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Promoting public bike-sharing: A lesson from the unsuccessful Pronto system

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Abstract

In 2014, Seattle implemented its own bike-sharing system, Pronto. However, the system ultimately ceased operation three years later on March 17th, 2017. To learn from this failure, this paper seeks to understand factors that encourage, or discourage, bike-sharing trip generation and attraction at the station level. This paper investigates the effects of land use, roadway design, elevation, bus trips, weather, and temporal factors on three-hour long bike pickups and returns at each docking station. To address temporal autocorrelations and the nonlinear seasonality, the paper implements a generalized additive mixed model (GAMM) that incorporates the joint effects of a time metric and time-varying variables. The paper estimates models on total counts of pickups and returns, as well as pickups categorized by user types and by location. The results clarify that effects of hilly terrain and the rainy weather, two commonly perceived contributors to the failure. Additionally, results suggest that users in the University District, presumably mostly university students, tend to use shared bikes in neighborhoods with a higher household density and a higher percentage of residential land use, and make bike-sharing trips regardless workdays or non-workdays. The paper also contributes to the discussion on the relationship between public transportation service and bike-sharing. In general, users tend to use bike-sharing more at stations that have more scheduled bus trips nearby. However, some bike-sharing users may shift to bus services during peak hours and rainy weather. Several strategies are proposed accordingly to increase bike ridership in the future.

Keywords

Bike-sharing; Built environment; Temporal factors; Generalized additive mixed model; Pronto

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Appendix A. Supplementary material
Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trd.2018.06.021.

1. Introduction

Bicycling, a green and healthy active travel mode, has recently regained popularity in US cities. To accommodate this increasing demand for bicycling and to attract new bicyclists from other travel modes, many cities have launched bike-sharing systems, which include both docked and/or undocked storage methods. The systems provide easy access to bikes, thereby greatly facilitating first-and-last mile trips via bicycling in an urban environment.

Seattle launched its first bike-sharing system, Pronto, on October 13th, 2014. The system included 500 bicycles available in 50 stations covering eight major divisions of the city. After two years of operation, Pronto released the two-year trip data along with bike and dock availability per minute per station. According to the data, Pronto facilitated over 200,000 trips during the two-year period, which amounts to approximately 10 trips per station per day. Unfortunately, the program's ridership was simply not large enough to attract continuous subsidization from the city of Seattle, WA (The Seattle Times, 2017). As a result, the program eventually ceased operations on March 17th, 2017.

This discrepancy between the general popularity of bike-sharing systems and the inefficiency of this particular program provided the impetus for investigating factors that encourage or discourage bike-sharing. To date, many studies have investigated the effects of the built environment on bike-sharing programs (Moudon et al., 2005; Cervero et al., 2009; Buck and Buehler, 2012; Shaheen et al., 2013; Noland et al., 2016; etc.), and some have incorporated temporal factors with built environment factors to test seasonal effects and temporal interaction effects (Faghih-Imani et al., 2014; Noland et al., 2016; Faghih-Imani and Eluru, 2016; Faghih-Imani et al., 2017). Among those, Seattle's Pronto is a representative example of failures that is worthy of attention. This paper contends that a more comprehensive investigation of both the built environment and temporal factors is necessary to avoid similar failure from happening in the future. Based on the released trip data from Pronto and the rich spatial and temporal datasets from Seattle, this paper investigates various factors, such as weather, elevation, and public transit, that may influence bike-sharing departure and arrival.

This paper further explores different usage patterns among various user groups. Previous studies have examined behavior differences between members and non-members of various bike-sharing programs (Shaheen et al., 2013; Faghih-Imani and Eluru, 2016). This paper advances the field by investigating behaviors of bicyclists in a university setting, which is one of the predominant user groups in bike-sharing programs (Shaheen et al., 2014). Moreover, the paper employs a generalized additive mixed model (GAMM), which helps to capture the non-linearity of temporal trends. Drawing from the experience of Pronto, hopefully, this paper can provide useful guidelines for the development of new bike-sharing programs, not only for Seattle but also for many other cities.

2. Research questions

This paper seeks to answer two research questions: (1) How do the built environment (spatial factors), temporal factors, and public transit trips affect the arrival and departure flow of bike-sharing at the station level? (2) How do these effects differ among various user groups? For the first research question, built environment factors investigated include land use, roadway design, and urban density; temporal factors include daily precipitation, peak hour, and non-work day. The effect of the number of public transit trips and its interactions with precipitation and peak hour are also investigated.

For the second research question, three types of users are investigated: annual members, short-term pass holders, and riders using stations in the University District (the University of Washington). Annual members are people frequently using Pronto's bikes who purchased a year-long usage pass with a one-time payment. Short-term pass holders include tourists, shoppers, and people who occasionally use Pronto's bikes. Stations in the University District were underperforming compared to other stations according to the data, which may indicate a lack of interests among students. To examine factors that motivate or demotivate users in the University District, trips from stations in this area are investigated separately.

3. Previous studies

3.1. The effect of built environment factors on bike-sharing

Over the past half-century, bike-sharing has evolved through three generations, from the very first bike-sharing program which opened in 1965 in Amsterdam, the Netherlands, to the current smart systems that incorporate electronically-locking racks, smartphone access, and other technological improvements (DeMaio, 2004). These new technologies have made bike-sharing more technically feasible (Hernandez et al. 2018) and as bike-sharing systems have gained popularity, there has been substantial interest in identifying factors that encourage individuals to use these systems (Faghih-Imani and Eluru, 2015). Along with this line of research, a key area of focus is the built environment.

In the previous research, many built environment factors have been identified as variables that encourage biking. For example, a compact urban environment – one with higher density, greater mixed land use, and more commercial facilities – helps reduce trip distances, which in turn is more suitable for non-motorized travel modes (Moudon et al., 2005; Cervero et al., 2009; Heinen et al., 2010; Winters et al., 2010, Chen et al., 2017). Bike infrastructure, such as cycle tracks and bicycle lanes which separate bicycles from vehicle traffic and creates a bicycle-friendly environment also plays a key role in encouraging bicycling activity (Reynolds et al., 2009; Buck and Buehler, 2012; Fishman et al., 2015; Chen, 2015; Chen and Shen, 2016). In addition to convenience and safety, aesthetic factors play an essential role in bicycle trip generation. Many bicycle trips are recreational, and the attractiveness of the built environment acts as a key element in determining bicycling routes (Lovasi et al., 2013; Stefansdottir, 2014).

3.2. The effect of public transportation services

The relationship between bike-sharing and existing public transportation services has also attracted considerable attention. Shaheen et al. (2013) discussed the impact of bike-sharing systems on modal shifts using online surveys with members of four major bike-sharing organizations in Montreal, Washington D.C., Toronto, and the Twin Cities. They found that bike-sharing service both works in conjunction with public transportation services, replacing some trips previously made by personal driving and taxi, and substitutes some bus and rail trips. An additional study (Shaheen et al., 2014) employed on-street surveys in three cities - Boston, Salt Lake City, and San Antonio - and included both members and casual users. Their analysis of survey responses shows that bike-sharing generally reduces the number of respondents using buses in large cities. In contrast, in small cities, such as the Twin Cities, bike-sharing increases the use of public transportation services. This discrepancy is ascribed to differences in city size, density, and the supply of public transit.

In another study of the Vélib bike-sharing system in Paris, France, Nair et al. (2013) examined system characteristics, utilization patterns, the connection between bike-sharing and transit, and the flow imbalance among bike stations. The study showed that stations proximate to bus stops and services generally have higher utilization rates. This finding is partly supported by the study of Chicago's Divvy system, in which Faghih-Imani and Eluru (2015) examined behavior patterns of bike-share customers at the trip level to analyze bicyclists' preferred destinations. The study found that regional train stations tend to be chosen by members as preferred destinations. However, such a complementary relationship only exists in trips of regular members, whereas, for daily customers, train stations show a negative impact on bike-sharing trip attraction.

A substitutional effect has also been identified by Fuller et al. (2012) and Saberi et al. (2018) in their studies that they evaluated bike-sharing trip changes in London when transit was not available during a strike. They both found that bike usage temporarily increased immediately after the strike, but gradually diminished to pre-strike levels after the strike ended. Their findings suggest that a substitutional effect exists between transit and bike-sharing systems. The finding also corresponds to Gebhart and Noland's analysis (2014) which found that bikes from bike-share stations near transit are less likely to be used during adverse weather.

Different from the above, Zhang et al. (2017) found that public transport facilities do not have a significant impact on both demand and the ratio of demand to supply at bike-sharing stations. Their result is consistent with findings of Chardon et al. (2017), which examined 75 bike-sharing systems across the world. The latter study also suggests that higher utilization rates of stations proximate to public transportation services may be affected by the number of public transit trips instead of the number of bus stops or train stations.

3.3. Temporal factors

In addition to studies that focus on the effect of built environment factors, many other studies focus on temporal factors that influence bike-share ridership. Some studies have adopted the Auto-Regressive Moving Average (ARMA) model to account for seasonal trends and correlations with bike usage from previous periods (Rixey, 2013; Giot and Cherrier, 2015). Other studies have investigated more explanatory variables. For instance, Borgnat et al. (2011) utilized temporal factors – including weather conditions and non-work days – to build a linear model to predict future trip flow. In Gebhart and Noland's (2014) analysis using hourly counted data, weather patterns and seasonality were correlated both with bike usage and trip duration. Their findings echo conclusions of El-Assi et al.'s (2015) study, in which effects of adverse weather conditions, such as snow, precipitation, and humidity levels, were negatively correlated with the total number of bike trips per month.

3.4. Studies on trip generation and attraction at station level

Among previous studies on trip generation and trip attraction at station level, Froehlich et al. (2009) explored different spatial clustering patterns that occur throughout the day, based on bike usage and available space each docking station in Barcelona's bike-sharing system. Kaltenbrunner et al. (2010) expanded the study by looking at various usage patterns by the time of a day, by the day of a week, and by land use at docking station areas.

Similar studies have also investigated bike-sharing systems in other cities. Lathia et al. (2012) measured the impact of opening the London bike-sharing system to "casual users" by providing customers possessing debit or credit cards access to the system. Their findings show that the overall geographic distribution of activities at the city level remains similar after the policy implementation but exhibits opposite trends at certain stations. In addition, Vogel et al. (2011) analyzed operational data from the bike-sharing system in Vienna. In accordance with studies mentioned above, their findings show that spatial clustering among similar groups of docking stations, suggesting that bike-sharing systems are used by different user groups at similar time periods and for similar trip purposes.

Faghih-Imani et al. (2014) examined effects of social-demographic characteristics, bike infrastructure, built environment features, and temporal factors on arrival flow and departure flow at the station level, using data obtained from the bike-sharing system in Montreal, Canada. A unique observation obtained from their study is that adding a docking station to expand the network has a predominantly stronger impact on bike flows compared to increasing station capacity. Their general conclusion is consistent with Wang et al.'s (2016) recent study on the correlation of the average daily station activity of the Nice Ride system in Minneapolis. Hyland et al. (2017) pointed out that newly added stations can increase bike-sharing usage only if they are not too close to the existing ones.

Noland et al. (2016) examined the bike-sharing system in New York City. To account for commonly observed spatial autocorrelations, they applied a negative binomial conditional autoregressive model based on Bayesian estimation techniques. They also estimated separate models with bike usage data from three different months, February, July, and November, and data by two types of users, registered member, and casual member, to represent variations in weather and usage across the year. Faghih-Imani and Eluru (2016) studied the same system with panel spatial lag and error models with random spatial effects. To account for the impact of neighborhood station from earlier time periods, temporally lagged dependent variables from three previous time periods – one hour, one day, and one week – are incorporated in the models. The outcomes show that all the three temporally lagged dependent variables have positive effects on the arrival and departure rates for members and daily customers.

Two modeling challenges may arise in the use of docking station data. The first challenge is that unobserved factors that influence the dependent variable of bike-sharing usage may also simultaneously influence the independent variable of bike-sharing infrastructure, which may overestimate the effect of the latter (Faghih-Imani and Eluru, 2016). To account for this, Faghih-Imani and Eluru (2016) proposed a measurement equation to separate the installation process from the usage equation. The measurement equation is obtained by combining both the number of bike stations and the total capacity in the TAZ while considering the area of the TAZ normalized by an average number of stations and average capacity and TAZ area. In addition, a multi-level mixed ordered logit model was estimated to further decompose the multi-level unobserved heterogeneity. The model fit measures show evidence for the effectiveness of the newly proposed model framework. The second challenge is the bias in the number of arrivals and departures when the system operators' movement of bikes for rebalancing purpose is not separated from regular trips (Faghih-Imani et al., 2017). To address this challenge, Faghih-Imani et al. (2017) incorporated a binary logit model to identify rebalancing time periods and a model framework to estimate the amount of rebalancing, using bike-sharing data from Barcelona and Seville, Spain.

3.5. Differences between members and casual users

Several studies have observed various differences between members and casual users in terms of group characteristics and travel behavior. Generally, members are riders who purchase a year-long usage pass with a monthly payment or an annual fee and have unlimited access to short trips (e.g. less than 45 min). Borecki et al. (2012) utilized intercept surveys at the five most busy bike-sharing stations to investigate various characteristics of casual users in The District of Columbia. This analysis suggests that casual users are generally well-educated, Caucasian females between the ages of 25 and 34, who use bikes frequently. Besides, the primary purpose of bike-sharing trips is for tourism. Some of above observations contrast with those from Shaheen et al. (2013)'s study where the majority of annual and three-hour members are males in their online survey.

Trip data have been analyzed in other studies to understand behavioral differences between members and non-members. For example, Faghih-Imani and Eluru (2015) found that while train stations tend to be preferred destinations for members of the bike-sharing system in Chicago, they have an opposite effect on non-members. In a more recent study of the bike-sharing system in New York City, Faghih-Imani and Eluru (2016) found that the presence of proximate train stations has a slightly higher effect on arrival and departure rates of members and that annual members are more likely to use the system on weekdays.

To summarize, previous studies have investigated various factors affecting the success of bike-sharing programs using a wide variety of data sources and methodologies. However, gaps in the literature remain. First, previous studies have not come to a consensus on the relationship between public transit and bike-sharing. Although some studies have suggested temporal conditions (Faghih-Imani and Eluru, 2016; Noland et al., 2016) and built environment factors (Shaheen et al., 2014) that may lead to the substitutional effect of transit, their findings can be further verified with more refined transit data (Chardon et al., 2017). Second, studies using survey data have identified a wide range of heterogeneities among bike-sharing users in terms of gender, age, and education background (Borecki et al., 2012; Shaheen et al., 2013). However, such heterogeneities have not been fully examined by studies using trip data, most of which have only focused on behavior differences between members and non-members. Third, empirical studies on bike-sharing often face the modeling challenge of temporal and spatial autocorrelations (Faghih-Imani and Eluru, 2016; Noland et al., 2016). Thus, incremental knowledge can be generated by specifying new models that address these issues.

In light of above arguments, this study builds upon previous studies in three ways. First, this study combines Pronto trip data with detailed built environment data, weather data, and the General Transit Feed Specification (GTFS) data, which creates a rich dataset to comprehensively reexamine factors that relate to the success, or the failure in Pronto's case, of the bike-sharing system. Secondly, the location of University District, which is isolated from the Downtown Seattle by water bodies, has almost created a separated system of stations that exclusively serves bikers on campus. This isolated clustering of stations provides the opportunity to study characteristics of trips taken place in a university setting, which is one location type that generates the highest membership rates (Shaheen et al., 2014) and, moreover, many bike-sharing programs have started on campuses (DeMaio, 2004). Therefore, examining this specific group of trips will help promote future bike-sharing programs that want to start similar businesses in other cities with universities or college towns. Thirdly, this paper implements the approach of the generalized additive mixed model (GAMM) to account for series correlation within time-varying variables and nonlinear relationships.

4. Data and methods

The dataset used in the analysis is composed of three sections, a bike trip count dataset compiled from Pronto bike-sharing data, a spatial dataset consisting of the built environment and public transit, and a temporal dataset containing weather, time, and date. The spatial dataset is linked to the bike-sharing data by docking stations, and the temporal dataset is joined to the bike-sharing data by time and date. Each section is described in detail below.

4.1. Bike-sharing data

The Pronto bike-share dataset was obtained directly from Pronto's website. The dataset consists of every trip from 15th, October 2014 to 31st, August 2016. The trip data include start time, end time, date, start station, end station, station ID, and each station's latitude and longitude. The trip data also distinguishes between members and short-term pass holders. A "member" is a rider who purchased a membership by either a monthly payment or an annual fee. Members receive access to the system for one year with unlimited trips up to 45 min each. Trips longer than 45 min incur incremental usage fees. A "short-Term Pass Holder" is a rider who purchased either a 24-hour or a three-day pass. Similarly, short-term pass holders will receive an incremental charge for holding a bike longer than 30 min.

Based on the start time and the origin station of each trip, individual trips are aggregated to one-hour, two-hour, and three-hour counts of bike pickups at each docking station. Similarly, based on the end time and the destination station of each trip, individual trips are aggregated to one-hour, two-hour, and three-hour counts of bike returns. The 'zitest' function of the 'countreg' package was used for zero inflation test. The test results show that the data suffer from zero inflation with aggregations at one-hour and two-hour time intervals. Thus, a three-hour time interval is used to avoid the inflation of zeros. The count of pickups represents the generation of trips and the count of returns indicates the attraction of trips at each docking station.

4.2. Service area

Studies on bike counts use different buffer sizes to quantify built environment factors (Dill and Voros, 2007; Griswold et al., 2011). Although buffer sizes vary, a general consensus is to use buffers with a radius of less than one mile, such as one tenth mile (Griswold et al., 2011), one eighth mile (Noland et al., 2016), a quarter mile (Dill and Voros, 2007; Griswold et al., 2011), half a mile (Dill and Voros, 2007; Griswold et al., 2011), and one mile (Dill and Voros, 2007). This study assumes that bike-sharing customers walk to the nearest docking station, and therefore a quarter mile (approximately 400-m) buffer around each docking station can be justifiably defined as the service area. This distance is also close to the 300-m service area suggested by the Institute for Transportation and Development Policy (2013). Since stations are close to each other, the service area defined by the buffer radius is sufficient to cover Downtown Seattle area and the University District without much gapping and overlaying. Built environment factors are quantified within buffers of bike-sharing stations.

4.3. Roadway design and public transit

Based on the literature review, roadway design can improve the safety and convenience of the bicycling environment, and therefore may encourage bike usage (Reynolds et al., 2009; Buck and Buehler, 2012; Chen, 2015; Chen and Shen, 2016). Accordingly, bike route length, street lights, street trees, and elevation are measured with GIS data supported by Seattle Department of Transportation (SDOT). A major goal for bike-sharing programs is to solve the first-and-last-mile problem (DeMaio, 2004). Thus, the relation between public transportation services and bike-sharing ridership has gained considerable prominence and traction. In exploring this area, most previous studies have used proximity to bus stops to capture this effect (Fuller et al., 2012; Gebhart and Noland, 2014; Faghih-Imani and Eluru (2015); Ma et al., 2015). However, the level of services varies at different stops significantly, and for each stop, the number of bus trips changes through a day. Deviations in terms of the level of service across stops and over different time periods make proximity to bus stops a less accurate measurement for capturing the effect of public transportation services, especially when it is used with longitudinal bike count data. Therefore, this study uses the number of bus trips per three-hour from the King County Metro (KCM) General Transit Feed Specification (GTFS), an open data format for public transportation schedules and associated geographic information. The original dataset contains scheduled stopping records for 7715 bus stops. A bus stop to docking station link table was created based on the quarter-mile buffer of each dock station. 437 bus stops were selected based on buffers and all bus trips to and from these stops were aggregated to each docking station based on the link table and time. GTFS data only provides scheduled bus trips, and therefore these data may deviate from actual bus trips. Nevertheless, transit users also tend to plan their trips based on bus schedules. One limitation of the GTFS data is that the city of Seattle only publishes data of one or two days for each month, which is assumed to be constant to represent the schedule pattern of a month, therefore the data cannot reflect scheduled differences between weekdays and weekends, and ad hoc schedule changes due to special events. Nevertheless, the data does reflect different capacities among stations and the general service changes over time.

4.4. Land use, elevation, and urban density data

Prior studies suggest that mixed land use, retail, and green space play positive roles in encouraging bike-sharing (Goetzke and Rave, 2010; Su et al., 2014; Chen et al., 2017). To verify these findings from previous studies in the context of Seattle, land use GIS data at the tax lot level was obtained from Puget Sound Regional Council (PSRC). Based on the data, percentages of four land use categories were calculated; namely, residential, commercial, office, and schools and green space. The land use of school and green space includes schools, recreation areas, parks and open spaces, and right of way. The University District falls into this category. Thus, schools and green space has the largest share of land use among the four categories.

Urban density correlates with bike usage. A higher population density and a higher employment density are assumed to supply more customers to proximate docking stations. In addition, the Institute for Transportation and Development Policy (2013) also suggests that a good bike-sharing system should have 10 to 30 bikes available for every 1000 residents. To test this assumption, demographic data were obtained from PSRC. Population and employment densities were calculated by dividing the total land area. The elevation is included to control for its effect on the number of pickups and returns (Mateo-Babiano et al., 2016). Descriptive statistics and data sources for all variables are presented in Table 1.

4.5. Weather information

Daily weather information is provided by Pronto. From the original dataset, daily precipitation, average daily humidity, average wind speed, average visibility, and average daily temperature are chosen as indicators of daily weather conditions. The five indicators are expected to influence the safety and convenience of bicycling, and thus have significant impacts on shared bike usage.

4.6. Events and time

Previous studies have shown different patterns of bike usage between work days and non-work days (Gebhart and Noland, 2014). To incorporate such a difference, a dummy variable was created with zero denoting work day and one denoting national holidays and weekends. Moreover, to better capture daily temporal patterns and seasonal trends, a peak hour dummy variable and an adverse season dummy variable were created. The peak hours include 7 am, 8 am, 9 am, 4 pm, 5 pm, and 6 pm. Temporal variables are linked to trip count data by time. Therefore, they are identical across 50 stations at each observed moment. Descriptive statistics and corresponding data sources for weather information and temporal variables are presented in Table 2. It is worth noticing that all temporal variables are measured at the city level, and thus are invariant across all 50 stations on the same date.

5. Descriptive analysis

Table 3 presents the two-year trip counts by user categories. Among total trips, 146,171 trips (or over 60%) were taken by members and 89,894 trips were taken by short-term pass holders. In terms of locations, 20,043, or 8.49%, of trips were taken in the University District. Even though there were only 12 stations in the University District, the trip number was much lower than the number of trips taken in Downtown Seattle.

Fig. 1 describes the spatial distribution of average daily pickups and returns by stations. Each black dot on the map represents a docking station and a larger radius indicates more bike pickups or returns. In general, at the city level, the network of bike stations is relatively sparse, and stations are grouped in two clusters, namely, Downtown Seattle and the University District. Stations in Downtown Seattle generated most of the trips while stations in the University District are underused. There is an obvious disconnection between two areas. One commonly perceived challenge for bike-sharing programs is the presence of hilly terrain (Faghih-Imani et al., 2017). As Fig. 1(a) and (b) shows, docking stations at high elevation levels have more pickups while docking stations at low elevation levels have greater returns. The pattern implies that customers are more likely to borrow bikes from stations at the top of the hill and then return them to stations at the foot of the hill. Thus, if bikes are not circulated back to origin stations in a timely manner, then there would be a lack of bikes at the stations at the top of the hill and a lack of docking spaces at stations at the foot of the hill.

Fig. 2 illustrates the temporal trend of a typical day with all 50 stations aggregated at hourly level. In general, based on Fig. 2(a), the number of pickups peaks during morning and afternoon rush hours on weekdays and around noon during weekends. Fig. 2(c) shows that the two daily spikes at rush hours are made predominantly by members who take most of their trips during weekdays. On the other hand, short-term users prefer to ride during weekends and their trips increase gradually towards noon and decline afterward in Fig. 2(d). Trips from stations in the University District in Fig. 2(b) exhibit a similar temporal pattern but have a much smaller number of trips per day.

Fig. 3 illustrates the temporal trend of the two-year study period with all 50 stations aggregated at a weekly level. As can be seen from Fig. 3(a), the number of pickups shrank significantly in the second year. Also, the trend exhibits repeated temporal patterns and seasonality over the two years. Spikes and valleys are observed within each week and each month. Furthermore, pickups are the lowest during winter months and then increases gradually, reaching its peak in summer months. Comparing Fig. 3(c) and (d) illustrates that short-term pass holders generate fewer trips than members on average but have more trip spikes.

6. Generalized additive mixed model (GAMM)

As mentioned in the previous section, the trip count data generated from docking stations exhibits temporal trends and seasonality, which violates the independent and identical distribution and normality assumption of ordinary least squares regression. Advanced models are required to tackle this serial correlation and nonlinear seasonality among bike counts of arrival and departure. To address these modeling challenges, a GAMM is implemented. GAMM is favored for its adequate modeling capacity for allowing various distributional assumptions, estimating nonlinear relationships between the dependent variable and independent variables, and accounting for heteroscedasticities (Wood, 2017).

The model specification of GAMM is expressed in Eq. (1) below. In this model, a time metric, $Time_{it}$, is introduced with a unique value for each observed time interval. The time metric ranges from 0 to 5354 with the first observed time interval "15th, October 2014, 8 pm" defined as 0 and last observed time interval "31st, August 2016, 12 am" defined as 5354. To keep the time metric variable on the same scale with other explanatory variables, the variable is rescaled into a range of zero to one by dividing each value by 5354. $f(Time_{it})$ is a non-parametric spline-based smooth function estimated to account for the nonlinear seasonality. A cubic regression spline is used as the smoothing basis. Detailed descriptions of the estimation procedure for $f(Time_{it})$ can be found in Hastie and Tibshirani (1990) and Schimek (2000).

$$\ln(u_{it}) = \beta_{00} + \beta_{0i}X_{it} + \beta_{1i}X_{it}Time_{it} + f(Time_t) + \xi_{oi} + e_i \tag{1}$$

In the model specification, $\ln(\mu_{it})$ is the natural logarithm transformation of the mean of bike counts at the 50 stations over 5355 intervals t. β_{00} is the overall intercept; X_i refers to the explanatory variables including time-varying variables and the built environment; $X_i{*}Time_{it}$ is the cross-level product for time changes. β_{0i} is the fixed-effect estimation parameter that varies across docking station i. β_{1i} captures the overall change rate of effects of time-varying variables. ξ_{oi} is the between-group random effect for the ith docking station and e_i is a Gaussian error term that captures the within-group residual at each docking station (Wood et al., 2017). It is worth noticing that only time-varying variables are included for modeling cross-level interaction effects. In addition, random effects are assumed to follow a multivariate normal distribution. The models are estimated using the "*gamm*" function from the "*mgcv*" R package.

6.1. Spatial autocorrelations

While the above model specification can account for temporal autocorrelations, they do not address spatial autocorrelations. To solve the problem, two spatial variables were introduced. First, to reduce the bias created by global clustering, a dummy variable was created, with one denoting stations located at the University District and zero denoting stations in Downtown Seattle. Because these two regions are heterogeneous when compared to each other but homogenous when compared to themselves, the dummy variable is expected to capture unobserved effects inside each region.

In addition to the global clustering problem, local spillover effects can bias the model. In other words, when customers cannot find available bikes or docks at one station, they will look for a bike at proximate stations. As a result, the bike count at one station is correlated with counts from proximate stations. To address the problem, a distance weight metric to account for spatial covariance was generated. The weight metric takes the form as Eq. (2) (Anselin and Rey, 2014).

$$w_i = \sum_j 1/d_{ij}^2 \tag{2}$$

where d_{ij} is the distance between station i and station j. In practice, w_i can be interpreted as the connectivity of station i to the bike-sharing network. A higher w_i indicates that the station is more connected to other stations, and therefore is more likely to be affected by the spillover effect. A station that is at the edge of the network would have a lower w_i. A side benefit is that it can control for the network effect identified in previous studies (Noland et al., 2016; Chardon et al., 2017).

7. Results and discussion

Models are tested for collinearity using variance inflation factor. Table 4 shows final estimates using three-hour pickups and returns for the GAMM specification. Interpreting fixed effects on the three-hour count of bike pickups shows that elevation is statistically significant and positively correlated with bike pickups, which corresponds to the spatial pattern observed in Fig. 1. Employment density is positively associated with both bike pickups and returns. The results are supported by previous studies suggesting urban density as one of the key factors for the success of bike-sharing programs (Institute for Transportation and Development Policy, 2013). It also suggests that bike-sharing trips are more likely to start and end near people’s working places (Fishman et al., 2015). In terms of land use, the percentage of office and the percentage of green and school land uses are negatively correlated with pickups. The percent of commercial land use is negatively correlated with returns, which suggests bike-sharing users are less likely to choose retails and business districts as their destinations. The number of street lights may relate to the safety of a biking environment (Chen et al., 2018). The variable is positively correlated with bike pickups and returns, which can be interpreted as users’ preference for a safer biking environment. The spatial weight, which represents the connectivity of each docking station to the network, is positively correlated with bike pickups and returns. However, the positive effect is insignificant in the model of bike returns. The results indicate that users may choose stations to pick up bikes based on how close they are connected to other stations but would not consider station connectivity when they choose their destinations. The dummy variable denoting the University District is negatively correlated with both bike pickups and returns, which shows the low usage of stations in the area.

As for temporal factors, daily precipitation is negatively associated with both bike pickups and returns. In addition, bike-sharing is more popular during peak hours and on workdays, which suggests a predominant use for commuting (Fishman, 2016). The number of bus trips is positively correlated with both bike pickups and returns. Also, interactions between bus trips and precipitation and between bus trips and peak hours are negatively correlated with bike pickups and returns. The result is supported by studies of Shaheen et al. (2013, 2014), which suggest that bike-sharing is often used in conjunction with public transit and helps to free some of the capacity of transit services. The above results help to further verify conditions under which bike-sharing is substitutional to transit. The negative coefficients suggest that travelers tend to shift from bike-sharing to public transit during rainy days and peak hours.

The interaction terms between the time metric and other temporal variables measure how the effects shift over time. The interactions of time and non-work day and time and peak hours show same directions of effects as their counterparts without the interaction, which suggests a reinforcing trend through time. In contrast, the interaction of time and precipitation shows a positive sign, which is opposite to the effect of precipitation. The result indicates that bike pickups and returns gradually increase in rainy days possibly due to travelers getting used to the weather in Seattle. The effect of the interaction term of time and bus trip also shows an opposite sign to the effect of bus trips, which may suggest transit users make less combined trips of bus and bike over time. Fig. 4 shows the estimated smooth function of time metric from the GAMM for pickups. The smooth function captures the nonlinear and seasonal effect of time. The estimated smooth functions from other GAMMs show similar pattern, thus are not presented here.

Table 5 presents model estimates on bike pickups and returns by members and short-term pass holders. The outcomes of the GAMMs indicate different behavior patterns between members and non-members. One noticeable difference between the two models is that the elevation is positively associated with pickups by members and negatively associated with returns by short-term pass holders. The elevation is insignificant in the models with short-term pass holders' pickups and members' returns. This is possible because members are more likely to use Pronto's bikes regularly, and thus are more aware of the terrain. Besides, most stations close to water bodies, which attract more casual users, are also at lower elevation levels. Since other results are largely consistent between the models for pickups and returns, only outcomes from the pickup models are discussed to avoid redundancy.

Results suggest that members take more commute trips while non-members are more likely to use shared bikes for recreational purposes. For example, the percent of office shows a negative sign in both models but is only statistically significant in the short-term pass holder model. Non-work day is negatively correlated with member pickups but positively correlated with short-term pass holder pickups. Peak hour is statistically significant and positively correlated with member pickups but insignificant in the short-term pass holder model. Such results are supported by a previous study (Faghih-Imani and Eluru, 2016).

In addition to showing strong behavioral differences, other subtle differences can be interpreted from these results. Precipitation is negatively associated with both pickups by members and by short-term pass holders. However, the negative effect is weaker on member pickups, which may indicate a stronger commitment from members. Besides, interpreting the interaction of time and precipitation suggests that, over time, members are more likely to use shared bikes in rainy weather, which is opposite to non-members.

Table 6 presents model estimates on bike pickups and returns in the University District. Again, results from the model of returns are presented only for comparison and are not fully discussed. The model tries to examine the preferences of users near the campus to understand the overall low usage rate in this area of the city. In general, results from the model show distinct behavior patterns compared with outcomes from other models. The first noticeable difference is that both household density and the percentage of residential land use show positive effects on bike pickups. The coefficients suggest that more bike-sharing trips taken in the University District start from stations near home, which is different from most other trips that start near workplaces. Another interesting finding is that the dummy variable of non-work day is insignificant in the University District model. This illustrates that university students make regular trips to campus regardless of workdays or weekends. Nevertheless, the number of pickups follows a similar hourly pattern, which increases during peak hours. The number of bus trips is positively correlated with pickups but has a larger coefficient value, suggesting a stronger reliance on buses. Besides, the model suggests that users in the University District are also more likely to shift to buses during rainy weather and peak hours.

In summary, model results have clarified the effects of some popularly perceived contributors, such as hilly terrain and rainy weather, to Pronto's failure (The Seattle Times, 2017). First, results indicate that, overall, users are more likely to rent bikes from stations at higher elevations. Nevertheless, such a behavior does not apply to non-members, who tend to use stations at lower elevations as often as those at higher elevations. A possible explanation is that stations at lower elevations are closer to water bodies, which are major attractions for tourists. Secondly, precipitation is found to discourage both members and non-members from using shared bikes. However, the coefficients of the time interaction terms suggest that, over time, the negative effect of precipitation becomes weaker on members but grows stronger on non-members.

Apart from the above, there are some other subtle clues drawn from the model results that may help to explain Pronto's failure. First, results suggest that the bike-sharing program has a higher usage rate during peak hours than non-peak hours. However, results also show that more riders shift to bus services during peak hours. The modal shift may indicate a lack of bikes during peak hours, which could drive commuters to use buses instead of shared bikes. In addition to the above challenge, results from the University District model suggest some unique patterns to the area. Results indicate that bike-sharing users near the campus are more likely to start a trip near home and are not affected by non-work days.

While results have shown many problems with the Pronto program, they also suggest ways to improve bike-sharing usage. For example, results suggest that a well-integrated bus system would not only encourage bike-sharing usage but also provide an alternative choice in adverse weather conditions, which can promote the overall quality of public transportation services. However, results suggest that users make less combined trips of bus and bike over time, which may partly explain Pronto's failure.

Although the paper presents some problems with the Pronto program, there are structural issues that cannot be identified by data from one city or one program because of a lack of heterogeneity. To shed light on these problems, in Table 7 we compared the general information of several representative bike-sharing programs in the nation. The data are compiled from multiple online sources, including bike-sharing program and public transit agency websites, tourism bureaus, and newspapers. By comparison, Pronto has the lowest price, especially when compared with the local public transit service. However, as mentioned above, the number of bike stations in the Pronto program is much smaller than the other three programs, which can be a major obstacle to success for a system that relies on network effect and the economy of scale. Another possible reason for Pronto's failure may be the relatively small number of tourists and visitors, which is a main source of ridership for bike-sharing systems.

8. Conclusions

In this paper, a GAMM is implemented for three-hour bike counts of pickups and returns at station level. The modeling framework incorporates built environment factors and temporal factors and addresses temporal and spatial autocorrelations. Furthermore, additional GAMM sub-models are examined to explore behavior differences among various bike-sharing user groups.

Based on results of the pooled model, the number of bus trips, street lights, station connectivity, density, and peak hours show positive effects on bike-sharing trip generation; on the contrary, the percentage of commercial land, the University District, and precipitation show negative effects on bike-sharing arrival and departure rates. Additionally, results from sub-models clarify effects of other contributors, such as rainy weather and hilly terrain, on Pronto's failure. Effects of these factors vary by user groups. In addition, an examination of trips in the University District shows a unique travel pattern starting from home regardless of workdays or weekends, which requires special accommodations to attract more users.

Although the results are drawn from Pronto's case, they provide general implications for other bike-sharing programs. Currently, cities are enthusiastic about launching public bike-sharing programs for their perceived environmental and health benefits. However, the challenges of developing a successful bike-sharing program have been frequently overlooked. This paper shows that a bike-sharing program is not only challenged by steep terrain and adverse weather conditions but also may compete with bus services during peak hours. Moreover, preferences of different user groups and behavior patterns at different neighborhoods vary greatly, which may increase the difficulty of operation. Hopefully, by empirically investigating Pronto's failure, this paper could raise the awareness of these challenges and help local agencies and investors to make better-informed decisions.

The paper also provides a useful reference for other bike-sharing studies. The estimated smooth function in GAMM addresses nonlinear seasonality, which is commonly observed in bike trip data (Gebhart's and Noland, 2014; Giot and Cherrier, 2015). The study also contributes to the discussion on the relationship between public transportation service and bike-sharing. In general, users use shared bikes more at stations that have more scheduled bus trips nearby. However, some users may shift to buses during peak hours and rainy weather. These findings echo with the existing discussion on the relationship between public transit and bike-sharing system (Shaheen et al., 2013; Fuller et al., 2012; Gebhart and Noland, 2014; Faghih-Imani and Eluru, 2015; Chardon et al., 2017).

The study provides several directions for further research. First, this study assumes that spatial and temporal autocorrelations can be measured separately. However, there can be a third term of autocorrelation that includes both spatial and temporal dynamics. Second, the bus trip data used in this paper cannot fully account for the real-time bus ridership at each station. Consequently, the variable cannot explain how many transfers are made between buses and shared bikes. Third, most explanatory variables are either spatially dynamic but temporally stationary or spatially stationary but temporally dynamic. Hopefully, with better urban sensors, more spatially and temporally dynamic data are accessible, and more accurate measurements of contributing factors are developed. Fourth, to fully understand factors that contribute to Pronto's failure, data from other bike-share programs should be collected to further compare structural factors, such as fares and related regulations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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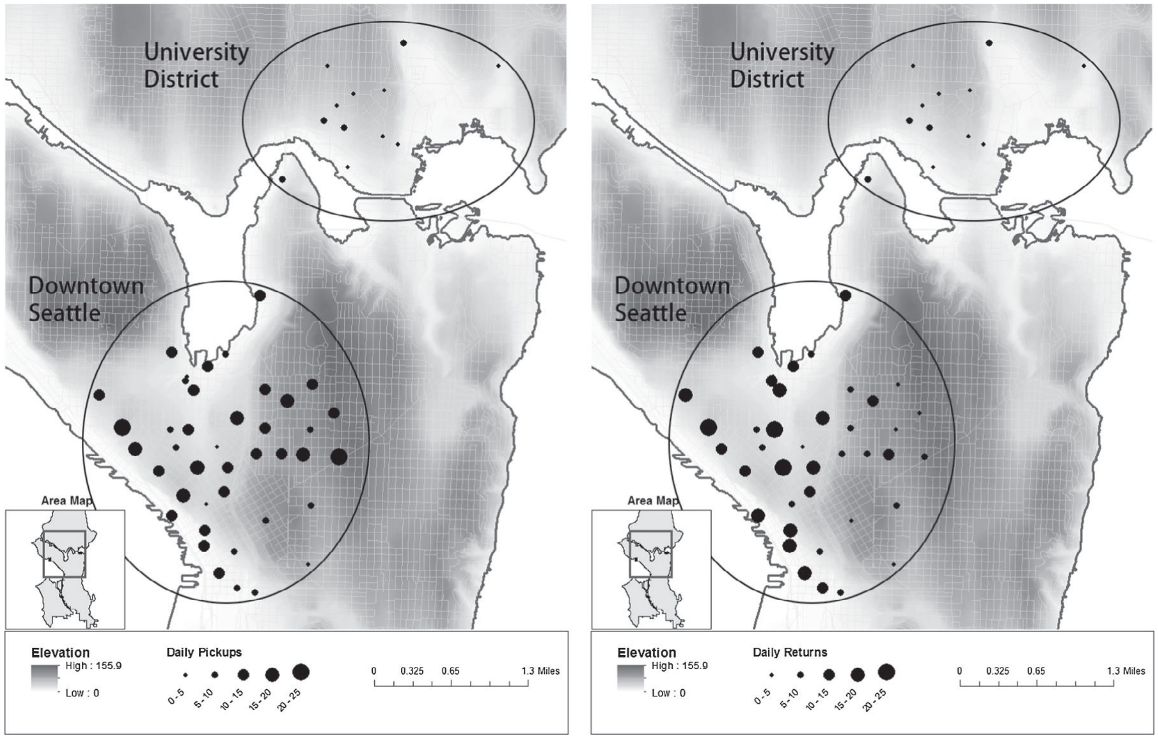
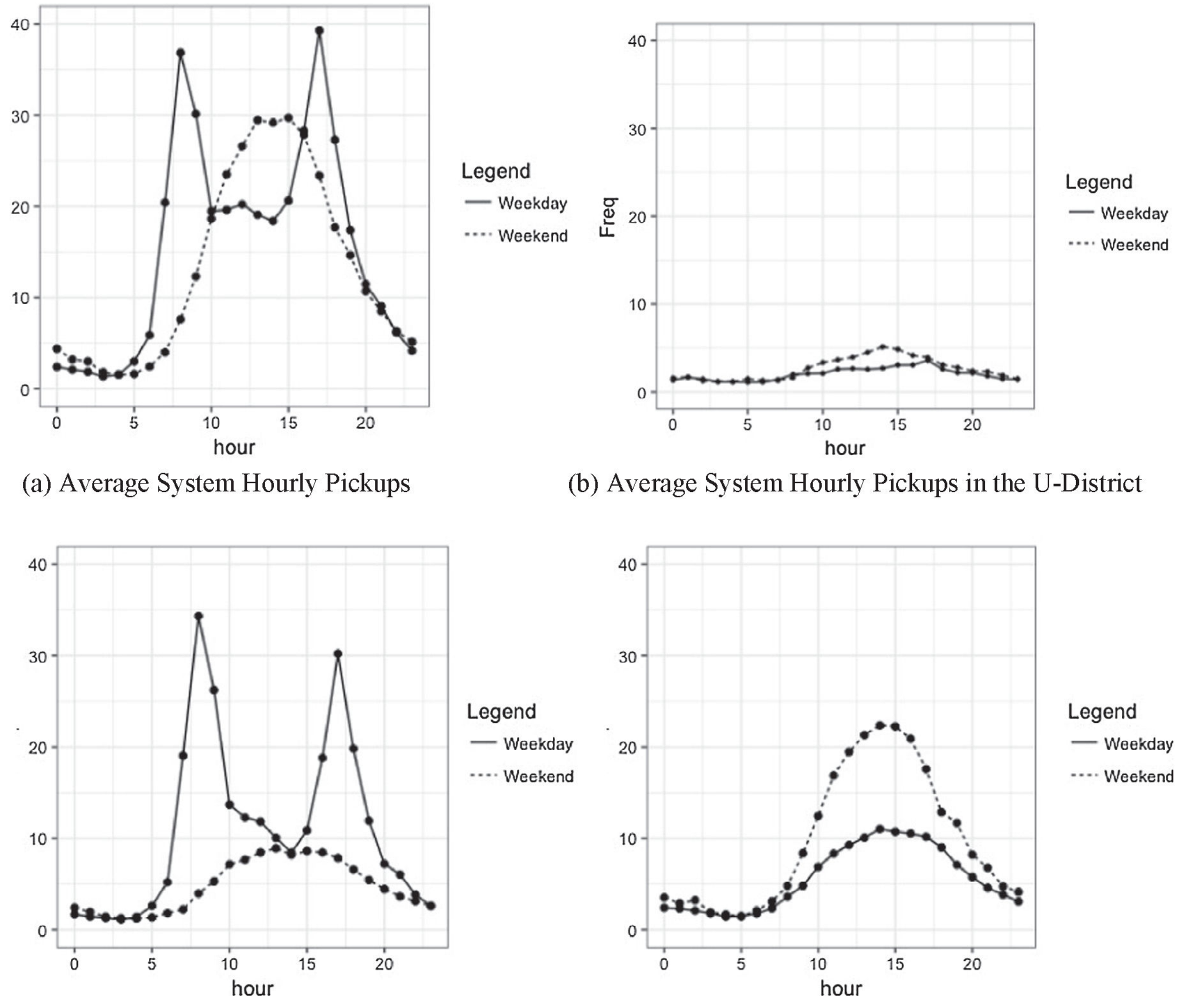


(a) Average Daily Pickups (b) Average Daily Returns

Fig. 1.
Spatial pattern: average daily pickups and returns.



(a) Average System Hourly Pickups

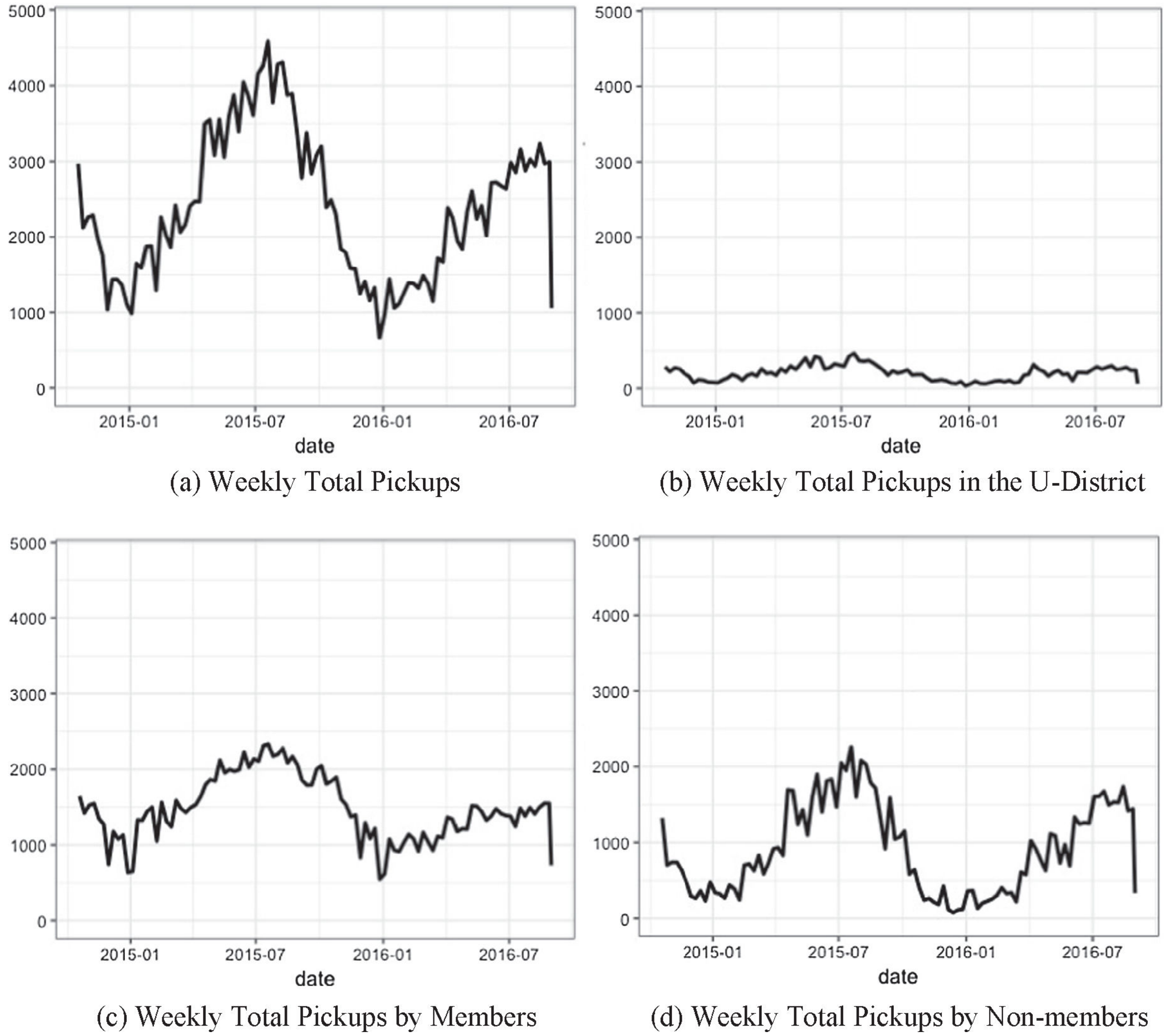
(b) Average System Hourly Pickups in the U-District

(c) Average System Hourly Pickups by Members

(d) Average System Hourly Pickups by Non-members

Fig. 2.

Temporal trend: hourly trip counts.



(a) Weekly Total Pickups

(b) Weekly Total Pickups in the U-District

(c) Weekly Total Pickups by Members

(d) Weekly Total Pickups by Non-members

Fig. 3.

Temporal trend: system weekly trip counts.

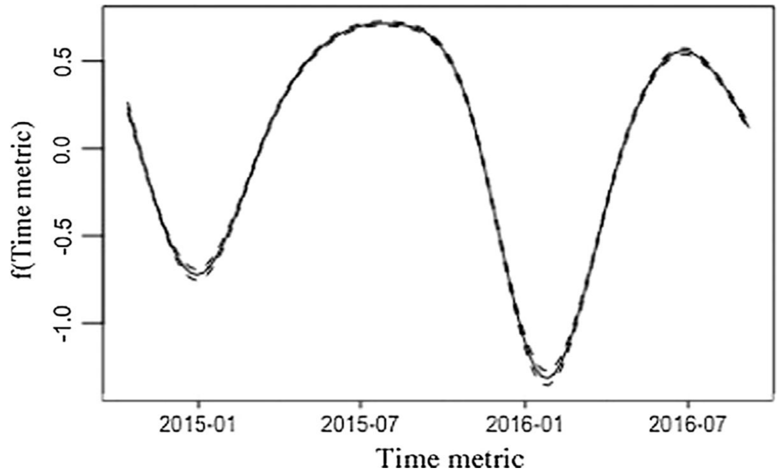


Fig. 4.
Estimated smoothing function of time metric.

Table 1

Descriptive statistics for built environment variables by station.

Category	Variable	N	Mean	Standard Dev.	Min	Max	Source
Land Use	Percent Residential	50	0.07	0.08	0.00	0.43	PSRC
	Percent Commercial	50	0.14	0.13	0.00	0.52	PSRC
	Percent Office	50	0.12	0.13	0.00	0.57	PSRC
	Percent School and Green	50	0.42	0.21	0.11	0.95	PSRC
Roadway design and Public Transit	*Bike Route Length (mile)*	*50*	*2.29*	*0.66*	*0.59*	*3.83*	*SDOT*
	Street Lights (100 per square mile)	50	2.96	1.08	0.78	4.80	SDOT
	Street trees (100 per square mile)	*50*	*0.20*	*0.11*	*0.03*	*0.48*	*SDOT*
	Elevation (meter)	50	41.83	33.55	1.20	125.3	SDOT
	Scheduled bus trips (thousand)	267,600	0.31	0.32	0.00	1.52	KCM
Urban Density	Household Density (10^6 per square mile)	50	0.11	0.12	0.00	0.48	PSRC
	Employment Density (10^6 per square mile)	50	0.68	1.18	0.00	5.44	PSRC

Note: Variables marked in “*Italic*” are excluded from final models because of multi-collinearity.

Table 2

Descriptive statistics for weather and temporal variables.

Category	Variable	N	Mean	Std. Dev.	Min	Max	Source
Weather	*Mean temperature (F)*	*689*	*65.48*	*12.34*	*39.00*	*98.00*	*Pronto*
	Precipitation (cm)	689	0.62	0.59	0.00	5.59	Pronto
	Mean humidity	*689*	*65.03*	*12.65*	*24.00*	*88.00*	*Pronto*
	Mean visibility (mile)	*689*	*9.39*	*1.23*	*3.00*	*10.00*	*Pronto*
	Mean wind speed (mph)	*689*	*4.18*	*2.49*	*0.00*	*14.00*	*Pronto*
Temporal	Non-work day	689	0.30	–	–	–	Generated from date
	Peak hour	5354	0.26	–	–	–	Generated from date

Note: variables marked in "*Italic*" are excluded from the final models because of multi-collinearity.

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Table 3

Two-year trip counts by user categories and locations.

	Member	Short-term Pass Holder	Total
University District	9490	10,553	20,043
	(4.02%)	(4.47%)	(8.49%)
Downtown Seattle	136,681	79,341	216,022
	(57.90%)	(33.90%)	(91.51%)
Total	146,171	89,894	236,065
	(61.92%)	(38.37%)	(100%)

Table 4

GAMM outcomes for pickups and returns.

	Pickups			**Returns**		
	Est.	**Sig.**	**S.E**	**Est.**	**Sig.**	**S.E**
(Intercept)	−2.7709	***	0.8318	−2.4360	***	0.7278
Elevation	0.0067	*	0.0029	−0.0058		0.0034
Household density	1.5149		1.3118	1.7522		1.1478
Employment Density	0.3748	***	0.1633	0.3382	*	0.1429
Percent residential	0.7752		1.5790	1.0187		1.3816
Percent commercial	−3.8659		1.2558	−3.2788	**	1.0988
Percent office	−2.3253	**	1.3207	−1.6348		1.1556
Percent school and green	−0.9541	*	0.8886	−0.3414		0.7775
Street light	0.0047	*	0.0018	0.0047	**	0.0016
Spatial weight matrix	0.3105	***	0.1363	0.2081		0.1192
Univ. District	−0.6761	***	0.3318	−0.7334	*	0.2903
Precipitation	−0.0267	***	0.0008	−0.0296	***	0.0008
Non-work day	−0.1020	***	0.0072	−0.1003	***	0.0072
Peak hours	0.3989	***	0.0071	0.3468	***	0.0071
Number of bus trips	1.6542	***	0.0071	1.4596	***	0.0063
Bus trip*precipitation	−0.0116	***	0.0003	−0.0071	***	0.0003
Bus trip*peak hours	−0.3914	***	0.0026	−0.3146	***	0.0023
Time*precipitation	0.0060	***	0.0004	0.0053	***	0.0004
Time*bus trips	−0.1855	***	0.0012	−0.1562	***	0.0011
Time*non-work day	−0.0174	***	0.0027	−0.0170	***	0.0027
Time*peak hours	0.1082	***	0.0025	0.0982	***	0.0026
f(Time)	Est. *d.f.*			Est. *d.f.*		
	8.998 ***			8.998 ***		
Random effect (Station ID)	Std. Dev.			Std. Dev.		
	0.8453			0.7395		
AIC	936,672.9			925,778.1		
BIC	937,522.7			926,627.6		
Log Link	−468,255.5			−462,808.1		
N	267,600			267,600		

Level of significance:

*** 0.1%

** 1%

* “5%”.

Table 5

GAMM outcomes for member pickups and returns versus short-term pass holder pickups and returns.

	Member Pickups			Member Returns			Short-term Pickups			Short-term Returns		
	Est.	**Sig.**	**S.E**	**Est.**	**Sig**	**S.E**	**Est.**	**Sig**	**S.E**	**Est.**	**Sig.**	**S.E**
(Intercept)	−3.3371	***	0.8036	−2.8200	***	0.6810	−3.3465	***	0.8422	−3.0882	***	0.7098
Elevation	0.0129	***	0.0038	−0.0032		0.0032	−0.0041		0.004	−0.0094	**	0.0034
Household density	1.8045		1.2673	2.2085	*	1.0738	1.14		1.3279	0.8097		1.1180
Employment Density	0.3311	*	0.1578	0.2822	*	0.1337	0.3901	*	0.1654	0.3280	*	0.1394
Percent residential	1.3233		1.5256	1.7005		1.2926	0.2509		1.5984	0.4068		1.3456
Percent commercial	−3.5486	**	1.2134	−2.9885	**	1.0282	−3.731	**	1.2716	−2.9011	**	1.0716
Percent office	−1.4894		1.2761	−0.6142		1.0811	−2.8828	*	1.3371	−2.0631		1.1262
Percent school and green	−0.7114		0.8585	−0.0021		0.7274	−1.2807		0.8995	−0.7054		0.7574
Street light	0.004	*	0.0017	0.0041	**	0.0015	0.0053	**	0.0018	0.0046	**	0.0015
Spatial weight matrix	0.2769	*	0.1317	0.1398		0.1116	0.3302	*	0.138	0.2672	*	0.1162
Univ. District	−0.899	**	0.3206	−1.0456	***	0.2716	−0.3768		0.3359	−0.3772		0.2828
Precipitation	−0.0203	***	0.0009	−0.0221	***	0.0009	−0.0398	***	0.0019	−0.0278	***	0.0032
Non-workday	−0.68	***	0.0109	−0.6773	***	0.0109	0.7537	***	0.0106	0.7368	***	0.0296
Peak hours	0.543	***	0.0088	0.4826	***	0.0088	0.0052		0.0122	0.0652	*	0.0329
Number of bus trips	1.5899	***	0.0094	1.3018	***	0.0078	1.5525	***	0.0115	1.3202	***	0.0246
Bus trip* precipitation	−0.0091	***	0.0004	−0.0063	***	0.0003	−0.0155	***	0.0008	−0.0141	***	0.0014
Bus trip*peak hours	−0.3942	***	0.0034	−0.2851	***	0.0029	−0.3077	***	0.0042	−0.3228	***	0.0115
Time*precipitation	0.0072	***	0.0004	0.0072	***	0.0004	−0.0021	*	0.0008	−0.0025		0.0014
Time*bus trips	−0.1907	***	0.0017	−0.1427	***	0.0014	−0.162	***	0.0019	−0.1240	***	0.0046
Time*non-work day	−0.0801	***	0.0044	−0.0820	***	0.0044	−0.0413	***	0.0039	−0.0409	***	0.0098
Time*peak hours	0.1383	***	0.0032	0.1213	***	0.0033	0.0703	***	0.0043	0.0802	***	0.0107
f(Time)	Est. *d.f.*			Est. *d.f.*			Est. *d.f.*			Est. *d.f.*		
	8.996 ***			8.996 ***			8.996 ***			8.967 ***		
Random effect (Station ID)	Std. Dev.			Std. Dev.			Std. Dev.			Std. Dev.		
	0.8165			0.6918			0.8554			0.7185		
AIC	565,480			561,157			355,761			351,225		
BIC	565,836			561,492			356,112			351,555		
Log Link	−282,706			−280,547			−177,847			−175,580		
N	267,600			267,600			267,600			267,600		

Level of significance:

*** 0.1%

** 1%

* “5%”.

Table 6

GAMM outcomes for pickups and returns in the university district.

	University District Pickups			University District Returns		
	Est.	**Sig.**	**S.E**	**Est.**	**Sig.**	**S.E**
(Intercept)	−1.4739		2.707	−2.4085		1.7603
Elevation	0.0478	**	0.017	0.0207		0.0110
Household density	12.1915	***	1.5507	10.6620	***	1.0105
Employment Density	−0.536		0.4545	−0.2096		0.2955
Percent residential	4.8998	*	2.2322	5.4254	***	1.4529
Percent commercial	−10.0253	***	2.3077	−7.6921	***	1.4984
Percent office	−1.6389		1.718	−0.1856		1.1152
Percent school and green	−11.4069	***	2.7228	−8.6826	***	1.7691
Street light	0.0018		0.0036	0.0038		0.0024
Spatial weight matrix	0.5378	***	0.0726	0.4255	***	0.0475
Precipitation	−0.031	***	0.0029	−0.0323	***	0.0028
Non-work day	0.03		0.0225	0.0342		0.0220
Peak hours	0.1624	***	0.0244	0.2450	***	0.0237
Number of bus trip	2.3396	***	0.0304	2.0498	***	0.0286
Bus trip* precipitation	−0.0203	***	0.0019	−0.0172	***	0.0018
Bus trip*peak hour	−0.4131	***	0.0129	−0.3971	***	0.0127
Time*precipitation	0.004	**	0.0014	0.0029	*	0.0013
Time*bus trip	−0.238	***	0.0058	−0.2042	***	0.0055
Time*non-work day	0.0584	***	0.0084	0.0575	***	0.0082
Time*peak hours	0.0703	***	0.0087	0.0505	***	0.0085
f(Time)	Est. *d.f.*			Est. *d.f.*		
	8.983 ***			8.985 ***		
Random effect (Station ID)	Std. Dev.			Std. Dev.		
	0.257			0.166		
AIC	343,374			340,621		
BIC	343,599			340,828		
Log Link	−171,662			−170,287		
N	58,872			58,872		

Level of significance:

*** 0.1%

** 1%

* “5%”.

Table 7

Information comparison among US representative bike-sharing programs.

	Pronto (Seattle)	Citibike (NYC)	Divvy (Chicago)	Capital bikeshare (Washington D.C.)
24-hour price	$8	$12	$9.95	$8
3-day price	$16	$24	–	–
Annual price	$85	$163	$99	$85
Number of bike stations	50	603	580	440
Bus fare	$2.75	$2.75	$2.00	$2.00
Subway/light rail fare	$2.75	$2.75	$2.25	$2.20
Annual city visitor volume (2015)	6.3 million	50 million	51 million	21.3 million