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Making Bicycling Comfortable: Identifying Minimum Infrastructure Needs by Population Segments Using a Video Survey

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Making Bicycling Comfortable: Identifying Minimum Infrastructure Needs by Population Segments Using a Video Survey

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16. Abstract In this study, researchers use survey data to analyze bicycling comfort and its relationship with socio-demographics, bicycling attitudes, and bicycling behavior. An existing survey of students, faculty, and staff at UC Davis (n=3089) who rated video clips of bicycling environments based on their perceived comfort as a part of the UC Davis annual Campus Travel Survey (CTS) is used. The video clips come from a variety of urban and semi-rural roads (designated California state highways) around the San Francisco Bay Area where bicycling rates vary. Results indicate considerable effects of socio-demographics and attitudes on absolute video ratings, but relative agreement about which videos are most comfortable and uncomfortable across population segments. In addition, presence of bike infrastructure and low speed roads are the strongest video factors generating more comfortable ratings. However, the results suggest that even the best designed on-road bike facilities are unlikely to provide a comfortable bicycling environment for those without a predisposition to bicycle. This suggests that protected and separated bike facilities may be required for many people to consider bicycling. Nonetheless, the results provide guidance for improving roads with on-street bike facilities where protected or separated facilities may not be suitable.		
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Making Bicycling Comfortable: Identifying Minimum Infrastructure Needs by Population Segments Using a Video Survey

A National Center for Sustainable Transportation Research Report

January 2020

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EXECUTIVE SUMMARY

Understanding what environments are comfortable (and perceived as safe) for bicyclists is essential for increasing bicycling, particularly for non-experienced riders. Surveys probing people's qualitative perceptions about bicycling environments can inform bicycle planning in important ways. In this study we use survey data to analyze bicycling comfort and its relationship with socio-demographics, bicycling attitudes, and bicycling behavior. We use an existing survey of students, faculty, and staff at UC Davis (n=3089) who rated video clips of bicycling environments based on their perceived comfort as a part of the UC Davis annual Campus Travel Survey (CTS). The video clips come from a variety of urban and semi-rural roads (designated California state highways) around the San Francisco Bay Area where bicycling rates vary. Our results indicate considerable effects of socio-demographics and attitudes on absolute video ratings, but we find relative agreement about which videos are most comfortable and uncomfortable across our sample population segments. In addition, presence of bike infrastructure and low speed roads (low posted *and* equal or lower prevailing speeds) are the strongest video factors generating more comfortable ratings. However, our results suggest that even the best (according to attributes in our data) designed on-road bike facilities are unlikely to provide a comfortable bicycling environment for those without a predisposition to bicycle. Nonetheless, our results provide guidance for improving roads with on-street bike facilities where protected or separated facilities may not be suitable.

Introduction

Many major cities in California have adopted the goal of increasing their bike mode share to reduce emissions and increase public health. To meet these goals, cities are making investments to change road environments to better accommodate bicyclists. However, the effect these investments is likely to have on bicyclist safety and on levels of bicycling is difficult to estimate. At the city level, investments in bike infrastructure are correlated with higher rates of bicycling (Pucher et al., 2011). Individual-level studies show that people prefer bicycle-specific infrastructure in their decision to bicycle and in their choice of routes (Broach and Dill, 2016). Before-and-after studies of infrastructure investments show a similar trend of increasing use of roads following bicycling investments (Monsere et al., 2014). However, despite substantial investments, bicycling rates in most cities remain below targets.

There is growing evidence that safe and comfortable bicycling environments are a necessary condition for bicycling to become a mainstream day-to-day travel mode. Besides distance, a lack of perceived safety may be the most important barrier to the decision to bicycle (Fowler et al., 2017; Handy et al., 2002; Sallis et al., 2013). Evidence overwhelmingly points to the importance of protected bike lanes and off-street paths for providing a safer and more comfortable bicycling environment, especially for less experienced bicyclists (Dill et al., 2015; Harris et al., 2013; Monsere et al., 2014; Teschke et al., 2012; Winters et al., 2013). However, cities often find it difficult to provide these types of facilities due to their higher costs, political opposition, and the challenge of integrating them into the transportation network. For this reason, on-road bike infrastructure such as mixed travel lanes and bike lanes remain important to the effort to increase bicycling, and planners face the challenge of designing such facilities to feel safe and comfortable despite the limited protection from traffic they provide.

Providing environments perceived to be safe for prospective bicyclists is made challenging by the fact that individuals differ as to the type of environments in which they feel safe. Research shows, for example, that women and men differ significantly in their comfort with and perceptions of safety for the same environments (Garrard et al., 2012). Most past studies have either focused on one segment of the population, often existing bicyclists, with less attention paid to variability across the population. One way for planners to get a practical handle on this variability is to classify potential bicyclists according to safety perceptions. However, the wide variety of social, personal, environmental variables that determine individual bicycling behavior makes a meaningful classification of potential bicyclists challenging. Some researchers approach the problem holistically and classify people by existing travel behavior and other characteristics (Damant-Sirois et al., 2014); others focus on a few key variables such as comfort and interest (Dill and McNeil, 2013).

Surveys are by far the most common way researchers probe people's feelings about bicycling comfort and safety. The distinction between perceived safety (from traffic) and comfort for bicycling is not clear; and unlike for driving, the two tend to be conflated. Being comfortable bicycling certainly implies feeling safe, and it may also be more causally related to the decision to ride a bike. Although attempts have been made to measure comfort more objectively (Doorley et al., 2015; Fitch, 2018), surveys remain the most feasible method. These types of

surveys require participants to score a qualitative concept (e.g., comfort) on a quantitative scale (e.g., Likert type scales). Such surveys rely on textual or visual cues to assess the influence of bicycling infrastructure on people's comfort. Video cues are becoming more commonly used because of their realism for portraying the road environment and the ease of use when administering a large-scale survey over the web. Although video surveys do not directly measure bicyclist comfort in the real world, past evidence suggests the bias may result in an equal or even conservative estimate of comfort. For example, Fitch and Handy (2017) show that video responses of bicycling comfort are more negative than responses following real bicycling on the road.

In this study we analyze the degree to which individuals perceive different types of bicycling environments as comfortable, with the goal of providing guidance on the quality of infrastructure needed to expand the pool of potential bicyclists. We use a video survey to measure variation in perceptions across a population that includes non-bicyclists as well as bicyclists, and our analysis identifies sub-populations that are relatively homogeneous with respect to their infrastructure preferences. The results of this study can inform planning efforts and investment decisions that aim to increasing bicycling as a mode of transportation. Our three primary research questions are as follows:

(1) How much variation in bicycling comfort is explained by personal characteristics compared to road characteristics?

(2) Which road characteristics have the strongest relationship with bicycling comfort? Do certain characteristics have stronger effects on some sub-populations?

(3) What are the infrastructure minimums for comfortable on-street bicycling?

Methodology

Data Collection

Survey

We administered the video survey as a part of the 2017 UC Davis Campus Travel Survey (CTS). The CTS is an annual survey of travel to and from the university administered on-line to a representative random sample of faculty, staff, and students (Wei, 2018). However, responses tend to be non-representative in many ways (e.g., much larger proportion of women respond than men). Respondents were recruited through email and incentivized with raffles for forty $50 pre-paid debit cards and two tablet computers.

The UC Davis population is unique with respect to bicycling behavior in that the majority bicycle to campus, encouraged by a relatively safe bicycling environment and strong bicycling culture. Thus, the sample used in this study provides a unique perspective on the link between infrastructure and bicycling comfort and perceived safety. Because many participants have experience bicycling in Davis, they are more aware of, and have likely reflected on, the attributes of a road that make them comfortable. This is not the same for prospective bicyclists in other cities who have little or no experience bicycling for day-to-day travel. In addition, the

UC Davis sample is dissimilar from existing bicyclist samples in larger cities of the San Francisco Bay Area (where the videos were recorded). In general, existing day-to-day bicyclists in the Bay Area are more willing than most to bicycle in non-ideal environments (e.g., mixed traffic, high speed roads). In this way, the Davis population offers a nice balance between experience (to help ensure the measure of comfort is accurate) and willingness to bicycle in non-ideal environments (many of which are likely similar to prospective bicyclists in the Bay Area). However, they are not representative of a wider prospective bicyclist population across California.

The sample size for this study is n=3089. Along with survey responses associated with the video experiment, described below, we measured many other variables in the main survey. These include main travel mode to campus, specific travel frequency by mode to campus in the prior week, campus role (student/grad student/faculty/staff), age, gender, household structure, bicycling confidence, bicycling comfort in a variety of environments (through textual descriptions), and some more specific travel attitudes. We measured bicycling confidence and comfort through textual descriptions. For example, we asked respondents to rate their bicycling ability. For those that could ride a bike, they were asked to select either *I can ride a bike, but I'm not very confident doing so*; *I am somewhat confident riding a bike*; or *I am very confident riding a bike*. For bicycling comfort, we asked, "In general, how comfortable would you be riding a bicycling on a **four-lane street (two lanes in either direction) without a bicycle lane,** in daylight and good weather?" Respondents were asked to select *Uncomfortable and I wouldn't ride on it*; *Uncomfortable but I would ride on it*; or *Comfortable*. All other travel attitudes we measured using statements and Likert-type responses from strongly disagree to strongly agree. For example, respondents selected how much the agreed or disagreed with the statement "I like riding a bike". We refer to the socio-demographic and attitudinal variables as individual-level characteristics in our analysis.

Experimental Design

In designing the video survey to answer the above research questions, we chose 25 videos (10 seconds in length) based on recordings taken from a variety of mostly urban arterials and some rural roads (designated California state highways) around the Bay Area from a prior study (Griswold et al., 2018). Owing to the purpose of this prior study, these videos represented on-street facilities but not protected bike lanes or off-street bike or shared-use paths.

We consider each video a different bicycling infrastructure treatment level (creating a nominal predictor variable for the models described below). Each video is assigned to one of five bicycle infrastructure classes (shared arterial, shared collector road, bike lane with high speeds, bike lane with moderate speeds, and buffered bike lane). To limit survey burden, we designed our survey to function as two parallel experiments, one in which participants see videos of very similar road environments with only subtle differences in road characteristics (within-class treatments), and one in which participants see videos of very different road environments with extreme differences in road characteristics (between-class treatments) (Table 1). This allowed us to examine if participants' comfort ratings (explained below) depended on the degree of

variation in the video clips they saw in the experiment. Our treatment assignment procedure was as follows:

(1) Randomly assign a person to the within-class treatment or the between-class treatment, while maintaining a balance in the assignments to the two treatments.

(2) For within-class treatments, randomly assign one of five bicycle infrastructure classes, also known as blocks in experimental research. Do this while maintaining balanced assignment across all five blocks. Then present the five videos of the block in random order.

(3) For between-class treatments, randomly assign one video from each of the 5 blocks and present them in random order. Do this while maintaining balanced assignment across all videos.

Table 1 demonstrates how the procedure results in a nearly balanced data collection across the two treatment types and the infrastructure classes. The video names in Table 1 are shorthand for the location of the video clip. For example, "4th_AddisonUniversity" indicates the video comes from 4th St between Addison and University in Berkeley, CA.

Table 1. Experimental Design

Infrastructure Class	Video name	Within-Class treatments	Between-Class treatments
Shared collector	Virginia_ChestnutWestStPath	X	One random video from 1-5
	4th_AddisonUniversity	X	
	4th_VirginiaDelaware	X	
	Chabot_CollegePresley	X	
	Skyline_SnakeManzanita	X	
Shared arterial	SanPablo_GilmanHarrison	X	One random video from 6-10
	SanPablo_CedarVirginia	X	
	Ashby_CaliforniaKing	X	
	Ashby_DeakinTelegraph	X	
	Ashby_ColbyRegent	X	
Bike lane adjacent to fast traffic or rural highway	Tunnel_OakRidgeUplands	X	One random video from 10-15
	SanPabloDam_WildcatOldSanPabloDam	X	
	Skyline_FortFunstonOlympic	X	
	Hwy1_MartiniCreek	X	
	GrizzlyPeak_SouthClaremont	X	
Bike lane adjacent to moderate speed traffic	SanPabloDam_FireTrailNo3	X	One random video from 16-20
	California_FranciscoDelaware	X	
	Channing_DanaEllsworth	X	
	Alcatraz_ColbyHillegass	X	
	Broadway_GoldenGateLakeTemescal	X	

Infrastructure Class	Video name	Within-Class treatments	Between-Class treatments
Buffered bike lane	Tunnel_HillerVincente	X	
	Tunnel_VicenteBridge	X	One random video from 21-25
	CaminoPablo_ElToyonal	X	
	Miles_CollegeForest	X	
	Sloat35_CreastlakeGabilan	X	

To measure comfort with each environment, the survey asked the following of each participant:

"Next you will view 5 short video clips (10 seconds each). For each clip, imagine that you are bicycling in the environment shown and then rate how comfortable you would feel"

Participants then viewed the video clip and responded based on a 7-point Likert-type response scale (see Figure 1). We removed all audio from the video clips. This reduced the realism somewhat because sound is often a good indicator of a soon to be passing vehicle. However, because we could not control the participants audio, we decided to exclude sound.

| Very uncomfortable | Moderately uncomfortable | Slightly uncomfortable | Neither comfortable nor uncomfortable | Slightly comfortable | Moderately comfortable | Very comfortable |

Figure 1. Example image of video survey with response categories.

Video and Infrastructure Data

While the videos are themselves treated as variables in our analysis, the characteristics of the videos are also a primary focus. We focus on the following features of the videos (i.e., road-level variables) that were collected in the field during video recording or after reviewing the videos from (Griswold et al., 2018):

- Posted speed limit

- Presence of bike lane
- Presence of buffered bike lane
- Presence of street parking
- Prevailing car speed
- Bike lane width
- Bike lane and parking lane combined width
- Shoulder width
- Outside car lane width (lane closest to bike lane, shoulder, or curb)
- Car volume
- Presence of divided road
- Total bicycling operating space (sum of bike lane width, parking lane width, and shoulder width)

Prevailing car speed was measured by reviewing the videos and timing when cars passed screen lines of known distances. Car volume was assigned as "None" (no moving cars in the same direction present), "Low" (at least one moving car present and no more than 2 passing cars), "High" (more than 2 passing cars). All other road-level variables were measured in the field.

We used these data and three common metrics of "bikeability" from Griswold et al. (2018), the Highway Capacity Manual Bicycle Level of Service (HCM BLOS) (National Research Council and Transportation Reserach Board, 2010), the National Cooperative Highway Research Program Bicycle Level of Service (NCHRP BLOS) (Dowling et al., 2008), and the Bicycle Level of Traffic Stress (BLTS) (Mekuria et al., 2012).

Analysis

The intention of the experimental design was to reduce survey burden while at the same time providing the ability to examine within- and between-class variability in comfort rating. When considering individual-level effects, we found that those in the "between" group tended to have higher variance in their ratings and less variance in their means compared to the "within" group, both of which results are expected for the experimental design. However, examination of the comfort ratings by these groups at their means or in the aggregate revealed negligible differences (Figure 2). While the differences observed in Figure 2 are unlikely to be due to chance with this large of a sample (χ^2 = 27.6, p = 0.0001), the strength of the relationship between video group and comfort rating is very weak (Cramer's V = 0.04). Given this finding, we ignore the video group treatment assignment in our statistical models and pool all the data from both treatments.
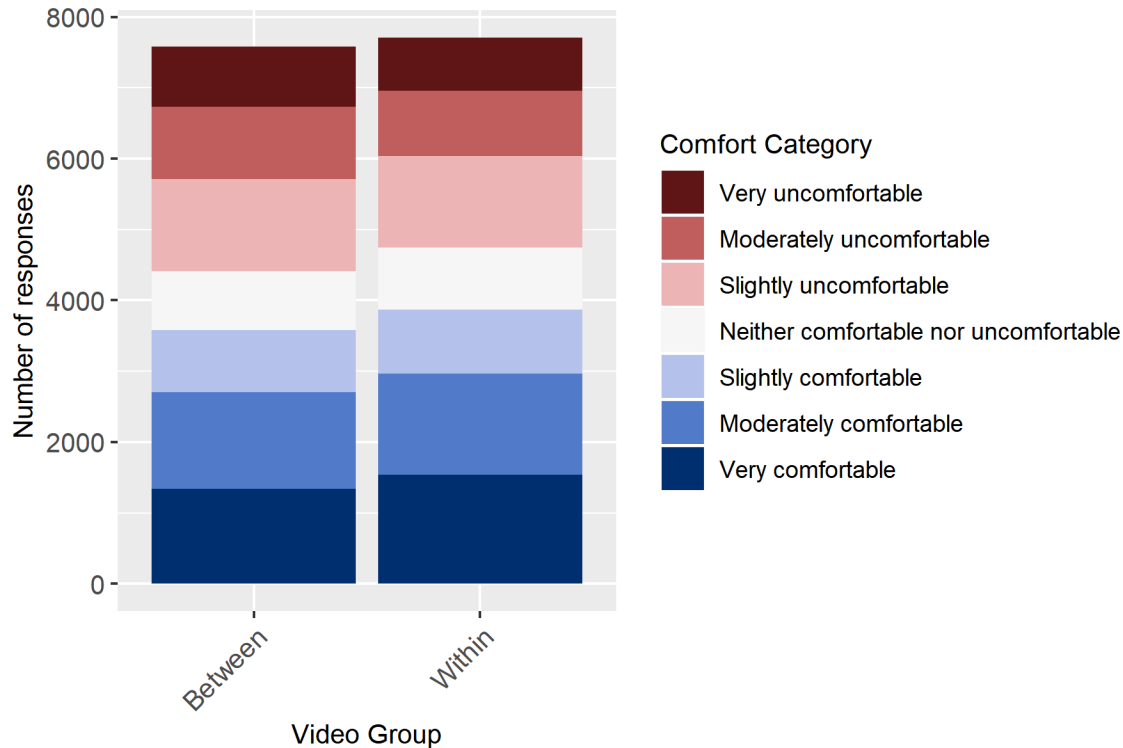
Figure 2. Comparison of scores by within and between group participants.

Descriptive and Bivariate Relationships

We used exploratory data analysis to examine the relationship between all the variables and bicycling comfort. This included both univariate and bivariate visualizations without formal tests of statistically significant differences. The exploratory analysis was primarily used to determine problematic variables (highly correlated, too much missing data, etc.) and to guide the transformation of variables for more formal statistical analyses.

Predictor Variables

Our data contains measurements of 20 road-level variables, including the three external composite scores of "bikeability", and about twice as many individual-level characteristics of the survey respondents. About half of the individual-level characteristics are attitudinal variables, such as how much an individual "likes riding a bike," measured on a five-point Likert-type scale. The rest are demographic, including one's primary role at the university (e.g., Undergraduate Student, Staff), gender, age, and household composition. We case-wise deleted missing values or removed variables with a large percentage of missing data. The only exception was the case of age, which we imputed missing values. We also reduced the number of variables through a series of exploratory analyses (see Appendix A: Extended Methods for details about variable cleaning and selecting). For easier model parameter interpretation (see below), we transformed all variables to the 0-1 scale. For categorical variables we simply used binary indicators for one less than the total number of categories. For the 5-point Likert-type responses we coded {Strongly disagree, Somewhat disagree, Neither agree nor disagree,

Somewhat agree, Strongly agree} as {0, 0.25, 0.5, 0.75, 1}. For numeric variables in units of distance we normalized based on the minimum and maximum (e.g., $x_i – min(x)/max(x) – min(x)$).

Statistical Modeling

We used an ordinal logistic regression model to analyze the bicycling comfort ratings (see Appendix A: Extended Methods for modeling details). This model type is most appropriate for the seven-level ordinal measure of comfort, the dependent variable in the models. We first conducted exploratory modeling using penalized (lasso) maximum likelihood estimation of model parameters to help us decide on which variables to remove before further, more computationally intensive analysis (see Appendix A: Extended Methods for details). We always included variables that could be supported by theory or prior empirical study, and we only used this technique to make decisions about variables for which we were uncertain about their effect on people's bicycling comfort ratings. With the reduced set of variables, we built a series of regression models with increasing complexity to examine the influence of model complexity and variables in groups (see Table 2 for a simple description and Appendix A: Extended Methods for more details). The models in Table 2 are named based on their "varying effects" and the groups of variables they include to explain bicycling comfort. Models with varying effects for *Person* indicate they allow the average rating to vary by person (making them multi-level models). I.e., the model estimates a unique average for each person and a spread of those averages to account for within- and between-person heterogeneity in ratings. Similarly, models with "varying effects" for *Video* indicate they allow the average rating to vary by video. I.e., the model estimates a unique average for each video and a spread of those averages to account for within- and between-video heterogeneity in ratings. The non-varying effects are traditional predictor variables in regression modeling.

Table 2. Description of Models

Model Name	Varying Effects	Non-varying Effects	
		Person level	**Video level**
Null-Person	Person		
Null-Person-Video	Person, Video		
Main effects-Person	Person	Socio-demographic, attitudes and perceptions	
Main effects-Person-Video	Person, Video	Socio-demographic, attitudes and perceptions	Street parking, operating space, vehicle volume and speed, bike infrastructure
Interaction-Person	Person	Socio-demographic, attitudes and perceptions	Street parking, operating space, vehicle volume and speed, bike infrastructure. Interactions between street parking and bike infrastructure, vehicle volume and bike infrastructure, operating space and speed limits, vehicle volume and speed limits
Interaction-Person-Video	Person, Video	Socio-demographic, attitudes and perceptions	Street parking, operating space, vehicle volume and speed, bike infrastructure. Interactions between street parking and bike infrastructure, vehicle volume and bike infrastructure, operating space and speed limits, vehicle volume and speed limits.

We use the six models (Table 2) to understand how influential the variables are for predicting comfort ratings (by comparing expected predictions between models). The Bayesian estimation procedure we employ to estimate all the models facilitates these assessments (see Appendix A: Extended Methods). In Appendix B: Model Parameter Summaries, we report the estimating prediction for the six models. The estimates suggest that including varying effects for person and video greatly influence ratings. Furthermore, that including all variables and those varying effects we can expect the best predictions. This indicates that even when we include person level and road level variables, we are missing some explanatory power from variables relating to both the video (e.g., other road level or context variables) and the person (e.g., other intrapersonal characteristics). However, when we examined interaction models, the expected prediction is very similar to the models without the interaction effects. This suggests we are limited by our data for examining road variable interactions. Because the interaction models did not provide better expected predictions for the main effect models, we selected the *Main effects-Person-Video* model for detailed inferences, scenarios analysis, and discussion.

Limitations

Like all study designs that employ surveys, our study is limited by the representativeness of the sample we obtain. Our UC Davis sample offers a unique view into bicycling comfort, but it should not be interpreted as representative of current or prospective bicyclists everywhere. Because our sample is from the UC Davis campus travel survey, it is dominated by young undergraduates (Figure 3). We also have about twice as many responses from women compared to men, and the share of bike commuters is also very high. These are common results from the annual UC Davis campus travel survey. Women tend to respond to the survey at much greater rates than men, and because Davis is a very bike friendly city and campus, bicycling is commonplace.
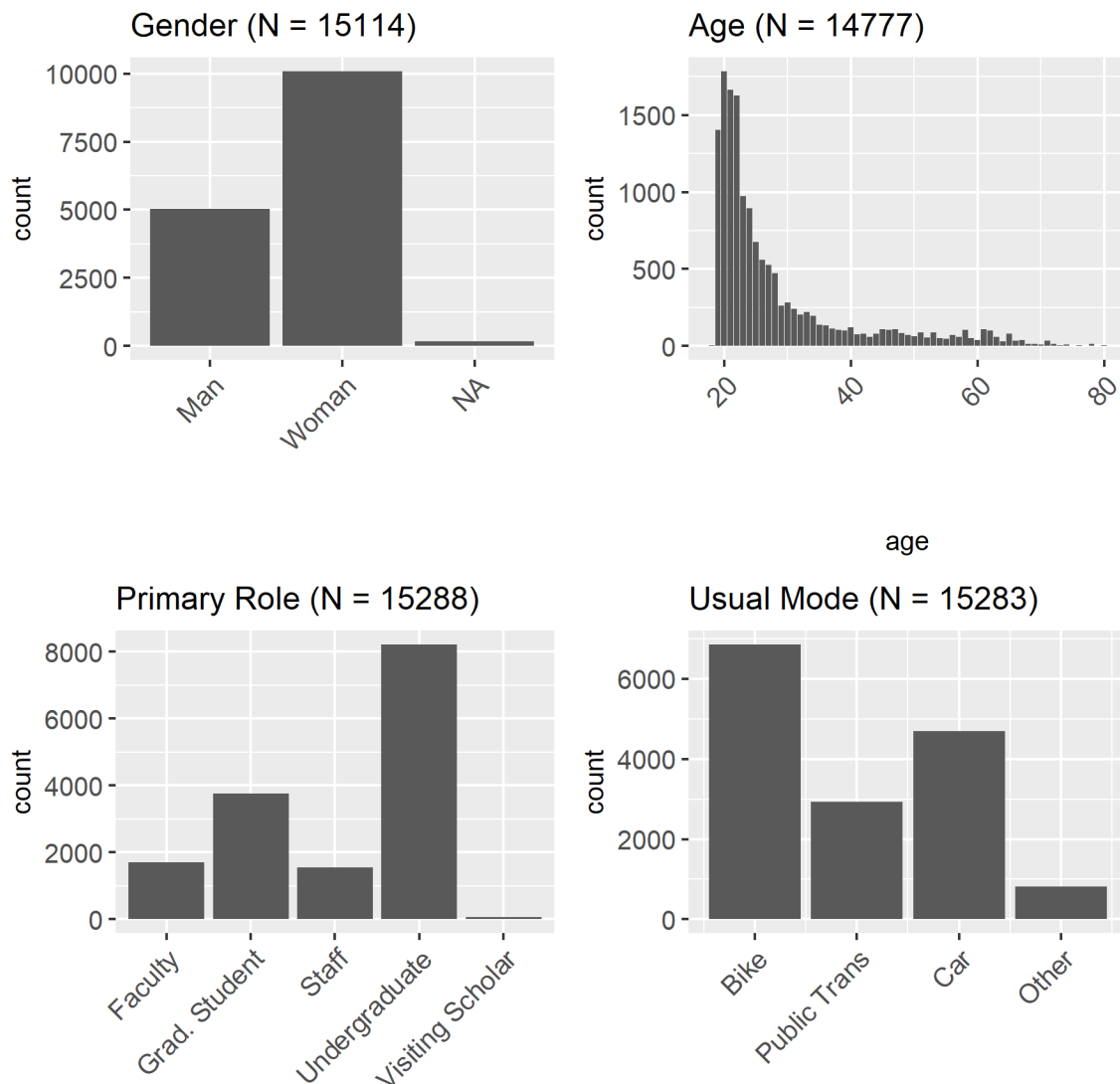
Figure 3. Sample characteristics in total counts of comfort responses.

Our study is also limited in the variety of road environments we examine. Because we use videos from a prior study focusing on urban and rural roads, we were not able to examine characteristics of protected bike lanes and off-street paths. This is unfortunate because prior research suggests that these types of infrastructure are very important for providing comfortable bicycling spaces. This limitation is most evident in our inability to simulate a comfortable environment for a large share of our respondents in our policy analysis section (see below). Notwithstanding these limitations, our study does help highlight the features of on-street roads that might be altered to increase bicycling comfort for some current and prospective bicyclists.

Results and Discussion

Bicycling Comfort and Personal Characteristics

Reported bicycling comfort varied substantially across the 25 videos (Figure 4). The videos are ordered by average rating from most comfortable to least comfortable to more easily observe trends in the data. While respondents never unanimously responded on one side of the comfort scale (e.g., either comfortable or uncomfortable) for any one video, many videos had a super majority of users report on one side of the comfort scale (see top seven videos and bottom three videos from Figure 4). However, most of the videos saw considerable variation in comfort, many with large numbers of people responding in opposing opinions on being comfortable bicycling in the environment shown in the video.
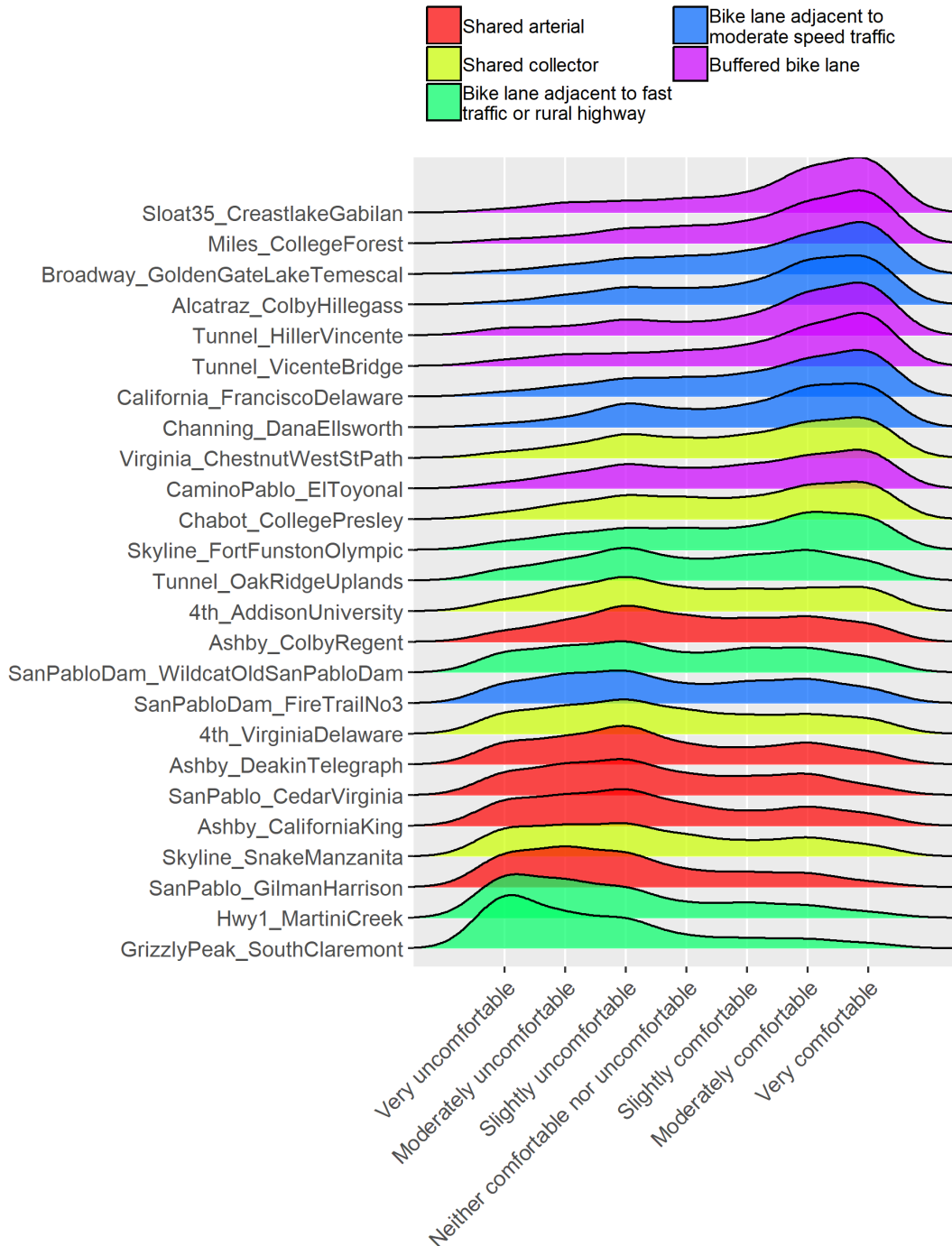
Figure 4. Kernel density estimates of the distribution of comfort responses by video name and infrastructure class.

Socio-Demographics

The socio-demographic variables are correlated with bicycling comfort to varying degrees (Figure 5). For example, women are less likely to rate videos as comfortable compared to men (Figure 5), and this finding holds for every single unique video (Figure 6). In most videos the

gender differences are small (a median difference of one if we consider the seven classes evenly spaced). Also, men and women are in general agreement about the relative comfort provided by each video (i.e., men and women all felt most uncomfortable on the same videos, and vice versa). Age also has a strong correlation with reported comfort on the uncomfortable side of the scale (Figure 5). The percentage of ratings on the comfortable side of the scale were nearly equivalent by age, but older respondents were much less likely to select a neutral response and instead more likely to indicate discomfort (Figure 5). To a lesser extent this same phenomenon can be seen in the correlation between university role and ratings (Figure 5), but since age and university role are heavily correlated, we only include age in our models (as we assume it is more likely to be causally related to bicycling comfort). These bivariate correlations are substantiated by the statistical models given that clear conditional effects are observed in the models even when accounting for all the other predictor variables (see below and Appendix B: Model Parameter Summaries).
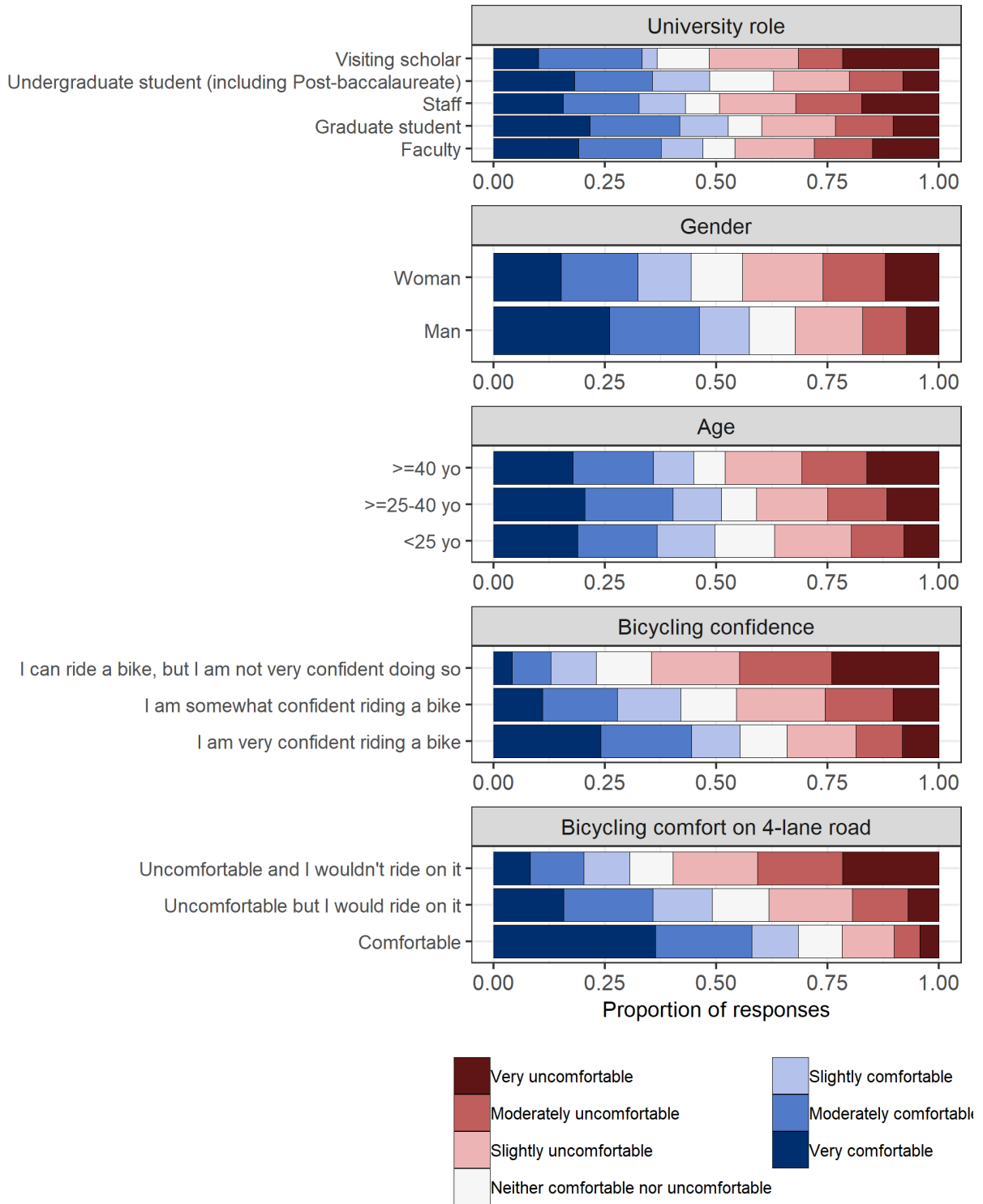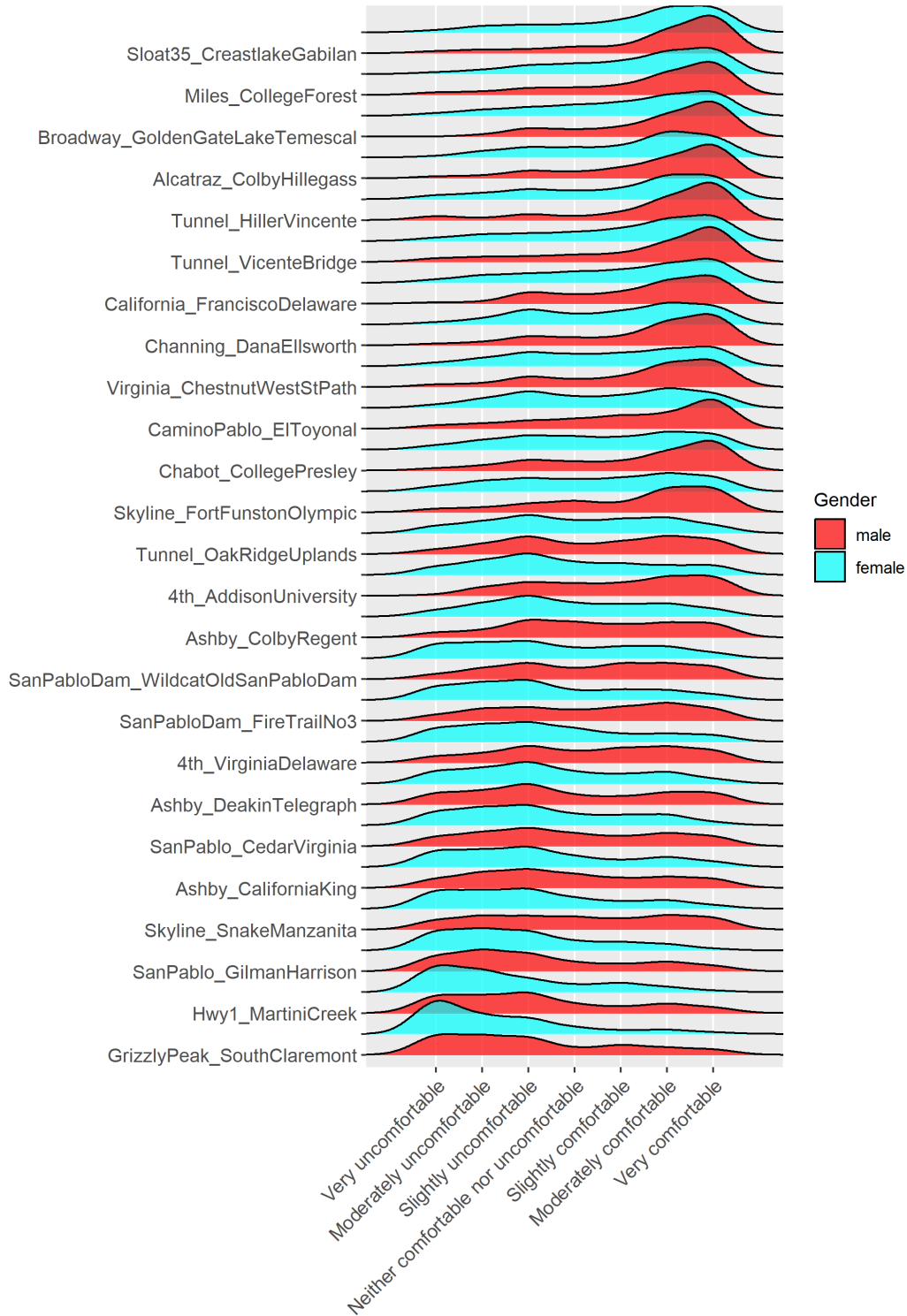
Figure 5. Video ratings by person level socio-demographics and bicycling perceptions.

Figure 6. Kernel density estimates of the distribution of comfort responses by video name and gender.

Attitudes and Perceptions

Beyond socio-demographics, some of the strongest person-level variables that correlate with comfort ratings are self-reported bicycling confidence and bicycling comfort on a generic four-lane arterial with no bike lane in daylight and good weather (Figure 5). Self-reported bicycling confidence is positively correlated with video ratings. With a three-class variable of bicycling confidence, video ratings seem to linearly rise with increased confidence. This can be seen in the difference in the proportion of red and blue bars for the different bicycling confidence classes (Figure 5). The self-reported bicycling comfort on a generic four-lane arterial is also positively correlated with video ratings. This is not surprising because we expect people's general and specific measures of bicycling comfort to be bi-directionally causal. For example, a person's general comfort is likely to have been constructed from a series of specific experiences as a bicyclist or as a traveler more generally. At the same time, that person's general comfort is likely to influence how they perceive new experiences.

Other bicycling and travel attitudes are also correlated with video ratings (Figure 7). People who agree with the statements "I like riding a bike", "I feel safe bicycling on campus", and to a lesser extent "I like using public transit" are more likely to rate the videos as comfortable. The opposite is true of people who agree with the statements "I need a car to do many of the things I like to do", "I need to dress professionally for my job", and "traveling to campus stresses me out". These results suggest that people with more favorable bike attitudes are more comfortable with the environments compared to people with less favorable bike attitudes. Also, people with jobs requiring professional dress and people with car lifestyles are less comfortable bicycling compared to others. Of course, a respondent could certainly have both strong bike attitudes and live a car-focused or professional lifestyle, but in the aggregate, they seem to have opposite associations with bicycling comfort.

Because responses to the statement "I like riding a bike" have shown strong associations with bicycling behavior (Handy et al., 2010), it is not surprising that this statement has strong associations with reported bicycling comfort in this video experiment. Those respondents who agree they like riding a bike (strongly and somewhat) show some interesting video rating patterns in comparison to those who don't (strongly and somewhat) (Figure 8). For example, the top-rated videos show large differences between the like-bike and the don't-like-bike groups. However, the same is not true of the lowest rated videos (Figure 8). In the lowest rated videos, the like-bike and the don't-like-bike groups are more in agreement that the videos pose an uncomfortable bicycling environment. This non-linear effect of bike attitudes at the video level suggests that bike attitudes may only be good for explaining the bicycling comfort in environments where some minimum infrastructure exists. Without that minimum infrastructure, even the like-bike group is uncomfortable bicycling.

This same infrastructure minimum may even hold for some people who report being comfortable bicycling on a four-lane road without a bike lane (Figure 9). However, some of those people (blue density in Figure 9) still report being comfortable even on the most uncomfortable (in the aggregate) videos. To a lesser degree, the opposite is true of the people

who are uncomfortable bicycling on a four-lane road (red density in Figure 9). Many of those people are uncomfortable even on the roads where most people report being comfortable.
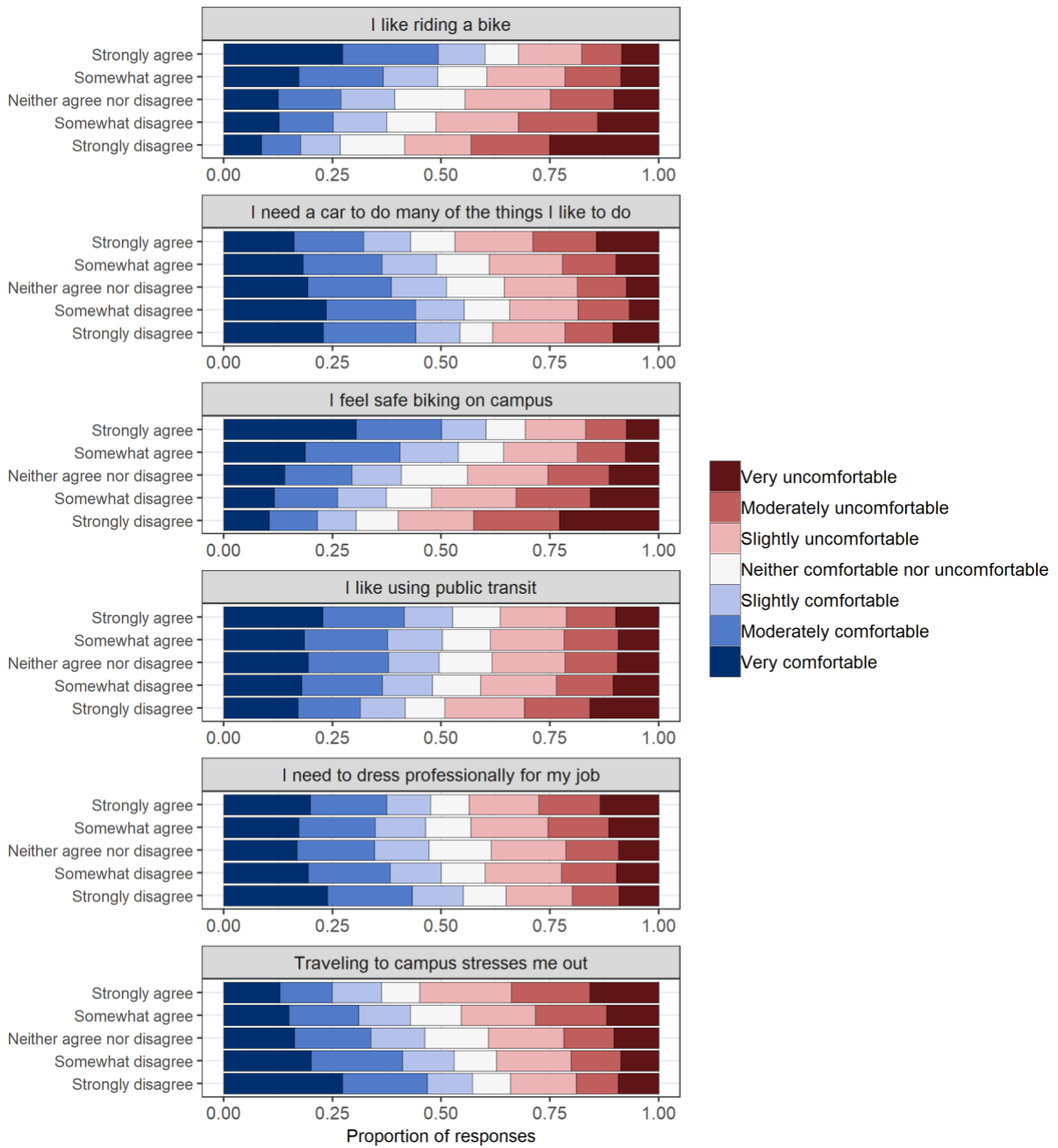
Figure 7. Video ratings by person level attitude statements.
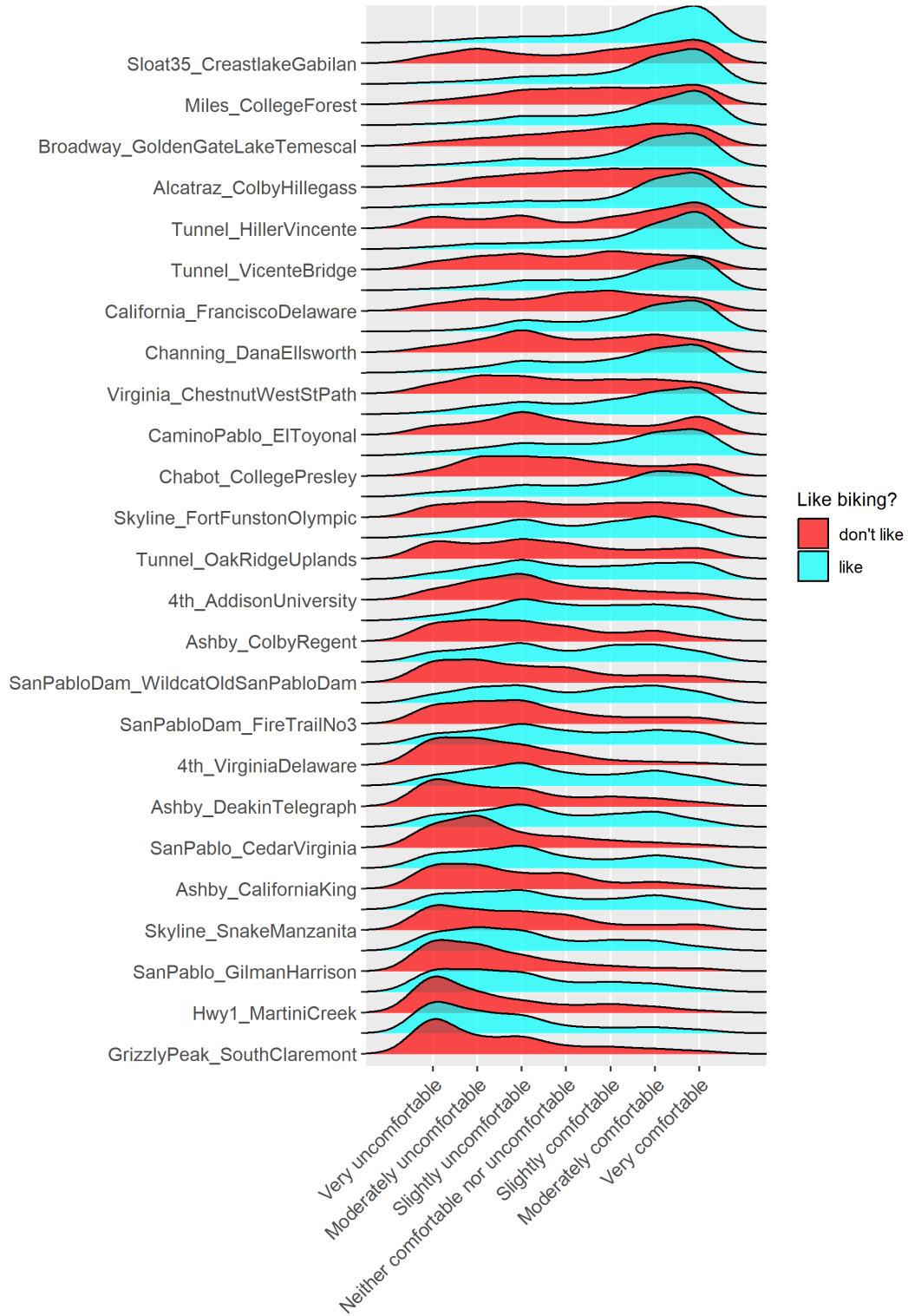
Figure 8. Kernel density estimates of the distribution of comfort responses by video name and liking biking.
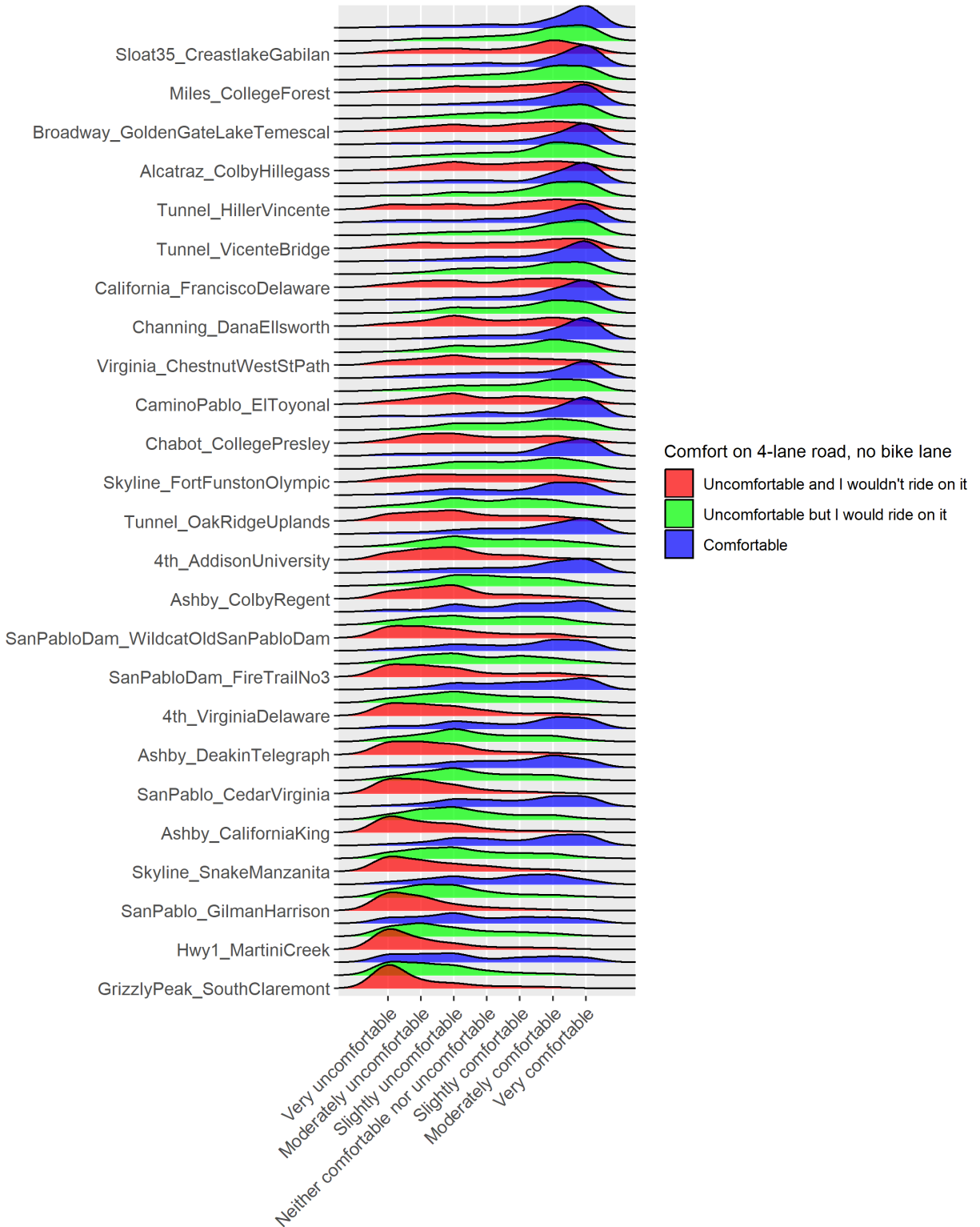
Figure 9. Kernel density estimates of distribution of comfort responses by video name and comfort.

Video-Level Variables

Wide variation in comfort responses between videos indicates that peoples' comfort is determined by features seen in the videos. Some of the features that correlate with comfort across the videos are presented in Figure 10. While these are only a subset of the countless features seen in the videos, they represent some of the most important road-level variables that have been observed in the literature to influence bicyclist comfort and safety (Buehler and Dill, 2016; Dill et al., 2013; Sanders, 2014). Many of the more subtle features of the videos (e.g., adjacent land use, turning movements of cars, pavement roughness, etc.), while not considered in our analysis independently, are roughly accounted for in the multi-level models in the following sections (see below). Figure 10 confirms that variables like presence of bike lanes and buffered bike lanes, number of car lanes, presence of medians, bike lane width, total bike operating space, and car volumes have clear correlations with bicycling comfort. However, posted speed limit, prevailing car speed, outside car lane width, and recording speed of the video are more ambiguous.

By far the strongest predictor of comfortable video ratings are the bike lane variables and the presence of only one vehicle lane in the direction of the bike traveler. However, these variables are not completely independent. For example, car volume and speed are associated with presence of bike lanes, so their individual level associations somewhat depend on each other. Furthermore, Figure 10 doesn't indicate sample sizes of these variables. Some levels of some variables (e.g., prevailing car speed) have very small sample sizes which limit the inferences we can make from their associations with video ratings. The model results (next section) help to improve our estimates of the associations between road-level variables and video ratings.
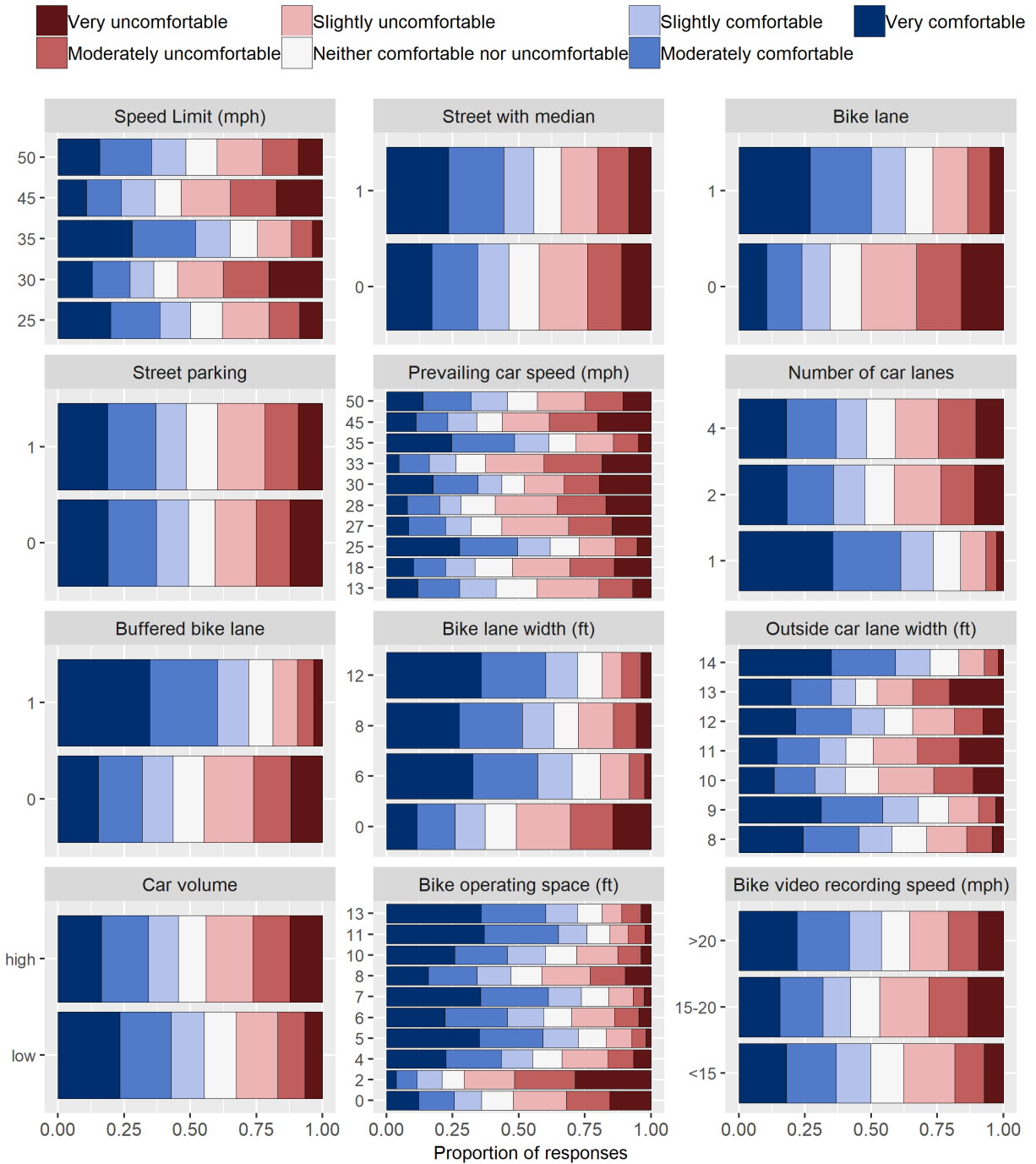
Figure 10. Road-level variable correlations with video responses. For dichotomous variables, 1 indicates presence, and 0 indicates absence of the variable.

Existing Level of Service Type Metrics Related to Bicycling Comfort

We also examined the relationship between reported bicycling comfort and three commonly used level-of-service metrics. While average comfort ratings correlated to some extent with the three metrics (Figure 11), the metrics do a poor job of reflecting the variation in comfort rating across all seven levels for all participants (Figure 12). Of the three scoring methods we consider, the HCM classification is the best predictor of comfort ratings in our data, and the NCHRP classification is the worst. However, when including these metrics in separate ordinal regression models, none provide very strong predictive ability. In fact, an ordinal regression model with two predictors "presence of a bike lane", and presence of a "buffered bike lane" has more predictive power than any of the models with the level-of-service metrics (results not shown). While the two BLOS metrics attempt to measure attributes beyond bicycling comfort, it is surprising that they do not do a better job of predicting reported bicycling comfort given that representing perceived safety is a top objective for those methods. This is especially the case for the Level of Traffic Stress (LTS) metric, since it is solely focused on bicyclist "stress" which is basically the inverse of our concept of bicycling comfort. These results highlight the inadequacy of current metrics to represent bicycling comfort, as has also been shown in other research (Griswold et al., 2018). More specifically, they suggest new metrics need to focus on extending the positive side of these metrics (e.g., categories A or 1).
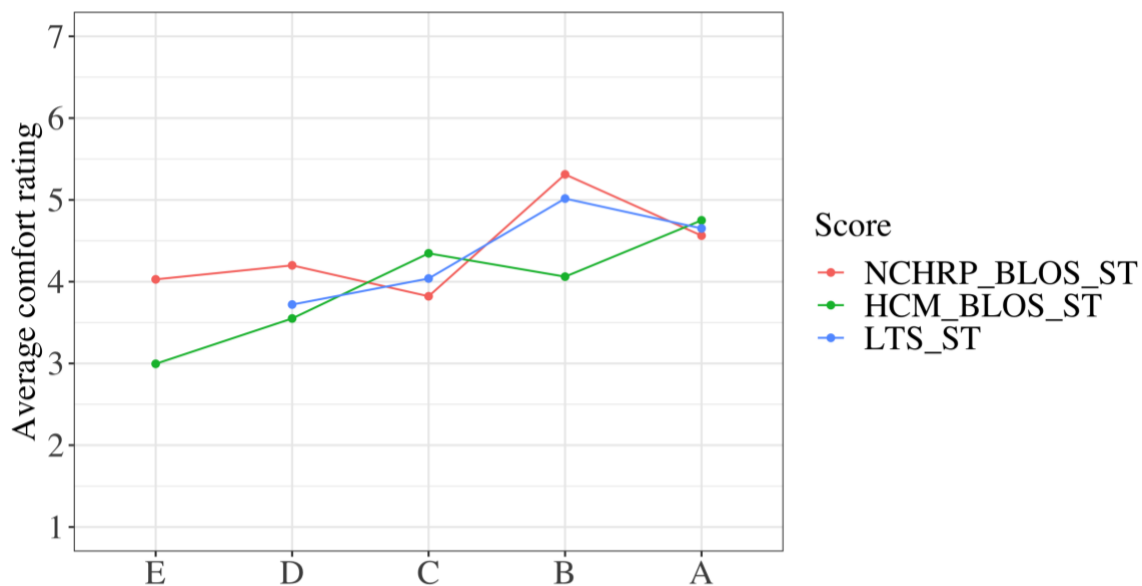
Figure 11. Average video rating by level-of-service metrics.
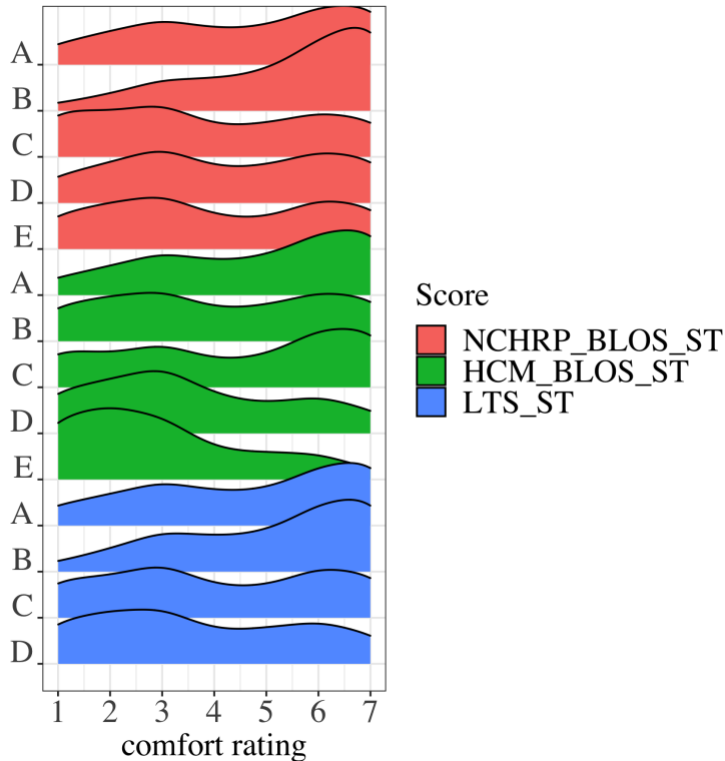
Figure 12. Kernel density estimates of distribution of comfort responses by level-of-service metrics. The LTS classes 1-4 have been labeled A-D for easier comparison with the other methods.

What Matters Most for Bicycling Comfort?

To examine how strongly the road characteristics influence bicycling comfort while considering the experimental design and individual differences through socio-demographics and attitudes, we used multi-variable models with varying effects by video and person (See Appendix A: Extended Methods for detailed description of our model development process). These models have the power of indicating conditional associations between the predictor variables and comfort ratings. For example, the effect of bike lanes on comfort rating in the models depends on all the other variables such as whether people like biking or whether they are confident bicyclists. This helps ensure the effect of bike lanes is adjusted to its *unique* effect on comfort ratings. Without this adjustment, the effect of bike lanes on comfort could be due to other correlated variables. We provide detailed summary of all the modeling results in Appendix B: Model Parameter Summaries, and only report one selected model for discussion in this section (*Main effects person-video*). The selected model includes parameters that allow the comfort scores to vary by video and by person (see standard deviation (SD) person ID and SD video name intercepts in Figure 13). The intercept parameters describe the average thresholds between the seven comfort response categories (i.e., very uncomfortable, moderately uncomfortable, slightly uncomfortable, neither uncomfortable nor comfortable, slightly comfortable, moderately comfortable, very comfortable). Because we used an ordered logistic regression, the parameters are on the log-cumulative odds scale making them difficult to

directly interpret. However, we scaled the predictor variables so that the magnitude of the parameters could be more easily compared. Thus, Figure 13 shows the relative strength of each predictor in explaining bicycling comfort. For example, identifying as a woman has a stronger effect on comfort compared to having a child in the household, even though both have negative effects on bicycling comfort. Age has a relatively strong negative relationship with bicycling comfort indicating that the youngest people in the sample are much more comfortable in comparison to the oldest people. The six attitudinal variables in the model show relationships in the expected direction (e.g., the bike attitudes are positive, and the car/work attitudes are negative), and they tend to be stronger predictors of comfort compared to both gender and children in the household. The variables specifically focused on bicycling confidence and comfort in general have the strongest (positive) relationships with comfort response. These multi-variate results substantiate some of the bi-variate results observed in Figure 9.

The remaining model parameters are the primary focus of this project because they provide the strongest evidence for identifying infrastructure minimums for comfortable bicycling. By including person-level variables, the modeled relationships between road-level variables and bicycling comfort are conditional on individual attitudes and preferences as far as we have defined them in the model. The first thing to observe about the road-level parameters in Figure 13 is the large uncertainty of the effect of most variables (clear from the broad densities). This is especially the case for the variable that indicates that bikes must share space with cars (e.g., no bike infrastructure). The wide uncertainty of these effects is most likely because we only have 25 videos to examine (i.e., 25 unique combinations of road-level variables), and when we include varying intercepts for those videos, the specific relationships between road-level variables become more uncertain (see Appendix B: Model Parameter Summaries). The few road variables that do show strong independent positive effects on comfort are the presence of a conventional bike lane or a buffered bike lane (Figure 13). Also, prevailing speeds at or below speed limits of 25 or 35 mph had strong effects on bicyclist comfort.

Along with estimates of road-level variables, the models indicate that person-level variation far outweighs the variation between the 25 videos (see standard deviation densities for SD person ID, and SD video name in Figure 13). This suggests that creating a comfortable bicycling environment for every participant with the features observed in these 25 videos will be impossible, and even that creating an environment that is comfortable for most participants will require the combination of many positive road attributes.
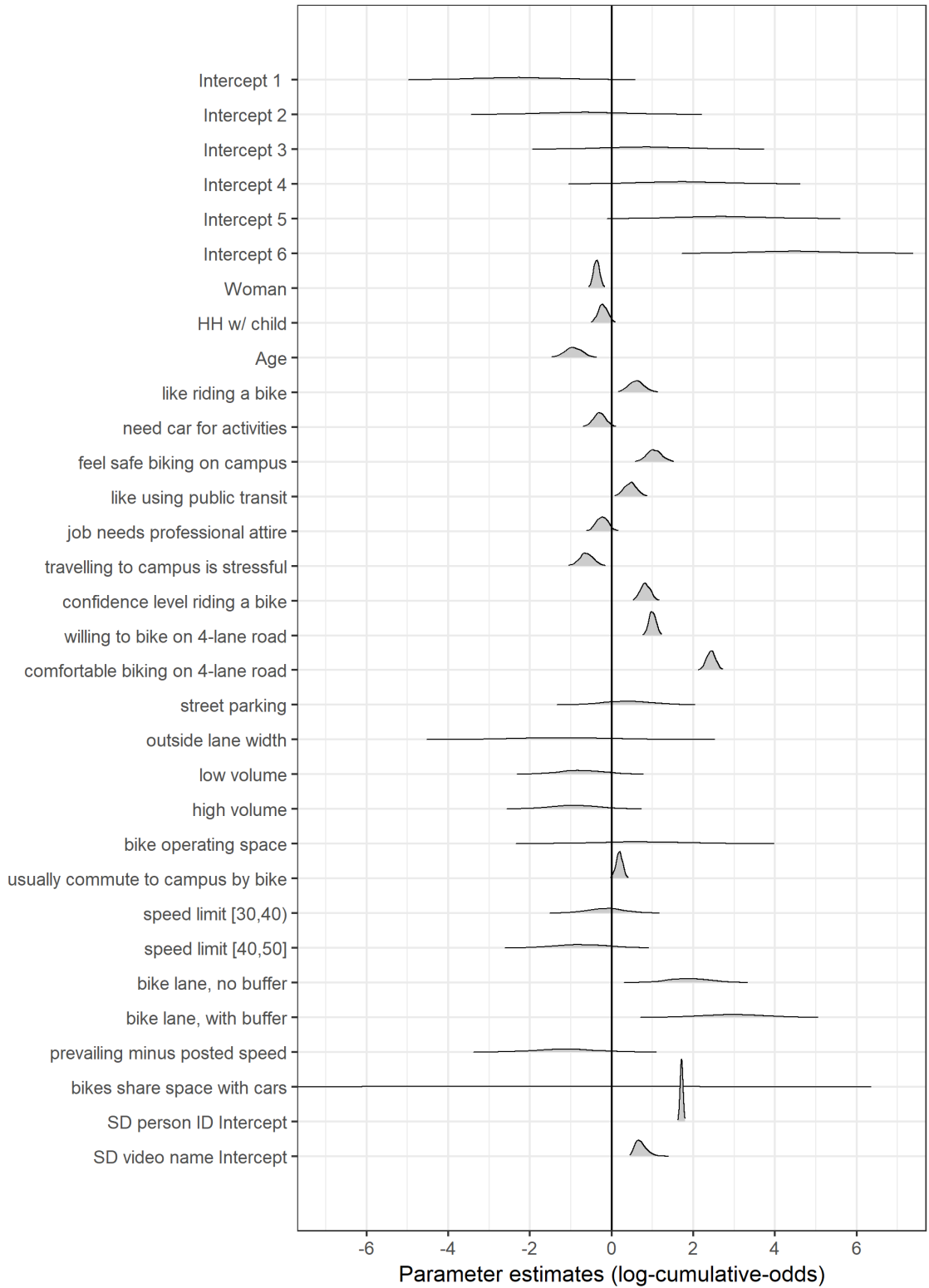
Figure 13. Model parameters describing the conditional relationships between each predictor variable and video response.

Estimating Minimum Infrastructure Needs

To estimate the minimum infrastructure needs for making bicycling comfortable for the participants in this study, we simulated new environments based on a combination of road features (Table 3). We fixed the person-level variables at levels that would create predictions for only a very conservative cohort from our sample. Specifically, we chose to simulate 57-year-old women without children in the household who are not very comfortable bicycling and in the 10th percentile for bike positive attitudes and 90% percentile for car-focused or professional lifestyle attitudes. Simulating a road environment that would be very comfortable for people fitting the above description proved very difficult. Even for the best possible collectors and arterials (given the constraints of our data), only 18-28% of simulated respondents would rate the roads as "very comfortable" (Figure 14). If we lower the bar to "at least slightly comfortable", we see that those best road environments are rated as comfortable for 50-65% of predicted responses. This finding highlights the inability of on-road facilities to enable comfortable bicycling for many in this conservative cohort and suggests that off-road or separated facilities may be the only environments that can provide a perceived safe and comfortable space to bike for people most uncomfortable bicycling on city streets.

Table 3. Attributes of simulated arterials and collectors

Scenario	Arterial			Collector		
	Poor	**Average**	**Good**	**Poor**	**Average**	**Good**
Vehicle Volume	High	High	High	High	Average	Low
Speed Limit	[40,50] mph	[40,50] mph	[30,40) mph	[30,40) mph	[30,40) mph	< 30 mph
Prevailing Speed – Speed Limit	5 mph	0 mph	-10 mph	5 mph	0 mph	-10 mph
Bike Lane type	None	Conventional	Buffered	None	Conventional	Buffered
On-Street Parking	Yes	Yes	Yes	Yes	Yes	Yes
Outside Lane Width	13 ft	11 ft	9 ft	13 ft	11 ft	9 ft
Bike Operating Space	0 ft	5 ft	11 ft	0 ft	5 ft	11 ft
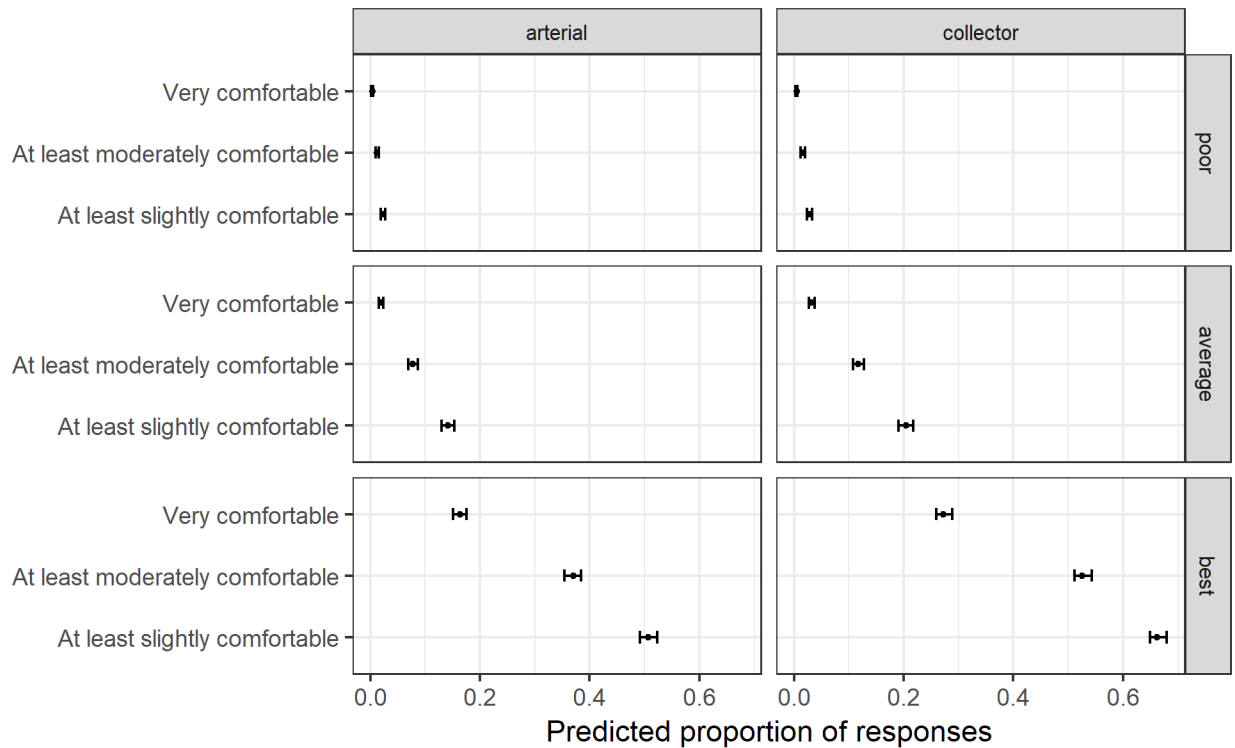
Figure 14. Model predicted responses for the comfortable side of the scale (cumulative comfort) to six simulated road environments for a conservative user group.

When separated or protected facilities really are not an option, the simulations in Figure 14suggest that the combination of low traffic volume and speed limits, narrow outside car travel lanes, prevailing speeds *below* the speed limit, and wide buffered bike lanes is likely to greatly increase perceived bicycling comfort. However, the values for these attributes need to be extreme to have a large impact (see Table 3 for specific values). Because we treated traffic volume as categorical based on present moving vehicles in the videos, we are not able to infer specific effects of more common measures of vehicle volume (e.g., AADT). However, our data does indicate specific guidance for managing vehicle speed. Speed limits at or above 40 mph indicate a strong reduction in comfort, but the difference between 25 mph speed limits and 30-35 mph speed limits is less certain. However, when the speed limit effects are paired with prevailing vehicle speeds lower than those limits, the effect of speed can be substantial (see Appendix B: Model Parameter Summaries for specific parameter values). This finding implies that both reductions to speed limits and engineering changes to roads are needed to increase bicycling comfort.

The strongest road variables in our models are clearly the effects of bike lanes and buffered bike lanes (Figure 13 and Appendix B: Model Parameter Summaries). But our models also indicate that adding a bike lane to a high volume, high speed road is not likely to provide a comfortable bicycling environment for most people. The real power of the bike lane effect is when paired with low vehicle volumes and speeds (see interaction models in Appendix B: Model Parameter Summaries).

While we observe considerable effects of socio-demographics and attitudes on ratings of comfortable bicycling environments, in general we find relative agreement across the infrastructure and other road attributes for influencing perceived comfort. For example, while in the aggregate women rate every video as less comfortable than men, women and men are in agreement on which videos present a more comfortable bicycling environment. The same is true when classifying this population by general attitudes of bicycling comfort and self perceptions of bicycling confidence. However, these effects are most prominent for the videos that were rated more comfortable on average. For the videos that were rated uncomfortable, the effects of socio-demographics and attitudes seem to be more attenuated. These results suggest that it may not be necessary to provide for minimum infrastructure needs by population segment, but instead provide a minimum infrastructure for just one conservative cohort, as satisfying the needs of a conservative cohort is very likely to satisfy the needs of the rest of the population. For example, the group of older women with attitudinal predispositions favoring car instead of bike travel could be a good conservative cohort to use as a standard for providing infrastructure minimums.

Of course exceptions will always exist, and any city or region looking to make bike infrastructure investments would be better informed about the expected effects of perceived bicycling comfort if they collect local survey data. Also, the lack of a strong relationship between common measures of "bikeability" and ratings of comfort suggest better metrics (classifications) of the network are needed. The current metrics (BLOS, LTS, etc.) seem to saturate when respondents just start to find comfort in a road design (i.e., BLOS level A and LTS level 4 are only providing comfortable bicycling environments for a small percentage of our survey population). This suggests the need for more refined classes on the comfortable/suitable range of those scales.

Our study of bicycling comfort is an important step to understanding how our roads need to change for bicycling to be a viable travel option. However, identifying road attributes that make bicycling comfortable is just one piece of the infrastructure puzzle. Ensuring that infrastructure projects that improve comfort are strategically placed within the context of a comfortable network of roads is vitally important for the success of changing perceptions and ultimately increasing bicycling.

Next Steps

This study improves our understanding of comfortable bicycling environments which can have important ramifications for increasing bicycling. Although we conclude that there may not be a need to design bicycling environments by population segments, future analysis of this data that includes interaction effects between person level variables and road variables or latent population stratification (i.e., "bicyclist types") may require a revision to this conclusion. Furthermore, the limitations of our sample characteristics and video stimuli indicate more research is needed to ensure the biases from our study are not the primary cause for our results. For example, analysis of the current video data—because the video experiment did not include off-street paths and protected bike lanes—stops short of providing evidence for environments that are truly comfortable for the super majority of the sample. In addition, this

study included a convenience sample from UC Davis that, while unique for gaging bicycling comfort, may not represent the perceptions and attitudes of prospective bicyclists or truly disadvantaged people. Further research that expands the range of road environments and tests these on diverse populations is needed to provide a more complete picture of comfortable bicycling environments.

References

Archer, K.J., Williams, A.A.A., 2012. L1 penalized continuation ratio models for ordinal response prediction using high-dimensional datasets. Stat. Med. 31, 1464–1474. https://doi.org/10.1038/jid.2014.371

Broach, J., Dill, J., 2016. Using Predicted Bicyclist and Pedestrian Route Choice to Enhance Mode Choice Models. Transp. Res. Rec. J. Transp. Res. Board 2564, 52–59. https://doi.org/10.3141/2564-06

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

Bürkner, P.C., 2017. brms: An R package for Bayesian multilevel models using Stan. J. Stat. Softw. 80. https://doi.org/10.18637/jss.v080.i01

Damant-Sirois, G., Grimsrud, M., El-Geneidy, A.M., 2014. What's your type: a multidimensional cyclist typology. Transportation (Amst). 41, 1153–1169. https://doi.org/10.1007/s11116-014-9523-8

Dill, J., Goddard, T., Monsere M, C., McNeil, N., 2015. Can protected bike lanes help close the gender gap in cycling? Lessons from five cities, in: 94th Annual Meeting of the Transportation Research Board. Washington, D.C. URL http://docs.trb.org/prp/15-3481.pdf

Dill, J., Handy, S.L., Pucher, J., 2013. How to Increase Bicycling for Daily Travel. Active Living Research. URL http://trid.trb.org/view.aspx?id=1251364 (accessed 3.21.14).

Dill, J., McNeil, N., 2013. Four Types of Cyclists? Transp. Res. Rec. J. Transp. Res. Board 2387, 129–138. https://doi.org/10.3141/2387-15

Doorley, R., Pakrashi, V., Byrne, E., Comerford, S., Ghosh, B., Groeger, J.A., 2015. Analysis of heart rate variability amongst cyclists under perceived variations of risk exposure. Transp. Res. Part F Psychol. Behav. 28, 40–54. https://doi.org/10.1016/j.trf.2014.11.004

Dowling, R.G., Reinke, D., Flannery, A., Ryus, P., Vandehey, M., Petritsch, T., Landis, B., Rouphail, N., Bonneson, J., 2008. Multimodal Level of Service Analysis for Urban Streets, NCHRP Report 616. Transportation Research Board, Washington, D.C.

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

Fitch, D.T., Handy, S.L., 2017. The relationship between experienced and imagined bicycling comfort and safety. Transp. Res. Board 97th Annu. Meet.

Fowler, S.L., Berrigan, D., Pollack, K.M., 2017. Perceived barriers to bicycling in an urban U.S. environment. J. Transp. Heal. 6, 474–480. https://doi.org/10.1016/j.jth.2017.04.003

Garrard, J., Handy, S., Dill, J., 2012. Women and Cycling, in: Pucher, J., Buehler, R. (Eds.), City Cycling. MIT Press, Cambridge. MA, pp. 211–234.

Griswold, J.B., Yu, M., Filingeri, V., Grembek, O., Walker, J.L., 2018. A behavioral modeling approach to bicycle level of service. Transp. Res. Part A Policy Pract. 116, 166–177. https://doi.org/10.1016/j.tra.2018.06.006

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

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. https://doi.org/10.1007/s11116-010-9269-x

Harris, M.A., Reynolds, C.C.O., Winters, M., Cripton, P.A., Shen, H., Chipman, M.L., Cusimano, M.D., Babul, S., Brubacher, J.R., Friedman, S.M., Hunte, G., Monro, M., Vernich, L., Teschke, K., 2013. Comparing the effects of infrastructure on bicycling injury at intersections and non-intersections using a case-crossover design. Inj. Prev. 19, 303–310. https://doi.org/10.1136/injuryprev-2012-040561

Mekuria, M.C., Furth, P.G., Nixon, H., 2012. Low-Stress Bicycling and Network Connectivity. Mineta Transportation Institute, San Jose, CA.

Monsere, C., Dill, J., McNeil, N., Clifton, K., Foster, N., Goddard, T., Berkow, M., Gilpin, J., Voros, K., Hengel, D. van, Parks, J., Communities, N.I. for T. and, 2014. Lessons from the Green Lanes: Evaluating Protected Bike Lanes in the U. S. National Institute for Transportation and Communities NITC-RR-583.

National Research Council, Transportation Reserach Board, 2010. HCM 2010 : highway capacity manual. URL http://www.hcm2010.org/

Pucher, J., Buehler, R., Seinen, M., 2011. Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. Transp. Res. Part A Policy Pract. 45, 451–475. https://doi.org/10.1016/j.tra.2011.03.001

Sallis, J.F., Conway, T.L., Dillon, L.I., Frank, L.D., Adams, M.A., Cain, K.L., Saelens, B.E., 2013. Environmental and demographic correlates of bicycling. Prev. Med. (Baltim). 57, 456–460. https://doi.org/10.1016/j.ypmed.2013.06.014

Sanders, R.L., 2014. Roadway design preferences among drivers and bicyclists in the Bay Area, in: 93rd Annual Meeting of the Transportation Research Board. Washington, D.C. URL http://docs.trb.org/prp/14-5454.pdf

Stan Development Team, 2018. Stan Modeling Language. User's Guid. Ref. Man. 1–488. URL http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102

Teschke, K., Harris, M.A., Reynolds, C.C.O., Winters, M., Babul, S., Chipman, M., Cusimano, M.D., Brubacher, J.R., Hunte, G., Friedman, S.M., Monro, M., Shen, H., Vernich, L., Cripton, P.A., 2012. Route infrastructure and the risk of injuries to bicyclists: A case-crossover study. Am. J. Public Health 102, 2336–2343. https://doi.org/10.2105/AJPH.2012.300762

Vehtari, A., Gelman, A., Gabry, J., 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. 27, 1413–1432. https://doi.org/10.1007/s11222-016-9696-4

Venables, W.N., Ripley, B.D., n.d. Modern Applied Statistics with S. Fourth Edition. Springer, New York.

Wei, A., 2018. Results of the 2017-18 Campus Travel Survey. URL https://itspubs.ucdavis.edu/wp-content/themes/ucdavis/pubs/download_pdf.php?id=2889

Winters, M., Brauer, M., Setton, E.M., Teschke, K., 2013. Mapping bikeability: A spatial tool to support sustainable travel. Environ. Plan. B Plan. Des. 40, 865–883. https://doi.org/10.1068/b38185

Data Management

Products of Research

Data was gathered for this project from the Fall 2017 UC Davis Campus Travel Survey (CTS). The data includes participant ratings of bicycling comfort in a block designed video experiment. Other variables related to socio-demographics, travel characteristics, travel attitudes, travel perceptions, and travel experiences were collected in the survey. Most survey questions are measured on ratio and nominal scales. The CTS was an online web-survey using Qualtrics.

The survey (and individual user) data will be preserved for long-term access by UC Davis researchers, Caltrans, and the general public by our hosting the data on the UC Davis ITS public facing server. Potential users include researchers, state/regional/local transportation planners, and bicycling advocacy organizations.

The data will stand alone as an evaluation of relative bicycling comfort on distinct state highways in California. The highway settings are primarily urban, but vary in traffic conditions, lane configurations, speeds, and bicycling infrastructure. The data can be used to help establish minimum environmental characteristics for people of a variety of backgrounds and situations to feel comfortable bicycling in. The data will be anonymized before release to the public. Any geographic data that might be used to identify respondents will be removed.

Data Format and Content

The processed and subset (for purposes of this project) survey data will be stored in one comma delimited text file. Associated metadata is provided in comma delimited text file. In addition, all computer code developed for analyzing the data as a part of this project will be provided.

Data Access and Sharing

Data has been published on the data repository, Dryad, in partnership with the UC Davis library (https://datadryad.org/stash) for general public access and can be found under the following DOI: https://doi.org/10.25338/B8KG77

Reuse and Redistribution

All rights of reuse and redistribution can be found at the data Dryad site (https://datadryad.org/stash). All data used for this project is public and available for unrestricted use, unless otherwise specified in the data citation. If the data are used, our work should be properly cited:

Fitch, Dillon; Carlen, Jane; Handy, Susan (2019), Bicycling comfort video experiment, v2, UC Davis, Dataset, https://doi.org/10.25338/B8KG77

NCST

Appendix A: Extended Methods

Variable Cleaning and Selection

Several predictor variables, such as an individual's housing unit type, had non-response rates over forty-five percent. We considered imputing missing data for several variables that had missing entries but found that only age could be reliably imputed. To impute missing ages (roughly three percent of the entries) we used primary role (e.g., student, faculty, etc.) because it had a strong correlation with age and no missing data itself. We used the version of the age variable with missing values imputed when estimating models. We excluded from modelling the variables with nearly half or more of responses missing, and as a result all variables considered had less than ten percent of responses missing. We excluded a small number of survey responses with missing values for many variables we included in the modeling. This resulted in the loss of data from fewer than 100 individuals out of our sample of 3089, with the exact number depending on the specific analysis.

We transformed some categorical variables to have fewer, more general categories. This helped to avoid small bin sizes that could lead to issues with model fitting (e.g., overfitting leading to unreliable inferences). For example, responses about one's usual mode of transportation to UC Davis from a 13-category variable including entries like "taxi services" and "electric bike" were converted to a four-category variable with possible values: "bike", "car", "public transit", "other" with 6869, 4688, 2923, and 812 entries respectively.

Some variables had strong correlations, such that including all available variables in a model could generate misleading results. For example, the correlation between whether a street is divided, and its number of lanes is 0.88 (all four-lane streets in our data are divided, 17 out of 19 two-lane streets are not, and one-lane streets cannot be divided by definition). The correlation between posted speed limit and prevailing car speed on streets in our data is over 0.9. Some opinion variables (treating them as numeric variables on a scale from one to five) also showed moderately strong correlations. For example, the correlation between whether someone is satisfied with their commute trips to the UC Davis campus and whether they think their commute trips usually go well is about 0.6, whereas those variables are negatively correlated (-0.5 and -0.4 respectively) with whether traveling to campus stresses the respondent out.

In some cases, we removed variables that were highly correlated with others, especially if one side of the correlated pair had more missing responses. For example, one's primary role (undergraduate student, graduate student, visiting scholar, staff or faculty) is highly correlated with one's reported level of education, but education level had more than fifty percent missing entries. The data show a similarly strong correlation between rent share (<5% missing) and rent split (~70% missing).

For the variables we kept after data cleaning we fit ordered regression models with and without penalty terms to explore conditional effects on comfort ratings and help us remove inconsequential variables. We used the lasso penalty term implemented in the R package

glmnetcr (Archer and Williams, 2012) and the polr function from the MASS (Venables and Ripley, n.d.) package for this exploratory analysis, and subsequently removed factors from further consideration which had both no clear theoretical motivation and provided little association with comfort ratings. For example, a respondent's opinion of how environmental concerns affect their choice of daily travel proved to have little association with comfort ratings, and it lacks a clear causal mechanism for effecting bicycling comfort. Figure A1 shows a summary of estimated penalized models with varying penalties. The paths in Figure A1 show the shrinking parameter values with increasing lasso penalties (from right to left). The faster the parameters shrink toward zero, the less likely the corresponding variable is to influence comfort ratings. From these we selected a pared down set of explanatory variables to include based on when the increase in the explanatory power of the model started to flatten (as shown by diminishing reductions in deviance as compared to a model with no explanatory variables).
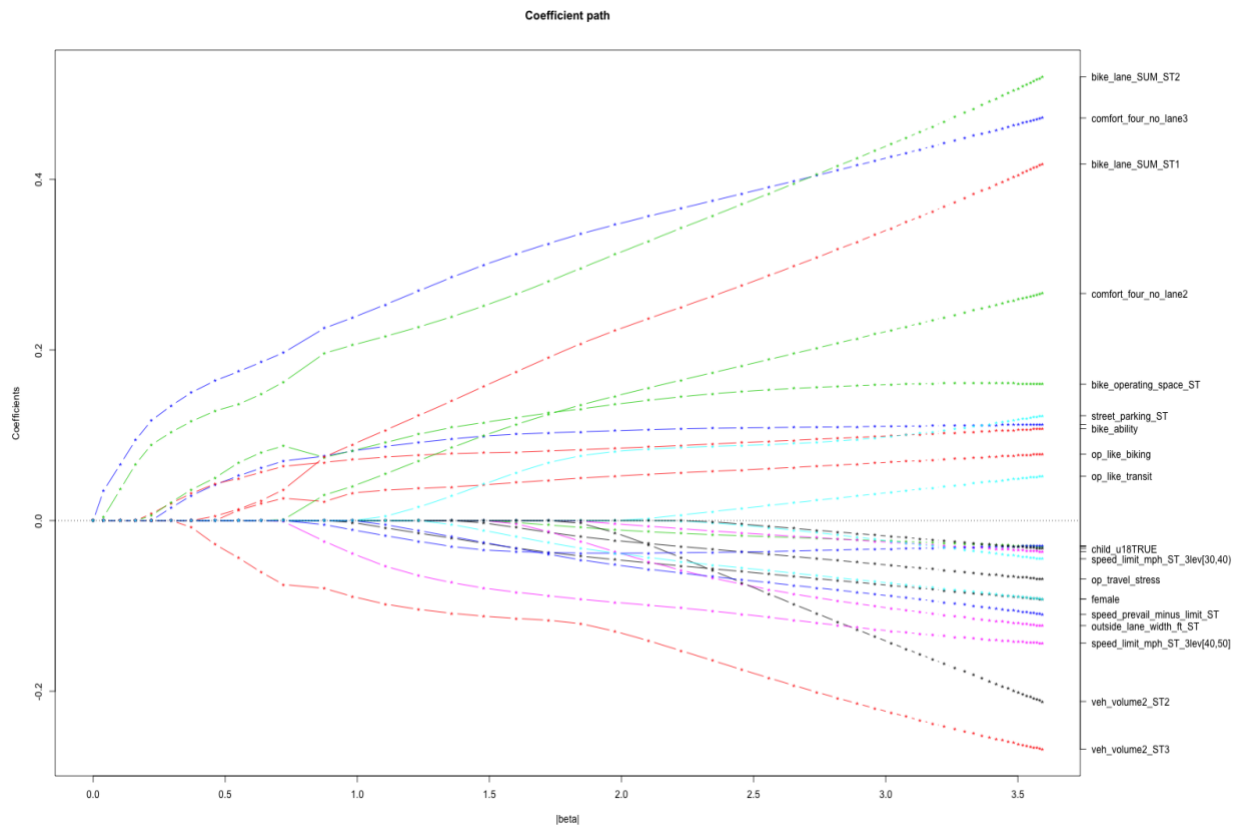
Figure A1. Change in model coefficients (each line) by iterative lasso penalty terms. As the penalty increases (from right to left), the parameters shrink toward 0.

Confirmatory Modeling

Varying Effects

All our preliminary models had a lot of unexplained variation in ratings. In other words, there is a limit to our ability to explain comfort ratings given the individual-level and street-level

variables in our data set. Some of this variation could be due to individual-level effects that we did not (or cannot) measure. Examining model fit, including outliers from non-varying-effect models, we found evidence of "low raters" and "high raters", who deviated consistently (below or above, respectively) from similar raters of a given video. Strong outliers from the models tended to be individuals who rated all streets very low on the comfort scale, but had attributes associated with high ratings, such as comfort biking on a four-lane road (not shown). This observation, along with the design of the experiment, motivated including varying effects in our models to capture this important variation. We included two varying intercept terms in our models, one for person and one for video.

Model Estimation, Comparison, and Selection

For our final models we chose a Bayesian analysis framework because of the ease with which we can protect against overfitting through priors, and for the ability to simulate scenarios that include all our models' sources of uncertainty. We considered models with strongly restrictive priors (e.g., shrinkage "horseshoe" prior distributions) to further cull our variable set but found that they did not exhibit the expected effect of shrinking some variable effects to zero while maintaining others. Instead those priors shrunk all parameters slightly toward zero which had negligible effects on inference. Ultimately, we chose the more standard Gaussian and half-student's t priors for unconstrained and positively constrained priors, respectively. The priors provide soft constraints (i.e. weakly informative) on all parameters to reduce the chance of overfitting but have little effect on the ultimate inferences because we chose wide standard deviations.

We compared a series of models which we summarize in Table 2 and report results in Appendix B: Model Parameter Summaries and chose one model for scenario simulation. We chose the Main Effects Person-Video model for scenario simulation because it had the less expected prediction error (Appendix B: Model Parameter Summaries) based on the approximated leave-one-out cross validation (Vehtari et al., 2017). While the Interaction Effects Person-Video model has a similar expected predictive error, it proved much more challenging to interpret parameter values directly (as in Figure 13).

To estimate our Bayesian models, we used the R package brms (Bürkner, 2017) which is an interface for the Stan computing language (Stan Development Team, 2018). We used the default estimation algorithm (dynamic Hamiltonian MCMC), with tuning parameters adapt_delta = 0.9, and max_tree_depth = 16, and ensured that each model parameter MCMC chain converged ($\hat{r}$ < 1.01), and that the model produced no other diagnostic warnings from Stan. Our general model structure is as follows:

$$\log\left(\frac{\Pr\left(y_i < k\right)}{1 - \Pr\left(y_i < k\right)}\right) = \alpha_k + \alpha_{person[i]} + \alpha_{video[i]} - \sum_{m=1}^{M} \beta_m X_{mi}$$

$$\alpha_{person[i]} \sim \mathrm{Normal}\left(0, \sigma_{person}\right)$$
$$\alpha_{video[i]} \sim \mathrm{Normal}\left(0, \sigma_{video}\right)$$
$$\underline{\mathrm{Priors}}$$
$$\alpha_k \sim \mathrm{StudentT}\left(3, 0, 5\right)$$

$$(\beta_1, \dots, \beta_m) \sim \text{Normal}(\,0\,,5\,)$$

$$\sigma_{person} \sim \text{HalfStudentT}(\,3\,,0\,,5)$$

$$\sigma_{video} \sim \text{HalfStudentT}(\,3\,,0\,,5)$$

Where $\log\left(\frac{\text{Pr}(y_i \leq k)}{1 - \text{Pr}(y_i \leq k)}\right)$ is the log-cumulative-odds that response value y_i is equal to or less than a possible response category k (very uncomfortable, …, very comfortable). α_k are the threshold intercepts for the k thresholds between the k+1 response categories. $\alpha_{person[i]}$ and $\alpha_{video[i]}$ are the varying intercepts for person and video indexed by response *i*. β_m is the vector of non-varying effects for each predictor variable X_m. σ_{person} and σ_{video} are the standard deviation parameters for the varying intercepts for person and video. Each $\beta_m X_{mi}$ term is subtracted from the intercepts to ensure a positive β_m value indicates that an increase in X_{mi} results in an increase in the average response. This is because a decrease (hence subtraction) in the log-cumulative-odds for every outcome below the maximum results in a shift of probability toward the higher response categories.

Appendix B: Model Parameter Summaries

Table A1. Model parameter summaries including the posterior mean and standard deviation, and the number of effective sample (*n* eff.). Also included are the expected out-of-sample model prediction errors (elpd_loo) where values closer to zero indicate less error.

	Null Person			Null Person-Video			Main Effects Person			Main Effects Person-Video			Interaction Person			Interaction Person-Video		
	mean	sd	*n eff.*	mean	sd	*n eff.*	mean	sd	*n eff.*	mean	sd	*n eff.*	mean	sd	*n eff.*	mean	sd	*n eff.*
Intercept[1]	-3.10	0.05	991	-3.95	0.32	357	-2.18	0.29	700	-2.27	1.08	1096	-2.30	0.30	858	-2.40	1.67	2095
Intercept[2]	-1.81	0.04	849	-2.34	0.32	355	-0.62	0.29	688	-0.65	1.08	1097	-0.70	0.30	839	-0.77	1.67	2091
Intercept[3]	-0.65	0.04	786	-0.86	0.32	355	0.81	0.29	676	0.84	1.08	1097	0.76	0.30	838	0.72	1.67	2091
Intercept[4]	0.03	0.04	763	0.02	0.32	355	1.65	0.29	682	1.73	1.08	1099	1.62	0.30	835	1.60	1.67	2092
Intercept[5]	0.77	0.04	836	0.97	0.32	355	2.57	0.29	681	2.69	1.08	1098	2.56	0.30	849	2.57	1.67	2092
Intercept[6]	2.20	0.04	1099	2.76	0.32	359	4.28	0.29	702	4.49	1.08	1098	4.32	0.30	853	4.36	1.67	2091
sd(person)	1.79	0.04	810	2.18	0.04	781	1.63	0.03	821	1.71	0.03	850	1.68	0.03	1038	1.71	0.03	771
sd(video)				1.57	0.25	552				0.73	0.16	838				0.81	0.25	816
Woman							-0.34	0.08	757	-0.37	0.08	776	-0.34	0.07	983	-0.37	0.08	1412
Age							-0.90	0.20	650	-0.94	0.21	632	-0.90	0.21	770	-0.93	0.21	1224
Child under 18 yo in household							-0.22	0.12	649	-0.21	0.12	787	-0.23	0.12	871	-0.21	0.12	1287
Usually bike for commute							0.17	0.08	657	0.19	0.08	627	0.18	0.08	881	0.19	0.08	1164
Like biking							0.61	0.18	815	0.61	0.19	516	0.49	0.15	926	0.50	0.15	1082
Need car							-0.28	0.15	513	-0.30	0.16	744	-0.23	0.12	939	-0.24	0.12	1455
Feel safe							1.00	0.18	778	1.04	0.18	614	0.82	0.14	978	0.83	0.15	1103
Like transit							0.44	0.15	686	0.46	0.16	560	0.34	0.13	975	0.36	0.13	1393
Need to arrive professional							-0.23	0.14	741	-0.23	0.15	599	-0.19	0.12	903	-0.19	0.12	1304
Stressed commuting							-0.58	0.16	737	-0.62	0.17	534	-0.47	0.13	945	-0.48	0.13	1462

	Null Person			Null Person-Video			Main Effects Person			Main Effects Person-Video			Interaction Person			Interaction Person-Video		
	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.
Confident bicyclist							0.78	0.12	595	0.83	0.12	617	0.81	0.12	934	0.82	0.13	1140
Uncomfortable on mixed arterial but would ride there							0.96	0.09	364	1.00	0.09	591	0.97	0.09	831	1.00	0.09	1190
Uncomfortable on mixed arterial and would NOT ride there							2.32	0.11	386	2.43	0.11	507	2.39	0.11	866	2.44	0.11	1306
On-street parking							0.40	0.07	1737	0.39	0.63	1060	0.99	0.15	1334	0.80	1.22	2060
Outside lane width							-1.14	0.13	2239	-1.15	1.22	887	-3.18	0.20	1400	-2.34	1.71	1587
Moderate vehicle volume							-0.67	0.07	1284	-0.75	0.59	666	0.57	0.11	1419	0.08	0.93	1576
High vehicle volume							-0.80	0.08	1116	-0.92	0.62	794	0.87	0.14	1135	0.37	1.20	1348
Bike operating space							0.43	0.15	1159	0.73	1.21	797	1.41	0.32	1925	0.97	2.29	2360
Speed limit [30,40)							-0.12	0.05	2073	-0.15	0.49	725	1.07	0.10	1798	0.87	0.88	1639
Speed limit [40,50]							-0.65	0.08	1897	-0.75	0.66	788	-0.84	0.39	1097	-0.47	2.44	1729
Conventional bike lane							1.83	0.07	1838	1.89	0.55	1007	3.05	0.21	1010	2.28	1.39	1535
Buffered bike lane							2.99	0.09	1550	2.97	0.78	966	4.36	0.30	885	3.35	1.84	1608
Prevailing vehicle speed - speed limit							-1.07	0.09	2334	-1.13	0.81	1348	-0.80	0.11	2193	-1.00	1.04	2426
Moderate or high vehicle volume with no bike operating space							-2.58	0.45	1119	-2.04	3.08	847	-1.81	0.13	1187	-1.49	1.12	1562
On-street parking * Conventional bike lane													-1.23	0.25	953	-0.42	1.63	1535

	Null Person			Null Person-Video			Main Effects Person			Main Effects Person-Video			Interaction Person			Interaction Person-Video		
	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.	mean	sd	n eff.
On-street parking * Buffered bike lane													-0.66	0.38	877	0.14	2.26	1575
On-street parking * Bike operating space													-3.20	0.36	1061	-2.20	2.39	1498
High vehicle volume * Conventional bike lane													-1.92	0.23	1080	-1.09	1.59	1568
High vehicle volume * Buffered bike lane													-2.13	0.25	1759	-0.79	1.91	1391
Speed limit [40,50] * Bike operating space													-1.92	0.36	1399	-1.03	2.46	2324
High vehicle volume * Speed limit [40,50]													1.11	0.26	1254	0.42	1.84	1652
High vehicle volume * Speed limit [30,40)													-1.85	0.15	1786	-1.46	1.37	1941
number of participants	3089			3089			3089			3089			3089			3089		
number of samples	15288			15288			15288			15288			15288			15288		
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	-25881.6	(85.8)		-23009.6	(100.1)		-22753.3	(97.1)		-22260.0	(99.5)		-22496.7	(98.7)		-22260.2	(99.6)	