Modeling Bicycling to Elementary and Junior High Schools with Bike Rack Counts

Dillon T. Fitch, Calvin G. Thigpen, and Susan L. Handy

The decline in active travel to school and the concomitant rise in numbers of children being driven to school in the United States over recent decades have affected the health of school-age children and contributed to environmental problems. In response, communities throughout the country are stepping up efforts to increase active travel, including bicycling, but they have few tools available to them to assess the potential effectiveness of proposed strategies. The purpose of this study was to develop a model with aggregated school-level data of the factors associated with bicycling to elementary and junior high schools and to examine the effectiveness of this model in predicting bicycling to school. With the use of repeated observations of bike rack counts at 11 public schools in Davis, California, binomial multilevel regression models that included factors thought to influence bicycling to school were specified. The models indicated that comfortable bicycling routes, the racial and economic makeup of the student population, and various factors that represented the daily context (e.g., day of week, season, weather) all were likely to influence rates of bicycling to school. The results indicated that models based on aggregated school-level data were not sufficient to predict the amount of bicycling to a given school on a given day but were sufficient to predict mean bicycling to a given school over a period of time. Thus this method may be sufficient for policy analysis whose aim is to increase average bicycling to school.

Travel to school by school-age children in the United States represented almost a quarter of overall person trips and travel time in 2009 (*1*). Most of this travel was by automobile, although it had not always been the case: the percentage of active travel to school declined from 41% in 1969 to 13% in 2009, while the share of children driven to school steadily increased (*1, 2*). This mode shift has contributed to environmental problems, such as poor air quality and increased greenhouse gas emissions, and has become a significant source of traffic congestion. These trends also have had a negative effect on the health and well-being of children (*3*).

For these reasons, it is important to understand the factors that could contribute to higher levels of walking and bicycling to school. The decline of active travel to school in the United States has been correlated with increased distances to school, which suggests that travel time is a major constraint on student travel (*2, 4*). During this period the percentage of students enrolled in their attendance-zone (i.e., assigned) public schools also declined (*5*). However, the decline in active travel to school is not solely a function of increased distances: even when distances are short (<1 mi), most students still get to school by car (*6*). Bicycling to school is particularly unpopular, and it may be that parental concerns about traffic safety are more of a barrier than is distance. The quality of bicycling infrastructure thus may play a key role.

The purpose of this study was to make use of easily collected data to analyze factors associated with bicycling to school. Aggregate data from the City of Davis, California, well-known for its bicycling culture, were used to develop models to quantify the effects of a variety of factors on bicycling to elementary and junior high schools. The models showed that comfortable bicycling routes, the racial makeup of the student population, and various factors that represented the daily context (e.g., day of week, season, weather) all influenced bicycling to school. These models can be used to test the potential impacts of proposed strategies to increase bicycling to school, and the method can be replicated easily in other communities.

BACKGROUND

Mode choice for travel to school can be framed as a joint choice between the child and parent (*7, 8*). Although the age of the child affects the child's influence on the decision, the choice involves a complex suite of considerations, including proximity to school, safety of neighborhood, safety of traffic, parent work schedule, proximity to parent workplace, weather, bus or car availability, and attitudes toward and preferences for particular modes. Although these factors are some of the most salient with respect to mode choice to school, they are difficult to measure, and this type of joint choice is difficult to model in most data contexts (*9*). In most research on school travel, a few parsimonious metrics are used to represent such factors (e.g., proportion of sidewalk coverage for traffic safety, proportion of houses with windows that face the street for neighborhood safety) as predictors of the choice to walk or bike to school (*10*).

However, these factors are likely to have different relationships with the decision to walk and with the decision to bike (*9, 11*). This variability is particularly likely with respect to characteristics of the built environment and the attitudes of parents and children. Factors that make an urban environment poor for walking, such as long blocks (i.e., low intersection density) and incomplete sidewalks (*12*), may not make it poor for bicycling (*13*). Attitudes and perceptions of children and of parents about bicycling have been shown to affect the choice to bicycle (*14, 15*). In Davis, parental encouragement and student comfort in riding a bike were found to influence bicycling to high school (*16*). The decision to bicycle to school also has been correlated with age, gender, neighborhood population density, school size, and grade level (*9, 15*).

Distance (or time) is a major constraint on school mode choice, just as it is in mode choice with respect to other activities (*4*). One study

D. T. Fitch and C. G. Thigpen, Institute of Transportation Studies, College of Engineering, and S. L. Handy, Department of Environmental Science and Policy, College of Agricultural and Environmental Sciences, and Institute of Transportation Studies, University of California, Davis, 1 Shields Avenue, Davis, CA 95616. Corresponding author: D. T. Fitch, dtfitch@ucdavis.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2587, Transportation Research Board, Washington, D.C., 2016, pp. 68–77.
DOI: 10.3141/2587-09

suggested that increased distances to school might have accounted for about 50% of the decline in active travel (*2*). This estimate was consistent with results from a national survey, which showed that roughly 55% of U.S. parents identified distance as a barrier to walking to school (*17, 18*). Not surprisingly, distances to school have increased as trip distances in general have increased as a result of metropolitan sprawl (*2, 9*). Along with increased distances to local schools as a result of decreased densities, districts have been consolidating schools and establishing magnet schools that draw from throughout the district. Parents often choose to place their children in a school other than their neighborhood school: from 1993 to 2007, the percentage of children who attended their assigned local school declined from 80% to 73% (*5*). However, in 2007, some 27% of students reported that they had moved to their current residence to attend a specific school (*5*). Thus some families stayed put and their children traveled farther to a neighboring school, while almost as many families decided to move to a neighborhood to attend a specific school.

Although distance is a major constraint on active travel to school, it may be that safety and comfort have more of an influence on bicycling. In a study of four Oregon middle schools, even when residents lived close to neighborhood schools (<1 mi), mode to school was still dominated by auto (>50% on the way to school), while only 15% of students bicycled as their primary mode (*11*). With nationwide bike mode share around 1%, safety is the primary concern for most would-be bicyclists (*19*). One of the major factors related to bicycling safety, especially for school-age children, is automobile traffic.

The level of safety and comfort to bicycle within a given roadway network's traffic can be measured with the bicycle level of traffic stress (BLTS) method (*20*). This method is based on Dutch design standards, which themselves are based on studies of adult bicycling behavior (*20*). Although this method was not intended to classify road networks from the perspective of young bicyclists, it may provide a useful indicator of bicycling comfort. Only simple measures of BLTS are provided in this present study. For a detailed investigation of the relationship between traffic stress and bicycling to school, see Fitch et al. (*21*).

METHODS

In most U.S. communities, bicycling represents a small share of school travel. Davis, the setting for this present study, is a notable exception (*22*). Davis, located near Sacramento, California, is a small city of about 65,000 people, a large share of whom are students at the University of California, Davis. The city has made significant investments over the past 50 years to build a network of on- and off-street bicycle facilities (*23*). Although models developed with data from this setting would likely overpredict bicycling if applied to other communities, the method employed here to develop the models could be replicated easily, particularly as bike mode shares rise across many cities in the United States.

Aggregate school-level data were used to model the relationship between predictor variables and bicycling to school. As described later in this paper, the data on bicycling were derived from repeated observations of the number of bicycles in the bicycle racks at selected schools. This approach was a cost-effective way to monitor bicycling to school that could be readily applied to other geographic areas. However, the use here of aggregate data raised the possibility that the relationships revealed in the models did not accurately represent the relationships that underlay individual decisions about mode of travel to school (i.e., ecological fallacy) (*24*). Nonetheless, the method may prove useful as a means to assess potential strategies to increase bicycling to school.

Data

In an effort coordinated by a local bicycle advocacy organization, parent volunteers collected bicycle count data for 11 public schools in Davis (eight elementary and three junior high schools) by counting bicycles parked at school racks in the morning several times over 2½ school years (Table 1). These data were collected on multiple occasions at each school between October 2012 and February 2015 and resulted in 214 observation day–locations, 20 of which occurred

TABLE 1 Summary Statistics for Davis Schools

School	Number of Days	Bike Rack Count		Mean Number of Enrolled Students	Mean Distance (mi)	Percentage by Network		Percentage by Demographic Group			
		Mean	SD			BLTS 1[a]	BLTS 2[b]	White	Hispanic	Asian	African-American
Emerson–DaVinci Junior High	12	194	65	731	1.9	33	86	66	15	9	3
Harper Junior High	18	205	63	653	1.7	39	71	50	21	18	3
Holmes Junior High	12	320	106	723	1.8	44	90	59	13	19	3
Birch Lane Elementary	21	163	40	606	1.0	67	88	62	14	11	3
Cesar Chavez Elementary	22	97	47	629	2.2	17	90	58	26	5	2
Korematsu Elementary	22	119	46	527	0.7	83	91	47	17	24	3
Montgomery Elementary	30	49	18	420	1.2	56	80	32	54	7	2
North Davis Elementary	25	147	55	587	1.2	46	89	52	16	23	3
Patwin Elementary	23	93	53	413	1.0	37	94	58	20	13	5
Pioneer Elementary	11	62	40	521	1.4	22	25	57	13	19	3
Willett Elementary	18	117	45	525	1.3	45	82	53	11	24	3

[a]BLTS 1 = students who could bike to the school on a network with all links classified as Stress Level 1.
[b]BLTS 2 = students who could bike to the school on a network with all links classified as Stress Level 1 or 2.

during a bike-to-school day event. Bike rack counts were validated with a single-day in-class travel survey, which produced consistent results (*22*). Additional data collected or compiled for this study came from a variety of sources as follows:

- Temperature. This value was collected at the time of each school count (for most counts). If the value was missing for a given date, the historic daily low for the city of Davis on that date was used (*25*).
- Rain. Heavy rain (not light rain or fog) was recorded at the time of each school count.
- Season. This factor was assigned on the basis of the date of the school count (i.e., fall was September through November; winter was December through February; and spring was March through May).
- Bike-to-school day. Several bike rack counts occurred on the promotional bike-to-school day, which was represented by a 1 or 0 dummy variable.
- Enrollment and school demographics. School enrollment and demographics were obtained from the Educational Data Partnership website for each corresponding school year (*26*). Data for the period of 2013 to 2014 were used for the 2014–2015 school year, because they were the only data available.
- Origins. The Davis school district has an open enrollment policy, which allows attendance by students beyond neighborhood boundaries. Because neighborhood boundaries would not provide an accurate representation of student origins, student home locations during February 2013 were obtained from the City of Davis. These origins were exhaustive for the school district during February 2013, and they served as a surrogate for all other time periods.
- Distance and bicycling comfort. All geographic information system data needed for the network analysis were obtained from the City of Davis or developed specifically for this study through heads-up digitization or through manual database editing (*27*).

Network Classification and Summary

The BLTS method was used to classify the road network on the basis of street characteristics associated with traffic stress for bicyclists (*20*). The method is a rule-based classification of road segments and intersections into four levels of stress, which range from low-stress BLTS 1 (e.g., quiet neighborhood roads) to high-stress BLTS 4 (e.g., major arterial roads). For ease of discussion of the model results, the term "comfortable" is used here to refer to routes with low traffic stress. The general steps taken to complete BLTS classification follow:

1. Update the existing geographic information system roadway network with bike paths, new roads, and other bike cut-throughs (e.g., parking lots);
2. Update attributes for the network on the basis of aerial image interpretation and existing geographic information system data;
3. Generate and update attributes for intersections;
4. Ensure that the network is topologically correct (e.g., no overlapping links, no dangling nodes);
5. Assign each link to one of the four BLTS classes on the basis of the number of lanes, on-street parking, speed limit, bike-lane width, lane blockage, and presence of a centerline or a raised median through the use of an automated routine;
6. Assign each intersection to one of the four BLTS classes on the basis of right-hand turn lane length, abruptness, and average speed with an automated routine; and
7. Update the BLTS classification of the links that begin or end, or both, at intersections with higher BLTS by increasing the BLTS of the link to match the highest intersection's BLTS (i.e., weakest link approach) (*20*).

After the classification was completed, a sample of roadway and intersection attributes was validated in the field, and manual updates were made to the network attributes, which resulted in adjustments to the classifications. This final network was subdivided into four subnetworks: BLTS 1 (all links classified as Stress Level 1), BLTS 2 (all links classified as Level 1 or 2), BLTS 3 (all links classified as Level 1, 2, or 3), and BLTS 4 (all links) (i.e., the entire network). Two aggregate measures of bicycling comfort were calculated from these networks for inclusion in the statistical models: (*a*) percentage of students who attended the school who could bike to school on a BLTS 1 network, and (*b*) percentage of students who could bike to school on a BLTS 2 network. For a more thorough analysis of BLTS, see Fitch et al. (*21*).

Model Development and Analysis

Aggregate binomial regression models were used to analyze the relationship between bike rack counts at each school and the predictor variables. The unit of analysis was the bike, which could be extended to the student, because all students were considered either to bicycle or not to bicycle to school. With the student as the unit, the sample size for this model was the number of observation days multiplied by the number of enrolled students ($n = 190{,}315$). Because the analysis used multiple measurements from each school, a standard binomial regression model would have been biased by the correlations between repeated observations at each school (*10*). A multilevel–hierarchical binomial regression model structure thus was chosen because it pooled the within-school variance (by estimating a unique intercept for each school). Such models have been shown to increase out-of-sample prediction (*28*).

To estimate the regression models, a Bayesian analysis framework was used, because to specify regularization of prior probabilities can guard against model overfitting, and because posterior probabilities associated with Bayesian analysis have simple interpretations (*29*). Through the use of the R statistical packages rethinking and rstan as an interface for the probabilistic statistical programming language Stan, the No-U-Turn sampler, a form of Hamiltonian Markov chain Monte Carlo, was used to estimate the models (*30*). All models were compared with the use of widely applicable information criteria (WAIC), which do not require multivariate Gaussian posterior distributions and are well suited to multilevel models. Like all information criteria, WAIC values constitute a relative measure, on the basis of model deviance, whose lower values indicate greater theoretical out-of-sample prediction (*29*).

Along with a simple varying intercept-only model, three models were specified with predetermined groups of variables thought to influence aggregate bicycling to school (Table 2). These were nested models, starting with parsimony and adding complexity. All models were specified with the same general form (i.e., the only differences were the addition of predictor variables). For illustration, one of the models including all of the variable groups (Full) is as follows:

TABLE 2 Model Specifications and Information Criteria

Model Name	Model Specification	WAIC	pWAIC	Weight
Intercept	na	125,756.8	11.0	0.00
Day	*f* (season, temperature, day of week, bike-to-school day)	121,969.9	20.0	0.00
School	*f* (season, temperature, day of week, bike-to-school day, free lunch, race or ethnicity, distance)	121,932.6	23.7	0.50
Full	*f* (season, temperature, day of week, bike-to-school day, free lunch, race or ethnicity, distance, BLTS 1, BLTS 2)	121,932.6	23.8	0.50

NOTE: pWAIC = effective number of parameters in the model due to shrinkage (*29*); weight = Akaike weight of the model in this set of four; na = not applicable. A model's weight is an estimate of the probability that the model will make the best predictions on new data, conditional on the set of models considered, according to McElreath (*29*).

$$n_{\text{bike},ij} \sim \text{binomial}(e_k, p_{ij})$$

$$\begin{aligned}\log\frac{p_{ij}}{1-p_{ij}} &= \alpha + \alpha_j + \beta_{\text{day}} * \text{day}_{ij} + \beta_{\text{temp}} * \text{temp}_{ij} + \beta_{\text{rain}} * \text{rain}_{ij} \\ &+ \beta_{\text{season}} * \text{season}_{ij} + \beta_{\text{bike}} * \text{bike}_{ij} + \beta_{\text{hisp}} * \text{hisp}_{ij} \\ &+ \beta_{\text{black}} * \text{black}_{ij} + \beta_{\text{Asian}} * \text{Asian}_{ij} + \beta_{\text{male}} * \text{maleper}_{ij} \\ &+ \beta_{\text{freeRed}} * \text{freeredper}_{ij} + \beta_{\text{dist}} * \text{meandistance}_{ij} \\ &+ \beta_{\text{blts1}} * \text{BLTS1}_{ij} + \beta_{\text{blts2}} * \text{BLTS 2}_{ij}\end{aligned}$$

priors:

$$\alpha_j \sim \text{normal}(0, \sigma)$$

$$\alpha \sim \text{normal}(0, 10)$$

$$\text{all } \beta\text{'s} \sim \text{normal}(0, 10)$$

$$\sigma \sim \text{Cauchy}(0, 1)$$

where

n_{bike} = number of bikes counted on observation i at school j;
e = school enrollment, assumed to be the same for each observation at school j (i.e., number of trials considered for each within-school observation is the same) but varies by year (subscript k);
p = probability of an enrolled student bicycling to school (i.e., that a particular trial was a success), modeled through the logit link function;
α = mean intercept;
α_j = intercept for school j;
each β = parameter for each predictor variable;
day = series of dummy variables for day of the week;
temp = morning temperature (°F);
season = series of dummy variables for fall, winter, and spring;
bike = dummy variable for presence of bike-to-school day event;
hisp, black, and Asian = percentages of Hispanic, African-American, and Asian students, respectively;
maleper and freeredper = percentages of males and students eligible for free or reduced lunches, respectively;
meandistance = mean shortest network distance to school (mi); and
BLTS 1 and BLTS 2 = percentages of students with access to school on each of those networks, respectively.

Although differences were expected in the factors that affected bicycling to elementary and junior high schools, the commonalities were likely to outweigh the differences (i.e., to know something about bicycling to elementary school helps to understand bicycling to junior high school, and vice versa). Thus bicycling to elementary schools and bicycling to junior high schools were modeled jointly, and the varying intercepts were used to pool within school variability.

RESULTS

Descriptive Results

Bicycle rack counts in Davis showed that junior high schools had a higher proportion of students who bicycled to school than did elementary schools (34% and 20%, respectively). The median proportion of students who bicycled to school in Davis ranged from 11% at Pioneer Elementary to 47% at Holmes Junior High (Figure 1). Intraschool variability was consistently high, especially at elementary schools (Figure 1). All elementary schools recorded their highest proportion of bicycling on a bike-to-school day; for some schools, proportions on these days were more than double their medians. The spatial distribution of safe bike access around the schools, as indicated by the BLTS classification, did not seem to correspond with proportions of bicycling to school (Figure 2). For example, Montgomery and Pioneer Schools had similarly low rates of bicycling to school. A high share of students around Montgomery had BLTS 1 access, while students at Pioneer did not. (Contact the authors for additional information and interpretation of colors used in Figure 2.)

The variation in the proportion of bicycling between schools also exhibited certain spatial patterns. South Davis schools (south of Interstate 80) had low proportions of bicycling (e.g., Pioneer and Montgomery), while centrally located schools had higher proportions (e.g., Holmes, North Davis, and Birch Lane). Although the spatial distribution of those who biked to school was not the focus of this study, the findings here might offer a new explanation for the relatively low rates of south Davis students who bicycled to high school, namely, experience in bicycling to school (*16*).

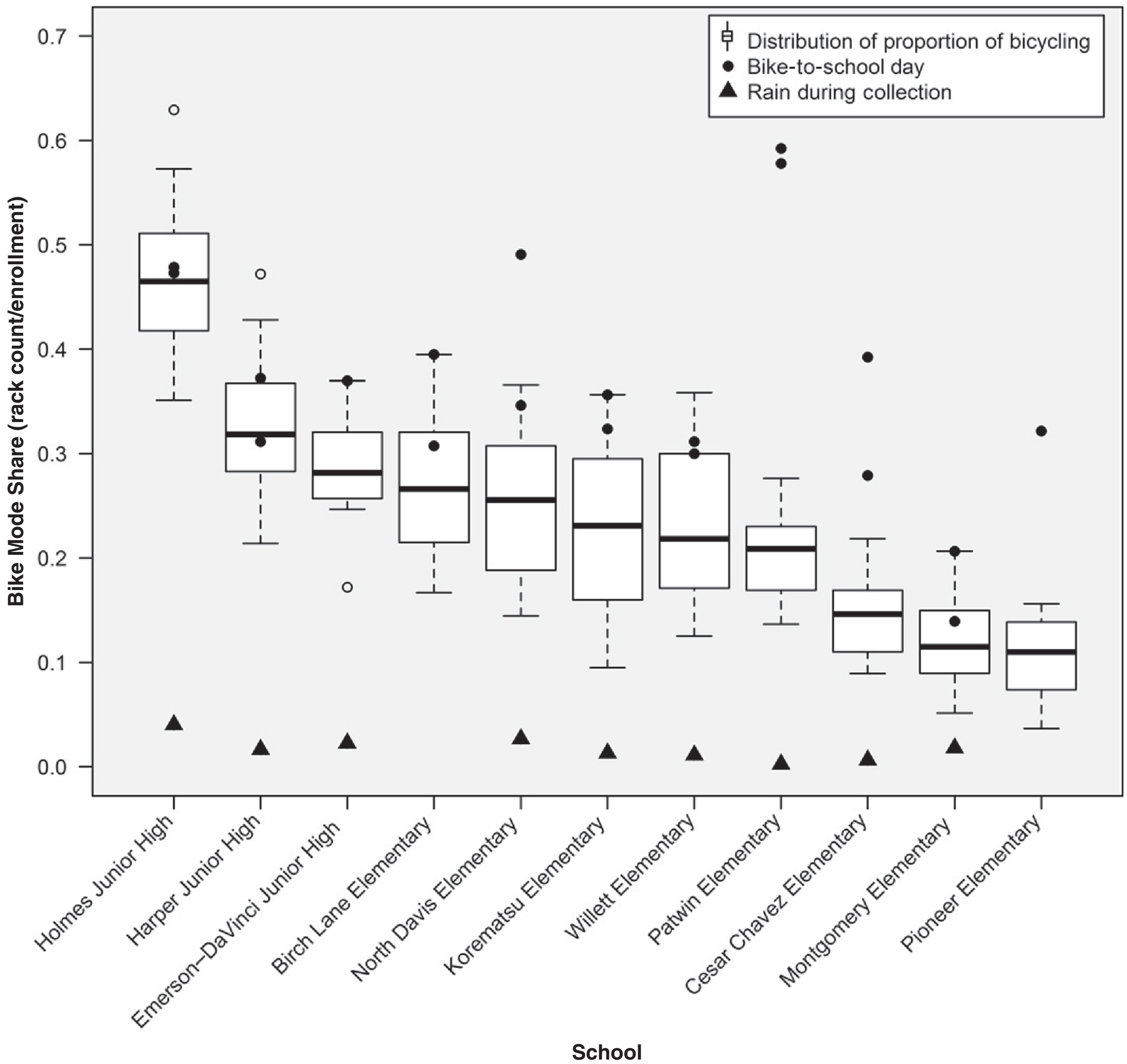

FIGURE 1 Box plots of proportion of bicycling to schools in Davis (filled dots = bike-to-school days; triangles = heavy rain).

Model Results

The intercept model, which was the first model, included only a mean intercept and a varying intercept for each school (i.e., no predictor variables) and provided information about the variability of bicycling at each school. Parameter estimates (i.e., intercepts) and their corresponding 90% highest posterior density intervals indicated considerable variance between schools (not shown). Cesar Chavez, Montgomery, and Pioneer Schools had confidently negative intercepts, which indicated a lesser likelihood of bicycling relative to the other schools, while Holmes and Harper Schools had positive values, which indicated a greater likelihood. However, these differences became more uncertain in later models in which added variables explained differences in bicycling to each particular school.

The day model added variables that reflected the context for each collection day, including day of week, morning temperature, morning rain, season, and bike-to-school day. All days of the week had parameter intervals closely centered around 0, which indicated that they might not have influenced bicycling. The exception was Friday, with a posterior density almost entirely in the negative range, which indicated less bicycling on Fridays (Figure 3). Higher morning temperatures and days in the fall season increased the likelihood of bicycling to school. Also, a bike-to-school day event increased the likelihood of bicycling to school, while rain had a confidently strong negative effect.

The school model added race, economic, and distance variables to the day model. A greater percentage of Hispanic students had a positive but uncertain effect on bicycling, while the percentage of African-American students had a negative effect, which was uncertain in magnitude. The percentage of male students had an uncertain effect, while the percentage of students who received a free or reduced-price lunch (a surrogate for household income) had a confidently negative effect on bicycling. Finally, the mean shortest distance to school had little to no expected effect on bicycling but with a large uncertainty (Figure 3).

The full model, which was the final one, added the percentage of students with access to school on BLTS 1 and BLTS 2 networks. Results indicated that BLTS 1 had an uncertain effect on bicycling to

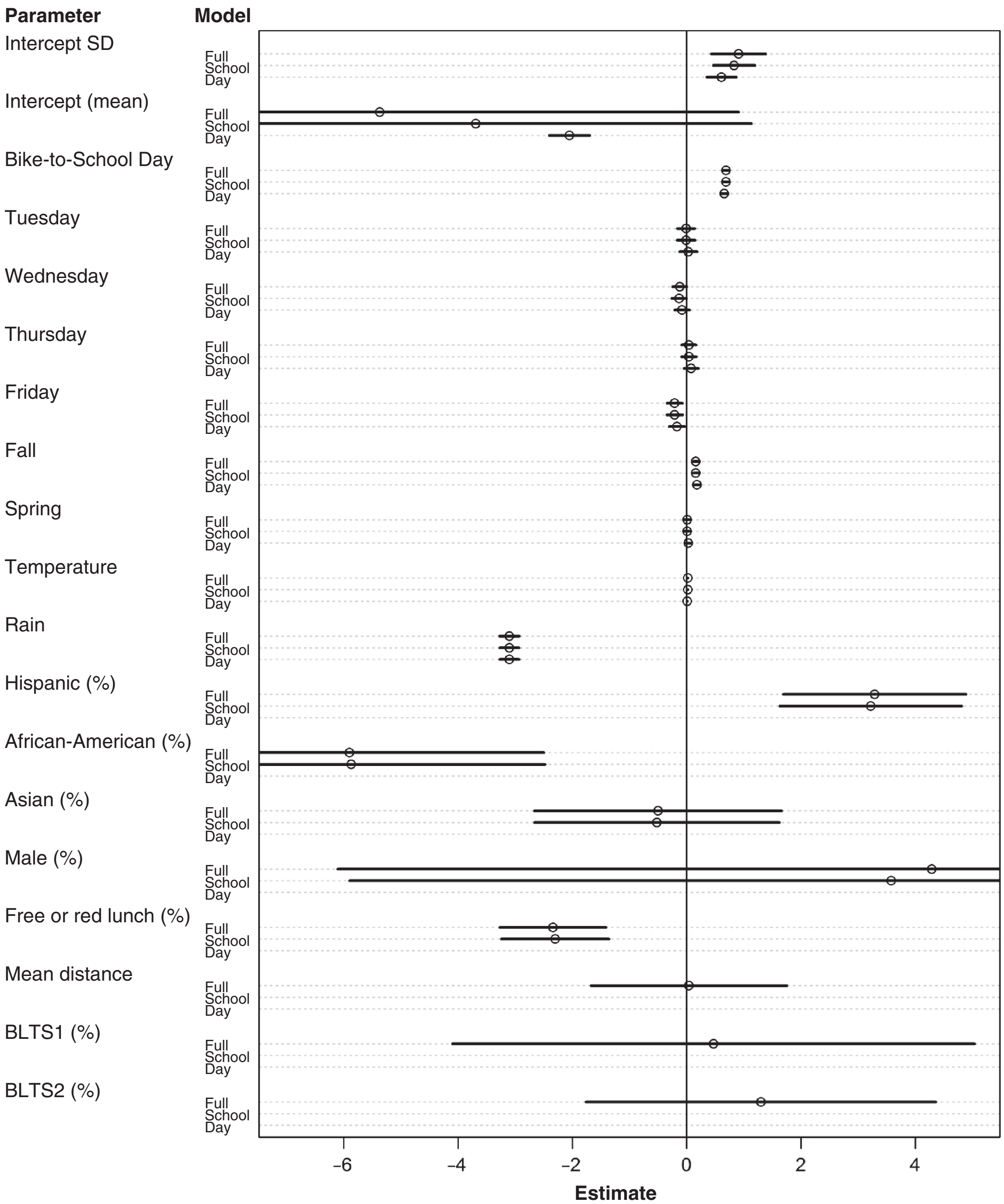

FIGURE 3 Parameter mean estimates (circle) and 90% highest posterior density intervals (bars) for three models (day, school, and full). Full intervals are not displayed for parameters with exceptionally large uncertainty (free or red lunch = free or reduced-price lunches).

school. Similarly, BLTS 2 had an uncertain effect, albeit a predominant one (as indicated by its posterior distribution), on bicycling to school (Figure 3). These results showed that aggregate measures of comfortable access to school might be indicative of greater bicycling but also that further examination of BLTS was likely to be needed to make such a statement confidently.

Overall, the school and full models had roughly equal predictive power (i.e., equal Akaike weight) (Table 2). An ensemble of these two models (i.e., synthesized estimates in which each model was weighted by its Akaike weight) predicted the mean bicycling rate at each school with considerable accuracy (±1%). However, the ensemble model contained considerable errors with respect to daily predictions at individual schools. Many observations had a residual variance that was greater than 20% (Figure 4). Future research should attempt to address these errors through consideration of new variables or theoretically motivated variable interactions.

DISCUSSION OF RESULTS

The results demonstrated that the daily variation in bicycling to school in Davis was wide, especially given that most data were collected on rain-free mornings. The findings suggested that, for a large group of students, bicycling to school was not a 5-day-a-week routine

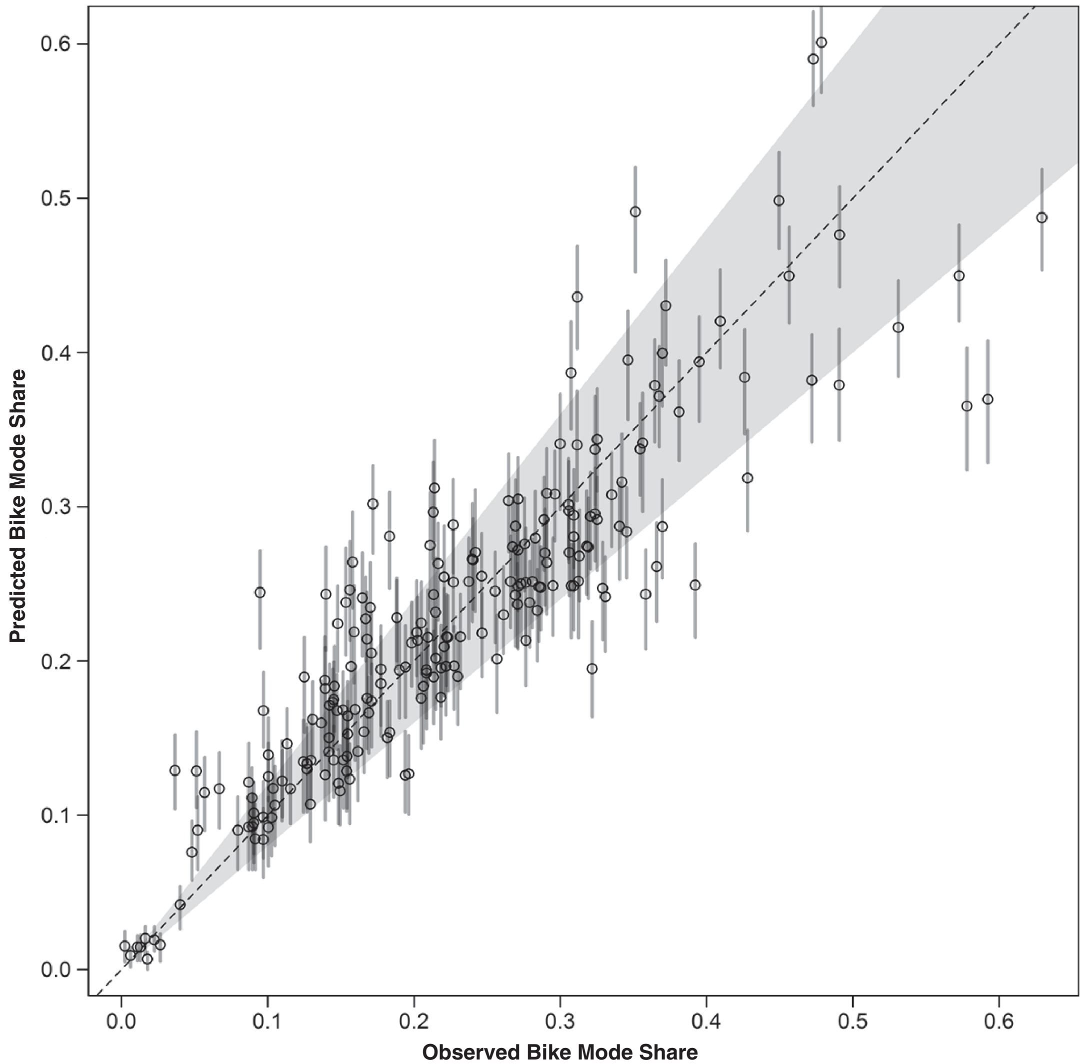

FIGURE 4 Observed bike mode share versus ensemble model predicted bike mode share for each observation (points = mean daily estimates; bars = simulated 90% prediction interval; all predictions in shaded region are within ±20% of observed daily mode share).

but an option among alternatives, which was chosen on some days but not on others.

This analysis did not reflect the various bike promotional programs at each school. A consideration of these programs was excluded primarily because it would have been difficult to quantify how each individual program might have affected bicycling to school rates without before and after rack counts. Although the school-specific intercepts in the model at least partly captured these differences, bicycling programs may have had a moderating influence on the relationship between the predictor variables and bicycling rates. To include varying slopes in future models may help account for these differences.

In a comparison of the statistical models, the full and school models had equivalent WAIC values, which suggested that they had equivalent predictive power. The WAIC values were expected to improve after BLTS variables were added but did not hinder inferences that BLTS variables might have helped to explain bicycling (particularly BLTS 2). It was suspected that the equivalent WAIC values were related to the large measurement error, which was added to the BLTS variables once they were aggregated from individuals to schools.

The most striking result from the model parameters was how uncertain the effects were of comfortable access on bicycling-to-school rates (Figure 3). The fact that access by BLTS 2 was more influential than was BLTS 1 suggested that, in Davis, parents and students might have accepted some traffic stress. These results may indicate that a culture of bicycling increases the perception (and perhaps the reality) that bicycling is safe and comfortable (i.e., safety in numbers) (*31*). Another surprising result was the lack of influence that distance had, whereas other studies of active travel to school have shown it to be influential (*9*). However, neighborhood schools in Davis have network distances to school that are much shorter than the national average (mean of 1.1 mi versus 4.4 mi, nationally) (*1*). Thus it may be that distance to neighborhood schools in Davis is less of a constraint than in other cities.

This study offers three alternative methodological explanations as to why the influence of BLTS and distance on bicycling is largely uncertain. First, the average shortest distance for all origins may not be appropriate to determine the probability of each student bicycling to school. This problem stems from the fact that, because the study modeled bicycling to school in the aggregate, it was necessary to aggregate individual measures of distance to school. Related to this problem were the limited data on student origins. Because data on origins were available only at one time period (February 2013), the distance and BLTS counts were subject to unknown measurement error in all other time periods. Second, it was possible that the BLTS classification was not a suitable measure of traffic stress for young students. Future analysis should explore which roadway characteristics contribute to a more appropriate classification for bicycling to school. Last, it may be that the effects of distance and comfort on bicycling are more complex than the models used in this study suggest. A recent study that focused on traffic stress and bicycling to school in Davis suggested that an interaction between distance and comfort might have a stronger association with bicycling at the school level (*21*).

The largely uncertain influence of the percentage of male students on bicycling rates was likely the result of a lack of interschool variance. Given that most schools had nearly 50–50 gender splits, the influence of gender on bicycling to school must be examined on a disaggregate level. The opposite effects of the percentages of Hispanic students and of African-American students were surprising, given that active travel to school in general was higher at schools with higher proportions of Hispanic and African-American students (*3*). The results suggested that the effect of Hispanic students in Davis was consistent with the literature, but the effect of African-American students was the opposite. It is speculated that in many communities the percentage of African-American students at a school may be more reflective of schools with predominately lower-income households but that outcome was not the case in this study. The percentage of African-American students at all schools was similar (~3%), with the exception of Patwin (5.4%), and because these effects were conditional on the percentage of students eligible for a free or reduced-price lunch (surrogate for income). Therefore, conditional on all the other variables, the results indicated that less bicycling to school occurred when the percentage was greater of African-American students or students of low household income. These results suggested that, in Davis, cultural differences may exist with respect to bicycling to school, and that income may not be a barrier to driving to school. Without a collection of mode choice data, however, no conclusions could be reached with certainty (i.e., schools with a higher percentage of low-income families could have had more options to walk or to take a bus even if they had fewer options to bicycle).

It was not surprising that lower morning temperatures, Fridays, and winter and spring all decreased the likelihood of bicycling to school in Davis. Morning temperatures in Davis winters can be below freezing, and in winter and spring considerably more rain can fall than in the autumn (although drought conditions prevailed from 2012 to 2014 when the data were collected). Also, lower attendance at school occurs on Fridays in general and often entails family plans for travel outside of the city, which could make bicycling inconvenient. Perhaps most striking in the day-level covariates was Wednesday's lack of a strong effect. On Wednesdays in Davis, elementary schools have shortened school days, and junior high schools start late. It was hypothesized that both of these factors might disrupt the normal routine of school travel. Furthermore, the most extreme ensemble model residuals were examined (e.g., those plotted outside of the shaded region of Figure 4), and it was discovered that most of those predictions were for Wednesdays. Thus the models had great difficulty in predicting bicycling on Wednesdays, even after a Wednesday dummy variable was added. The implication was that there might be unobserved variables (e.g., parental work status) whose addition would improve Wednesday travel predictions.

CONCLUSIONS

New evidence is presented on variables that influence bicycling to school in various contexts, including day-to-day and intraschool variations. The results of this study suggest the need for further investigations into the use of BLTS to evaluate comfortable access to school. In addition, the results indicate that the racial and socioeconomic makeup of a student population and various factors that reflect the daily context (e.g., day of week, season, weather) all influence the rate of bicycling to school. Model predictions showed that aggregated school-level data were not sufficient to predict daily bicycling to each school (i.e., errors of ±23% on average) but that the data were sufficient to predict average bicycling to each school (±1%) and thus may be sufficient for policy analysis whose aim is to increase the average rate of bicycling to school. The modeling framework presented here, with the use of aggregated bike rack counts, is a low-cost approach to measure bicycling and can be used by any school district or planning agency to examine programs to encourage biking to school.

ACKNOWLEDGMENTS

This research was supported by fellowships from the University of California, Davis, College of Engineering Toward Outstanding Postgraduate Students program and the University of California Transportation Center.

REFERENCES

1. McDonald, N. C., A. L. Brown, L. M. Marchetti, and M. S. Pedroso. U.S. School Travel, 2009: An Assessment of Trends. *American Journal of Preventive Medicine,* Vol. 41, No. 2, 2011, pp. 146–151.
2. McDonald, N. C. Active Transportation to School: Trends Among U.S. Schoolchildren, 1969–2001. *American Journal of Preventive Medicine,* Vol. 32, No. 6, 2007, pp. 509–516.
3. Davison, K. K., J. L. Werder, and C. T. Lawson. Children's Active Commuting to School: Current Knowledge and Future Directions. *Preventing Chronic Disease,* Vol. 5, No. 3, 2008, pp. 1–11.
4. McDonald, N. C. Children's Mode Choice for the School Trip: The Role of Distance and School Location in Walking to School. *Transportation,* Vol. 35, No. 1, 2008, pp. 23–35.
5. Planty, M., W. Hussar, T. Snyder, G. Kena, A. KewalRamani, J. Kemp, K. Bianco, and R. Dinkes. *The Condition of Education 2009.* National Center for Education Statistics, Washington, D.C., 2009.
6. Martin, S. L., S. M. Lee, and R. Lowry. National Prevalence and Correlates of Walking and Bicycling to School. *American Journal of Preventive Medicine,* Vol. 33, No. 2, 2007, pp. 98–105.
7. McMillan, T. E. Urban Form and a Child's Trip to School: The Current Literature and a Framework for Future Research. *Journal of Planning Literature,* Vol. 19, No. 4, 2005, pp. 440–456.
8. Mitra, R. Independent Mobility and Mode Choice for School Transportation: A Review and Framework for Future Research. *Transport Reviews,* Vol. 33, No. 1, 2013, pp. 21–43.
9. Ewing, R., W. Schroeer, and W. Greene. School Location and Student Travel: Analysis of Factors Affecting Mode Choice. In *Transportation Research Record: Journal of the Transportation Board, No. 1895,* Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 55–63.
10. McMillan, T. E. The Relative Influence of Urban Form on a Child's Travel Mode to School. *Transportation Research Part A: Policy and Practice,* Vol. 41, No. 1, 2007, pp. 69–79.
11. Schlossberg, M., J. Greene, P. P. Phillips, B. Johnson, and B. Parker. School Trips: Effects of Urban Form and Distance on Travel Mode. *Journal of the American Planning Association,* Vol. 72, No. 3, 2006, pp. 337–346.
12. Handy, S. L. Understanding the Link Between Urban Form and Nonwork Travel Behavior. *Journal of Planning Education and Research,* Vol. 15, No. 3, 1996, pp. 183–198.