Is Bicycling Contagious? Effects of Bike Share Stations and Activity on System Membership and General Population Cycling

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ABSTRACT

This paper presents new evidence about the role of bike share systems in travel behavior using a diffusion of innovation framework. We hypothesize that bike share systems have a contagion or spillover effect on ($H1$) propensity to start using the system and ($H2$) propensity to bicycle among the general population. We test the first hypothesis by modeling membership growth as a function of both system expansion *and* the existing membership base. We test the second hypothesis by using bike share activity levels near one's home in a model of household-level bicycle participation and trip frequency.

Our study shows mixed results. Bike share membership growth appears to be driven, in a small part, by a contagion effect of existing bike share members nearby. However, we did not identify a significant relationship between proximity to bike share and cycling participation or frequency among the general population. The findings hold implications for marketing, infrastructure investments, and future research about bike share innovation diffusion and spillover effects.

KEYWORDS: *Bike Share; Diffusion of Innovation; Travel Behavior*

INTRODUCTION AND BACKGROUND

This paper presents new evidence about the role of bike share systems in travel behavior using a diffusion of innovation framework. We hypothesize that bike share systems have a contagion or spillover effect on ($H1$) propensity to start using the system and ($H2$) propensity to bicycle among the general population. We test the first hypothesis by modeling membership growth as a function of both system expansion *and* the existing membership base. We test the second hypothesis by using bike share activity levels near one's home in a model of household-level bicycle participation and trip frequency.

Our study shows mixed results, and holds numerous implications for policy, practice, and research. Bike share membership growth appears to be driven, in a small part, by a contagion effect of existing bike share members nearby. However, in this early stage of bike share's evolution, we did not identify a significant relationship between proximity to bike share and cycling participation or frequency among the general population.

At the time of writing, this is the first paper the authors are aware of that attempts to assess the effect of presence of bike share stations and trip activity on propensity to bicycle among the proximate population.

The next section reviews relevant literature about bike share and bicycle mode choice and participation. The following section describes the data and methodology used. We then share findings about whether bike share influences its own membership and general population decisions to bicycle, respectively. Finally, we discuss the implications, limitations, and opportunities for future research.

LITERATURE REVIEW

While bicycling is not a new mode, modern bicycle sharing schemes (bike share) are a new phenomenon and can be used as a special case study of the innovation diffusion framework. The rich datasets available from bike share systems open the door for future study about diffusion of system membership, with both social/cultural influences and increasing utility as additional users join the system. Parkes et al. (*1*) studied the spread of bike share systems through Europe and North America. The number of systems in place over time follows an S curve in Europe and appears to be approaching maturity as of 2012. In North America, the curve appears to still be in the "birth" or early "growth" phase. Therrien et al. (*2*) studied bike share diffusion at the individual level using a stated preference survey in Vancouver, BC, where residents indicated how likely they would be to use a proposed bike share system. Their binary logistic regression model identified characteristics associated with self-reporting as likely to use the new system, and they stratified their sample based on these characteristics into Rogers' (1962) categories of adopters.

Effects of Cycling and Bike Share on Other Modes

At the time of writing, this is the first research that the authors are aware of that uses bike share system activity or use measures as explanatory variables for general population cycling. However, research about externalities of cycling and spillover effects of technological adoption is not new. Recent research has explored potential relationships between bike share systems and transit use (*3*) (*4*). Ma et al (*3*) studied association between Capital Bike Share and Washington, DC's Metro rail system. They found that bike share activity within a transit station's catchment area was positively associated with transit ridership, and asserted a spillover effect, though the direction of causality in their findings was not clearly established. Wang et al (*5*) study neighborhood social effects on mode choice, and Efthymiou et al (*6*) study factors associated with adopting vehicle sharing systems. More generally, research about nonmotorized transportation oftentimes focuses on public health externalities (*7*) (*8*).

Diffusion of Innovation

Diffusion of innovation theory emerged in the first half of the 20th century. Technological innovations diffuse into society following a logistic growth curve. Early demand for the innovation motivates additional future demand. Early diffusion of innovation scholars identified two plausible causal mechanisms for the observed trajectory: (1) income distribution of the population affecting who is able to assume the risks associated with new technologies, and (2) and a heterogeneous population in which certain people are more inclined to be "early adopters" than others(*9*).

Bicycling, although not a "new" innovation, can be analyzed from this framework. From this perspective, the presence of bicyclists on the street has the potential to induce additional demand for bicycling. There is evidence of both the income distribution and heterogeneous population diffusion mechanisms operating for bicyclists.

Duesenberry's (1949) income distribution theory posits that the cost of an innovation falls with greater consumption, enabling a larger segment of the population to afford it(*9*). For bicycling, one major cost is risk or perception of risk. The visibility of cyclists changes driver behavior, which increases the safety for bicyclists (lowers the risk/cost), which in turn increases utility of bicycling for others (*10–12*). Jacobsen (*12*) observed an inverse relationship between rates of bicycling and incidence of collisions with motor vehicles across multiple cities, countries, and over time. As drivers see more bicyclists on the street, they learn to anticipate the presence and behavior of bicyclists and drive more cautiously. This is consistent with Duesenberry's cost theory. As the number of bicyclists on the street increases, their visibility triggers greater acceptance and caution among drivers, increasing safety for bicyclists. Put another way, the cost (in terms of risk) falls as more people bike, so bicycling becomes accessible to new segments of the population.

Rodgers (1962) argued that innovations diffuse through heterogeneous populations based on individual propensity to adopt new technologies. Rodgers groups the population into five categories based on their adoption speed: Innovators, Early Adopters, Early Majority, Late Majority, and Laggards. Innovators and early adopters readily consume new technologies, while slower groups need to see the technology tested among their peers before they adopt it. With bicycling, this can be thought of as a social influence effect. As bicycling becomes increasingly visible, popular, and normalized, slower adoption groups become more comfortable with the idea of bicycling (*13*, *14*). Evidence from literature suggests that an individual's decision to bike is influenced by their exposure to bicycling in their social network and around the city. Goetzke and Rave (*15*) found a positive relationship between one's social network and city's bicycle culture and one's propensity to bike for shopping and recreation trips in Germany. Fuller et al. (*16*) studied the effects of the BIXI public bicycle-sharing scheme (bike share) on all types of bicycling, and found that people who are exposed to the BIXI system are more likely to bike.

METHODOLOGY

Theory and Hypothesis

In Rogers' heterogeneous population diffusion of innovation theory, bike share systems (e.g., Nice Ride Minnesota) can be thought of as a "brand" of cycling. Adoption of the brand and the technology depend on individual tendencies toward innovation and imitation, and overall rates of adoption. The high visibility of bike share systems and bicycles suggests that bike share systems may have a distinct effect on further adoption of the system and cycling in general. Additionally, the rich datasets available from bike share systems provide a unique opportunity to study diffusion and spillover effects of bicycling.

Equation (1) describes the probability of adopting a technology ($b_i(t)$) as a function of both inclinations toward innovation ($p_i(t)$) and imitation ($q_i(t)$) and the proportion of adopters ($G(t)$) at time t, using the equation presented by (*9*).

$$b_i(t) = p_i + q_i G(t) \tag{1}$$

Nice Ride, as a "brand" of bicycling, is highly visible. People who have a higher exposure to Nice Ride users are expected to have an increased likelihood of bicycling, due to the larger effects of imitation (q_i). In other words, the probability that an individual adopts Nice Ride (a "brand" of bicycling for the purposes of this study) is a function of that person's tendency toward innovation (early adoption) and their tendency to imitate their peers, taking into account how many of their peers are in fact using the technology (bicycling).

We hypothesize that bike share systems have a contagion or spillover effect on:

H1. Propensity to start using the system, and

H2. Propensity to bicycle among the general population.

We use two different models to test these hypotheses, using Nice Ride Minnesota as a case study. For H1, we use a lagged variable regression model to predict net bike share system membership change in a Census Block Group as a function of prior bike share system membership levels, controlling for system expansion both locally (nearby stations) and system-wide. A positive and significant coefficient on the prior bike share system membership would indicate a potential diffusion of innovation effect in which early bike share adopters influence the decisions of people around them.

For H2, we model a household's propensity to bicycle and frequency of bicycle trips as a function of bike share trips starting or ending near the household, controlling for dedicated bicycle infrastructure and population density near the home location and sociodemographic characteristics of the household. A positive and significant coefficient on bike share trip activity would suggest a potential diffusion or spillover effect of bike share on general population cycling, where the visibility of a specific brand (bike share cycling activity) nearby changes one's own propensity to use the technology (any type of cycling).

Data Sources

This study used two main sources of data: trip and subscriber records from the local bike share system, and regional travel behavior inventory survey data about general population households and daily trips.

The Nice Ride Minnesota bike share system in Minneapolis and St. Paul has completed five seasons of operation. Ridership has increased steadily from the first season (about 100,000 trips) through 2013 (over 300,000 trips). Nice Ride Minnesota provided a database of subscribers and trips taken on the Nice Ride bike share system. The origin station, destination station, start time, end time, and subscriber ID are electronically recorded for every trip. The subscriber database contains the date joined, age, geographic location, gender, and subscription type. FIGURE 1 shows the geocoded approximate locations of Nice Ride's subscribers. Walk-up day pass users are not included in the subscriber database or the map.

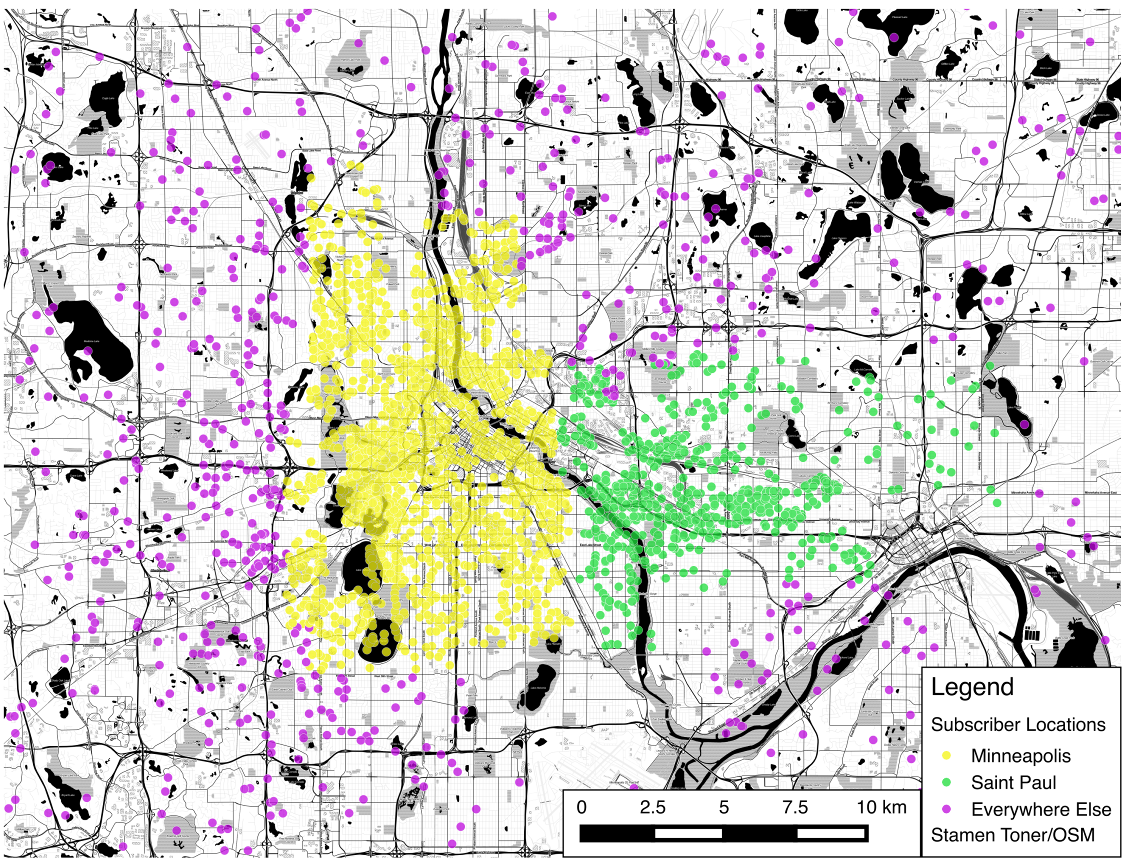

FIGURE 1 Map of Nice Ride Minnesota Monthly, Annual, and 30-day Pay As You Go Subscribers.

The regional planning agency (Metropolitan Council) administers a travel behavior inventory (TBI) every decade, which includes travel diaries for all members of households that participate. Data from the 2011 TBI were provided by the Metropolitan Council to explore effects of Nice Ride on cycling among non-Nice Ride subscribers (general population). The TBI surveyed 14,055 randomly selected households (about 1%) in the Minneapolis-St. Paul Metropolitan Region. Each resident over the age of 5 kept a 24-hour diary with a record of all trips made by all modes. The survey was administered on weekdays spanning from December 2010 to February 2012, including Nice Ride's 2011 season. The analysis only includes Minneapolis households (N=1,941) due to Nice Ride's limited presence in St. Paul at that time.

Each household record contains the number of trips made by all members of the household, the number of bicycle trips, sociodemographic characteristics, and a set of spatial measures around the household (e.g., population density and availability of bicycle infrastructure near the home). These variables are defined in the next section.

Variables and Modeling

This study included two main sets of models: One testing H1: effects of Nice Ride system membership on membership growth; and one testing H2: effects of Nice Ride trip activity on household cycling participation and frequency among the general population.

Nice Ride Membership Growth Model (H1)

The effect of Nice Ride system membership on membership growth was analyzed using a lagged variable linear model of *net change* in membership density on census block groups from the previous season as a function of the density of members in the previous season, controlling for local system growth and system-wide growth. Equations 2A and 2B show these relationships, and variable symbols definitions and descriptive statistics are presented in TABLE 1. Local growth is measured as net change in station density from the previous season. System-wide growth is modeled in two different ways: an indicator variable for the current season, using the 2011 season as the base case (Equation 2A), or the net change in number of stations system-wide from the previous season (Equation 2B). For example, there were 65 stations in 2010, and 116 stations in 2011, so the system growth variable for 2011 is 116 7 65 = 51. The model was built using data from the 2010, 2011, 2012, and 2013 systems, and 4,199 census block groups in the cities of Minneapolis and St. Paul.

$$\Delta\, m_{t_0 \rightarrow t_1, i} \rightarrow f(m_{t_0, i},\, \Delta\, s_{t_0 \rightarrow t_1, i}, t_1) \qquad \text{(2A)}$$

$$\Delta\, m_{t_0 \rightarrow t_1, i} \rightarrow f(m_{t_0, i},\, \Delta\, s_{t_0 \rightarrow t_1, i}, \Delta \mathrm{S}_{\mathrm{t_0 \rightarrow t_1, I}}) \qquad \text{(2B)}$$

General Population Cycling Model (H2)

Households near Nice Ride stations, particularly Nice Ride stations with high levels of use, are hypothesized to have both higher rates of participation in cycling (defined as any household member making at least one trip by bicycle) and frequency of bicycle trips than households not near Nice Ride stations. The general population cycling model explores household participation in and frequency of bicycling. Participation is defined as whether any household member reported making one or more bicycle trips on their assigned travel day. Frequency is the total number of bicycle trips made by all members of the household. Participation and frequency are modeled jointly using a zero-inflated negative binomial regression model. The explanatory variables included the number of Nice Ride bike share trips starting or ending within 400 meters (1/4 mile) of the household, along with other sociodemographic and built environment variables, summarized in TABLE 1. The researchers selected the number of Nice Ride trips starting or ending within 400m as the key variable of interest. We hypothesized that Nice Ride's visibility is the causal mechanism behind a potential spillover effect. Trip activity at a station implies both visibility of the station itself and visibility of bicyclists using Nice Ride on the streets around the station, whereas a simple measure of stations near the household is an incomplete measure of visibility. Due to multicollinearity between Nice Ride measures, it was inappropriate to use multiple Nice Ride station and trip activity measures in the same model.

TABLE 1 Descriptive Statistics of Modeling Variables

Variable	Description	N	Mean	SD	Min	Max
Hypothesis H1 / Model 1: Spillover Effects on System Membership						
$\Delta m_{t_0 \rightarrow t_{1,i}}$	Dependent variable: Net subscribers per 1,000 residents from t_o to t_1 for block group i	4,199	0.56	2.97	-30.36	62.20
$m_{t_{0,i}}$	Subscribers per 1,000 residents in t_o for block group i	4,199	1.55	4.71	0.00	78.95
$\Delta s_{t_0 \rightarrow t_{1,i}}$	Net stations per km^2 from t_o to t_1 for block group i	4,199	0.06	0.87	-23.02	23.02
$\Delta S_{t_0 \rightarrow t_{1,I}}$	Net stations from t_o to t_1 for entire system I	4,199	35.00	11.43	25.00	51.00
$t_1 = 2011$	2011 season binary indicator (base case)					
$t_1 = 2012$	2012 season binary indicator					
$t_1 = 2013$	2013 season binary indicator					
Hypothesis H2 / Model 2: Spillover Effects on General Population Cycling						
h_b	Dependent variable: Household participation in cycling (binary)	1,941	0.12	0.33	0.00	1.00
h_{rb}	Dependent variable: Number of household bike trips	1,941	0.40	1.34	0.00	12.00
s_{od}	Number of Nice Ride trips within 400m (1,000's)[1]	1,941	0.86	2.46	0.00	15.34
e_k	Population density within 400m (people per acre)	1,941	14.31	7.80	0.58	49.32
e_l	Km of bike lanes within 400m	1,941	0.20	0.46	0.00	2.88
e_p	Km of bike trails within 400m	1,941	0.11	0.23	0.00	1.82
h_r	Number of trips by any mode[2]	1,941	7.81	5.36	1.00	37.00
h_w	Number of workers	1,941	1.04	0.81	0.00	4.00
h_u	Student(s) (binary)	1,941	0.22	0.42	0.00	1.00
h_c	Child(ren) under 6 (binary)	1,941	0.08	0.28	0.00	1.00

[1] 2010 Nice Ride system data
[2] Sample restricted to Minneapolis households that made at least one trip

RESULTS

Diffusion effects on expanding membership

TABLE 2 presents the findings for the diffusion models 1A and 1B of bike share membership on membership growth. The R^2 for both models are approximately 0.07, meaning that 7% of the change in block group Nice Ride membership per 1,000 residents can be explained by system growth (new stations) and membership growth nearby. All variables in both models are significant. The coefficients for subscribers and increase in stations are nearly identical between the two models.

TABLE 3 shows the elasticities of each variable with other variables held at their means for Model 1B. A 1% increase in the base year's members per 1,000 residents is associated with 0.1 additional new members in the following season, suggesting a modest spillover effect of membership on future membership. The elasticities show that the system wide growth variable has largest effect on membership growth at the block group level, with a 1% change in the number of new stations across the system added associated with an almost 4% change in membership growth, or 2.2 additional new members in a block group. With the system wide new station variable held at its mean, each 1% increase in stations per kilometer in a block group is associated with 0.02 additional new members.

TABLE 2. OLS Regression Model of Spillover Effects on Membership Growth

	Model 1A Seasonal indicator variables			**Model 1B** System growth variable		
Variable	**Coef**		**SE**	**Coef**		**SE**
$m_{t_{0,i}}$	0.061	***	0.010	0.061	***	0.010
$\Delta s_{t_0 \rightarrow t_{1,i}}$	0.300	***	0.052	0.300	***	0.052
$t_1 = 2011$	*(Base Case)*					
$t_1 = 2012$	-1.353	***	0.110			
$t_1 = 2013$	-1.681	***	0.111			
$\Delta s_{t_0 \rightarrow t_{1,I}}$				0.064	***	0.004
Constant	1.456	***	0.078	-1.781	***	0.149
R^2	0.0714			0.0713		

*** Significant at $p < 0.01$
** Significant at $p < 0.05$
* Significant at $p < 0.10$

TABLE 3. Marginal Effects of Model 1B Variables on Membership

	% Change in $\Delta m_{t_0 \rightarrow t_{1,i}}$ (ey/ex)	**Numeric change in $\Delta m_{t_0 \rightarrow t_{1,i}}$ (dy/ex)**
1% change in $m_{t_{0,i}}$	0.170	0.095
1% change in $\Delta s_{t_0 \rightarrow t_{1,i}}$	0.033	0.019
1% change in $\Delta s_{t_0 \rightarrow t_{1,I}}$	3.990	2.226

Elasticities calculated with other variables held at means

Spillover effects on general population cycling

TABLE 4 presents the results from three different models of bicycling participation and frequency.

The binary logistic regression of participation in cycling has the highest Pseudo-R2, at 0.0810. Although McFadden Pseudo-R2 does not have the same interpretation as R2 in linear regression, this still indicates that bicycling is not well explained by this set of variables. The α parameter is significant in all three models is significant, suggesting that the dependent variable h_{rb} is over-dispersed and negative binomial regression is appropriate (shown in TABLE). Additionally, a Vuong test comparing the zero-inflated models to standard negative binomial regression is significant at the p<0.01 level (not shown).

TABLE 4. Models of Spillover Effects on General Population Cycling Participation and Frequency

	Model 2A Binary logit model of participation			**Model 2B** Negative binomial model of frequency			**Model 2C** Zero-inflated negative binomial model of participation and frequency		
	Coef		**SE**	**Coef**		**SE**	**Coef**		**SE**
Participation Equation									
s_{od}	-0.045		0.041				-0.051		0.042
e_k	0.047	***	0.010				0.045	***	0.010
e_l	-0.180		0.197				-0.185		0.205
e_p	0.606	**	0.302				0.741	**	0.332
h_r	0.076	***	0.014				0.067	***	0.015
h_w	0.392	***	0.098				0.453	***	0.104
h_u	0.313	*	0.175				0.282		0.182
h_c	0.006		0.233				0.063		0.248
Constant	-3.897	***	0.244				-3.714	***	0.256
Frequency Equation									
s_{od}				-0.026		0.040	0.022		0.025
e_k				0.050	***	0.012	0.010		0.007
e_l				-0.104		0.236	0.007		0.146
e_p				0.277		0.394	-0.351		0.237
h_r				0.123	***	0.021	0.044	***	0.010
h_w				0.227	*	0.123	-0.183	**	0.075
h_u				0.334		0.218	0.134		0.117
h_c				-0.222		0.318	-0.192		0.162
Constant				-3.206	***	0.293	0.657	***	0.188
ln (α)				2.369	***	0.096	-1.754	***	0.328
McFadden Pseudo-R^2	0.0810			0.0353			0.0650		

*** Significant at $p < 0.01$
** Significant at $p < 0.05$
* Significant at $p < 0.10$

The variable of interest, the number of Nice Ride trips starting and ending near a household (s_{od}), is not significant in any of the models. This analysis does not find evidence of a spillover effect of Nice Ride on household participation in and frequency of bicycling. Additional models using the number of stations within 400 meters instead of trip activity were also insignificant.

Several other variables were significant in the models, however. Population density was positive and significant in all three models (participation equation only in 2C). Bike paths or trails within 400 meters of home were positively associated with participation in cycling (Models 2A and 2C). Additionally, the household structure (number of workers, the presence of students, and over- all number of trips made) was associated with participation and frequency.

DISCUSSION

This research showed a potential diffusion or spillover effect of existing bike share members on future system adoption and membership growth. However, the effect was not apparent when we generalized the research; we found no evidence of spillover effects onto traditional cycling in the 2010-2011 system and survey data. It is possible that this is because bike share members are unique and distinct from traditional cyclists; however, other research suggests this is not the case. For example, bike share members own their own bicycles at roughly similar rates (*17*).

We proposed that bike share trip activity would increase propensity to cycle among people nearby because Nice Ride's presence is particularly visible. However, the system may be too young or too small of a component in the transportation system to have a measurable effect at this time. Bicycling comprises only a small percentage of trips made in Minneapolis and St. Paul, with slightly fewer than 90,000 bicycle trips per day between the two cities (or 5% and 2% mode shares, respectively)(*18*). In comparison, there were only about 217,000 Nice Ride bike share trips during the entire 2011 season, from April to November, or about 1,000 trips per day – a tiny percentage of an already small mode share. That bike share membership has spillover effects on future members suggests there is potential for broader spillover effects as systems mature. Bike share systems worldwide continue to expand, affording opportunities for future research into spillover effects on larger, more established systems. However, at this time with the levels of data available in this study, there is no evidence of these effects.

The findings, especially the significant effect of existing membership on membership growth, have several implications for policy. While the *overall system-wide* growth variable had the largest effect on membership growth in Model 1b, existing membership levels in a block group had a larger effect than *local* system growth. Bike share organizations may be able to harness this energy through "Take your friend on a bike ride" types of marketing schemes. Unless and until future research shows otherwise, bike share systems should not be treated as a substitute for other infrastructure improvements that increase propensity to cycle, such as providing safe facilities.

The study design and findings also provide a foundation for new research into bike share diffusion of innovation effects. As bike share systems continue to emerge and evolve throughout the world, so too will new sources of bike share data and opportunities for exploring these relationships. This research has several notable limitations that invite further inquiry to the topic. The travel behavior inventory was administered after Nice Ride had only been operational for one season. Nice Ride's largest system expansion after the initial investment occurred over the second season, which coincided with light rail construction in many of the areas that received new stations. Small segments of the population, such as cyclists, are difficult to represent in general population surveys administered to a low percentage of the population.   Although preliminary models controlling for weather did not produce different results in the household bicycling participation and frequency models (not shown in the final model), weather is always a concern when researching nonmotorized travel in extreme climates such as Minnesota.

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