Modeling Bike Share Station Activity: Effects of Nearby Businesses and Jobs on Trips to and from Stations

Xize Wang[1]; Greg Lindsey[2]; Jessica E. Schoner[3]; and Andrew Harrison[4]

Abstract: The purpose of this research is to identify correlates of bike station activity for Nice Ride Minnesota, a bike share system in the Minneapolis–St. Paul Metropolitan Area in Minnesota. The number of trips to and from each of the 116 bike share stations operating in 2011 was obtained from Nice Ride Minnesota. Data for independent variables included in the proposed models come from a variety of sources, including the 2010 U.S. Census; the Metropolitan Council, a regional planning agency; and the Cities of Minneapolis and St. Paul. Log-linear and negative binomial regression models are used to evaluate the marginal effects of these factors on average daily station trips. The models have high goodness of fit, and each of 13 independent variables is significant at the 10% level or higher. The number of trips at Nice Ride stations is associated with neighborhood sociodemographics (i.e., age and race), proximity to the central business district, proximity to water, accessibility to trails, distance to other bike share stations, and measures of economic activity. Analysts can use these results to optimize bike share operations, locate new stations, and evaluate the potential of new bike share programs. **DOI: 10.1061/(ASCE)UP.1943-5444.0000273.**

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Introduction

Bike Sharing

Bike share systems, which are designed to provide inexpensive bicycle rental at strategic locations throughout cities for quick one-way trips from station to station, are among the world's fastest-growing urban cycling innovations. As of 2010, there were an estimated 100 programs in approximately 125 cities worldwide, with over 139,300 bicycles (Shaheen et al. 2010). New programs are being established annually (DeMaio 2009).

In the United States, bike sharing has also attained popularity, partially because of increasing concerns about environmental sustainability and partially because of the success of prior programs (Shaheen et al. 2010). By the end of 2012, 15 bike share systems claiming 172,070 users had been established in the United States (Shaheen et al. 2012). Planners, policy makers, and advocates for cycling believe that these systems provide many benefits to users: convenience, improved access to destinations and jobs, increased physical activity and health, increased mobility, positive environmental impacts, low cost, and more efficient use of infrastructure and other space (Shaheen et al. 2010). Bike share programs are also helpful in promoting the positive image of cycling (Goodman et al. 2014) because factors like social norms have a very strong influence on attitudes regarding cycling (Underwood et al. 2014).

The history of bike share systems can be traced to the free bike systems begun in 1993, through coin-deposit systems, and finally to current IT-based systems. Despite operational improvements associated with these innovations, challenges remain, specifically with respect to system rebalancing (Shaheen et al. 2010). System rebalancing refers to the operational problems that occur because of unequal numbers of rides to and from stations. For example, as riders go from stations with low activity to popular destinations, docking stations at destinations can be filled and bikes from areas of origin can be depleted. Managers need tools to predict which bike share stations will "gain" or "lose" bicycles. A new generation of bike share programs—demand-responsive, multimodal systems—has been proposed to overcome this limitation (Shaheen et al. 2010). However, these systems have not been deployed. The current research, which identifies factors associated with variation in bike share station activity, provides insights essential to developing more efficient, user-friendly systems.

Research Needed to Strengthen Program Operations

Research on bike share systems is booming, but most such studies are gray literature reports focusing on descriptive analyses of bike share systems and their benefits, application rates, and user characteristics. Systematic, quantitative analyses of bike share operations or their impact on transportation systems remain limited (Fishman et al. 2013). Published studies have shown that bike share system users' main trip purposes are commuting and utility travel, including the last-mile option for transit trips. As a result, bike share systems may be helping to reduce the level of driving (Fishman et al. 2013). Researchers also have documented the advantages of bike sharing as a transportation mode. In Lyon, France, for example, Jensen et al. (2010) measured the speed of the city's *Vélo'v* bike share system using the 11.6 million bicycle trips in the city provided by its operator. The average speed of shared-bicycle trips during rush hour was as high as 15 km/h, which is higher than the average speed of motor vehicles in downtown European cities

[1]Sol Price School of Public Policy, Univ. of Southern California, 650 Childs Way, Los Angeles, CA 90089 (corresponding author). E-mail: xizewang@usc.edu

[2]Humphrey School of Public Affairs, Univ. of Minnesota–Twin Cities, 301 19th Ave. S, Minneapolis, MN 55455. E-mail: linds301@umn.edu

[3]Dept. of Civil Engineering, Univ. of Minnesota–Twin Cities, 500 Pillsbury Dr. SE, Minneapolis, MN 55455. E-mail: jschoner@gmail.com

[4]San Francisco Municipal Transportation Agency, 1 S. Van Ness Ave., San Francisco, CA 94103. E-mail: andrew.harrison@sfmta.com

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(10–15 km/h). This illustrates the practical feasibility of reducing driving through bike share programs.

Looking forward, the focus of bike share system research will likely be on ongoing refinement of practical operations (e.g., predicting and meeting demand, improving redistribution of bicycles across stations) as well as on understanding customer behavior and local bike-sharing impacts (Pucher et al. 2011). For example, researchers recently reported studies of optimizing bike-sharing stations using mathematical network models (Lin and Yang 2011) and GIS-based models (García-Palomares et al. 2012). Krykewycz et al. (2010) applied a two-stage model, including a geographic information system (GIS) raster analysis and quantitative estimation, to estimate the demand for bicycle-sharing systems in peer European cities. A recent analysis of the August 2010 rentals of 65 Nice Ride stations in Minneapolis is most relevant for this study. Maurer (2012) found that monthly rentals are related to trip generation factors (e.g., population size), trip attraction factors (e.g., number of "attracters," or destinations such as shopping centers or museums), and transportation network factors (e.g., existence of bikeways). However, these researchers studied only a narrow window of Nice Ride Minnesota operations. (one month). The system size of Nice Ride has since doubled, and additional study is needed.

This paper is a part of a larger study to identify economic activity associated with the Nice Ride Minnesota bike share system in Minneapolis and St. Paul, (Schoner et al. 2012). It assesses whether bike share station activity is associated with the presence of retail businesses and job accessibility in addition to other sociodemographic, built-environment, and infrastructure variables. These relationships are tested with different regression models.

Correlates of Bicycle Traffic

Insights into factors associated with the use of bike share stations can be obtained from studies of general nonmotorized traffic—that is, bicycling and walking. For instance, many studies (e.g., Hankey et al. 2012; Lindsey et al. 2007) have shown that nonmotorized traffic volumes in particular segments of transportation networks are correlated with the sociodemographic characteristics of nearby populations, characteristics of the built environment or urban form (Stinson and Bhat 2004; Coutts 2009), characteristics of linked transportation infrastructure (Maurer 2012), and other factors, including weather (Wang et al. 2014). Research has shown that a higher supply of bicycle and pedestrian infrastructure such as bike lanes, separate bike paths, and "bicycle boulevards" helps to increase levels of bicycle and pedestrian travel (Dill 2009; Krizek et al. 2009). Higher population density is also related to higher levels of bicycling and walking (Handy et al. 2002). Another important factor is land use mix, which has been shown to be associated with higher levels of active travel. Frank et al. (2004) found that people tend to bike and walk more when they live in places with a higher level of entropy, which is a measure of land use mix. Safety is also believed to be important to active travel levels. Higher crime rates in a neighborhood are usually related to lower active travel levels (Joh et al. 2012).

Because each of the general categories of variables—sociodemographic, built environment, and transportation infrastructure—have been shown to be related to nonmotorized traffic volumes, it is helpful to make them control variables.

The next section of this paper briefly introduces the Nice Ride bike share system in Minneapolis–St. Paul, Minnesota. It also summarizes the study data and the methods used to evaluate the study models. The following section presents the results, including the two models' average total station activity for the 116 Nice Ride stations in operation in 2011. The section after discusses potential applications for the models in transportation planning and management. The final section summarizes the study's main findings, notes the limitations of the study, and suggests areas for future research.

Bike Share System in Minneapolis–St. Paul

Since its beginning in the spring of 2010, the Nice Ride Minnesota bike share system has attracted large numbers of bike commuters, leisure cyclists, and new cyclists. The Nice Ride system initially had 65 stations in or near the Minneapolis central business district (CBD), other commercial areas, and the University of Minnesota campus. By the end of the 2011 season, Nice Ride had expanded to include 116 stations throughout Minneapolis and St. Paul (Fig. 1), had enrolled 3,693 subscribers, and was providing bicycles for thousands of daily users. The total number of Nice Ride bike trips for 2011 surpassed 217,000.

Nice Ride Minnesota initially located bike share stations to maximize ridership through practical and intuitive understanding of factors believed to be associated with ridership. These factors included presence in the CBD, proximity to retail and commercial businesses, proximity to other destinations or features (university campus, libraries, lakes, parks, etc.), presence in higher-density residential areas, nearby bike infrastructure, and other factors that have been shown to be associated with bicycling. These decisions generally were made with an understanding of neighborhood characteristics rather than based on detailed research about the presence of specific types of businesses. A community outreach program helped inform expansions into the North Minneapolis area and the city of St. Paul. Specifically, Nice Ride was criticized for ignoring lower-income, minority areas. To address equity concerns, Nice Ride established eight additional stations outside the Minneapolis CBD. In addition, nine stations were located along a corridor in advance of construction of a new light rail line (the Central Corridor between Minneapolis and St. Paul) despite lower population densities and limited accessibility to stations.

To further optimize system performance, Nice Ride has tracked station use, shared station trip records with a number of research organizations, and adjusted operations based on its station use records. As shown in Fig. 2, eight of the top ten most used stations—measured in average trips per day—are located in high concentrations of retail land uses: six are near the Minneapolis CBD, one is near a major retail hub in a trendy uptown neighborhood south of the CBD called Calhoun Square, and one is on the periphery of the University of Minnesota campus, where many restaurants and shops are located. The remaining two are on the campus itself. Conversely, the ten least used stations are in areas with lower concentrations of retail and consumer-oriented businesses, including North Minneapolis for equity reasons and the future light rail corridor.

Economic theories of transportation demand suggest that the availability of bicycle stations for inexpensive public use throughout a city should affect travel and consumption patterns, although the extent of these effects is not known. Bicycle share stations selectively increase accessibility to areas around each station by increasing the number of people who can reach particular places within reasonable travel times. Increases in accessibility also increase the potential for changes in local economic activity (i.e., consumption and spending). If bike share stations are associated with local economic activity, it is hypothesized that the number of trips to and from stations should be positively associated with higher concentrations of nearby businesses, including food-related destinations, and accessibility to jobs.

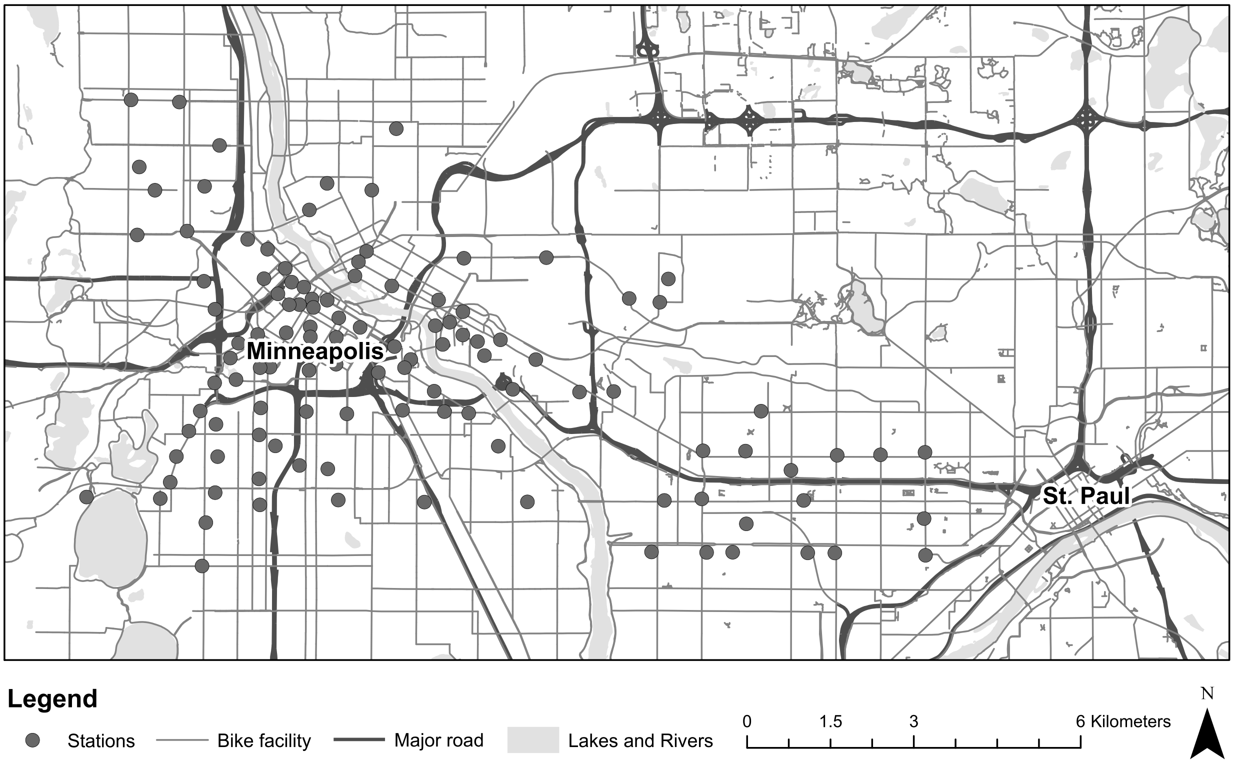

Fig. 1. Nice Ride stations at the end of the 2011 Season (data from Nice Ride Minnesota 2014; MetroGIS 2014)

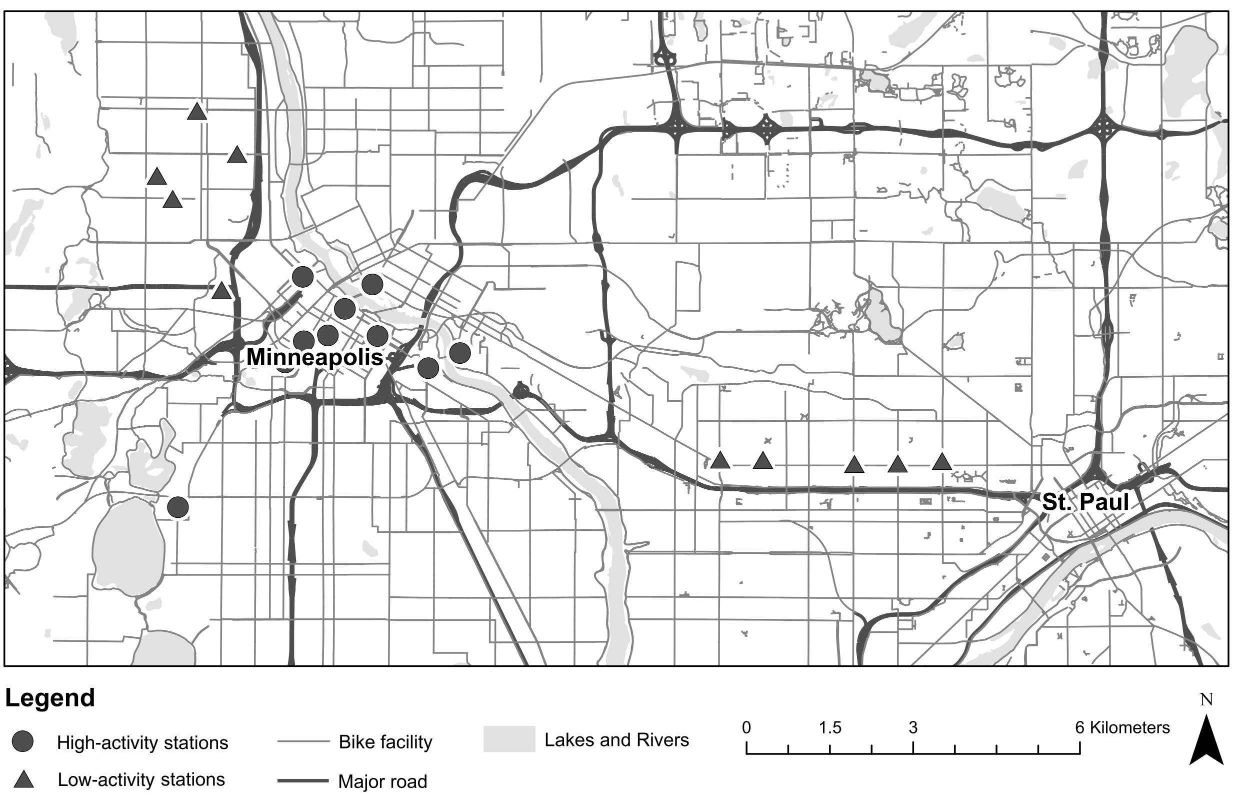

Fig. 2. Top ten origin and destination stations in 2011 (data from Nice Ride Minnesota 2014; MetroGIS 2014)

To test this hypothesis quantitatively, the current study evaluates log-linear and negative binomial models that use the total number of trips to and from stations as dependent variables. Independent and control variables include indicators of economic activity (i.e., number of food-related retail establishments and job accessibility), neighborhood sociodemographics, the built environment, transportation infrastructure, and other dummies specific to the study area.

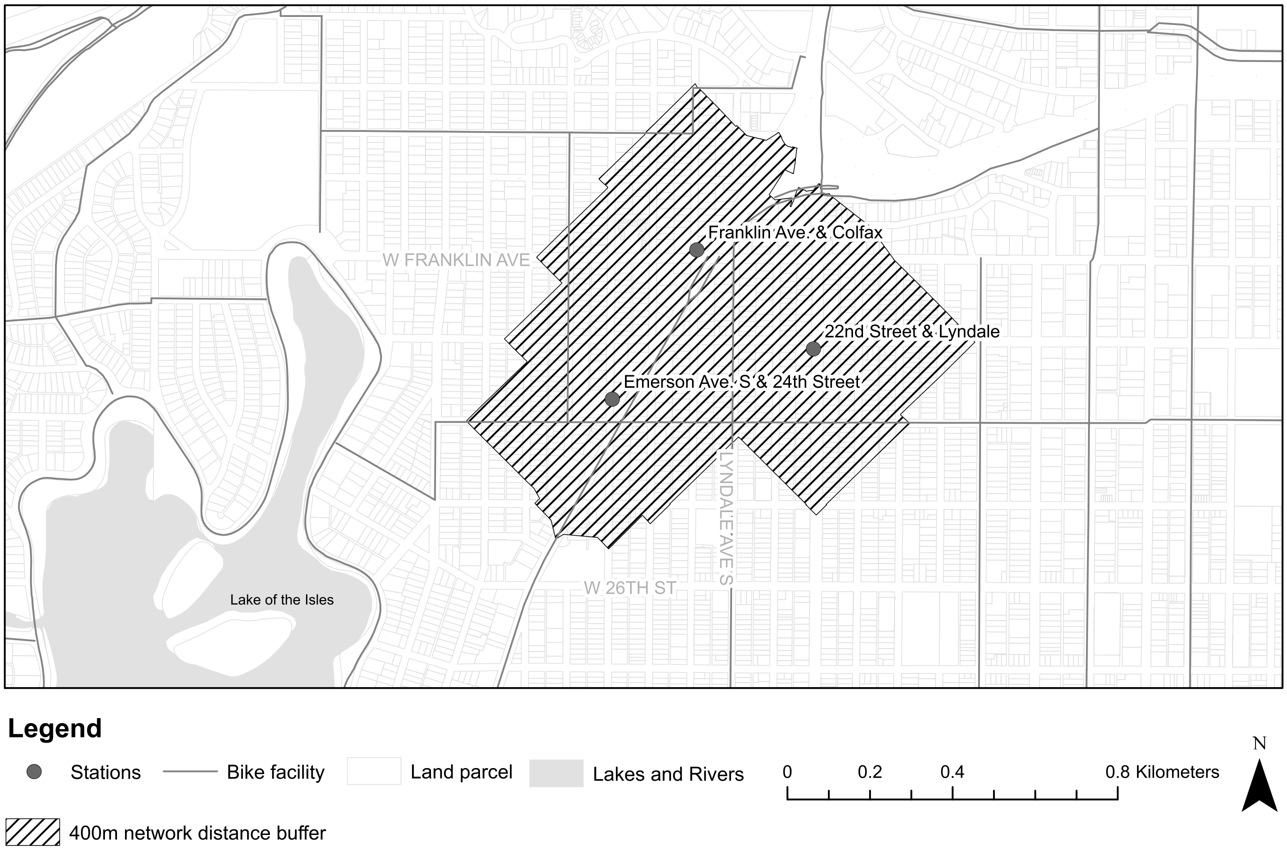

Fig. 3. 400-meter walking distance buffer around Lowry Hill East stations (data from Nice Ride Minnesota 2014; MetroGIS 2014)

Data and Methods

Regression modeling is used to identify the relationship between activity at 116 Nice Ride stations during the 2011 season and a set of 13 independent and control variables that reflect different relevant characteristics of the station area, which is defined as an area with a 0.4-km (0.25-mi) network distance buffer for each station. Fig. 3 is an example station area in Minneapolis' Lowry Hill East neighborhood. The number of stations (116) is large enough to reflect considerable variation in activity and, given the number of independent variables (13), there are sufficient degrees of freedom for estimation.

Correlates of Nice Ride Station Activity

Dependent Variables

For the purposes of this study, bike share "station activity" is defined as the sum of trip origins and destinations. The average daily station activity is measured in order to sort out the different operating dates among different stations. The descriptive statistics of the trips to and from the 116 Nice Ride stations are shown in Table 1. The "total trip" numbers (both trip origins and trip destinations) among the 116 stations range from 83 to 20,544, with an average of 3,749. The number of trip origins for each station ranges from 37 to 9,843, with an average of 1,875. The number of trip destinations ranges from 39 as the lowest to 10,701 as the highest. The average number of trip destinations is 1,874. The stations with larger numbers of trip destinations also tend to have larger numbers of trip origins. The distributions of total trips, trip origins, and trip destinations are not distorted by different capacities among bike share stations because the Nice Ride Minnesota system keeps track of the number of remaining bikes in each location (Mitch Vars, Nice Ride Minnesota, personal communication, 2011). These statistics show that the distributions of total trips are skewed by the stations with higher values, which, as will be discussed, makes the logarithm transformation appropriate in the ordinary least-square (OLS) modeling. Also, the fact that the trip variable is a nonnegative integer (i.e., a count) makes the use of negative binomial models appropriate (Long and Freese 2005).

Table 1. Descriptive Statistics for 2011 Nice Ride Station Activity

Trip type	Average	Maximum	Minimum
Trips per day	19.47	96.45	0.916
Total trips	3,749	20,544	83
Trip origins	1,875	9,843	37
Trip destinations	1,874	10,701	39

Sociodemographic Variables

Using 2010 U.S. Census data (U.S. Census Bureau 2012), two sociodemographic control variables are constructed for a 0.4-km (0.25-mi) network distance buffer around each station (Table 2). The variable whitepct controls for the racial structure of the analytical units, specifically the proportion of residents who are White/Caucasian. The variable ynoldpct controls for the age structure of the analytical units; it is the proportion of residents who are younger than 5 years or older than 64 years. It is expected that station activity positively correlates with a larger percentage of White/Caucasian and middle-aged people.

Table 2. Independent Variables Used in Modeling Station Usage Frequency

Variable	Description	Mean	Units/notes	Exposure sign
		Sociodemographic variables		
whitepct	Percentage of White/Caucasian[a] residents	60.51	Unit: all census blocks interacting with 0.4-km (0.25-mi) station buffer area	+
ynoldpct	Percentage of residents younger than 5 years or older 64 years[a]	13.04	Unit: all census blocks interacting with 0.4-km (0.25-mi) station buffer area	−
		Built-environment variables		
diswater	Distance to nearest lake or river[b]	0.9973	Unit: km	−
discbd	Distance to nearest CBD of each city for bike share stations in Minneapolis or St. Paul[b]	2.904	Unit: km; CBD is centroid of downtown reduced-transit-fee areas defined by metro transit	−
dispark	Distance to nearest park land-use type[b]	0.2366	Unit: km; park defined as land-use type 170	−
campus	Station at University of Minnesota campus[b]	0.1293	1 if on Minneapolis or St. Paul campus; else 0	+
		Transportation infrastructure variables		
trail	Paved trail in station area[b]	0.2672	1 if paved trail within 0.4-km (0.25-mi) station area buffer; else 0	+
neardis	Distance to nearest station	0.5142	Unit: km	−
opdate	Days of station operation in 2011	167.9	November 6th, 2011: last day of service for year	+
		Economic activity variables		
access	Total jobs within 30-min transit accessibility in 2006[c]	37.24	Unit: 1,000 jobs; includes all census blocks interacting with 0.4-km (0.25-mi) station buffer area	+
food	Total number of businesses in "food" category[d]	7.545	Unit: 0.2-km (0.125-mi) station buffer area	+
		Controlling factors		
northmpls	Stations in North Minneapolis established mainly according to spatial equality criteria[e]	0.06897	1 if located in North Minneapolis area; else 0	−
open2010	Dummy variables for stations opened in 2010	0.5603	1 if first opened in 2010; else 0	+
cclrt	Stations heavily affected by ongoing LRT construction[e]	0.07759	1 if located in affected areas; else 0	−

[a]Data from U.S. Census Bureau (2012).
[b]GIS data from MetroGIS (2014).
[c]Data from Fan et al. (2012).
[d]Data from U.S. Census Bureau (2012).
[e]Authors' assessments.

Built Environment Variables

To control for the effects of the built environment around each station on station activity, variables for proximity to various notable destinations are constructed that are believed to be trip attractors or generators (Table 2). The variables *diswater*, *discbd*, and *dispark* measure the proximity of the station in kilometers to the nearest lake or river, the downtown Minneapolis or St. Paul CBD, and parks. The *campus* dummy variable indicates whether the station is located on the University of Minnesota campus. It is expected that station activity is positively associated with being closer to parks, water, and downtown and campus locations.

Transportation Infrastructure Variables

The study hypothesizes that transportation infrastructure such as bike trails supports Nice Ride station activities because it increases access to individual stations (Table 2). The variable *trail* indicates whether a paved trail exists in the 0.4-km (0.25-mi) station network buffer area. There is also a base case that indicates no paved trail within the station area. The variable neardis measures the distance to the next nearest Nice Ride station. The variable opendate, which measures the operating dates of the stations in 2011, serves as the exposure variable to ensure that variation in Nice Ride station activity is not because some stations were not open for the whole season. It is expected that station activity is positively related to the presence of paved trails and proximity to the nearest bike share station.

Economic Activity Variables

After controlling for the sociodemographic, built-environment, and transportation infrastructure variables described previously, the marginal relationship between indicators of economic activity and station activity (trips) is isolated. The variable *access* calculates job accessibility, measured as the total number of jobs accessible within a 30-min transit ride (i.e., bus or light rail) from the station using 2006 transit and employment data from Fan et al. (2012). Jobs accessible via transit are used because of the study's particular interest in the last-mile problem for transit users. An accessibility measure is used that incorporates both transit and jobs rather than a variable such as number of bus stops because it is hypothesized that accessibility better reflects the relationship between bike share and transit. The variable food indicates the total number of businesses categorized as "food" within a 0.2-km (0.125-mi) walking distance buffer around the station. These businesses were identified using the data from the Census Bureau and categorized by North American

Industry Classification System (NAICS) according to the protocol developed by Horning et al. (2008) for measuring nonmotorized accessibility. Both of the economic activity variables are expected to be positively associated with 2011 station activity. Also tested was a measure defined as total businesses in the station area, but this variable was not associated with station use and is not reported here.

Controlling Factors

Three controlling factors, in addition to the variables discussed previously, are included to better estimate the effects on the bike share station activity (Table 2). The variable *northmpls* is a dummy variable indicating whether the stations are located in the North Minneapolis area. These stations were installed either for reasons of equity, rather than network optimization, or because Nice Ride managers anticipated high levels of use. The variable *cclrt* is a dummy variable indicating whether the stations are located in areas within the future Central Light Rail Transit Corridor but are heavily affected by the project's ongoing construction. Among other factors, the population and destination densities in the corridor are different from those in and near the Minneapolis CBD. The variable *open2010* is a dummy variable that indicates the stations that first opened in 2010 rather than 2011. The station activity is expected to be negatively associated with the variables *northmpls* and *cclrt* but positively associated with the variable *open2010*. The variable *opendate* indicates the number of days stations operated during 2011, which is the exposure variable of the negative binomial regression.

Model Development and Estimation

Both log-linear OLS regression and negative binomial regression are used in this study to evaluate the station activity models. The logarithm form estimates the average station activity because its distribution is skewed to the right-hand side. Negative binomial regression estimates the total station activity counts because they are non-negative integer values.

Similar to Poisson distribution, the dependent variable y in the negative binomial regression model is also a non-negative integer. The probability that y equals m conditioning on the linear combination of $x1, x2\ldots$ and a parameter λ is as follows (Long and Freese 2005):

$$P(y = m|x_1, x_2, \ldots) = \frac{e^{-\lambda} \times \lambda^m}{m!} \quad (1)$$

The negative binomial regression model assumes that the mean of y is λ and the variance of y is $\lambda + \alpha\lambda^2$. Maximum likelihood estimation (MLE) is used to estimate α and the βs of the following generalized linear model:

$$\ln \lambda = \beta_0 + \beta_1 \times x_1 + \beta_2 \times x_2 + \ldots \quad (2)$$

If the observations of dependent variable y are from time lengths, an exposure factor must be added to control the effect of the different time periods (Long and Freese 2005).

Because the dependent variables in both models are transformed into the natural logarithm form, the marginal effect of the independent variables is different from that in basic OLS models. Specifically, if the coefficient of an independent variable is β, an increase in the variable by one unit is correlated with a $100 \times [\exp(\beta) - 1]\%$ increase in the dependent variables, or to its $\exp(\beta)$ times. The adjusted R-square is a measure of the goodness of fit of the OLS model, and the Cox-Snell pseudo R-square is a measure of the goodness of fit of the negative binomial model.

The two models, estimated by *Stata* and *SPost 9* (Long and Freese 2005) are

- Log-linear: the dependent variable is the natural logarithm of total station activity (trip origins plus trip destinations) per operating day of the 2011 season; and
- Negative binomial: the dependent variable is the total station activity (trip origins plus trip destinations) of the 2011 season, with an exposure time–controlling variable, *opendate*.

In both models, the effects on the dependent variables measured are the average daily trips rather than the total daily trips. Also estimated are models for average daily origins and departures; they are not reported here because the results are essentially the same as for the models for average daily trips and because average daily trips better reflect overall station activity.

Results

The results of the two models are shown in Table 3. Model 1 has a very high fit: the adjusted R-square value is 0.847, indicating that nearly 85% of the variation in trip activity across stations can be explained by these variables. The F-statistic of Model 1 (80.14) is significant at a 0.0001 level, indicating the joint significance of the variables and the reliability of the adjusted R-square value. The pseudo R-square for Model 2 is 0.863, which is is not directly comparable to the adjusted R-square of the log-linear model. However, the fact that it has an even higher significance than that of the log-linear model indicates that it also has a very good fit. The likelihood ratio chi-square value of Model 2 (230.27) is also significant at a 0.0001 level and also supports the good fit of the model. In addition, the significance of the dispersion factor confirms that the negative binomial regression model is theoretically sounder than a Poisson model.

Overall, in both models all independent variables are significant at the 10% significance level, and the majority are significant at the 5 or 1% level. The fact that all independent variables are significant underscores the strength of the study model fit and indicates the validity of the underlying, hypothesized theoretical relationships. The signs of all but one coefficient are in the expected direction. The marginal effects of the two models are quite similar, indicating very robust estimations. The results of the tests of joint significance (F-test and likelihood ratio test) confirm the reliability of these results.

Both of the sociodemographic variables are significant at a 10% significance level at the least. The coefficient of *whitepct* is positive in both models, indicating that a higher activity level of a bike share station is positively related to a higher share of Caucasians in the population in the station area. Specifically, a 1% increase in the share of the White population at the 0.4-km (0.25-mi) station buffer area is related to a 1.4–1.5% increase in daily station activity. The coefficient of *ynoldpct* is negative, showing that the share of middle-aged residents is related to a higher level of station activity. Specifically, a 1% increase in the share of the population older than age 64 or less than age 5 in the buffer zone is associated with a 1.0–1.4% decrease in bike share station activities.

All of the four built-environment variables are significant at least at a 10% significance level. As hypothesized, *diswater*, *discbd* and *dispark* have a negative effect on the 2011 daily average Nice Ride station activities: bike share stations nearer to water bodies, to CBDs, and to parks have higher levels of activities. That implicitly shows that people tend to use Nice Ride bikes for recreational purposes more frequently around rivers, lakes, and parks, whereas they tend to use them for commuting purposes in downtown areas. For instance, being 1 km nearer to the CBD of Minneapolis or St. Paul

Table 3. Station Activity Regression Models

Variables	Model 1 (log-linear) Coefficient	Standard error	Marginal	Model 2 (negative binomial) Coefficient	Standard error	Marginal
Dependent variable	Station activity (origin + destination) per opening day			Station activity (origin + destination) per opening day		
			Sociodemographic			
whitepct	0.015[a]	[0.003]	1.5%	0.014[a]	[0.002]	1.4%
ynoldpct	–0.014[b]	[0.007]	–1.4%	–0.010[b]	[0.006]	–1.0%
			Built environment			
diswater	–0.421[a]	[0.086]	–34.4%	–0.444[a]	[0.088]	–35.9%
discbd	–0.123[a]	[0.043]	–11.6%	–0.122[a]	[0.042]	–11.5%
dispark	–0.486[b]	[0.270]	–38.5%	–0.485[b]	[0.253]	–38.4%
campus	0.355[b]	[0.193]	42.6%	0.395[a]	[0.153]	48.4%
			Transportation infrastructure			
trail	0.409[a]	[0.120]	50.5%	0.383[a]	[0.099]	46.7%
neardis	0.668[a]	[0.228]	95.0%	0.643[a]	[0.227]	90.2%
			Economic activity			
access	0.009[a]	[0.004]	0.9%	0.008[c]	[0.003]	0.8%
food	0.017[a]	[0.004]	1.7%	0.017[a]	[0.005]	1.7%
			Controlling factors			
northmpls	–0.472[c]	[0.182]	–37.6%	–0.544[a]	[0.190]	–42.0%
open2010	0.481[a]	[0.124]	61.8%	0.505[a]	[0.123]	65.7%
cclrt	–0.482[a]	[0.168]	–38.2%	–0.522[a]	[0.171]	–40.7%
opendate	—	—	—	(Exposure)	—	—
Constant	1.426[a]	[0.446]	N/A	1.582[a]	[0.408]	N/A
Dispersion factor (α)	—	—	—	0.161[a]	[0.021]	N/A
Number of observations	—	116	—	—	116	—
Joint significance	80.14 (F-statistics), $p = 0.0000$			230.27 (LR chi-square), $p = 0.0000$		
R-squares	0.847 (adjusted)			0.863 (Cox-Snell pseudo)		

[a]$p < 0.01$.
[b]$p < 0.1$.
[c]$p < 0.05$.

is associated with an 11.5–11.6% increase in bike share station use. Plus, at the University of Minnesota campuses the average daily station trips are 42.6 or 48.4% higher according to the two models.

Transportation infrastructure variables also play a significant role in explaining bike share station activity levels. *Trail* has a positive effect, indicating that 50.5 or 46.7% more trips occur at stations connecting to paved trails. There is a positive effect of *neardis*, indicating that the stations within 1 km of other stations tend to have on average 90.2 or 95.0% fewer trips. The sign of the coefficient, however, is not consistent with the hypothesis. This result might be because stations in close proximity may serve the same group of people and reduce the use of individual stations.

As to the economic activity variables of interest, both are significant at a 5% level. The stations in areas with 1,000 more jobs connected via transit (variable *access*) tend to have 0.8 or 0.9% more bike share trips. The variable *food* is also significant, showing that the number of bike share trips at a station is strongly and positively correlated with the number of restaurants, cafeterias, and cafes around it. Specifically, the presence of one additional food-related business is correlated with 1.7% more station trips. One interesting finding is that the marginal effects of the two models are consistent. As noted previously, the effect of total businesses in the station area was also tested, but no significant effects were found.

Finally, the three control factors are all significant at a 5% significance level. The stations in North Minneapolis, which were installed for equity reasons, were found to average 37.6 or 42.0% lower levels of station activity compared to other stations according to the log-linear model and the negative binomial model, respectively. The stations heavily affected by the Central Corridor Light Rail Transit project have 38.2 or 40.7% lower station activity levels compared to other stations according to the two models. The stations that first opened in 2010 have 61.8 or 65.7% higher levels of station activities compared to the stations that opened in 2011. In sum, the models are able to capture the wide variation in activity associated with the stations even though different criteria were used for siting them.

Observations, Applications, and Conclusions

The study results provide new insights into factors that correlate with bike share station activity and can be used by managers and planners to optimize systems, locate new stations, and explore the feasibility of new systems. Bike share stations are unique in transportation systems, being designed to provide people with new efficient options for multiple short rides. Bike share programs theoretically are best suited for locations with higher population densities and higher numbers of destinations that can be easily accessed. Nice Ride managers have not limited station locations to these types of areas, and in fact have sited stations for reasons of equity even though high activity levels were not anticipated. The results affirm initial decisions by Nice Ride managers to focus on locating stations near the Minneapolis CBD, on campuses, near

J. Urban Plann. Dev., 2016, 142(1): 04015001

parks and water bodies, and with access to off-street paths. These variables are highly significant in both models and associated with the largest marginal effects on station use. They also indicate that Nice Ride serves both utilitarian and recreational purposes. The sociodemographic characteristics (e.g., age, race) of station areas are associated with station use, as are economic variables (e.g., access to jobs and proximity to food establishments), but their marginal effects on station use may be smaller depending on variation across station areas. For example, the marginal effect on station use of a paved urban trail in the station area is approximately 50%, whereas an additional food establishment in the station area increases use by about 1.7%. As noted, stations located specifically for reasons of equity have, as anticipated, significantly fewer trips originating from or arriving at them.

The unanticipated negative coefficient on the measure of proximity to other bike share stations indicates that station oversaturation may present a challenge for system management. Relocation, monitoring of station use, and re-estimation of models may provide insights into the optimal number of stations, which can make the overall system more efficient.

Although Nice Ride managers already know in real time how use varies across stations, the results here provide new information about why station use varies. The models also can be used to predict the effects of exogenous changes (e.g., the effects on campus stations when universities are not in session), creation of a cycle track, or the opening of new food-related businesses. If more detailed information is needed to improve logistics and system balancing, models can be estimated for origins and destinations separately.

To assist with the siting of new stations or the opening of new systems, planners can predict station use at particular locations by obtaining values for the various variables and estimating the equations. System-wide effects of adding new stations or removing existing ones can be modeled to help optimize the number of stations and determine priorities or sequences for new stations. Insights gained from these models may also inform marketing campaigns to increase use or outreach to potential sponsors.

In sum, this study fills a gap in research on bike share systems by providing an empirical modeling framework to evaluate the correlates of bike share station activity using data from a comprehensive time window. The proposed models provide guidance for both practitioners and researchers interested in bike share system management and can inform transportation policy more generally. The fact that the proposed models includes sites established for reasons of equity independent of the goal of maximizing use means that managers and policy makers can assess the consequences of siting stations in a variety of different locations.

One limitation of this research is that the models were estimated with data from only one system (i.e., Nice Ride). It would be interesting and useful to validate them by testing them with data from other systems. Integration of data across systems would also help to identify new factors associated with bike share use.

Although this research provides new insights into bike share station use and system operations, it also raises new questions and identifies needs for additional research. One limitation of the proposed models is that, because they involve cross-sectional analyses, it is possible only to show association and not causation. Use of models in a controlled experiment (e.g., with a pre-post design) would yield additional useful insights [e.g., Funderburg et al. (2010)]. Additional analyses of the sensitivity of the models to station area size and to different measures of proximity to other stations would also be interesting. For example, gravity models could be integrated into the modeling approach. Finally, additional research into specific types of retail and food establishments that affect use could provide important information for bike share managers.

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J. Urban Plann. Dev., 2016, 142(1): 04015001