,263,094
Average monthly trips (2016)	103,016	292,868	54,034	54,588	277,815
%stations within ½ mile of transit	53.48	39.41	11.11	58.09	36.90

* Numbers are calculated based on historic bikeshare data

[2] Except for the Minneapolis case, which does not operate the entire year. The data used for Minneapolis includes the last operation period for which the data was available: April- November 2016.

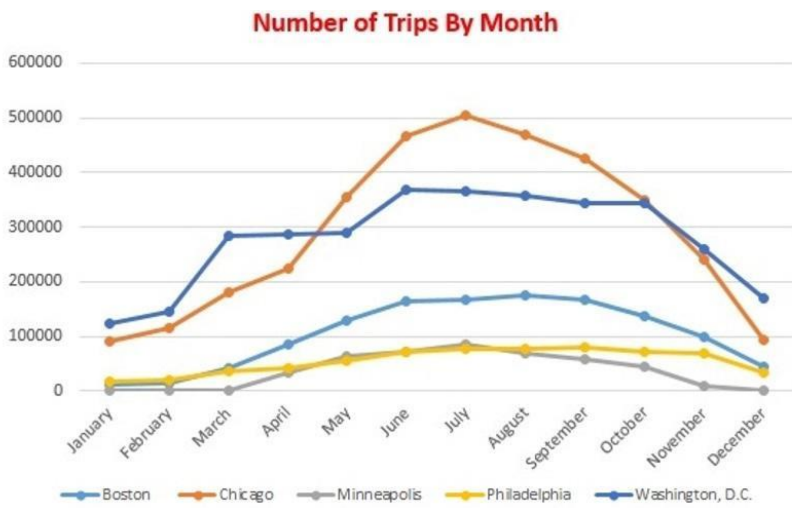

Figure 1 Monthly trip trend in 2016.

Figure 1 presents the total number of monthly trips in all study areas. As it indicates, June-August has the highest bikesharing demand in all cities and December-February period attracts the least number of trips by the users. The chart in Figure 1 also indicates that Chicago has the most active system among all five cities with the highest number of trips year-round, even though the overall weather conditions in Chicago are less bike-friendly than other cities such as Washington, D.C. and Philadelphia. However, Chicago has the largest bikesharing network, with over 580 stations and around 6000 public bikes among all study areas; therefore, the size of the bikesharing system is a significant factor influencing the overall number of trips made.

3. ANALYSIS

We built a multilevel mixed effect regression model in order to better explore the effects of both local and metropolitan-level urban form on bikesharing demand. The number of trips originated from each station during 2016 was used as our dependent variable and the land use characteristics at both station level and metropolitan level as our explanatory variables. The location of bikeshare stations was considered as random effect and all the built environment variables measured at different scales as fixed effect.

Results are presented in Table 3. Based on these results, car ownership level at the local leveldid not prove to be a significant factor influencing bikeshare usage. Population density, level of mixed use development, and network density in terms of pedestrian-oriented links all have significant positive relationship with the bikeshare demand, consistent with what previous research suggested (Buck and Buehler, 2012; Rixey, 2013; Faghih-Imani et al., 2014). Employment density, however, is negatively correlated with the number of bikeshare trips and the relationship is statistically significant. Job accessibility via transit and job accessibility via driving (the percentage of station area employment within 45 minutes of auto travel) both are significantly and positively correlated with the bikesharing demand with very similar effects in terms of the magnitude. However, the binary variable (which shows the existence of at least one rail transit stop within a half-mile buffer distance of docking stations) and the intersection density for the auto-oriented intersections are not significantly influencing our dependent variable. These coefficients indicate that the relationship between transit and bikesharing as measured by the variables discussed above is more complicated and needs further investigation.

Table 3 Mixed Effect Model Results

Fixed Effects			
Variable	**Coefficient**	**Std. Error**	***p-value***
Intercept	8.355e-01	6.344e-01	0.188
P_autoown2+	1.552e-01	2.931e-01	0.597
BG_Popdens	2.203e-03	5.309e-04	0.000035***
BG_empdens	-1.239e-03	3.341e-04	0.000217***
BG_Entropy	6.754e-01	1.333e-01	<0.00001***
BG_Rdntwrk_Ped	2.280e-02	4.771e-03	<0.00001***
BG_intrsctdens_auto	3.947e-03	3.133e-03	0.208
BG_rail050	1.914e-01	1.037e-01	0.0652
BG_45Auto	2.567e-06	6.453e-07	0.000073***
BG_45Transit	2.274e-05	2.294e-06	<0.00001***
M_WalkScore	3.545e-02	6.984e-03	<0.00001***
Emp_Bikeshare	3.581e-02	7.607e-03	<0.00001***
Random Effects	**Variance**	**Std. Dev.**	
Intercept (CBG)	1.4093	1.1871	
Residual	0.4907	0.7005	

Significance level: 0 '***'

Many variables such as population and employment densities and level of mixed-use development measured at the regional (metropolitan) level were eliminated from the final model specification, as they did not show statistically significant relationship with the stations' activity. Results indicate that walkability in the entire metropolitan area and the number of jobs accessible via the overall bikeshare network both have significant positive influence on number of bikeshare trips. This implies that providing a walkable environment in a large scale as well as a well-connected bikeshare network close to employment opportunities both significantly influence the demand for sustainable modes such as biking. However, the overall results suggest that the bikesharing activity in a particular station is not necessarily as correlated with the overall built environment pattern as it is with the built environment and accessibility measures of the immediate neighborhood of that particular station. It might be because bike trips are usually shorter compared to auto and transit trips and thus most likely both the origin and destination of bike trips would be located in a single neighborhood. Therefore, bike trips are not as influenced by the large-scale urban form pattern, even though some regional factors, such as the overall walkability and job accessibility through a bikesharing network, would influence the bikesharing demand at station levels.

4. CONCLUSIONS AND RECOMMENDATIONS

This study investigated the influence of urban form on bikesharing demand in five U.S. metropolitan areas with relatively large bikesharing systems. Results suggests that regional level built environment characteristics, such as the overall walkability and job accessibility via the bikesharing network are as effective on bikesharing usage as is the urban form at the local (station) level. However, bikesharing is more influenced by the local-level urban form.

The current research has several limitations and identifies additional research possibilities. The first limitation is the lack of users' sociodemographic characteristics and attitude, which limits the possibility of controlling for self-selection bias. This data limitation prevents the present study and other past studies to look at how individuals with different sociodemographic background use the bikesharing system, for what trip purposes, and for how long. Second, the current analysis fails to take into account the effect of historic weather data and a city's topography on bikesharing usage, as it is a station-level analysis rather than a trip-based analysis. Certainly, including additional variables like weather conditions and elevation would significantly enhance the predictability and validity of the current models, as these are important factors affecting the choice of bike as a transportation mode. Finally, the effect of regional-level built environment on bikesharing demand would be captured more carefully and effectively if the sample size was larger, by providing data on additional cities as in the current model; there is not much variation observed among the cities in terms of their metropolitan-level variables and that would influence the reliability of the models.

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