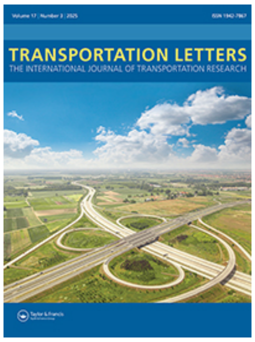

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Transportation Letters
The International Journal of Transportation Research

ISSN: 1942-7867 (Print) 1942-7875 (Online) Journal homepage: www.tandfonline.com/journals/ytrl20

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To cite this article: Dillon T. Fitch-Polse, Hossain Mohiuddin & Susan L. Handy (2025) Can bike-share change attitudes? Evidence from the Sacramento, California region, Transportation Letters, 17:3, 458-469, DOI: 10.1080/19427867.2024.2360336

To link to this article: https://doi.org/10.1080/19427867.2024.2360336

Published online: 09 Jun 2024.

TRANSPORTATION LETTERS
2025, VOL. 17, NO. 3, 458–469
https://doi.org/10.1080/19427867.2024.2360336

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Can bike-share change attitudes? Evidence from the Sacramento, California region

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ABSTRACT
Many existing studies of bike-share services focus on system dynamics and user characteristics, but less is known about how bike-share influences bicycling more broadly. In this study, we examine how a bike-share system influenced travel attitudes of residents through a repeated cross-sectional survey conducted before and after the opening of the system. The study focused on one of the largest dock-less electric-assisted bike-share systems in the US in 2018, the Jump system in three California cities: Sacramento, West Sacramento, and Davis. Results suggest that the bike-share system is likely to have been responsible, at least in part, for more favorable attitudes toward bicycling and less favorable attitudes toward driving. This research demonstrates that the benefits of bike-share can go beyond the general use of the system. Bike-share can also be seen as an intervention that has widespread psychological effects that may increase the likelihood of bicycling.

ARTICLE HISTORY
Received 14 March 2023
Accepted 22 May 2024

KEYWORDS
Bike-share; travel attitudes; e-bikes; travel behavior

Introduction

Bike-share systems have rapidly expanded across US cities over the last decade. The introduction of dockless electric bike-share and scooter-share systems suggests that these one-way rental services are likely to continue to grow (NACTO 2022). These services have the potential to offer a healthier and more environmentally sustainable mobility option if used as an alternative to car travel and to connect to transit. Although it is not clear if bike-share is the cause, users of bike-share, in comparison to non-users, are more likely to live in a zero car household, walk and bike, and use other mobility services, and they are more comfortable and confident bicyclists, according to multiple studies (Fishman, Washington, and Haworth 2013; D. T. Fitch, Mohiuddin, and Handy 2020; Godavarthy, Mattson, and Taleqani 2017; Mohiuddin, Fitch, and Handy 2022; Xu 2020). However, some effects are likely to vary by city context. For example, some studies show that bike-share increases transit use, while others show the opposite (Godavarthy, Mattson, and Taleqani 2017; Xu 2020). Variation is especially wide when comparing results from Chinese bike-share systems to those in the U.S. and western Europe (Fishman, Washington, and Haworth 2013).

Bike-share systems not only can provide a new travel option, but also they may have other indirect effects on people's travel decisions. For example, bike-share may influence travel attitudes, especially attitudes toward bicycling, the latter of which have been shown to be strongly associated with bicycling frequency (S. L. Handy, Xing, and Buehler 2010). Although causality is likely to run both directions, more positive attitudes toward bicycling are likely to lead to greater amounts of bicycling (Kroesen, Handy, and Chorus 2017). In some cases, higher rates of bicycling have further potential positive effects on social norms and the bicycling cultures of communities (Buehler and Handy 2008; De Geus et al. 2008; S. L. Handy, Xing, and Buehler 2010; Willis, Manaugh, and El-Geneidy 2015), and have been shown to increase safety for existing bicyclists through the phenomenon of safety-in-numbers (Elvik and Bjørnskau 2017; Fyhri et al. 2017; Jacobsen 2003; Jacobsen, Ragland, and Komanoff 2015). However, few studies examine the influence of the emergence of bike-share on attitudes. Studies from the European context exploring the link between values and attitudes with intention to use bike-share suggest that attitudes toward bike share and the environment are likely to influence bike-share use (Kaplan et al. 2015; Munkácsy and Monzón 2017; Wang et al. 2018). That evidence mirrors the general bike literature showing that attitudes have strong associations with bicycling (S. L. Handy, Xing, and Buehler 2010). It has been suggested that a better understanding of how bike-share influences attitudes, and how attitudes influence the use of bike-share, is an important direction for bike-share research (Fishman, Washington, and Haworth 2013).

The goal of this paper is to explore the effects of bike-share on travel attitudes by examining data from a before-and-after evaluation of bike-share in the greater Sacramento region of California from 2016 to 2019. This bike-share system provided dockless, electric-assisted bikes and was operated by Jump/Uber (prior to the sale of Jump to Lime and prior to COVID-19). The study uses a repeated cross-section survey in which we measured group differences but not individual-level change before and after bike-share. In our models, we include a series of covariates measured from the survey to adjust for the differences in the survey waves in order to strengthen our case for drawing causal inferences. Results suggest that the bike-share system is likely to have been responsible, at least in part, for more favorable attitudes toward bicycling and less favorable attitudes toward driving.

Literature review

The association between attitudes toward bicycling and bicycling behavior is strong (S. L. Handy, Xing, and Buehler 2010). Researchers have found that bicyclists have the most positive attitudes toward bicycling and that those who never intend to ride a bicycle have the least positive attitudes toward bicycling (Gatersleben and Appleton 2007; Xing, Handy, and Mokhtarian

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/19427867.2024.2360336

2010). Some studies also show that concern for the environment (Dill and Voros 2007) and negative attitudes toward driving (Dill and Voros 2007; Xing, Handy, and Mokhtarian 2010) can be associated with greater rates of bicycling. It is not surprising that liking bicycling and deciding to bike are strongly associated. One study in the context of a bike-oriented US city (Davis, California) shows that this association reflects a complex mix of responses to bicycling, including physical sensations, bonding with friends and family, feelings like freedom and happiness, among others (S. Handy and Lee 2020). Evidence of the link between attitudes toward bicycling and bicycling behavior has been found in a variety of contexts. For example, in a medium-side Brazilian city, people with a positive attitude toward bicycling also had stronger behavioral control with respect to bicycling and perceived weaker barriers to bicycling (de Souza, Sanches, and Ferreira 2014). Evidence from the Netherlands suggests that while bike-positive attitudes drive bicycling behavior, bicycling behavior also drives bike-positive attitudes (Kroesen, Handy, and Chorus 2017). In fact, the latter may be the stronger causal link (Kroesen, Handy, and Chorus 2017).

The relationship between bicycling attitudes, bicycling, and bicycling infrastructure is not entirely straightforward. Bicycle-related infrastructure influences attitudes toward bicycling and bicycling behavior itself. Dill and Carr (2003), using data from 43 cities across the US, show that the provision of bike infrastructure is associated with higher rates of bicycling. Infrastructure likely influences bicycling behavior by influencing attitudes and perceptions, for example, by increasing safety perceptions, reducing perceived travel time, or increasing comfort and enjoyment (Dill and Carr 2003; S. L. Handy, Xing, and Buehler 2010). A recent study in Chile confirms that bike infrastructure explains bicycling choice through changes in attitudes (Lizana, Tudela, and Tapia 2021). On the other hand, another recent study in Colombia shows that the quality of bicycling infrastructure is indirectly influenced by pro-bike attitudes (Vallejo-Borda, Rosas-Satizábal, and Rodriguez-Valencia 2020). In other words, good bicycling infrastructure might exist in a community because its residents have positive attitudes toward bicycling and thus support investments in bicycling infrastructure, suggesting a reverse causal effect.

Social norms and bicycling culture can also influence bicycling. For example, high rates of bicycling in the Netherlands are linked to the Dutch identity (Pelzer 2010). In other places, where bicycling is not linked with the national culture, local-scale culture is important in establishing bicycling as a normal practice (Aldred and Jungnickel 2014). Interventions aimed at changing culture as well as attitudes can complement efforts to improve the bicycling environment. The importance of culture in encouraging bicycling points to the possibility that seeing other people bicycling can influence attitudes toward bicycling, just as one's own bicycling can influence one's attitudes. On the other hand, a study in Davis, California, found that positive attitudes toward bicycling declined over prolonged exposure to a pro-bicycling environment (Thigpen 2019), suggesting that bicycling culture does not always have a positive effect on bicycling.

The active transportation landscape is evolving with the introduction of newer shared mobility services offering access to dockless bikes, e-bikes, and e-scooters. Several previous studies have explored the influence of shared e-bikes on bicycling. Another study from the Sacramento region using the same data from this analysis found that bicycling increased among the users of bike-share (D. T. Fitch, Mohiuddin, and Handy 2021). A European study found a two and half times increase in bicycling after the initiation of bike-share system (Félix, Cambra, and Moura 2020). Not all studies have found a positive effect of bike share on bicycling, however. An Australian study did not find any significant change in bicycling after the introduction of a bike-share system (Bauman et al. 2017). A Canadian study found that the introduction of a bike-share system may have positively affected bicycling among those who both lived and worked within the bike-share service boundary, but that the effect attenuated quickly (Hosford et al. 2018). It is possible that bike-share may have a longer-lasting influence on bicycling through the psychological pathway of attitude formation, specifically attitudes toward bicycling, and by promoting a positive bicycling culture in the community. To explore this possibility, this study focuses on the following questions:

Q1. Can bike-share change attitudes towards bicycling and other modes among users as well as non-users of the service?

Q2. How does the change in attitudes towards bicycling and other modes due to bike-share vary among cities with different bicycling cultures?

Methods

This study examines the effect of the electric bike-share system in the greater Sacramento, California region. The bike-share system was launched in the summer of 2018 and included approximately 900 electric-assist bicycles (e-bikes) as of November 2018. The system was dockless, meaning that the vehicles could be parked anywhere because they could be locked to themselves. By May 2019 the number of e-bikes increased to closer to 1,000, and 100 e-scooters were also available in Sacramento and West Sacramento but not Davis. Because the system is predominantly e-bikes (and not e-scooters) and because we have collected a much richer set of data about e-bike use, we will refer to the system as a bike-share system. The system – both e-bikes and e-scooters – was suspended in March 2020 owing to the COVID-19 pandemic.

We collected surveys from residents in the areas served by the system, including downtown Sacramento, West Sacramento, and Davis. While Davis has a rich history of bicycling (Buehler and Handy 2008), West Sacramento and Sacramento have not historically catered to bicyclists. However, recent investments in bicycling infrastructure in downtown Sacramento and in parts of West Sacramento reflect a shift in priorities given to bicycling as a mode of travel in those cities. We also collected data from residents of the Natomas area of Sacramento, which was outside of the bike-share service area, as a pseudo-control group: these residents did not have access to bike-share from home but they might have seen it and could use it when in the nearby service area.

Survey recruitment

We conducted a before-and-after household survey designed to examine whether the bike-share systems influenced the non-users of the service. In April 2016, we randomly recruited residents via mail to take a survey before the introduction of bike-share in the region. The initial sample for the 'before' survey (wave 1) comprised 14,000 addresses including 5,000 addresses in Davis, 2,000 addresses in West Sacramento, 5,000 addresses in downtown Sacramento, and 2,000 addresses in the Natomas neighborhood of Sacramento, all randomly selected. (Davis residents were oversampled relative to the other areas for the purposes of a separate study.) In May 2019, we conducted the 'after' survey (wave 2). We used the approximate response rates from the 'before' survey to get a more balanced (by population size) sample from the same neighborhoods from an initial sample of 11,000 addresses. This resulted in the random selection of 1034 addresses in Davis, 2584 addresses in West Sacramento, 4429 addresses in downtown Sacramento, and 2953 addresses in Natomas.

In each wave of the survey, we sent a recruitment letter to the initial sample of addresses. The letter invited individuals to participate in an online survey developed in the Qualtrics platform. The first page of the survey stated that only individuals over 18 years of age could participate in the survey. A reminder post card was sent 1 week after the initial recruitment. For individuals unwilling or unable to complete the survey online, the recruitment letter offered the option to request a physical copy of the survey in the mail with a postage paid return envelope, although none were requested. Instead, a few respondents elected to answer the survey over the phone while the primary author recorded their responses in the online survey. After accounting for undeliverable addresses, we achieved a response rate of 14% in the before survey and 10% in the after survey.

Data

The survey instruments included questions about access to and use of different transportation modes, experience with bike-share services in other regions, and socio-demographic characteristics including income and race/ethnicity (Table 1). Because wave 1 over-represented residents from Davis, we included a city-weighted version of the summary statistics to compare to the wave 2 summary statistics. Table 1 also includes study area characteristics from the 5-year 2016 and 2019 American Community Surveys, some of which do not exactly match the survey responses (e.g. travel measured in mode share, not days used). In addition, the survey included a battery of statements about attitudes toward and perceptions of bicycling and other aspects of transportation (Table 2). Table 2 also shows how different statements collected from the survey are associated with the different assumed attitude constructs. Attitude statements used in this study to measure *Bicycling Affinity* combine to capture a person's feelings as well as experiences with bicycling and have been used in several previous studies (S. Handy 2019; S. Handy and Lee 2020; Mohiuddin, Fitch-Polse, and Handy 2023). Statements used to measure *Bicycling Social Norms* capture perceptions that bicycling is common or normal in the community (S. L. Handy, Xing, and Buehler 2010). Statements used for *Driving Affinity* combine measures of the preferences for driving and dependency on driving for daily needs (S. L. Handy, Xing, and Buehler 2010). In addition to the previously used statements, we explore two more constructs with single items, specifically the statement 'There are good bicycle lanes and paths in areas I need to go' to measure perception of *Bicycling Infrastructure*, and 'I like using public transit' to measure *Liking Transit*.

The before survey (2016) yielded 1959 responses, and the after survey (2019), a total of 988 responses.

Analysis

We employed a multivariate-ordered regression model to estimate the effects of bike-share on the attitudinal constructs (Table 2). The model is multivariate in that it is a joint estimation of five ordered models (one for each attitudinal construct), two of which include responses to a single item, and three including responses to two or more items. We chose the ordinal models because they can use the available information in the data that has natural ordering (Ananth and Kleinbaum 1997), which in our case is present in the responses of the statements shown in Table 2. The multivariate model allowed correlation across constructs for the constructs with multiple items. The conceptual complexity as well as the ability to fully treat uncertainty in the model motivated our use of a Bayesian statistical

Table 1. Sample Characteristics.

Variable		Wave 1 (2016)	City Weighted Wave 1 (2016)	Wave 2 (2019)	Study area characteristics
Sample Size		1959		988	
Response Rate		14%		10%	
Percent of Sample by City	Davis	48.2%		15.0%	
	Sacramento	36.7%		50.6%	
	West Sacramento	5.6%		18.1%	
	Natomas	9.5%		16.3%	
Student		15%	10%	8%	34%
Races	White alone	70%	75%	69%	48%
	Black, Hispanic, and Others	18%	16%	23%	38%
	Asian alone	12%	9%	8%	14%
Education Status	College Education or higher	85%		90%	32%
	No College Education	15%		10%	68%
Age*		46	46.7	51	Davis 25.2 Others 34.0
Employment Status	Works	64%	68%	64%	62%
	Doesn't Work	36%	32%	36%	38%
Gender	Women	56%		56%	51%
Household Income	Less than or equal $25,000 (Low Income)	22%	18%	12%	20%
	More than $25,000 (Not Low Income)	78%	82%	88%	80%
Bicycling commuting days per week	0	67%	77%	77%	Bike Commute
	1–3	12%	11%	9%	Mode Share
	4–5	16%	10%	10%	2016: 6.24%
	More than 5	4%	2%	2%	2019: 5.34%
Driving commuting days per week	0	27%	21%	24%	Drive Commute Mode Share
	1–3	17%	15%	15%	2016: 70.17%
	4–5	37%	42%	41%	2019: 70.64%
	More than 5	17%	22%	20%	
Transit commuting days per week	0	82%	85%	85%	Transit Commute Mode Share
	1–3	8%	7%	7%	2016: 3.73%
	4–5	8%	7%	7%	2019: 3.98%
	More than 5	1%	1%	1%	

*Mean is shown for the survey waves; median is shown for the study area.

Table 2. Distributions of responses for the attitudinal statements by attitude construct.

Attitude Statements	Survey	Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
Bicycling Affinity (BA)						
I like riding a bicycle	wave 1	7%	7%	18%	40%	29%
	wave 2	4%	6%	18%	46%	26%
I feel comfortable bicycling in the areas I need to go	wave 1	11%	20%	20%	31%	17%
	wave 2	9%	21%	27%	32%	11%
I know how to get around by bicycle in the areas I need to go	wave 1	5%	11%	16%	41%	27%
	wave 2	3%	12%	17%	46%	21%
Bicycling Social Norms (BN)						
Bicycling is a normal mode of transportation for adults in my community	wave 1	6%	18%	19%	36%	20%
	wave 2	7%	23%	25%	35%	10%
Many of my friends or family or neighbors bicycle regularly	wave 1	9%	21%	25%	31%	14%
	wave 2	8%	27%	28%	30%	8%
Bicycling Infrastructure (BI)						
There are good bicycle lanes and paths in the areas I need to go	wave 1	6%	16%	19%	39%	20%
	wave 2	7%	19%	23%	43%	7%
Driving Affinity (DA)						
I like driving a car	wave 1	4%	9%	21%	38%	27%
	wave 2	4%	11%	25%	39%	21%
I need my car to do many of the things I like to do	wave 1	4%	7%	10%	38%	41%
	wave 2	5%	8%	9%	49%	30%
I need my car to carry shopping or children	wave 1	6%	7%	13%	35%	38%
	wave 2	5%	9%	10%	47%	29%
I try to limit my driving as much as possible	wave 1	4%	14%	29%	37%	16%
	wave 2	6%	19%	25%	37%	13%
Liking Public Transit (LT)						
I like using public transit	wave 1	11%	21%	32%	28%	7%
	wave 2	16%	27%	28%	22%	7%

approach. We estimated the models using the R package brms (Bürkner 2017) which is an interface for the Stan computing language (Stan Development Team 2018). We used the default estimation algorithm (dynamic Hamiltonian Markov Chain Monte Carlo (MCMC)), with tuning parameters adapt_delta = 0.98, and max_tree_depth = 10, and ensured that each model parameter MCMC chain converged ($\hat{r}$ <1.01), and no other Stan diagnostic warnings occurred. The model structure follows the ordered logit distribution such that:

$$y_i = \text{Categorical}(\mathbf{p})$$
$$p_1 = q_1$$
$$p_k = q_k - q_{k-1} \text{ for } K > k > 1$$
$$p_K = 1 - q_k$$
$$\text{logit}(q_k) = \tau_k - \phi_i$$

Where y_i is the response category for an observation (survey response) i, and $\mathbf{p}$ is a vector of probabilities of each response (k) with maximum response (K). The probability of each response value k is defined by threshold parameters τ_k. Linear terms ϕ_i are subtracted from the thresholds to decrease the log-cumulative-odds of every response value k, which shifts probability toward higher response categories. This ensures that an increase in a linear predictor results in an upward shift in log-cumulative-odds. We use this formulation for each of the attitudinal constructs and jointly estimate them by including person-level parameters and modeling their correlation, as we assume each attitude is distinct, yet correlated. We write this as a multivariate ordered logit model with a ϕ_i replaced by letter combinations and τ_k subscripted by the same letter combinations for each attitudinal construct below.

$$y_i = MultivariateOrderedLogit\left(BA_i, BN_i, BI_i, DA_i, LT_i, \tau_{BA,k}, \tau_{BN,k}, \tau_{BI,k}, \tau_{DA,k}, \tau_{LT,k}\right)$$

$$BA_i = \alpha_{BA,person[i]} + \alpha_{BA,item[i]} + \beta_{BA,city[i]}A_i + \sum_{m=1}^{M} \beta_{BA,m}X_{mi}$$

$$\text{BN}_i = \alpha_{BN,person[i]} + \beta_{BN,city[i]}A_i + \sum_{m=1}^{M} \beta_{BN,m}X_{mi}$$

$$\text{BI}_i = \beta_{BI,city[i]}A_i + \sum_{m=1}^{M} \beta_{BI,m}X_{mi}$$

$$DA_i = \alpha_{DA,person[i]} + \alpha_{DA,item[i]} + \beta_{DA,city[i]}A_i + \sum_{m=1}^{M} \beta_{DA,m}X_{mi}$$

$$\text{LT}_i = \beta_{LT,city[i]}A_i + \sum_{m=1}^{M} \beta_{LT,m}X_{mi}$$

$$\begin{bmatrix} \alpha_{BA,person} \\ \alpha_{BN,person} \\ \alpha_{DA,person} \end{bmatrix} \sim \text{MultivariateNormal}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \sigma \right)$$

$$\sigma = \begin{pmatrix} \sigma_{BA,p} & & \\ & \sigma_{BN,p} & \\ & & \sigma_{DA,p} \end{pmatrix} \Omega \begin{pmatrix} \sigma_{BA,p} & & \\ & \sigma_{BN,p} & \\ & & \sigma_{DA,p} \end{pmatrix}$$

$$\left(\tau_{BA,1}, \ldots, \tau_{LT,k}\right) \sim \text{StudentT}(3, 0, 1)$$
$$\left(\beta_{BA,\text{city}[1]}, \ldots, \beta_{LT,city[4]}\right) \sim \text{Normal}(0, 1.5)$$
$$\left(\beta_{BA[1]}, \ldots, \beta_{LT[M]}\right) \sim \text{Normal}(0, 1.5)$$
$$\left(\alpha_{BA,item[1]}, \ldots, \alpha_{BA,item[3]}\right) \sim \text{Normal}\left(0, \sigma_{BA,item}\right)$$
$$\left(\alpha_{DA,item[1]}, \ldots, \alpha_{DA,item[4]}\right) \sim \text{Normal}\left(0, \sigma_{DA,item}\right)$$
$$\left(\sigma_{BA,p}, \sigma_{BN,p}, \sigma_{DA,p}\right) \sim \text{HalfStudentT}(3, 0, 1)$$
$$\left(\sigma_{BA,item}, \sigma_{DA,item}\right) \sim \text{HalfStudentT}(3, 0, 1)$$
$$\Omega \tilde{L}KJcorr(2)$$

Where y_i is the response category for observation (survey response) i, and assumed to be distributed according to the ordered (cumulative) logit function of one of the attitudes, construct linear models $(BA_i, \text{BN}_i, \text{BI}_i, DA_i, \text{LT}_i)$ for which the observation is assumed to measure (see Table 2 for items and constructs). Each generalized linear model is notated with parameters with the first subscript notating the attitude construct (e.g. BA) and the second subscript notating the identifier and index (e.g. *city[i]*). Each model is a function of an τ_k vector of k thresholds between the K response categories. Models of attitude constructs with multiple items have an α_{person} vector of person-specific parameters, and constructs with three or more items have an α_{item} vector of item-specific parameters. Constructs with two items include a β parameter for one of the two items to account for variation in item response for the construct. The primary parameters of interest are the β_{city} parameters representing the city-specific effect of after bike-share (A_i). Each model is also a function of a $\beta_m$vector of parameters for the covariates X_m which include indicators for race, student status, education, employment, and a continuous standardized measurement of age.

The models are estimated jointly, and the three models with person-specific effects are modeled with correlation matrix , factored as a diagonal matrix of person-level standard deviations ($\sigma_{BA,p}, \sigma_{BN,p}, \sigma_{DA,p}$) and correlation matrix Ω. The correlation matrix has ones on the diagonal and three off-diagonal parameters representing the correlation between the three person-varying parameters. This equation is slightly generalized from the actual model because the R package brms automatically parameterizes models (for efficiency reasons) by centering all variables and converting the correlation matrices to Cholesky factors prior to estimation (Bürkner 2017). In addition, we took the advantage of the built-in Stan procedure (reduce sum) within brms to speed up estimation through within-chain parallelization (see supplemental material for code).

We selected priors through iterative prior predictive simulation by visualizing predictions from the model (without data) to ensure that the model produced reasonable responses, including some extremes (vast majority of responses in one category), but did not always produce extremes. While priors like Normal (0, 1.5) might seem strongly informative, on the logit scale they are roughly flat across the probability space. We selected *Student's t* priors for the thresholds and standard deviation parameters to allow for larger variation following the guidance of McElreath (2020). We chose the LKJ prior for the correlation matrix Ω to slightly regularize the estimated correlations amongst constructs. This was based on theory, as correlations near zero are unlikely given they are related attitude constructs and correlations near one are similarly unlikely given they are distinct constructs, and also on general guidance for prior selection from McElreath (2020).

We selected the model based on conceptual linkages between measured variables and the attitude outcomes with the specific focus of estimating the effect of bike-share on attitudes. To evaluate the effect of bike-share on attitudes, we stratified by city (hence the β_{city} parameters of interest) for three reasons: (1) recruitment was conducted by randomly sampling addresses in each city and the sample is heavily imbalanced, (2) one of the neighborhoods (Natomas) was chosen as a pseudo-control neighborhood because bike-share did not operate there and thus residents did not have access to bike-share from their homes, and so we expected that the effect of bike-share would be less for those residents, and (3) Davis has a unique history of bicycling, and we suspected that any influence the bike-share had on bicycling attitudes was likely to be different in Davis than in other cities. Because the residents of Natomas (technically not a separate city, but a neighborhood of Sacramento) are not a true control group (i.e. they were 'exposed' to bike-share in that they saw it and potentially used it although they could not use it from their home), we did not calculate effects as contrasts between the other cities and Natomas as is common in experimental designs. Instead, we elected to report city effects as comparisons.

Initial analysis of the attitude data suggested slight but consistent increases in bike-positive statements and decreases in car-positive statements (D. Fitch, Mohiuddin, and Handy 2020). However, because the sample is imbalanced by city, and many other variables were not considered in those analyses, the apparent effects may have been misleading. In the model we present below, we predict the probability of responses in each of the five response categories for each attitude construct, while conditioning on the covariates (Table 1) to better estimate the effect of bike-share on attitudes. However, we did not include travel behavior variables such as bicycling frequency because we hypothesized that (1) travel behavior may be just as likely to be caused by changes in attitudes as it is to cause changes in attitudes (Kroesen, Handy, and Chorus 2017), and (2) travel behavior could act as a mediating path between the effect of bike-share on attitudes. If those assumptions hold, including behavior variables would bias our estimation of the total bike-share effects (McElreath 2020).

To validate the model, we conducted 5-fold cross-validation, holding out a fifth of the data and re-estimating the model five times while predicting on the held-out data. While 10-fold cross validation is more common, we chose five folds because of limited computational resources. We included three metrics to evaluate the out-of-sample prediction error: (1) response-level mean percent correctly predicted, (2) response-level mean percent correctly predicted within one class (because predicting ordinal data within one class is better than predicting two or more classes away), and (3) predicted – actual aggregated shares of responses in each class.

Limitations

Several limitations of this study should be noted. The study uses a repeated cross-sectional survey rather than a panel survey, which would have enabled an analysis of individual-level change and provided stronger evidence of causal effects. We built our statistical models using assumed causal conceptual models, so our causal inferences are only as strong as those assumptions and the repeated cross-sectional design. Although we attempted to generate a representative sample by recruiting using a random sample of addresses, self-selection bias is always a concern: people who choose to respond may have behavioral and attitudinal predispositions toward bike-share. This is especially true of the second wave of the household survey since the recruitment letter indicated that the survey was about the regional bike-share system because we asked users of the bike-share system to take an extended survey. Self-selection is likely a primary driver of differences in education, race, and age compared to population since recruitment was random-address based. These differences suggest that our results may not generalize to the study population (external validity).

Differences in the composition of the samples for the wave 1 and wave 2 surveys could bias the results, although the inclusion of multiple covariates in the analysis helps to correct for this possibility (adjusting for confounding). Still, it is possible that respondents to the household survey in wave 2 are biased toward using the bike-share service. In addition, the time-lapse between the before survey in 2016 and the after survey in 2019 was longer than intended, given a delay in the implementation of the bike-share service in the Sacramento region beyond the originally anticipated date. This long time-lapse leads to an increase in the possibility that factors other than the implementation of the bike-share service affected travel behavior as well as attitudes, though the use of a pseudo geographic control group helps to correct for such effects. These limitations are important to acknowledge as we use causal language when interpreting the results and discussion.

Finally, the system studied was a privately owned and operated system, meaning that the results may not be generalizable to city-owned docked systems. However, because many city-owned systems are privately operated and are also shifting to electric-assisted bikes, the results may apply to bike-share in general.

Results

Bicycling affinity

Figure 1 shows the predicted average effect (and uncertainty) of bike-share on the attitudinal statements related to bicycling affinity by neighborhood. The predictions hold all co-variates at their mean or reference category and predict each outcome independently at the mean varying by city and item. We account for item-level uncertainty by including those varying effects from the posterior that are applicable to each outcome. Person-level uncertainty is ignored in these predictions. Each line represents a single posterior mean prediction, with transparency added to communicate the concentration of predictions. White areas indicate no predictions, light gray areas indicate some predictions, and dark gray areas indicate predominate predictions. Lines above the zero line in the plot for a statement indicate predicted increases in response

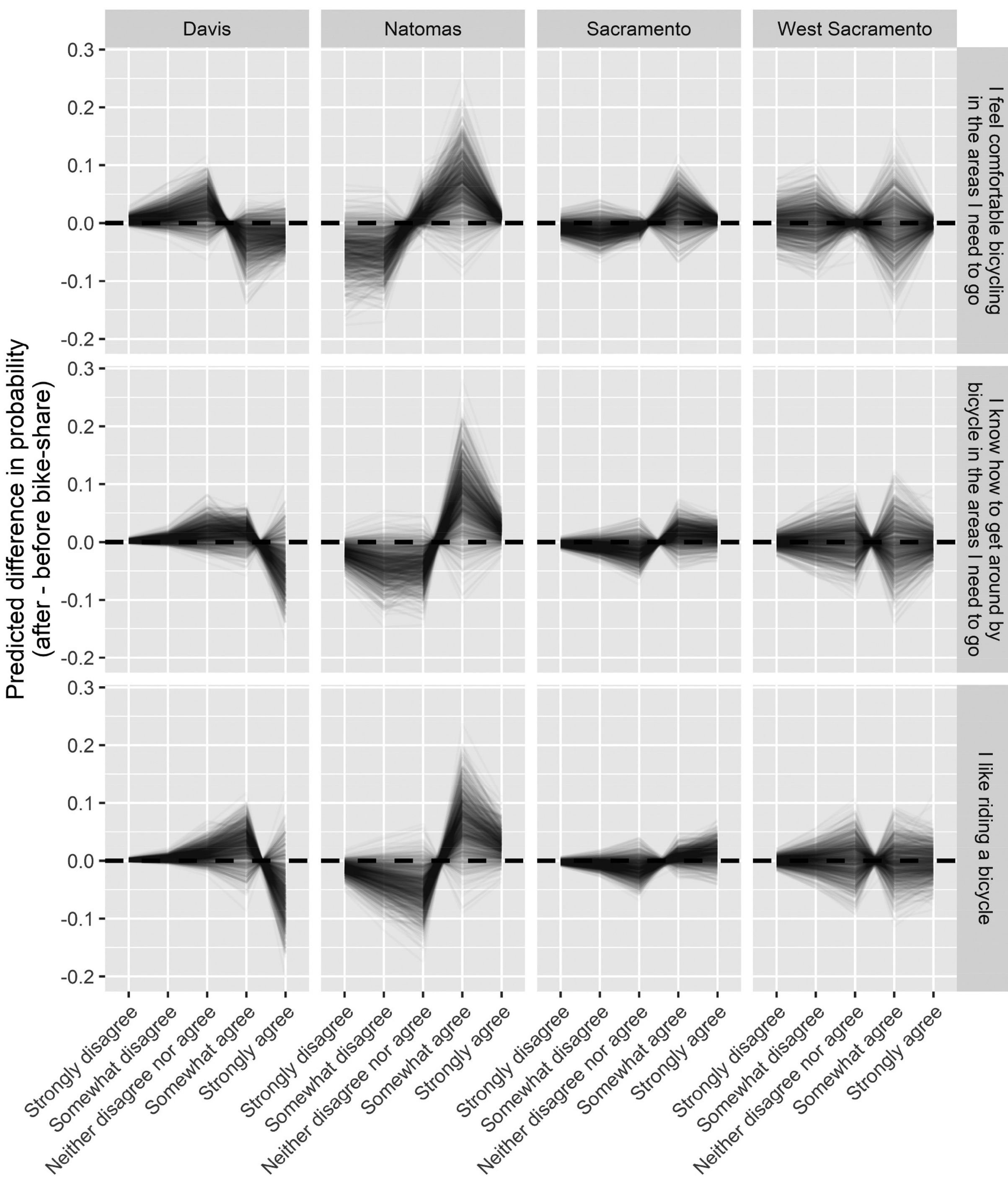

Figure 1. Difference in the predicted probabilities of statement responses associated with bicycling affinity before and after bike-share.

probability after bike-share and lines below the zero line indicate predicted decreases. The effects vary widely between neighborhoods but also within them for different statement responses. The effects for some statements in some neighborhoods indicate that bike-share may have had limited effects on average (as indicated by the mass of lines near zero). In the case of Davis, which has an established bicycling culture, the effect of bike-share is predicted to have resulted in more negative attitudes toward bicycling. For Natomas and Sacramento, the opposite is true, and little to no difference is predicted in West Sacramento, although for West Sacramento the effects are uncertain. For the specific statement *I like riding a bicycle*, the effects were most pronounced in Natomas (where bike-share is unavailable from home) with predicted agreement much more probable after bike-share (Figure 1).

Bicycling social norms

One strong predicted bike-share effect was for the statement *bicycling is a normal mode of transportation for adults in my community* (Figure 2). The effects were largest in Sacramento and West Sacramento (with more uncertainty). In Davis and Natomas, these effects were negligible, although uncertain. Another statement related to bicycling norms, *Many of my friends, family, and neighbors bicycle regularly*, showed a positive shift in Sacramento and West Sacramento while on average, the effects in Davis and Natomas were negligible.

Bicycling infrastructure

Model predicted change in attitudes toward bicycle infrastructure suggest bike-share had a positive effect in Sacramento and West Sacramento, negative effect in Davis, and inconclusive effect in Natomas (Figure 3). Most of the decline in probability in Davis is for the ‘strongly agree’ category and associated increases in neutral and disagreement. On the other hand, the increases in Sacramento and West Sacramento are primarily in the ‘somewhat agree’ category and decreases in the ‘somewhat disagree’ category.

Driving affinity

The predicted probability of statements describing individuals’ attitudes toward driving are illustrated in Figure 4. Overall, the

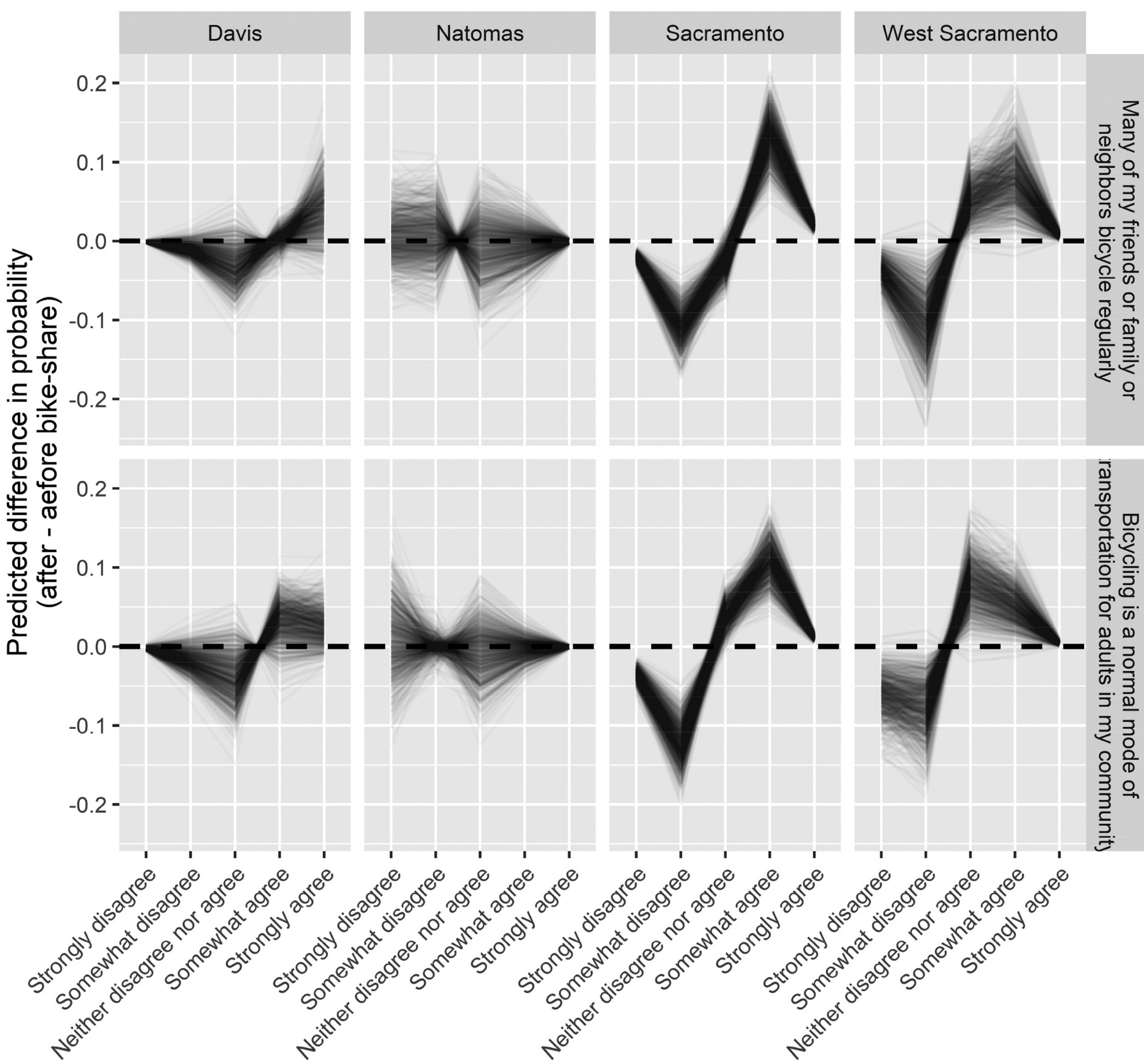

Figure 2. Difference in the predicted probabilities of statement responses associated with bicycling social norms before and after bike-share.

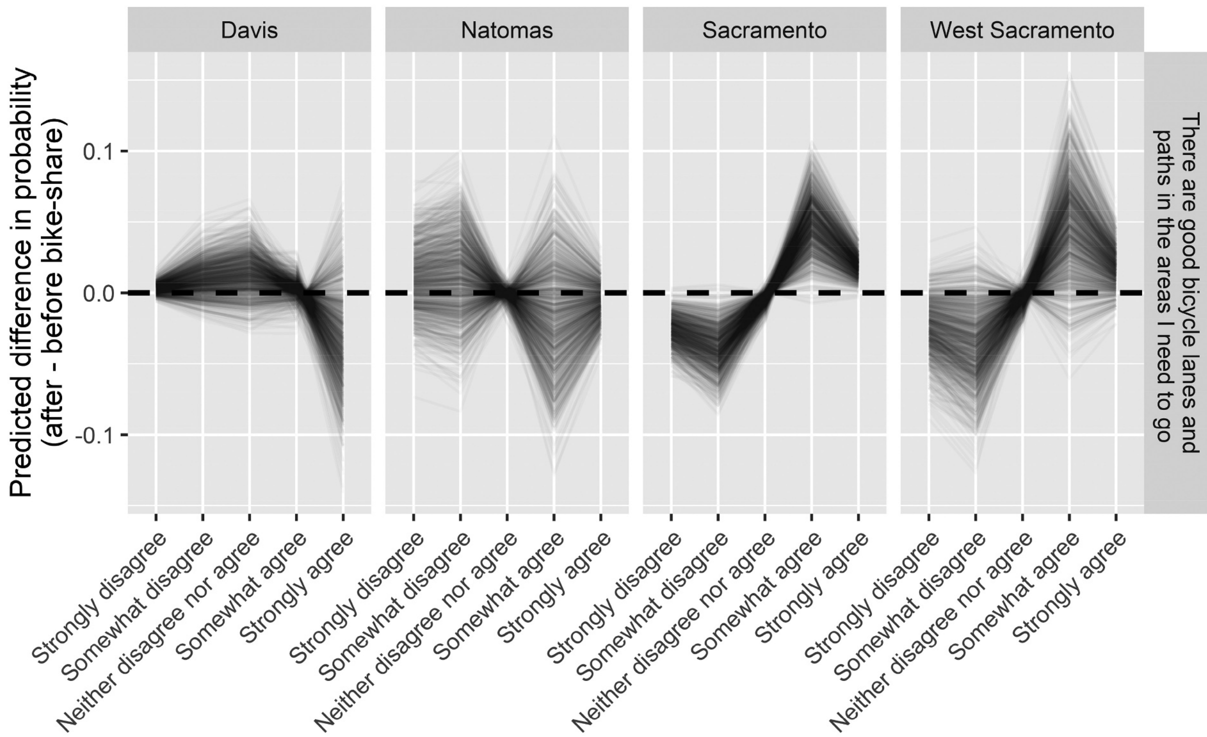

Figure 3. Difference in the predicted probabilities of the statement response associated with bicycling infrastructure before and after bike-share.

results indicate that attitudes toward driving were less favorable after bike-share in all neighborhoods, although more uncertain in Natomas and West Sacramento. However, in all cities, attempts to limit driving showed either no difference or declines as well (that is people were predicted to be less likely to like and need cars, *and* less likely to try to reduce their driving).

Liking transit

Davis residents were the only city to see greater liking of transit after bike-share, as predicted by the model (Figure 5). All other neighborhoods were predicted to like transit less after bike-share (Figure 5). The strong declines in driving affinity and liking transit across all cities, besides Davis, vary in magnitude, with most of the declines in driving affinity coming from the 'strongly agree' response which the declines in liking transit were most prevalent in the 'somewhat agree' response.

Attitude variation and correlations

Person-level variation in attitudes was generally large with average standard deviations ranging from 1 to 2 on the log cumulative odds scale (Appendix A). This suggests wide-ranging attitudes in the sample, especially regarding *Bicycling Affinity*. Given the diversity of the sample with respect to bicycling norms and infrastructure, variation was expected. The model predicted correlation amongst attitudes were moderate (−0.11–0.37) with *Bicycling Affinity* and *Bicycling Social Norms* having a positive correlation, *Bicycling Affinity* and *Driving Affinity* a negative correlation, and *Bicycling Social Norms* and *Driving Affinity* a negative correlation (Appendix A).

Model validation

Five-fold cross validation (a form of out-of-sample prediction) indicated person-level correct classification of ordered category was approximately 30% on average across attitudes (Table 3). Prediction within one neighboring category of the correct response was approximately 70% correct on average. These results suggest that while the model struggled to predict the precise response category, it is fairly accurate at predicting the general ratings of respondents.

When assessing the out-of-sample prediction in the aggregate as the percent of the sample responding to each category by attitude, errors are minimal (Table 4). All shares are predicted within a quarter of a percent in the aggregate.

Discussion

Model results suggest that bike-share is likely to have increased pro-bicycling attitudes in some cities and decreased in others (Figures 1, 2, and 3). It is possible that other factors contributed to the differences is bike attitudes between 2016 and 2019. One explanation may be that investments in bicycling infrastructure during this period increased pro-bike attitudes, like the findings of Lizana et al. (2021). Importantly, perceptions of adequate bike infrastructure rely on the individual's frame of reference (e.g. identification as a cyclist), and those frames could have changed in tandem during this time. In Sacramento and West Sacramento, perceptions about bike infrastructure shifted in the positive direction after bike-share. Although Davis has a rich history of bicycling, interest toward bicycling in Sacramento and West Sacramento is relatively new. This may imply that investments in bike infrastructure as well as the promotion of bicycling in these areas could have been a co-cause in the shift toward positive attitudes toward bicycling infrastructure. In Davis, model predictions suggest declines in bicycling affinity and perceptions of good bicycling infrastructure and this

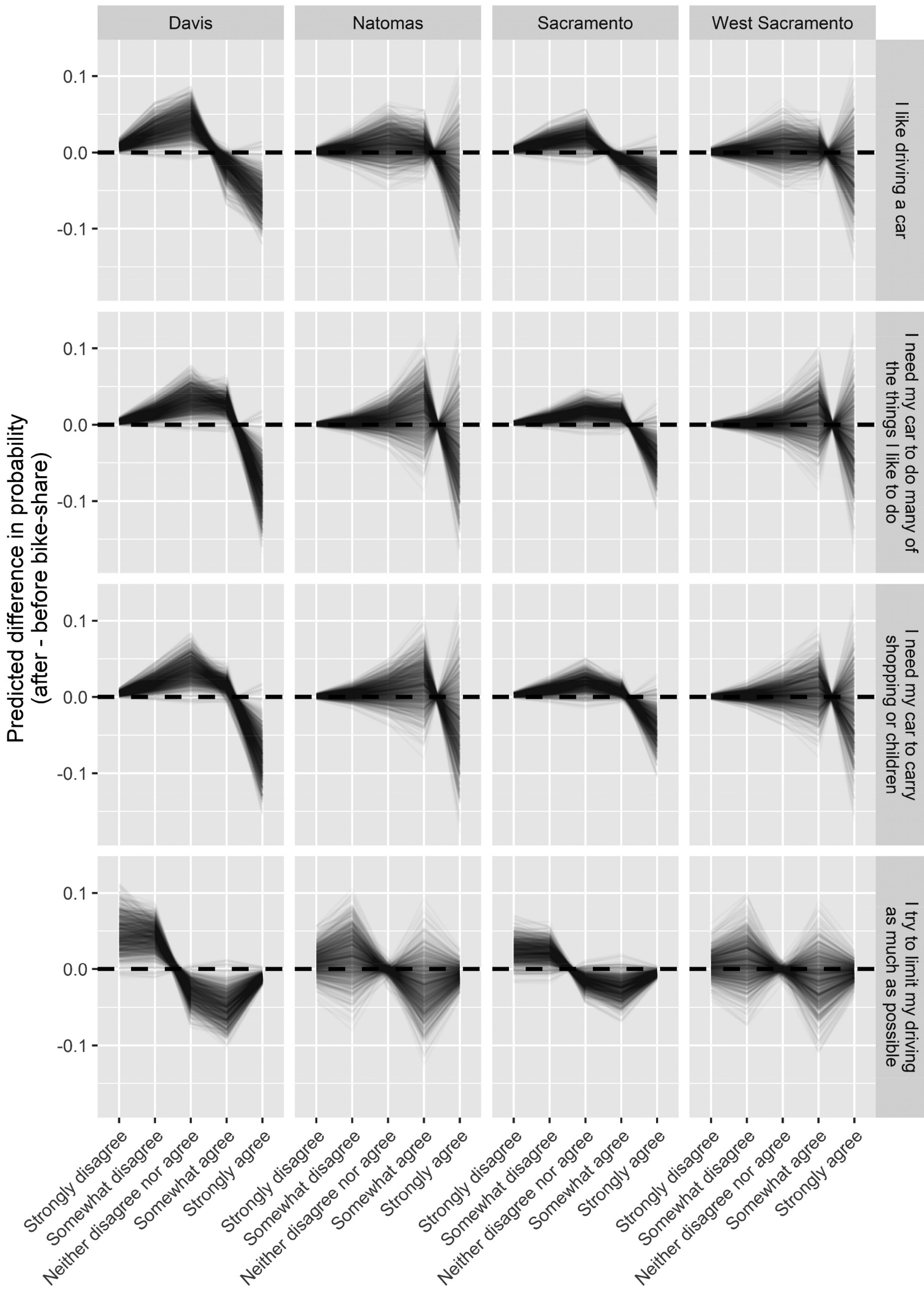

Figure 4. Difference in the predicted probabilities of statement responses associated with driving affinity before and after bike-share.

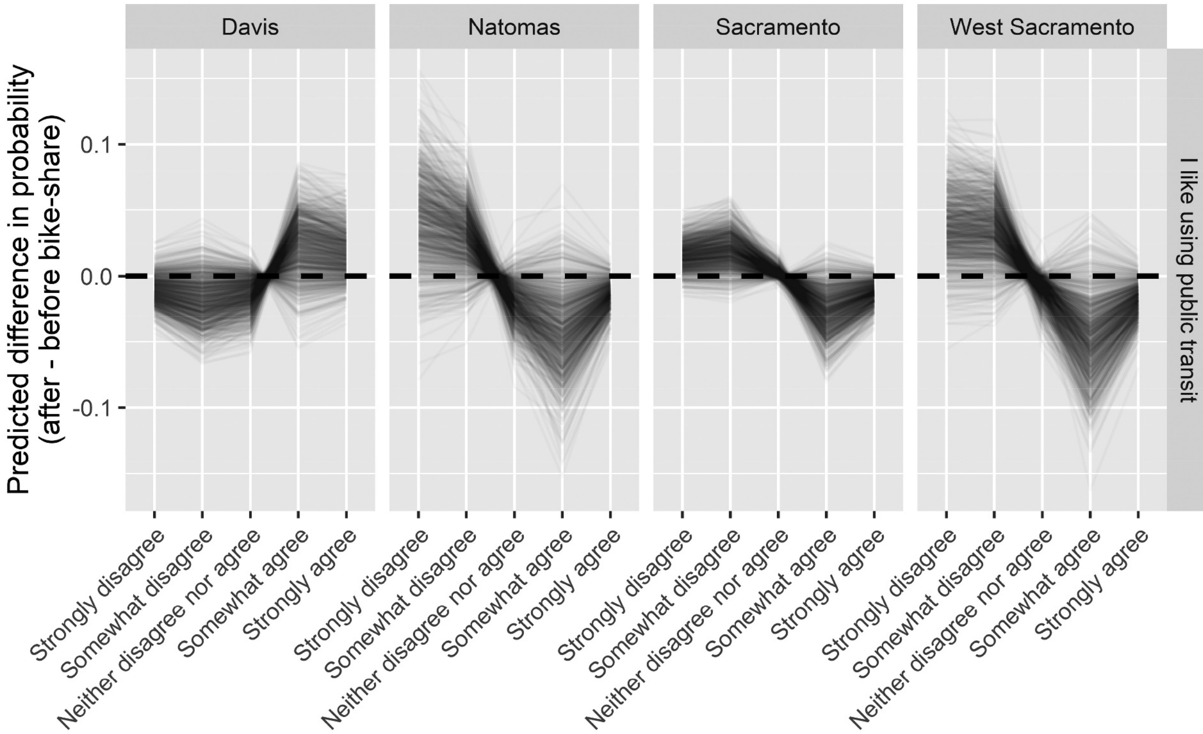

Figure 5. Difference in the predicted probabilities of the statement response associated with liking public transit before and after the bike-share.

Table 3. Response-level validation.

	Response-level classification	
Attitude	Mean percent correct	Mean percent correct within neighboring class*
Bicycling Infrastructure	29.0%	69.3%
Bicycling Social Norms	31.0%	73.4%
Bicycling Affinity	31.9%	71.6%
Driving Affinity	30.9%	72.1%
Liking public transit	24.5%	65.0%
Average	**29.5%**	**70.3%**

*Calculated as the percent correct within a neighboring ordinal category. Percent correct on the end classes (strongly agree and strongly disagree) only include one neighboring category (somewhat agree and somewhat disagree, respectively), while all other categories include categories on either side of the target category.

corresponded with relatively little actual change in bicycling infrastructure given the well-developed bike network in Davis. The opposite was true of Sacramento (models predicted increase in both *Bicycling Affinity* and *Bicycling Infrastructure* and during that time Sacramento saw relatively (compared to Davis) greater increases in bicycling infrastructure). However, the results in Natomas, rising bicycling affinity and uncertain effects on bicycling infrastructure perceptions, and the exact opposite in West Sacramento suggest less clear effects of bike-share on *Bicycling Affinity* and *Bicycling Infrastructure*.

Because we did not measure actual changes in bicycling infrastructure, more research is needed to differentiate how much of the objective change is attributable to perceptive changes and resulting pro-bike attitudes. At least one study in Portland, Oregon has noted that often the perception of bicycling infrastructure might hold a stronger and more causal relationship with behavior than objective measures (Ma, Dill, and Mohr 2014). Bicycling rates in the Sacramento region are not regularly measured, but it is possible that bicycling increased between 2016 and 2019, which itself would likely have influenced bike attitudes. However, bike-share bicycling was perhaps more visible than conventional bicycling (given that JUMP bikes were bright red and parked everywhere), meaning that if any bicycling behavior is responsible for the shifts in bicycling attitudes, bike-share use is likely to play a strong mediating role in that effect. This hypothesis is also supported by prior analysis of this data indicating that bike-share use was the primary path of increased bicycling after bike-share in the region (D. T. Fitch, Mohiuddin, and Handy 2021). In general, the effects we describe as ‘after bike-share’ could mean a great complex interaction of all that took place during the rollout of bike-share. Although we cannot be sure, the fact that bike-share was a very visually conspicuous change during the time

Table 4. Aggregated response category validation.

	Aggregate-level predicted – actual category shares				
Attitude	Strongly disagree	Somewhat disagree	Neither disagree nor agree	Somewhat agree	Strongly agree
Bicycling Infrastructure	0.35%	0.09%	−0.40%	−0.24%	0.21%
Bicycling Social Norms	0.22%	−0.39%	−0.22%	0.31%	0.08%
Bicycling Affinity	0.18%	−0.09%	−0.15%	−0.09%	0.15%
Driving Affinity	−0.02%	−0.78%	0.17%	0.64%	−0.01%
Liking public transit	0.42%	−0.09%	−0.48%	−0.12%	0.27%
Average	**0.23%**	**-0.25%**	**-0.21%**	**0.10%**	**0.14%**

suggests it is a plausible explanation for the modeled difference. This bike-share system was touted by JUMP as one of their best performing, and for one month of the study period we calculated bike density at approximately 17 and 12.5 bikes per square mile and approximately 3000 and 1200 trips per day in Sacramento/West Sacramento and Davis, respectively. While not all neighborhoods within the service area experienced the same presence of bike-share, anecdotally during this period it was unlikely one could travel through the main commercial areas of these cities and not observe parked and actively used bike-share bikes.

Future research could improve on the differentiation between bike-share effects and other infrastructure effects in a few ways. For example, researchers could work with cities to develop data schemas that properly document infrastructure attributes and their installation dates. This would allow for the creation of a timeseries of infrastructure that could be used in before-and-after studies of behavior change. Alternatively, use of existing timeseries data from Google street view or other spatio-temporally registered photographs could be useful for defining the state of infrastructure over time.

The predicted change in bicycling social norms in Sacramento and West Sacramento is perhaps the most compelling pattern in the data. The effect is much attenuated in Davis, likely due to the already strong bicycling culture, and uncertain in Natomas, where bike-share didn't operate. We hypothesize that simply seeing people regularly using bike-share in Sacramento and West Sacramento was the mechanism for this predicted effect of bike-share on perceiving bicycling as a normal mode of travel in those cities.

The after bike-share effects on attitudes toward driving were strongly negative in Davis and Sacramento, but uncertain in Natomas and West Sacramento (Figure 4). The mechanism for how bike-share could increase bicycling affinity is much clearer than the mechanism for how it could reduce driving affinity. While people can hold both bicycling affinity and driving affinity attitudes (S. Handy 2019), it is possible that the primary mechanism by which bike-share affects attitudes toward driving is through a shift toward more favorable attitudes toward bicycling first. If that is the case, we might expect that only a fraction of the bike-share effect on bicycling affinity attitudes would pass through to produce less favorable attitudes toward driving, meaning that the effect on driving attitudes would be weaker than the effect on bicycling attitudes, and this is not what we generally observed. At the same time, residents across all neighborhoods were less likely to agree that they *try to limit* [their] *driving as much as possible*. The combined results that residents are less likely to *limit their driving* but are also less likely to report *liking driving* or *needing a car* after bike-share warrants further exploration. One hypothesis is a circular relationship between limiting, liking, and needing to drive. If one is less likely to limit driving, they essentially drive more, which might expose them to more of the negatives of driving (e.g. traffic), and thus lead to less liking and possibly a feeling of less need out of a search for alternatives. Alternatively, someone may have no need to drive and experience the negatives of driving through interactions as a non-driver (e.g. as a bicyclist or pedestrian) which could lead to a more negative attitude toward driving. Beyond a universal explanation, nuance in Figure 4 indicates this pattern of not limiting and not liking and needing a car as much because of bike-share was strongest in Davis and Sacramento, and more uncertain in Natomas and West Sacramento. Natomas and West Sacramento are the least 'bicycling friendly' of the four cities and most car dependent (within the geographies of the sampling). It may be that in places where bicycling and driving compete more equally, bike-share acts as a psychological opening of the potential for bicycling and in turn the recognition of disliking cars and not needing them without the next step in the behavioral process of setting intention to limit driving, though why the reverse effect for limiting driving is still difficult to explain.

Although the focus of this analysis was on attitudes toward bicycling and driving, the single statement *I like public transit* also saw strong shifts from agree to disagree after bike-share (Figure 5). Davis was the only city that saw a positive effect of bike-share on liking transit, and considering the low student response rate of the survey (Table 1) and the fact that students are the dominant users of the Davis bus system (Lee 2019), the positive effect in Davis suggests that many respondents may have seen its potential as a connection to the city's only train station (for intercity rail connections). In fact, train connections were one reason for support of bike-share in Davis given only infrequent bus connections to the train station. We caution that this is only conjecture as bike-share trips connecting to or from transit are rare in this data set (D. Fitch, Mohiuddin, and Handy 2020). It may be that changes in liking transit between 2016 and 2019 were due to other concurrent factors related specifically to changes in transit operations and service quality in the region and unrelated to bike-share. If so, the three cities with worsening attitudes toward transit might actually have contributed to bike-share use given that we observed a positive correlation between liking transit and using bike-share.

While we find some evidence that the 'after bike-share' effect, which we assume to be primarily about bike-share, caused some changes in travel attitudes, the evidence is equivocal in some cases and many other factors could have contributed to the attitudinal changes we measured. For example, broader societal changes, such as increased attention to the climate crisis, public debate about micromobility services, and changing concerns about traffic safety may have affected attitudes. Other direct but unobserved factors, such as improvements to transit services, changes to infrastructure, and changes in travel costs may have been important drivers of the results.

Conclusions

One of the most important reasons for estimating the effects of bike-share on attitudes is to better understand potential benefits of such systems that are often overlooked in transportation investment decisions. Even if bike-share takes time to attract riders, it may serve as an important nudge toward bicycling and away from driving in the community more generally. It may also spur investment in bicycling infrastructure and other positive feedbacks that remove longstanding barriers to bicycling. Our results from one US urban region indicate that in the short-term, bike-share may prompt more favorable attitudes toward bicycling for residents and not just users. We also observe declines in pro-car attitudes but simultaneously a decline in trying to limit driving, suggesting that bike-share may help to reduce perceptions of car dependence even if it does not lead to a reduction in driving. It is important to note that these effects are for the general population – not just the users of bike-share – which suggests that bike-share may have broader impacts beyond its direct benefit as a new mobility service. And the impacts may be rapid: these effects were observed within one year of the opening of the bike-share system in the greater Sacramento region. Attitudes may have continued to shift following the after survey, and they may have shifted further following the return of bike-share to the region after the pandemic. Evidence for long-term attitudinal change due to bike-share will require additional research that uses more sophisticated techniques, such as longitudinal panel designs to track the benefits of bike-share to the fullest extent possible.

Acknowledgments

This research was funded by California Senate Bill 1. Specific thanks to Sacramento Area Council of Governments and JUMP Inc. for partnering on this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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