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Incorporating the impact of spatio-temporal interactions on bicycle sharing system demand: A case study of New York CitiBike system

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ABSTRACT

Recent success of bicycle-sharing systems (BSS) have led to their growth around the world. Not surprisingly, there is increased research towards better understanding of the contributing factors for BSS demand. However, these research efforts have neglected to adequately consider spatial and temporal interaction of BSS station's demand (arrivals and departures). It is possible that bicycle arrival and departure rates of one BSS station are potentially inter connected with bicycle flow rates for neighboring stations. It is also plausible that the arrival and departure rates at one time period are influenced by the arrival and departure rates of earlier time periods for that station and neighboring stations. Neglecting the presence of such effects, when they are actually present will result in biased model estimates. The major objective of this study is to accommodate for spatial and temporal effects (observed and unobserved) for modelling bicycle demand employing data from New York City's bicycle-sharing system (CitiBike). Towards this end, spatial error and spatial lag models that accommodate for the influence of spatial and temporal interactions are estimated. The exogenous variables for these models are drawn from BSS infrastructure, transportation network infrastructure, land use, point of interests, and meteorological and temporal attributes. The results provide strong evidence for the presence of spatial and temporal dependency for BSS station's arrival and departure rates. A hold out sample validation exercise further emphasizes the improved accuracy of the models with spatial and temporal interactions.

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1. Introduction

Many benefits of bicycle sharing systems (BSS) have led to the rapid growth of these systems around the world in the recent years. In fact, over 1000 cities have already started or are considering the initiation of a BSS (Meddin and DeMaio, 2015). A bicycle sharing system provides individuals increased flexibility to bicycle without the traditional burdens of owning a bicycle (such as the need to secure their bicycles or perform regular maintenance). BSS provides a healthier and affordable transport mode for short trips especially in dense urban areas. A well designed and planned bicycle-sharing system can serve as an access/egress for other public transportation systems mode – a potential last mile solution (Jäppinen et al., 2013). BSS are in tune with the millennials' proclivity for shared transportation systems (Davis et al., 2012; Dutzik and Baxandall, 2013). Further, earlier research efforts provide evidence that BSS were successful in improving the driver awareness towards cyclists and consequently increased the safety for cyclists (Murphy and Usher, 2015). BSS have also assisted in encouraging the

public perception of cycling as an everyday travel mode and thus broadening the cycling demographic (Goodman et al., 2014). Cities, by installing BSS, are focusing on inducing a modal shift to cycling, and subsequently decrease traffic congestion and air pollution.

Given the growing attention towards bicycle-sharing systems, it is important to examine the current performance of BSS operation to improve the effectiveness of BSS schemes (Fishman et al., 2013). Further, understanding factors influencing BSS demand will allow us to better coordinate the installation of new systems or modify existing systems. A useful characterization of BSS demand involves considering bicycle usage as arrivals (depositing bicycles) and departures (removal of bicycles) at BSS stations. Researchers have examined BSS usage to determine contributing factors to BSS demand (Nair et al., 2013; Rixey, 2013; Faghih-Imani et al., 2014; Gebhart and Noland, 2014; O'Brien et al., 2014; Rudloff and Lackner, 2014). These studies usually examine the impact of various attributes on BSS usage at different levels of temporal and spatial aggregation. Variables considered include BSS infrastructure (such as number of BSS stations and stations' capacity), transportation network infrastructure (such as length of bicycle facilities, streets and major roads), land use (such as population and job density), point of interests (such as presence of subway stations, restaurants, businesses and universities), and meteorological and

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temporal attributes (such as temperature and time of day). However, the earlier research efforts have neglected to adequately consider spatial and temporal interaction of BSS station's demand (arrivals and departures). To elaborate, it is possible that bicycle arrival and departure rates of one BSS station are potentially inter connected with bicycle flow rates for neighboring stations. The demand (for an empty slot or a bicycle) might materialize at a neighboring station when a station is totally full or empty. It is also plausible that the arrival and departure rates at one time period are influenced by the arrival and departure rates of earlier time periods for that station and neighboring stations. Neglecting the presence of such effects, when they are actually present will result in biased model estimates.

The major objective of this study is to accommodate for spatial and temporal effects (observed and unobserved) for modelling bicycle demand in a bicycle-sharing system. For this purpose, trip data from New York City's bicycle- sharing system (CitiBike) is used to obtain hourly stations' arrivals and departures. Along with the compiled arrivals and departures data, we take into account the impact of several exogenous attributes including BSS infrastructure, transportation network infrastructure, land use, point of interests, and meteorological and temporal attributes. The proposed research effort allows us to examine the impact of these aforementioned factors on BSS demand while incorporating the spatial and temporal interaction of arrivals and departures. We also account for any spatial dependency between the stations' usage and their nearby stations. We investigate the relation between arrivals (departures) at one station with arrivals (departures) at neighboring stations. Furthermore, as we have multiple repeated observations of the dependent variable (hourly rates for each station) we employ spatial panel models in our analysis. Although spatial panel models have recently become prevalent in econometric literature in general, we believe our study is the first attempt to adopt such models with such a large number of repeated observations.

The remainder of the paper is organized in the following order. A brief overview of earlier research is presented in Section 2. Section 3 describes the data and the sample formation procedures. In Section 4, the methodology used and model structures are described. Section 5 presents the model results and validation. Finally, Section 6 summarizes and concludes the paper.

2. Literature review

The bicycle-sharing systems have evolved since its initiation in the 1960s (DeMaio, 2009; Shaheen et al., 2010). There is increased research on bicycle-sharing systems over the past few years (see Fishman (2015) for a review of recent literature on BSS). There have been several quantitative studies examining bicycle-sharing systems from different dimensions – BSS and bicycling infrastructure, land use and built environment, public transportation infrastructure, temporal and meteorological attributes, and user socio-demographics (Nair et al., 2013; Rixey, 2013; Faghih-Imani et al., 2014; Gebhart and Noland, 2014; O'Brien et al., 2014; Rudloff and Lackner, 2014). For example, several studies demonstrate that increasing BSS infrastructure (number of stations and capacity) or increasing bicycle routes around stations increases BSS usage (Buck and Buehler, 2012; Faghih-Imani et al., 2014; Wang et al., 2015). The impact of land use and urban form attributes on BSS usage are also investigated. Studies found that stations in areas with higher job or population density or stations with higher number of point of interests (such as restaurants, retail stores and universities) in the vicinity experience higher arrivals and departures (Rixey, 2013; Faghih-Imani et al., 2014). Another study showed that ignoring the self-selection impact of BSS infrastructure installation decision process in modelling usage results in an over-estimation of BSS infrastructure effect on usage (Faghih-Imani and Eluru, 2014). Furthermore, the relationship between BSS and other public transportation systems such as subway or bus transit system are also examined by several research

efforts (Nair et al., 2013; Faghih-Imani et al., 2014; Faghih-Imani and Eluru, 2015; González et al., 2015).

The analyses on temporal attributes of BSS show that the peak arrivals and departures are observed during the evening peak hours while weekdays tend to have higher usage rates compared to the usage rates for weekend days. The results indicate the adoption of BSS for commuting purposes on weekdays (O'Brien et al., 2014; Faghih-Imani et al., 2014; Murphy and Usher, 2015). Several studies analyze the impact of weather information (such as temperature and humidity) on BSS usage (Gebhart and Noland, 2014; Faghih-Imani et al., 2014; Mahmoud et al., 2015). Users' socio-demographics and preference towards BSS is another aspect of recent research efforts. Convenience of BSS as well as the presence of a BSS station closer to home location were found to be important reasons for individuals to use the system (Fuller et al., 2011; Bachand-Marleau et al., 2012). Several studies highlighted the differences between BSS short-term users and BSS annual members' preferences towards the use of the system (Lathia et al., 2012; Buck et al., 2013; Faghih-Imani and Eluru, 2015). Studies found that BSS users prefer shorter trips with all else same (Faghih-Imani and Eluru, 2015; Mahmoud et al., 2015). Gender gap between the users of BSS is found to be an issue where the majority of BSS users are male (Faghih-Imani and Eluru, 2015; Murphy and Usher, 2015). Further, research efforts demonstrated that BSS users prefer to use the existing bicycle facilities such as bicycle lanes (Faghih-Imani and Eluru, 2015; González et al., 2015).

2.1. Current study in context

The earlier studies, while providing useful insights on the BSS usage patterns, ignored the possible spatial and temporal interaction of BSS's demand. Several studies analyzed the effect of neighboring stations in a bicycle-sharing system. Rudloff and Lackner (2014) employed count models to analyze demand profiles of Citybike Wien system in Vienna, Austria. They incorporated the neighboring stations effect in the modelling framework by considering dummy variables whether a station is full or empty for the three closest stations. Several research efforts focused on the prediction of the BSS usage in the near future (Froehlich et al., 2009; Kaltenbrunner et al., 2010; Borgnat et al., 2011; Giot and Cherrier, 2014; Han et al., 2014) by employing time series analysis considering temporal and meteorological variables while ignoring land-use and built environment effects. Faghih-Imani et al. (2014) analyzed hourly arrival and departure rates of Montreal BIXI system using a linear mixed model. They assessed the impact of meteorological data, temporal characteristics, bicycle infrastructure, land use and built environment attributes on arrival and departure flows at the station level. However, in their analysis the authors did not consider either observed or unobserved influence of surrounding stations on BSS usage. To elaborate, the demand at a neighboring BSS station for the preceding time period (hour or day or week) is a useful predictor for demand in the current hour. At the same time, the demand experienced at the neighboring stations at the current time or in the preceding time period (hour or day or week) also can enhance our model understanding. In summary, considering such spatio-temporal interactions when they exist can allow for improved accuracy in model estimates as well as model fit. Of course, considering such predictors requires us to develop models that are statistically valid.

Towards this end, the current study draws heavily from spatial econometric literature. Spatial panel models have been used for examination of regional labor markets, economic growth, public expenditures, tax settings, and agricultural productions (Elhorst, 2014). Recently, several studies employed spatial panel models in transportation literature in various analyses including land use development (Frazier and Kockelman, 2005; Wang and Kockelman, 2006; Wang et al., 2012; Ferdous and Bhat, 2013; Shen et al., 2014), real estate pricing (Efthymiou and Antoniou, 2013; Dubé et al., 2014), spillover effect of transportation infrastructure (Chen and Haynes, 2014; Tong et al.,

2013; Yu et al., 2013), tourism activity (Yang and Wong, 2012), and air-fare pricing (Daraban and Fournier, 2008). In the current study, we estimate comprehensive econometric models to incorporate for the influence of observed and unobserved spatio-temporal interactions on bicycle arrival and departure rates for a bicycle-sharing system. Specifically, we consider the pooled panel spatial lag and spatial error models in our analysis. The model development is undertaken at three levels: a) simple models without considering spatio-temporal effects; b) spatial error models with and without observed spatio-temporal effects; c) spatial lag models with and without observed spatio-temporal effects. We develop separate models for arrivals and departures. The data for the analysis is drawn from hourly observation of arrival and departure rates for CitiBike system in New York City.

3. Data

New York's CitiBike system is the latest major public bicycle-sharing systems around the world and the largest in the United States. CitiBike started its service in May 2013 with 330 stations and 6000 bicycles in the lower half of Manhattan and some parts of Northwest Brooklyn. The system is set up around the city's main commercial business districts and some residential areas with an average daily ridership of 34,000 trips. New York City is the most populous city in the US and a host to millions of visitors every year. In 2013, the mode share of cycling in New York City reached 1% from about 0.5% in the 2007 (Kaufman et al., 2015). According to NHTS (2009), bicycle trips accounts for about 0.4% of total trips in New York metropolitan area while 71.7% of trips are made by private vehicles. About 49.7% of trips are less than 2 miles; among these trips, the share of private vehicles reduces to 57.1% while the share for bicycle mode increases to 0.7%. These numbers clearly indicate that there is substantial potential for the success of a well-designed BSS in New York City as one of the dense urban cores in the world. Moreover, about 74% of CitiBike stations are within a half mile of subway stations, providing a solution for the public transit users' problem "last-mile to destination". The city's dense and walkable urban form provide a good opportunity for the success of a well-designed BSS.

The data used in our research was obtained from CitiBike website (https://www.citibikenyc.com/system-data). The CitiBike website provides trip dataset for every month of operation since July 2013. The trip dataset includes information about origin and destination stations, start time and end time of trips, user types i.e. whether the user was a customer with an annual membership pass or a temporary pass, and the age and gender for members' trips only. Additionally, the stations' capacity and coordinates as well as trip duration are also provided in the dataset. The built environment attributes such as bicycle routes and subway stations are derived from New York City open data (https://nycopendata.socrata.com/) while the socio-demographic characteristics are gathered from US 2010 census and the weather information was obtained for the Central Park station from National Climatic Data Center.

3.1. Data assembly and exogenous variable generation

A series of data compilation exercises were required to create the sample of hourly arrivals and departures used for analysis in this study. Earlier studies showed that there is a significant difference between the behaviour of annual members and customers with temporary pass towards the use of BSS (Lathia et al., 2012; Buck et al., 2013; Faghih-Imani and Eluru, 2015). In this paper, we distinguish between arrivals and departures made by different type of users. Number of trips originated from and destined to one station are equal to the number of departures and arrivals for that station. Thus, we aggregated the number of trips originated from/destined to one station by different user types at an hourly level to obtain hourly arrivals and departures by members and daily customers at a station level. Then we normalized

stations' arrivals and departures with station capacity to consider the station capacity effect on demand. In our modelling efforts, we employ logarithm of the hourly normalized arrivals and departures as the dependent variable. We focused on the month of September, 2013; i.e. the peak month of the usage in 2013. Therefore, the final sample consists of 237,600 records (330 stations × 24 h × 30 days). The data assembled has a panel structure of 720 repetitions per station.

The exogenous attributes considered in our study can be broadly classified into three categories: (1) weather, (2) temporal and (3) spatial variables. For the first group of variables, we consider hourly temperature and relative humidity, and the hourly weather condition characterized as an indicator variable for presence of rain. The second group of variables, temporal variables, recognizes the impact of time-of-day and day-of-the-week on BSS usage. Specifically, five time periods were created considering the start time of the trips for departures and end time of the trips for arrivals,: AM (7:00–10:00), Midday (10:00–16:00), PM (16:00–20:00), Evening (20:00–24:00), and Night (0:00–7:00). A categorical variable indicating weekends was created to capture the differences in BSS usage between weekday and weekends.

Several variables were considered under spatial variables group. Population density was calculated at census block level and employment density at zip code level. Other attributes were considered at a station buffer level.[1] For the station buffer level variables, we employed a radius of 250-m around each station considering the distances between CitiBike stations and the dense urban form of New York City; a typical New York City block is about 60 m (Kaufman et al., 2015). The transportation system attributes including the length of bicycle routes and streets, the presence of subway and Path train stations, the number and capacity of CitiBike stations (excluding the origin/destination station) are considered at the station buffer level. These variables recognize the impact of street network and cycling facilities, public transit and the BSS infrastructure on arrival and departure rates. Further, the number of restaurants (including coffee shops and bars), and area of parks within the 250-m vicinity of CitiBike stations were also considered as point of interest attributes in our analysis.[2]

3.2. Sample characteristics

A descriptive summary of sample characteristics is presented in Table 1. It can be observed that arrivals and departures of annual members are significantly higher than the daily customers' rates; indicating that regular users form a larger component for BSS usage in New York. Moreover, the temporal trend of arrival and departure rates are clearly different for the two type of users: members' arrivals and departures have morning and afternoon peak trends while the daily customers' arrivals and departures have only the afternoon peak trend. In general, BSS usage is substantially higher in the PM period compared with any other time of day. Furthermore, BSS usage is spatially different by user types. Figs. 1 and 2 illustrate average arrival and departure rates in AM and PM by annual members and daily customers, respectively. It must be noted that due to different level of usage by members and daily customers, in these two figures, arrival and departure rates categories are different. For members figure, the average hourly arrivals and departures are categorized as: Very Low (0–4 bicycles), Low (4–8 bicycles), Medium (8–12 bicycles), and High (12 + bicycles) while for the customers with temporary passes, the categories are: Very Low (0–0.5 bicycles), Low (0.5–1.5 bicycles), Medium (1.5–3 bicycles), and High

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[1] Considering all variables at the same spatial unit level would be ideal; however, due to data availability we considered variables in the 250-m buffer, census tract and zip code level. To reduce potential bias due to various spatial units, we consider density representations of the variables for census tract and zip code level. For the 250-m buffer, by maintaining a constant area, we are effectively considering a density representation.

[2] The reader would note that we employed a 250-m buffer around the CitiBike stations for variable generation. It might be more appropriate to adopt a 250-m network distance based approach. However, it increases the complexity of the task substantially and is beyond the scope of our research effort.

Table 1
Descriptive summary of sample characteristics.

Continuous variables	Min	Max	Mean	Std. Deviation
Hourly arrivals (annual members)	0	83.00	3.74	5.26
Hourly arrivals (daily customers)	0	39.00	0.61	1.50
Hourly departures (annual members)	0	102.00	3.74	5.36
Hourly departures (daily customers)	0	34.00	0.61	1.49
Temperature (°C)	8.3	34.4	19.64	4.82
Relative humidity (%)	27.0	94.2	60.96	16.01
Length of bicycle facility in 250 m buffer (m)	0	1022.7	314.95	178.82
Area of parks in 250 m buffer (m²)	0	95,209.9	10,181.87	15,169.65
Number of restaurants in 250 m buffer	0	545	54.35	92.21
Number of CitiBike stations in 250 m buffer	0	4.00	1.24	1.01
Capacity of CitiBike stations in 250 m buffer	0	169.00	43.93	38.93
Station capacity	3.00	67.00	34.35	10.76
Pop density (people per m² × 1000)	0.01	67.20	24.87	14.68
Job density (jobs per m² × 1000)	0	432.52	55.83	53.83

Categorical variables	Percentage
Rainy weather	2.6
Weekends	30.0
Subway station in 250 m buffer	49.7
Path train station in 250 m buffer	4.2

The average hourly arrival and departure rates by time of the day and user type

	AM	Midday	PM	Evening
Arrivals (annual members)	5.260	4.536	7.664	2.987
Arrivals (daily customers)	0.236	1.049	1.321	0.450
Departures (annual members)	5.423	4.577	7.659	2.769
Departures (daily customers)	0.294	1.118	1.236	0.405

(3 + bicycles). The figures clearly show the distinct usage pattern of members and daily customers.

4. Methodology

In this paper, BSS usage is characterized as hourly arrivals and departures for each station for a month of data. In order to recognize the multiple repeated observation of a spatial unit (CitiBike stations), we employ spatial panel models in our analysis (see Elhorst, 2014 for complete econometric model details). Let q = 1, 2, …, Q (in our study Q = 330) be an index to represent each station (spatial unit) and t = 1, 2, …, T (in our study T = 24 h × 30 days = 720) be an index for each hour. A pooled linear regression model for panel data considering spatial specific effects without considering spatial dependency can be written as:

$$y_{qt} = \beta' x_{qt} + \mu_q + \epsilon_{qt} \tag{1}$$

where y_{qt} is the log-normal of normalized arrival and departure rates as dependent variable, x_{qt} is a column vector of attributes at station q and time t, and β is the corresponding coefficient column vector of parameters to be estimated. The random error term, ϵ_{qt}, is assumed to be an independently and identically distributed normal error term for q and t with zero mean and variance σ^2, and μ_q represents a spatial specific effect to account for all the station-specific time-invariant unobserved attributes.[3] This spatial specific effects can be treated as fixed effects or random effects. In the fixed effects model, for every station a dummy variable is created while in the random effects model, μ_q is treated as random term that is independently and identically

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[3] The reader would note that temporal lag variables are considered within x_{qt}.

distributed with zero mean and variance σ_μ^2. In addition, the spatial random effects and random error term are assumed to be independent. The fixed effects methodology is not appropriate in the presence of time-invariant independent variables (such as population density or length of bicycle routes in the buffer in our empirical context). In addition, the fixed effects models estimate a large number of parameters (one parameter specific to each station); fixed effect models are computationally cumbersome for large systems as ours. Therefore, in our study, we restrict ourselves to spatial random effects.

In traditional econometric literature, spatial dependency is incorporated in model in two main forms: 1) by a spatially lagged dependent variable known as the spatial lag model, or 2) by a spatial autocorrelation process in the error term known as the spatial error model. In our study, the spatial lag model proposes that arrivals (departures) at one station depend on the arrivals (departures) in neighboring stations while spatial error model posits that unobserved factors are correlated across neighboring stations.

A spatial lag model can be written as follows:

$$y_{qt} = \delta \sum_{j=1}^{Q} w_{qj} y_{jt} + \beta' x_{qt} + \mu_q + \epsilon_{qt} \tag{2}$$

where δ is called the spatial autoregressive coefficient and w_{qj} is an element from a spatial weight matrix W. The spatial weight matrix W defines the spatial arrangement of the stations or in the other words the neighboring stations. Several types of spatial matrices are introduced in earlier literature. For example, W could be based on inverse of square distance between stations or neighboring stations within a threshold distance. In our study, we adopt the second approach by considering stations within a 500 m network distance (not the direct distance). While it is possible to explore several distance thresholds, for active modes of transportation accounting for spatial dependency within a 500 m distance seems reasonable. Hence, the spatial W matrix is a 330 × 330 matrix with elements equal to 1 for the stations that are within 500 m of each other and zeros for the rest of elements. It must be noted diagonal of W matrix is set to be zero to prevent the use of y_{qt} to model itself. For stability in estimation, a row-normalized form of the W matrix is employed as our spatial weight matrix (see Elhorst, 2014 for more details on W matrix).

A spatial error model may be written as follows:

$$y_{qt} = \beta' x_{qt} + \mu_q + \varphi_{qt} \tag{3a}$$

$$\varphi_{qt} = \rho \sum_{j=1}^{Q} w_{qj} \varphi_{jt} + \epsilon_{qt} \tag{3b}$$

where φ_{qt} accounts for the spatial autocorrelated error term and ρ reflects the spatial autocorrelation coefficient. Both spatial lag model and spatial error model can be estimated using maximum likelihood approach (see Elhorst (2014) for details on likelihood functions). In this paper, we adopt Matlab routines provided by Elhorst (2003, 2009), to estimate pooled spatial lag and error models with spatial specific random effects.

5. Analysis and discussion

In our research effort, a systematic procedure was employed to demonstrate the influence of spatial and temporal interactions on modelling arrival and departures rates. The models were estimated for two user groups (members and daily customers) - separately for arrivals and departures. Thus we estimated 4 groups of models. More importantly, for each model group, the effort was to evaluate the improvement in data fit with addition of spatial and temporal interactions. Towards this end, we started with a pooled spatial model with random effects (model described in Eq. (1) – IM1). To this model we added temporally
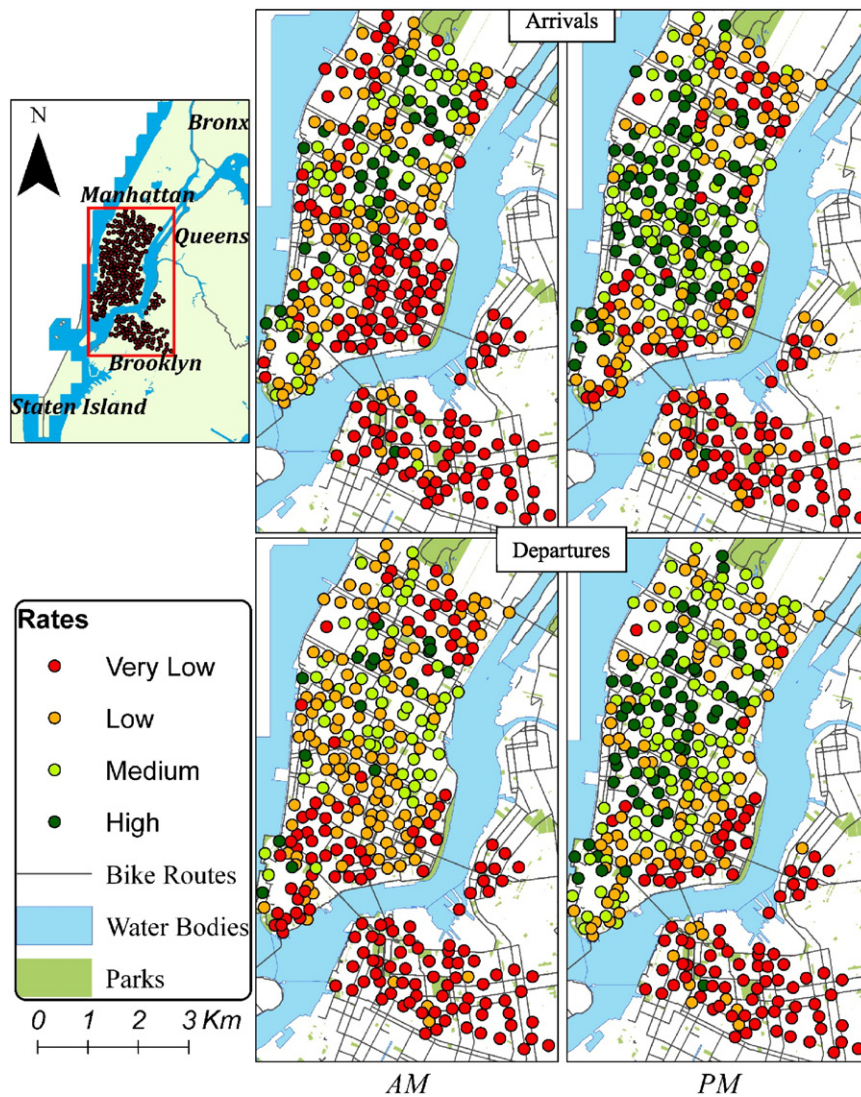
Fig. 1. Average hourly arrival and departure rates for members in peak hours.

lagged observed variables i.e. the dependent variable for the station from previous time periods including 1 h, 1 day, and 1 week as independent variables. The model is labelled as IM2. As a next step, we added spatially lagged dependent variables using the W matrix. The model accounts for the impact of neighborhood station from earlier time periods on the dependent variable. The model is labelled as IM3. The three independent models account for random effects specific to the station but do not consider any spatial autoregressive (spatial lag) or autocorrelation (spatial error) parameters. For each of these independent models a corresponding spatial lag and spatial error versions are estimated thus giving rise to SL1, SL2, SL3, SE1, SE2 and SE3 models. For instance, the difference between IM1 and SL1 is the additional autoregressive parameter estimated for lagged dependent variables (see Eq. (2)). The difference between IM3 and SE3 is the additional spatial autocorrelation term estimated in the spatial error format (see Eqs. (3a) and (3b)). We estimated 9 models per group thus yielding 36 models in total.

5.1. Model fit measures

Table 2 presents a summary of the goodness of fit measures. The reader would note that the final specifications were obtained after a systematic procedure of examining several specifications based on intuitiveness supported by statistical inference. The final results for members' and daily customers' usage models are presented in Table 2.

For each model type, the log-likelihood at convergence, the number of parameters estimated, and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which penalize the modelling frameworks for additional parameters are presented. For a given empirical model, $AIC = 2K - 2\ln(L)$ where K is the number of parameters and $\ln(L)$ is the log–likelihood value at convergence and, $BIC = -2\ln(L) + K\ln(Q)$ where Q is the number of observations. The BIC imposes higher penalty than AIC for over-fitting. The lower the AIC or BIC is, the more preferable the model is in terms of goodness of fit. The following observations can be made from a comparison between models. *First*, incorporating observed interactions - either as temporally lagged dependent variables or temporally and spatially lagged dependent variables significantly improve model fit measures. *Second*, addition of spatial autoregressive (spatial lag) or autocorrelation (spatial error) parameters offers substantial improvement in model fit, with the spatial lag model offering more improvement. *Finally*, the spatial lagged model with both temporally lagged and temporally spatial lagged variables provide the best model fit.

The comparison exercise provides strong evidence in support of our hypothesis that model incorporating the spatial and temporal observed or unobserved effects in the modelling of BSS usage offers a more accurate estimation framework. Ignoring these spatial and temporal dependencies would result in biased and inaccurate parameters estimates. Presenting all the 36 models is not possible in the context of this
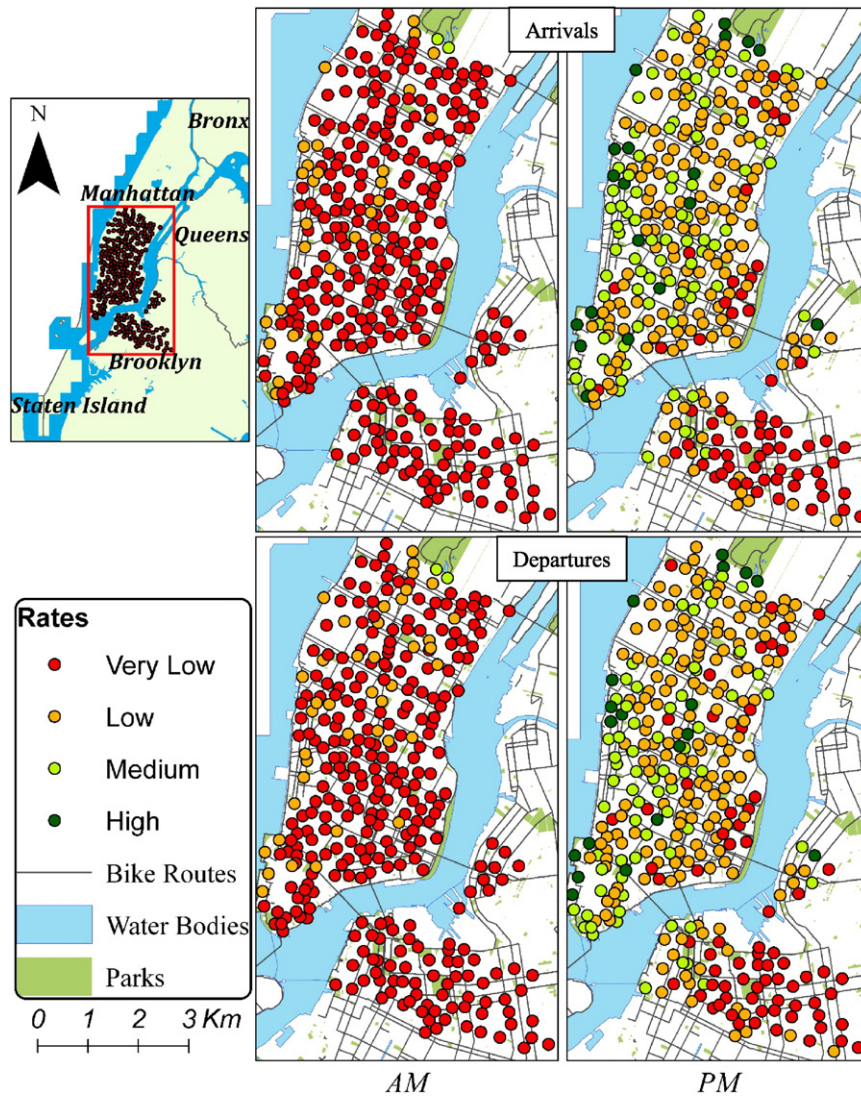
Fig. 2. Average hourly arrival and departure rates for daily customers in peak hours.

Table 2
Summary of Estimated Models.

			IM1	IM2	IM3	SE1	SE2	SE3	SL1	SL2	SL3
	Model Type	Temporally lagged Y	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
		Spatial error	No	No	No	Yes	Yes	Yes	No	No	No
		Spatial lag	No	No	No	No	No	No	Yes	Yes	Yes
		Temporally & spatially lagged Y	No	No	Yes	No	No	Yes	No	No	Yes
Arrivals	Members	# Parameter	19	22	23	20	23	22	18	21	24
		LL	−291,388	−246,056	−241,249	−271,578	−243,884	−239,445	−270,913	−240,844	−239,354
		AIC	582,814	492,156	482,545	543,195	487,814	478,935	541,862	481,731	478,755
		BIC	583,014	492,388	482,787	543,406	488,056	479,167	542,051	481,952	479,008
	Daily customers	# Parameter	14	17	22	15	18	19	17	20	23
		LL	−213,408	−203,575	−200,863	−210,466	−202,863	−200,456	−210,433	−202,204	−200,372
		AIC	426,845	407,184	401,771	420,962	405,762	400,950	420,901	404,448	400,790
		BIC	426,992	407,363	402,002	421,120	405,951	401,150	421,080	404,659	401,032
Departures	Members	# Parameter	19	21	21	20	22	21	18	20	22
		LL	−289,752	−250,568	−245,586	−271,474	−247,943	−243,498	−271,026	−244,941	−243,381
		AIC	579,541	501,179	491,214	542,988	495,930	487,038	542,088	489,922	486,806
		BIC	579,741	501,400	491,435	543,198	496,161	487,259	542,277	490,133	487,038
	Daily customer	# Parameter	13	15	20	14	16	16	17	19	21
		LL	−217,584	−205,929	−204,019	−215,288	−205,425	−203,723	−215,217	−204,908	−203,656
		AIC	435,193	411,889	408,078	430,603	410,882	407,478	430,469	409,853	407,355
		BIC	435,330	412,047	408,289	430,751	411,050	407,647	430,648	410,053	407,576

Table 3
Estimates of spatial lag model with temporal and spatial lagged variables.

		Members				Daily customers			
		Arrivals		Departures		Arrivals		Departures	
		Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	tS	Coefficient	t-Stat
	Constant	−0.3611	−9.843	−0.3635	−9.633	−1.4010	−35.586	−1.4444	−39.453
Time & weather variables	AM	0.2472	24.525	0.2356	26.516	0.0604	7.458	0.0774	18.996
	Midday	0.1524	28.284	0.1491	33.337	0.1952	50.106	0.2044	49.926
	PM	0.1561	16.036	0.1361	15.104	0.1857	25.949	0.1782	36.405
	Evening	0.0092	1.748	–	–	0.0440	11.389	0.0423	10.896
	Weekend	−0.0491	−13.617	−0.0493	−13.453	0.0863	27.156	0.0860	26.662
	Relative humidity	−0.1562	−14.960	−0.1604	−15.331	−0.0418	−4.781	−0.0245	−2.762
	Rainy	−0.2201	−25.216	−0.2298	−25.905	−0.1011	−13.652	−0.1136	−15.120
Built environment attributes	Length of bicycle routes in buffer	–	–	–	–	0.0475	1.948	0.0418	1.988
	Length of rails in buffer	−0.0828	−3.593	−0.0915	−3.761	−0.1052	−4.516	−0.0896	−4.458
	Presence of subway station in buffer	0.0839	2.912	0.0937	3.081	0.0624	2.171	0.0564	2.274
	Area of parks in buffer	–	–	–	–	2.0842	2.214	1.5096	1.849
	Area of parks in buffer * weekend	1.1051	5.694	1.0925	5.537	1.0257	6.203	0.9912	5.909
	Number of restaurants in buffer	0.3549	2.322	0.3865	2.394	–	–	0.2338	1.754
	Population density	2.4118	2.453	2.4503	2.360	–	–	–	–
	Population density * AM	−1.5093	−5.329	0.9810	3.414	−0.4198	−1.749	–	–
	Population density * PM	2.1641	8.597	0.8257	3.240	0.6880	2.819	–	–
	Job density * AM	0.8418	10.790	–	–	0.1819	3.230	–	–
	Job density * PM	−0.1741	−2.549	0.2881	4.184	–	–	–	–
Lag variables	Temporally lagged dependent variable								
	1 h	0.1916	99.137	0.1808	93.650	0.1379	68.178	0.1839	91.621
	1 day	0.1549	80.076	0.1441	74.223	0.0839	42.454	0.0983	50.198
	1 week	0.1994	102.068	0.1934	98.620	0.0995	49.664	0.0953	48.157
	Temporally & spatially lagged dependent variable								
	1 h	0.0807	27.213	0.0723	24.981	0.1340	37.013	0.0953	26.315
	1 day	0.0217	7.401	0.0343	11.748	0.0431	12.722	0.0296	8.818
	1 week	0.1060	34.066	0.1152	36.951	0.1195	33.417	0.1161	32.743
	Spatial autoregressive coefficient	0.1620	60.759	0.1750	66.019	0.0839	30.543	0.0740	26.792
	Spatial specific random effects SD	0.0967	18.250	0.0931	18.244	0.0811	18.225	0.0954	18.248

paper. So, for the sake of brevity, only the spatial lagged model of arrivals and departures that provided the best fit measures are discussed in this section and presented in Table 3.

5.2. Model estimation results

5.2.1. Time and weather variables

Time period specific indicator variables corresponding to AM, Midday, PM, and Evening have statistically significant impact on arrivals and departures for both users' types. It must be noted that the effect of AM and PM variables should be carefully taken into account because of the interaction of these variables with population and job density variables. Still, the results demonstrate that the CitiBike system is extensively used during the PM period compared to other times of the day by both annual members and daily customers. The weekend variable provides interesting results. Annual members are prone to use the system more on weekdays than weekends, while daily customers tend to bicycle more on weekends. It might indicate that the usage of CitiBike system by customers with temporary passes are more likely for recreational activities. As expected, people are less likely to use CitiBike system in rainy or very humid time periods as highlighted by negative coefficients of rainy and relative humidity variables. The temperature variable did not yield a statistically significant effect.

5.2.2. Built environment variables

In this section, we discuss the results for built environment and land use attributes. The length of bicycle routes in the 250-m buffer around CitiBike stations has positive impact on the arrivals and departures for daily customers. However, the variable has no significant effect for members. The results indicate that placing BSS stations near bicycle facilities increases the non-members' usage of the system. It is possible that daily customers are less familiar with the city street network and

are generally more cautious; thus prefer being close to city's bicycle routes. On the contrary, the length of railway line near a CitiBike station decreases the usage of system for both user types as the railways are barrier's to cyclist's movement. As expected, the presence of subway station near CitiBike station has positive significant impact on the station's arrival and departure rates with slightly higher impact in members' models. For the daily customers, the area of parks in the buffer variable has positive impact on the arrival and departure rates. This impact is higher on weekends. For annual members, the parks area variable does not have significant impact on weekdays but on weekends there is positive effect on members' arrivals and departures. As expected, both user types' arrivals and departures increase when there are higher number of restaurants around CitiBike station.

The arrival and departure rates of daily customers are less sensitive to population and job density variables than the arrival and departure rates of members. As expected, the population density variable has positive impact on arrivals and departures by members. Although the interaction of population density with AM and PM variables are both positive for members' departure model, these variables have interestingly opposite impact on arrivals for members. The impact is also opposite for arrivals by daily customers as highlighted by negative coefficient of population density in AM and positive coefficient in PM. CitiBike stations in areas with higher job density are more likely to have higher arrivals in AM and higher departures in the PM as highlighted by positive coefficients of the interaction of job density variable with AM and PM variables. The population and job density variables become statistically insignificant in the departure model for daily customers. Overall the coefficients of population density, job density and their interaction with AM and PM periods clearly demonstrate the use of CitiBike system for daily commute to work in the morning and back to home in the evening especially for regular member users (similar to findings of Faghih-Imani et al., 2014 study for Montreal system).

5.2.3. Spatial and temporal observed effects

In this section, the results for the temporally lagged dependent variables and the temporally lagged spatial lag variables are discussed. All the three temporally lagged dependent variables – the observed dependent variable from 1 h, 1 day and 1 week before – have strongly positive impact on the arrival and departure rates for members and daily customers. The results show that incorporating the observed demand in the modelling procedure substantially enhances the accuracy of the model estimation. Furthermore, incorporating the observed spatial lag variable for earlier time period (in our analysis 1 h, 1 day and 1 week before) also has strong impact in the usage models. The significant impact of spatial lag variable and the temporally lagged spatial lag variables confirm our hypothesis that the arrival and departure rates in one station are correlated with the arrival and departure rates of neighboring stations.

5.2.4. Autoregressive parameter and random effects

In the spatial lag model, an autoregressive parameter that relates the usage (arrivals and departures) from the current stations to the usage of stations in the vicinity is considered. As expected, the parameter is positive indicating a positive dependency in BSS usage. The magnitude of this impact in members models is almost double than the one in daily customers. This spatial effect might have several plausible explanations. One possible explanation might be that stations in the same vicinity share the same attractors (jobs, restaurants or tourist spots). Another reason might be that when we have higher arrivals (departures) for one station, it is possible that station becomes full (empty). Thus, people go to the nearby stations to return (pick up) their bicycles thus transferring the demand to stations in the vicinity.

The random effects parameter accounts for common unobserved factors specific to a station that affects usage. In our context, we observe that the common unobserved factors are drawn from a zero mean distribution with a standard deviation ranging from 0.0811 through 0.0967 across the models.

5.3. Model validation

For the model validation purposes, we use data from first week of October, 2013 (exactly one week after the data employed for estimating the model) for CitiBike system. The same data processing exercises presented in Section 3.1 were undertaken to prepare the validation sample

for annual members and daily customers. The SL3 model discussed in previous section was used to compute predicted arrival and departure rates. For members' and daily customers' arrivals and departures SL3 model, the predicted rates were compared with the observed arrivals and departures in validation sample. The reader would note that the spatial panel models can be applied in the planning process of BSS even when the future usage rates are not observed (see Elhorst (2014) for exact prediction equations for spatial panel models). We computed Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as overall metrics for error in prediction. In addition, we summed the absolute error of members' and daily customers' model predictions to obtain total arrivals or departures absolute error as a proportion of station capacity and examined the number of stations with error less than 5%, 10%, 15%, 20% and 25% of station capacity. We presented these error metrics for the entire sample and for specific time periods of the day. Table 4 presents the validation results.

The validation exercise results demonstrate an outstanding predictive performance by the proposed SL3 model. It is observed that the daily customers' models provide better results with the MAE of about 0.68 bicycles per hour compared to the MAE of about 1.8 for members' models. The better performance of daily customers' models is expected; the range of usage values for daily customers is much lower than the corresponding usage values for members. Further, it can be seen that the prediction for the arrival model is marginally better than the prediction for the departure model. Specifically, considering the error in prediction within 10% of station capacity as threshold, the validation results showed that about 90% of the records for arrivals and more than 75% of the records for departures demonstrated satisfactory prediction. Throughout the day, the prediction performance of models are superior during the PM and Evening periods. Overall, the validation exercise shows the enhanced predictive capability of the models incorporating spatio-temporal interactions in analyzing BSS usage.

6. Conclusion

With the growing installation of BSS infrastructure there is substantial interest in identifying factors contributing to the demand of these systems (arrivals and departures). Earlier research efforts have neglected to adequately consider spatial and temporal interaction of BSS station's demand. It is possible that bicycle arrival and departure rates of one BSS station are potentially inter connected with bicycle

Table 4
Validation results for spatial lag model with temporal and spatial lagged variables.

		Overall	Night	AM	Midday	PM	Evening
Arrival	Mean absolute error						
	Members	1.816	2.767	2.014	2.902	1.665	0.704
	Daily customers	0.675	0.476	0.920	1.010	0.612	0.395
	Root mean square rrror						
	Members	3.085	4.667	2.901	4.383	2.465	1.282
	Daily customers	1.071	0.595	1.439	1.560	0.820	0.480
	Percentage of total arrivals with absolute error less than						
	5% station capacity	67.73	62.50	53.78	42.90	69.78	94.95
	10% station capacity	88.19	84.98	83.87	74.72	91.82	98.91
	15% station capacity	94.77	92.58	93.36	87.79	97.03	99.62
	20% station capacity	97.25	95.92	96.67	93.26	98.73	99.75
	25% station capacity	98.37	97.33	98.09	96.00	99.37	99.83
Departure	Mean absolute error						
	Members	1.898	3.065	2.084	3.135	1.579	0.716
	Daily customers	0.686	0.523	0.963	0.984	0.599	0.398
	Root mean square error						
	Members	3.362	5.138	3.008	4.957	2.413	1.520
	Daily customers	1.092	0.675	1.493	1.553	0.815	0.474
	Percentage of total departures with absolute error less than						
	5% station capacity	53.17	39.80	36.45	27.62	54.29	87.20
	10% station capacity	76.33	64.94	68.20	57.32	81.61	96.03
	15% station capacity	87.21	78.53	83.81	74.76	91.76	98.35
	20% station capacity	92.44	86.16	91.12	83.83	96.17	99.06
	25% station capacity	95.23	90.40	94.93	89.22	97.97	99.42

flow rates for neighboring stations. It is also plausible that the arrival and departure rates at one time period are influenced by the arrival and departure rates of earlier time periods for that station and neighboring stations. Neglecting the presence of such effects, when they are actually present will result in biased model estimates. This paper presented comprehensive econometric models to incorporate for the influence of observed and unobserved spatio-temporal interactions on bicycle arrival and departure rates employing data from CitiBike system in New York City.

In our research effort, a systematic procedure was employed to evaluate the effects of spatial and temporal interactions on modelling arrival and departures rates. The model estimation was conducted in three increments: (1) a pooled spatial model with random effects, (2) temporally lagged observed variables and (3) temporally and spatially lagged dependent variables using the W matrix. For each of the three increments, an independent pooled model, spatial error pooled model and spatial lag pooled model are developed. The models were estimated for two user groups (members and daily customers) - separately for arrivals and departures. We estimated 9 models per group thus yielding 36 models in total. We observed that incorporating observed interactions - either as temporally lagged dependent variables or temporally and spatially lagged dependent variables significantly improve model fit measures. We observed that addition of spatial autoregressive (spatial lag) or autocorrelation (spatial error) parameters offers substantial improvement in model fit, with the spatial lag model offering more improvement. The spatial lag model with both temporally lagged and temporally spatial lagged variable provided the best model fit. The results provide strong evidence for the presence of spatial and temporal dependency between of BSS station's arrival and departure rates. Ignoring these dependencies would lead to biased and inaccurate parameters estimates. Further, separating the demand modelling for members and daily customers demonstrated that there is clear distinction in the usage of the system by daily customers and annual members especially in temporal pattern of system usage.

The best spatial lag model estimation results were used to predict usage for a hold-out sample. Overall, the proposed framework provided satisfactory predictions of usage. The daily customers' models provided better results with the MAE of about 0.68 bicycles per hour compared to the MAE of about 1.8 for members' models. Further, it is observed that the output for the arrival model is marginally better than the output for the departure model. The results also showed that for arrivals about 90% of the records have the error in prediction within 10% of station capacity while for departures more than 75% of the records have the error in prediction within 10%. The results indicated that incorporation of observed and unobserved spatial-temporal interactions improved the accuracy of parameters estimated and the predictive capability of modelling frameworks.

The proposed framework is applicable for analyzing an existing BSS or a future BSS. For an existing BSS system, the model developed can be employed directly to study how redistribution of capacity will enhance BSS usage. In this process, the analysts will have to identify potential station locations and the distance matrix for the new stations in relation to the existing system. Further, the land use variables around proposed stations will need be generated. Subsequently, the model developed can be applied to generate new usage values for the existing stations and newly added stations. Thus the proposed model provides improved ability for decision makers to study changes to demand prior to adding or removing stations in the system. For the installation of a new BSS, the proposed model for New York can be employed to obtain expected demand by considering various planned station locations (with information on the inherent distance matrix, and land-use buffer variables) and station capacity. An iterative process that generates optimum usage can be developed by altering the location and capacity variables. To be sure, the iterative application requires the analyst to be aware of the urban region and inherent bicycling patterns. The analysis will allow for developing a reasonable quantitative framework for demand estimation for the new system.

To be sure, the proposed study is not without limitations. In our model development, we have considered arrivals and departures separately. However, it is possible that arrivals and departures share common observed and unobserved attributes that affect each other. Incorporating such unobserved dependencies would increase the complexity of the model framework and would require substantial additional work. This is an avenue for future work.

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