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The relation of the road environment and bicycling attitudes to usual travel mode to school in teenagers

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ABSTRACT

Although active travel to school for primary school students has been widely studied, research into the determinants of teenage active travel to school is noticeably lacking. Understanding the determinants of teen active travel to school is important given that teenage travel may have implications for the formation of habits that carry over to adulthood. We present evidence linking travel to school with bicycling attitudes and with road environments on plausible paths to school using data from a large cross-sectional survey of students at three high schools in Northern California. Results suggest that the relationship between attitudes and bicycling are stronger than the relationship between road environments and bicycling. Students' perceived social pressure to bicycle has a particularly strong association with bicycling. Hypothetical intervention scenarios suggest that students would walk and bicycle to school at substantially greater rates if they had better road environments for walking and bicycling, shorter distances to school, and more positive bicycling attitudes.

1. Introduction

Adolescence is arguably one of the most dynamic and formative stages in the development of an individual's travel preferences and habits. Teenagers are granted more freedom to travel from their caregivers (although this may be declining (Carver et al., 2014)), and thus have more say in their own travel decisions than younger children. In many parts of the world, particularly in the US, teenagers have the option of transitioning from car passenger to car driver, with the additional freedoms but also responsibilities that this entails. The choices that teenagers make about their travel have immediate implications for their health and well-being as well as for the environment, but they may also have long-lasting implications by contributing to the formation of habits that shape their travel behavior as adults (Baslington, 2008). One of the most frequent and therefore habit-forming travel teenagers engage in is their daily travel to and from school. A steady decline in active travel to school in the US is therefore especially troubling (Baslington, 2008; McDonald et al., 2011), and planners, health officials, policy makers, and others are seeking effective strategies for reversing the trend.

Most strategies to increase active travel to school seek to change road environments to improve conditions for active travel or to change attitudes toward active travel through education and encouragement. We use the term road environments in the broad sense, encompassing physical characteristics of the road (or street) that people experience when traveling including natural features like

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hills and built features such as number of travel lanes and the presence of sidewalks, but also traffic characteristics and other qualities that reflect the use of the road. Evaluations of intervention strategies have largely focused on primary and not high schools, leaving an important gap in the research with respect to the relation of the road environment and attitudes to the active travel decisions of teens. The limited evidence available points to the importance of both attitudes (of parents and students) and road environments but the magnitudes of these relationships are uncertain.

In this study, we examine usual mode choice to high school, focusing specifically on the magnitude of these relationships. We analyze the influence on travel mode to school of travel attitudes and road environments along plausible paths to school using data from a large cross-sectional survey of students at three high schools in Northern California.

Given its cross-sectional design, the study does not provide definitive evidence of causal relationships but the associational evidence it generates is important for establishing the likely magnitudes of relationships between variables. The results can inform conceptual models of teen travel and provide direction for future studies. Improving our knowledge of the factors influencing teen travel to school contributes to the development of effective strategies for increasing the number of teenagers who walk and bicycle to school and who carry these habits into adulthood.

2. Travel to school

Travel mode choice to school can be framed as a joint choice between parent and student and as a potential joint travel outcome (parents escorting their children). Joint travel outcomes significantly add to the complexity of mode choice, because parents' travel constraints (e.g. schedules, mode options, commute directions) and preferences interact with their children's constraints and preferences. As children become more independent, this joint choice and potentially joint travel outcome changes (Mitra, 2013), further adding to the complexity. While travel to school is repeated and mandatory and is therefore likely to follow routine or habitual behaviors, teenagers are a particularly diverse cohort in that they span key developmental years where household and peer relationships are in flux, and for most, travel mode options are expanding.

Although growing concern over the decline in active travel to school in the U.S. has motivated numerous studies of travel to primary and middle school (Ewing et al., 2004; McDonald, 2008; McDonald et al., 2011; Noland et al., 2014), less is known about mode choice to high school, particularly the choice to walk or bicycle. In studies of mode choice to school, age and gender are commonly identified as important predictors. In general, older and male students are more likely to walk or bicycle to school (Ewing et al., 2004; Kamargianni and Polydoropoulou, 2013; McDonald et al., 2011). However, the effect of age may be reversed for older teens because of reliance on the car after driver's licensing (Clifton, 2003). Indeed, access to a car, whether as a passenger or a driver, is likely to be a key factor in mode choice. Though studies show that teen licensing rates have declined, teens still travel predominantly by car, especially older teens (Blumenberg et al., 2012; Clifton, 2003; McDonald et al., 2011). Of course, car access is heavily dependent on familial economic status: in many cases teens that do not drive do so because of economic restraints, not choice. For teens that do begin to drive, evidence from longitudinal data on female teen travel suggests that acquiring a driver's license primarily changes the amount of parent chauffeuring, while the connection to active travel is less clear (McDonald et al., 2015). These findings suggest that active travel may not be increasing even as teen licensing rates decline in the U.S.

The physical environment influences the choice to walk or bicycle to school in many ways. Evidence suggests that distance to school is the primary barrier for walking and bicycling (Emond and Handy, 2012; McMillan, 2007, 2005; Schlossberg et al., 2006). Attempts at decreasing travel distance to school tend to conflict with attempts to provide flexibility and choice in public education (He and Giuliano, 2017). At the high school level, the conflict between promoting active travel to school and freedom of school choice is likely weaker than for primary schools because distances to neighborhood high schools are further to begin with; fewer students live within reasonable walking and bicycling distance to their local high school than to their local primary school. Longer distances to high school suggest a clear policy challenge for getting more teens walking and bicycling to school. This distance challenge is part of the broader challenge of increasing sustainable travel in U.S. cities shaped by decades of planning for low-density development with segregated land uses.

In addition to distance, evidence suggests that urban characteristics measured for areas (e.g. for a neighborhood or for a buffer around origin or destination) like residential density and street connectivity are associated with active travel to school (Carlson et al., 2014; Mitra and Buliung, 2015). Urban features such as sidewalk coverage have been shown to influence walking to school as well (Ewing et al., 2004; Noland et al., 2014). However, other studies do not find consistent relationships between urban characteristics and active travel to school. Mitra (2013) reviewed 42 studies on school travel (only six which cover teenagers) and reported results for variables such as intersection density, sidewalks, street connectivity, and mixed land use to be generally inconclusive with respect to active travel to school. The main problem is that these area-based measures do not capture the specific environments experienced by individual students on their path to and from school.

Studies that focus on the environments along the routes that individuals take rather than on general school-area environments show that width and quality of sidewalks influence teen mode choice to school, although the effects varied by urban environment (Kamargianni et al., 2015; Kamargianni and Polydoropoulou, 2014). Other linear characteristics (e.g. route directness, major street crossings) influence teen travel mode to school according to one study (Mitra and Buliung, 2015). However, these characteristics are more strongly associated with travel to school by younger (11 year old) compared to older (14–15 year old) students (Mitra and Buliung, 2015). In theory, and according to some empirical evidence, individual route-based features of the built environment more strongly influence active travel compared to non-route-based features (Broach, 2016; Handy et al., 2002); however, very little evidence exists on the relationship between route-based features and teen travel to school.

Specific aspects of the built environment that promote bicycling are less clear since many studies of active travel to school do not separate bicycling and walking behavior, muting the unique factors that influence the choice to walk *or* bicycle to school (McDonald, 2008). Evidence from bicycling research beyond school travel would suggest that perceptions that access to school is safe and comfortable (as might be the product of bike lanes, separated paths, limited traffic, slow traffic), along with trip-end facilities such as bike racks would be important factors (Pucher et al., 2010).

The attitudes and perceptions of both students and parents about bicycling also affect mode choice according to several studies (Dill and McNeil, 2013; Driller and Handy, 2013; McDonald, 2012). A 2009 survey of high school students in Davis, CA, showed that parental encouragement and students' comfort riding a bike influence bicycling to high school (Emond and Handy, 2012). In an altogether different geographic context, the latent attitude "willingness to walk or bike" was associated with active travel in a survey of teen travel to school in Cyprus (Kamargianni and Polydoropoulou, 2013). Interestingly, both studies show that students tend to use the same travel mode as their parents. These findings suggest considerable parental influence, although some of this association may be due to parents and students traveling in similar environments.

Student and parent perceptions and attitudes about active travel safety are likely to influence travel mode decisions given that negative perceptions correlate with less active travel in younger children (McMillan, 2007; Timperio et al., 2004). Perceptions about safety for walking and bicycling relate to both the physical environment and how other people use that environment. For example, Woldeamanual et al. (2016) provide evidence suggesting that chauffeuring of teens is positively correlated with parent perceptions of the amount of traffic. This positive correlation runs counter to the standard assumption that traffic is psychologically noxious and increases travel time, relationships that mean that traffic should negatively correlate with chauffeuring. Instead, the positive correlation seems to imply that (1) parents who chauffeur are more aware of traffic, and/or (2) parent's attitudes about the safety risk of walking and bicycling in traffic outweigh the inconvenience of driving through it to drop off students. The latter rationale ensures a vicious cycle of chauffeuring. This example highlights one of many roles attitudes and perceptions play in the complex decision of teen mode choice to school.

3. Methods

3.1. Study setting

In this study, we analyze usual mode choice to school of students from three Northern California high schools: Davis Senior High in Davis, CA, Sequoia High in Redwood City, CA, and Tamalpais High in Mill Valley, CA. This study is an extension of an initial study of bicycling to high school in Davis in 2009 (Emond and Handy, 2012). Because Davis is an especially bicycling-oriented city with numerous off-street bike paths and a long history of bicycling (Buehler and Handy, 2008), two additional schools were surveyed to represent more typical suburban environments in California to enhance the generalizability of these results to other cities.

Redwood City and Mill Valley are within 100 miles of Davis. They have some bicycling activity but it is not a primary mode of travel as it is in Davis. Beyond the differences in bicycling rates, these three communities differ in their socio-demographics, surrounding topography, and bicycling infrastructure. Mill Valley, where Tamalpais High is located, has the highest median family income ($158,906) and Redwood City the lowest ($93,257), but all three have median incomes above the state average (US Census Bureau, 2013). Mill Valley also has considerable topography compared to the other communities; Tamalpias High is located in a valley where most residences are at higher elevations requiring uphill travel on the return trip from school. Mill Valley is also known for its mountain biking, and Tamalpais High is the only school (of the three) to have a mountain biking club.[1] Davis is also surrounded by non-urban land (agriculture) with the nearest city more than 10 miles away. Redwood City is notably different in that is shares borders with many other cities. It has a comparatively larger percentage of Hispanic population compared to Davis and Mill Valley. Davis has a comparatively larger Asian population, and Mill Valley a larger White population (US Census Bureau, 2013). The survey results, reported below, show that the three schools are strikingly similar with respect to driver's licensing and distributions of distances to school. However, like the demographics of the cities, the percentage of Hispanic, Asian, and White students differ.

3.2. Survey data

School volunteers administered an in-class two-page questionnaire (adapted from the 2009 survey) during the first week of May 2013, when the weather in Northern California is typically ideal for active travel. The survey included questions on usual travel mode, demographics (age, gender), personal attitudes, parental education level (as a surrogate for socio-economic status), and nearest cross street to home (for the full survey instrument see Lovejoy and Handy (2013)). We defined usual travel mode in five classes: drive (students who drove themselves with or without passengers), chauffeured (students who were passengers in a car driven by a guardian or a fellow student), walk, bike, and bus. Reported travel modes of skateboard, motorcycle, and train were so small they were added to walk, drive, and bus, respectively. We treated a few nonsense responses (e.g. travel via "hot air balloon" or "teleport") as missing data. Also, we reduced parental education level and race to two categories each because of few responses in some categories. Attitudinal questions were posed using a Likert 5-point response scale from *Strongly Disagree* to *Strongly Agree*, and focused on perceptions and preferences about travel to school, particularly bicycling.

Since the surveys were administered in class, and 83% of classrooms participated, a large number of surveys were collected: 3076 total surveys (Davis = 1227 (71% of enrolled), Sequoia = 1088 (54% of enrolled), Tamalpais = 761 (62% of enrolled)). Although

[1] Davis has a mountain biking club that is not associated with the high school, but draws high school students from Davis Senior High and surrounding schools.

Table 1
Bicycling attitudinal constructs and their respective Likert items.

Likert statement	Attitude	Reliability (α)[a]
I like bicycling. I am confident in my bicycling ability. I feel comfortable bicycling on a busy street with a bike lane.	Enjoyment	0.72
It's hard to ride a bicycle wearing my normal clothes. I worry that bicycling to school means being sweaty when I get there. I worry my hair won't look that great after bicycling to school.	Self-image	0.70
Bicycling is considered the coolest way to get to school. My friends bicycle to school. My parents/guardians encourage me to bicycle. Lots of people bicycle in my community.	Social pressure	0.69
I live too far away from school to bicycle there. There is a safe route to bicycle from my home to school. It is hilly between my home and school.	Environment	0.64

[a] Cronbach's where k is the number of items, is the mean item covariance, and is the mean item variance.

participation was high, many students chose to skip some key questions. Case-wise deletion for any missing value reduced the sample nearly in half. Most of this reduction was due to missing home cross streets or difficulty geocoding home cross streets, but data on parent education, attitudes, and travel behavior was also often missing. Because of the extent of missing data we imputed values using multiple imputation by chained equations from the R statistical package MICE (Van Buuren and Groothuis-Oudshoorn, 2011).[2] The MICE algorithm imputes missing data one variable at a time and iteratively updates imputations (see Azur et al. (2011) for a full description). We imputed five full datasets to account for uncertainty in the imputation, retained only the records with reported values (not imputed) for the dependent variable of mode choice to school (n = 2814),[3] ran each statistical model (see Section 3.4 below) on each of the five datasets independently, and pooled the estimated parameters from the five estimations of each model for summarizing the models.

3.3. Defining bicycling attitudes

The original purpose of the survey was to explore bicycling behavior across the three high schools as a follow-up to an earlier study of Davis alone (Emond and Handy, 2012). For this reason, and to keep the length of the survey to only two pages, the survey included many questions on attitudes towards bicycling but very few on attitudes toward other modes (Lovejoy and Handy, 2013). Thus, while we explore road environments with regards to walking and bicycling, we focus on student attitudes toward bicycling but not walking. The omission of walking attitudes is a notable limitation of this study that researchers should rectify in future studies.

The Likert items were designed to explore the attitudinal and perceptual differences among teenagers who travel by bike compared to other modes. The items were based on past survey work (Emond and Handy, 2012) with a few minor changes to reduce social desirability bias. We compared two methods of analysis for the Likert data, one in which all attitudinal items were treated as independent predictors, and the other in which attitudinal items were summed to create four composites (Table 1). We reversed the scales of items with expected negative correlation with bicycling to make composite scores meaningful and for ease of item comparison. The composites were loosely based on the different levels of a social ecological model of active living (see Sallis et al. (2006)). While all the composites are intrapersonal in the sense that they represent psychological constructs, the constructs themselves reflect different social ecological domains. For example, *Enjoyment* and *Self-image* are constructs related to the intrapersonal domain, *Social pressure* is related to the social cultural environment domain, and *Environment* is related the perceived environment domain (Sallis et al., 2006). The items relating to social pressure might also be called social norms, but the two items with the strongest correlations with bicycling are clearly about social pressure (Table 1) and so we choose to label the construct *Social pressure*. We also conducted more advanced techniques such as exploratory factor analysis and integrated choice and latent variable models (see Vij and Walker (2016)) but these offered little inferential improvement (see Fitch (2018)).

3.4. Road characteristics and walking and bicycling environments

We coded several road attributes in a Geographic Information System (GIS) to describe the bicycling and walking environments in

[2] We followed default estimation procedures for the MICE package (i.e. predictive mean matching for numeric variables, logistic regression for binary variables, polytomous regression for the unordered response variables, and proportional odds model for the ordered Likert variables). We restricted chained equations for the Likert variables to other Likert variables, school, shortest distance to school, and usual travel mode to school. All other variables included all existing variables in their chained equations. When imputed shortest path distances were beyond the surveyed maximum walking/bicycling distance of the sample by school, we assumed the student lived beyond a reasonable walking/bicycling distance and removed walking and bicycling from those choice sets. Similarly, if the imputed value for driver's licensure was "none" or car access was "no", we removed driving from those choice sets.

[3] Removing records with an imputed dependent variable arguably improves the precision of imputation by exchanging variance between data sets for variance within data sets. This improved precision may be especially helpful when using a small number of imputed datasets as we have done (see von Hippel (2007)).

each community. The attributes include the number of travel lanes, speed limit, median presence, bike lane presence and width, on-street parking, parking width, and signalized intersections. We chose road environment measures that corresponded with the literature on perceived bicycling safety and convenience. For example, evidence suggests that low car speed and volume roads (e.g. two-lane roads, posted speeds < 25mph) and bike specific infrastructure (e.g. bike lanes, off-street paths) influence perceived bicyclist safety (Buehler and Dill, 2016). We use slope (measured as percent) and number of traffic signals to represent bicycling convenience. We based the road attributes on local city GIS files, OpenStreetMap data, and visual inspection of Google's Street View imagery. We used historical Street View images from 2013 when available to match the GIS data to the survey period. Where 2013 imagery was unavailable, we used the image with a date nearest to May 2013 to code the GIS data. We limited the geographic extent of our data to roughly 4 miles surrounding each high school, which we assumed was beyond what most teens would consider a reasonable walking or bicycling distance to school.

We summarized the road environment through route-based instead of area-based measures (e.g. buffers around homes) because those measures include information that is irrelevant at the trip level and may miss important information along the route (Broach, 2016). Because data on students' routes to school were unavailable, we simulated plausible routes by using a route choice set generation algorithm based on Broach et al. (2010). The algorithm utilizes a network cost that is a function of distance and one road attribute at a time (e.g. bike lane), and uses a range of weights to determine the influence of the road attribute on network cost. The purpose of including a range of weights is to generate paths reflecting the unknown trade-offs students make between distance and the quality of the walking or bicycling environment. We used this algorithm (see below) over a series of road attributes and then compiled a single value for each road attribute by using path weights based on the square of inverse distance of all generated paths per student. The inverse distance weight effectively treats shorter paths as more likely to be chosen. More formally, we considered a set of road attributes L = {street crossing, traffic signals, two-lane road, bike lane, bike lane without on-street parking, wide bike lane (≥14 ft along parking or ≥6 ft not along parking), off-street paths, percent slope[4], adjacent to commercial land use, speed limit less than 25 mph, BLTS[5] level 1, BLTS level 2, BLTS level 3}, with 1 for presence, and 0 for absence on each network link. And a set of distance weights, D = {0.95, 0.9, 0.75, 0.5}, representing the percentage of influence distance has on link cost compared to the road attribute. We then:

(1) Define the network as a series of nodes (intersections) and links (roads and off-street paths).
(2) Define the cost for each network link based on distance only and call that the first network.
(3) Define the cost for each network link by each road attribute and distance weight combination (see Broach et al. (2010) for another example of this approach):

$$C_{ijk} = D_j \times \delta_k + (1 - D_j) \times L_i$$

where C_{ijk} is the cost for one road attribute i and one distance weight j on link k; δ is the link length, D_j are distance weights, and L_i are road attributes. This results in 53 unique networks (4 distance weights * 13 road attributes + 1 network based only on distance) for each school.

(4) Solve the least cost path for each student (from home to school) on each of the 53 networks and remove redundant paths resulting in a unique set of paths for each student. This results in a minimum of 1 and maximum of 53 paths per student.
(5) For each student, using inverse distance weights for all simulated paths, create a single variable for each of the following road attributes: number of signals, percent two lane roads, percent vehicular speed < 25 mph, percent bike lane, percent off-street path, percent of slope over 3% (see Fig. 1 for a visual example of percent bike lane). The equation for one student and one road attribute dropping their respective subscripts is:

$$L^* = \sum_p L_p \times \left(\frac{\left(\frac{1}{\delta_p / \left(\sum_p \delta_p\right)^2} \right)}{\sum_p \left(\frac{1}{\delta_p / \left(\sum_p \delta_p\right)^2} \right)} \right)$$

where δ_p is the distance for the path p, $\sum_p \delta_p$ is the sum of simulated path distances, L_p is the percent of path length of the road attribute on path p, and L^* is the final distance weighted statistic.

For example, assume a student has three paths (A, B, C) with lengths 0.6, 0.5, 1.0 miles and bike lanes along 50, 30, and 80% of those paths respectively (Fig. 1). Using the equation in step 5 above, short paths are given greater weight than longer paths when summarizing each road attribute. In Fig. 1, path B gets 43% of the weight (as opposed to 33% weight in an equal weighting scheme), whereas path C only gets 21% of the weight. This student would get a final L^* value of 51% bike lane (18% + 13% + 2%). This represents a distance-weighted bike lane percent based on plausible paths to school. For each road attribute, this procedure

[4] Slope is the only continuous attribute, all others are dichotomous (1/0).
[5] BLTS = Bicycle Level of Traffic Stress. A road classification scheme commonly used in bicycle planning, developed based on Dutch bicycle design guidelines (Mekuria et al., 2012).

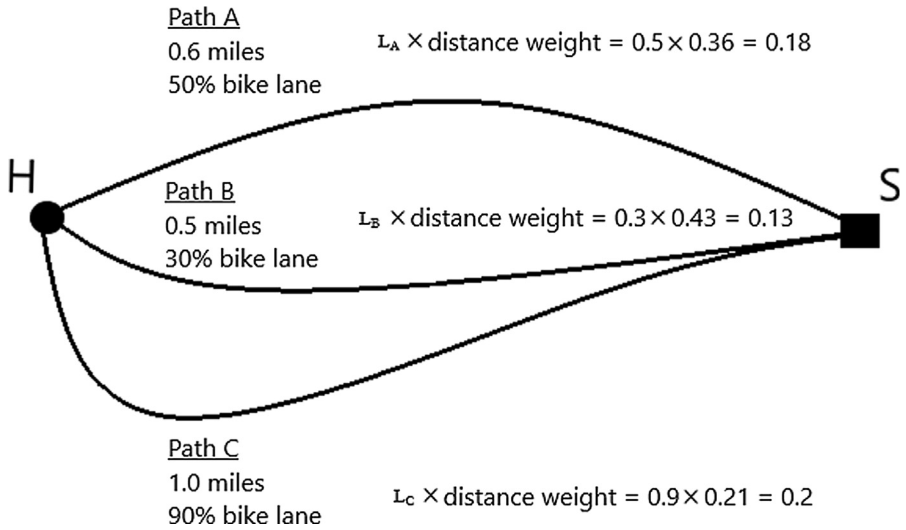

Fig. 1. Diagram of three home to school paths for one student and the resulting distance weighted statistics for each path based on percentage of bike lane along each path.

Table 2
Model descriptions.

Model Name	Predictor variables and constraints[a]
(1) Base	Distance, age, gender, parent bachelor's degree or higher, not White or Asian, parking access, varying intercept for school by alternative, driver's license (constraint for drive choice), live in town (constraint for walk/skate and bike choices)
(2) Road Environment	Base model with plausible path variables for bike and walk alternatives (number of signals, percent two lane roads, percent vehicular speed $<$ 25 mph, percent bike lane, percent off-street path, percent of slope over 3%)
(3) Attitudes as Likert items	Base model with attitudes as raw Likert items
(4) Composite Attitudes	Base model with Z-scored item sums for four attitudes (Enjoyment, Self-image, Social Pressure, Environment) (see Table 1)
(5) Full	Road Environment model with composite attitudes (combination of models 2 and 4)

[a] All variables are individual specific with alternative varying parameters.

ultimately results in a single summary statistic for each road attribute for each student.

3.5. Model Development and analysis of behavior

Along with bivariate summary statistics, we analyzed travel behavior using a series of categorical regression models (i.e. multinomial logit with one response per case) and compare their estimated effects and prediction performance (see Table 2 for model descriptions). We specified the models by selecting variables that had prior evidence for influencing teen mode choice. For example, socio-demographic and travel constraint variables are in all models (Table 2), road environment variables in models 2 and 5, and attitudes in models 3–5. For the walking utility equation, we only use path summaries of two-lane roads, posted speed $<$ 25 mph, and number of traffic signals as these attributes have been linked to both comfort and perceived safety of walking (Handy and Clifton, 2001). We did not have walk specific environment measures (e.g. sidewalk coverage, crossings) that are also reported in the literature (Kamargianni et al., 2014). In our statistical models we included varying intercepts by school because of the clustered nature of the data. Differences in the intercepts for the three schools reflect the fundamental differences between the schools related to context, culture, and other omitted factors. This is a common approach to relax model assumptions and improve inference (Gelman and Hill, 2007; Train, 2009).

We use a Bayesian analysis framework for all modeling because it produces easily interpretable posterior probabilities (i.e. a distribution of probable values for each parameter) and because prior probabilities are an easy tool for reducing model overfitting (see Kruschke and Liddell (2018) for a detailed discussion of other advantages of Bayesian inference). Beyond these fundamental statistical reasons, we chose a Bayesian modeling approach because its flexibility allowed us to model mode choice with varying choice sets (see below) and varying intercepts, aggregate results from five models (because of imputation), and predict aggregate travel outcomes and their uncertainty. In all models we use so called "weakly informative" prior probabilities to guard against overfitting (Gelman, 2006). Through the R statistical package *Rstan* as an interface for the probabilistic statistical programming language Stan, we estimated the models with the No-U-Turn (NUTS) sampler, a form of Hamiltonian Markov chain Monte Carlo (MCMC) simulation (Stan Development Team, 2017).

The general model form is as follows:

$$y_i \sim Categorical\,Logit\,(U_{ij})$$

$$U_{ij} = \alpha_j + \alpha_{j,school\,[i]} + \sum_{m=1}^{M} \beta_{mj} X_{mi}$$

$$\alpha_{j,school\,[i]} = \widetilde{\alpha}_{j,school\,[i]} \times \sigma_j$$

Prior probability distributions:

$$\widetilde{\alpha}_{j,school\,[i]} \sim Normal\,(0,\ 1)$$

$$(\beta_{11}, ..., \beta_{mj}) \sim Normal\,(0,\ 2)$$

$$(\alpha_1, ..., \alpha_j) \sim Normal\,(0,\ 10)$$

$$(\sigma_1, ..., \sigma_j) \sim HalfStudentT\,(3,\ 0,\ 2)$$

where y_i is the travel mode choice for person *i*. U_{ij} is the utility of choice alternative *j* for each person. α_j is the alternative specific constant. $\alpha_{j,school\,[i]}$ is the alternative specific constant that varies by school, indexed by person (i.e. varying intercept) and scaled by the alternative specific school standard deviation (σ_j). We scale the varying intercepts by their standard deviations to improve sampling. This is known as the non-centered parameterization (McElreath, 2015, p. 403). $\widetilde{\alpha}_{j,school\,[i]}$ is the unscaled varying intercept. β_{mj} are alternative specific regression coefficients for predictor variables (X_{mi}), M in number. When we drop subscript *i* for clarity, the categorical logit sampling statement for one person implies the probability of each choice is:

$$\Pr(y = k) = \frac{e^{U_k}}{\sum_{j=1}^{J} e^{U_j}}$$

where *k* is the chosen alternative among *J* choices. To handle situations where not all travel modes are available for a given student, a varying choice set model is appropriate. This entails a reduction of *J* for students with travel mode constraints. We had two constraints in our model. The first was for students without any form of driver's license. Because those students cannot legally drive, we removed drive from their choice set. In one case, a student reported having no form of license but indicated they drove to school. In that case, we allowed drive in that student's choice set. The second constraint was for reasonableness of walking and bicycling to school. We constrained choice sets by removing bike and walk options for students who lived beyond the extent of our GIS data which we built to roughly cover 4-mile network distances to school. In 18 cases we removed bike and walk for students either living between 3 and 4 miles from school but who lacked reasonable access (i.e. highway riding or walking), or who reported physical conditions that limited their ability to walk or ride a bike. Given that walking and bicycling generally occur at much shorter distances (Chillón et al., 2016, 2015), these assumptions are conservative in their behavioral representation. In 4 cases students reported bicycling from outlying cities with one-way travel distances greater than 10 miles. We included walk and bike in those students' choice sets assuming that either they have another home location that they ride from (e.g. their distance estimate is inaccurate for their "usual" mode to school) or that they are unlike their peers and really have a very long regular bike commute. To avoid confusing notation, we have not included choice set constraints in the above model equation. However, we do limit the choice set (*J*) to one of four based on the above constraints. The sets are: {chauffeured, bus}; {chauffeured, drive, bus}; {chauffeured, bike, walk, bus}, {chauffeured, drive, bike, walk, bus}.

Because we imputed missing data prior to model estimation, we assessed the convergence and sampling success of three Markov chains on each of five datasets (five imputations) using standard Stan diagnostics (Stan Development Team, 2017). For inference, we pooled all 15 chains (3 chains * 5 datasets) to assess the full uncertainty across all imputations. We use in-sample predictions[6] of mode choice of each of the 5 datasets and pool the results to assess model performance. We also use two measures of out-of-sample prediction: widely applicable information criteria (WAIC), and pareto smoothed importance sampling estimate of leave one out cross validation (LOOIC) (Vehtari et al., 2017). Each of the out-of-sample prediction measures is on the deviance scale and is interpreted as a relative (between models) measure of predicted deviance just like other common information criteria (e.g. AIC, DIC). The advantage of these methods is their applicability for multilevel models and their use of the entire posterior distribution (as opposed to point estimates of other information criteria) to assess out-of-sample prediction (Vehtari et al., 2017).

4. Results and discussion

4.1. Mode choice by school and socio-demographics

The three schools have a similar total share of active travel to school of around 30–40%, although the split between bicycling and walking is reversed for Davis High compared to Tamalpais High and Sequoia High (Fig. 2). The difference in bicycling between Davis and the other schools was expected as a part of the study design. However, the rate of walking at the other two schools was

[6] Sometimes called retrodiction (McElreath, 2015, p. 64) because it is predicting past data the model has already learned from. We use the term prediction because it is more familiar even though not as precise.

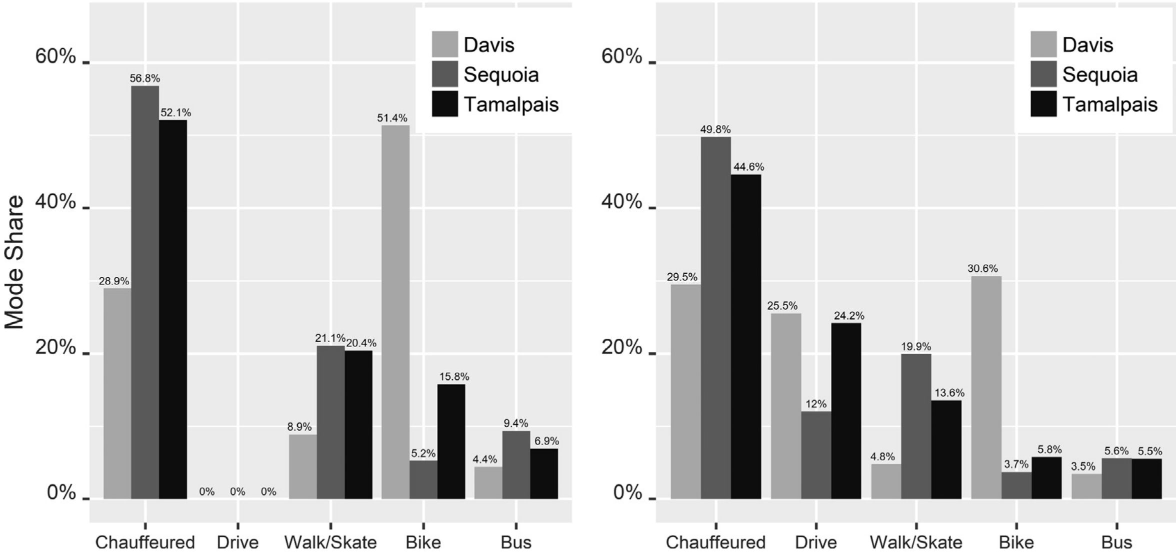

Fig. 2. Self-reported most common travel mode to school: mode to middle school (left), mode to high school (right).

unexpected given that the distances to school are similar across schools. This bivariate analysis suggests that perhaps Davis students are substituting bicycling for walking rather than car travel. However, modeling results suggest a more complex tradeoff, as discussed in Sections 4.2–4.5.

A form of car travel (e.g. driving, chauffeuring) is the dominant mode to school for teenagers at all three schools, and the share of active modes declines by age (Fig. 2). This is good evidence that these schools are at least similar to many suburban high schools in the U.S. where car travel to school is the norm. Most students reported using the same mode to and from school; however, at all three schools, a small share of students get a ride to school in the morning and then walk or bus home in the afternoon. Survey results for mode to school show less bicycling and walking in high school versus middle school (Fig. 2). This is especially true in Davis, where bicycling declines precipitously presumably as driving replaces it.

Mode to school varies by parent education, race, and whether a student has a driver's license (Table 3). Parent education seems to be a proxy for income since students whose parents have a Bachelor's degree or higher are much more likely to drive (i.e. have access to their own car). However, higher parent education is also associated with more bicycling (Table 3). Similarly, White and Asian students drive and bicycle at greater rates compared to other races. However, this result is dominated by differences in Davis, not Sequoia and Tamalpais, suggesting that the race/travel mode correlations may be a result of a "Davis" effect. Most students with a driver's license are driving to school, but the rates of walking/bicycling are similar to chauffeuring for students with driver's licenses. Although the percentage of students with a driver's license who do not drive to school is small, this pattern suggests that licensure has a larger impact on decreasing chauffeuring than it does on decreasing walking/bicycling, consistent with other studies of the impact of licensure on teen travel (McDonald et al., 2015).

Travel mode seems fairly consistent across genders even though the chi-square test statistic suggests an association. The only clear difference is that females bicycle less and are chauffeured more than males (Table 3). This gender difference (chauffeured substituting

Table 3
Travel mode by student characteristics.

		Chauffeured	Drive	Walk	Bike	Bus	Missing or Other	Sample size (n)
Gender*	Male	36.4%	20.1%	12.5%	19.4%	4.7%	6.9%	1440
	Female	44.4%	20.5%	11.9%	10.9%	4.8%	7.3%	1553
Parent education*	< BA	45.2%	12.0%	17.4%	8.1%	7.9%	9.2%	1364
	≥BA	36.4%	27.3%	8.1%	20.6%	2.1%	5.5%	1667
Race*	White or Asian	38.2%	26.2%	8.7%	18.6%	2.5%	5.8%	2030
	Not White or Asian	45.5%	8.0%	20.0%	6.8%	9.5%	10.2%	928
License and car access*	No	53.1%	0.0%	15.2%	17.5%	6.5%	7.6%	2092
	Yes	8.5%	72.9%	4.1%	9.2%	0.4%	5.0%	848
Grade*	9	64.6%	0.0%	18.6%	5.0%	5.3%	6.6%	457
	10	48.4%	5.9%	12.9%	20.4%	5.4%	7.0%	928
	11	34.8%	26.5%	9.5%	16.2%	4.9%	8.1%	863
	12	23.0%	42.7%	11.0%	13.2%	3.5%	6.6%	782

* Chi-square test statistics have p-values < 0.05 suggesting each row variable is associated with travel mode.

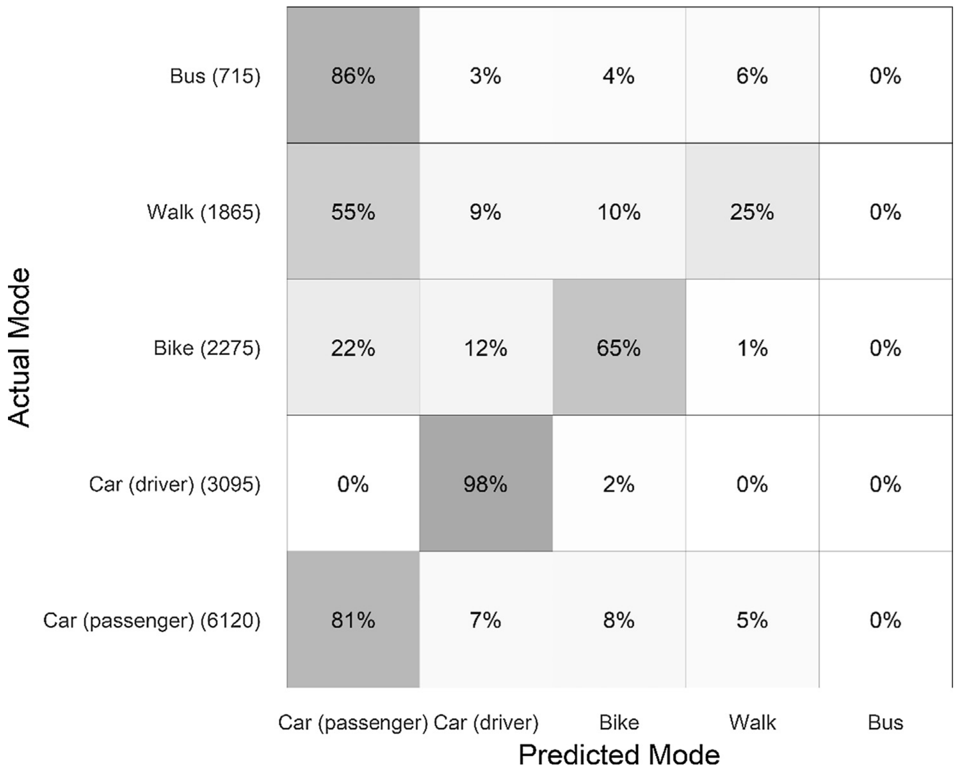

Fig. 3. Confusion plot for Model 5. Row percentages and color gradient represent matching classification, and numbers in parentheses of the row labels indicate total number of students choosing each mode for all five imputed datasets combined (i.e. surveyed totals are roughly one fifth these sizes).

for bicycling) is less pronounced in Davis, with 41% of bicyclists being female, compared to 24% and 21% at Sequoia and Tamalpais, respectively. In the following sections we focus on how the road environment and bicycling attitudes explain these differences through multivariable analyses.

4.2. Statistical model evaluation

We present model estimation results and parameter summaries in Appendix A. The predictive success of the models varies dramatically by travel mode. Fig. 3 shows a "confusion" plot of the in-sample mode choice predictions using Model 5. A model perfectly predicting the sample would have 100% of cases on the diagonal (i.e. cases off the diagonal are misclassified by the model). Most prominent in Fig. 3 is the misclassification of students who took the bus to school. Most of those students are misclassified as having been chauffeured. This is not surprising given that we have no variable representing household income (only surrogates), which is known to correlate (negatively) with taking a bus to primary school (McDonald, 2008). Nor are there measures of bus attitudes or bus availability in the models. Similarly, walk/skate is often confused for chauffeured, a result also likely explained by the lack of walk-specific attitude data and more detailed walk-specific road environment data (e.g. percent sidewalks, crosswalks, etc.). It is unclear if the models are poorer with respect to the bus alternative than in other travel behavior studies because rarely do such studies report in-sample prediction checks.

The predictive performance of the models (as indicated by decreases in information criteria values) improves with increasing

Table 4
Model estimated out-of-sample prediction through information criteria.

	LOOIC[a]	(se)	p_{LOO}	(se)	WAIC[a]	(se)	p_{WAIC}	(se)
(5) Full (Composite Attitude and Road Environment)	4551.2	(94.1)	150.0	(9.3)	4566.7	(95.0)	157.7	(10.5)
(3) Attitude Likert	4645.3	(105.8)	180.5	(22.3)	4746.8	(131.7)	231.3	(43.5)
(4) Composite Attitude	4752.5	(107.3)	178.5	(24.6)	4855.4	(135.3)	230.0	(46.5)
(2) Road Environment	4881.4	(92.6)	156.2	(9.3)	4897.1	(93.5)	164.0	(10.5)
(1) Base	5100.9	(104.7)	183.9	(23.6)	5199.7	(131.2)	233.3	(44.6)

[a] Approximated leave-one-out information criteria (LOOIC), widely applicable information criteria (WAIC), and associated estimated effective number of parameters (p_{LOO}, p_{WAIC}) and their standard errors.

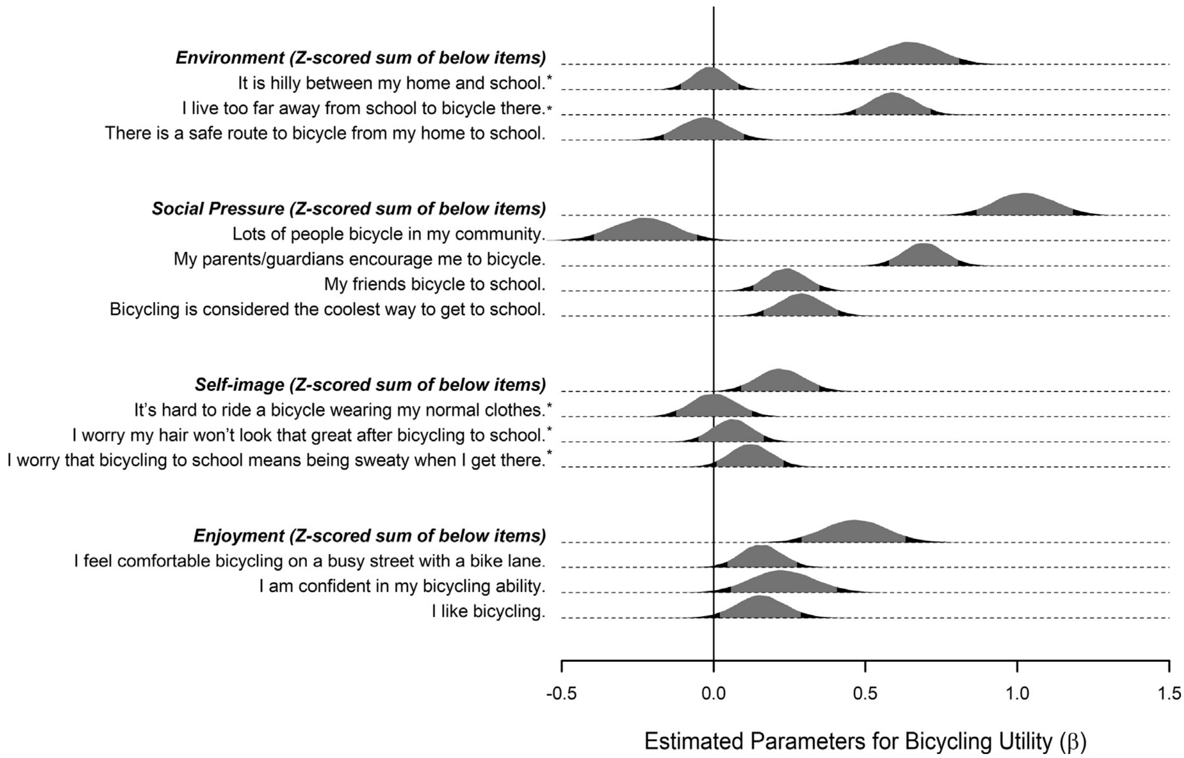

Fig. 4. Posterior distributions of parameters reflecting the Likert item (Model 3) and composite attitude (Model 4) associations with bicycling school compared to being chauffeured conditional on the other variables specified in the models. The grey portions of the posterior densities for the parameters contain the 90% most likely parameter values. Reversed scales reported for * items to allow composites of items worded in the positive and negative, and to allow clear comparison between composites.

complexity (Table 4). For example, Model 5 has a LOOIC of 4551.2 compared to Model 1 with a LOOIC of 5100.9 showing a decrease of nearly 550 units of deviance, where less deviance is equivalent to less expected predictive error. Prediction is improved independently when road environment or attitudinal variables are included. Road environment variables offer only about half of the improvement gained from the attitude variables (see deviance differences between models in Table 4). However, when attitudes and road environment variables are both included, their combined influence is additive resulting in the best performing model (Model 5 in Table 4).

4.3. Attitudes about bicycling

We examine the relationship between attitudes measured using Likert item responses and travel mode through parameter values in Model 3 (Fig. 4). Most Likert item responses have confidently positive associations with travel mode to school. Items such as “I live too far away from school to bicycle there” and “My parents/guardians encourage me to bicycle” clearly have a stronger association with bicycling to school than the other items (Fig. 4). Most interesting are the differences in item coefficients within the environment and social pressure groupings. For the three items related to bicycling environment, only the perception of *not* living too far to bicycle was positively associated with bicycling (not perceptions of hilliness and safety). This is surprising because other evidence from adults suggests that perceptions of safety are more influential than objective measurements of environments for bicycling (Ma et al., 2014). It may be that distance is such a strong barrier that many students don't even consider other environmental barriers once they hold the position that it is simply too far to bicycle to school. Alternatively, teens are notoriously risk taking (Romer, 2012), suggesting that perceptions of safety may not be good predictors of bicycling. The lack of clear connection with perceived safety suggests that many students who do not bicycle to school think it is safe to do so.

The four items related to social pressure have different relationships with bicycling (Fig. 4). Parental influence is the strongest followed by the two items related to peers. Because of the different wording of the Likert items, it is difficult to compare the magnitudes of parent and peer influence precisely. Most surprising is the negative association between the item “lots of people bicycle in my community” and bicycling to school. This is surprising because the bivariate relationship between bicycling and this item shows a slightly positive relationship (r = 0.22). Collinearity of predictors may be a reason for this effect, as some items do have moderate correlations with each other (r = 0.2–0.3). The negative relationship may also be an indication of the major difference between the schools; most Davis students strongly agree that bicycling is common in their community no matter how they travel to school, while Sequoia and Tamalpais have nearly an equal share of agreement and disagreement that bicycling is common. One thing

Table 5
Mean composite attitudes as Z-scores by school and travel mode to school.

School	Enjoyment	Self-Image	Social Pressure	Environment
Davis	0.30	0.01	0.51	0.17
Sequoia	−0.28	0.00	−0.48	−0.01
Tamalpais	−0.10	−0.02	−0.15	−0.28
Travel mode to school				
Chauffeured	−0.21	−0.09	−0.16	−0.27
Drive	0.12	−0.21	−0.15	−0.15
Bike	0.68	0.37	1.00	0.68
Walk/Skate	−0.20	0.20	−0.31	0.44
Bus	−0.35	−0.04	−0.34	−0.34

is clear: the contributions of parent, peer, and community pressures to bicycle are likely unequal. Given that the survey purposely (to decrease bias) measured peer and community pressures with indirectly worded Likert items, it would be prudent to verify these specific results in future studies.

Some results from our analysis using single Likert items (from Model 3) can be compared to the prior high school travel study in Davis (Emond and Handy, 2012). Even considering that the comparison between Emond and Handy (2012) is not ideal (they used a binary bicycling/not bicycling model instead of categorical mode choice model), the strength of the relationships between the commonly-used Likert items and bicycling are strikingly similar. For example, Emond and Handy (2012) report odds ratios of 1.3–1.4 for "I like bicycling" and 2.0–2.1 for "my parents/guardians encourage me to bicycle" depending on model specification. Exponentiating the posterior means from Model 3 (see Appendix A for parameter means) gives odds ratios of 1.2 and 2.0 for those same items. This similarity suggests that perhaps attitudes about bicycling have a consistent association with bicycling across at least the three contexts examined in this study.

Composite attitudinal variables were on average most positive for Davis students and most negative for Sequoia students (Table 5). The slightly more positive attitudes about bicycling at Tamalpais compared to Sequoia (except for *Environment*) may be a result of more frequent bicycling in middle school (Fig. 1), but could also be associated with recreational bicycling. In addition, the association between attitude and travel mode is stronger than the association between attitude and school (Table 5). This result suggests that these attitudes are not just a reflection of bicycling culture in Davis but rather generalizable factors across schools. Model 4 regression results (Fig. 4) confirm the inference from the individual Likert items that some bicycling attitudes are more important than others. Although the scale of the composite attitudes (z-scores) are not directly comparable to the Likert items (raw 5-point rating) (Fig. 4), the differences between the attitudes within each model are comparable in magnitude. More specifically, social pressure to bicycle and perceptions of the bicycling environment have stronger relationships with travel mode choice than do bicycling enjoyment and self-image.

4.4. Road characteristics and travel mode to school

Compared to the other schools, plausible paths to school in Davis are an order of magnitude different in terms of road environment variables. Fig. 5 shows the distribution (the gray "violin" is a kernel density estimate of the distribution), median, interquartile range, and full range (box and whiskers) of each distance weighted road environment variable by school. X-axes vary by road environment variable, but are comparable between schools. Fig. 5 shows that gentle slopes, low speed limits, two-lane roads, off-street paths, and bike lanes are more prevalent along plausible paths to school in Davis compared to Sequoia and Tamalpais. This is the case even though distances to school are comparable across schools. Paths to Sequoia and Tamalpais primarily differ by slope (Tamalpais being by far the steepest) and percentage bike lane, but only to a small degree by other road environment variables. Because most students who bicycle to school also bicycle home (only 4% take an alternative mode home), the terrain around

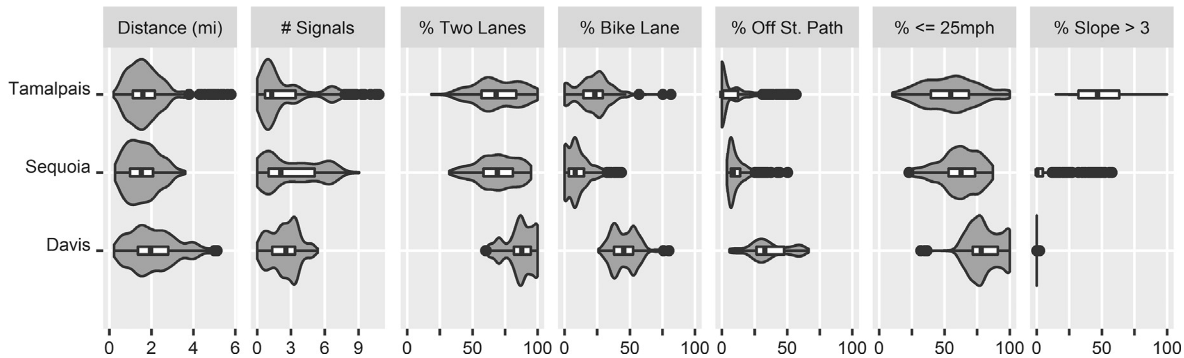

Fig. 5. Bivariate box and violin plots of distance weighted road environment variables along plausible paths to school by school.

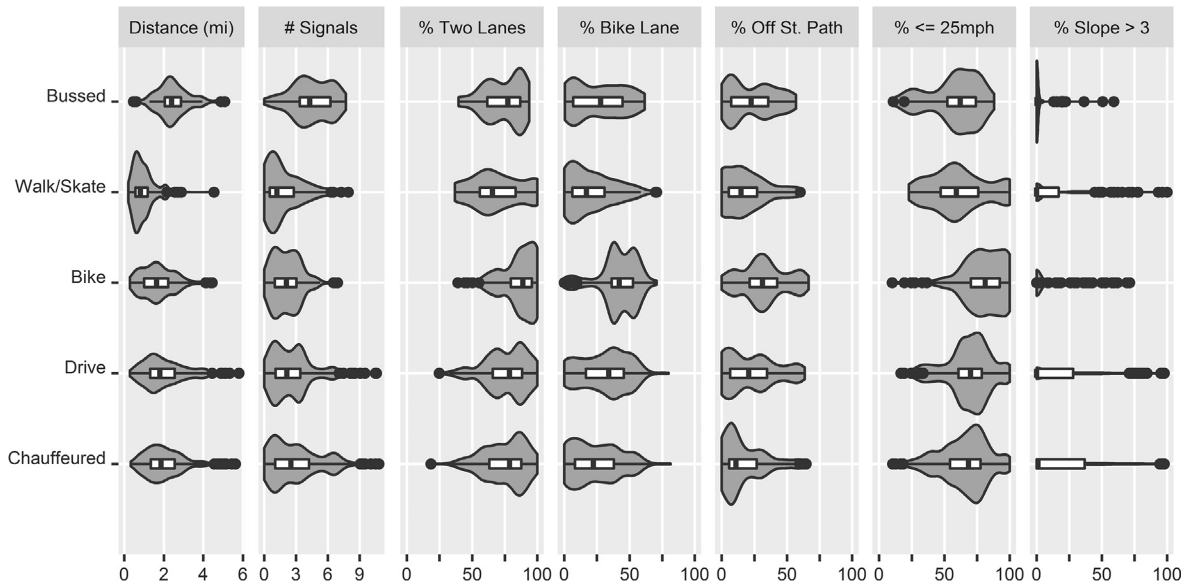

Fig. 6. Bivariate box and violin plots of distance weighted road environment variables along plausible paths to school by travel mode.

Tamalpais is likely a strong deterrent for bicycling at Tamalpais because of steep uphill travel home.

Differences in road environment variables by mode are more moderate compared to differences by school (Figs. 5 and 6). Distances are clearly shortest for walk/skate, and therefore number of traffic signals are fewest. Those students who bicycle have a greater percent of two lane roads, bike lanes, off-street paths and slow-speed roads on their plausible active travel paths to school compared to student who are chauffeured and drive. The opposite is true of students who walk/skate. This suggests that students may be walking when the road environment is not conducive for safe bicycling. It also suggests that students who travel by the other travel modes (bus, chauffeured, and drive) likely have paths to school that are more stressful and less comfortable for bicycling.

The marginal effects of each road environment variable on walking and bicycling are best represented by the posterior densities of the parameters in Models 2 and 5 (see Fig. 7 for Model 5 estimates). Fig. 7 shows large uncertainty in the estimates of most variables apart from *number of signals* and *distance* (these two variables are respectively counts of signals and miles while the others are all percentages). The large uncertainty is likely due to our use of road environment variable summaries along plausible paths to school. Had we had data on actual paths to school, marginal effects would likely have been more precise. However, it is clear from these results that off-street paths, bike lanes, and slow-speed roads have confidently positive associations with bicycling, while steep roads and long distances have confidently negative associations with bicycling (Fig. 7). Slow-speed roads have a more uncertain influence on walking since two lane and low speed limit roads do not align in their effects (Fig. 7). The negative association between low speed limit roads and walking is counterintuitive given that it is reasonable for students to prefer walking in low vehicle speed environments because they are less noxious and easier to cross. However, given that Tamalpais and Sequoia are located very near major arterials, most walkers do not have the option of detouring to slow speed roads. This lack of options is evident from Fig. 6 where the walk/skate group has the lowest percent of two lane and low speed limit roads in their plausible paths. If walkers do not have low speed road alternatives in their plausible paths, the influence of low speed roads on walking cannot be assessed. The same reasoning can be used to question the confidently negative association between number of signals and walking. While students with fewer signals along plausible paths would be more likely to walk, most walkers have only one signal on their path to school. What is more likely is that distance is the primary barrier, which is evident from Fig. 6 as well. For bicycling, the influence of distance is clearly negative, but less so than for walking.

4.5. How teen travel mode share might look with better road environments and stronger attitudes toward bicycling

We have thus far examined both the road environment and bicycling attitudes in association with travel mode. From model comparisons, we showed that bicycling attitudes are nearly twice as strong predictors of mode choice as the road environment (Table 4). However, the magnitude of individual variable relationships with mode choice has been difficult to assess since the predictor variables are on different scales and the coefficients are on the log-odds scale. To better understand the magnitude of these relationships, we use counterfactual predictions of travel mode based on differences in road environments and attitudes. These predictions do not assume a causal model, that is, the question is not: how does changing the road environment for student X change the likelihood of student X bicycling? Instead, the question is: considering hypothetical cohorts of students (e.g. a future class) with better road conditions and stronger bicycling attitudes, what is their mode share? In this way, we can compare the strength of the associations without assuming that changing those predictor variables would *cause* a change in individual mode choice. The rationale for this type of simulation closely follows the argument posed by Chorus and Kroesen (2014) which challenges the causal language

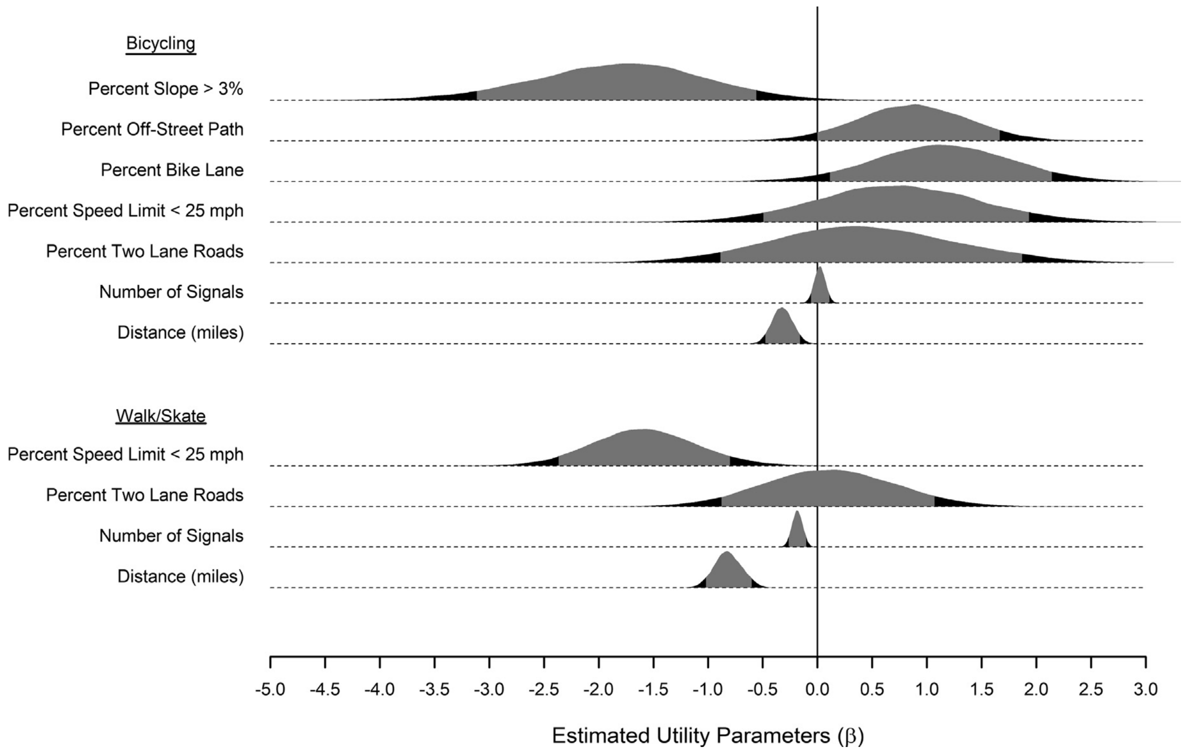

Fig. 7. Posterior distributions of parameters reflecting the association between road environment variables for both walking and bicycling to school compared to being chauffeured conditional on the other variables specified in model 7. The grey portions of the posterior densities for the parameters contain the 90% most likely parameter values.

often used when modeling with cross-sectional data and latent variables. We use the simulation to provide clarity about the strength of the associations discussed above but also to take seriously the inability to draw firm causal inferences from this data.

We start by assuming that the simulated students resemble the sampled students by leaving unchanged all variables (see Table 6 base scenario). Then we keep all the sociodemographic variables (i.e. those from Model 1) unchanged, but make attitudes more positive, improve road environments, and decrease distances, all by 20% in varying combination in the next five scenarios (see Table 6). For example, the 20% reduction in distance corresponded to reducing the median distance to school from 1.9 miles to 1.5 miles and the mean distance from 2.9 miles to 2.1 miles. Fig. 8 shows the predicted probabilities from Model 5 for all 6 scenarios. Improving the road environment alone results in about a 5-percentage point (p.p.) greater bicycling and lower chauffeured, drive, and walk mode shares. Improving the road environment and having students live closer to school results in greater bicycling (9p.p.) and walking (10p.p.), with predominantly fewer students being chauffeured (−16p.p.). The lack of strong negative difference in drive (−3p.p.) for this scenario suggests that even when distances are short and environments are conducive to bicycling, students are likely to drive at similar rates. When distances and environments are unchanged but students have stronger bicycling attitudes, we see a large positive difference in bicycling (15p.p.) and a large negative difference in chauffeured (−11p.p.). This result suggests that attitudes have a stronger influence on bicycling than do distance and road environment variables for the same percentage change (also supported by model comparisons in Section 4.2). However, a 20% change may not be equally plausible for each variable.

The last scenario, which combines 20% improvements in attitudes, road environments, and distance, shows that bicycling can increase nearly 29p.p. compared to the baseline scenario. The "effects" of improving the road environment and attitudes seem to be nearly additive on bicycling (also supported by model comparisons in Section 4.2). Our results also suggest that the main mode tradeoff for bicycling is being chauffeured, as the declines in driving and walking are much smaller in these scenarios. The only scenarios that saw rises in walking and bicycling are those in which distances to school were reduced. The distance barrier for walking suggests that improvements to the road environment without concurrent decreases in distance will likely only influence bicycling, and only to a small degree. A caveat to this inference is that this analysis lacked data on walking attitudes and environments from home to school. If we had better data on walking environments (e.g. sidewalks, crosswalks), we might find that walking-specific features had a strong association with walking (even at moderate distances).

The driving mode share is the most confident and consistent estimate across the scenarios (Fig. 8). The consistency suggests that it may be very challenging to reduce driving to school. On the other hand, chauffeuring is much more responsive to these scenarios, although with considerably more uncertainty.

Table 6
Counterfactual Scenario Descriptions.

Scenario	Variables Changed	Change % (average absolute)
(1) Baseline	None	None
(2) Improved road environment	% two lanes	+20%
	% posted speed ≤ 25 mph	+20%
	% bike lane	+20%
	% off street path	+20%
(3) Improved road environment and shorter distances to school	% two lanes	+20%
	% posted speed ≤ 25 mph	+20%
	% bike lane	+20%
	% off street path	+20%
	Distance	−20% (~1.2 miles)
	Number of signals	−20% (~1.5 signals)
(4) Stronger bicycling attitudes	Enjoyment	+20% (~0.5 std. devs.)
	Self-image	+20% (~0.5 std. devs.)
	Social pressure	+20% (~0.8 std. devs.)
	Environment	+20% (~0.5 std. devs.)
(5) Improved road environment and stronger bicycling attitudes	% two lanes	+20%
	% posted speed ≤ 25 mph	+20%
	% bike lane	+20%
	% off street path	+20%
	Enjoyment	+20% (~0.5 std. devs.)
	Self-image	+20% (~0.5 std. devs.)
	Social pressure	+20% (~0.8 std. devs.)
	Environment	+20% (~0.5 std. devs.)
(6) Improved road environment, short distances to school, and stronger bicycling attitudes	% two lanes	+20%
	% posted speed ≤ 25 mph	+20%
	% bike lane	+20%
	% off street path	+20%
	Distance	−20% (~1.2 miles)
	Number of signals	−20% (~1.5 signals)
	Enjoyment	+20% (~0.5 std. devs.)
	Self-image	+20% (~0.5 std. devs.)
	Social pressure	+20% (~0.8 std. devs.)
	Environment	+20% (~0.5 std. devs.)

5. Conclusions

Bicycling studies in Davis, CA can produce unique insights into bicycling behavior (because bicycling is a normal travel mode), but they may not be generalizable to most other places in the US where bicycling for day-to-day travel is an exception. By combining data from two similar schools without a large bicycling mode share, we get a unique look at teen travel that generalizes beyond Davis. Nonetheless, these three schools represent only suburban-style communities with high levels of car access among teens, and generalizing to dense urban or rural environments or to populations will low levels of car access is not appropriate. Nonetheless, the results may prove generalizable to many of the numerous suburban high schools in the U.S.

Travel mode choice to high school is a complex process involving some variables that were unavailable in this study (e.g. parent work schedules), and many variables that may be bi-directionally causal (e.g. attitudes, driver's licensure). This makes inference challenging. Nonetheless, the evidence we have replicates many previously-found associations between socio-demographics and teen travel (see Appendix A for all parameter values), and suggests strong relationships between bicycling attitudes and bicycling to school, and moderate relationships between the road environment and bicycling to school.

What do these results say about potential interventions to increase walking and bicycling to high school? The cross-sectional nature of the data limits our ability to conclude that changing road environments and attitudes will result in changes in current student behavior. The case for a causal link between the road environment and travel behavior is stronger. Although we do not account for "self-selection" through residential location choice (i.e. parents choosing to live where it is easier or safer for walking and bicycling to school), one study of bicycling that accounts for "self-selection" suggests that the road environment still influences bike ownership and use (Handy et al., 2010). Our results clearly indicate that simulated students who match those of the sample but with more safe and comfortable access to school, shorter travel distances, and stronger pro-bicycling attitudes would be walking and bicycling to school much more frequently. A way to think about this counterfactual is in the planning for new students. Consider that every four years the student population at high school completely turns-over. We would expect a new wave of students to bicycle more if policies could successfully improve the road environment for bicycling. In addition, policies aimed at increasing local attendance should reduce travel distances resulting in greater walking and bicycling to school.

The effectiveness of programs aimed at changing travel attitudes may be more uncertain given that behavior change may be needed to change travel attitudes (reverse causality) (Chorus and Kroesen, 2014; Kroesen et al., 2017). However, some specific

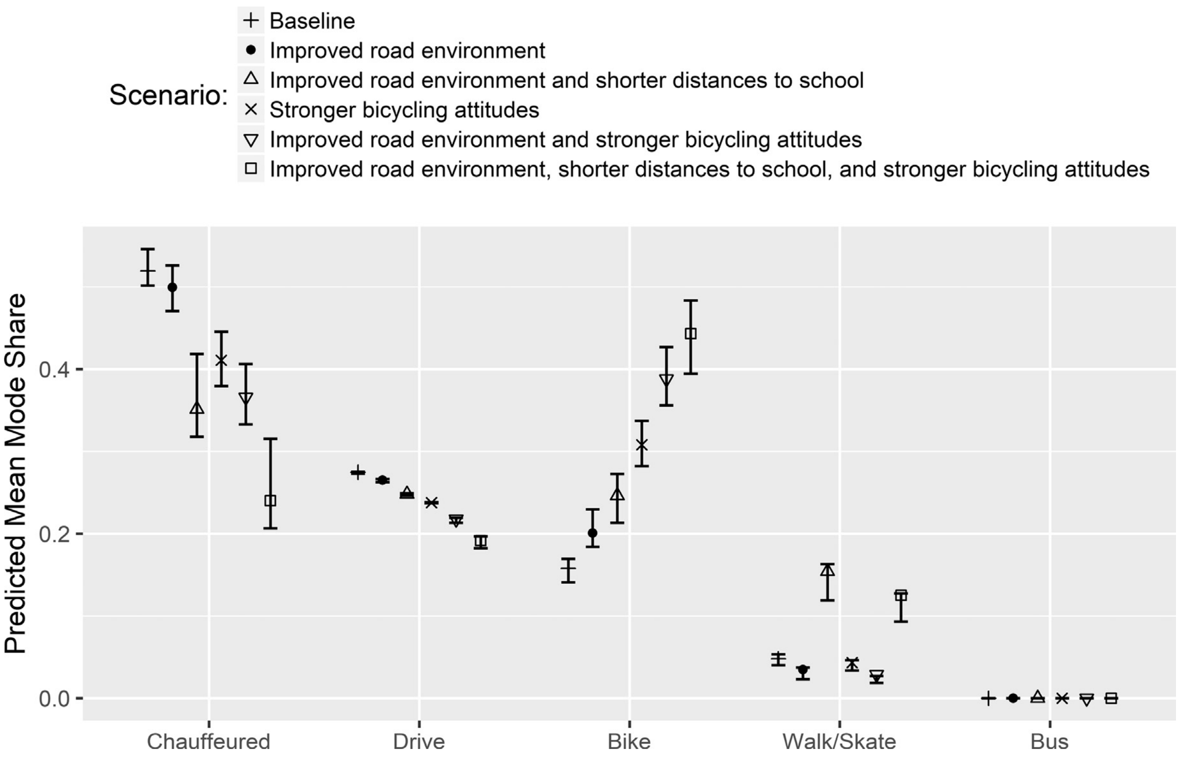

Fig. 8. Predicted travel mode shares to school (mean and 90% range) by scenario.

attitudinal constructs (e.g. social pressure) may have more theoretically straightforward causal chains from attitude to behavior (i.e. a student is more likely to feel social pressure to bicycle before they begin bicycling, not after they begin bicycling). Perhaps policies aimed at convincing parents to encourage their teens to walk and bicycle to school, or those aimed at getting parents walking and bicycling themselves to lead by example can be effective.

Ultimately what we need are evaluations of a variety of programs and policies aimed at improving teen active travel to school. The evidence here suggests that policies should aim to improve road environments along plausible paths to school, promote local attendance, and generate social pressure to walk and bicycle.

Acknowledgment

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Appendix A. Model estimation and parameter summaries

All five statistical models were estimated using the default No-U-Turn (NUTS) sampler in Stan (Stan Development Team, 2017). All models included 2000 warmup iterations for MCMC adaptation, followed by 2000 iterations used to draw inference on the posterior probability of all parameter values. Start values were randomly selected based on definitions of prior probabilities. To avoid divergent iterations (i.e. when the resolution of the sampler is not fine enough to sample the features of the posterior) which can bias parameter estimates (Stan Development Team, 2017), we increased the step size (adapt_delta) from the default 0.8 to 0.99 for all models. In addition, to improve sampling efficiency, we increased the tree depth from the default 10 to 18 after warnings that sampling was terminating prematurely.

Table A1 summarizes the model parameters by their posterior mean and standard deviation (sd) which represent the marginal influence and respective uncertainty of each variable. Because chauffeured is the base case for the categorical model, all constants and regression parameters can be interpreted as the difference compared to chauffeured on the logit scale. All estimation diagnostics suggested the estimation properly converged and explored the posterior distribution of all parameters. To demonstrate model

Table A1
Parameter estimates, effective samples, and convergence diagnostics.

		Model 1			Model 2			Model 3			Model 4			Model 5		
		(Base)			(Road Environment)			(Attitudes Likert)			(Composite Attitudes)			(Full)		
		mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
Alternative Specific Constants	α[drive]	0.89	(0.47)	3806	1.09	(0.47)	3722	0.84	(0.47)	3566	0.80	(0.47)	4169	1.03	(0.48)	3911
	α[bike]	−0.44	(0.94)	2339	−1.58	(0.90)	2608	−8.86	(1.16)	2692	−1.62	(0.74)	2645	−2.39	(0.80)	3446
	α[walk]	−0.10	(0.45)	2142	1.44	(0.42)	2879	−0.08	(0.47)	1887	−0.08	(0.49)	1843	1.47	(0.41)	3401
	α[bus]	−2.39	(0.53)	2195	−2.40	(0.56)	2185	−2.39	(0.55)	1849	−2.39	(0.55)	2254	−2.39	(0.55)	2184
Varying Effects (scales)	σ[drive]	0.26	(0.32)	2749	0.25	(0.31)	3084	0.26	(0.32)	2985	0.26	(0.30)	2904	0.26	(0.32)	2687
	σ[bike]	1.51	(0.72)	2995	1.07	(0.59)	3081	1.44	(0.70)	3219	1.13	(0.60)	3134	0.82	(0.53)	3116
	σ[walk]	0.57	(0.42)	2539	0.24	(0.32)	2411	0.57	(0.43)	2439	0.58	(0.44)	2178	0.24	(0.30)	2462
	σ[bus]	0.70	(0.48)	2633	0.72	(0.51)	2521	0.69	(0.48)	2215	0.70	(0.49)	2305	0.71	(0.49)	2547
Varying Effects (constants)	school[drive,davis]	0.00	(0.26)	3075	0.00	(0.24)	3480	0.00	(0.25)	3124	−0.01	(0.25)	3843	−0.01	(0.26)	3225
	school[drive,sequoia]	−0.04	(0.26)	2346	−0.04	(0.25)	2590	−0.04	(0.26)	2406	−0.03	(0.25)	2653	−0.03	(0.27)	3279
	school[drive,tam]	0.05	(0.26)	2149	0.05	(0.24)	2268	0.04	(0.26)	1852	0.06	(0.25)	1834	0.05	(0.27)	2895
	school[bike,davis]	1.55	(0.92)	2113	0.48	(0.74)	2177	1.38	(0.93)	1863	1.01	(0.72)	2239	0.24	(0.62)	2173
	school[bike,sequoia]	−0.91	(0.93)	3050	−0.91	(0.72)	3385	−0.87	(0.93)	3083	−0.61	(0.72)	3815	−0.57	(0.60)	3279
	school[bike,tam]	−0.72	(0.93)	2352	0.39	(0.76)	2369	−0.72	(0.93)	2362	−0.42	(0.72)	2634	0.29	(0.63)	3007
	school[walk,davis]	−0.34	(0.41)	2115	−0.03	(0.26)	2081	−0.34	(0.43)	1826	−0.35	(0.45)	1795	−0.04	(0.24)	2570
	school[walk,sequoia]	0.10	(0.41)	2170	0.05	(0.26)	2202	0.10	(0.42)	1875	0.10	(0.45)	2309	0.05	(0.24)	2146
	school[walk,tam]	0.24	(0.41)	2976	0.00	(0.26)	3327	0.23	(0.42)	3016	0.23	(0.45)	3634	−0.01	(0.24)	3104
	school[bus,davis]	0.06	(0.50)	2348	0.06	(0.53)	2392	0.05	(0.52)	2376	0.05	(0.51)	2638	0.04	(0.51)	3056
	school[bus,sequoia]	−0.45	(0.50)	2141	−0.46	(0.53)	2030	−0.44	(0.53)	1844	−0.44	(0.52)	1769	−0.45	(0.52)	2628
	school[bus,tam]	0.36	(0.50)	2177	0.38	(0.53)	2100	0.36	(0.52)	1823	0.36	(0.52)	2225	0.37	(0.52)	2063
Categorical Regression Parameters	Distance (miles)[drive]	0.13	(0.05)	6000	0.10	(0.05)	6000	0.13	(0.06)	6000	0.14	(0.05)	6000	0.10	(0.05)	6000
	Distance (miles)[bike]	−0.32	(0.06)	6000	−0.46	(0.08)	5591	−0.10	(0.06)	6000	−0.16	(0.06)	6000	−0.32	(0.10)	5863
	Distance (miles)[walk]	−0.56	(0.10)	6000	−0.83	(0.13)	6000	−0.56	(0.10)	6000	−0.56	(0.10)	6000	−0.82	(0.13)	6000
	Distance (miles)[bus]	0.06	(0.03)	6000	0.06	(0.03)	6000	0.06	(0.03)	6000	0.06	(0.03)	6000	0.06	(0.03)	6000
	Age (fractional yrs)[drive]	0.26	(0.14)	6000	0.28	(0.14)	6000	0.20	(0.14)	6000	0.21	(0.14)	6000	0.21	(0.14)	6000
	Age (fractional yrs)[bike]	0.10	(0.07)	6000	0.08	(0.07)	6000	0.24	(0.08)	6000	0.24	(0.08)	6000	0.19	(0.08)	6000
	Age (fractional yrs)[walk]	0.19	(0.06)	6000	0.14	(0.06)	6000	0.19	(0.06)	6000	0.19	(0.06)	6000	0.14	(0.06)	6000
	Age (fractional yrs)[bus]	0.24	(0.09)	6000	0.24	(0.09)	6000	0.24	(0.09)	6000	0.24	(0.09)	6000	0.24	(0.09)	6000
	Female[drive]	0.08	(0.18)	6000	0.07	(0.18)	6000	0.05	(0.18)	6000	0.10	(0.18)	6000	0.06	(0.18)	6000
	Female[bike]	−0.93	(0.13)	6000	−0.95	(0.14)	6000	−0.50	(0.17)	6000	−0.46	(0.16)	6000	−0.45	(0.16)	6000
	Female[walk]	−0.21	(0.13)	6000	−0.20	(0.13)	6000	−0.22	(0.13)	6000	−0.22	(0.13)	6000	−0.21	(0.13)	6000
	Female[bus]	−0.04	(0.18)	6000	−0.04	(0.18)	6000	−0.05	(0.18)	6000	−0.05	(0.18)	6000	−0.05	(0.18)	6000
	ParentHighEducation[drive]	−0.03	(0.22)	6000	−0.05	(0.22)	6000	0.01	(0.22)	6000	−0.02	(0.22)	6000	−0.04	(0.22)	6000
	ParentHighEducation[bike]	0.45	(0.15)	6000	0.47	(0.15)	6000	0.35	(0.18)	6000	0.32	(0.17)	6000	0.33	(0.17)	6000
	ParentHighEducation[walk]	−0.25	(0.15)	6000	−0.27	(0.15)	6000	−0.25	(0.15)	6000	−0.25	(0.15)	6000	−0.28	(0.16)	6000
	ParentHighEducation[bus]	−0.91	(0.23)	6000	−0.91	(0.23)	6000	−0.90	(0.23)	6000	−0.90	(0.23)	6000	−0.90	(0.23)	6000
	Non-White or Asian[drive]	−0.59	(0.27)	6000	−0.54	(0.26)	6000	−0.62	(0.26)	6000	−0.60	(0.26)	6000	−0.58	(0.26)	6000
	Non-White or Asian[bike]	−0.66	(0.18)	6000	−0.63	(0.19)	6000	−0.28	(0.21)	6000	−0.43	(0.20)	6000	−0.41	(0.21)	6000
	Non-White or Asian[walk]	0.50	(0.16)	6000	0.65	(0.16)	6000	0.50	(0.16)	6000	0.50	(0.16)	6000	0.65	(0.16)	6000
	Non-White or Asian[bus]	1.06	(0.22)	6000	1.07	(0.22)	6000	1.05	(0.22)	6000	1.05	(0.22)	6000	1.06	(0.23)	6000

(*continued on next page*)

Table A1 (*continued*)

		Model 1			Model 2			Model 3			Model 4			Model 5		
		(Base)			(Road Environment)			(Attitudes Likert)			(Composite Attitudes)			(Full)		
		mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
Categorical Regression Parameters Continued	On-campus Parking[drive]	0.62	(0.41)	5603	0.56	(0.42)	5341	0.72	(0.42)	5601	0.69	(0.42)	5681	0.69	(0.42)	5719
	Number of Signals[bike]				−0.01	(0.05)	5866							0.02	(0.05)	6000
	Number of Signals[walk]				−0.18	(0.05)	5852							−0.18	(0.05)	5880
	% Two Lane Roads[bike]				0.55	(0.79)	5127							0.42	(0.84)	5273
	% Two Lane Roads[walk]				0.17	(0.58)	4829							0.11	(0.59)	5169
	% Posted Speed ≤ 25 mph[bike]				1.27	(0.68)	4212							0.73	(0.74)	4636
	% Posted Speed ≤ 25 mph[walk]				−1.59	(0.47)	5566							−1.58	(0.48)	5824
	% Bike Lane[bike]				1.54	(0.56)	6000							1.14	(0.62)	6000
	% Off Street Path[bike]				0.75	(0.45)	6000							0.87	(0.51)	6000
	% Slope > 3%[bike]				−2.76	(0.75)	6000							−1.82	(0.78)	5885
	I like bicycling[bike]							0.16	(0.08)	6000						
	I am confident in my bicycling ability[bike]							0.23	(0.11)	5852						
	I feel comfortable bicycling on a busy street with a bike lane[bike]							0.16	(0.07)	6000						
	It's hard to ride a bicycle wearing my normal clothes [bike]							0.12	(0.07)	5910						
	I worry that bicycling to school means being sweaty when I get there[bike]							0.06	(0.07)	5895						
	I worry my hair won't look that great after bicycling to school[bike]							0.00	(0.08)	6000						
	Bicycling is considered the coolest way to get to school[bike]							0.29	(0.08)	6000						
	My friends bicycle to school[bike]							0.24	(0.07)	6000						
	My parents/guardians encourage me to bicycle[bike]							0.69	(0.07)	6000						
	Lots of people bicycle in my community[bike]							−0.23	(0.10)	6000						
	I live too far away from school to bicycle there[bike]							−0.03	(0.08)	6000						
	There is a safe route to bicycle from my home to school[bike]							0.59	(0.08)	5942						
	It is hilly between my home and school[bike]							−0.01	(0.06)	6000						
	Enjoyment[bike]										0.47	(0.10)	6000	0.50	(0.10)	6000
	Self-image[bike]										0.22	(0.08)	6000	0.23	(0.08)	6000
	Social Pressure[bike]										1.03	(0.10)	6000	1.00	(0.10)	6000
	Environment[bike]										0.65	(0.10)	6000	0.55	(0.11)	6000
	Sample size (n)	2814			2814			2814			2814			2814		
	15 parallel chains runtime (hrs)	3.40			5.22			4.75			3.08			5.29		
	Minimum BFMI	0.82			0.86			0.86			0.84			0.89		

estimation success, we report estimated number of effective samples (n_{eff}) (i.e. efficiency), and model-level minimum Bayesian Fraction of Missing Information (BFMI) (a Stan diagnostic used to describe how well each Markov chain explored the posterior distribution, with values less than 0.3 deemed problematic) (Betancourt, 2016). In addition, the potential scale reduction factor ($\hat{R}$) was < 1.01 for all parameters suggesting MCMC convergence (Gelman et al., 2013, pp. 285–286), and no MCMC iterations resulted in divergences or exceedance of the maximum tree depth (two other diagnostics reported by Stan).

References

Azur, M.J., Stuart, E.A., Frangakis, C., Leaf, P.J., 2011. Multiple imputation by chained equations: what is it and how does it work? Int. J. Methods Psychiatr. Res. 20, 40–49. http://dx.doi.org/10.1002/mpr.329.Multiple.

Baslington, H., 2008. Travel socialization: a social theory of travel mode behavior. Int. J. Sustain. Transp. 2, 91–114. http://dx.doi.org/10.1080/15568310601187193.

Betancourt, M., 2016. Diagnosing Suboptimal Cotangent Disintegrations in Hamiltonian Monte Carlo, Working Paper. URL < http://arxiv.org/abs/1604.00695 > .

Blumenberg, E., Taylor, B.D., Smart, M., Ralph, K., Wander, M., Brumbaugh, S., 2012. What's youth got to do with it? Exploring the Travel Behavior of Teens and Young Adults, UCTC-FR-2012-14. University of California Transportation Center.

Broach, J., 2016. Travel mode choice framework incorporating realistic bike and walk routes. PSU. http://dx.doi.org/10.1017/CBO9781107415324.004.

Broach, J., Gliebe, J., Dill, J., 2010. Calibrated labeling method for generating bicyclist route choice sets incorporating unbiased attribute variation. Transp. Res. Rec. J. Transp. Res. Board 89–97. http://dx.doi.org/10.3141/2197-11.

Buehler, R., Dill, J., 2016. Bikeway networks: a review of effects on cycling. Transp. Rev. 36, 9–27. http://dx.doi.org/10.1080/01441647.2015.1069908.

Buehler, T., Handy, S., 2008. Fifty years of bicycle policy in Davis, California. Transp. Res. Rec. J Transp. Res. Board 52–57. http://dx.doi.org/10.3141/2074-07.

Carlson, J.a., Sallis, J.F., Kerr, J., Conway, T.L., Cain, K., Frank, L.D., Saelens, B.E., 2014. Built environment characteristics and parent active transportation are associated with active travel to school in youth age 12–15. Br. J. Sports Med. 48, 1634–1639. http://dx.doi.org/10.1136/bjsports-2013-093101.

Carver, A., Panter, J.R., Jones, A.P., van Sluijs, E.M.F., 2014. Independent mobility on the journey to school: a joint cross-sectional and prospective exploration of social and physical environmental influences. J. Transp. Heal. 1, 25–32. http://dx.doi.org/10.1016/j.jth.2013.12.003.

Chillón, P., Molina-García, J., Castillo, I., Queralt, A., 2016. What distance do university students walk and bike daily to class in Spain. J. Transp. Heal. 3, 315–320. http://dx.doi.org/10.1016/j.jth.2016.06.001.

Chillón, P., Panter, J., Corder, K., Jones, A.P., Van Sluijs, E.M.F., 2015. A longitudinal study of the distance that young people walk to school. Heal. Place 31, 133–137. http://dx.doi.org/10.1016/j.healthplace.2014.10.013.

Chorus, C.G., Kroesen, M., 2014. On the (im-)possibility of deriving transport policy implications from hybrid choice models. Transp. Pol. 36, 217–222. http://dx.doi.org/10.1016/j.tranpol.2014.09.001.

Clifton, K., 2003. Independent mobility among teenagers: exploration of travel to after-school activities. Transp. Res. Rec. J. Transp. Res. Board 1854, 74–80. http://dx.doi.org/10.3141/1854-08.

Dill, J., McNeil, N., 2013. Four types of cyclists? Transp. Res. Rec. J. Transp. Res. Board 2387, 129–138. http://dx.doi.org/10.3141/2387-15.

Driller, B.K., Handy, S.L., 2013. Exploring the influence of parents on children's bicycling in Davis, CA. In: 92nd Annual Meeting of the Transportation Research Board, Washington, DC.

Emond, C.R., Handy, S.L., 2012. Factors associated with bicycling to high school: insights from Davis, CA. J. Transp. Geogr. 20, 71–79. http://dx.doi.org/10.1016/j.jtrangeo.2011.07.008.

Ewing, R., Schroeer, W., Greene, W., 2004. School location and student travel analysis of factors affecting mode choice. Transp. Res. Rec. 1895, 55–63. http://dx.doi.org/10.3141/1895-08.

Fitch, D.T., 2018. The Road Environment and Urban Bicycling: Psychophysiological and Behavioral Responses. University of California, Davis URL < https://ncst.ucdavis.edu/wp-content/uploads/2016/11/Fitch_Dissertation_FullManuscript.pdf > .

Gelman, A., 2006. Prior distribution for variance parameters in hierarchical models. Bayesian Anal. 1, 515–533. http://dx.doi.org/10.1214/06-BA117A.

Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D.B., 2013. Bayesian Data Analysis, third ed. Chapman & Hall/CRC.

Gelman, A., Hill, J., 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press https://doi.org/10.2277/0521867061.

Handy, S.L., Boarnet, M.G., Ewing, R., Killingsworth, R.E., 2002. How the built environment affects physical activity: aiews from urban planning. Am. J. Prev. Med. 23.

Handy, S.L., Clifton, K.J., 2001. Evaluating neighborhood accessibility: possibilities and practicalities. J. Transp. Stat. 4, 67–78.

Handy, S.L., Xing, Y., Buehler, T., 2010. Factors associated with bicycle ownership and use: a study of six small U.S. cities. Transportation (Amst) 37, 967–985. http://dx.doi.org/10.1007/s11116-010-9269-x.

He, S.Y., Giuliano, G., 2017. School choice: understanding the trade-off between travel distance and school quality. Transportation (Amst) 1–24. http://dx.doi.org/10.1007/s11116-017-9773-3.

Kamargianni, M., Ben-Akiva, M., Polydoropoulou, A., 2014. Incorporating social interaction into hybrid choice models. Transportation (Amst) 41, 1263–1285. http://dx.doi.org/10.1007/s11116-014-9550-5.

Kamargianni, M., Dubey, S., Polydoropoulou, A., Bhat, C., 2015. Investigating the subjective and objective factors influencing teenagers' school travel mode choice - An integrated choice and latent variable model. Transp. Res. Part A Policy Pract. 78, 473–488. http://dx.doi.org/10.1016/j.tra.2015.06.011.

Kamargianni, M., Polydoropoulou, A., 2014. Generation Y's travel behavior and perceptions of walkability constraints. Transp. Res. Rec. J Transp. Res. Board 59–71. http://dx.doi.org/10.3141/2430-07.

Kamargianni, M., Polydoropoulou, A., 2013. Development of a hybrid choice model to investigate the effects of teenagers' attitudes towards walking and cycling on mode choice behavior. In: 92nd Annual Meeting of the Transportation Research Board, Washington, D.C.

Kroesen, M., Handy, S., Chorus, C., 2017. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. Transp. Res. Part A Policy Pract. 101, 190–202. http://dx.doi.org/10.1016/j.tra.2017.05.013.

Kruschke, J.K., Liddell, T.M., 2018. The Bayesian New Statistics: Hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective. Psychon. Bull. Rev. 25, 178–206. http://dx.doi.org/10.3758/s13423-016-1221-4.

Lovejoy, K., Handy, S., 2013. High school bicycling survey 2013: summary report. Research Report – UCD-ITS-RR-13-27 High. UC Davis Institute of Transportation Studies.

Ma, L., Dill, J., Mohr, C., 2014. The objective versus the perceived environment: what matters for bicycling? Transportation (Amst) 1135–1152. http://dx.doi.org/10.1007/s11116-014-9520-y.

McDonald, N.C., 2012. Children and Cycling. In: Pucher, J., Buehler, R. (Eds.), City Cycling. MIT Press, Cambridge, MA, pp. 235–255.

McDonald, N.C., 2008. Children's mode choice for the school Trip: the role of distance and school location in walking to school. Transportation (Amst). 35, 23–35. http://dx.doi.org/10.1007/s11116-007-9135-7.

McDonald, N.C., Brown, A.L., Marchetti, L.M., Pedroso, M.S., 2011. U.S. school travel, 2009: an assessment of trends. Am. J. Prev. Med. 41, 146–151. http://dx.doi.org/10.1016/j.amepre.2011.04.006.

McDonald, N.C., Merlin, L., Hu, H., Shih, J., Cohen, D.A., Evenson, K.R., Mckenzie, L., Rodriguez, D.A., 2015. Longitudinal analysis of adolescent girls' activity patterns: understanding the influence of the transition to licensure. J. Transp. Land Use 9, 1–24. http://dx.doi.org/10.5198/jtlu.2015.652.

McElreath, R., 2015. Statistical Rethinking. Chapman & Hall/CRC.

McMillan, T.E., 2007. The relative influence of urban form on a child's travel mode to school. Transp. Res. Part A Policy Pract. 41, 69–79. http://dx.doi.org/10.1016/j.tra.2006.05.011.

McMillan, T.E., 2005. Urban form and a child's trip to school: the current literature and a framework for future research. J. Plan. Lit. 19, 440–456. http://dx.doi.org/10.1177/0885412204274173.
Mekuria, M.C., Furth, P.G., Nixon, H., 2012. Low-Stress Bicycling and Network Connectivity. Mineta Transportation Institute, San Jose, CA.
Mitra, R., 2013. Independent mobility and mode choice for school transportation: a review and framework for future research. Transp. Rev. 33, 21–43. http://dx.doi.org/10.1080/01441647.2012.743490.
Mitra, R., Buliung, R.N., 2015. Exploring differences in school travel mode choice behaviour between children and youth. Transp. Policy 42, 4–11. http://dx.doi.org/10.1016/j.tranpol.2015.04.005.
Noland, R.B., Hagen, L.A.Von., Chatman, D.G., 2014. A mode choice analysis of school trips in New Jersey. J. Transp. Land Use 7, 111–133.
Pucher, J., Dill, J., Handy, S., 2010. Infrastructure, programs, and policies to increase bicycling: an international review. Prev. Med. (Baltim) 50 (Suppl. 1), S106–S125. http://dx.doi.org/10.1016/j.ypmed.2009.07.028.
Romer, D., 2012. Adolescent risk taking, impulsivity, and brain development: implications for prevention. Dev. Psychobiol. 52, 263–276. http://dx.doi.org/10.1002/dev.20442.Adolescent.
Sallis, J.F., Cervero, R.B., Ascher, W., Henderson, K.A., Kraft, M.K., Kerr, J., 2006. An ecological approach to creating active living communities. Annu. Rev. Public Health 27, 297–322. http://dx.doi.org/10.1146/annurev.publhealth.27.021405.102100.
Schlossberg, M., Greene, J., Phillips, P.P., Johnson, B., Parker, B., 2006. School trips: effects of urban form and distance on travel mode. J. Am. Plan. Assoc. 72, 337–346. http://dx.doi.org/10.1080/01944360608976755.
Stan Development Team, 2017. Stan Modeling Language. User's Guid. Ref. Man, pp. 1–488. URL < http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102 > .
Timperio, A., Crawford, D., Telford, A., Salmon, J., 2004. Perceptions about the local neighborhood and walking and cycling among children. Prev. Med. (Baltim) 38, 39–47. http://dx.doi.org/10.1016/j.ypmed.2003.09.026.
Train, K.E., 2009. Discrete Choice Methods with Simulation, second ed. Cambridge University Press.
US Census Bureau, 2013. 2009–2012 American Community Survey 5 year estimate. Table B19113.
Van Buuren, S., Groothuis-Oudshoorn, K., 2011. Multivariate imputation by chained equations. J. Stat. Softw. 45, 1–67. http://dx.doi.org/10.1177/0962280206074463.
Vehtari, A., Gelman, A., Gabry, J., 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. 27, 1413–1432. http://dx.doi.org/10.1007/s11222-016-9696-4.
Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transp. Res. Part B: Methodol. 90, 192–217. http://dx.doi.org/10.1016/j.trb.2016.04.021.
von Hippel, P.T., 2007. Regression with missing Ys: an improved strategy for analyzing multiply imputed data. Sociol. Methodol. 37, 83–117.
Woldeamanuel, M., 2016. Younger teens' mode choice for school trips: do parents' attitudes toward safety and traffic conditions along the school route matter? Int. J. Sustain. Transp. 10, 147–155. http://dx.doi.org/10.1080/15568318.2013.871664.