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Traffic stress and bicycling to elementary and junior high school: Evidence from Davis, California

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ABSTRACT

The purpose of this study is to examine the influence of stress stemming from proximity to automobile traffic on bicycling to elementary and junior high school. A growing body of evidence shows that students who walk or bike to school have higher levels of overall physical activity. Turning around the decline in active travel to school in the U.S. could thus produce improvements in the health and well-being of students. Despite considerable research on the influence of the urban environment on walking to school, a better understanding of the factors specific to bicycling to school is needed. We conducted a study of bicycling to school in Davis, California using data from repeated observations of bike rack counts at 11 neighborhood schools. We adopt the bicycle level of traffic stress (BLTS) methodology for estimating traffic stress from roadway characteristics as an inverse measure of bicycling comfort. We use Bayesian binomial multi-level regression models to analyze the influence of traffic stress and other covariates on bike rack counts. Results suggest that changing the street environment to reduce traffic stress (according to BLTS categorization) along routes to school in concert with encouraging shorter travel distances to school will increase the number of students bicycling and thereby increase student health.

1. Introduction

A growing body of evidence shows that students who walk or bike to school have higher levels of overall physical activity (Alexander et al., 2005; Cooper et al., 2005; Faulkner et al., 2009; Tudor-Locke et al., 2010). In turn, greater physical activity is associated with lower incidence of chronic disease and better physical and psychological wellbeing (Humphreys et al., 2013; Martin et al., 2014). This association is especially important considering the increasing prevalence of obesity-related diseases (e.g. type II diabetes, cardiovascular disease), and the tracking of health from childhood to adulthood (Biddle et al., 2004; Telama et al., 2014). Although the direct relationship between active travel to school and general measures of health is uncertain (Davison et al., 2008; Heelan et al., 2005; Lubans et al., 2011; Rosenberg et al., 2006; Tudor-Locke et al., 2010), it is reasonable to expect mostly positive effects. Indeed, at least one study has documented a relationship between bicycling to school and cardiorespiratory fitness (Cooper et al., 2006).

The Netherlands and Denmark stand out as the two countries with high bicycling to school rates, on the order of 45–60% (Jensen, 2008; Kemperman and Timmermans, 2014). In Scandinavia, active travel rates (combined walking and bicycling) are also high (45–68%) (Johansson et al., 2012). All of these countries have well established policies promoting bicycling to school which include education and road improvements. These programs are also set within the broader contexts of major national investments for bicycling and substantial national bicycling cultures (Jensen, 2008; Pucher and Dijkstra, 2003). Besides these success stories, active travel to school rates are particularly low in many comparable Western countries. In Australia, active travel to school rates have declined from 37% in 1985 to 26% in 2001 (Hume et al., 2009); in Canada, active travel rates are moderate (~30–44% from 1996–2001) (Pabayo et al., 2011); and in the US, the percentage of active travel to school declined from 41% in 1969 to 13% in 2009 (McDonald, 2007; McDonald et al., 2011). Considering bicycling is just a fraction of the overall active travel to school rates in these countries (McDonald et al., 2011; Salmon et al., 2005), the opportunity to improve student health by increasing the percentage of bicycling to school is substantial.

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In the US, safe routes to school (SRTS) programs, first established in the 1990s, have been the primary mechanism for encouraging active travel to school. The benefits of SRTS could go far beyond improvements in student health, as improvements on schools' routes contribute to an improved environment for active travel throughout the community (Watson and Dannenberg, 2008) and because increasing bicycling among children now has the potential to instill behaviors that will last into adulthood (Johansson, 2005). Despite the loss of dedicated federal funding for such programs with the passage of the current transportation bill (MAP-21), it is clear that the legacy of SRTS has continued, helped along by the continuation of a national SRTS partnership (Safe Routes to School National Partnership, 2005). As of Summer 2015, federal SRTS programs have channeled over $1 billion of funding toward active travel to school (National Center for Safe Routes to School, 2015), with the majority of the funding going toward physical improvements to the road environment (Cradock et al., 2012). However, the most common investment has been directed toward walking (i.e. sidewalk improvements) rather than bicycling (National Center for Safe Routes to School, 2011). Two circumstances may explain the limited attention to bicycling in SRTS programs: the very low share of bicycling in most US communities among children as well as adults, and a limited understanding on the part of transportation planners of the most effective strategies for encouraging bicycling to school.

The choice to bike to school has been conceptualized as a joint choice between the student and caregiver, with greater student influence on the joint choice with increasing student age (McMillan, 2005; Mitra, 2013). The Previous research shows that bicycling to school depends on access to bicycles, distance/time from home to school, parent work schedules, and weather (Emond and Handy, 2012; McMillan, 2007, 2005; Mitra, 2013; Schlossberg et al., 2006). Attitudes and perceptions about bicycling on the part of both students and parents are also important, and reflecting this, widely reported barriers to bicycling to school are neighborhood and traffic safety (Hume et al., 2009; McMillan, 2005). However, the influence of the street environment (e.g. cycle paths, bike lanes, traffic speed, etc.) on bicycling to school is not well studied, and current evidence is inconsistent across cities and countries (Boarnet et al., 2005; Carver et al., 2014; Ewing et al., 2004; Jensen, 2008; McMillan, 2007; Panter et al., 2010). Research into the relationship between the street environment and the decision to bicycle to school using novel measures that more directly reflect bicycling barriers could provide better guidance to planners on promoting bicycling to school as one part of a large portfolio of programs and policies promoting bicycling in general (Pucher et al., 2010).

This paper focuses on how traffic safety, measured using a method of categorizing roadways and intersections based on their theoretical "traffic stress" on a bicyclist, influences bicycling to school. While there are numerous methods for classifying roadways based on suitability for bicycling (e.g. bicycle level of service (Landis et al., 1997), bicycle compatibility index (Harkey et al., 1998)), we used the bicycle level of traffic stress (BLTS)[1] method (Furth and Mekuria, 2013) because (a) it is relatively easy to apply over entire urban areas, (b) takes into account characteristics specifically focused on traffic safety, and (c) uses descriptive language geared toward young bicyclists. In this paper we address two questions: (1) to what extent is there a relationship between traffic stress on routes to school and bike rack counts at elementary and junior high schools? (2) how effective might road improvements that reduce traffic stress be in increasing the number of students bicycling to school?

2. Methods

2.1. Setting and data collection

In this study we examine bicycling to elementary and junior high school in Davis, California, well known for having among the highest levels of bicycling in the US. We use data from repeated observations of bike rack counts at 11 neighborhood schools in Davis over the course of 2½ school years (2012–2015), with a range from 11 to 30 mornings counted for each school, resulting in a total of 214 morning observations (see Table 1). This method of estimating bike mode share to school is easy to implement and very cost effective, therefore it can be applied in any school setting that has observable bike parking. In order to preserve sample size, bike rack counts are our unit of analysis, but we often present aggregated results as bike mode share (calculated as bike rack count divided by enrollment). The key explanatory variables considered in this study are measures of distance and BLTS (i.e. the likely stress imposed on a bicyclist by automobile traffic). This methodology assigns traffic stress for each segment of a network (See Table 2 for a description of each class). For ease of discussion, we use the term "comfortable" to refer to low traffic stress routes in discussing model results.

Through semi-automated and manual construction of a Geographic Information System (GIS) network, each link in the network was classified by traffic stress from level 1 (low stress) to level 4 (high stress) based on street width, presence of bicycle lanes, bicycle lane barriers, presence of parking lanes, speed limit, and intersection configurations. This network was subdivided into four sub-networks: BLTS 1 (all links classified as stress level 1), BLTS 2 (all links classified as level 1 or 2 with none at 3 or 4), BLTS 3 (all links classified as level 1, 2, or 3 with none at 4), and BLTS 4 (all links (i.e. the entire network)). We obtained anonymous student home locations during February 2013 from the City of Davis, and used these as the distribution of home locations for each school for all study years. We then calculated the shortest path from each home location to that student's school on each of the sub-networks, and then summarized those individual distances to school by school using two approaches: (1) finding the percentage of students with access to school on each BLTS sub-network regardless of distance, and 2. determining the percentage of students with access to school on each BLTS sub-network within ¼ mile distance bins. After visual inspection of this data (presented in Section 3.1), we generated six *comfort* variables for use in the statistical models:

1. % of students with access on BLTS 1
2. % of students with access on BLTS 2
3. % of students with access on BLTS 1 within 1 mile for elementary schools
4. % of students with access on BLTS 2 within 2.5 miles for junior high schools
5. % of students with access on BLTS 2 within 1 mile for elementary schools

[1] We add the "B" to the original LTS acronym to be clear that this method only describes the theoretical traffic stress on bicyclists.

Table 1
Summary statistics for Davis schools.

School	# Days	Bike rack count		Mean # enrolled students	Mean distance (miles)	Comfort variables (percentages of students)					
		Mean	S.D.			1	2	3	4	5	6
						BLTS access					
						1	2	1	2	2	3
						Distance band (miles)					
						–	–	1	2.5	1	2.5
Emerson/DaVinci Jr High	12	194	65	731	1.9	33%	86%	–	57%	–	67%
Harper Jr High	18	205	63	653	1.7	39%	71%	–	58%	–	61%
Holmes Jr High	12	320	106	723	1.8	44%	90%	–	65%	–	74%
Birch Lane	21	163	40	606	1.0	67%	88%	44%	–	45%	–
Cesar Chavez	22	97	47	629	2.2	17%	90%	11%	–	13%	–
Korematsu	22	119	46	527	0.7	83%	91%	72%	–	81%	–
Montgomery	30	49	18	420	1.2	56%	80%	25%	–	40%	–
North Davis	25	147	55	587	1.2	46%	89%	26%	–	38%	–
Patwin	23	93	53	413	1.0	37%	94%	36%	–	66%	–
Pioneer	11	62	40	521	1.4	22%	25%	22%	–	25%	–
Willett	18	117	45	525	1.3	45%	82%	39%	–	45%	–

Table 2
Bicycling level of traffic stress description.

Class	Description
BLTS 1	Presenting little traffic stress and demanding little attention from cyclists, and attractive for a relaxing bike ride. Suitable for almost all cyclists, including children trained to safely cross intersections. On road sections, cyclists are either physically separated from traffic or are in an exclusive bicycling zone next to a slow traffic stream with no more than one lane per direction, or are in mixed traffic with a low speed differential and demanding only occasional interaction with motor vehicles. Next to a parking lane, cyclists have ample operating space outside the zone into which car doors are opened. Intersections are easy to approach and cross.
BLTS 2	Presenting little traffic stress but demanding more attention than might be expected from children. On road sections, cyclists are either physically separated from traffic or are in an exclusive bicycling zone next to a well-confined traffic stream with adequate clearance from a parking lane, or are on a shared road where they interact with only occasional motor vehicles with a low speed differential. Where a bike lane lies between a through lane and a right-turn lane, it is configured to give cyclists unambiguous priority where cars cross the bike lane and to keep car speed in the right-turn lane comparable to bicycling speeds. Crossings are not difficult for most adults.
BLTS 3	Offering cyclists a mostly exclusive cycling zone (e.g., bike lane) requiring little negotiation with motor traffic, but in close proximity to moderately high speed traffic; or mixed traffic requiring regular negotiation with traffic with a low speed differential. Crossings may be stressful, but are still considered acceptably safe to most adult pedestrians.
BLTS 4	Requiring riding in close proximity to high speed traffic, or regularly negotiating with moderately high speed traffic, or making dangerous crossings.

Furth and Mekuria (2013).

6. % of students with access on BLTS 3 within 2.5 miles for junior high schools

Although we use aggregate data that may not accurately describe individual decision processes (known as the “ecological fallacy” (Freedman, 2001)), our repeated measures approach helps to ensure that our conclusions about aggregate bicycling are robust. In addition, planners and policy makers often have only aggregate data to make decisions; therefore, this method is valuable for its practicality. Another limitation to our approach is that the BLTS methodology has yet to be “validated” across individuals (e.g. related to human perceptions or other measures of stress) or across geographies. We see this as an important topic for future research, but argue that bicyclist facility preferences generally align with the descriptions for each BLTS class (Tilahun et al., 2007). Finally, a number of socio-demographic and travel behavior variables (e.g. parent education, caregiver work schedules) that may be important determinants of bicycling to school were unavailable. Future applications of our method would benefit from incorporating some of these factors when the data is available.

2.2. *Model development and analysis*

We conducted a Bayesian analysis using multilevel binomial regression models to examine the relationship between bike rack counts at each school (observed on multiple occasions) and comfort variables. The models are estimated with a varying intercept specified for each school; this pools the variance from each school to improve prediction and explanation. The models are aggregate in that the dependent variable is the count of bikes at each school on each observation date. In our models, each bike counted is considered a unique Bernoulli trial (i.e. each student either bikes or does not bike to school). For example, if a school has 500 enrolled students, then for each observation we estimate 500 Bernoulli trials, each with a possible outcome of 1 or 0, and then sum these results to get an estimated count of bikes at that school on that observation (see Fitch et al. (in press) for a detailed description of the model structure). Through the R statistical packages *rethinking* and *rstan* as an interface for the probabilistic statistical programming language Stan, we used the No-U-Turn (NUTS) sampler, a form of Hamiltonian Markov chain Monte Carlo (MCMC) (McElreath, 2015; Stan Development Team, 2015a, 2015b). We used the widely applicable information criteria (WAIC) (Watanabe, 2010) for comparing out-of-sample prediction of our models (Gelman et al., 2013b; Vehtari and Gelman, 2014), and we made inferences about variable effects (and uncertainty) directly from parameter posterior distributions as opposed to a classical hypothesis tests of the null (e.g. p-values) (Gelman et al., 2013a, p. 95).

Initial specification of the model of bike rack counts[2] included covariates, justified based on past literature and local anecdotal observations: day of week, season, Bike to School Day, rain, temperature, race, gender, and share of students qualifying for free or reduced cost lunches (results not shown). We then compared four model specifications to examine the relationship between BLTS measures and rates of bicycling to school. *Model A* includes mean distance and no comfort variables to provide a baseline against which to assess how much the comfort variables in other models add to the prediction of bike rack counts. *Model B* maintains the mean distance variable and adds comfort variables 1 and 2. This model corresponds to our hypothesis that in Davis, where distances to school are generally short, the effect of distance and comfortable access may be independent, meaning a greater percentage of students with comfortable access will lead to greater biking regardless of distance. *Model C* drops mean distance and adds comfort variables 3 and 4, which combine comfortable access with distance. This model follows the hypothesis that distance moderates the effect of comfortable access, and that comfortable access is best described by BLTS 1 and 2 for elementary and junior high students, respectively, based on the assumption that junior high students have a greater tolerance for traffic stress than elementary students. *Model D* is similar to *Model C* except that it uses comfort variables 5 and 6 in place of 3 and 4. This model follows the same hypothesis of *Model C* except that it assumes that comfortable access is better described by allowing slightly more traffic stress: BLTS 2 and 3 for elementary and junior high students, respectively (see Table 3 for model specification details). In accordance with the Bayesian analysis framework, we specified prior probabilities for all unknown model parameters. We specified weakly informative (or regularizing) priors to guard against overfitting (McElreath, 2015).

3. Results

3.1. Descriptive results

Bicycle rack counts in Davis show that junior high schools have a higher number of students bicycling to school than do elementary schools (Table 2). The median proportion of students bicycling to school in Davis ranges from 11% at Pioneer elementary to 47% at Holmes Junior High (Fig. 1), all of which are considerably greater than the U.S. average of around 1% (McDonald et al., 2011). Intra-school variability is consistently high, especially at elementary schools where bike rack counts have standard deviations of 18 to 55 students. Similarly, inter-school variability is large with some schools having twice the bike mode share of others. Distances to school are larger for junior high schools (Table 2, Fig. 1) with the exception of Cesar Chavez Elementary (a magnet elementary school that draws students from throughout the city).

The relationship between student distances to school by BLTS networks and aggregate bike mode shares are presented in Fig. 1 as distance histograms. Schools with more students located nearby tend to have higher bike mode shares, but not always. Schools with more students living near the school with BLTS1 and BLTS2 access also tend to have greater bike mode shares. The notable exception is Korematsu Elementary, where nearly every student has access to school via BLTS 1 or 2 with less than 1.5 miles of riding each way, and yet two other elementary schools have consistently greater bike mode shares. Pioneer and Chavez elementary schools are also outliers in that Pioneer has a fairly small share of students with comfortable access nearby, and no students with comfortable access beyond approximately 1 mile, and Chavez has a nearly uniform distribution of student distances to school from 0 to 5 miles. Looking for a distance threshold to test variables that combine distance with comfortable access, we used this visualization to decide on 1 and 2.5 miles for elementary and junior high schools, respectively, as cutoffs because they showed good variation between schools and are reasonable bicycling distances for students at those grade levels.

3.2. Model results

All model parameters have Gaussian-like posterior densities (besides *st. dev. school* which is constrained to be positive), and thus we summarize the parameters by their mean and standard deviation (Table 3). All models show consistent effects of the covariates pertaining to type of day and characteristics of the school demographics. Conditional on the model specifications, schools with a high Hispanic percentage have more bicycling, while those with a high Black percentage have less bicycling. The effect of percentage male students was positive but extremely uncertain, while the percentage of students with access to free or reduced lunches (indicator of low household income) was confidently negative. Low temperatures and presence of rain both have an expected negative effect. The effect of Fridays, on which travel may be less habitual due to weekend plans, was also negative on bicycling rates. All of these covariates are stable across all four models.

In *Model A*, conditional on all the covariate effects, mean distance has a mean parameter estimate that is small (near 0) with a large standard deviation indicating the posterior distribution spans almost equally over the positive and negative range. This indicates that we cannot make confident conclusions about the effect of distance on bicycling to school. Similarly, *Model B* shows that the effect of mean distance is inconclusive with a slightly more positive but also wider posterior distribution. *Model B* also suggests that, conditional on the covariates, students with access on BLTS levels 1 and 2 may be more likely to bicycle, however a great portion of the posterior distribution spans the positive and negative range making these effects inconclusive.

Models C and *D* consider the effect of comfort within distance thresholds. *Model C* shows that, conditional on all the covariates, percent of BLTS 1 access to elementary schools within 1 mile (comfort 3) has a positive influence on bicycling, although the magnitude of the positive effect still has considerable uncertainty. Similarly, this model shows the same result for percent of BLTS 2 access to junior high schools within 2.5 miles (comfort 4), with a somewhat stronger effect. *Model D* exhibits the same general effects of comfort 5 and 6 for elementary and junior high schools, with slightly dampened effects and smaller parameter standard deviations.

The models are effectively equivalent in their expected out-of-sample prediction of bike rack counts, as indicated by their effectively equivalent WAIC values in Table 3. This is also observed through the relatively equal Akaike weight given to each model (Table 3). Because

[2] "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" (McElreath, 2015).

Table 3
Model parameter estimates.

		Model A		*Model B*		*Model C*		*Model D*	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Intercepts									
std. dev. school		0.89	0.24	0.92	0.3	0.71	0.22	0.66	0.21
mean intercept		−3.41	3.25	−5.22	3.98	−3.9	2.74	−4.5	2.68
School−specific varying intercepts	Birch Lane	0.29	0.41	0.13	0.5	0.43	0.35	0.56	0.32
	Chavez	−0.79	0.68	−0.86	0.74	−0.21	0.54	−0.02	0.55
	North Davis	0.23	0.31	0.14	0.39	0.72	0.33	0.63	0.28
	Montgomery	−1.41	0.39	−1.42	0.44	−0.93	0.38	−0.99	0.34
	Willett	−0.05	0.48	−0.09	0.54	0.21	0.45	0.2	0.43
	Pioneer	−0.85	0.3	0	0.9	−0.43	0.31	−0.22	0.35
	Korematsu	0.12	0.58	−0.07	0.73	−0.38	0.64	−0.29	0.52
	Patwin	0.36	0.44	0.3	0.78	0.62	0.31	0.21	0.39
	Emerson JH	0.18	0.45	0.1	0.48	−0.37	0.42	−0.45	0.39
	Holmes JH	1.27	0.38	1.11	0.48	0.49	0.48	0.48	0.44
	Harper JH	0.38	0.43	0.47	0.48	−0.15	0.44	−0.06	0.39
Slopes									
Bike To School Day		0.69	0.03	0.69	0.03	0.69	0.03	0.69	0.03
Tuesday		−0.01	0.09	−0.01	0.1	−0.01	0.09	−0.01	0.09
Wednesday		−0.13	0.08	−0.13	0.08	−0.13	0.08	-0.13	0.08
Thursday		0.03	0.08	0.04	0.08	0.04	0.08	0.04	0.08
Friday		−0.22	0.08	−0.22	0.09	−0.22	0.08	−0.21	0.08
Fall		0.16	0.03	0.16	0.02	0.16	0.03	0.16	0.03
Spring		0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.03
Temperature (F)		0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
Presence of Rain		−3.1	0.1	−3.1	0.1	−3.1	0.1	−3.1	0.1
% Hispanic		3.28	0.97	3.31	0.97	3.26	0.96	3.15	0.97
% Black		−5.86	2.06	−5.91	2.05	−5.72	2.02	-5.89	2.04
% Asian		−0.52	1.33	−0.47	1.3	−0.59	1.29	−0.61	1.25
% Male		3.41	6.04	4.03	6.6	2.1	5.37	3.05	5.16
% Free or Reduced Cost Lunch		−2.31	0.57	−2.34	0.57	−2.32	0.57	−2.34	0.57
Mean Distance to School		−0.12	0.64	0.01	1.04				
Comfort 1				0.43	2.64				
Comfort 2				1.37	1.82				
Comfort 3						2.12	1.5		
Comfort 4						2.67	1.22		
Comfort 5								2.02	1.2
Comfort 6								2.54	1.05
WAIC		121932.6		121932.8		121932.6		121932.8	
Akaike weight		0.27		0.24		0.26		0.24	

WAIC=widely applicable information criterion, Akaike weight=weight of each model for the ensemble[2]. All models converged with $\hat{R} < 1.01$, number of effective samples > 1000 (see Stan Development Team, (2014) for details of these two convergence metrics), and with Markov chains showing stationarity and good mixing for all parameters.

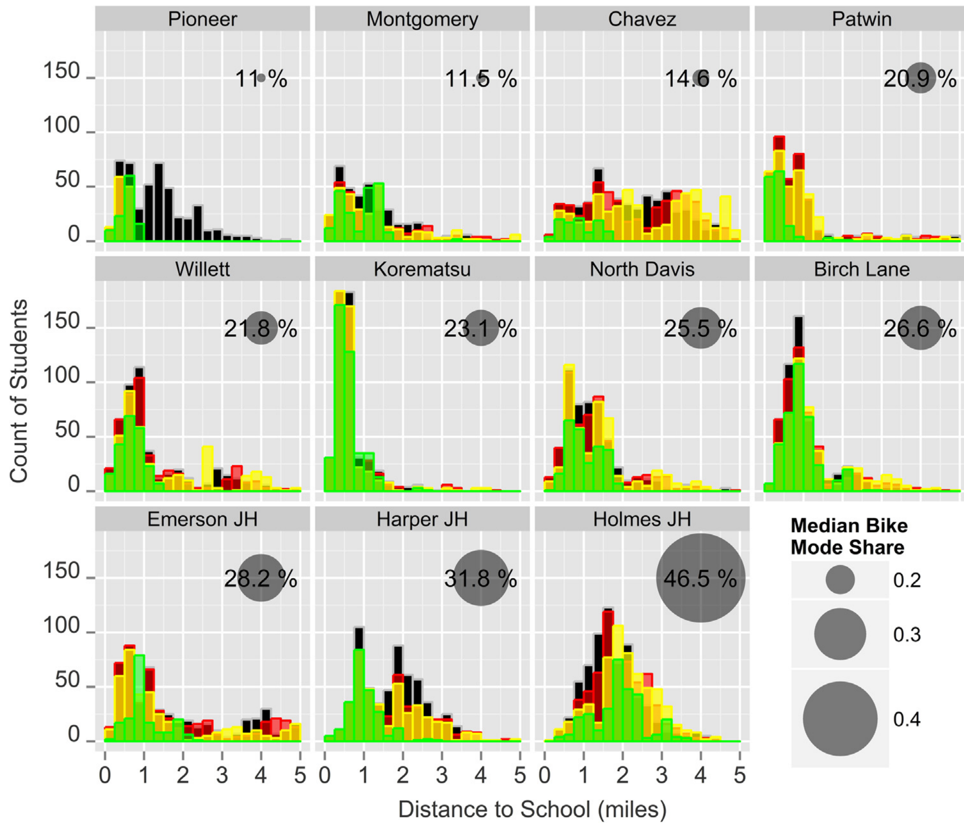

Fig. 1. Student distances to school in ¼ mile bins, by BLTS networks (green = BLTS 1, yellow = BLTS 2, red = BLTS 3, black = BLTS 4), and school bike mode shares (circles). All bars overlap each other with slight transparency such that orange reflects BLTS 2 overlapping BLTS3. Each student is counted in each BLTS class (color) using which they can get to school. For example, a student attending Holmes Junior High that lives 0.9 miles from school with access on BLTS 3 is counted in both the red and black bar of the 0.75–1 mile bin of the Holmes plot. In addition, if that same student can divert around the high stress links and arrive at school via BLTS 2 riding 1.9 miles, then that student is also counted in the yellow, red, and black bars of the 1.75–2 mile bin of the Holmes plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

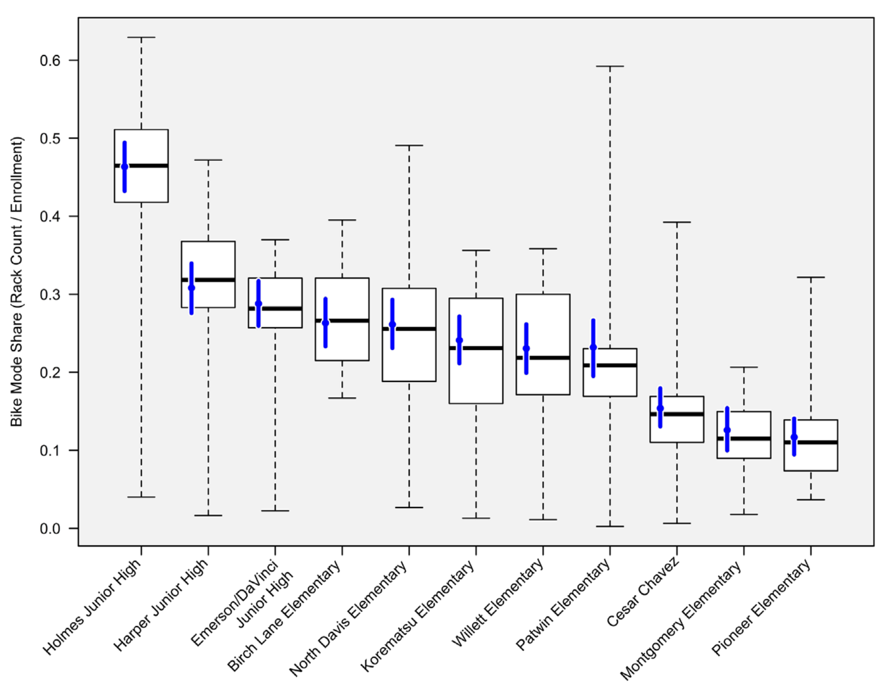

Fig. 2. Boxplots of observed median, interquartile range, and full range of bike mode share for each Davis school. Blue dot and bar indicate the ensemble predicted median bike mode share and the 95% confidence interval.

of this, we employed an ensemble technique to average the predictions of all four models using the Akaike weights to conservatively evaluate predictions given model uncertainty (McElreath, 2015). Results indicate that the ensemble model predictions of *daily* bike rack counts have considerable uncertainty (not shown), but predictions of *median* bike rack counts are accurate (as indicated by the overlap in the prediction confidence interval and the observed median in Fig. 2).

4. Discussion

These results demonstrate that the relationship between comfort variables and bike rack counts is positive but uncertain. Results in Fig. 1 shows a general correlation between schools with a high share of students having comfortable access and schools with high bicycling mode shares (evident from the *taller* BLTS 1 and 2 bars at *shorter* distances to school for schools with *greater* bike mode share). However, inter-school variation somewhat obscures this correlation which is why we focus our discussion on our multivariate analysis. In our multivariate analysis, our statistical models have equivalent WAIC values suggesting that each model has equivalent predictive power. Although we expected WAIC to improve when adding comfort variables, it does not hinder our inferences that comfort variables help explain bicycling. We suspect the equivalent WAICs are related to the large measurement error which is added to the comfort variables when we aggregate from individuals to schools. We also suspect that there exists an important omitted variable (or variables) because after examining daily model residuals (not shown), all of the models have a particularly difficult time predicting bicycling on Wednesdays. This is likely because elementary schools have shortened school days and junior highs have late starts on Wednesdays. Because of this, even though we have a dummy variable for Wednesdays, we argue that we are likely missing a covariate related to flexibility of caregiver work schedules. For example, if a caregiver normally accompanies their child to school by bicycling with them, but does not have the time given the shortened school day, they might instead resort to driving their child to school. This is a difficult variable to estimate in the aggregate, and so we let our results stand with this caveat.

Model results show that distance and comfortable access, independent of each other, are less associated with bicycling than when combined (see comfort variable parameter estimates for *Models B*, *C*, and *D* in Table 3). In addition, BLTS 2 and 3 access (comfort 5 and 6) were nearly as influential as BLTS 1 and 2 access (comfort 3 and 4) which suggests that in Davis, parents and students may be accepting of a moderate level of traffic stress. In this light, these results indicate, at least for Davis, that improving roads from BLTS 2 to 1 for elementary access and BLTS 3 to 2 for junior high access might have limited effects on bicycling levels. However, care must be taken in other communities before making this determination because it is expected that comfortable bicycling environments and social cultures of bicycling are reciprocally causal. In Davis, the bicycling culture may increase the perception (and perhaps reality, i.e. safety in numbers (Jacobsen, 2003)) that bicycling is safe and comfortable even if each roadway is not completely free of traffic stress (Handy, 2011).

A surprising result was the inconclusive evidence for the influence of distance, in contrast to other studies of active travel to school in the U.S. that have shown distance to be influential (Emond and Handy, 2012; Ewing et al., 2004; McDonald, 2008). However, considering that the schools in Davis have much shorter network distances to school compared to the national average (mean of 1.4 miles compared to 4.4 miles nationally (McDonald et al., 2011)), it may be that distance to schools in Davis is less of a constraint compared to other cities. Alternatively, it may be that mean distance is too coarse of a metric in Davis, but that when comfort and proximity are combined (e.g. *Models C* and *D*), distance does matter. In environments where distance to school is short on average ($\sim$ 1 mile in Perth, Western Australia), a small negative effect (odds ratio ≈ 0.8) of distance (km) on biking to school has been reported (Trapp et al., 2011). In the aggregate our results are too uncertain to make this claim, but we might expect a similar mean effect in Davis had we data on individual mode choice; indeed the effect of distance on mode choice for high school students in Davis is similar: Emond and Handy (2012) report a mean coefficient of -0.242 (distance in miles) which is equivalent to an odds ratio ≈ 0.85 for distance (km).[3]

To address our second major research question of how effective road improvements aimed at decreasing traffic stress along routes to schools would be at increasing bicycling to school, we generated counterfactual plots for *Model C* which demonstrate the expected bicycling mode share (e.g. bike rack counts/enrollment) given three scenarios of comfort variables 3 and 4: (1) 0% of students have access to school on BLTS 1 and 2 for elementary and junior high, respectively, (2) 50% of students have access to school on BLTS 1 and 2 for elementary and junior high, respectively, and (3) 100% of students have access to school on BLTS 1 and 2 for elementary and junior high, respectively (Fig. 3). We chose *Model C* because it is slightly more conservative in the estimated effect of traffic stress compared to *Model D*. Importantly, a policy based on the guidance of *Model C* would both focus road improvement projects on short routes schools and encourage shorter travel distances to school (e.g. through incentives to attend neighborhood schools). Fig. 3 shows the expected rates of bicycling to school with varying BLTS 1 and 2 access within the distance thresholds. *Model C* clearly shows a consistent increase in mean bicycling rate with an increased share of students having comfortable access within the distance thresholds. This is especially true for the three schools with the lowest bicycling mode shares (Chavez, Montgomery, and Pioneer), suggesting that focusing policies on schools with the lowest bicycling rates may have a slightly larger impact than on schools with moderate bicycling rates, although the uncertainty around these estimates is large.

We offer three possible methodological explanations as to why the influence of comfortable access and distance on bicycling rates is uncertain. First, we only considered a sample of origins from one school year as representing the origins for all three years of data (because of limited data availability). It may be that the variability in origins due to student matriculation over time is the cause for the uncertainty in the effects of comfortable access and distance. Second, aggregating individual route information at the school level removed all the intra-school variability from the analysis; this intra-school variability may be very important in estimating the effects of comfort and distance on aggregated bike rack counts. Third, it is possible that the BLTS classification is not an appropriate measure of traffic stress for young students. Although Fig. 3 exhibits considerable uncertainty in the effect of comfortable access, it is important to note that when 0% of students have comfortable access, bike mode shares are considerably lower than they currently are

[3] $e^{(-0.262/1\text{mile} \times 0.62\ \text{miles}/1\ \text{km})}$

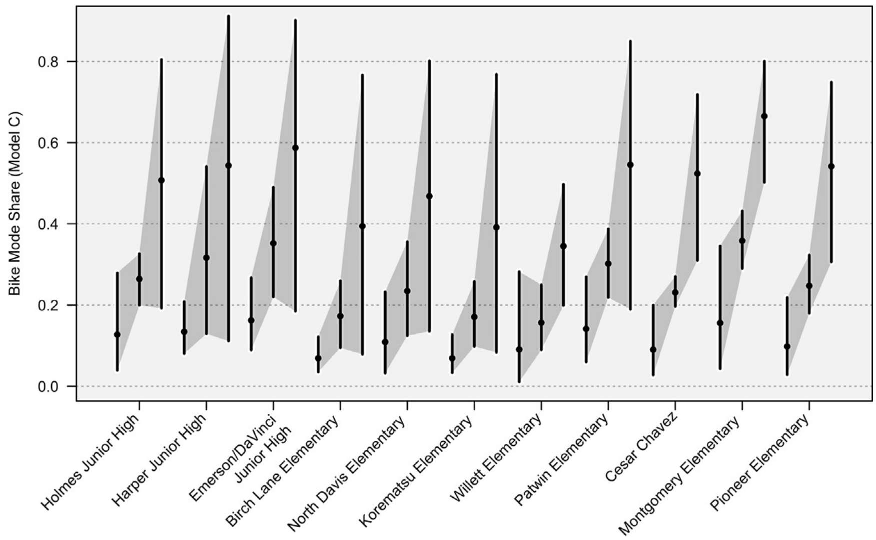

Fig. 3. M*odel C* counterfactual plot of 0, 50, and 100% BLTS 1 access within 1 mile of elementary schools (comfort 3), and BLTS 2 access within 2.5 miles of junior high schools (comfort 4) (from left to right bars). Dots and bars represent the median bike mode share prediction and 95% confidence intervals for each of the three BLTS percentages while holding constant other covariates. These results represent the expected bike mode share on an average Wednesday in the spring season, with average temperature, no rain, and for a year where the racial makeup of each school is average.

in Davis. This suggests that if students did not have comfortable bicycling access within short distances from their school, bike mode shares at all schools would drop. Conversely, it also suggests that even when 0% of students have comfortable access, bike mode shares would still stay moderately high (10-15%) suggesting a good portion of students are willing to bike (and their parents are willing to let them bike) with added traffic stress.

Future analysis should explore alternative roadway characteristics (other than those in BLTS) that might contribute to a classification that has more certain effects on bicycling to school. In particular there is a need to better understand acute stress when bicycling in traffic through surveys, ride along and standard interviews, and possibly psychophysiological measurements. There is also a need to look across geographical contexts to explore if and how people adapt to traffic stress. Because Davis is a unique bicycling environment in the U.S., one might argue that our results would not generalize to other environments. We agree that it would be a mistake to expect effects such as those from the counterfactual plot (Fig. 3) to directly transfer to other cities, but our method of estimating traffic stress impacts on bike mode share is possible anywhere where bikes can be counted. Although the magnitude of the effects may differ, it is reasonable to expect positive effects in most environments. The effects from these types of comfort variables might even be greater in environments that have more traffic stress surrounding schools. Although we focus on evaluating BLTS road metrics for bicycling to school to aid infrastructure planning, numerous other programs and policies are likely needed in most communities to increase bicycling to school. Programs such as bicycling education and training, social events, and marketing, and policies such as reduced vehicle speed limits, installing guarded bike parking, and strict traffic enforcement have been used around the world (Pucher et al., 2010). In addition, while we use BLTS to aid our understanding of bicycling to school, it has the potential to be used for broader purposes; indeed the method was first used to evaluate the entire citywide connectivity of the bicycling network (i.e. low stress bicycling for all residents) in San Jose, California using aggregate origin–destination pairs (Furth and Mekuria, 2013).

5. Conclusions

While traffic stress is just one of many factors influencing bicycling to school, it is likely one of the primary ways in which the urban environment influences bicycling to school. We find evidence from Davis, CA that schools that have a greater number of students with access to school by way of relatively comfortable routes (according to BLTS) and within short distances have greater bike mode shares, conditional on environmental and socio-demographic covariates. Because bicycling to school varies considerably between and within cities, bike rack counts must be observed locally and the model re-estimated for the local setting before intervention effects can be reasonably estimated. Nonetheless, the results suggest that changing the street environment to reduce BLTS classification along routes to school and encouraging shorter travel distances to school will increase the number of students bicycling.

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