The Road Environment and Urban Bicycling: Psychophysiological and Behavioral Responses

By

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ABSTRACT

This dissertation is about bicycling as a mode of transportation. More specifically it is about how road environments influence perceptions of safety and attitudes about bicycling, and how policies aimed at changing the road environment might influence travel behavior more broadly. In this dissertation I present three distinct studies that are all connected by this fundamental relationship between road environments and bicycling. In the first study, I examine bicyclist acute psychological stress in different road environments through a cross-over field experiment. I find evidence that bicyclist stress is least for low speed and low traffic roads, but less reliable evidence for differences in stress between road environments with more subtle differences such as presence of bike lanes. Furthermore I find that psychophysiological measures of bicyclist stress are difficult to validate. While psychophysiological measures may hold near real-time, objective reflections of stress, it is still unclear if they offer more than survey measures of bicycling experiences in determining attitudes and behavior.

In the second study, I examine the relationship between road environments and bicyclist route behavior through two observational case studies in Davis and San Francisco, CA. Bicycling route behavior in a small bike friendly city (Davis) by a predominantly student cohort with a wide range of bicycling experience, indicates that route detouring from shortest paths is minimal, and that bike lanes and off-street paths have uncertain effects of routing decisions. Conversely, bicyclist route behavior in a large city with a growing number of bicyclists (San Francisco) by a presumably more experienced and confident bicyclist cohort shows larger route detouring. In addition, I find evidence for a strong influence of protected bike lanes and off-street paths, and a less but still certain influence of conventional bike lanes on routing decisions.

In the third and final study, I examine students' usual travel mode to school at three northern California high schools. I find that road environment characteristics such as bike lanes and off-street paths along plausible routes to school have a strong effect on the decision to bike to school. Furthermore I find that attitudes such as a feeling of social pressure to bicycle have a strong correlation with bicycling. The combined results from these studies and review of the literature demonstrate that large scale changes to road environments may be needed to influence bicycling perceptions, attitudes, and behavior.

Preface and Acknowledgements

The dramatic rise in urban bicycling over the past two decades is a great indicator of the possibility of population scale travel behavior change. Twenty years ago bicycling was considered a 'fringe' travel mode in the US. While some might still agree with this characterization, most large US cities consider bicycling a key component of future mobility. Increasing bicycling rates and growth in bicycling research in the US go hand in hand. Therefore, my first thank you goes out to everyone who rides their bike. Without you choosing to ride, this dissertation might not have been possible. I also owe a great thanks to the residents of the city of Davis for being an inspiration in my work, and an inspiration to many cities looking to make their cities more bike friendly.

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1 Introduction

Historically, street designs have favored car travel in the US (Southworth and Ben-Joseph, 1995) creating environments that are unsafe and unappealing for walking and bicycling. In addition, and in part because of the focus on car travel, over time US cities have sprawled resulting in increased travel distances, adding to the barriers of walking and bicycling. While car travel has generated opportunities for economic growth and convenience, it has come with great environmental and social cost. For example, although toxic emissions have been greatly reduced (Sperling and Gordon, 2008, p. 16), mobile sourced (from transportation) air toxics are still the largest contributor of airborne human health risk (U.S. Environmental Protection Agency, 2015). In addition to air toxics, greenhouse gas emissions from cars (and other transportation) exhaust is roughly 14% of global levels (Intergovernmental Panel on Climate Change, 2014) and nearly double that (28.5%) in the US (U.S. Environmental Protection Agency, 2018) making our current transportation system one of the most pervasive determinants of global warming. This problem is exacerbated by the recent growth in unconventional oil extraction (e.g. tar sands) which on average produce about 20% more greenhouse gases from the upstream oil extraction processes (Cai et al., 2015). Both air toxics and greenhouse gas emissions have incredible social costs. Rising cancer rates and other non-cancer hazards (e.g. organ damage, central nervous system and reproductive damage, developmental problems) all increase with greater concentrations of air toxics. Indirect effects of car use such as declining physical activity also claim pandemic status (Sallis et al., 2016). In addition, global warming may pose the greatest challenge our society has ever faced.

The environmental and social problems exacerbated by the car monoculture have prompted governments to change the goals for transportation systems. For example, through mandated regional transportation planning, the federal government requires that urban regions address traditional transportation goals such as economic growth through mobility and system efficiency, and at the same time find ways to increase accessibility, protect the environment, and improve quality of life (Handy, 2008). Although policies surrounding technological solutions (e.g. vehicle electrification and automation, low carbon fuel standards) will play a key role in addressing some of these concerns, evidence suggests that technological solutions will not solve them all (Dray et al., 2012; Gössling and Cohen, 2014). Thus, to adequately address these concerns, transportation planning needs to foster travel behavioral change.

One of the many strategies implemented in the U.S. to address social and environmental costs is investment in bicycling as a normal mode of travel. In theory, shifting car travel to bike travel has the potential to reduce greenhouse gas emissions by reducing vehicle miles traveled, and increase public health through increased physical activity. Making bicycling more safe and enjoyable may also help provide a travel mode option that is affordable for all socio-economic groups thus aiding social equity. Although bicycling in U.S. cities is rare, especially compared to some European and Asian cities (Buehler and Pucher, 2012a; Handy et al., 2012; Pucher et al., 2012), bicycling mode share is currently growing in many US cities (Pucher et al., 2011; Pucher and Buehler, 2017), in response to and in turn fueling a growing interest in bicycle travel among transportation researchers and planners (Clarke, 2000; Pucher and Buehler, 2017).

Increases in bicycling are most likely a result of complex interactions between physical and climactic environments, transportation policies, people's characteristics, as well as socio-cultural and economic settings (Heinen et al., 2010). Because of these interactions, investments in bicycling infrastructure are likely to be more effective if cities adopt complimentary promotional programs, land use plans, and restrictions on car use (Pucher et al., 2010). Nonetheless, infrastructure investments (or more broadly changes to road environments) are likely to remain one of the most effective strategies that local and regional governments have at their disposal, and are a necessary condition for improving the environment for bicycling. Although evidence shows that infrastructure investments correlate with bicycling and that people prefer bicycling-specific infrastructure (Buehler and Dill, 2016; Dill, 2009; Furth, 2012; Krizek, 2006; Krizek et al., 2007; Pucher et al., 2010; Tilahun et al., 2007), many questions remain surrounding the most effective type and placement of these investments for increasing the safety and prevalence of bicycling. Moreover, while most infrastructure investments are minor retrofits to existing road environments (e.g. bike lanes), knowing the important characteristics of entire road environments for safe and comfortable bicycling is paramount if communities want to make bicycling a normal mode of travel.

1.1 Research motivation

Road environments directly influence bicycling safety through control of driver behavior. In addition, road environments have a strong influence on many personal level attributes such as perceptions and attitudes toward bicycling, which in turn influence bicycling behavior (both choosing to ride and choosing where to ride). The primary motivation for this dissertation is to improve our understanding of the influence of road environments on perceptions and behavior. A better understanding of these relationships will improve the effectiveness of bicycling policies, specifically those aimed at adding bicycling infrastructure or making other physical changes to roads.

Below I introduce some relevant theories and empirical evidence for understanding bicycling as a normal model of travel. I provide both a broad conceptual model for bicycling behavior, and discuss specific variables that play a key role in the policy questions of how and where to improve bicycling environments.

1.2 Theories of Travel Behavior and Implications for Bicycling

People travel for two primary reasons: travel for the sake of travel, or to gain access to activities in specific places and at specific times. Travel for the safe of travel is more commonly called recreational, exercise, leisure, or more broadly 'undirected'[1] travel, but really the list of reasons people might travel for the sake of travel is quite broad (Ory and Mokhtarian, 2005). Although just about everyone participates in some travel for the sake of travel, it is generally agreed that most travel is motivated by reaching a destination and is thus destination-oriented travel[2]. Of course, people choose life-styles. Some people choose to live in the suburbs far from their activities, requiring long travel distances, while others choose to live near activities where travel distances are short. Some people enjoy driving their convertible, while others enjoy riding their bike. The concept of life-styles can both be used to reflect travel behavior and also determine it (Kitamura, 2009). In the case of bicycling, life-styles oriented toward bicycling may be important since about half of bicycling trips are recreational (travel for the sake of travel) (Pucher et al., 2011). In addition, the enormous magnitude of the recreational bicycling industry (Southwick Associates, 2012) relative to the low bike commute mode share (Schroeder and Wilber, 2013), suggests people invest in bicycling equipment primarily for recreation. For example, Americans spend more on bicycling gear and travel (~$81 billion) than they do on air travel (~$51 billion) (Southwick Associates, 2012). Considering that improving public health (through physical activity) is a major societal goal, transportation planners may need to broaden the traditional destination-oriented focus of travel behavior to consider bicycling for pleasure and exercise when planning the transportation system.

Two of the core components of how people travel are their travel mode and route. As is the case for

[1] Because the destination is ancillary to the travel (Mokhtarian and Salomon, 2001).
[2] More commonly called 'utilitarian' travel; but this is confusing because certainly someone derives more direct utility from say an exercise trip than they do from a trip to the grocery store. The utility of the grocery store travel is only derived from the activity. I prefer the term 'destination-oriented' travel because it focuses on the ultimate reason for the travel, to arrive at a destination.

behaviors more broadly, the causal mechanisms underlying an person's mode and route behaviors are complex, which is why they have been studied from numerous perspectives: most commonly as independent behaviors, but also as habituated or learned behavior over time (Arentze and Timmermans, 2003; Schneider, 2013), as integrated with other behaviors like residential choice (Salon, 2009) or ownership of vehicle (Handy et al., 2010), and most holistically as integrated with entire life courses (Chatterjee et al., 2013; Scheiner and Holz-Rau, 2013). Each of these perspectives allows a different understanding of how people travel, and are therefore complementary.

The theory most traditionally applied to mode and route behavior is expected utility theory. The expected utility model is often labeled a "rational" behavioral model, but can more precisely be defined as a "beliefs, preferences, and constraints model" (Gintis, 2009). This model assumes individuals make decisions or choices that maximize their expected individual utility, where utility is the desirability or value of an outcome. It is important to note that (1) rational choices are not equivalent to selfishness (i.e. it can be rational to give to charity if one perceives it has normative value), and (2) a liberal interpretation of utility allows people's choices to change (be inconsistent) over time (Gintis, 2009). In the context of destination-oriented travel, utility is indirect because travel is primarily induced by some activity which occurs at a location that requires mobility[3]. It has been argued that a plethora of information remains to be gathered about travel behavior within the context of utility maximization (McFadden, 2000), particularly with respect to better describing how an individual arrives at her expected utility. In addition, alternative (non-utility based) economic theories (e.g. prospect theory, regret theory) have been hotly debated in the travel behavior field (Chorus and van Cranenburgh, 2018; Ramos et al., 2014; Rasouli and Timmermans, 2018; Timmermans, 2010; van de Kaa, 2012). Although the predictive improvement of statistical models based on non-utility based economic theories (compared to utility based modes) may be marginal (Ramos et al., 2014), they offer distinct constructs (e.g. regret, reference points) that may hold value for understanding travel behavior.

Beyond the economic representation of travel behavior, many additional behavioral theories have improved our understanding of travel behavior. From psychology, numerous generalized human behavioral theories offer rich conceptual models of behavior (e.g. theory of planned behavior (Ajzen, 1991), social-cognitive theory (Bandura, 1989), and other psychodynamic and developmental perspectives) which consider behavioral intents (precursors to behaviors), self-perceptions, norms, attitudes, social-dynamics, life stages, learning processes, and other social and psychological constructs

[3] travel as derived demand.

as influencing and being influenced by behavior. These concepts have proven helpful in explaining bicycling behavior. For example, evidence shows that attitudes, social norms, and other psychological variables are strongly indicative of bicycling (Muñoz et al., 2013; Xing et al., 2010).

Possibly the most general theoretical framework applicable to bicycling might be the ecological model that has been applied to health behaviors (Sallis et al., 2008). The ecological model stresses a hierarchy of effects at different levels (e.g. environment, familial, individual, etc.), and like social-cognitive theory (Bandura, 1989) supposes a bidirectional influence between people and their environment. That is, human behavior affects environments, just as environments affect human behavior. In the following section I will consider the above theoretical perspectives used to understand travel behavior and focus more specifically on the determinants of bicycling behavior.

1.3 Bicycling Behavior

Bicycling for destination-oriented travel in the US is considerably less common than in many European countries (Buehler and Pucher, 2012b). Framing this discussion within the hierarchical structure of an ecological model (Sallis et al., 2008), I present a working conceptual diagram (Figure 1) of bicycling behavior (both choosing to ride and choosing where to ride). I adopt hierarchical domains from the Sallis et al. (2006) ecological model diagram of active living, but provide more conceptual detail for bicycling behavior.

The outermost level of the hierarchy (and thus the most indirect influence on bicycling behavior in this model) is the political setting. The political setting influences bicycling in two primary ways: (1) through policy directly related to the built environment, and (2) through other policies and laws which promote bicycling or demote other competing modes of travel. Political influences are particularly evident in places where both mechanisms are supported at the national level (e.g. The Netherlands and Denmark, with bike mode shares ~18-27% (Pucher and Buehler, 2008)). In the US, attention on the car has dominated transportation planning at all levels of government, although interest in bicycling as a mode of transportation has been growing for the past 20-30 years (Pucher and Buehler, 2012), policy metrics still focus on automobility (Handy, 2008). Conceptually, policies and laws affect bicycling behavior through social norms and accessibility. For example, in many states, laws mandate that all motorists must give bicyclists a specified operating space when passing (National Conference of State Legislators, 2015). These laws intend to provide bicyclists with added safety by altering the expected social norm of interacting drivers and bicyclists. Another example is are policies to fund local bike to school and bike to work days. These outreach programs seek to remove perceptual barriers to bicycling by demonstrating that in many cases, school and work are *accessible* by bike.

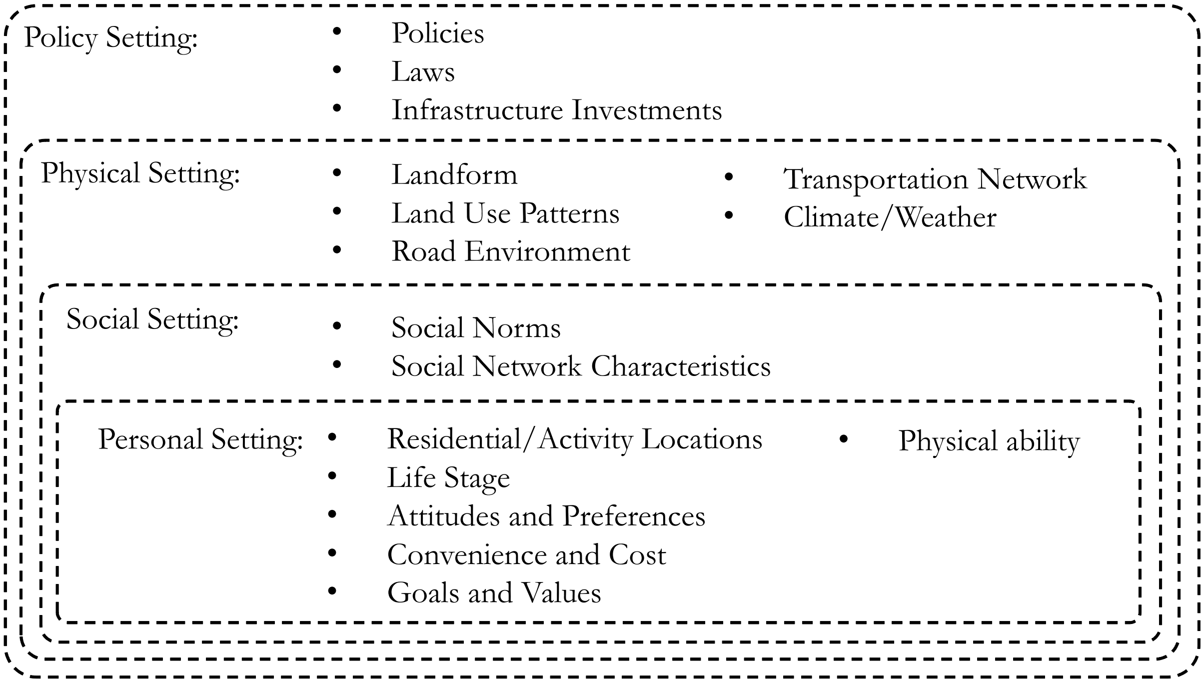

Figure 1. Conceptual ecological model of bicycling behavior.

The physical setting—defined by Handy (2005) as the built (roads, buildings) and natural (trees, parks) space for human use— is the next level of the hierarchical influence on bicycling. Land use planning largely determines the geographic patterns of where people live, work, recreate, shop, and socialize. Importantly, the separation of land uses disperses activity locations and thus directly impacts distances between people's activities. Evidence overwhelmingly suggests distance is one of the strongest, if not primary determinant of destination-oriented bicycling (Kroesen and Handy, 2013; Winters et al., 2010; Xing et al., 2010).

While land use patterns and the transportation network together influence distance to activities, the road environment largely determines whether bicycling is safe.[4] Safety from traffic is primarily a function of how the road environment influences driver behavior. Bicyclists are a vulnerable road user because they rarely have anything shielding them in the case of a crash. Aggregate statistics of risk show that per distance traveled, bicycling is much less safe than driving[5] (Shinar, 2016), and one study

[4] Safety from crime (i.e. "neighborhood safety" or "stranger danger") is also important. This facet of safety is mostly a function of land use and demographic patterns and is often a concern for young bicyclists and their guardians (Hume et al., 2009; McMillan, 2005; Timperio et al., 2004).

[5] Unfortunately exposure in terms of time is rarely reported, so distance has to suffice. Also, this risk does not consider the health benefits of bicycling.

suggests bicyclists are 12 time more likely than car occupants to be killed in the US (Pucher and Dijkstra, 2003). The same study indicates that by distance or trip exposure, American bicyclists are twice and three times as likely to be killed compared to German and Dutch bicyclists, respectively (Pucher and Dijkstra, 2003). Bicycling risk may be worse considering the underreporting of crashes (Winters and Branion-Calles, 2017). However, comparing risk exposure of travel modes by distance is problematic because of differences in model speeds. When considering exposure time, the relative risk for bicycling can be shown to be equal or even less than that of driving (Mindell et al., 2012; Wardlaw, 2002). Furthermore, added health benefits from bicycling can be thought of as reducing overall risk of death (de Hartog et al., 2010; Wardlaw, 2002). The real problem with traffic safety for bicycling is that the risk is almost entirely borne by collisions with cars (driver behavior), which is in turn largely a product of road design. Concerns about traffic safety have motivated many local and national policies and programs to reshape road environments for walking and bicycling (e.g. complete streets, vision zero, bicycle and pedestrian master plans). Perhaps the most dramatic and famous is the example of the Netherlands. Since the 1970's dramatic increases in bicyclist safety and numbers have been made through comprehensive transportation networks designed to separate bicyclists from cars or integrate them when speeds of cars and bikes are similar (Schepers et al., 2014). The success of the Netherlands shows that road environment design is a great determinant of bicycling safety.

In addition to the built environment, other physical characteristics (e.g. weather and topography) influence bicycling by causing personal discomfort and physical effort (Heinen et al., 2010; Winters et al., 2011). These characteristics interact with the built environment by acting as constraints to planners (e.g. topography requires roads to have slope), and to bicyclists directly (e.g. winter snow makes bicycling more difficult). Finally, both the natural and built aspects of the physical setting define how attractive a city is for distinct types of bicycling. For example, off-street paths along rivers (e.g. Minneapolis, MN), are attractive for recreational/exercise cycling but may not connect homes with activity locations. Alternatively, compact land use patterns and network connectivity (e.g. Davis, CA) make distances to activities relatively short, thus increasing the attractiveness of destination-oriented bicycling.

The social setting, both influencing and influenced by the political setting, plays an important role in bicycling travel (Goetzke and Rave, 2011; Pelzer, 2010; Xing et al., 2010). Car travel in the US is the norm, even for short distances, and cars themselves are key possessions of social status and attractiveness (Dunn and Searle, 2010). Bicycles are a much less common possession of social status, and bicycling tends to be seen by non-bicyclists as a sport (cycling), not a mode of transportation (Steinbach et al., 2011). Even if non-bicyclists care little about the status of car ownership, if they do not consider themselves 'sporty' (or can't identify as a 'cyclist'), they may be unlikely to take up bicycling. Even if social status and identity are not a barrier for some prospective bicyclists, destination-oriented bicycling can harm physical appearance (e.g. sweat from exercise, frizzy hair from wind) which may act as a social barrier for bicycling. This is why, for example, companies have designed special bicycling helmets enabling people to be safe without messing up their hair ("Hövding Sverige AB," n.d.), and why many existing bicyclists eschew helmets.

In the personal setting, familial and personal characteristics have been shown to heavily influence destination-oriented bicycling (Driller and Handy, 2013; Handy et al., 2010; Xing et al., 2010). Longer term individual decisions such as residential, workplace, and school locations interact with social norms (Van Acker et al., 2010), and provide the personal accessibility setting which defines distances to these primary activities. Life stage of a household dictates the types of activities that are likely to occur outside the household. For example, adults with children tend to be less likely to bicycle for travel because they have to balance their work schedules with the need to chauffer their children to and from activities (McDonald, 2008; Mitra and Buliung, 2014; Seyda and Agrawal Weinstein, 2015). Individual preferences and attitudes help to explain destination-oriented bicycling conditional on the political, physical, and social settings. Preferences for bicycling (usually because of general enjoyment, or life-style orientation) have a strong relationship with bicycling. In addition, general attitudes toward bicycling, driving, parking, safety, and other related attributes of the travel domain have been shown to have a considerable influence on destination-oriented bicycling (Handy et al., 2010). The reverse is also true: bicycling behavior can influence a person's travel attitudes (Kroesen et al., 2017). Financial cost and convenience are major factors in determining car use (and thus bicycling). Car ownership is relatively inexpensive in the US (Pucher and Buehler, 2006), although people don't usually fully internalize the costs of car ownership. In addition, long travel distances translate into large travel times for bicycling compared to driving, thus making bicycling much less convenient for many activities.

There is no question that the road environment influences people's decisions to bicycle (Heinen et al., 2010; Pucher et al., 2010), but how it does this is less certain. Evidence suggests perceptions of environments influence bicycling (Handy et al., 2010; Ma et al., 2014; McMillan, 2007), and likely play a role in forming attitudes which more directly relate to behavior. For example, if I perceive the road environment between my home and workplace as safe for bicycling, I may be more likely to form an attitude that bicycling is safe in my city. Psychological evidence suggests that I don't even have to be aware of my perceptions for this to occur (Merikle et al., 2001). Evidence suggests that fear of traffic collisions is a major barrier for people considering bicycling, and is a major concern for those who already bicycle (Sanders, 2015). Although objective and perceived bicycling risk may differ, they are likely to be aligned in many respects. For example, bicycling facilities improve both perceived and objective measures of safety (Buehler and Dill, 2016; Reynolds et al., 2009).

Related to perceived safety, the concept of bicycling comfort is widely used to predict individuals' bicycling behavior (Dill et al., 2015; Ma et al., 2014; Sanders, 2014). Comfort is a difficult multidimensional construct to define. Some dimensions (e.g. physical, emotional) have been covered in the literature under other terms such as perceived safety and effort (Broach et al., 2012; Landis et al., 1997; McMillan, 2005; Menghini et al., 2010). Indeed, the relationship between perceived safety and comfort is probably very strong. At least one study showed evidence for a three-level bicycling attitude hierarchy with safety, comfort, and enjoyment all being built upon each other (Lovegrove, 2017).

1.4 Specific studies and research methods

Although the variables in each of ecological model levels can have substantial effects on bicycling behavior, in this dissertation I focus on the fundamental link between the personal and physical settings. Specifically, I concentrate on the physical road environment and its relation to bicycling perceptions, attitudes, and behaviors in each of the remaining chapters. Because perceived safety and related concepts (e.g. comfort, stress) are likely the primary barriers to bicycling behavior (besides distance), I consider how the road environment shapes these personal level variables. Knowing how bicycling experiences (or even watching other bicyclists' experience) influence perceptions and attitudes of bicycling safety could greatly improve the efficacy of bicycling interventions. This is because safety perceptions pervade many levels of bicycling behavior.

At the most fundamental level, road environments influence car driver behavior, which in turn cause acute psychological stress to bicyclists. I hypothesize that this stress largely determines safety perceptions. Many personal and social level variables might moderate this effect (e.g. experience might lessen the strength of acute stress in determining perceived safety, seeing other bicyclists nearby might do the same[6]). Nonetheless, for the inexperienced and risk averse (i.e. prospective or new bicyclists) acute stress is likely to determine perceived safety. It is this level of the human/environment relationship that I focus on in Chapter 2 when I examine bicyclist acute psychological stress in distinct road environments. In this study I describe a cross-over field experiment of 20 female undergraduate students at UC Davis. Past research has assumed that specific characteristics of the road have varying levels of environmental stress (Furth and Mekuria, 2013). I use both psychophysiological and survey techniques to measure stress and related perceptions and attitudes. I intend for this small, all female sample to reflect a cohort of bicyclists that are sensitive to the risk of bicycling with car traffic and thus offer a conservative estimate of the experience of existing bicyclists. I intend this study to provide basic scientific knowledge about bicyclist environmental stress that can be used for more targeted applied research.

Safety perceptions of road environments are also likely to play a role in route behavior of bicyclists. If a person perceives a road to be dangerous when bicycling, she might detour her route. Her chosen route is likely to include environmental attributes that reduce stress and/or increase perceived safety (relative to the alternatives). I cover this level of the human/environment relationship in Chapter 3 when I compare road attributes of bicyclists chosen and alternative routes. In Chapter 3 I evaluate bicyclist route behavior using a mix of cross-sectional and longitudinal survey and crowdsourced data. This study is a comparison of two specific cases of bicycling (Davis, CA, and San Francisco, CA) that offer a wide range in environments and socio-demographics. Bicyclist route behavior has only recently been investigated in the literature, and the limited existing evidence comes from single city studies over short time periods (thus no change in road environments). This study attempts to improve our understanding of how road environments influence bicyclist routing by comparing two cities, and by examining route behavior during changes in road environments. The goals of this study are to understand the willingness of bicyclists to detour (take a longer route) to bicycle in preferable road environments, and to provide policy makers with results that can directly translate into strategies for improved transportation planning.

Lastly, I cover the high-level effect of road environments and perceptions of safety on the decision to bicycle. If a person is considering bicycling or taking some other travel mode for a trip, her perception of unsafe road environments is likely to cause her to choose an alternative mode. More

[6] Perhaps this is the perceived safety corollary to the well-known 'safety in numbers' phenomenon where bicycling crash risk is reduced with increasing number of bicyclists (Aldred et al., 2017; Elvik and Bjørnskau, 2017; Fyhri et al., 2016; Jacobsen, 2003; Jacobsen et al., 2015).

importantly, if her safety perceptions of a neighborhood or city has led her to an attitude that it is unsafe to bicycle in general, she might never even consider bicycling. In Chapter 4 I examine travel mode choice to high school and consider attributes of road environments along alternative paths to school as well as attitudes toward bicycling. This study focuses on the relationship between road environments and the decision to bicycle, as well as the relationship between specific bicycling attitudes and travel mode choice using cross-sectional survey data collected from three High Schools in Northern California. Teenagers are a relatively under-studied cohort with respect to travel behavior. However, they represent an important transition time in travel behavior, one in which driving first becomes an option. This turning point is important for understanding the implications for how suitable environments for walking and bicycling instill travel behaviors that may have lasting effects into adulthood. The goal of this study is not to understand if teen travel behavior has lasting effects; for that longitudinal data would be needed. Instead, the goal is to focus on the relationship road environments have on one specific cohort (teens) for one specific travel purpose (school). This chapter has important ramifications for targeted programs such as safe routes to school, which in the past have largely focused on elementary schools, but may also support general bicycle planning.

In each of the following three chapters I present distinct studies of bicycling at the individual level that I intend to stand alone. Because of the variety of data in these three chapters, I tailor my methods to the specific data and research questions at hand. I attempt to make this work accessible for general audiences by using data visualization as my primary method for communicating results. In all studies I use Bayesian statistical techniques for multivariable analysis which by their nature include complex algorithms for estimating the relationships between variables. I do not review these algorithms but instead rely on statistical references for those descriptions. Although some may consider the complexity that comes with Bayesian analysis unwarranted, I find the approach intuitive and easily adaptable to the diverse sets of data in this dissertation.

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2 The Relationship between Bicyclists' Psychological Stress and the Road Environment

Abstract

Understanding how road environments stress bicyclists (and prospective bicyclists) has important implications for road design and network planning. With the rise of wearable bio-sensing technology, the potential for measuring real-time environmental stress is emerging. In this naturalistic cross-over field experiment, I investigate bicyclist stress through heart rate variability (HRV) and survey responses. I examine the relationship between HRV and the road environment through a series of bivariate and multivariate statistical models. Results suggest participants' HRV and survey responses have a weak but certain correlation, suggesting HRV may be a valid measure of bicyclist stress. However, only one (the local road) of five road environments certainly differs by participants' HRV. The differences in HRV between two collectors and two arterials are far more tenuous. This chapter is based partially on work presented at the Scientists for Cycling Colloquium (Velo-city) (2017) and the Transportation Research Board 96th Annual Conference (2017) (Fitch and Handy. *Defining safe bicycling environments through human physiology,* papers 5 and P17-20750, respectively), and at the 6th Annual International Cycling Safety Conference (2017) (Fitch, Sharpnack, and Handy. *The road environment and bicycling psychophysiological stress,* paper 24).

Below I've included a list of terms and acronyms from psychophysiology that I use through this chapter which may be unfamiliar for many transportation audiences.

Definition of Key Terms

Terms	Definition	Importance
ANS	autonomic nervous system	Part of the nervous system that controls bodily functions (not consciously) such as heart beats.
anxiety	psychological meaning applied to stress by individuals	The conscious representation of stress (i.e. what people mean when they say "it was stressful").
dual n-back	Working memory computer task	Working memory task where participants have to remember an auditory letter and visual block on a computer screen and respond for matching stimuli through keyboard buttons.
GSR	galvanic skin response	Conductance of the skin (usually measured in the fingers). High conductance relates to large sympathetic nervous system activity and thus strong emotional arousal.
HF-RR	high frequency inter-beat interval	High frequency filtered version of RR intervals (see below).
HRV	heart rate variability	General term for the variability in time between successive heart beats. Large variability is associated with relaxed states, while little variability is associated with stress.
PSNS	parasympathetic nervous system	One of two branches of the autonomic nervous system responsible for controlling internal organs, blood vessels, and glands. Withdrawal of PSNS activity is associated with stress.

QRS complex	electric signal of a heart beat	The QRS represents graphical deflections of an electrocardiogram (i.e. the depolarization of the left and right ventricles of the heart) lasting approximately 0.05 to 0.1 seconds. The peak amplitude of this signal (the "R" wave) is the common measure for the time of the heart beat.
RR	inter-beat interval	Specific term for the time between two successive heart beats. RR refers to the time between two R wave peaks from the QRS complex.
RSA	respiratory sinus arrhythmia	Frequencies of heart rate variability associated with respiration and vagal tone (see below).
SNS	sympathetic nervous system	One of two branches of the autonomic nervous system that prepares a body to respond to a perceived threat to safety. Increase in SNS activity is associated with stress.
stress	automatic (not conscious) physiological response to unsafe situations	Represents a continuous and rapidly changing physiological response to internal and external stimuli. In this study, stress is operationalized through heart rate variability.
vagal tone	electric activity of the vagus nerve (PSNS)	Describes the level of parasympathetic activity. Increased tone leads to greater heart rate variability and thus relaxed states.

2.1 Introduction and Background

2.1.1 Motivation for measuring psychological stress of bicyclists

The main motivation for this study is to improve city street design and planning for bicycling through a better understanding of bicyclists' stress and comfort. Knowing what stresses bicyclists would allow engineers to tailor street designs to improve perceived (and perhaps objective) safety, and allow planners to design bicycling networks that are most likely to increase bicycling for the masses. In addition, at least two secondary motivations to study bicyclists' stress and comfort exist.

The first secondary motivation is the study of bicyclist stress for understanding the psychological health impacts of bicycling. Current psychophysiological evidence indicates that chronic stress is likely to have a normative component associated with repeated environmental acute stressors over time (Cacioppo et al., 2007, p. 753). Therefore, measuring acute bicyclist stress should be an indicator for chronic stress related to bicycling. Bicycling is likely to improve psychological health (compared to non-active travel modes) due to the positive relationship between physical activity and psychological health. Indeed, longitudinal evidence from the UK suggests active commute travel has positive psychological effects compared to driving (i.e. chronic "psychological distress" as measured by the GHQ-12 standardized questionnaire (Hankins, 2008) is reduced) (Martin et al., 2014). Integrating research on acute stress (through experiments) and chronic stress (through longitudinal surveys) of bicyclists is needed to better understand the psychological health associated with bicycling travel.

The other secondary motivation is the use of information about bicyclist stress to understand the interaction between bicyclists and automobiles (i.e. human drivers or automated vehicles). Even if drivers (or vehicles) identify and avoid bicyclists, driving behavior can still cause significant psychological stress to bicyclists. If automated vehicles replicate existing driver behaviors (e.g. drive fast, provide short lateral distances between car and bicyclist) we might expect emerging vehicle technologies to fail at removing an important existing barrier to bicycling. With quickly evolving automated vehicle control systems, understating the psychological impacts of bicyclist/automobile interactions may become integral to increasing bicycling as a normal mode of travel.

2.1.2 Measuring psychological stress

Stress is a difficult concept to define. Beyond its use in physics, the term began to have psychological meaning in the early to mid-20th century (Quick and Spielberger, 1994). The term stress carries many different meanings depending on research domain. It is now common for people to refer to their "stress" broadly, as something that is a function of their daily life demands or current situation. However, in the following chapter I will define stress narrowly, and make a distinction between it and anxiety, which I define more broadly. Borrowing from Cacioppo et al. (2007), I define psychological stress as a physiological response to environmental or internal stimuli. I define anxiety as a negative feeling in response to stress. In this sense, I consider individuals' reported "stress" as anxiety. Stress and anxiety can be divided into two dimensions, each with two categories: acute vs. chronic stress (Cacioppo et al., 2007), and state vs. trait anxiety (Cattell and Scheier, 1961). In this proposal, I am only interested in the short-term components (acute stress and state anxiety), because those are most likely to influence bicycling behavior. Many measures of physiology relate to psychological stress (e.g. skin conductance, cortisol, etc.) (Cacioppo et al., 2007), but among the most widely used are measures of the heart's electrical conduction system.

Most current theoretical models of the human stress response describe it as a human alarm for a potential safety threat (dating back to early conceptions of the "fight or flight" response conceptualized by Walter Cannon (Quick and Spielberger, 1994)). This threat includes cognitive biases resulting in perceived threats even when objective safety is certain. However, alternative theories suggest that stress is not generated from perceived threats to safety, but instead it is the default neurobiological response (Brosschot et al., 2016). In other words, we are by default stressed, but if we perceive safety we inhibit that default response and become relaxed. This theoretical reversal is primarily based on the survival value of the stress response from an evolutionary perspective.

Although this debate may have important implications for understanding human physiology, in terms of measuring psychological stress, is it probably less important since the relationship between cardiac response and acute psychological stress is consistent with both theories (see below).

2.1.3 Electrical conductivity of the heart as an indicator of psychological stress

The description of heart (cardiac) response to stress starts with the autonomic nervous system (ANS) and its component sympathetic and parasympathetic nervous systems as a bidirectional interface with the central nervous system (Montano et al., 2009) (see Figure 2.1). Heart beat speed is controlled by the two ANS branches, often described as antagonistic (or complementary), whereby the sympathetic nervous system (SNS) mobilizes the body for action under stressful conditions, and the parasympathetic nervous system (PSNS) responds by returning the body to a relaxed state in a dynamic equilibrium (Taylor, 2006). This response can be perceived (i.e. individuals are consciously aware of heart beat changes), or can occur before or without individual awareness (Sharpley, 2002). The classic view that the SNS and PSNS are in balance (i.e. withdrawal of one system is linearly associated with activation of the other, known as the sympathovagal balance) has recently been criticized (Laborde et al., 2017). It has been suggested that in some conditions (e.g. low intensity exercise) the SNS and PSNS relationship is more complex (Draghici and Taylor, 2016). The SNS and PSNS have different frequency responses associated with their electrical conductance of the heart. The PSNS is associated with high frequencies and the SNS associated with low frequencies (see Figure 2.1). This means that changes to heart beats due to PSNS activity are clearer at short time scales, compared to changes in SNS activity.

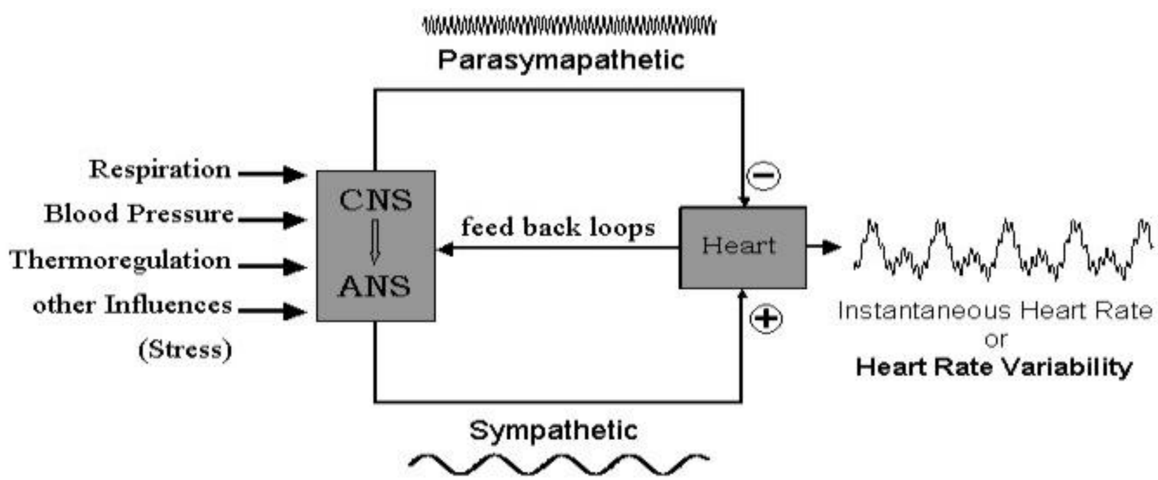

Figure 2.1 Representation of the ANS bidirectional control of the cardiovascular system. A simplified version of a block diagram from McCraty et al. (1996).

Heart beat variability, the variability in the time between successive heart beats (more commonly called heart *rate* variability (HRV))[1], is widely used in psychology because of its ease of measurement, its longstanding correlation with stressful events, and theoretical support. HRV has theoretical support as a stress marker through the linking of heart beat control to the vagus nerve (cranial nerve X) that transmits PSNS activity. Five theories link HRV to psychology (Laborde et al., 2017). Each of the theories has in common the connection between HRV and "vagal tone" (i.e. the activation of the vagus nerve in controlling heart beats). Vagal tone is associated with heart beat variability during spontaneous breathing, known as respiratory sinus arrhythmia (RSA). RSA represents the variability of the time between successive heart beats which matches respiratory processes. During inspiration HRV decreases, and during expiration, HRV increases. RSA has been considered a direct measure of vagal tone (Porges, 2011), although considerable disagreement about this conclusion exists (Grossman and Taylor, 2007), which makes defining a single appropriate stress measure from HRV difficult. Disagreement on how to handle respiration while using HRV to assess vagal tone is also longstanding (Laborde et al., 2017). Although HRV associated with spontaneous breathing is most closely linked to vagal tone, respiratory parameters that are not associated with the vagus can alter HRV. Therefore, respiration is a potential confounding variable in using HRV to assess vagal tone if not properly controlled (either through paced breathing or statistically through multivariate analysis) (Laborde et al., 2017). The situation is even more complicated when assessing psychological stress because stress can cause both the withdrawal of vagal influence on the heart (reduced vagal tone) and substantial changes in breathing (e.g. tidal volume) (Suess et al., 1980).

Methods used to measure HRV vary by study and by purpose such as physiological function (e.g. stress response) or pathology (e.g. coronary heart disease) (Berntson et al., 1997). General guidance on the quantification of HRV (Berntson et al., 2007, 1997; Malik, 1996) suggests that within-subject differences are more likely to be associated with vagal tone (and thus stress), than between-subject differences (Andreassi, 2006, p. 287; Berntson et al., 2007, 1997; Laborde et al., 2017). Within-subject differences are stronger than between-subject differences because personal characteristics such as age, race, and sex may influence HRV, and because individual differences in respiratory rates are better accounted for; in effect, each participant acts as their own control.

Measuring HRV depends on the technology used to measure electrical conduction of the heart, but always rests on the estimation of the time series of the heart beat-to-beat interval. In laboratories,

[1] I use the acronym HRV because of its ubiquity, but really it is a bit of a misnomer (Draghici and Taylor, 2016).

electrocardiography (ECG or EKG) measures the depolarizing muscles of the heart during each heartbeat. In a normal sinus rhythm (heart beat beginning at the sinus node), the most pronounced electrical component is the triad wave representing the depolarization of the right and left ventricles (i.e. QRS complex), where the peak amplitude of the R wave is the main "beat". The QRS complex is identified using an algorithm (or by hand) and the time difference between successive R peaks represents the beat-to-beat interval (known as the RR interval, inter-beat interval, or heart period) (Tarvainen, 2014). I will refer to the RR intervals over time as the RR time-series or the RR signal.

In many cases, the use of laboratory ECG is not conducive to measuring HRV (e.g. naturalistic settings). However, recent technological advances have generated portable devices that collect ECG, process the signal into RR intervals on the device in near real-time, and store the interval data with considerable temporal resolution (1 ms) (Parak and Korhonen, 2013). In a naturalistic setting (and even in a laboratory setting), numerous internal and external factors influence the detection of normal heartbeats (e.g. loose electrode contact, ectopic beats). Because of this, RR interval data is inherently "noisy," and is often "cleaned" by removing erroneous RR intervals resulting in the so called normal-to-normal intervals (Berntson et al., 2007; Karim et al., 2011; Tarvainen, 2014). Assuming a clean time series is generated, researchers use three[2] basic approaches to modeling RR interval data: (a) time domain, (b) frequency domain, or (c) time-frequency domain. The time and frequency domains are two complementary ways of representing RR variability, where the time domain aggregates across frequencies (e.g. standard deviation of RR intervals with units of time (ms)), while the frequency domain aggregates across time (e.g. density of power for a selected frequency range in units of time/frequency (ms^2/Hz)) (Berntson et al., 2007). Summary statistics of the time-series at predefined intervals (epochs) are usually generated for further analysis. The larger the summary interval, the better the signal-to-noise ratio, but the worse the power of any following statistical analysis. Statistical summaries of HRV most associated with vagal tone include the temporal summaries of successive heart beat differences, heart beat differences associated with the "peak" and "trough" of RSA, and high frequency HRV (Laborde et al., 2017). The joint time-frequency domain analysis combines the characteristics of the two domains by assuming that psychological events evolving over time influence cyclical physiological processes (Gratton, 2007). In that case, stress is indeed an evolving "event" that manifests in differing HRV over time. The joint time-frequency domain does not rely on statistical

[2] I've ignored co-called "non-linear" HRV methods (e.g. Poincaré plots, etc.) because their use generally requires long term recording (Draghici and Taylor, 2016).

summaries over time or frequency, thus it can preserve the original time series sample size. Instead, this domain of methods "involves a segmentation of the time series in shorter epochs, the determination of the amplitude of the frequency of interest in each epoch (the analysis of which is performed in the frequency domain), and the analysis of the time course of modulation of the amplitude of the frequency of interest (the analysis of which is performed in the time domain)" (Gratton, 2007, p. 843). Most commonly the time-frequency domain includes some sort of low or high-pass filter at fixed or varying (locally adaptive) frequencies.

2.1.4 HRV while bicycling

The psychological effects of exercise both for improving athletic performance and for understanding the psychological benefits of physical activity are broadly covered in the fields of exercise and sports psychology. However, psychological measurement using HRV *during* bouts of exercise is much more challenging because physical exertion may dominate cardiac response, masking psychological stress. The reason physical exertion may mask any correlation between HRV and psychological stress is because of the balance of sympathetic and parasympathetic control of the heart (see Figure 2.1 and discussion above). At rest, vagal (PSNS) control of the heart dominates. However, with increasing exertion, SNS activity increases and PSNS activity is withdrawn (Grossman et al., 2004). In addition, changes in respiration patterns and body movement are likely to interact with measurement of vagal tone (Grossman et al., 2004; Suess et al., 1980). In theory, exertion is likely to both decrease vagal influence on the heart, and decrease the signal to noise ratio of the remaining vagal influence on the heart. Empirically, the relationship between exertion and vagal tone is more complex. At least one study has shown that PSNS activity is initially withdrawn at the onset of "light dynamic leg exercise", but slowly increases when light exercise is maintained (Fagraeus and Linnarsson, 1976). This result suggests that vagal tone can be measured through HRV during sustained light exercise. However, another study demonstrated that high frequency oscillations of HRV during exercise may be more related to "nonneural" mechanisms (i.e. not vagal tone) (Casadei et al., 1996). Yet other studies employing more complex signal processing techniques have shown that HRV (or RSA) can be measured even during intense bouts of exercise (e.g. 139 heart beats per minute) (Hatfield et al., 1998), and that this HRV is likely associated with vagal tone (Tulppo et al., 1996).

The important determination for this chapter is whether HRV describes physiological response (be it though changes in vagal tone and perhaps respiration) associated with psychological stress during exertion. Evidence suggests that cognitive performance and psychological states are affected following a stationary bicycling task (e.g. McGowan et al. (1985)), but this says little about psychophysiological measurement during bicycling. To my knowledge, only one study (Rousselle et al., 1995) has examined psychological stress through HRV *during* a bicycling task. Rousselle et al.'s (1995) study focuses on understanding combined physical and mental stressors and their associated cardiac and respiratory responses using stationary bicycling and mental arithmetic as stressors. The primary findings are that cardiac response to moderate exercise shows a different pattern than to mental arithmetic when alone. With both stressors, results suggest a synergistic effect on the heart, whereby exercise does not mask psychological stress. A potential synergistic effect is important because it suggests that psychological stress is associated with HRV while bicycling. This view is generalized by Andreassi when he claims that when exercise and psychological stress are combined, there seems to be a combined (but not necessarily additive) stress effect as measured by cardiac response (Andreassi, 2006, p. 271).

Existing bicycling studies predominantly measure stress through surveys and interviews. For the purpose of clarity, I will continue to distinguish these as measures of anxiety. I review the few research projects attempting to measure bicyclist stress directly (see section 2.1.6) because they are few and foundational to this research. Before addressing those studies, I provide a brief discussion of the expected stress of bicycling in a road environment.

In general, the task of bicycling requires attention, physical balance, and exertion (even if participants are to ride at a moderate pace). Each of these components is likely to vary in difficulty and salience between individuals based on experience, ability, and other behavioral characteristics. This variability is important because evidence suggests that physiological arousal is increased as experimental task increases in difficulty (Andreassi, 2006, p. 282). Between-individual differences in cardiovascular reactivity to stress is also quite large (Andreassi, 2006, p. 287), hence the common use of within-subject designs to improve measurement sensitivity of psychophysiological variables (Jennings and Gianaros, 2007). In addition, two important factors are likely to add to between-individual differences with regard to the stress of bicycling with vehicular traffic: fear and vigilance.

Evidence suggests that the physiological response to "fearful stimulus" is highly dependent on whether the individual indeed fears the stimulus. Not only is the physiological response to the fearful stimuli attenuated for the fearless, but it can be reversed for the fearless (Andreassi, 2006, p. 285). This point is crucial because fear of interacting with vehicular traffic while bicycling is likely to vary from person to person. Between-individual variability in vigilance, which I define as sustained attention over time, is also likely. People with great vigilance tend to have higher heart rates compared to those who lack vigilance (Andreassi, 2006, p. 337). This relationship between heart rate and vigilance is important for urban bicycling because people who pay more attention to the task of bicycling are likely to exhibit more stress, but presumably have less crash risk.

Extrapolating from previous literature, the validity of measuring stress (through HRV) while bicycling will be challenged by the between-individual differences in psychological predispositions and exertion related changes to HRV. Within-individual experimental designs help to control for individual differences, but exertion remains an important potential confounding variable. Nonetheless, HRV is currently the most promising physiological marker of psychological stress while bicycling because it is relatively noninvasive and has a strong theoretical link to stress response (Cacioppo et al., 2007; Porges, 2011).

2.1.5 Road characteristics associated with bicyclist comfort

The focus on the relationship between the road environment and stress is an example of the overarching concept of *environmental stress*: environmental characteristics that lead to psychological discomfort (Evans and Cohen, 1987). In the case of day to day bicycling, the road environment may only have a small direct influence on bicyclists' stress (e.g. pavement roughness can make bicyclists worry about crashing their bikes). However, the road indirectly controls driver behavior (e.g. wide lanes lead drivers to increase their speed), which has a direct relationship with bicyclists' stress. With a better understanding of how the environment influences bicyclists' stress, we can provide better guidance to planners and engineers about how to design roads that increase safety and encourage bicycling.

Three main attitudinal factors are associated with bicyclist safety and comfort. The first is the physical effort required to power the bike which is influenced by non-road variables (e.g. wind speed and direction, fitness of the bicyclist, etc.) and road variables (e.g. topography and road surface roughness). Topography causes increased bicyclist effort to climb hills, while rough road surfaces translate into bicycle vibration making powering the bicycle more difficult and less enjoyable (Thigpen et al., 2015). The second factor is personal safety or fear of crime when bicycling or when leaving a parked bicycle (e.g. theft, robbery, assault). This factor is largely beyond the scope of road design, but not beyond the scope of urban planning in general, which can foster or inhibit personal safety through urban design and local policies. The third factor, and the focus of the remainder of this section, is the comfort associated with interacting with vehicular traffic (traffic safety).

Having to navigate a bicycle through vehicular traffic is one of the most critical barriers for urban bicycling (Winters et al., 2011). Although mixed bicycling and vehicular traffic are the norm in many US cities, considerable evidence that people prefer to have separation from vehicular traffic exists (Handy et al., 2010; Winters et al., 2011). Leading European transportation authorities have identified the most critical road improvement interventions associated with greater bicycling rates and safety, which have been succinctly summarized by Wardlaw (2014) as: (1) decrease vehicular speeds, (2) provide separated facilities when vehicular speeds and density are high (with careful consideration of junction design), and (3) improve sight lines and general expectations of micro bicyclist and driver behaviors. These general improvements can be accommodated in a number of road designs. Standard road designs in the US (with bicycling in mind) are found in the American Association of State Highway Transportation Officials (AASHTO) and the National Association of City Transportation Officials (NACTO) design guides. Recent evidence shows that these new road improvements have positive associations with bicycling rates and safety, and are overwhelmingly preferred to non-improved roads by most bicyclists (Monsere et al., 2014).

Lastly, a few empirical studies have illustrated some potential specific road characteristics that are likely to influence bicyclist comfort:

(1) Increased vehicular volumes and speeds all decrease bicyclist comfort (Buehler and Dill, 2016; Epperson, 1994; Landis et al., 1997).
(2) On street parking may have bi-directional causal effect of bicyclist comfort depending on type and turnover (e.g. opening car doors are a hazard, but on-street parking generally slows vehicular speeds; or wide parking lanes can act as a buffer for bikes or cause drivers to park further from the curb (Duthie et al., 2010; Furth et al., 2010; Tilahun et al., 2007)).
(3) Operating space for bicyclists adjacent to vehicular traffic (e.g. bike lane widths, wide outside lanes) are important for providing separation (Buehler and Dill, 2016; Landis et al., 1997), but may also increase vehicular speed.
(4) Abrupt vehicular turn lanes (causing reduced speeds) partnered with bicyclist "pocket lanes", bike boxes, and intermediate turn boxes may increase bicyclist comfort.
(5) Any bike specific infrastructure that has considerable separation from vehicular travel (e.g. separated path) must consider the heightened safety hazard of junction conflict zones (Wardlaw, 2014).

2.1.6 Existing evidence for measuring bicyclist psychological stress through human physiology

Studying bicyclist stress through human physiology is in the proof-of-concept research stage. To my knowledge, one peer reviewed publication (Doorley et al., 2015), a handful of conference presentations (Caviedes et al., 2017; Caviedes and Figliozzi, 2016; Doorley et al., 2015; Vieira et al., 2016), and one non-peer reviewed research report (Jones et al., 2016) are the only existing studies examining the link between physiology and bicyclist stress. To date, only HRV and galvanic skin response (GSR) have been used to measure psychological stress through physiology. Doorley et al. (2015) used heart rate monitors to record participants heart rates during a bicycling task in Cork, Ireland. They correlated HR to subjective safety ratings at specific locations along the bicycling course. Importantly, they did not measure HRV, nor did they measure physical exertion (or a surrogate for exertion) so their measure of HR encompasses stress from exertion, task attention (finding and responding to the rating cue on the side of the course), and fear of interacting with traffic. The lack of control for these confounds are perhaps why the correlations between HR and subjective safety ratings are weak. Nonetheless, this study was the first to relate physiology to psychology of a bicyclist in a naturalistic setting, and suggests human physiology might be an important marker for safety. Vieira et al. (2016) use HRV (particularly the controversial LF/HF ratio (Laborde et al., 2017)) to measure bicyclist stress. This measure rests on the assumption of a linear sympothavagal balance which is unlikely during exercise. The authors take a very exploratory "data mining" type approach to search for stressful events (e.g. car passing on left, ground irregularities, no obstacle, bicyclist turn) using video image processing and relate high LF/HF ratios to video identified events. The authors qualitatively show situations where correlations between HRV and close passing vehicles exist. However, it is unclear how many false positives exist in the data (i.e. high LF/HF ratios with no stressful event).

The two conference papers by Caviedes et al. (2017; 2016), and the report from Jones et al. (2016) use GSR to measure psychological stress. Jones et al. (2016) only report preliminary qualitative associations between aggregated GSR along an urban bicycling course and individual narratives of enjoyment, safety concerns, and exertion. Until further analysis of their data, it is unclear how effective GSR is in indexing psychological stress. Caviedes et al. (2017; 2016) report quantitative differences between GSR of bicyclists during different bicycling road and traffic conditions (e.g. bike facility type, traffic period, etc.). The first study included only one participant, the later five participants, where they report average within-subject "response ratios" for different road and traffic categories. Response ratios describe the balance between the amplitude and duration of skin conductance following an event.[3] The authors report large skin conductance differences for some categories (175% differences between peak and off-peak traffic), but only report p-values for others (e.g. bike facility types, speed limit, etc.). Most

[3] It is not clear how the authors determined "events" during a continuous bicycling task.

notably, the authors use a bicycle power meter and GPS to measure participant physical exertion; however, they do not report any multivariate analyses where they use these measures to statistically account for exertion. Also, in the discussion the authors report a correlation between GSR and subjective measures of threat and safety, but not the specific correlations.

Measuring stress through GSR may be more challenging than other physiological responses. This challenge stems from GSR's sensitivity to arousal in general. GSR cannot differentiate whether this arousal is triggered by a positively evaluated stimulus, a negatively evaluated stimulus, or by a novel stimulus (Krosnick et al., 2005). In addition, GSR does not have as clear a foundation of support from physiology as an indicator of the human stress response as compared to HRV. GSR is more often associated with the SNS (not PSNS) branch of the autonomic nervous system and thus not usually linked to vagal tone. It may be that combined heart and skin conductance sensors can improve physiological measurement of psychological stress (HRV reflecting withdrawal of PSNS, and GSR reflecting increase in SNS), but to my knowledge, this has not yet been attempted for bicycling.

It is likely that many of the questions that go unanswered in these unpublished papers are due to their preliminary nature and inability to provide exhaustive coverage of their studies due to word limits. However, they all provide positive evidence for the use of human physiology for measuring bicyclist psychological stress.

2.1.7 Research questions

I focus this study on the relationship between road environments and the psychological stress and comfort of bicyclists. I have three overarching substantive research questions:

(1) How do road environments relate to survey measures of comfort and safety?
(2) How well do survey measures and physiological measures of stress relate?
(3) How do road environments influence bicyclist psychophysiological stress?

In addition, I have two methodological research questions:

(1) Can psychophysiological stress be measured while bicycling in a natural environment?
(2) Can the influence of psychological stress be isolated from the influence of physical exertion when bicycling at moderate levels of exercise?

By combining answers to these questions I aim to provide information on the relationship between road environments and bicyclist stress and open new avenues for research on human physiological measurement for understanding bicycling environments.

2.2 Methods

I examine the relationship between road environments, psychophysiological stress, and survey measures of the bicycling experience through a naturalistic bicycling experiment in Davis, CA. Participants bicycled on five roads with varying characteristics thought by me to influence their psychological stress response. Participants also responded on paper based surveys and to interview questions about their experience, attitudes, travel behavior, and other socio-demographic characteristics with particular emphasis on bicycling comfort and safety. Table 2.1 shows all the experimental components and their purpose.

Table 2.1 Experimental Components

Experimental Component	Format	Purpose
Pre-Experiment Survey	Paper	Measures participants' general health, socio-demographics, travel behavior, and attitudes (about safety and comfort).
Mental Stress Test (Dual-n-back)	Computer	Measures participants' stress response to a complex working memory task.
Bicycling Speed Trial	Off-street Path	Measure HRV, audio/video, and speed/position from GPS.
Bicycling Conditions	Road	Measure HRV, audio/video, and speed/position from GPS. Followed by paper surveys of comfort and safety.
Rest Conditions and Surveys	Outdoor	Used between bicycling conditions as both a "washout" period to ensure they don't have carryover physiological effects from prior rides, and to measure immediate impressions of participants' comfort and safety.
Open Ended Interview	Indoor	Measures participants' experience in the bicycling experiment and allows them to reflect on their prior survey responses. The interview is used to determine specifically uncomfortable moments, and reveal any new important variables.

2.2.1 Materials and measurements

2.2.1.1 Measurement of response variables

To measure stress physiologically, I used the BodyGuard II heart beat-to-beat interval measuring device manufactured by Firstbeat Inc. I measured participants' attitudes toward bicycling comfort through a series of paper survey questions administered during rest periods of the experiment (Appendix A). In addition, I administered a pre-experiment survey of individual characteristics associated with travel behavior, general stress, and bicycling ability, vigilance, fear, and comfort (Appendix B). Finally, I conducted a short post-experiment structured interview to explore more nuanced attitudes and perceptions related to bicycling comfort and anxiety (Appendix C).

To account for the influence of exertion on HRV, I measured bicycling speed through a helmet mounted GPS, and use speed as a surrogate for exertion. Although exertion is also a function of participant fitness, bike design, tire pressure, and wind speed/direction, many of those parameters were controlled during the experiment through exclusion. For example, I roughly controlled participant fitness by limiting the study to female undergraduates with normal BMI. While I didn't control bike design (due to the need for participants to be comfortable riding a familiar bike), tire pressure was ensured to be at that specified by the individual participant's tires. Finally, I conducted the experiment only when wind speeds were less than 15 meters per second, when temperatures were less than 90 degrees Fahrenheit, and during non-rain conditions. Therefore, speed is expected to be an adequate, albeit noisy, estimate for physical exertion. In addition to measuring speed, participants were instructed to ride at a moderately slow pace to limit the role of exertion on HRV. Because exertion and psychological stress coexist in the on-road bicycling tasks, I used two independent tasks to try and isolate the effects of exertion and psychological stress. First, I measured physical exertion due to bicycling in a speed trial that has no added psychological stress from interacting with vehicular traffic (Table 2.1). Second, I measured HRV at a seated baseline[4] and during a psychological stress test (working memory task) without exercise. I used a demanding version of a classic visual computer task (*n*-back[5]) called the dual *n*-back[6]. In this task, a computer simultaneously presents an auditory letter and visual block (spatial location of a square on a 3 by 3 grid) on a computer screen to the participant in three second intervals. Participants were instructed to decide if the present combined stimulus matched the combined stimulus *n* stimuli back, and press a button response for each of the stimuli (auditory and visual). For example, in a 2-back task, if a participant heard the letters *A*, *F*, *A*, and saw the squares in positions *left-center*, *center*, *center*, the correct response would be to only push the button response for an auditory 2-back, since the letter was the only stimuli to be repeated two times back. Had the squares been located in the *left-center*, *center*, *left-center* positions, the correct response would have been to push both the auditory and visual buttons, and had neither been repeated two times back,

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4 Participants were seated for a minimum of ten minutes and then a "vanilla" two-minute baseline commenced when participants were listening to instructions about how to play the *n*-back computer game. The term "vanilla" refers to a task requiring sustained attention with minimal cognitive load. The vanilla task is used to distract from the physiological measurement that can itself cause stress in classic no-task baseline conditions (Laborde et al., 2017).

5 The *n*-back is a classic working memory and speed information processing task (Miller et al., 2009) first devised by Kirchner (1958).

6 The more complicated dual *n*-back task was originally used as a training task to improve fluid intelligence (Jaeggi et al., 2008), and thus adaptively increased and decreased in difficulty (changed *n*) based on participant performance. My use of this task did not adaptively change *n* (*n* is static at 2), but with minimal practice at *n*=1 and 2, this task is still very demanding (correct identification of both auditory letter and spatial location on average was 56% with standard deviation 19%).

the correct response would have been to avoid pushing all buttons. This task is very demanding for participants unfamiliar with its structure, and has been shown to have a physiological response (Nugent et al., 2011). Heart signal response to stress from a challenging working memory task may be different than response to stress while bicycling amongst vehicles. However, because they are both psychological, they both represent a psychological component to heart beat control.

Using information from isolated HRV responses to exertion and mental stress, I compared five methods for removing low frequency (<0.125 Hz) trends in the RR signal most likely to be unrelated to vagal tone and thus unrelated to psychological stress while bicycling (See Appendix D). Following my selection of the so-called Maximal Overlap Discrete Wavelet Transform (MODWT) method, I conducted a dual objective sensitivity analysis for high and low frequency noise filtering (see Appendix D for details). The first objective in the sensitivity analysis was to find a transformation of raw RR signals that shows strong correlation with participant speed in the speed trial and also consistent with theoretically justified heart signal frequencies associated with vagal control of the heart (spontaneous breathing range). The second objective is to find a transformation of raw RR signals that shows strong correlation with the isolated psychological stress task while also being theoretically consistent with known frequencies of vagal heart control. Determining a RR signal transformation that shows strong independent relationships with exertion and psychological stress allows me to make stronger conclusions about effects from the on-road conditions where the two sources of stress are combined.

2.2.1.2 Measurement of Predictor Variables

Field measurements on all roads where participants rode their personal bike[7] included road segment characteristics (see Table 2.2) and intersection configurations (e.g. pocket lanes, abruptness and length of vehicle right turn lanes, length of intersection, bike box, etc.).[8] If a road had changes in these characteristics, they were linear referenced by segmenting each road and recording new variables by "sub-segment." A sub-segment was defined when any major change in the design of a road occurred (e.g. change in on-street parking, width of bike lane or outside lane, approach to an intersection, intersection). This segmentation allows for within-road environment variation to be included in multivariable analyses. Because operating space is important for bicyclist comfort (Buehler and Dill, 2016), two within-road variables that describe changes in operating space are used in the multivariable

[7] A tradeoff exists between having participants ride their personal bike (more realistic comfort) vs. a standard bike (more control over exertion). I chose to use personal bikes because I didn't want the unfamiliarity of a standard bike to confound stress and comfort.

[8] Intersection variables were later dropped because HF-RR signals exhibited too much noise during acceleration and deceleration events in and around intersections.

analyses (bike lane width for those roads with bike lanes or outside lane width for Russell Blvd.).

In addition to the environmental characteristics thought to influence psychological stress, I measured a series of "control" variables (potential confounds). These covariates come from three general sources (individual, environmental, and traffic) and potentially influence both psychological stress and physical exertion. Table 2.2 provides a list of the major covariates along with their source of measurement. Only a subset of these variables are analyzed in this chapter. I based the decisions of which variables to include on prior evidence of bicycling perceived safety and moderators of acute stress. For some of the road environment measures, I used exploratory bivariate statistics and visualizations (not shown) between predictor variables and summaries of HF-RR intervals, as well as correlations among predictor variables to determine the variables. This prior exploratory work was needed to reduce collinearity of variables. At the individual level, I include two key variables from the pre-experiment survey when modeling HF-RR variability (*Vigilance and Fear*). *Vigilance* is the z-score of two unstandardized Likert items ("When bicycling, I always keep a watchful eye on cars", "I am a cautious bicyclist") (α = 0.83)[9], and *Fear* the z-score of three unstandardized Likert items ("When I ride my bike I'm afraid of turning cars when approaching intersections", "When I ride my bike I'm afraid when trucks pass me on the road", "When I ride my bike I am afraid of cars that pass me on the road") (α = 0.91) (see Appendix B for response scales and question prompts). These person level variables have the potential to confound the main treatments in that people who are more vigilant and more fearful are likely to exhibit more stress, and variation in stress between different road environments.

Table 2.2 Primary Variables and Covariates

	Psychological Stress	Physical Exertion
Individual	• Bicycling comfort in general (pre-survey) • Bicycling vigilance (pre-survey) • Bicycling fear (pre-survey) • Frequency (pre-survey)	• Type of Bike (pre-survey) • Speed (GPS)
Environmental	• Bike lane width (field) • Vehicle lane width (field) • On-street parking (field) • Number of lanes (field) • Percent shade (video)	• Wind Speed and Gusts (Davis weather station) • Temperature (Davis weather station)

[9] Reliability as measured by Cronbach's $\alpha = \frac{k\bar{c}}{\bar{v}+(k-1)\bar{c}}$ where k is the number of items, $\bar{c}$ is the mean inter-item covariance, and $\bar{v}$ is the mean variance of each item.

	• Loud noise events (audio)	• Time of Day
Traffic	• Obstacles (e.g. trash cans, leaf piles, parked cars) (video) • Number of passing cars, trucks, and bikes (close and normal passing distance) (video)	

The environmental variables thought to influence physical exertion (i.e. prevailing wind speed, wind gusts, temperature, time of day) were collected from public sources to ensure compliance with Internal Review Board protocol for ethics that the experiment was conducted in day light, with no precipitation and safe temperature (<90 degrees Fahrenheit) and wind environments (< 15 m/s). Although these conditions varied (mostly due to a nearly equal split of morning and afternoon sessions), I assumed this variation had negligible effects. A simple comparison of HRV for each road by morning and afternoon showed no clear systematic difference (not shown). However, it is possible that changing temperatures and windspeed during the experiment may have influenced HRV.

The traffic variables represent the most direct influencing variables on participant psychological stress. However, the goal of this experiment is to examine the relationship between road environments (because that is what engineers and planners have control over) and bicyclist stress. Traffic characteristics can be considered a downstream effect of road environments and in this view they only add to the variability in the individual experience bicycling on a particular road. Because traffic varies by participant, it has the potential to confound the main treatment effects. Although numerous traffic and other situational variables were recorded from participant video analysis (Table 2.2), only two variables are used in the models: the number of passing vehicles on a sub-segment, and the presence of a passing truck or bus on a sub-segment. I based this decision off of bivariate correlations between traffic variables and HF-RR and collinearity amongst traffic variables. I aggregated the traffic variables to the sub-segment level to reduce the burden of video analysis (e.g. counting cars by segment instead of recording the time for each passing car). This aggregation also simplifies the modeling of traffic effects by making them a sub-segment level variable. Had the time for each passing car been recorded, assumptions about the latency of each car's effect on HF-RR variability would be needed to properly model the traffic effect.

2.2.2 Bike course and participant selection

I selected the bike course based on balancing road characteristic variability, experimental control, and experimental convenience. Experimental convenience constrained the course to begin and end on the UC Davis campus because the application of the heart-beat monitor required a private room and because it was most convenient for participants who all attended UC Davis. Experimental control constrained the course to have a beginning and end which provided access to each road environment within a short distance because I used rest periods in between bike rides for surveying and to allow physiology to return to baseline (washout). Finally, the course needed to provide a variety of road characteristics with little to no elevation change (limit effect of exertion). Table 2.3 provides the roads and their associated characteristics and Figure 2.2 shows the route configuration.

Table 2.3 Experimental Roads and their Characteristics

Road	Characteristics
College Park	Low speed (no data) local road, 2 lane, no road centerline, on-street parking, low traffic (average daily cars unknown)
Oak Ave.	Low speed (no data) collector, 2 lane, road centerline, bike lane, on-street parking, low traffic (average daily cars~ 2,000)
B St.	Low speed (~25 mph) collector, 2 lane, road centerline, buffered bike lane, no on-street parking, moderate traffic (average daily cars ~ 6,000)
Anderson Rd.	Medium speed (~25-30 mph) collector, 2 lane, road centerline, bike lane, on-street parking, moderate traffic (average daily cars ~ 10,000)
Russell Blvd.	Medium speed (~30-35 mph) arterial, 4 lane, center median, no bike lane, on-street parking mixed, high traffic (average daily cars ~ 20,000)

I recruited female undergraduate students through the UC Davis campus travel survey, and students from Regional and Urban Planning (ESP 171). I chose a female undergraduate cohort because (1) a cohort study helps control for individual characteristics that are difficult to measure or require much larger sample sizes to generalize across populations, (2) women have been shown to be more sensitive to traffic conditions while bicycling (Beecham and Wood, 2013; Emond et al., 2014), and (3) percentage of female bicyclists has become a barometer for bicycling comfort since when an equal share of men and women bicycle, bicycling shares tend to be much higher (Garrard et al., 2012). Since one of the major goals of planning for urban bicycling is to increase bike mode shares in general, women are an important cohort to study because without women bicycling, overall bike mode shares are less likely to rise.

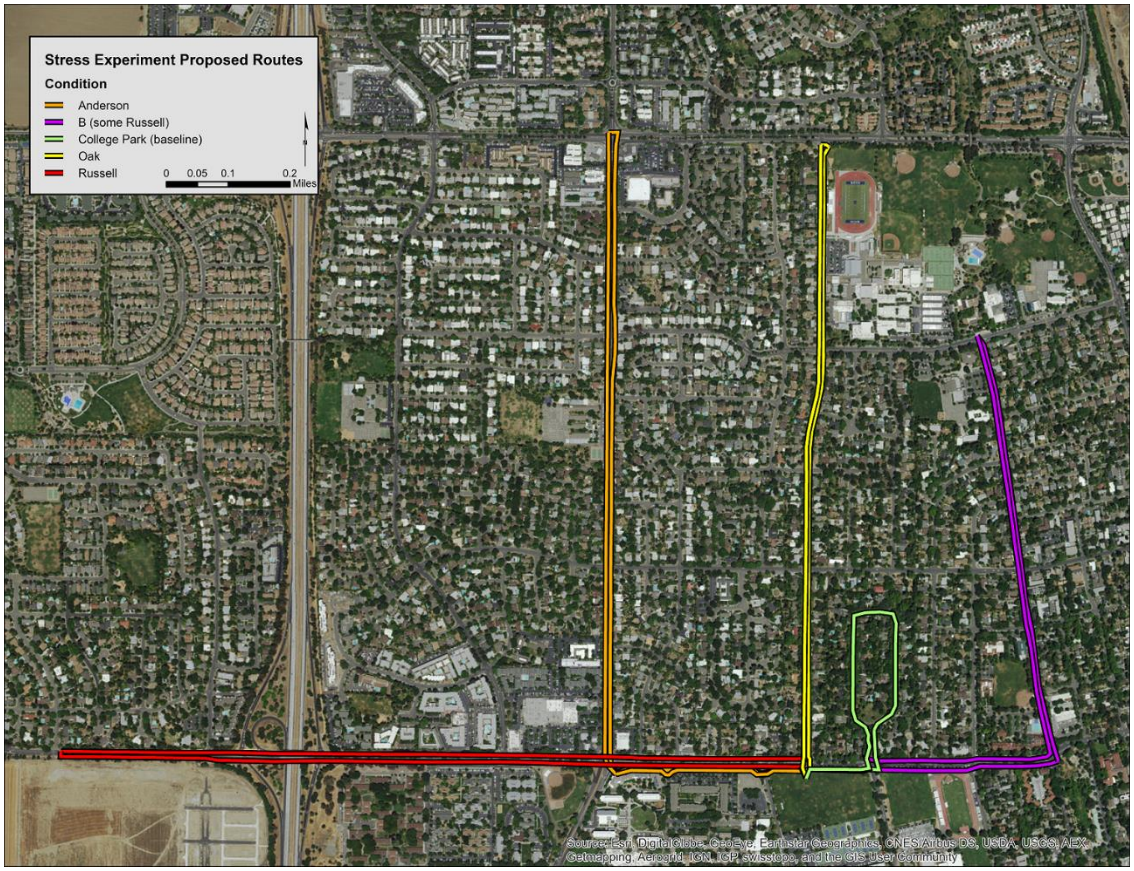

Figure 2.2 Map of road environments (experimental treatments). Participant rode three loops around College Park to ensure a similar duration to the other out-and-back style treatments.

Participants self-screened themselves to ensure they met the following conditions: normal blood pressure[10], normal vision (or corrected by lenses), normal BMI (18.5 – 25), were non-smokers, and were not taking any medication that affects heart rate (e.g. amphetamines, anti-depressants, thyroid hormones, bronchodilators for respiratory disorders). In addition, prior to the experiment, participants were instructed to abstain from all illicit drugs, alcohol and caffeine for 24 hours.

2.2.3 Summarized experimental procedure

The following is a summary of the experimental procedure. The experiment follows the common crossover (or within-subject) design principle where all participants are subject to all treatments[11] (bicycled in five road environments). I attempted to balance the order of treatments across participants to remove first order carry-over effects (carry-over of physiological signals from prior treatment). Because no design could balance carry-over effects for all twenty participants with all

[10] Normal range for 18-24 year olds was reported to participants at time of screening (Systolic 105-132, Diastolic 73-83).
[11] I use the term "treatment" to refer to each road environment because that is the common term used to discuss experimental designs.

treatments, I settled on a partial balanced, partial random design. Twelve of the twenty subjects received treatments in a pre-specified order to ensure each treatment followed all the other treatments exactly two times. The other eight participants received treatments in random orders. Because multiple RR intervals are recorded during each treatment, in effect, the experiment is a "repeated measures" design (where repeated measures of a condition are received in sequential time order). Compared to a two-group (control/treatment) design, this design has the advantage of reducing the influence of confounding covariates because all participants receive the same[12] treatments and act as their own controls.

Below is a numbered list outlining the major steps in the experimental protocol:

(1) The experimenter meets with participant and both sign the consent form.
(2) Participant is instructed on how to install the heart beat monitoring device, and then they install the device themselves in a private room.
(3) Participant takes the paper pre-experiment survey. This time also served as a "run-in" period to decrease any observer effect from participants being unusually stressed by installing a beat-to-beat monitoring device.
(4) Participant is instructed on how to take the psychological stress test (Dual *n*-back task). Baseline measurement commences during instruction.
(5) Participant practices short trials of the Dual *1*-back and Dual *2*-back until they verbally acknowledge they understand the task and their accuracy scores show improvement. Participant takes the full two-minute Dual *2*-back.
(6) Experimenter attaches the GPS video camera to participant's helmet (or provided helmet) and check participants bike tire pressure. If participant's tire pressure is too low, tires are inflated to minimum of recommended inflation range as indicated by the tire manufacture to ensure the safety of participant.
(7) Experimenter rides alongside the participant (on her own bike) to Russell Field and start first rest period. During this ride the experimenter gauges the participant natural bicycling speed to help describe any changes the participant should make for bicycling during the experiment.
(8) The participant is asked to ride on a predefined route, and following the ride take a short written survey and a four minute visualization task. This process is repeated for each of the five road environments during daylight hours on rain free days. Participants are instructed to ride at a leisurely pace such that they do not feel like they are "getting exercise". Individual comments based on experimenter observations are made to help achieve a consistent speed for all subjects. The exception to the leisurely pace is during the speed trial where

[12] "Same" in the sense of the same road, although road conditions vary somewhat since any naturalistic study takes place over time and thus, environmental conditions are bound to vary by time.

participants are instructed to ride at three different paces, slowly but not slow enough to make balancing difficult, a leisurely pace, and as quickly as safely possible.

(9) Experimenter rides with the participant back to the starting conference room for removal of monitoring device and brief audio recorded interview.

This procedure took approximately 2-3 hours per participant. As an incentive, students received a $25 downtown Davis gift card at the beginning of the experiment when signing the consent form. Any student wishing to end participation could do so at any time and can keep the $25 gift card. Only two participants chose to refuse participation in any way. They both rode on the outward segment of Russell Blvd. and decided they were too uncomfortable (because of traffic safety) to ride on the return leg and so returned on the parallel off-street path. They both continued to participate in the remaining portions of the experiment.

2.2.4 Statistical analyses

Table 2.4 summarizes the analysis approach for each research question in this study. To examine the relationship between survey measures of bicycling comfort/safety with physiology, and the main effects of the experimental treatments (road environments) with physiology, I use two approaches. The first approach relies on physiological measurement during remembered experience, and the second on real-time experience. Following each on-road bicycling task, participants visualized their prior ride and focused on how they felt with regard to comfort and safety. The use of visualizations after each ride were intended to evoke a stress response that was representative of the prior bicycling experience. The benefit for this approach is twofold. First, because the participant is in a seated rest, physical exertion is no longer a potential confound. Second, a remembered experience is more likely to influence future behavior (e.g. the decision to bike on that road again), thus making it a potentially important link between stress and bicycling behavior. The disadvantages of this approach includes the difficulty of the task, participant variability in how they approach the task (nearly half of the participants seemed to lose focus), and the inability to directly relate HRV to context specific covariates (e.g. passing vehicles). The second approach relies on physiological measurement during the bicycling experience. This direct measure of psychological stress while bicycling benefits from being able to correlate with time sensitive covariates. The primary disadvantage of this approach is the difficulty in separating physical exertion and psychological stress from HRV. However, I attempt to disentangle the effect of physical exertion and psychological stress on HF-RR variability through multivariable analyses.

Table 2.4 Research Questions, Primary Variables, and Analysis Methods

Research Question	Dependent Variable	Comparisons / Predictor Variables	Method
How do road types relate to survey measures of comfort and safety?		• Survey measures of comfort and safety (Appendix A, questions 1-3)	Correlation
How well do survey measures and physiological measures of stress relate?	HF-RR (visualization, on-road)	• Survey measures of comfort and safety	Correlation
How do road environments influence bicyclist psychophysiological stress? Can the influence of psychological stress be isolated from the influence of physical exertion when bicycling at moderate levels of exercise?	HF-RR (computer stress task, speed trial, visualization, on-road)	**Personal:** • vigilance (Appendix B, question 3) • fear (Appendix B, question 3) • **Environment:** • Bike lane width • Outside lane width **Situational:** • Number of passing cars • Presence of passing truck/bus • Speed (GPS)	Multilevel Model

First, I compare within-participant differences in HF-RR between treatments (i.e. contrasts). I use the standard deviation of RR intervals to measure HRV (a commonly used statistic (Laborde et al., 2017)). Due to the experiment being in a natural uncontrolled environment, each treatment (road environment) is likely to vary over time in its effect on each individual's stress. To account for this variability, I consider statistics generated from the entire individual time series (this ranges from 4 minutes for the visualization tasks to upwards of 15 minutes for road conditions), and also bootstrapped samples of those time-series to provide confidence intervals of the variability. The specific method I use is the stationary blocked bootstrap, originally discussed by Politis and Romano (1994) and coded in the boot R library (Canty and Ripley, 2017). This bootstrap method is a resampling method that attempts to ensure samples mimic the stationarity of the original time-series. Given a time-series (in this case the physiological signal for one person during one treatment) the procedure works as follows. Randomly sample a continuous block of the time-series such that the starting point is random (based on the discrete uniform distribution over the time-series length) and the length of the continuous block is random (based on the geometric distribution with user provided mean (in this case I selected a mean of 120 which corresponds to 30 seconds of data (30 seconds * 4 Hz = 120)). Repeat the random sample (with replacement of both the starting point and the block length) for as many samples as needed (I use 1000 samples for each person for each treatment). This resampling helps summarize and provide a confidence intervals for comparing HRV between treatments at the person level.

Second, I use multilevel (by participant) regression models to examine the influence of the road environment on HF-RR while controlling for a series of covariates (discussed in section 2.2.1.2). The linear regression in this chapter differs from that commonly found in statistics in that I model the standard deviation (scale) of the HF-RR using a log link function (making this a generalized linear model) not the mean (location) using an identity link function. I model the standard deviation because it is a direct measure of HF-RR dispersion which describes the vagal influence on the heart. The mean of HF-RR is fixed at 0 due to the signal transformation. Large standard deviations relate to strong vagal control and thus relaxed states, while small standard deviations relate to weak vagal control and thus stressed states. I compare results from two model forms to infer the influence of key predictor variables. The first is a varying intercept model which allows the mean deviation of HF-RR to vary by participant. The second is a varying intercept and slope model which allows the mean deviation of HF-RR and the influence of prespecified predictor variables to vary by participant. Using the notation from Gelman and Hill (2007, p. 285), the two models are as follows:

Varying Intercept Model

$$\text{HF-RR}_i \sim \text{Normal}(\,0\,,\sigma_i\,)$$
$$\log(\sigma_i) = \alpha_{person,j[i]} + X_i B$$
$$\alpha_{person,j[i]} \sim \text{Normal}\big(\,\alpha\,,\sigma_{person}\,\big)$$

Priors

$$\alpha \sim \text{Normal}(\,0\,,4\,)$$
$$B \sim \text{Normal}(\,0\,,4\,)$$
$$\sigma_{person} \sim \text{HalfStudentT}(\,3\,,0\,,2\,)$$

Varying Intercept and Slope Model

$$\text{HF-RR}_i \sim \text{Normal}(\,0\,,\sigma_i\,)$$
$$\log(\sigma_i) = X_i B_{j[i]} + X_i^0 B^0$$
$$B_j \sim \text{MVNormal}\big(\,U_j G\,,\Sigma_B\,\big)$$

$$\Sigma_B = \begin{pmatrix} \sigma_{person[1]} & & \\ & \ddots & \\ & & \sigma_{person[k+1]} \end{pmatrix} \Omega \begin{pmatrix} \sigma_{person[1]} & & \\ & \ddots & \\ & & \sigma_{person[k+1]} \end{pmatrix}$$

<u>Priors</u>

$$B^0 \sim \text{Normal}(\,0\,,4\,)$$

$$G \sim \text{Normal}(\,0\,,4\,)$$

$$\sigma_{person} \sim \text{HalfStudentT}(\,3\,,0\,,2\,)$$

$$\Omega \sim \text{LKJcorr}(\,2\,)$$

Where HF-RR is the high frequency filtered signal for time point *i* from 1 to *n*. σ is the standard deviation of the signal, $\alpha_{person,j[i]}$ is the varying intercept for person indexed by *j* (from 1 to J=20) and given a prior centered around the grand mean (α) with standard deviation σ_{person}. In the varying intercept model, X is the $n \times k$ matrix of predictors and B is a vector of length *k* of time-point level regression parameters. I chose broad normally distributed priors (sd = 4) for α and B to provide some guarding against overfitting the model to the sample, while at the same time letting the data and likelihood dominate inference given the lack of existing prior evidence of HRV while bicycling. I give σ_{person} a prior (this is the "hyper-prior" for the varying intercept for person) that is half Student's *t*-distributed with three degrees of freedom to provide a "fatter" tail for large standard deviations that are plausible.[13] In the varying intercept and slope model, X is the $n \times k$+1 matrix of predictors in design matrix form where the first column of X is a column of ones and the remaining columns are *k* predictors variables. B_j is a $j \times k$+1 matrix of varying effects for the time-point level regression parameters. For any person *j*, B_j is a vector of an individual intercept and slopes for predictors in X. U_j is the $j \times l$+1 matrix of *l* person level predictors. G is the l+1 $\times$ k matrix of parameters for the person level regression. Σ_B is the covariance matrix for the B_j matrix, parameterized as the product of diagonal matrix of varying parameter standard deviations (σ_{person} is now a vector from 1 to *k*+1), varying parameter correlations (Ω), and the same varying parameter standard deviations. This parameterization allows the separate interpretation of varying parameter scales and correlations. Like the varying intercept model, I give σ_{person} priors that are independent half Student's *t*-distributed with three degrees of freedom, and varying parameter correlations (Ω) a weakly informative LKJ prior as suggested by McElreath (2015). X_i^0 is the $n \times m$+1 matrix of predictors in design matrix form

[13] I originally chose broader half-Cauchy distributed priors, as recommended by McElreath (2015), but found a 30% reduction in computational time when using Student's t without any noticeable change to parameter values.

where the first column of X is a column of ones and the remaining columns are *m* predictors variables that do not vary by individual. B^0 is a vector of length *m* of time-point level regression parameters that do not vary by individual (sometimes referred to as "fixed-effects").

I 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. In all models I use so-called *weakly informative* prior probabilities to guard against overfitting (Gelman, 2006) (see above for specific priors). Through the R statistical package *Rstan* as an interface for the probabilistic statistical programming language Stan, I used the No-U-Turn (NUTS) sampler, a form of Hamiltonian Markov chain Monte Carlo (MCMC) to estimate the models (Stan Development Team, 2017).

I measure out-of-sample prediction using the deviance information criteria (DIC) (the multilevel model version of Akaike information criteria (AIC)). I chose not to use the more robust widely applicable information criteria (WAIC), or pareto smoothed importance sampling estimate of leave one out cross validation (LOOIC) (Vehtari et al., 2017) because storage of pointwise log likelihood values caused large increases in model runtime, and inference of heart-beat level prediction is irrelevant to this study. Ideally, out-of-sample inference at the person × road level would be most appropriate, but I could not determine how to conduct a pointwise prediction at that level when speed varied by heart-beat.

2.2.5 Methodological limitations

Several factors of this study limit the intended inferences about a causal link between psychological stress and road environments. Already noted are the assumptions that HF-RR variability represents psychological stress, even under conditions of moderate exertion, and that speed of the bicyclists fully describes physical exertion. These assumptions may not entirely hold, which poses a strong threat to this study's validity. Nonetheless, other study design options had similarly strong assumptions. More minor but still important potential limitations are the multiple testing and pre-processing of data prior to statistical modeling. Any data dependent decision prior to statistical modeling has the potential to inflate confidence in the resulting inference. In this study, two specific cases of multiple testing and pre-processing are most likely to have influenced the ultimate model outcomes. First, I explored numerous techniques for extracting the "stress" signal from raw RR data (see Appendix D). I based my decision on the ability of the algorithm to represent the psychophysiological signal of interest, and allow positive statistical properties (e.g. local signal adaptivity). However, had I made another pre-processing decision, the ultimate results may have changed, although visual comparisons of alternative pre-processing algorithms suggest that this limitation may be minor (see Appendix D). Lastly, I also conducted bivariate statistics (correlations and visual plots) to help motivate variable selection for two of the five statistical models (e.g. variables related to the road environment and traffic). Like multiple testing problems, this variable selection may inflate the confidence of some of the model results. However, considering the large sample size compared to number of model parameters, this limitation is also likely to be of minor consequence.

2.3 Results and discussion

2.3.1 Sample characteristics and experimental observations

The 20 participants are predominantly young White or Asian women, with two Hispanic/Latina participants and one Black participant. Most participants rode their bikes for normal day-to-day travel and were familiar with at least one of the roads in the experiment, some as many as three. Only two participants had trouble navigating, both during the B St. bicycling route (I attempted to minimize navigation stress by only using simple out-and-back bicycling routes). One participant stopped for about 30 seconds before making the correct navigation decision. The other rode on the wrong street and so her data for B St. is missing. In two cases participants rode one direction on Russell Blvd (the four-lane arterial with no bike lane), and because they did not feel safe they chose to ride on a parallel off-street bike path on their return. For these participants, the later part of Russell data is missing. Besides these exceptions, the data is complete.

Compared to a large population representative sample, these participants are in general less chronically stressed (see Table 2.5). Their attitudes/feelings about key bicycling variables related to perceived bicycling comfort and safety suggest a conservative cohort of bicyclists in terms of personal safety risk taking. The cohort's similar view of bicycling comfort and safety is not surprising considering that the participants had similar bicycling backgrounds. All had learned to bicycle when they were children, only 4 of the 20 bicycled to school (or for recreation) beyond primary school ages, and none were regular bicyclists before moving to Davis.

Most of the above sample characteristics (Table 2.5) are independent of each other. An exception is the negative correlation between the *stress overload scale* and *BMI* (r = -0.39). This measure of "stress" has known positive correlations with depression and general illness (Amirkhan, 2012), but it is unclear why it might be negatively correlated with BMI. Because of the small sample size and limited variability in BMI, it may be that this correlation is spurious or due to chance.[14] Among the bicycling variables, *bicycling fear* and *comfortable bicycling with vehicles* are negatively correlated (r = -0.65). This correlation is not surprising given that the most important component of being comfortable bicycling in traffic is to lack fear of traffic. *Bicycling fear* and *vigilance* (ϱ = 0.31)[15] are moderately correlated suggesting that those who are fearful are more vigilant. Most surprising is the lack of correlation between *bicycling ability* and other variables found in Table 2.5. The lack of correlation may be because this cohort of women varies only slightly in their *bicycling ability* (Table 2.5).

Table 2.5 Sample Characteristics

Variable		Median	SD
Body mass index (BMI) (kg/m^2)		21.1	1.8
Age (yrs)		22.0	5.8[*]
Stress Overload Scale[**] (24-120)		46.7	15.1
Comfortable Bicycling with Vehicles (5 pt. response scale)	A two-lane street, *without* a bicycle lane, and *no* parked cars. A two-lane street, *without* a bicycle lane, along parked cars. A four-lane street, *without* a bicycle lane, and *no* parked cars. *A four-lane street, without a bicycle lane, along* parked cars.	3.25	0.95
Bicycling Fear (5 pt. response scale)	When I ride my bike I am afraid of cars that pass me on the road. When I ride my bike I'm afraid when trucks pass me on the road. When I ride my bike I'm afraid of turning cars when approaching intersections.	3	1.30
Bicycling Vigilance (5 pt. response scale)	I am a cautious bicyclist When bicycling, I always keep a watchful eye on cars	4	0.75
Bicycling Ability beginner (1), advanced beginner (2), intermediate (3), advanced (4), expert (5)		3	0.72

* large standard deviation because of one older undergraduate (47 years old), without her the standard deviation of age is 1.5.

** measured from the stress overload scale questionnaire (Amirkhan, 2012). In the normative sample (n = 1518), mean value was 66.

2.3.2 Surveying bicycling comfort and safety

Post-ride survey responses for road environments show the expected relationships. The local residential road (College Park) has the lowest reported *anxiety* and highest reported *comfort/safety* while the four-lane arterial (Russell Blvd.) has the highest reported *anxiety*[16] (Figure 2.3) and lowest reported

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[14] Using 100,000 simulations, the correlation of two independent random variables have a 95% confidence interval of approximately +/- 0.38.

[15] Polychoric correlations (ϱ) reported for single Likert item comparisons.

[16] I measure anxiety using a short form (Marteau and Bekker, 1992) of the classic state trait anxiety inventory (STAI) (Spielberger, 1983) adapted for bicycling (see Appendix A, question 1).

comfort/safety[17] (Figure 2.4). One participant is a clear outlier for the *anxiety* measure, but does not seem to be mistaking the direction of the scale given she rated Russell the most anxiety producing (Figure 2.3). Survey measures about the minor arterial (Anderson Rd.) and two collectors (Oak Ave. and B St.) fall in between those of College Park and Russell Blvd. on both measures, although no clear difference exists between the three. The lack of differentiation between Anderson, Oak, and B by the participants is surprising considering the differences in characteristics (see Table 2.3 for descriptions of the road environments). During the interview process participants reviewed their post ride survey responses and were asked to "correct" any responses to the comfort/safety 10-point scale given they had now completed all experimental conditions. This "correction" was an attempt to examine any anchoring and adjusting of survey responses based on the order of experimental conditions received by each participant. Participants only altered 13 of 100 scores, and all but two of those scores were changed by only one or two points on the 10-point scale. Because the changes were small, it is unclear if those changes were true adjustments or merely a result of a participant expectancy effect (i.e. the participant felt inclined to change something).[18] Importantly, those adjustments did not result in any further differentiation of Anderson, Oak, and B in terms of comfort/safety.

Familiarity with each of the roads in the experiment by participants was another important variable captured by the interview. Some participants regularly bicycled on Anderson Rd. because they lived nearby. Others had regular bicycling experience on multiple roads because of normal routes to work/school. Familiarity, as coded as a binary variable based on review of the interview transcriptions, is positively correlated with post-ride comfort ($r = 0.2$—0.46 ranging over the five roads) and therefore may be influencing how participants rate their experience. However, familiarity is inconsistently (sometimes positively, sometimes negatively) associated with safety, comfort/safety, and anxiety. Therefore, it is unlikely that familiarity is causing a lack of differentiation among Anderson, Oak, and B.

Anxiety is the only variable that differs somewhat between Oak and the other roads, although the difference is subtle (Figure 2.3). The similarity between Anderson, Oak, and B suggests that the road environment is more important than the traffic environment as a determinant of perceived comfort/safety and anxiety because the three roads are similar in their physical environments (all are two lane roads with bike lanes) but differ in their traffic speed and volume. This isn't to say that traffic

[17] I measure the combined variables of comfort and safety through a 10 point scale (see Appendix A, question 3).
[18] I worded the question such that participants knew it was fine to leave all the scores unchanged. Nonetheless, most participants changed at least one score.

speed and volume don't matter for comfort and safety, just that in these environments the differences in traffic do not correlate with surveys of comfort and safety. However, because the survey sample size is small, these results are only suggestive.

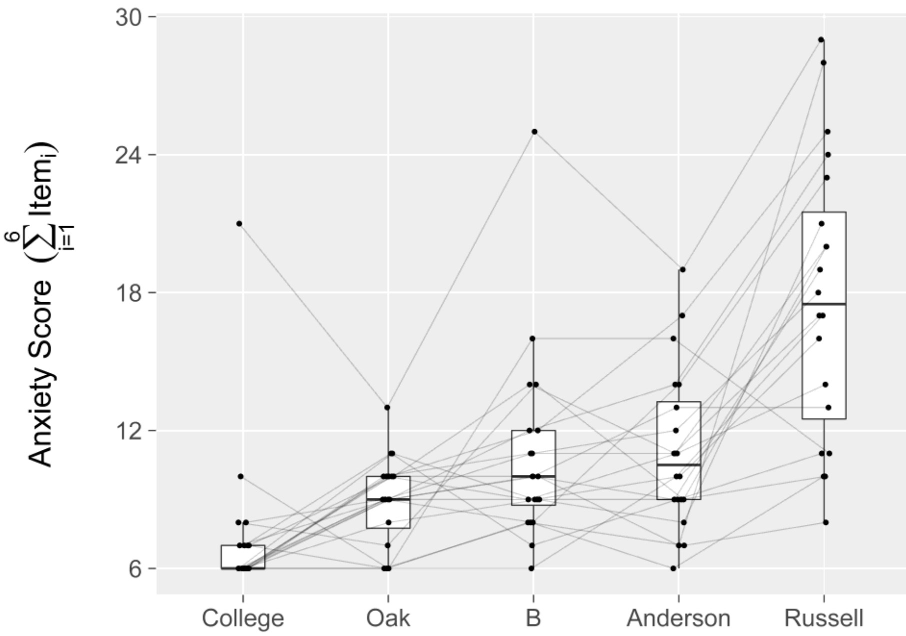

Figure 2.3 Boxplots of surveyed anxiety by road environment. Line segments link participant specific responses.

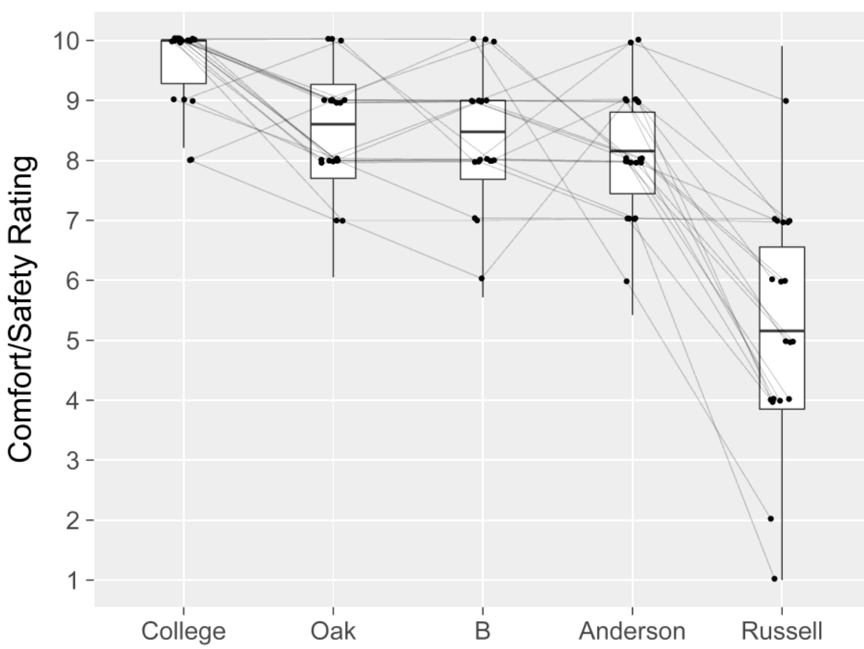

Figure 2.4 Boxplots of surveyed comfort/safety by road environment. Line segments indicate participant specific responses.

Independent measures of bicyclists' comfort and safety are strongly correlated (Figure 2.5, ϱ = 0.68—0.95 by road). Differences between comfort and safety were greatest on Anderson Rd. Interestingly, participants more strongly agreed that Anderson was comfortable than that Anderson was safe. This result is counter to recent evidence suggesting perceived safety is a prerequisite for comfort and enjoyment (Lovegrove, 2017). Nonetheless, given the small sample size, the strength of the correlations suggests that participants consider safety synonymous with comfort when describing short-duration bicycling experiences.

Participants' feelings of protection, worry, and tiredness are similar for all road environments except Russell Blvd. (Figure 2.5). Only on Russell Blvd. do most participants disagree they were protected from traffic and agree they were worried about vehicle maneuvers. Participants report similar physical and emotional tiredness for all road environments, suggesting that the acute stress of bicycling did not exhaust them. The fact that survey responses about Russell Blvd. were nearly unanimously worse than all other road environments is an important result because it confirms the intended differences in the road environments from the research design. However, the wide variability in ratings on Russell (the worst environment) compared to College (the best environment) suggests that even in this conservative cohort of female undergraduates, individual variability in comfort/safety can be large (Figures 2.3 and 2.4).

Some person level attributes (variables from Table 2.5) correlate with post-ride surveys. For example, *bicycling ability* (and *bicycling fear* to a lesser degree) tend to be negatively correlated with post-ride surveys of *anxiety* (r = -0.64 — 0.1 ranging over the five roads) and positively correlated with *comfort* (r = 0.12 — 0.66). However, the *stress overload scale* and *vigilance* do not have consistent correlations with post-ride surveys of comfort, safety or anxiety. The *stress overload scale* is intended to measure chronic anxiety, so the lack of a clear correlation with post-ride survey responses suggests chronic stress may not influence judgment of specific bicycling experiences. The lack of correlation between person level vigilance and any post-ride surveys suggests vigilance may not play a role in perceptions at the cognitive level, even if it influence heart rates (Andreassi, 2006, p. 337). However, given the lack of power for all person level correlations (n=20), I do not report any formal hypothesis tests. Instead, these hypotheses should be evaluated in future studies with larger samples.

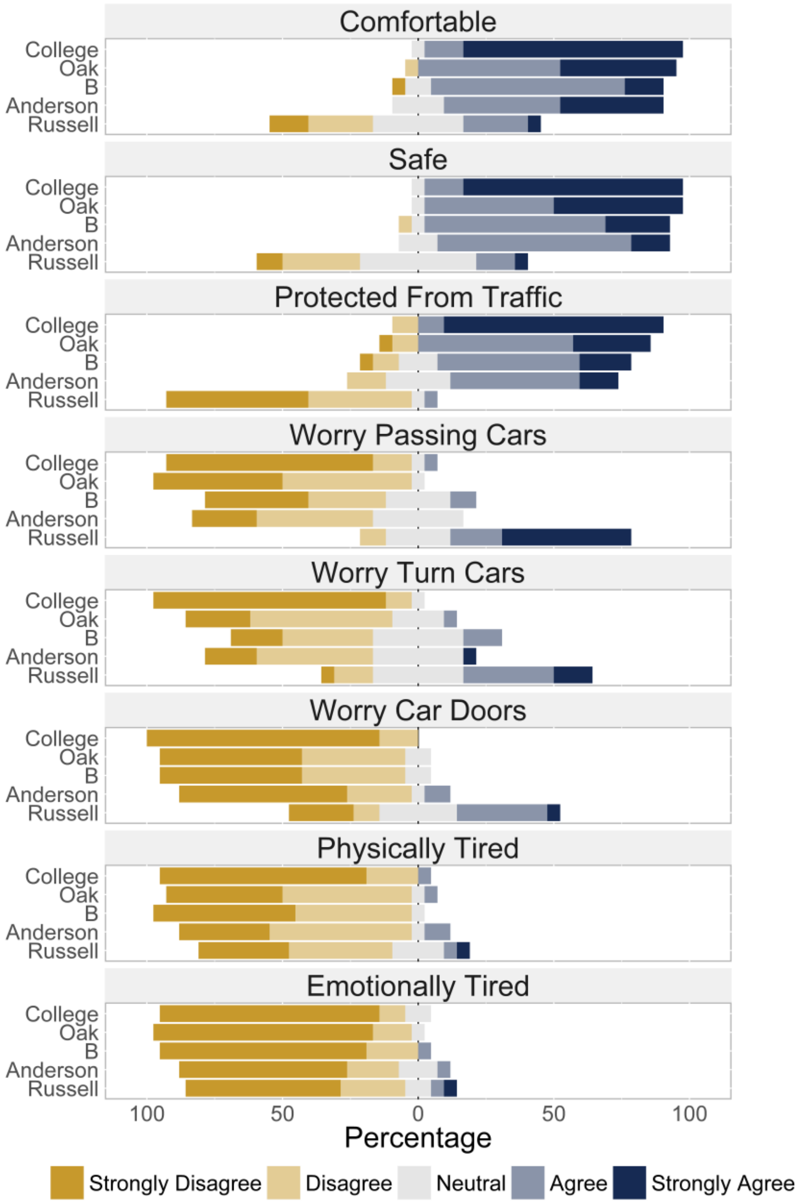

Figure 2.5 Aggregate survey responses to individual Likert items of bicycling safety and comfort following each treatment.

2.3.3 HRV baseline and mental stress test

During baseline, most participants showed heart rates in the normal range (60-90 bpm), and five participants had moderately high heart rates (90-110 bpm) (see Table 2.6 for RR values). In the five cases of elevated heart rates, all five had periods of normal heart rate during the "run in" rest time where they were filling out a paper survey. The elevated heart rates suggest that the "vanilla" baseline task (listening to instructions) may have stressed these participants (perhaps due to increased focus). Even though these participants had high heart rates at baseline, four of the five exhibit an increase in stress (decrease in HRV) from the mental stress task (dual 2-back) as expected. Table 2.6 shows the mean RR, standard deviation of RR, and standard deviation of HF-RR during baseline and the mental stress task (dual 2-back) for each participant. Because the HF-RR primarily differs from RR by the removal of low frequency trends, large differences between the RR and HF-RR results in Table 2.6 suggest that low frequency trends occur even in situations of no physical exertion. Because HF-RR is likely to best represent vagal tone when low frequency trends are present, the estimated effect of the mental stress task is only estimated on the HF-RR dependent variable. The model results show an expected negative main effect (i.e. decreased HF-RR variability) of the mental stress task when contrasted with the baseline (β = -0.153 (0.073), Figure 2.6) (see Appendix E for all parameter values), but this effect is uncertain. This result suggests that HF-RR is related to mental stress in the expected way (i.e. increased stress is associated with decreased HF-RR variability). However, this average effect does not adequately describe the relationship between HRV and the mental stress task. Figure 2.6 also shows baseline/mental stress task contrasts at the individual level (i.e. varying slopes by participant). These individual effects demonstrate the large between-individual differences in HRV response to the mental stress task. The cause for large individual differences could be associated with variability in participant effort or understanding of the task, but is likely also due to random differences in cardiac response to mental stress.

Table 2.6 Baseline and Mental Stress (dual 2-back) Task Participant HRV in milliseconds

	Mean RR		Std. dev. RR		Std. dev. HF-RR	
Participant	Baseline	Dual 2-back	Baseline	Dual 2-back	Baseline	Dual 2-back
1	772.0	798.1	68.6	54.5	25.9	31.0
2	572.0	700.2	96.2	75.9	15.9	19.1
3	977.9	1053.1	132.1	71.6	58.9	50.5
4	591.1	565.0	48.7	25.0	13.2	7.0
5	548.5	570.5	26.8	15.2	9.5	6.5
6	586.0	613.8	23.1	24.1	8.5	9.0
7	811.6	824.5	74.8	51.3	31.9	14.9
8	930.2	894.9	64.8	60.3	29.2	23.7
9	716.9	778.3	53.9	47.4	22.2	23.8
10	688.0	685.4	69.5	28.7	31.7	17.7
11	665.3	703.0	41.2	38.4	19.3	23.1
12	718.8	762.0	46.2	17.3	5.3	5.7
13	715.5	688.0	34.3	27.8	13.3	11.9
14	814.9	851.1	61.1	49.8	20.1	24.1
15	777.9	794.8	45.2	25.7	15.7	10.3
16	791.2	773.5	76.1	55.7	27.8	22.8

17	783.5	806.8	47.7	50.4	21.1	22.5
18	796.0	819.4	51.0	37.5	25.2	25.4
19	832.9	885.9	95.2	66.9	40.5	37.1
20	632.5	626.5	72.4	41.3	15.5	9.9

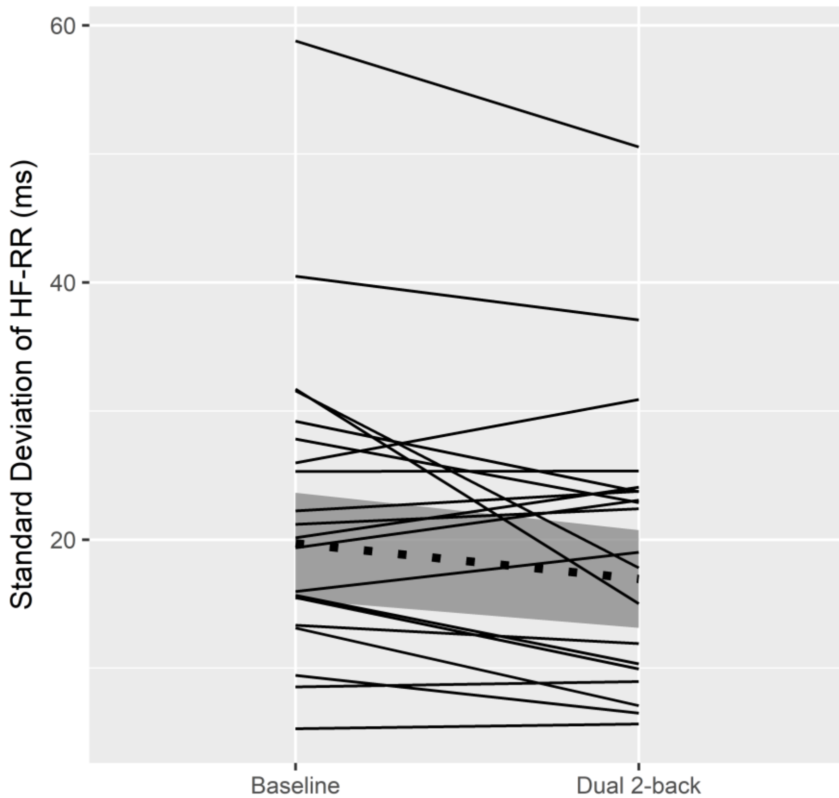

Figure 2.6 Varying intercept and slope model estimated effects of the dual 2-back mental stress task on HF-RR. Dotted line and shaded region represent the mean effect and 90% highest posterior density interval (HPDI, similar to a confidence interval), and the solid lines represent the participant specific effects.

2.3.4 HRV during exertion without traffic stress

During the speed trial (where participants bicycled on an off-street path at three different speeds), increased participant speed resulted in decreased HF-RR variability. Using the same varying intercepts and slopes model, speed had a negative effect across all participants (β = -0.708 (0.083), $\sigma_{\beta_{person}}$= 0.370 (0.059)) (see Appendix E for all parameter values). The mean effect of increasing speed on HF-RR is strongest when speeds are slow, although very uncertain at the individual level (see shaded regions of Figure 2.7). The opposite is true once participants reached faster speeds. By speeds of about 6 m/s, all participants had greatly reduced HF-RR variability, and by speeds of 7-8 m/s HF-RR variability approaches 0 (Figure 2.7). These results suggest that speed is representing physical exertion and its influence on HRV. They also indicate that at speeds above 7 m/s, HRV is so minimal, that measuring psychological stress from the remaining variability may be challenging. However, because of the speed trial's short duration, these results don't rule out the possibility that once high speeds are maintained (for minutes rather than seconds), vagal control of the heart would start to increase allowing for continued analysis of HRV as it is suggested in prior research (e.g. Hatfield et al., 1998).

During major acceleration and deceleration events HRV changes dramatically (results not shown). This result is consistent with prior evidence suggesting that onset of physical exertion results in a rapid withdrawal of vagal control of the heart (Fagraeus and Linnarsson, 1976). It isn't clear from the speed trial data that speed is able to account for these rapid changes in HRV, hence the large variability in HF-RR during slow speeds which correspond to the beginning and end of acceleration and deceleration events. Given these results, measuring psychological stress from HRV during dramatic changes in speed may be very challenging. Unfortunately, this means that HRV may be a poor metric for assessing real-time bicyclist psychological stress in and around intersections where acceleration and deceleration events are common. Since intersections are a common place where bicyclist/vehicle conflicts occur, this puts a real limit on the use of HRV for assessing bicyclist psychological stress. More complex experimental setups with instrumented bicycles and/or monitoring of participant ventilator parameters may help to mitigate this problem. Alternatively, bicycle simulator studies may be more appropriate to measure HRV as a stress indicator for virtual intersection environments.

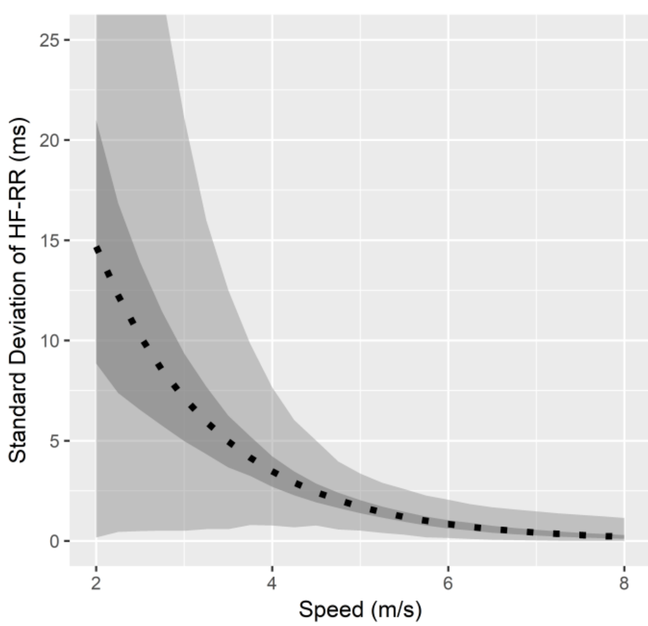

Figure 2.7 Varying intercept and slope model estimated effects of speed on HF-RR. Dotted line represents the mean effect, dark shaded region the 90% HPDI of the mean, and light shaded region the 90% HPDI marginal of person (prediction interval).

2.3.5 The relationship between stress and surveys of bicyclist comfort, safety, and anxiety

The relationship between stress (HF-RR variability) and surveys of bicyclists experience can be thought to serve two purposes. First, the relationship helps establish the validity of HF-RR variability as a measure of psychological stress that theoretically leads to perceptions and attitudes of comfort and safety. At the same time it serves to distinguish psychological stress (as defined in section 2.1.2) from these same downstream variables. Block bootstrapped correlations between survey responses and stress during on-road bicycling (Figure 2.8) and post-ride visualizations of on-road bicycling (Figure 2.9) show that the relationships between stress and bicyclist survey responses are weak (but certain). Each variable presented in Figure 2.8 and 2.9 was centered on (i.e. differenced from) the participant mean (both stress and the survey variables) so that the correlations represent that of within-participant differences.[19] Importantly, all the survey variables expected to positively correlate with stress and thus negatively correlate with HF-RR variability (e.g. *Worried about passing cars, Worried about car doors, Worried about turning cars, Anxiety*) show small negative correlations. However, this is only for the on-road stress (many of the post-ride visualization correlations have considerable densities on either side of zero suggesting little to no correlation) (Figure 2.9). In contrast, both HF-RR variability during on-road and post-ride visualizations show small positive correlations with surveys of comfort and safety (Figures 2.8 and 2.9). It isn't clear why only some of the survey variables (*Worried about passing cars, Worried about car doors, Anxiety*) show a marked difference in correlations when looking at on-road and post-ride stress. One hypothesis about why *Worried about turning cars* shows the strongest correlation with stress during visualization is that this worry may be the most salient in memory following a riding experience. Other differences in on-road and post-ride stress correlations with survey variables are easier to explain. For example, the difference in correlation with *Physically tired* may represent participants recovering from the physical exertion of bicycling as their heart approaches baseline. The slightly weaker but similar correlations between comfort and stress and safety and stress suggest that visualizations are just a weaker form of the real experience. However, because the on-road stress is confounded by physical exertion, physical exertion may be the main reason why the correlations differ.

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[19] This centering of the variables helps ensure that the between participant differences in HF-RR variability (as also noted in their baseline measures) and use of the survey scales don't bias the relationship between HF-RR variability and survey responses. This potential bias is especially relevant for the survey measures reflected by only one Likert item. For example, imagine some participants who had large HF-RR variability compared to others tended to use only the upper half of the survey scale (say 5-10 on a 10 point scale). In this case, large HF-RR in general would be associated with the upper half of the survey scale even if the individual level relationship was reversed (e.g. within-participant large HF-RR was associated with survey responses of 5-7 while small HF-RR associated with survey responses of 9-10).

HF-RR variability, to a small extent, seems to track survey measures of bicycling experience. However, the small magnitude of the correlations suggest that most of HF-RR variability as a measure of stress is capturing something unrelated to these survey measures. Whether that means HF-RR variability is capturing psychological stress that is un-measurable from surveys (from some unconscious process), or simply adding noise to more concrete psychological constructs (as measured through the survey) is difficult to say. Much like the correlations reported from Doorley et al. (2015) of bicyclist "risk ratings" in different road environments, the correlations in this study suggest only a tenuous relationship between physiology and survey responses.

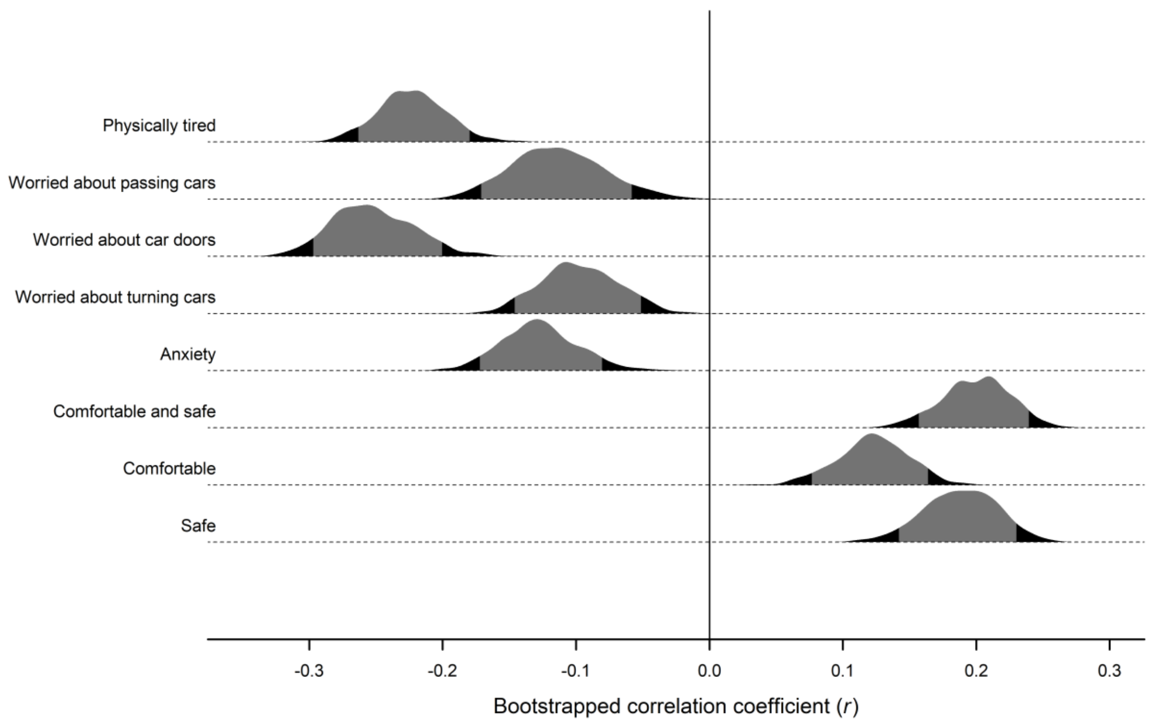

Figure 2.8 Bootstrapped on-road HF-RR variability correlations with survey measures.

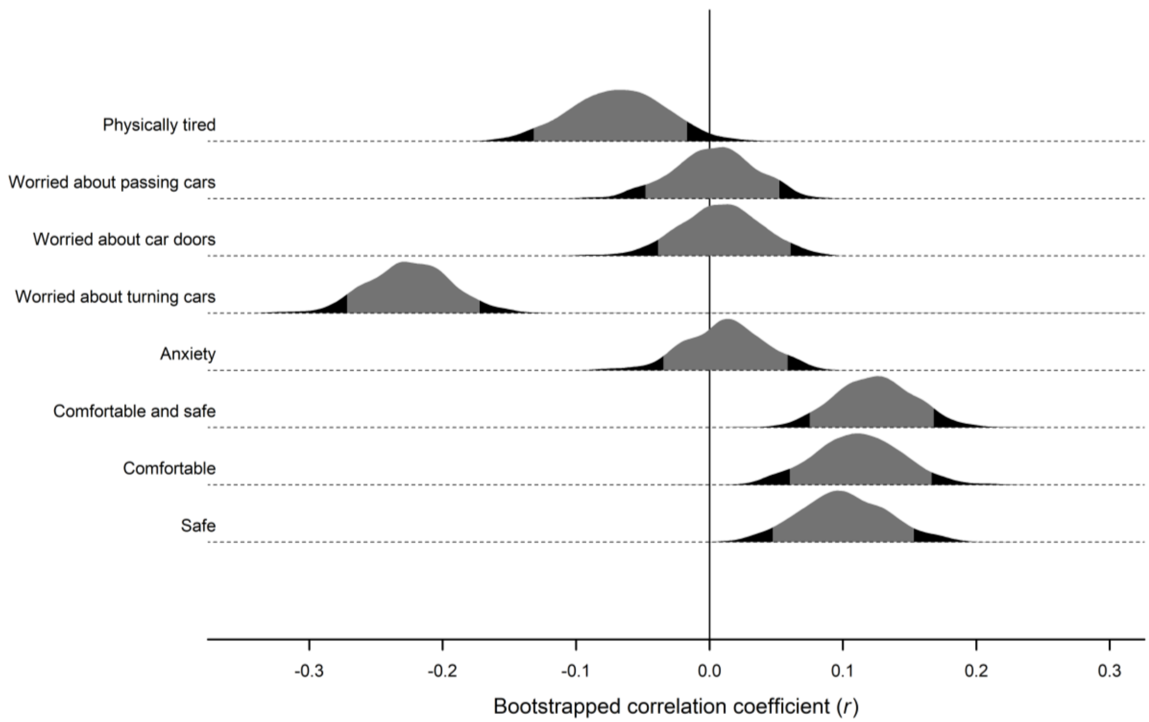

Figure 2.9 Bootstrapped visualization HF-RR variability correlations with survey measures.

2.3.6 Stress and the road environment

2.3.6.1 Mean and individual differences in stress by road environment

Comparison of participant level HF-RR variability (mean and standard deviation of the bootstrapped standard deviation) for each of the five road environments during on-road bicycling and post-ride visualizations are presented in Tables 2.7 and 2.8, respectively. Most notable are the clear differences in HF-RR variability during physical exertion (Table 2.7) and rest (Table 2.8). In addition, large participant differences are clear from both tables (as was the case for the baseline and dual-n-back experimental conditions). The small standard deviations in Table 2.7 and 2.8 indicate that for most participants, within road environment stress (HF-RR variability) is much less than between road environment stress. However, the differences in stress between road environments are not consistent across participants and often don't follow the hypothesized direction of effect. For example, while Russell shows more stress (less HF-RR variability) compared to College for participant #1, participant #3 shows no such difference. In fact, for the visualization task, participant #3 has less stress (more HF-RR variability) for Russell than College. These counterintuitive results follow for many road environment contrasts. Some participants show clear differences in the expected direction, others little to no differences, and still others differences in the "wrong" direction. The variation in treatment effects suggests that measurement noise may be a limiting factor for the ability of HF-RR to distinguish real-time psychological stress. This "noise" may be due to numerous sources that are poorly controlled in this experiment. Some of the likely factors contributing to measurement noise include incomplete control of physical exertion and situational characteristics (e.g. noise, wind, temperature), and within-person variability in attention while bicycling. Improving the control of these variables is likely to decrease the uncertainty in the estimated effects of different road environments on bicyclists HF-RR variability. In addition, larger sample sizes are likely needed to counteract the noise of HRV.

Table 2.7 Bootstrapped Standard Deviations of HF-RR (ms) during Visualization[20]

	College		Oak		B		Anderson		Russell	
participant	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
1	18.89	0.78	10.80	0.60	13.35	1.00	13.64	1.08	9.35	0.52
2	20.81	0.73	21.24	0.59	21.34	1.11	20.73	0.81	20.93	0.98
3	17.71	0.70	19.16	0.41	19.21	0.92	17.44	0.40	19.17	0.44
4	10.93	0.58	13.91	0.56	12.09	0.90	15.08	0.80	14.58	0.80
5	9.08	0.30	12.99	0.50	9.45	0.39	11.36	0.42	13.52	0.40
6	4.70	0.32	4.17	0.19	4.83	0.22	5.77	0.32	5.69	0.36
7	15.99	1.50	17.34	1.32	13.16	1.24	13.75	1.18	15.39	1.07
8	21.73	1.09	24.82	1.07	16.49	1.63	22.07	1.00	20.32	1.06
9	22.72	0.59	21.58	1.13	14.07	0.61	18.97	0.72	17.52	0.74
10	24.79	0.82	23.76	1.27	25.15	0.86	22.04	0.73	20.94	0.77
11	50.90	3.34	49.14	4.70	60.26	2.70	67.76	3.98	66.33	2.38
12	39.11	1.16	41.41	1.15	-	-	58.05	1.74	62.13	1.85
13	13.20	0.61	11.73	0.63	13.68	0.36	13.53	0.86	10.99	0.71
14	19.26	0.79	18.59	0.77	12.98	0.56	21.50	0.88	19.78	0.67
15	17.49	1.02	16.96	1.06	10.27	0.35	18.58	1.12	17.24	0.67
16	44.56	1.64	45.11	1.68	19.50	1.44	43.60	1.84	38.07	1.56
17	41.38	1.58	39.86	2.92	38.53	2.07	43.00	1.81	34.58	1.25
18	35.08	0.74	29.76	0.74	30.42	0.74	35.62	1.02	29.48	0.60
19	43.56	1.73	39.32	1.18	37.01	2.64	38.45	1.28	41.34	1.88
20	38.16	1.01	35.44	1.11	28.58	0.85	35.77	1.14	35.46	1.00

[20] During post-ride route visualizations, all participants had elevated heart rates compared to their baselines, even after taking a brief survey in between the end of the bicycle ride and the beginning of the visualization task. Not only were visualization heart rates elevated, but HF-RR variability showed a subtle "return to baseline" trend where RR intervals steadily increased throughout the visualization task. Because of this low frequency trend, Table 2.7 shows summaries of HF-RR variability instead of raw RR summaries as was the case for the baseline and dual n-back conditions.

Table 2.8 Bootstrapped Standard Deviations of HF-RR (ms) during On-road Bicycling

	College		Oak		B		Anderson		Russell	
participant	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
1	4.80	0.12	0.46	0.05	1.60	0.08	0.32	0.07	2.91	0.47
2	6.78	0.18	5.42	0.33	4.79	0.33	7.79	0.73	4.31	0.30
3	6.34	0.17	4.63	0.35	4.99	0.33	6.62	0.20	6.63	0.30
4	2.81	0.10	3.78	0.13	3.67	0.17	1.89	0.07	5.79	0.41
5	2.48	0.05	3.34	0.09	2.41	0.13	1.72	0.05	2.85	0.10
6	1.91	0.05	1.43	0.03	1.52	0.06	0.81	0.03	1.47	0.07
7	1.27	0.07	1.15	0.09	1.53	0.15	0.89	0.07	1.40	0.08
8	4.21	0.15	2.70	0.14	1.68	0.09	2.10	0.13	1.22	0.07
9	8.24	0.41	5.16	0.42	3.69	0.26	1.73	0.14	5.33	0.38
10	6.65	0.17	4.04	0.15	4.35	0.46	1.64	0.11	6.26	1.00
11	9.57	0.34	18.03	1.59	15.27	1.55	4.30	0.30	10.98	1.60
12	8.42	0.23	10.49	0.33	-	-	3.60	0.10	8.30	0.24
13	3.02	0.09	2.01	0.15	11.19	0.32	1.84	0.12	2.82	0.22
14	4.63	0.21	4.66	0.27	3.17	0.30	3.07	0.25	4.18	0.27
15	6.07	0.22	4.04	0.13	3.54	0.24	4.23	0.20	4.75	0.22
16	5.18	0.12	3.63	0.13	2.61	0.11	3.83	0.11	8.06	1.06
17	17.07	0.94	6.72	0.50	13.06	1.02	8.99	0.53	5.75	0.23
18	12.36	0.35	5.15	0.41	8.75	0.25	7.69	0.36	5.68	0.68
19	7.19	0.28	10.90	1.01	8.31	0.45	4.14	0.55	6.86	0.82
20	6.82	0.16	8.29	0.41	7.10	0.22	4.61	0.36	4.43	0.81

Because the residual effect of exertion on heart beats appearing during visualization for most participants, it is impossible to know if the HF-RR variability is due to the recovery from exercise or instead the visualization of the prior bicycle ride. I expected that since the participants were bicycling at a moderately slow pace, the post-ride survey would act as the recovery period, and by the beginning of the visualization task heart rates would be constant. However, clear heart rate trends (toward baseline) existed for most participants during most visualization tasks. Mitigating the effect of residual exertion on HF-RR variability during visualization may be possible (e.g. using a lagged variable of speed before the visualization task). However, because the large magnitude of noise in the data shown in Table 2.8, I abandoned further analysis of the visualization data and instead focus on the on-road bicycling data.

Through a series of five multilevel models of the on-road bicycling data, a clearer picture of the relationship between HF-RR variability and the road environment emerges. I summarize the five model specifications and their estimated model performance (DIC) and number of effective parameters (pD) in Table 2.9. Results show that varying slopes by person improves model performance (large drop in DIC). Adding road and traffic environment predictors results in three clear benefits. First, model prediction improves, again evidenced by a large drop in DIC. Second, conditioning on the intra-road variability as well as situational traffic differences by person allows a more statistically efficient estimate of the treatment (see Appendix E for the change in posterior standard deviations of treatment parameters). Third, and perhaps most important, associations between HF-RR variability and these covariates can be used to explore explanations for the unexpected treatment effects (see below). These three benefits also exist for the person-level variables, although the magnitude of effect they have is much less dramatic (see Table 2.9). The full model is practically equivalent to the road and traffic model in its expected predictive ability, but because it includes all variables, I use it to explore the relationship between all the covariates and HF-RR variability in the following sections.

Table 2.9 Multilevel Model Specifications and Information Criteria

Model Name	Specification	DIC	pD
Base #1 (Varying Intercept)	Heart-beat level predictors: Road (1 base case, 4 indicators), Speed (smoothed GPS estimate speed meters/second)	878068	25.2
Base #2 (Varying Intercept and Slope)	Base #1 model adding varying (by person) slopes for Road and Speed	830748	123.2
Road and Traffic Environment	Base #2 with Intra-Road level predictors: Bike Lane width, Outside lane width, number of passing cars, presence of passing truck/bus	826505	121.2
Personal	Base #2 with person level predictors: Vigilance and Fear	828603	124.7
Full	Base # 2 with predictors from Road and Traffic Environment, and Personal models	826503	119.2

Models Base #1 and Base #2 show very similar predicted stress outcomes on average, but very different individual level predictions (Figure 2.10). These differences in predicted stress (HF-RR variability) at the person level, and the large difference in infromation criteria between the models (Table 2.9) suggest that between-person variation is important for prediction. The differences in information criteria between Base #2 and the Full model are less dramatic suggesting the real model improvement comes from letting the treatment and speed effects vary by person. All models suggest that on average College differs from all of the other road environments in terms of bicyclist stress. The comparisons of all road environments are presented in section 2.3.6.4. The predicted average HF-RR variability on the road environments suggests College has twice as much HF-RR variability compared to the other roads, indicating a potentially large effect. If we equate differences in HF-RR variability in milliseconds to psychological stress (albiet a strong and complicated assumption), the results suggest that bicycling on a collector or arterial is about twice as stressful as bicycling on a local road (e.g. College). The more tenuous differences between all the other road environments indicates that the experiment may not be able to conclusively show that HF-RR variability differs from different collector designs or even between collectors and arterials. However, because this is not a true randomized experiment (participants were assigned treatments to minimize order effects, not randomly assigned), the inclusion of covariates not only improves the statistical efficiency of the treatment effects, but corrects the direction of effect for individual differences (Gelman and Hill, 2007, p. 179). The predictive plot generated from the full model suggests slight changes to the treatment effects compared to the Base #2 model (Figure 2.10), but given the considerable model uncertainty, it isn't clear from the predictive plot which treatment differences should be trusted. A more detailed comparison of treatment contrasts is presented in section 2.1.6.4.

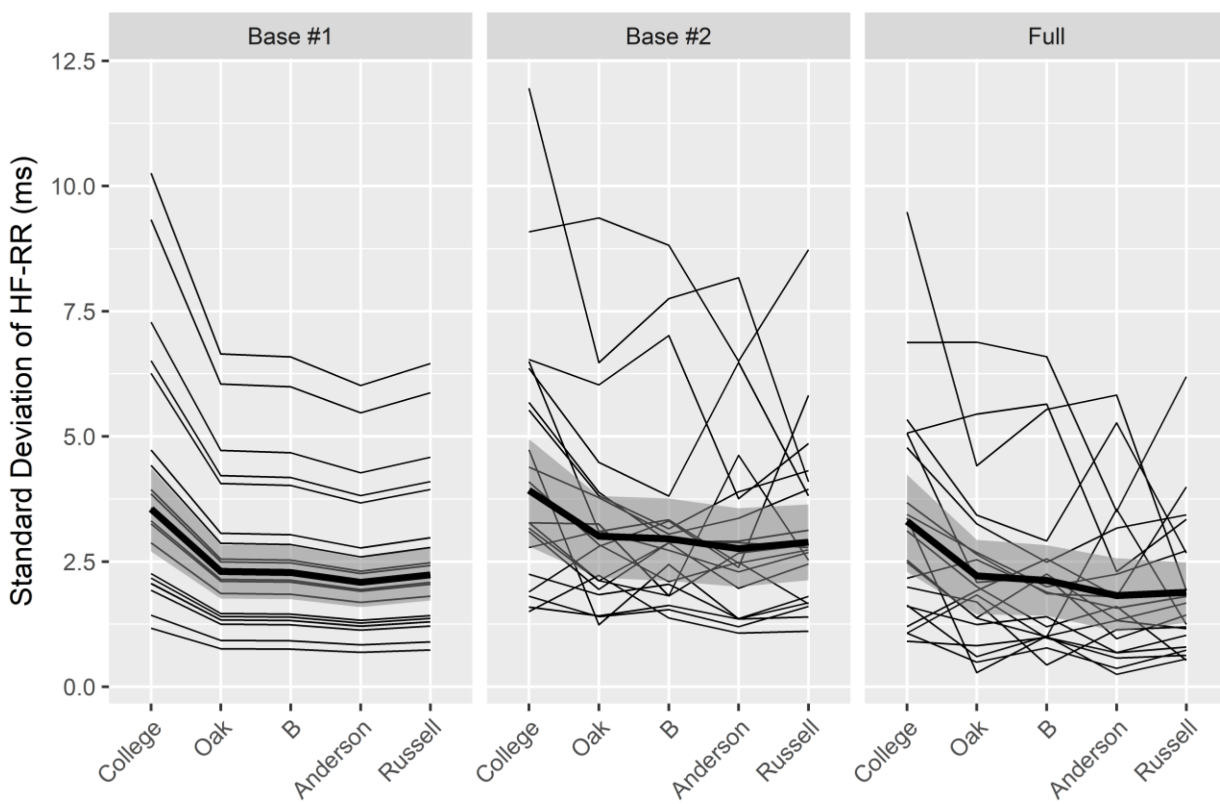

Figure 2.10 Model predictions of HF-RR intervals (ms) from the Base #1 (varying intercept), Base #2 (varying intercept and slope), and Full models. Thick line and shaded area represent the grand mean and 90% HPDI around the grand mean when speed, and all other covariates in the Full model, are constant at the grand mean. Thin lines represent the individual participant means when speed is constant at individual means.

2.3.6.2 Accounting for within-road variability in environment and traffic conditions

When considering the influence of the road environment and traffic (situational) variables within each treatment, the same characteristics can have opposing effects depending on the road enviornment. For example the influence of number of passing vehicles is associated with a small decrease in HF-RR variability when the road environment has only two lanes of traffic and a bike lane (e.g. Anderson Rd.). However, on Russell Blvd., where bicyclists have to share the outside vehicular lane, the number of passing cars is associated with less stress (more HF-RR variability) (Figure 2.11). The same opposing effect is found for presense of a passing truck or bus (Figure 2.11), although the magnitudes are not comparable due to differing variable scales. The results for the collectors and the minor arterial (as represented by the Anderson Rd. example in Figure 2.11), are to be expected since the literature on bicycling comfort clearly indicates that more traffic leads to less comfort. However, the counterintuitive positive effects of traffic on Russell Blvd. requires a more detailed discussion.

On Russell Blvd., the positive effect of traffic variables also corresponds with a negative effect of outside lane width. While studies generally show that more operating space (wider outside lane) of a shared lane would lead to more separation between bicyclist and vehicles and therefore less bicyclist stress (Epperson, 1994; Landis et al., 1997), these results suggest the opposite. A fully-supported rationale for this effect is not available from this data because the experiment was not designed to test the difference between different traffic conditions or within-road design variation. However, I suspect that the counterintuitive results of traffic and outside lane width on Russell are caused by specific real-time speeds of passing vehicles. The sections of Russell Blvd. that have wide outside lanes tend to correspond with no on-street parking where bicyclists ride near the gutter, well away from the center part of the outside lane. In these sections, vehicle speeds may be considerably faster when passing bicyclists than in the sections where the separation between vehicles and bikes is smaller. Further exploratory analysis is needed to support this hypothesis, but from the interviews it was clear that participants were most stressed on the Russell Blvd. blocks approaching the entrance and exits of a freeway. This area is known to have slightly faster vehicular speeds (although again I suspect considerably faster passing speeds) and wider outside travel lanes. I also hypothesize that a greater number of vehicles pass where primary destinations are present (where outside lanes are narrow and on-street parking is present) and vehicle passing speeds are slower. If this is true it would mean that the positive effects of the traffic variables on Russell Blvd. may be spuriously associated with lower stress due to slower vehicle passing speeds. Of course, without real-time measurement of vehicle passing speeds (normal traffic speed surveys won't suffice) this explanation remains speculative, but it points to a much more complex interaction between the effects of traffic on bicyclist stress than is commonly reported (i.e. average traffic volume and speed are negatively associated with bicyclist comfort (Buehler and Dill, 2016)). In fact, Epperson (1994) noted that in early bicycling studies "right-lane widths greater than 4.25 [meters] yielded nonsensical (i.e., negative [percieved bicyclist comfort]) results". Maybe these early results were less "nonsensical" than first thought. It seems possible, and probable in some road environments, that narrower shared travel lanes can increase bicyclist comfort (or descrease stress) if they are accompanied by slower real-time (not average) passing speeds of vehicles.

Although the explanation of vehicular speed as the cause for the above results is speculative, the results do clearly show that wider sections of shared travel lanes on Russell Blvd. result in more stress (less HF-RR variability). On the roads with bike lanes (Oak, B, and Anderson), wider bike lanes show less stress (more HF-RR variability). The fact that bike lane width has only a small effect may be due to the predominantly wide bicycle lanes on all of B, Oak, and Anderson. All the effects for within-road environmental variables should not be seen to have the same validity as the road treatments themselves because they were not manipulated as a part of the experimental design. The primary confound for the effects of within-road variables are the carry-over effects between segments of each road (there were no rest periods between sub-segments of each road). In addition, aggregating the variables by sub-segment of each road may have had an important influence on how the traffic variables affect HF-RR variability in the models.

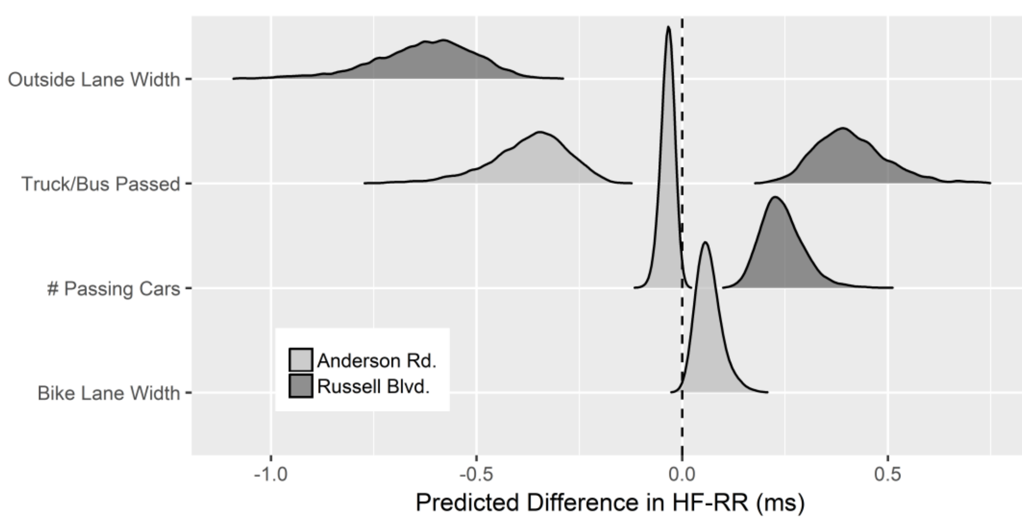

Figure 2.11 Influence of road and traffic variables on HF-RR variability on Anderson Rd. and Russell Blvd. The densities represent the difference between each variable at 1 standard deviation above and 1 standard deviation below the mean (with the exception of Truck/Bus Passed, which is the difference between presence and absence of a Truck or Bus).

2.3.6.3 Accounting for person level factors

The small sample size (*n*=20 with respect to person level variables) severely limits inferences about person level factors associated with HF-RR variability. Model comparison shows little improvement when adding personal variables once the model is conditional on road and traffic variables (see Table 2.9). Because of the small sample size, I only included two person-level variables in the multivariate analyses (vigilance and fear). The parameters describing the influence of vigilance and fear on overall stress are negative but uncertain. The influence of vigilance and fear on the road effects and speed are all uncertain and vary in and around zero suggesting no evidence for interaction effects (see Appendix E for parameter values). In separate analyses, fear and vigilance seem to be similar in the magnitude of their impact on stress such that a person with 2 standard deviations more fear or more vigilance is likely to have 0.5-0.75 (ms) less HF-RR variability (Figure 2.12). The density plots for fear and vigilance in Figure 2.12 report predictions for each variable keeping the other at its mean. If we assume that someone is vigilant because they are afraid (as might theoretically be the case)[21] the top density plot of Figure 2.12 indicates that we can be more certain that a person scoring 2 standard deviations above another on both variables is likely to be more stressed (have less HF-RR variability (1.5 ms on average)) and little chance of being more relaxed. Overall, given that between-individual differences in HF-RR variability are quite large, and that sample size is small for person level variables, these data only suggest that vigilance and fear influence stress.

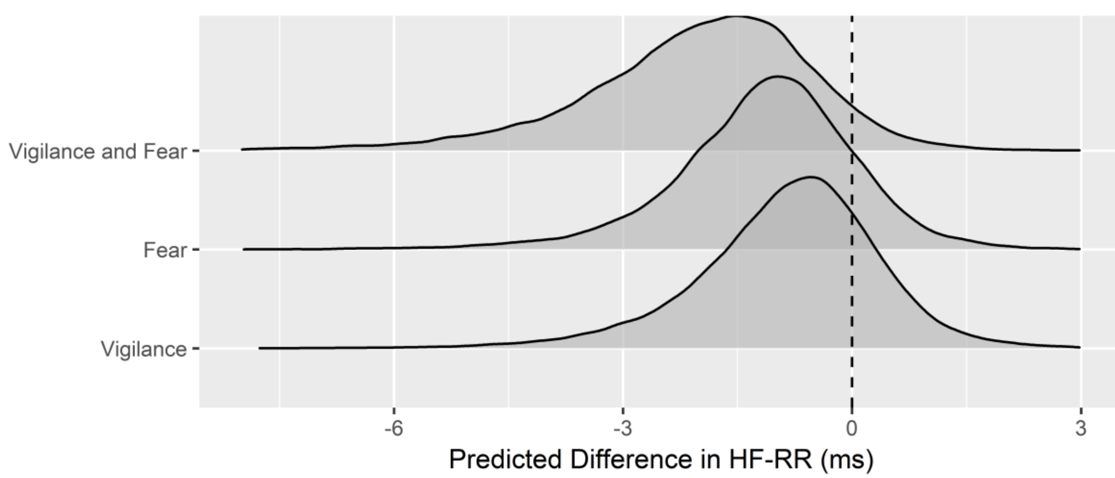

Figure 2.12 Model predictions of HF-RR intervals (ms) from the person covariate model for the influence of vigilance and fear. The densities represent the difference between each variable at 1 standard deviation above and 1 standard deviation below the mean when speed and all other variables are constant at their means.

[21] See section 2.3.2 for sample correlations.

2.3.6.4 Treatment effects

Including the covariates from the road environment, traffic, and person level improve model prediction, as measured by DIC (see Table 2.9). Furthermore, the main effects of the road environments are relatively unchanged conditional on these covariates (see Appendix E for parameter values). Figure 2.13 shows the predicted stress for each treatment condition (another visualization of the same effects in Figure 2.10 right panel), and Figure 2.14 shows the predicted stress as treatment contrasts of all road environments from the full model. The results confirm that College Ave. is expected to exhibit less stress (more HF-RR variability) than all the other roads, but the magnitude of the effect is highly uncertain. The contrast plots for the non-College comparisons show that B and Oak are indistinguishable at their mean, as are Anderson and Russell. However, they suggest that B and Oak may differ from Anderson and Russell in the expected direction (i.e. less stress (more HF-RR variability)). The differences between B/Oak and Anderson/Russell have no additional uncertainty (all posterior contrasts have similar scales), but they have considerable density that crosses zero. Having posterior density that spans zero suggests that the mean direction of effect is more likely to be erroneous.

Why is College Ave. the only road environment that is certainly less stressful for these bicyclists? This is a challenging question to answer with this data. While College was expected to be the least stressful environment for bicycling, it was also expected that Russell Blvd. would have certainly exhibited the most stress relative to the other roads. It could be that the College effect is due to other environmental variables not included in these models. For example, College has a dense canopy of tree foliage on both sides of the road. While trees are prevalent on all the other road environments, none as dense as College. Since greeness has been shown to reduce stress (James et al., 2015), it may have influenced the HRV of participants bicycling on College. Also, College was the only non-out-and-back treatment. It may be that the nature of the College Ave. loop has an effect on stress.

One of the primary challenges of field experiments is the inability to control all the variables within each treatment. It is likely that the influence of the environment on stress when bicycling is determined by various factors that cannot be controlled. One way to improve this design would be to examine many similar roads through random sampling to account for uncontrollable factors. However, designing a field experiment on randomly selected roads would be logistically challenging. Perhaps another approach is in using a similar experimental design in the context of a bicycling simulator where researchers have complete control over road environments. However, the improvement in the validity of the specific stressors comes at the cost of the external validity of the simulated bicycling experience. Future experiments might benefit from a combined simulator/field study of bicycling stress. Even with these types of experimental improvements, large within-person variability in HF-RR response is still likely. This variability challenges the validity of using HRV to understand bicyclist psychological stress.

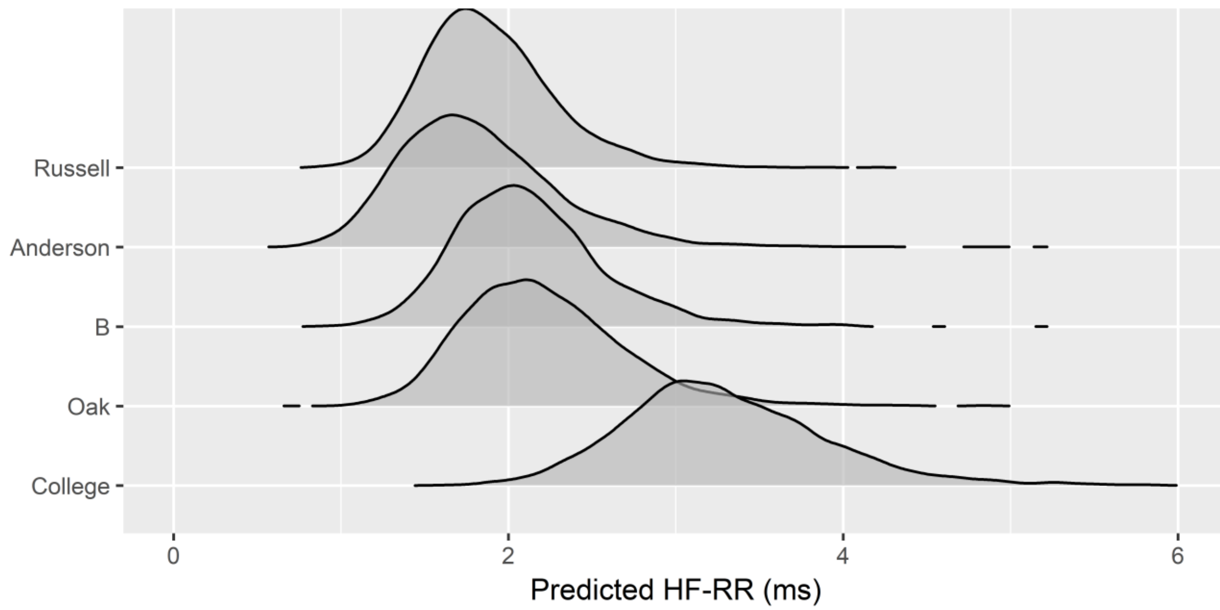

Figure 2.13 Model predictions of HF-RR intervals (ms) from the Full model. The densities represent the expected HF-RR values for each treatment when speed and all other variables are constant at their means.

2.3.7 Summary of Findings

In this study I sought to answer some specific research questions about bicyclist stress. Below I've summarized the results and limitations of the results in answering each of the questions in turn.

How do road environments relate to survey measures of comfort and safety?

- Self reported comfort, safety, comfort/safety, and anxiety all show that off-street paths and local roads are the most safe and comfortable and least likely to cause anxiety
- Self reported comfort, safety, comfort/safety, and anxiety all show that the major arterial with no bike lane is the least safe and comfortable and most likely to cause anxiety
- Self reported comfort, safety, comfort/safety, and anxiety of different configurations and existing traffic of collectors and minor arterials are ambiguous
- Results are limited by the small sample size of 20 people

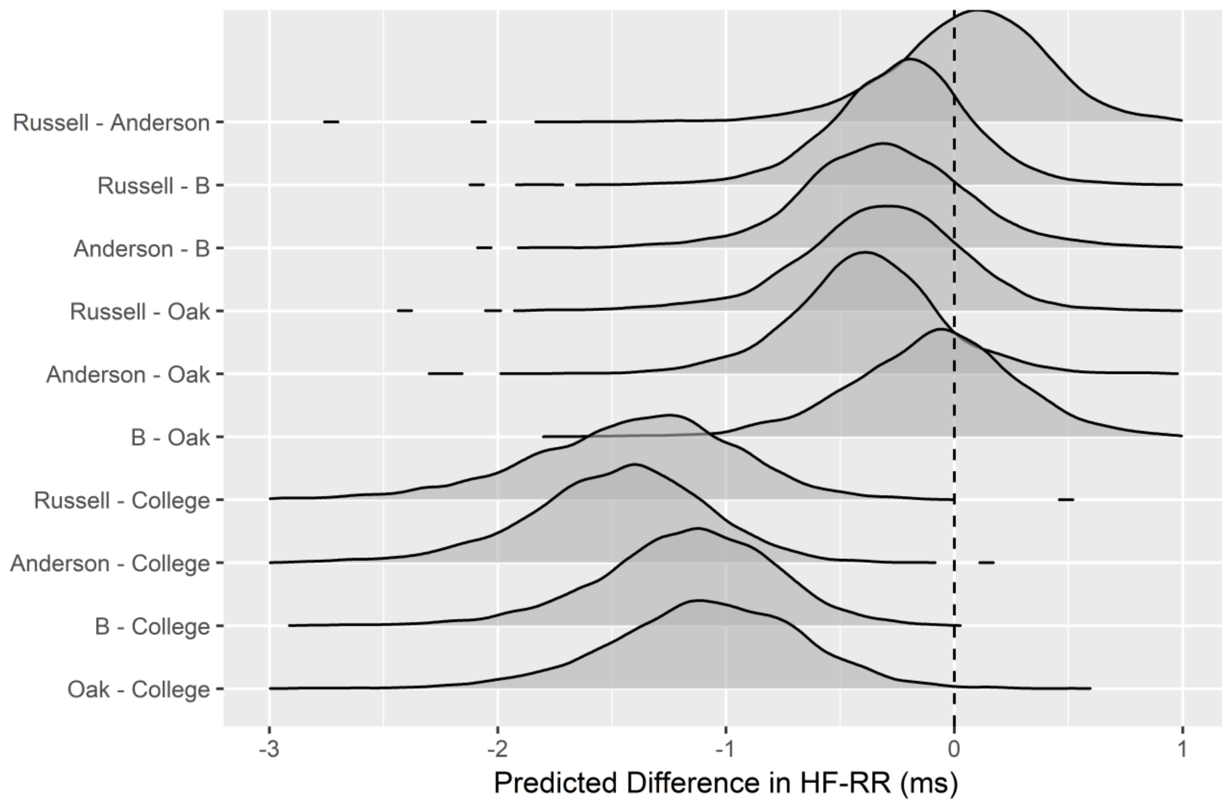

Figure 2.14 Model predicted treatment contrasts of HF-RR intervals (ms) from the Full model. The densities represent the expected difference in HF-RR values for each contrast when speed and all other variables are constant at their means.

How well to survey measures and physiological measures of stress relate?

- Evidence for weak correlations between stress and survey measures for on-road bicycling
- No evidence for correlations between stress and survey measures for visualizations of bicycling
- Not clear how much HF-RR is measuring an important added psychological component that is missing from survey measures, or how much is noise

How do road environments influence bicyclist psychophysiological stress?

- Differences between the local road (College) and all the other roads showed the local road to be lower in stress
- Differences between the two low traffic collectors and the arterials are only suggestive of differences in stress
- Difference in stress between arterials shows no clear trend.
- Exertion may not be fully accounted for give a moderate correlation between stress and self reported "physically tired" after bicycling
- Uncertainty in the ability of HF-RR to measure psychological stress while bicycling is an important limitation

2.4 Conclusions

Bicyclist stress is an important variable because it is connected to bicycling safety and it likely influences bicycling behavior (the decision to bike and where to bike). It offers an intuitive representation of the effect of road environments on the willingness to bicycle, as is evidenced by the use of the term "stress" in bicycling research (Geelong Bike Plan Commitee, 1984; Sorton and Walsh, 1994), and planning practice (Mekuria et al., 2012). Although survey measures of bicycling "stress" (e.g. comfort, perceived safety) are still the best available methods for gauging the influence of road environments on bicycling behavior, objective measures of human physiology have the potential to inform this relationship.

One of the positive results from this study was a strong difference in HRV between bicycling on a local road (College Ave.) compared to all the other roads. Whether this difference is due to road design parameters most commonly thought to influence bicycling comfort (e.g. road width, parking, operating space) and their downstream effects of traffic (e.g. vehicle volume and speed), or other unmeasured variables (e.g. greenness, noise) remains to be seen. Nonetheless, this evidence suggests that bicyclist physiological signals can systematically differ by environment. The lack of differentiation of the collector/minor arterial roads (Oak, B, and Anderson) is not surprising given that the survey measures tend to also lack differentiation. However, given that bicyclists clearly felt Russell Blvd. was unsafe and uncomfortable, the lack of consistently lower HRV on Russell Blvd. puts limits on the validity of HRV as a measure of bicyclist psychological stress.

In addition, small but consistent correlations between physiology and survey measures of the bicycling experience suggest two possible (and not necessarily mutually exclusive) stories for the validity of HRV as a measure of bicyclist stress. First, large between person variability suggests the causal link between HRV and stress is complicated by unobserved individual-level variables. This variability is not special to the case of bicycling (hence the focus on within-subject variability for most HRV studies), but nonetheless results in uncertain expected effects when generalizing to a population. This uncertainty is likely to occur even in the most well designed experiments. Second, HRV as a measure of bicyclist stress occurs involuntarily in real time and is likely to systematically differ from the more cognitive survey responses after bicycling. The survey responses require subjective assessment of questions and answer responses and the summarizing of experience over time. Although it is tempting to consider HRV a "gold standard" for measuring bicycling stress because it is objectively observed, the fact that there still exists considerable debate about the mechanism relating HRV to stress, and physiological measurements to psychophysiological theories in general (Cacioppo et al., 2007, pp. 12–13), suggests otherwise. Instead, HRV might best be viewed as a supplemental measure of the psychological experience of a bicyclist. Furthermore, individual subjective impressions of stress may be more likely than physiological signals to influence decisions to ride and decisions of where to ride. Conversely, feelings of fear and anxiety or comfort and safety are difficult to even define let alone internally evaluate on a survey. Although HRV in this experiment seems unable to distinguish between subtle differences in the road environment, it may be able to provide evidence for detailed environment/behavior relationships (e.g. near misses) that occur in real-time. Additional exploratory analysis of this and other bicycling HRV data, much like that of Vieira et al. (2016), may be an important research direction for the use of HRV for detecting unsafe and uncomfortable bicycling situations.

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Appendix A. Experimental survey questions

(1) A number of statements which people have used to describe themselves are given below. Read each statement and then select the most appropriate number to the right of the statement to indicate how you felt during the bike ride you just finished. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your feelings best.[22]

	Not at all	A little	Sometimes	Often	A lot
1. I felt calm	☐1	☐2	☐3	☐4	☐5
2. I was tense	☐1	☐2	☐3	☐4	☐5
3. I felt upset	☐1	☐2	☐3	☐4	☐5
4. I was relaxed (Reverse Key)	☐1	☐2	☐3	☐4	☐5
5. I felt content (Reverse Key)	☐1	☐2	☐3	☐4	☐5
6. I was worried	☐1	☐2	☐3	☐4	☐5

(2) In the bike ride you just finished, did you feel:

	Not at all	A little	Sometimes	Often	A lot
1…worried about parked car doors?	☐1	☐2	☐3	☐4	☐5
2…worried about passing vehicles?	☐1	☐2	☐3	☐4	☐5
3…comfortable? (Reverse Key)	☐1	☐2	☐3	☐4	☐5
4…worried about turning vehicles?	☐1	☐2	☐3	☐4	☐5
5…physically tired? (Effort control)	☐1	☐2	☐3	☐4	☐5
6…emotionally tired?	☐1	☐2	☐3	☐4	☐5
7…safe?	☐1	☐2	☐3	☐4	☐5
8…protected from traffic?	☐1	☐2	☐3	☐4	☐5

(3) Please indicate the range of comfort/safety regarding the interaction with car traffic you felt in the bike ride you just finished (1-10):

	Uncomfortable /Unsafe									Comfortable/ Safe
On Average	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10
Range of comfort (check all that apply)	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8	☐9	☐10

(3) In general, how would you rate the surface of the road (i.e. pavement quality)?

[22] This paragraph and list is adapted from the short-form state scale in Marteau and Bekker (1992) which itself was adapted from the State-Trait Anxiety Inventory (Spielberger, 1983). The 5-point response categories were adopted from Amirkhan (2012).

□ Acceptable □ Unacceptable

(4) Please indicate the range in comfort/safety with regard to the surface of the road (1-10):

	Uncomfortable /Unsafe									Comfortable/ Safe
On Average	□1	□2	□3	□4	□5	□6	□7	□8	□9	□10
Range of comfort (check all that apply)	□1	□2	□3	□4	□5	□6	□7	□8	□9	□10

Appendix B. Pre-experiment paper survey

(1) This survey asks for information about your level of stress in a variety of difference contexts. There are no right or wrong answers, please provide your subjective feelings and opinions[23].
IN THE PAST WEEK, have you felt:

	Not at all	A little	Sometimes	Often	A lot
1…calm?	□1	□2	□3	□4	□5
2…strained?	□1	□2	□3	□4	□5
3…inadequate?	□1	□2	□3	□4	□5
4…overextended?	□1	□2	□3	□4	□5
5…confident? (Reverse Key)	□1	□2	□3	□4	□5
6…bored?	□1	□2	□3	□4	□5
7…no sense of getting ahead?	□1	□2	□3	□4	□5
8…swamped by your responsibilities?	□1	□2	□3	□4	□5
9…that the odds were against you?	□1	□2	□3	□4	□5
10…that there wasn't enough time to get to everything?	□1	□2	□3	□4	□5
11…generous?	□1	□2	□3	□4	□5
12…like you were rushed?	□1	□2	□3	□4	□5
13…like you couldn't cope?	□1	□2	□3	□4	□5
14…like you had a lot on your mind?	□1	□2	□3	□4	□5
15…like nothing was going right?	□1	□2	□3	□4	□5
16…carefree?	□1	□2	□3	□4	□5
17…powerless?	□1	□2	□3	□4	□5
18…overcommitted?	□1	□2	□3	□4	□5
19…like your life was "out of control"?	□1	□2	□3	□4	□5
20…like things kept piling up?	□1	□2	□3	□4	□5
21…like you could focus on the important things?	□1	□2	□3	□4	□5
22…like you had to make quick	□1	□2	□3	□4	□5

[23] Items and scale from the Stress Overload Scale (SOS) (Amirkhan, 2012). Each of these 30 items relate to two factors associated with stress overload: "Event Load, a sense that life's demands are burgeoning, and Personal Vulnerability, a sense of susceptibility to those demands" (Amirkhan, 2012, p. 61).

decisions?					
23…like asking "what else can go wrong?"	□1	□2	□3	□4	□5
24…like you didn't have time to breathe?	□1	□2	□3	□4	□5
25…like things couldn't get worse?	□1	□2	□3	□4	□5
26…peaceful?	□1	□2	□3	□4	□5
27…like there was no escape?	□1	□2	□3	□4	□5
28…like you were carrying a heavy load?	□1	□2	□3	□4	□5
29…like just giving up?	□1	□2	□3	□4	□5
30…like there was "too much to do, too little time"?	□1	□2	□3	□4	□5

(2) Did anything particularly stressful happen to you *this* morning? If yes, please explain:

____

____

____

____

____

____

(3) To what extent do you agree or disagree with the following statements? Please answer the following within the context of daylight and good weather.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I like riding a bike.	□1	□2	□3	□4	□5
I bicycle for transportation as often as I can.	□1	□2	□3	□4	□5
I would rather bike than drive when going short distances (< 2 miles roundtrip).	□1	□2	□3	□4	□5
I would rather bike than drive when going	□1	□2	□3	□4	□5

moderate distances (between 2 and 5 miles roundtrip).					
When I ride my bike I am afraid of cars that pass me on the road.	□1	□2	□3	□4	□5
When I ride my bike I worry about parked car doors opening.	□1	□2	□3	□4	□5
When I ride my bike I'm afraid when trucks pass me on the road.	□1	□2	□3	□4	□5
When I ride my bike I'm afraid of turning cars when approaching intersections.	□1	□2	□3	□4	□5
I am a cautious bicyclist	□1	□2	□3	□4	□5
As a bicyclist, I obey the traffic laws	□1	□2	□3	□4	□5
When bicycling, I always keep a watchful eye on cars	□1	□2	□3	□4	□5

(4) In general, how comfortable would you be riding a bicycle in the following kinds of streets in daylight and good weather? By two-lane or four-lane we mean the total vehicle lanes (i.e. one or two in each direction, respectively).

	Uncomfortable				Comfortable	Would you ride on it?	
An off-street bicycle path	□1	□2	□3	□4	□5	yes	no
A quiet residential street	□1	□2	□3	□4	□5	yes	no
A two-lane street, *with* a bicycle lane, and *no* parked cars.	□1	□2	□3	□4	□5	yes	no
A two-lane street, *with* a bicycle lane, along parked cars	□1	□2	□3	□4	□5	yes	no
A two-lane street, *without* a bicycle lane, and *no* parked cars.	□1	□2	□3	□4	□5	yes	no
A two-lane street, *without* a bicycle lane, along parked cars.	□1	□2	□3	□4	□5	yes	no
A four-lane street, *with* a bicycle lane, and *no* parked cars.	□1	□2	□3	□4	□5	yes	no

A four-lane street, *with* a bicycle lane, along parked cars.	☐1	☐2	☐3	☐4	☐5	yes	no
A four-lane street, *without* a bicycle lane, and *no* parked cars.	☐1	☐2	☐3	☐4	☐5	yes	no
A four-lane street, without a bicycle lane, along parked cars.	☐1	☐2	☐3	☐4	☐5	yes	no

Personal and Socio-demographic Questions:

(5) What year were you born? ________________________

(6) What is your approximate Height and Weight?

Height ___________ feet ____________ inches Weight ____________________lbs

(7) What is your race or ethnicity? Please select all that apply:
- ☐ African-American or Black ☐ Latino/Latina
- ☐ Asian ☐ Caucasian or White
- ☐ Pacific-Islander or Native Hawaiian ☐ American Indian or Alaskan Native
- ☐ Hispanic

(8) How often are you physically active? By physically active we mean a minimum of 20 minutes of exercise.
- ☐ less than once per month ☐ several times per month
- ☐ several times per week ☐ daily
- ☐ never

(9) How often do you bicycle in Davis, not for recreation?
- ☐ less than once per month ☐ several times per month
- ☐ several times per week ☐ daily
- ☐ never

(10) How often *did* you bicycle for travel before coming to Davis?
- ☐ less than once per month ☐ several times per month
- ☐ several times per week ☐ daily
- ☐ never

(11) In which cities (state and zipcode) have you lived and regularly bicycled in? (example: San Diego, CA (92102); Santa Cruz, CA (95060))

---

(12) How would you classify your bicycling ability? By ability, we mean your balance, steering, and general technical control of your bicycle.

Beginner	Advanced Beginner	Intermediate	Advanced	Expert
☐1	☐2	☐3	☐4	☐5

(13) What type of bike are you riding today?

□ Cargo □ City/Traditional □ Cruiser □ Fixed-gear

□ Folding □ Hybrid □ Mountain □ Recumbent

□ Road □ Touring □ Other____________________________

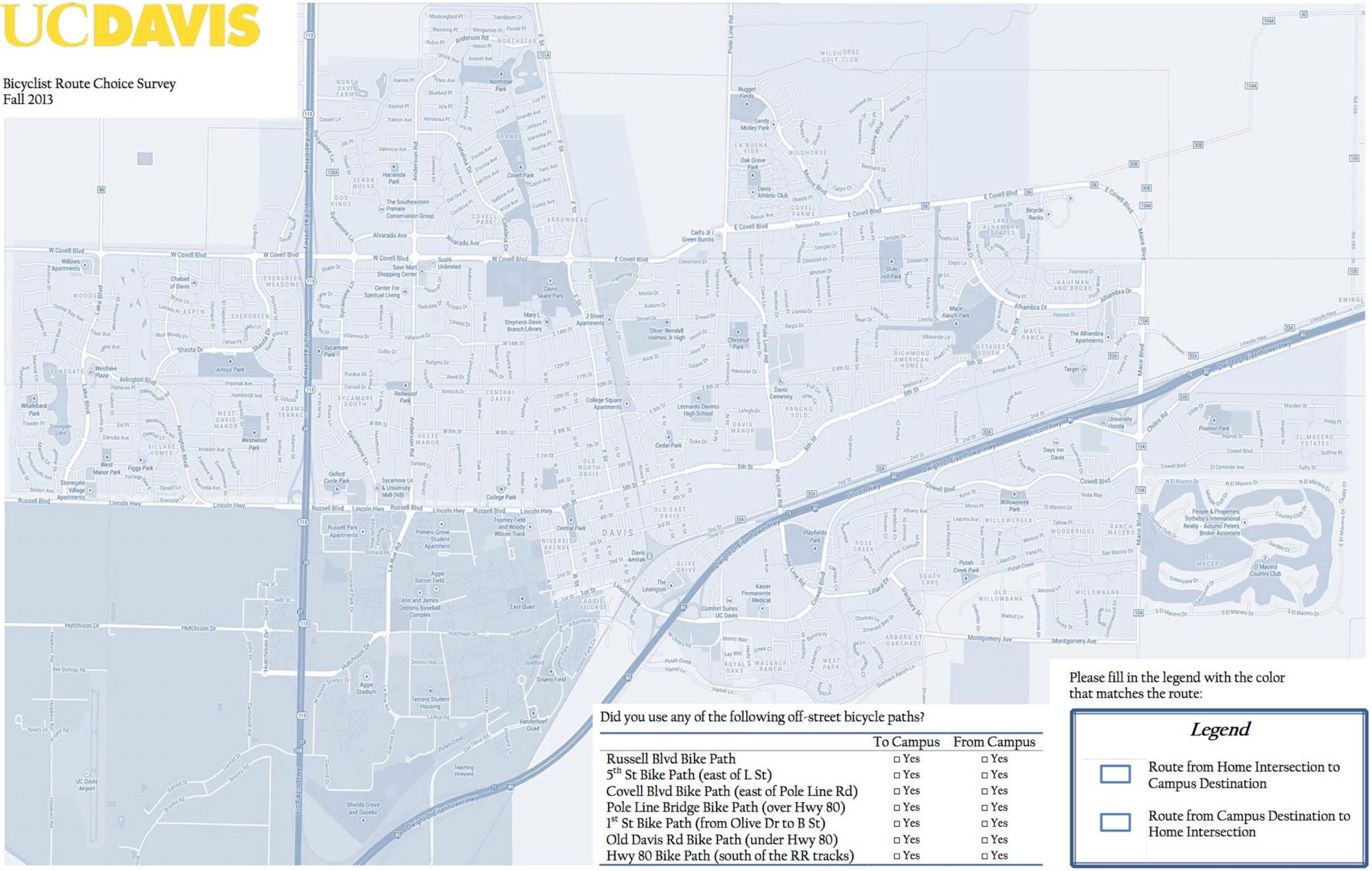
(14) What are the closest cross streets to your house?

____ And ____

(15) If you regularly bike around town, on the map below, please indicate your normal route from home to work/ school. Also, indicate any other regular bike routes you take in an alternate color and write their purpose (e.g. grocery, work, school, entertainment, shopping, etc.) next to each route.

UCDAVIS

Bicyclist Route Choice Survey
Fall 2013



Did you use any of the following off-street bicycle paths?

	To Campus	From Campus
Russell Blvd Bike Path	□ Yes	□ Yes
5th St Bike Path (east of L St)	□ Yes	□ Yes
Covell Blvd Bike Path (east of Pole Line Rd)	□ Yes	□ Yes
Pole Line Bridge Bike Path (over Hwy 80)	□ Yes	□ Yes
1st St Bike Path (from Olive Dr to B St)	□ Yes	□ Yes
Old Davis Rd Bike Path (under Hwy 80)	□ Yes	□ Yes
Hwy 80 Bike Path (south of the RR tracks)	□ Yes	□ Yes

Please fill in the legend with the color that matches the route:

Legend

□ Route from Home Intersection to Campus Destination

□ Route from Campus Destination to Home Intersection

Appendix C. Post-experiment audio recorded structured interview

(1) Now that you have ridden on all the roads would you like to change any of your overall scores?
(2) How familiar are you with any of these roads? Do you regularly ride on any of them? Do you regularly avoid bicycling on any of these roads? Why?
(3) When were you most stressed during this experiment? Please describe where you were and what happened?
(4) Which ride was the most stressful? Why? What did you fear most?
(5) Which ride was the least stressful? Why? What made it so comfortable?
(6) Did anyone tail you or bicycle closely behind you while riding any of the routes? Did that bother you? Why?
(7) Describe why you bicycle in Davis? (i.e. what are the reasons? Cost? Safety? etc.)
(8) In the opening survey I asked you to draw your normal bike routes around Davis. Why do you choose those routes? Are they the fastest? Do they avoid certain things? Do the reasons vary depending on the route or trip purpose?
(9) Do you think the words "comfort" and "stress" are opposites? If not, how do these concepts differ for you when you think about bicycling?

Appendix D. Detrending RR time-series and dependent variable sensitivity analysis

Selecting a filtering method

I evaluated numerous methods for removing the low-frequency trends (< 0.125 Hz) (the most important source of "noise" in determining HF-RR) in the RR time-series. All the comparison methods are used as a filter for isolating spontaneous breathing range HF-RR. I show below that the so-called Maximal Overlap Discrete Wavelet Transform (MODWT) method can closely approximate other methods for removing low frequency trends in the RR time-series. Furthermore, because the MODWT method decomposes the signal into frequency components that approximate the spontaneous breathing frequency range, it is naturally suited to filter RR time-series. I list and describe the comparison methods below

(1) Local polynomial regression (LOESS): A second order local polynomial model with fixed span.
(2) Moving polynomial filter (Savitzky-Golay filter): A third order local polynomial using fixed span. This method is commonly used for trend removal for RR time-series when quantifying RSA (Lewis et al., 2012).
(3) Smoothness priors: A regularized least squares trend algorithm with one regularization parameter (lambda). This method is commonly used to filter RR signals because of its implementation in the popular free HRV analysis software Kubios (Tarvainen et al., 2002).
(4) Trend filtering: A locally adaptive second order polynomial with one regularization parameter (lambda).
(5) MODWT: a redundant discrete wavelet transform (shifts in levels are needed to reconstruct the original signal) that is more consistent across time than the standard discrete wavelet transform because it does not down-sample (see Zhang et al. for details). This method requires the specification of a mother wavelet (I chose the Daubechies least asymmetric (symmlet) of length eight) (Garcia et al. (2013) suggest more research is needed to understand the effect of wavelet type/length for detrending RR signals), and the number of wavelet levels for decomposition (I chose five because the resultant frequency bands closely align with the spontaneous breathing frequencies after resampling the RR time-series to 4Hz without sacrificing the temporal resolution of the signal by descending too many levels (García et al., 2013)).

Using an example time-series, I show that MODWT can closely approximate the other algorithms at identifying the low-frequency variation in the signal (Figures 2.D1 and 2.D2). I intentionally selected algorithm tuning parameters to approximate frequencies below 0.125 Hz for each algorithm (some algorithms are locally adaptive (trend filtering, Smoothness priors) and cannot be equated with a single frequency band). The results indicate that with proper tuning, all algorithms can roughly approximate each other in identifying low frequencies in RR time-series. Therefore, I decided to use MODWT for low frequency trend removal because of its natural ability to isolate the frequency ranges commonly reported for analyzing RR intervals.

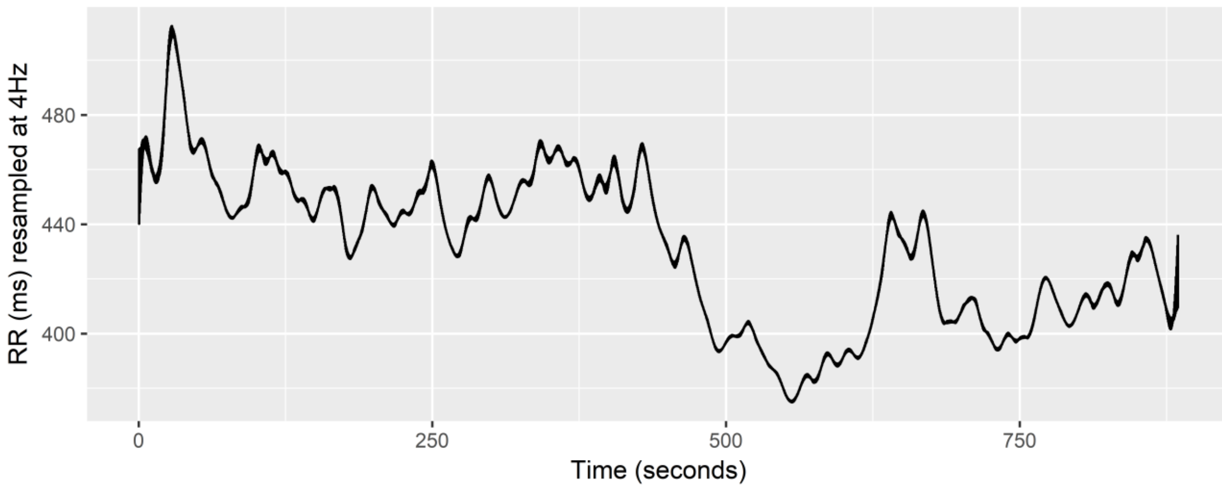


Figure 2.D1 Example of the range of estimated low frequency 'trend' from participant #7 on Oak Ave. by plotting all algorithms on top of each other.

Selecting a Filter

Following the selection of MODWT as the low frequency filter method, I conducted a sensitivity analysis for determining how to filter "noise" (both very high-frequency and residual low-frequencies) based on the dual objectives stated in Section 2.2.1.1. Below are the processing steps starting with the preprocessing of the signal, and ending with the sensitivity analysis to generate the dependent variable for this study:

(1) *Preprocess raw data*: RR data has artifacts (large outliers) which may interfere with inference. The artifacts are a result of technical problems associated with measurement (i.e. loss of electrode contact) at unpredictable time periods. I remove artifacts from the RR time-series through fixed filtering (remove all intervals < 300 ms and > 2400 ms because they are not physiologically plausible), and visual inspection.

(2) *Transformation and Filter*: Spectral decomposition and extraction of spontaneous breathing frequency range (vagally influenced) of HRV is a common way of isolating psychologically relevant signal components. I use the MODWT to isolate frequencies of interest while also allowing for locally adaptive filtering through wavelet coefficient thresholding (see above for further justification for this method). Spontaneous breathing range of heart beats is commonly defined as the 0.12-0.4 Hz frequency (between 9 and 24 breath cycles per minute). However, with moderate exertion, that range could be closer to 0.12-1Hz (between 9 and 60 breaths per cycle) (Hatfield et al., 1998). However, because I do not measure participant respiration, I do not know participants' breathing frequency. Therefore, in this step I take two approaches to filtering and generate a series of signals to use in the following steps. The filters are as follows:

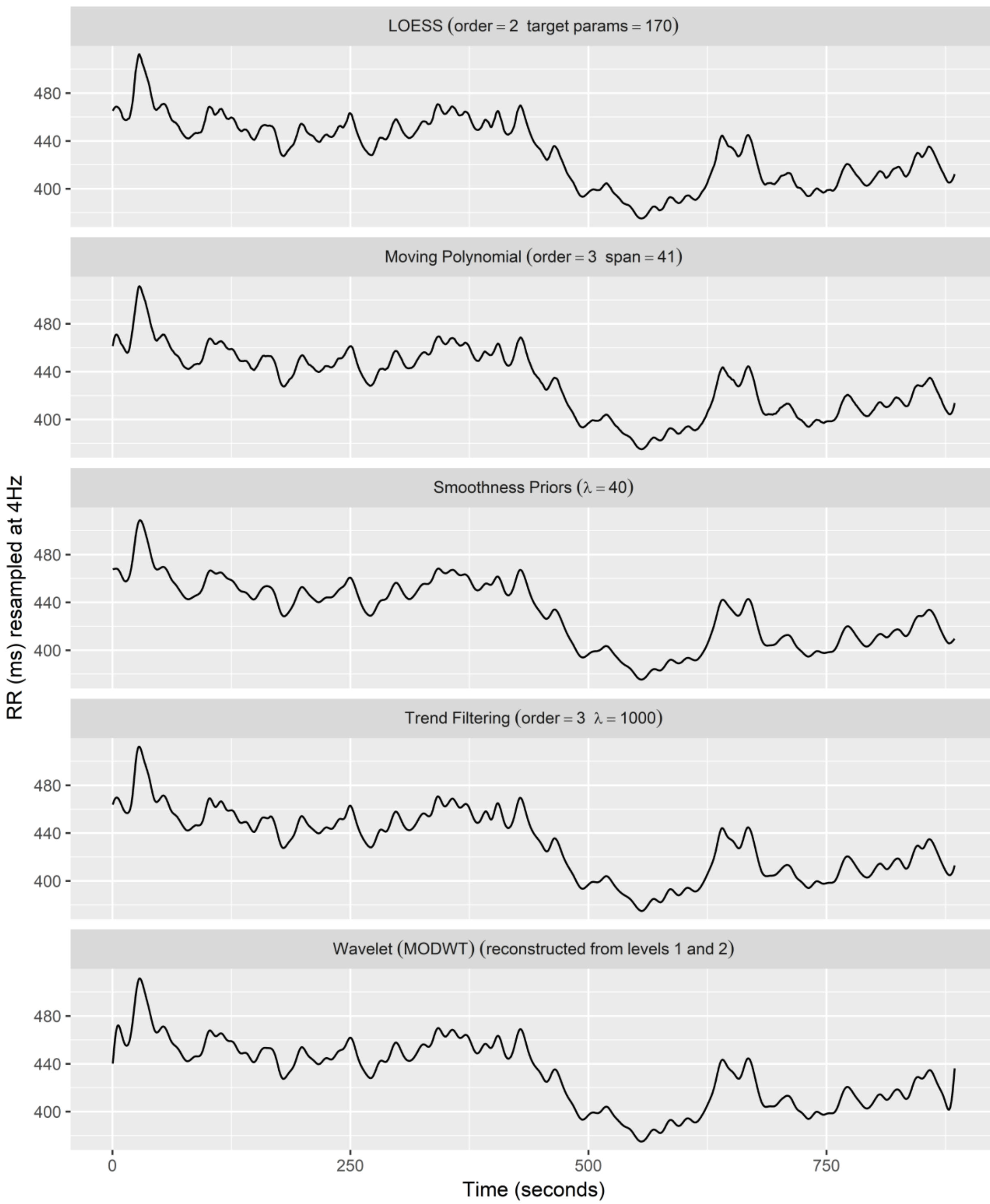


Figure 2.D2 Example of estimated low frequency 'trend' from participant #7 on Oak Ave. by five algorithms.

a. Assume the entire spontaneous breathing rage frequencies provide information about stress throughout the bicycling component of the experiment. With this assumption, I conduct linear transformations of the raw RR signals by hard thresholding all wavelet coefficients at levels beyond spontaneous breathing range frequencies.

   b. Assume both low and high frequency noise can be removed to provide a stronger signal of stress during the bicycling component of the experiment. With this assumption I conduct non-linear (locally adaptive) transformations of the raw RR signals by hard thresholding wavelet coefficients based on estimates of "noise" within the wavelet levels associated with spontaneous breathing.

(3) *Compare and rank signals* for maximizing the magnitude and precision of the regression parameter for speed and the computer stress task. I do this by running repeated multilevel models (varying intercepts by individual) of the baseline and computer stress test data, and the speed trial data independently (Table 2.D1) (see section 2.2.4 for model details).

(4) *Select final dependent variable*: The final dependent variable is based on balancing the ranking of signals for the goals of steps 3 and 4 above. In this chapter I refer to this selected variable as high frequency heart rate variability (HF-RR).

Table 2.D1 shows the wavelet coefficient thresholds for the sensitivity analysis. All thresholds are hard (i.e. wavelet coefficients = 0 if they pass the given threshold) based on the individual and experimental condition specific wavelet coefficients. I set wavelet coefficients at levels one and five to zero because they are beyond the spontaneous breathing range of humans with moderate exertion. I filtered wavelet coefficients at levels two, three, and four based on λ and η. λ is the *universal threshold*, originally proposed by Donoho and Johnstone (1994), where the high frequency noise is estimated based on the median absolute deviation of the finest level wavelet coefficients (Level 1) from the individual baseline period for the mental stress model and the slow bicycling period for the speed model. η is the same universal threshold using the median absolute deviation from the coarsest level wavelet coefficients (Level 5) from the individual baseline period for the mental stress model and the slow bicycling period for the speed model. Wavelet coefficients *below* the threshold values for each high frequency filter (Table 2.D1) were set to zero. Wavelet coefficients *above* the threshold values for each low frequency filter (Table 2.D1) were set to zero. This way λ and η have inverse meanings. As the high-frequency threshold *increases* toward λ, more high frequency data is removed. As the low-frequency threshold *decreases* toward η more low-frequency data is removed. I considered all possible permutations of low and high frequency filters resulting in 25 (5^2) potential dependent variables. I did not consider thresholds beyond λ and η because those wavelet coefficients likely represent important information about vagal tone and any model comparison suggesting stronger filtering ($>\lambda$ and/or $<\eta$) may be overfitting to the baseline, mental stress test, and speed trial data.

Table 2.D1 Filtering algorithms considered in the sensitivity analysis

Filtering Frequencies	Threshold Type	Filter ID	Level 2	Level 3	Level 4
High Freq.	Linear	1	NA	NA	NA
	Locally adaptive	2	0.25λ	0.25λ	0.25λ
		3	0.5λ	0.5λ	0.5λ
		4	0.75λ	0.75λ	0.75λ
		5	λ	λ	λ
Low Freq.	Linear	1	NA	NA	NA
	Locally adaptive	2	2.00η	2.00η	2.00η
		3	1.66η	1.66η	1.66η
		4	1.33η	1.33η	1.33η
		5	η	η	η

Sensitivity analysis results

Table 2.D2 shows the versions of HF-RR that have the strongest correlation with both bicycling speed and the dual 2-back mental stress test. These results come from running repeated regressions (see section 2.2.4) using the transformations and filtering of the raw RR time-series as outlined above. I modeled the effect of the mental stress test independently from the effect of bicyclist speed. The reported models have the largest regression parameter magnitude, smallest coefficient of variation of the regression parameter, and smallest information criteria across the two models. Results suggest that high amplitude (threshold=λ) locally adaptive high frequency filters consistently have the strongest and most precise regression effects (Table 2.D2). On the other hand, the influence of locally adaptive low frequency filters did not show a consistent trend. All five low frequency filters show up in the top six models suggesting that the threshold is unlikely to have a strong influence on the relationship between the output signal and either psychological stress nor speed. The filtered HF-RR time-series with the best performance for both models was the combination of both a high (λ) and low (η) frequency adaptive filter (Table 2.D2 Filter ID (5 , 5)). This result suggests that by adaptively filtering out some high and low frequencies in the spontaneous breathing range (0.125 – 1Hz) we might expect a stronger signal-to-noise ratio for estimating heart beat changes in response to physical exertion and psychological stress. More extensive sensitivity analyses might help fine tune filtering parameters for increasing the relationship between HF-RR and stress. However, given how similar the results are for the top 6 models (Table 2.D2), it is unlikely that much can be gained from a more fine-tuned sensitivity analysis. Using the chosen filter (Filter ID (5 , 5)), Figure 2.D3 shows the reconstructed HF-RR signal for one participant during one on-road bicycling interval and Figure 2.D4 shows the filtering process leading to the HF-RR signal. shows the resulting reconstructed HF-RR signal.

Table 2.D2 HF-RR Sensitivity Analysis Selected Model Results

	Dependent Variable Filter ID (HF , LF) parameters	(5 , 5) λ, η	(5 , 1) λ, NA	(5 , 3) λ, 1.66η	(5 , 4) λ, 1.33η	(4 , 5) 0.75λ, η	(5 , 2) λ, 2η
<u>Model</u> Baseline & Dual *2*-back	β	-0.144	-0.135	-0.135	-0.135	-0.143	-0.135
	σ	0.011	0.010	0.010	0.010	0.010	0.011
	Coef. Var.	0.074	0.077	0.076	0.078	0.072	0.079
	LOOIC*	166800	167019	167020	167020	167036	167020
	β rank	1	7	8	9	2	6
	Coef. Var. rank	3	7	4	8	1	14
	LOOIC rank	1	2	4	3	6	5
<u>Model</u> Speed	β	-0.518	-0.536	-0.535	-0.529	-0.463	-0.535
	σ	0.003	0.003	0.003	0.003	0.003	0.003
	Coef. Var.	0.006	0.006	0.006	0.006	0.006	0.006
	LOOIC*	163313	164852	164380	163955	167503	164445
	β rank	5	1	3	4	10	2
	Coef. Var. rank	6	1	2	4	11	5
	LOOIC rank	1	5	3	2	6	4

* approximated leave-one-out information criteria (Vehtari et al., 2017), lower values indicate comparatively better predictive accuracy.

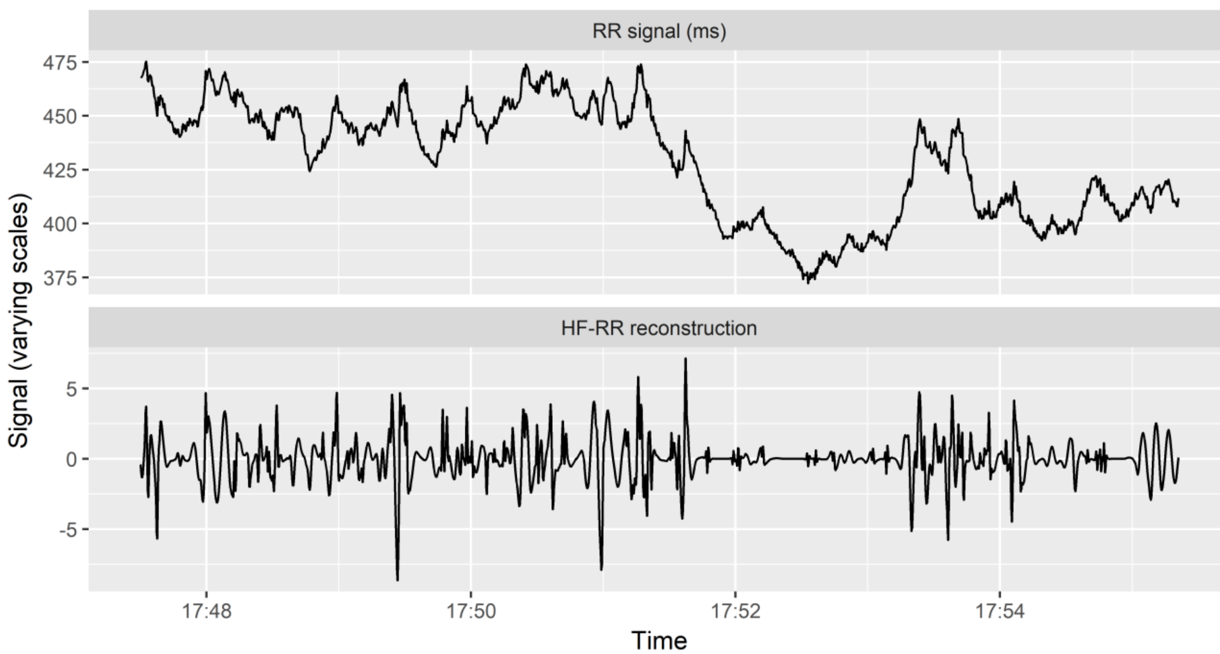


Figure 2.D3 Reconstructed HF-HRV signal of participant #7 on Oak Ave. The top row is the untransformed signal in milliseconds (ms), the bottom row is the reconstructed signal following the transform in Figure 2.D1.

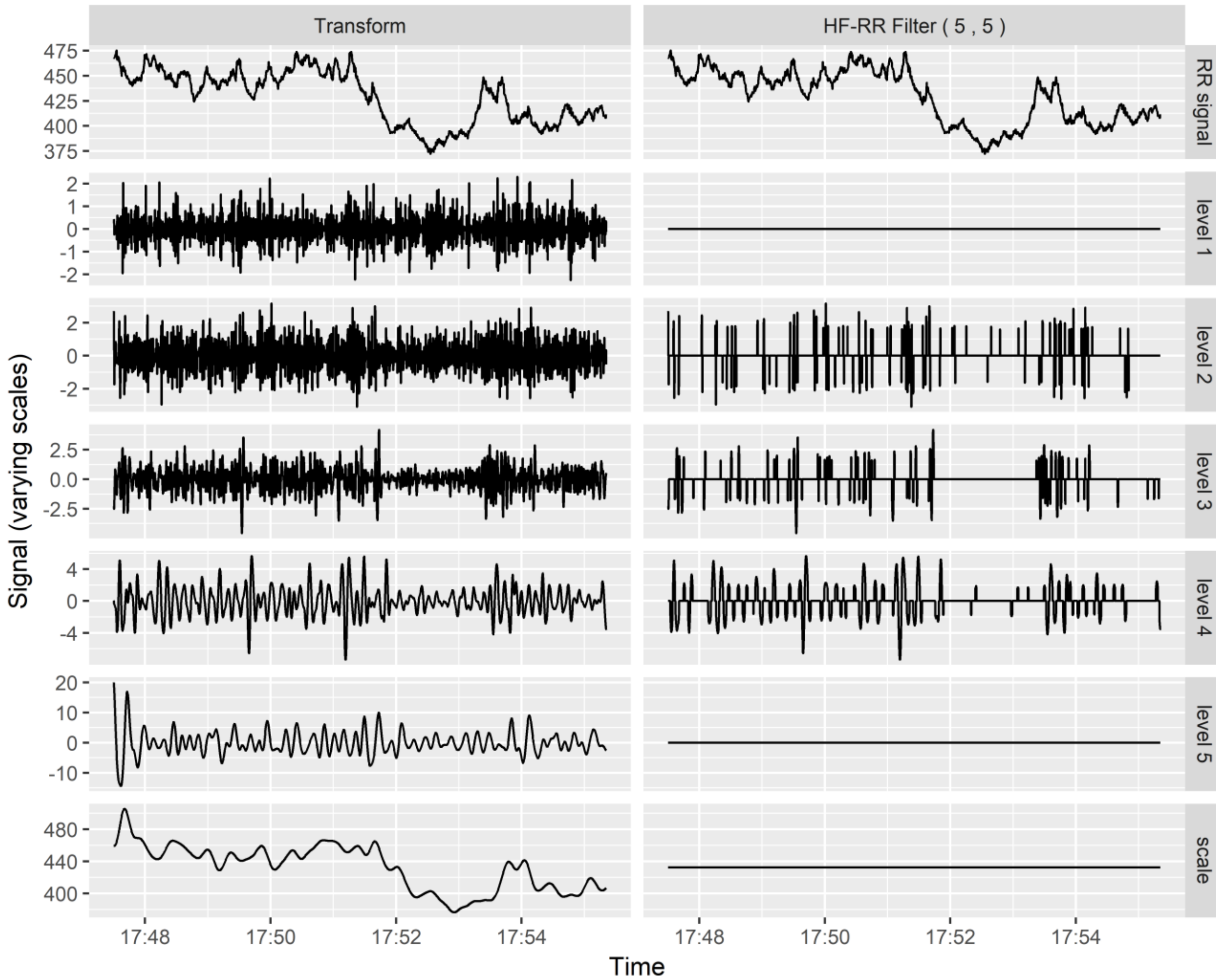


Figure 2.D4 Wavelet transformation and filtering (HF-RR) of participant #7 on Oak Ave. The top row is the untransformed signal in milliseconds (ms), the remaining rows represent wavelet coefficients at varying levels of decomposition. The left column shows all wavelet coefficients, and the right column shows the resulting coefficients after hard thresholding using the locally adaptive (HF=5 , LW=5) filter (see Table 2.D1).

Appendix E. Model Parameters

The following tables present summaries of the posterior distributions of the parameters of interest. Individual varying effect parameters are not included, only their "hyperparameters" describing varying effect variation.

Table 2.E1 Baseline and Dual n-back model results

Descriptor	Parameter	mean	sd	*n* eff
mean intercept	α	2.972	0.133	2000
Dual 2-back	β	-0.153	0.073	2000
Variation in intercepts	$\sigma_{person[1]}$	0.616	0.111	2000
Variation in slopes	$\sigma_{person[2]}$	0.320	0.056	2000
Intercept-slope correlation	Ω	-0.100	0.207	2000
Sample size	n		19224	
Mean deviance	-2 * LogLik		166770	

Table 2.E2 Speed trial model results

Descriptor	Parameter	mean	sd	*n* eff
mean intercept	α	4.069	0.417	2000
Speed (m/s)	β	-0.708	0.083	2000
Variation in intercepts	$\sigma_{person[1]}$	1.858	0.297	2000
Variation in slopes	$\sigma_{person[2]}$	0.370	0.059	2000
Intercept-slope correlation	Ω	-0.961	0.021	2000
Sample size	n		29062	
Mean deviance	-2 * LogLik		156360	

Table 2.E3 Visualization model results

Descriptor	Parameter	mean	sd	*n* eff
mean intercept	G [1,1]	2.677	0.188	4000.0
Oak	G [1,2]	-0.045	0.054	3337.2
B	G [1,3]	-0.214	0.093	4000.0
Anderson	G [1,4]	-0.029	0.055	3176.3
Russell	G [1,5]	-0.082	0.061	3177.8
Variation in intercepts	$\sigma_{person[1]}$	0.827	0.152	4000.0
Variation in slopes	$\sigma_{person[2]}$	0.232	0.039	4000.0
	$\sigma_{person[3]}$	0.389	0.073	4000.0
	$\sigma_{person[4]}$	0.234	0.041	4000.0
	$\sigma_{person[5]}$	0.269	0.044	4000.0
Intercept-slope correlations	Ω [1,2]	-0.128	0.200	4000.0
	Ω [1,3]	-0.162	0.215	4000.0
	Ω [1,4]	0.102	0.200	4000.0

	Ω [1,5]	-0.138	0.195	3235.9
	Ω [2,3]	0.077	0.227	3313.1
	Ω [2,4]	0.304	0.190	4000.0
	Ω [2,5]	0.528	0.159	3494.9
	Ω [3,4]	0.195	0.194	4000.0
	Ω [3,5]	0.202	0.200	4000.0
	Ω [4,5]	0.497	0.164	2893.2
Sample size	n		29062	
Mean deviance	-2 * LogLik		156360	

Table 2.E4 Base #1 model results

Descriptor	Parameter	mean	sd	n eff
mean intercept	α	2.700	0.147	3386.2
Oak	$B_{[1]}$	-0.434	0.005	1027.2
B	$B_{[2]}$	-0.443	0.005	1570.3
Anderson	$B_{[3]}$	-0.533	0.006	2083.8
Russell	$B_{[4]}$	-0.463	0.005	985.9
Speed (m/s)	$B_{[5]}$	-0.315	0.002	338.8
Variation in intercepts	σ_{person}	0.663	0.116	2867.9
Sample size	n		188813	
Mean deviance	-2 * LogLik		878043	

Table 2.E5 Base #2 model results

Descriptor	Parameter	mean	sd	n eff
mean intercept	G [1,1]	2.463	0.255	3141.9
Oak	G [1,2]	-0.430	0.148	3022.8
B	G [1,3]	-0.431	0.126	4000.0
Anderson	G [1,4]	-0.601	0.155	4000.0
Russell	G [1,5]	-0.521	0.152	3155.2
Speed (m/s)	G [1,6]	-0.283	0.038	3351.7
Variation in intercepts	$\sigma_{person[1]}$	1.134	0.184	4000.0
	$\sigma_{person[2]}$	0.656	0.107	4000.0
	$\sigma_{person[3]}$	0.552	0.097	4000.0
Variation in slopes	$\sigma_{person[4]}$	0.686	0.114	4000.0
	$\sigma_{person[5]}$	0.689	0.111	4000.0
	$\sigma_{person[6]}$	0.167	0.027	4000.0
	Ω [1,2]	-0.208	0.180	4000.0
	Ω [1,3]	-0.250	0.191	4000.0
	Ω [1,4]	0.046	0.185	4000.0
Intercept-slope correlations	Ω [1,5]	-0.274	0.169	4000.0
	Ω [1,6]	-0.629	0.138	4000.0
	Ω [2,3]	0.327	0.188	4000.0
	Ω [2,4]	0.475	0.163	4000.0

	Ω [2,5]	0.392	0.167	4000.0
	Ω [2,6]	0.195	0.177	4000.0
	Ω [3,4]	0.167	0.188	4000.0
	Ω [3,5]	0.482	0.165	4000.0
	Ω [3,6]	0.254	0.186	4000.0
	Ω [4,5]	0.390	0.170	4000.0
	Ω [4,6]	-0.075	0.184	4000.0
	Ω [5,6]	0.013	0.179	4000.0
Sample size	*n*		188813	
Mean deviance	-2 * LogLik		830625	

Table 2.E6 Road and Traffic model results

Descriptor	Parameter	mean	sd	*n* eff
Bike lane width (z-score)	B^0[1]	0.018	0.007	1249.9
Outside lane width (z-score)	B^0[2]	-0.167	0.004	4000.0
# Passing Cars with bike lane (z-score)	B^0[3]	-0.010	0.003	4000.0
# Passing Cars without bike lane (z-score)	B^0[4]	0.065	0.004	4000.0
Presence of passing truck/bus with bike lane	B^0[5]	-0.234	0.019	4000.0
Presence of passing truck/bus without bike lane	B^0[6]	0.199	0.014	4000.0
mean intercept	G [1,1]	2.416	0.247	3128.8
Oak	G [1,2]	-0.407	0.148	2787.8
B	G [1,3]	-0.443	0.127	4000.0
Anderson	G [1,4]	-0.613	0.161	4000.0
Russell	G [1,5]	-0.561	0.152	3108.0
Speed (m/s)	G [1,6]	-0.273	0.037	4000.0
Variation in intercepts	$\sigma_{person[1]}$	1.124	0.184	4000.0
	$\sigma_{person[2]}$	0.658	0.103	4000.0
	$\sigma_{person[3]}$	0.556	0.096	4000.0
Variation in slopes	$\sigma_{person[4]}$	0.699	0.119	4000.0
	$\sigma_{person[5]}$	0.681	0.107	4000.0
	$\sigma_{person[6]}$	0.164	0.027	4000.0
	Ω [1,2]	-0.196	0.174	4000.0
	Ω [1,3]	-0.232	0.192	4000.0
	Ω [1,4]	0.040	0.182	4000.0
	Ω [1,5]	-0.247	0.175	4000.0
	Ω [1,6]	-0.623	0.131	4000.0
	Ω [2,3]	0.327	0.185	4000.0
Intercept-slope correlations	Ω [2,4]	0.481	0.159	4000.0
	Ω [2,5]	0.427	0.167	4000.0
	Ω [2,6]	0.188	0.181	4000.0
	Ω [3,4]	0.190	0.183	4000.0
	Ω [3,5]	0.504	0.156	4000.0
	Ω [3,6]	0.222	0.182	4000.0

	Ω [4,5]	0.398	0.168	4000.0
	Ω [4,6]	-0.091	0.185	4000.0
	Ω [5,6]	-0.019	0.182	4000.0
Sample size	n		188813	
Mean deviance	-2 * LogLik		826384	

Table 2.E7 Personal model results

Descriptor	Parameter	mean	sd	n eff
mean intercept	G [1,1]	2.463	0.258	3227.6
Oak	G [1,2]	-0.428	0.153	4000.0
B	G [1,3]	-0.425	0.137	4000.0
Anderson	G [1,4]	-0.601	0.165	4000.0
Russell	G [1,5]	-0.519	0.165	4000.0
Speed (m/s)	G [1,6]	-0.285	0.040	3549.6
Vigilance × mean intercept	G [2,1]	-0.160	0.290	3114.4
Vigilance × Oak	G [2,2]	0.076	0.167	2859.7
Vigilance × B	G [2,3]	0.001	0.151	4000.0
Vigilance × Anderson	G [2,4]	0.139	0.180	4000.0
Vigilance × Russell	G [2,5]	0.081	0.183	4000.0
Vigilance × Speed (m/s)	G [2,6]	-0.016	0.045	3031.7
Fear × mean intercept	G [3,1]	-0.179	0.290	3011.0
Fear × Oak	G [3,2]	-0.180	0.172	4000.0
Fear × B	G [3,3]	-0.079	0.148	4000.0
Fear × Anderson	G [3,4]	-0.079	0.180	4000.0
Fear × Russell	G [3,5]	-0.038	0.188	2968.7
Fear × Speed (m/s)	G [3,6]	0.001	0.044	3435.5
Variation in intercepts	$\sigma_{person[1]}$	1.140	0.182	4000.0
Variation in slopes	$\sigma_{person[2]}$	0.673	0.114	4000.0
	$\sigma_{person[3]}$	0.584	0.110	4000.0
	$\sigma_{person[4]}$	0.719	0.128	4000.0
	$\sigma_{person[5]}$	0.734	0.123	4000.0
	$\sigma_{person[6]}$	0.175	0.030	4000.0
Intercept-slope correlations	Ω [1,2]	-0.271	0.182	4000.0
	Ω [1,3]	-0.292	0.197	4000.0
	Ω [1,4]	0.074	0.190	4000.0
	Ω [1,5]	-0.263	0.185	4000.0
	Ω [1,6]	-0.683	0.132	4000.0
	Ω [2,3]	0.290	0.197	4000.0
	Ω [2,4]	0.472	0.171	4000.0
	Ω [2,5]	0.377	0.180	4000.0
	Ω [2,6]	0.183	0.191	4000.0
	Ω [3,4]	0.168	0.198	4000.0

	Ω [3,5]	0.475	0.173	4000.0
	Ω [3,6]	0.231	0.193	4000.0
	Ω [4,5]	0.367	0.181	4000.0
	Ω [4,6]	-0.047	0.190	4000.0
	Ω [5,6]	0.012	0.193	4000.0
Sample size	n		188813	
Mean deviance	-2 * LogLik		828478	

Table 2.E8 Full model results

Descriptor	Parameter	mean	sd	*n* eff
Bike lane width (z-score)	B^0[1]	0.018	0.007	1705.4
Outside lane width (z-score)	B^0[2]	-0.167	0.004	4000.0
# Passing Cars with bike lane (z-score)	B^0[3]	-0.010	0.003	4000.0
# Passing Cars without bike lane (z-score)	B^0[4]	0.065	0.004	4000.0
Presence of passing truck/bus with bike lane	B^0[5]	-0.233	0.019	4000.0
Presence of passing truck/bus without bike lane	B^0[6]	0.199	0.014	4000.0
mean intercept	G [1,1]	2.423	0.251	4000.0
Oak	G [1,2]	-0.407	0.151	4000.0
B	G [1,3]	-0.446	0.131	4000.0
Anderson	G [1,4]	-0.610	0.163	4000.0
Russell	G [1,5]	-0.564	0.159	4000.0
Speed (m/s)	G [1,6]	-0.272	0.038	4000.0
Vigilance × mean intercept	G [2,1]	-0.178	0.280	4000.0
Vigilance × Oak	G [2,2]	0.072	0.168	3554.0
Vigilance × B	G [2,3]	-0.007	0.148	4000.0
Vigilance × Anderson	G [2,4]	0.143	0.183	4000.0
Vigilance × Russell	G [2,5]	0.083	0.181	4000.0
Vigilance × Speed (m/s)	G [2,6]	-0.012	0.044	4000.0
Fear × mean intercept	G [3,1]	-0.185	0.272	4000.0
Fear × Oak	G [3,2]	-0.182	0.169	4000.0
Fear × B	G [3,3]	-0.072	0.146	4000.0
Fear × Anderson	G [3,4]	-0.080	0.182	4000.0
Fear × Russell	G [3,5]	-0.046	0.178	4000.0
Fear × Speed (m/s)	G [3,6]	0.002	0.043	4000.0
Variation in intercepts	$\sigma_{person[1]}$	1.114	0.182	4000.0
	$\sigma_{person[2]}$	0.675	0.114	4000.0
	$\sigma_{person[3]}$	0.586	0.110	4000.0
Variation in slopes	$\sigma_{person[4]}$	0.729	0.132	4000.0
	$\sigma_{person[5]}$	0.723	0.122	4000.0
	$\sigma_{person[6]}$	0.172	0.030	4000.0
Intercept-slope correlations	Ω [1,2]	-0.255	0.180	4000.0
	Ω [1,3]	-0.276	0.193	4000.0

	Ω [1,4]	0.074	0.189	4000.0
	Ω [1,5]	-0.237	0.180	4000.0
	Ω [1,6]	-0.665	0.132	4000.0
	Ω [2,3]	0.290	0.197	4000.0
	Ω [2,4]	0.475	0.172	4000.0
	Ω [2,5]	0.418	0.177	4000.0
	Ω [2,6]	0.172	0.186	4000.0
	Ω [3,4]	0.190	0.195	4000.0
	Ω [3,5]	0.489	0.167	4000.0
	Ω [3,6]	0.200	0.186	4000.0
	Ω [4,5]	0.375	0.177	4000.0
	Ω [4,6]	-0.068	0.194	4000.0
	Ω [5,6]	-0.024	0.192	4000.0
Sample size	n		188813	
Mean deviance	-2 * LogLik		826385	

3 Road Environments and Bicyclist Route Behavior: The cases of Davis and San Francisco

Abstract

Bicyclist route behavior (where people choose to ride) provides valuable insights into the importance of road environments for bicycling. In this chapter I examine the role of road environments on route behavior using two diverse and extreme cases. The first case is bicycling to the UC Davis campus by students, faculty, and staff. This case represents the most bike friendly environment and likely the most diverse population in terms of bicycling experience and comfort in the country. The second case is bicycling to many destinations for many purposes in San Francisco. It is more representative of a large US city, but also has a relatively large existing proportion of bicycling. It serves as an important case for examining the new innovative type of bicycling infrastructure that has been installed in North American cities over the past decade. Results suggest that large heterogeneity in preference for road attributes exist. In terms of preferences, Davisites show a wide variety of preferences, which may be an indication of the need for varied road environments to support a large bicycling mode share. San Franciscans show strong preferences for innovative bicycling facilities and are willing to detour considerable amounts to ride on them. This chapter is based partially on work presented at the 56th Annual Conference of the Association of Collegiate Schools of Planning in Portland, OR (2016), the Transportation Research Board 96th Annual Conference in Washington D.C. (2017) (Fitch, Thigpen, Cruz, and Handy. *Bicyclist behavior in San Francisco: a before-and-after study of the impact of infrastructure investments*, papers 207 and 17-02265, respectively), and the National Center for Sustainable Transportation research report by the same title (Fitch et al., 2016a) which is referenced throughout this chapter.

3.1 Introduction

Many cities focus on altering road environments to improve safety for bicycling and increase bicycling rates. In the aggregate, clear positive associations between bicycling infrastructure and safety (Harris et al., 2013; Reynolds et al., 2009; Teschke et al., 2012)as well as bicycling infrastructure and bicycling rates exist across North America (Pucher et al., 2011). We know from numerous individual level studies that slower vehicular speeds, lower traffic volumes and dedicated bicycling spaces make for more comfortable bicycling environments (Buehler and Dill, 2016). Some bicycling infrastructure investments have also been shown to cause a shift in travel mode at the aggregate level (Skov-Petersen et al., 2017; Van Goeverden et al., 2015). However, many cities face the challenge of deciding where and what type of investments to make. Knowing the importance of road attributes in determining bicyclist route behavior helps describe what is needed to make bicycling safe and comfortable for existing bicyclists. Furthermore, knowing what is important for current bicyclists may help us understand the importance of infrastructure for encouraging more people to bicycle.

The methods for observing existing bicycling behavior are now extensive (GPS tracking, recalled travel paths, "ride-along" surveys, etc.), and each method has its own relative strengths and weaknesses (Pritchard, 2018). Generalizing behavior from existing to prospective (would-be) bicyclists (observational studies) may be more valid than assuming people will do what they say they would do when presented with different bicycling environments (survey studies) for a few reasons. Reported hypothetical behavioral changes (from surveys) are likely overestimates of change due to the inertia of habitual travel behavior and the need for many associated behaviors to change at the same time (e.g. destination locations, rescheduling activities, etc.). Survey responses are also prone to many biases (e.g. social-desirability) which may also inflate purported future bicycling. Observed bicycling behavior does not present these problems. For existing bicyclists, route behavior is usually treated as conditional on already choosing to bicycle (although this hierarchy of choice may be questionable), and so clear cause and effect is a fairly safe inference. However, observed bicycling behavior cannot for certain be generalized to prospective bicyclists because prospective bicyclists may require different environments. This means that inferring the effect of environmental interventions on spurring new bicycling is difficult. Not only is generalizability a problem, but residential self-selection is also a problem because now we are trying to infer mode choice. Residential self-selection occurs when people choose to live in a bicycling supportive environment, and thus their predisposition to bicycle and residential choice may be the primary cause for using bicycling facilities. Evidence suggests that residential self-selection for bicycling can be important for choosing to bike (Handy et al., 2010; Schoner et al., 2015). At least one study suggests that observed bicyclist route behavior may align with prospective travel mode choice (Broach and Dill, 2016), but more studies on this link are needed to ensure we can use current bicyclist route behavior to understand potential mode shift.

Past bicyclist route choice studies have focused on average effects of environmental variables. However, people are likely to exhibit a wide array of preferences for different environments. Especially considering most route choice data comes from non-random samples of existing commuters and bicycling advocates, understanding the heterogeneity in bicyclist route choice may be important for determining the infrastructure needs for a wider variety of bicyclists. In this study, I examine the bicyclist route behaviors of two different populations in two different environments: one small bicycling friendly city of Davis, CA, and one large city with a growing bicycling population, San Francisco, CA.

3.2 The distance tradeoff

The most important policy question related to bicyclist route behavior is: how important are road attributes in determining route choice? One way to identify importance of road attributes is to consider their distance tradeoff. The distance tradeoff is the increased distance (or time) (beyond the shortest route) bicyclists are willing to go to ride in preferable road environments. By framing the influence of road attributes in distance values, it is possible to directly compare the importance of road attributes. For most day-to-day destination oriented bicycling, this increased distance is commonly assumed to reflect individual road environment preferences (e.g. to ride on bike lanes, to avoid steep hills, etc.). Of course, for exercise or recreational bicycling, this assumption may not hold. In fact, many exercise and recreational bicycling trips start and end at the same location. These behavioral differences suggest that planning may need to jointly consider two different bicycling behaviors: one that looks like traditional travel and assumes minimizing generalized travel cost (where cost includes aspects of distance (or time), exertion (e.g. topography, wind, etc.), and unsafety (e.g. environmental factors, bicyclist perceptions and attitudes)), and one that fixes distance (or time) a priori and maximizes safety and even perhaps exertion for improving public health.

Like many bicyclist route behavior studies (Broach et al., 2012; Hood et al., 2011; Menghini et al., 2010)), I choose to focus on day-to-day destination-oriented travel. This is primarily because interventions aimed at changing day-to-day travel behavior offer the largest potential to decrease transportation emissions and increase physical activity (Sallis et al., 2013).

3.3 Bicyclist route behavior: environmental and individual factors

Chapter one discusses a few broad frameworks for considering travel behavior in general, and in this case it is also worth noting that bicyclist route decisions may be jointly determined with travel mode decisions or they may follow travel mode decisions. This line of reasoning (i.e. considering behavior as joint decisions) can continue to other related behaviors such as destinations people choose to travel to, and even where people choose live, work, and recreate. For simplicity, we might consider route behavior the lowest component in this hierarchy of decisions. If we assume that route behavior can exist independently from these other related decisions, we can consider that the motivating factors for choosing a route might fall into two broad classes: the environment and the individual. The environment describes all the variables about how a bicyclist interacts with the world when bicycling such as weather, topography, pavement conditions, road design (e.g. bike facilities), traffic, etc. The individual describes characteristics that are psychological (socio-demographics may be surrogates) and include factors like geographic knowledge, travel enjoyment, fear of traffic, preferences for facilities, dislike of hills, importance of travel time, etc.

Recent reviews of the environmental and individual factors associated with bicycling (both the decision to bicycle and the decision of where to bicycle) can be found in Pucher and Buehler (2008) Heinen et al. (2010), Pucher et al. (2010), Handy et al. (2014), Buehler and Dill (2016), and the multi-authored book edited by Pucher and Buehler (2012). Because these sources offer exhaustive reviews, I will only summarize the variables related to this study, which means I skip many important policy related variables (e.g. education and promotional programs) and mode choice related variables (e.g. trip end infrastructure).

The influence of distance has been consistently the most influential factor on bicyclist routing for destination-oriented travel (Aultman-Hall et al., 1997; Broach et al., 2012; Ghanayim and Bekhor, 2018; Hood et al., 2011; Menghini et al., 2010; Stinson and Bhat, 2003; Winters et al., 2010). Topography is another important physical environmental variable, where upslopes are avoided in bicyclist routing due to added physical exertion (and time) for climbing hills (Broach et al., 2012; Hood et al., 2011). In terms of perceived safety, large vehicular volume and fast vehicular speeds are commonly reported to be strong deterrents for route choice in stated preferences surveys (Sener et al., 2009; Stinson and Bhat, 2003), while bicycling specific infrastructure is strongly preferred (Sener et al., 2009; Tilahun et al., 2007). Bicycling specific facilities act to attract bicyclists in most observational studies as well, although it isn't clear they can always counteract the deterrents of vehicular traffic (Broach et al., 2012). The magnitude of influence for different bicycling infrastructure varies by study design and location but most agree that off-street paths have a stronger effect than bike lanes (Hood et al., 2011; Tilahun et al., 2007). Most new bicycling infrastructure (e.g. National Association of City Transportation Officials (NACTO) style interventions) has yet to be examined in the context of observed route choice. Intercept surveys show that protected and green painted bike lanes may have a substantial effect on bicyclist routing and may even be able to encourage more women to bicycle (Dill et al., 2015; Monsere et al., 2014).

Trip purpose (most commonly commute v. recreation) is thought to moderate the influence of environmental variables on bicyclist routing. The results comparing commute and recreational trips tend to show that people are more sensitive to environmental variables thought to increase comfort and safety whey they are bicycling recreationally (Broach et al., 2012). Influence of commute trip type has also been shown to decrease the effect of topography San Francisco (i.e. commute trips have less avoidance of steep slopes) (Hood et al., 2011).

Personal factors are more commonly related to the decision to bicycle than bicycle routing. However, individual characteristics sometimes moderate the influence of road characteristics on route decisions. Many studies consider age and gender as moderating (interacting) variables for route attributes. For example, through stated preference surveys of existing Texas bicyclists, Sener et al. (2009) show that age and gender moderated the influence of on-street parking effects of route decisions, gender moderated the influence of topography, and gender and bicycling experience moderated the influence of traffic signals, cross streets and traffic speed. Similarly, Caulfield et al. (2012) show that women were more deterred by traffic volume, traffic speed, and infrastructure types but not travel time than men. They also show some moderating effects of bicycling confidence, but those results are more tenuous. In San Francisco, reported cycling frequency lessened the effect of bike lanes, and women detoured further from shortest paths compared to men to avoid upslopes (Hood et al., 2011). In one of the earliest studies of bicyclist behavior, Lott et al. (1978) showed that age had a moderating effect on bicyclist route detouring for using a new bike lane in Davis, CA (college-age people were less likely to detour compared to older people). Besides age and gender, it is not well understood how personal characteristics influence bicycling route decisions. This is especially true if we consider that the causal mechanisms for personal variables are hard to define and measure (e.g. confidence, experience).

3.4 Case contexts

I use two samples of bicyclists in this study (UC Davis commuting, general day-to-day travel in San Francisco). The two cases, while primarily chosen out of pragmatic concerns for data availability and proximity to me as a researcher, also exemplify characteristics that combine common methods for selecting cases in case study research (Seawright et al., 2008). Davis and San Francisco are *diverse* with respect to previously evidenced environment and individual variables explaining bicycle routing. The cases are both *extreme* in the rate of bicycling (compared to similar small and large US cities)[1] and the environment afforded to bicyclists which helps maximize the variance of variables. And, the Davis case is a *deviant* case in that it has a unique bicycling culture beginning decades before the current bicycling boom.

3.4.1 Bicycling in Davis

Davis serves as a useful case study because of the ubiquity of bicycling as a normal mode of travel,

[1] A few large cities in the US have San Francisco like bicycling rates (e.g. Portland (OR), Minneapolis (MN), Washington DC).

and has a long history of regular day-to-day bicycling (Buehler and Handy, 2008). It is known as the first US city to install a bicycle lane, but more notable for current bicyclists is its extensive network of off-street bike paths. As a small city with a population of roughly 70,000, Davis has low traffic volumes and low vehicle speeds compared to any city in the US. In addition, Davis is a rare "college town" in California with a substantial portion of residents working or attending UC Davis. Although an accurate estimate of bicycling mode share is not available, considering bicycling to UC Davis is around 45% (Gudz et al., 2016b) and prior studies of bicycling in Davis show a range of 14.2-32.3% for commuting (Handy et al., 2010), the overall bicycling mode share is almost certainly large. Many people chose to bicycle in Davis who would not choose to bicycle if they lived in other cities. This makes Davis bicyclists a rare cohort with the potential to serve as a unique window into prospective bicyclists in other cities, i.e. those who would bicycle if the conditions were more like those in Davis.

3.4.2 Bicycling in San Francisco

San Francisco serves as an excellent case study for examining the relationship between bicycle infrastructure and bicyclist routing given the quirks of its recent bicycling history and its unique prioritization of non-automobile modes as part of its Transit-First Policy (City and County of San Francisco, 2007). In 2006, San Francisco's Bicycle Plan was served a court injunction as part of a California Environmental Quality Act (CEQA) challenge of the plan's environmental review resulting in a dormancy in bicycling infrastructure investments until 2009, when the injunction was lifted (San Francisco Municipal Transportation Agency Bicycle Program Staff, 2010). The San Francisco Municipal Transportation Agency (SFMTA) thereafter rapidly made a variety of bicycle infrastructure investments across the city (Gordon and Tucker, 2010; San Francisco Municipal Transportation Agency, 2012). Within six months after the August 2010 ruling, SFMTA had installed new bicycle lanes on 11 miles of city streets (James, 2011). And by the end of 2012, 20 miles of bicycle lanes and 41 miles of shared lane markings (sharrows)[2] were installed over 2009 levels, increases of 45% and 178%, respectively (San Francisco Municipal Transportation Agency, 2012). Along with a rise in bicycling infrastructure investment, overall bicycling volumes in San Francisco have increased steadily since counts began in 2006. Bicycling volumes have risen 206% over 2006 levels in the published counts in 2014 (San Francisco Municipal Transportation Agency, 2015). Even with this rise, only a small share of residents choose to bicycle for day-to-day travel in San Francisco. This is most likely

[2] Sharrows are painted arrows in the travel lane to indicate bicyclists are welcome to use the entire lane for travel. Sharrows are a commonly added feature to traditional signed bike routes. Signed bike routes (without sharrows) have no on-road provisions for bicyclists, just a green street sign marking the identification of the road as being a part of the 'bike route".

due to travel distances, but also likely due to availability of many public transit options and general fear of bicycling in the available road environments. However, the small share of residents who bicycle can tell us a lot about the influence of road environments on their bicycling. Even if the behavior in San Francisco cannot generalize to prospective bicyclists, we learn about how road attributes create perceived safe and comfortable environments for current bicyclists.

3.5 Research questions

In this chapter I focus on the heterogeneity of bicyclist route choice behavior with particular attention to the trade-off between distance and route level attributes. The overarching research questions are as follows:

(1) How much distance are bicyclists willing to add to their routes?
(2) Does added travel distance vary by road environments?
(3) For what type of environments are bicyclists willing to add travel distance?
(4) Do trip types and personal attributes moderate the effect of road environments on adding distance?

As described below, the data in this chapter is rich with details about many aspects of bicycling behavior. The goal of this chapter is not to exhaustively cover all the ways each variable describes bicyclist routing, indeed many new research endeavors are possible with these data. Instead, the focus on the distance tradeoff is intentional to inform bike planning. By understanding the distance tradeoff for different bicycling environments, we can learn two things. First, we learn about the necessary densities of bicycling networks needed for increasing bicycling behavior (this was argued by Winters et al. (2010)). Second, we learn what types of environments are needed to create a bicycling network that is appropriate for the masses.

3.6 Methods

3.6.1 Survey and route data

3.6.1.1 Davis

The Davis route data was intended to be part of an evaluation of a road diet (reduction from four to two vehicular travel lanes with a center turn lane) completed in August 2014 (see Gudz et al. (2016a)). However, because recruitment was through an unrelated survey of travel patterns to UC Davis and not through interception in and around the road diet, the route data was unable to offer any insight into bicyclist route behavior change due to the specific road diet. I use this route data for the alternative purpose of evaluating the environmental and personal factors influencing bicyclist route behavior more generally.

The data was collected through a repeated measures survey of people's primary bicycling route to the UC Davis campus in 2013 and 2014. A raffle of a $100 gift card incentivized participation. The survey[3] contained an online map on which participants were asked to indicate their usual route to campus, questions related to travel characteristics, socio-demographics, bicycling comfort and experience, attitudes and preferences, and perceptions of route conditions. The second survey contained an online map and survey with follow up questions pertaining to residential relocation, primary route to campus, and some repeated perceptions of route choice characteristics. The goal of the second survey was related to an evaluation of a road diet, but I use the second wave of observations only when they are not exact repeats of the first survey routes.

The first sample was recruited through a combination of a snowball email (49 responses), and a concurrent stratified randomly sampled survey (862 responses) which resulted in 523 completed (a 57% completion rate), and 14 partially completed surveys. The second sample was a follow up email to all first-round participants willing to participate a second time (n = 428), resulting in 262 completed (a 61% completion rate) and 14 partially complete surveys. Participation in the survey was roughly 41% undergraduates, 30% graduate students, 12% faculty, and 16% staff (see Table 3.1 for more details). The aggregated route data is displayed in Figure 3.1 to demonstrate the geographic distribution of routing in the dataset. Origin and destination locations are not included because they distracted from the overall goal of the map, but all trips originate or terminate somewhere on the UC Davis campus.

Table 3.1 Demographic and Route Characteristics in Davis

Variable Type	Variable	% or Mean	SD
Socio-demographics	Female	59%	NA
	Student	68%	NA
	Age	31yrs	13yrs
Attitudes	Low bicycling comfort	75%	NA
	Low bicycling ability	12%	NA
Trip	Distance (miles)	2.1 miles	0.86 miles
		Mean % of chosen path	**SD % of chosen path**
Road Attributes*	Two-Lane road	91%	15%
	Bicycle Lane	30%	24%
	Bicycle Lane (no parking)	8%	11%
	Wide Bicycle Lane	16%	16%
	Off-street path	38%	22%
	Commercial	19%	16%
	25 mph Posted Speed	85%	20%

* Non-exclusive categories

3 Using SurveyGizmo.com for the majority of participants, but paper for the first 350 participants.

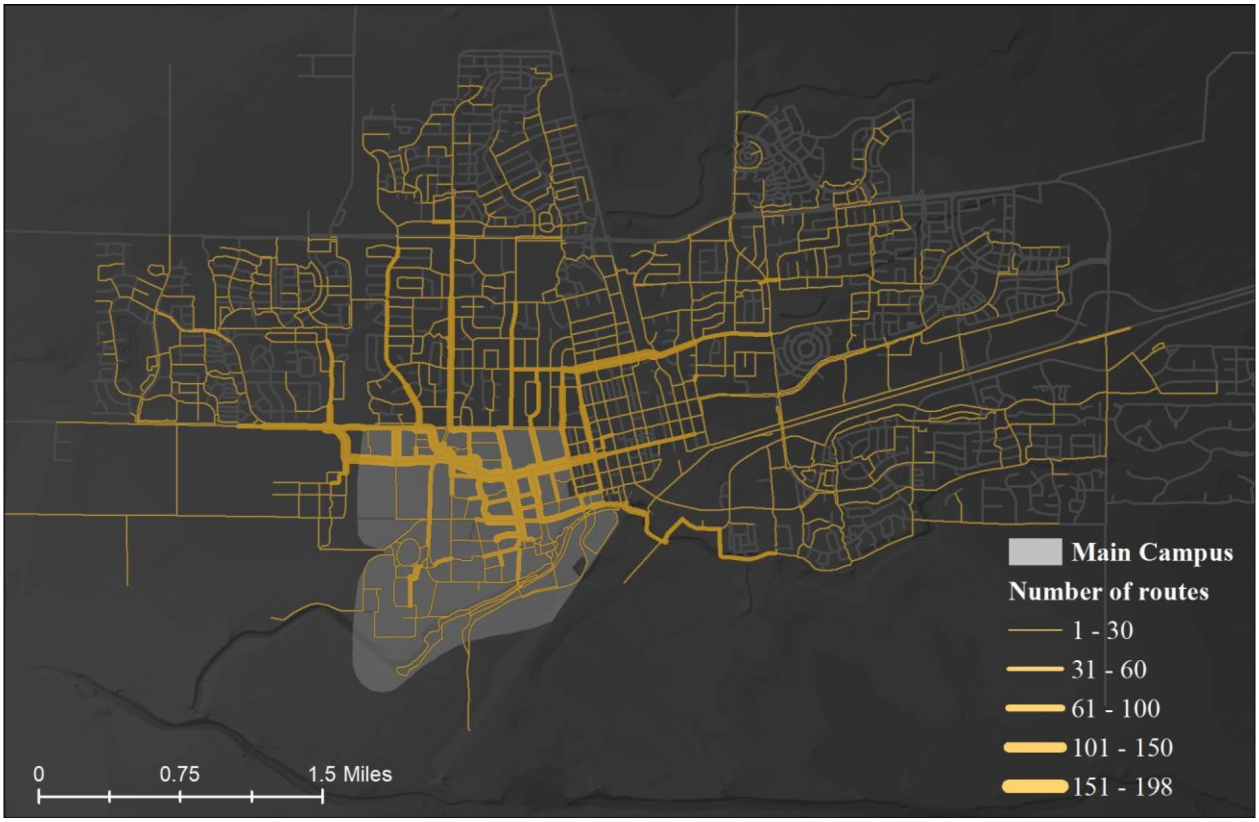


Figure 3.1 Davis sample aggregate paths to and from UC Davis

3.6.1.2 San Francisco

The San Francisco route data comes from the smartphone application CycleTracks, where bicyclists voluntarily install and record their routes. This application was the first of its kind, designed by SFCTA in 2009 to collect bicycle route data for planning purposes. The development team focused on making the application free, easy to download and use, and energy efficient (so as to avoid draining the user's battery) (Charlton et al., 2011). In addition to collecting the GPS traces of users' bicycle routes, several additional pieces of information are requested in the CycleTracks application. It requests that users provide basic socio-demographic information, including age, email address, gender, home location ZIP code, work location ZIP code, school location ZIP code, and cycling frequency. At the end of each trip, users are asked to select a trip purpose from the following options: commute, school, work-related, exercise, social, shopping, errand, and other.

Using the first six months of data collected in San Francisco, Hood and his colleagues estimated a bicyclist route choice model (Hood et al., 2011), which they then incorporated into the SFCTA travel demand model SF-CHAMP (Zorn et al., 2012). Since then, the open-source code for CycleTracks has been used and modified in other regions, such as Atlanta and Reno.

In my case, I use a subset of CycleTracks route data that was a part of a National Center for Sustainable Transportation (NCST) funded project to evaluate infrastructure investment in San Francisco (see Fitch et al (2016a)). The NCST report has the full details of the data collection process and outreach. Below I include only the details that are important for understanding inferences about route behavior in this chapter.

The subset of CycleTracks data includes routes from November 2009 through March 2010, and November 2013 through March 2014. These two periods contain bicyclist route behavior roughly before and after major bicycling infrastructure investments in San Francisco (see above). In addition to these two time-frames, I included all recorded routes from participants who took an online survey about route preferences and attitudes in 2014. Future analysis of this subsample is planned but not included in this chapter.[4] CycleTracks person and trip characteristics are summarized in Table 3.2 and Figure 3.2. The data collected from the CycleTracks smartphone application included detailed bicyclist locations reported by the internal GPS (and other positioning features) of each participant's phone. The sampling frame for this study included all people who travel by bicycle within the county/city limits of San Francisco and who possess an Android or iOS smartphone. The 2013-14 sample was recruited through outreach efforts similar to the efforts in 2009-10 (Hood et al., 2011) which included postcards at bicycle shops and emails from bicycle organizations. It should be noted that although this method presents several opportunities for sample bias (e.g. smartphone users, bicycling advocates), past comparisons with traditional travel diaries in the Bay Area (e.g. BATS) have indicated that the bias from CycleTracks samples is negligible in terms of representing *existing* bicyclists (Hood et al., 2011). The overall starting sample consisted of 696 participants with > 9,000 total recorded routes.

Table 3.2 Summary Participant Characteristics and Infrastructure Use

Variable	Percent of sample	Percent of trips
Female	15% total (22% unknown)	13%
Daily Bicycling	68%	74%
	Mean % of chosen path	**SD % of chosen path**
Distance (miles)	2.7 (miles)	1.9
Bike Route	24%	21%
Conventional Bike Lane	39%	27%
Buffered Bike Lane	1.4%	4.5%
Protected Bike Lane	1.1%	4.5%
Off-street Path	4.4%	10.4%

[4] Survey details can be found in Fitch et al. (2016a)

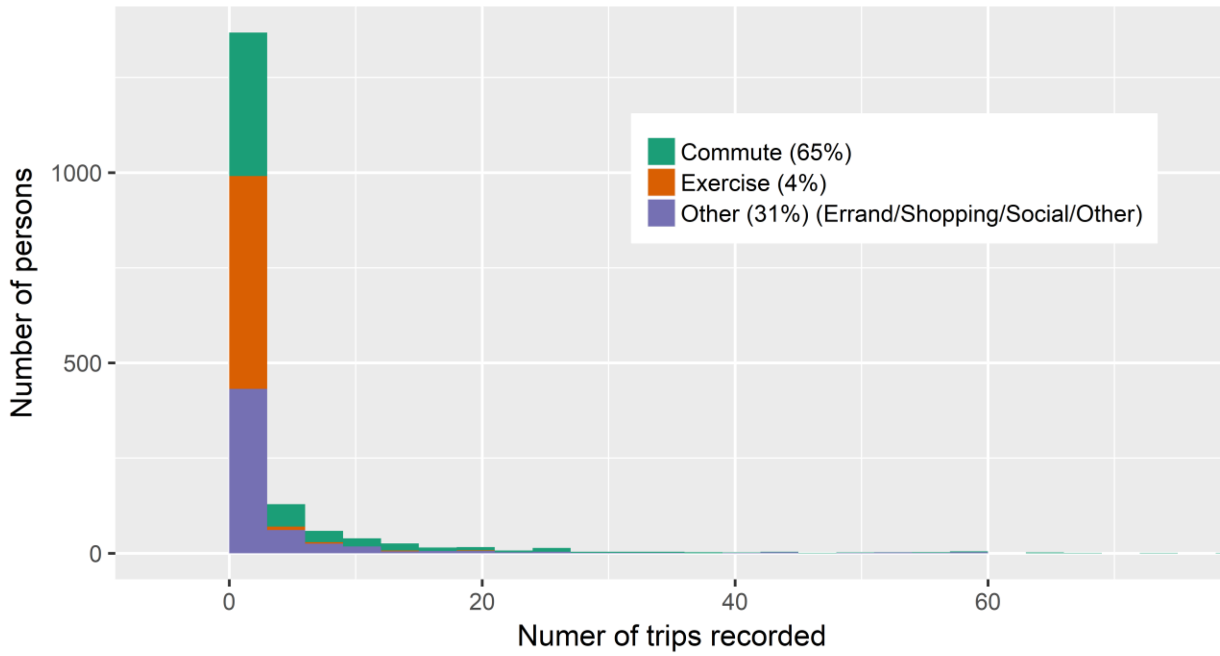


Figure 3.2 Number of CycleTracks recorded trips by person and trip type. 17 users recorded more than 75 routes (not displayed).

The geographic distribution of CycleTracks trips is shown in Figures 3.3 and 3.4. Those maps display weighted aggregations of bicycled paths by person from unique origin-destination neighborhood[5]. Direct aggregations are dominated by heavy CycleTracks users with repeated trips (some users recorded hundreds of routes). The weighting scheme reduces the influence of people with repeated trips to and from the same neighborhoods, but at the same time gives more weight to people who record many routes to and from different neighborhoods. This is a balance between overweighting the behavior of heavy CycleTracks users with underweighting those same users who provide a diverse set of routes and thus diverse route behavior. The resulting maps are therefore not an unbiased representation of the sample (like Davis above) but instead a representation of the diversity in routes in the dataset. Most of the bicycling in the data occurs in the core of the city; however, nearly every neighborhood has some riding.

5

$$\forall\, n: \sum_{i} \sum_{j} \frac{1}{R_{nij}}$$

Where R is a trip for person (*n*) from origin neighborhood (*i*) to destination neighborhood (*j*). If person *n* has only a single trip from *i* to *j*, their weight reduces to 1, otherwise it is their fraction of trips from *i* to *j*.

Figure 3.3 Weighted bike volume as proportion of network link use. Reprinted from "Bicyclist behavior in San Francisco: a before-and-after study of the impact of infrastructure investments," by Fitch et al. (2016a). National Center for Sustainable Transportation Research Report.

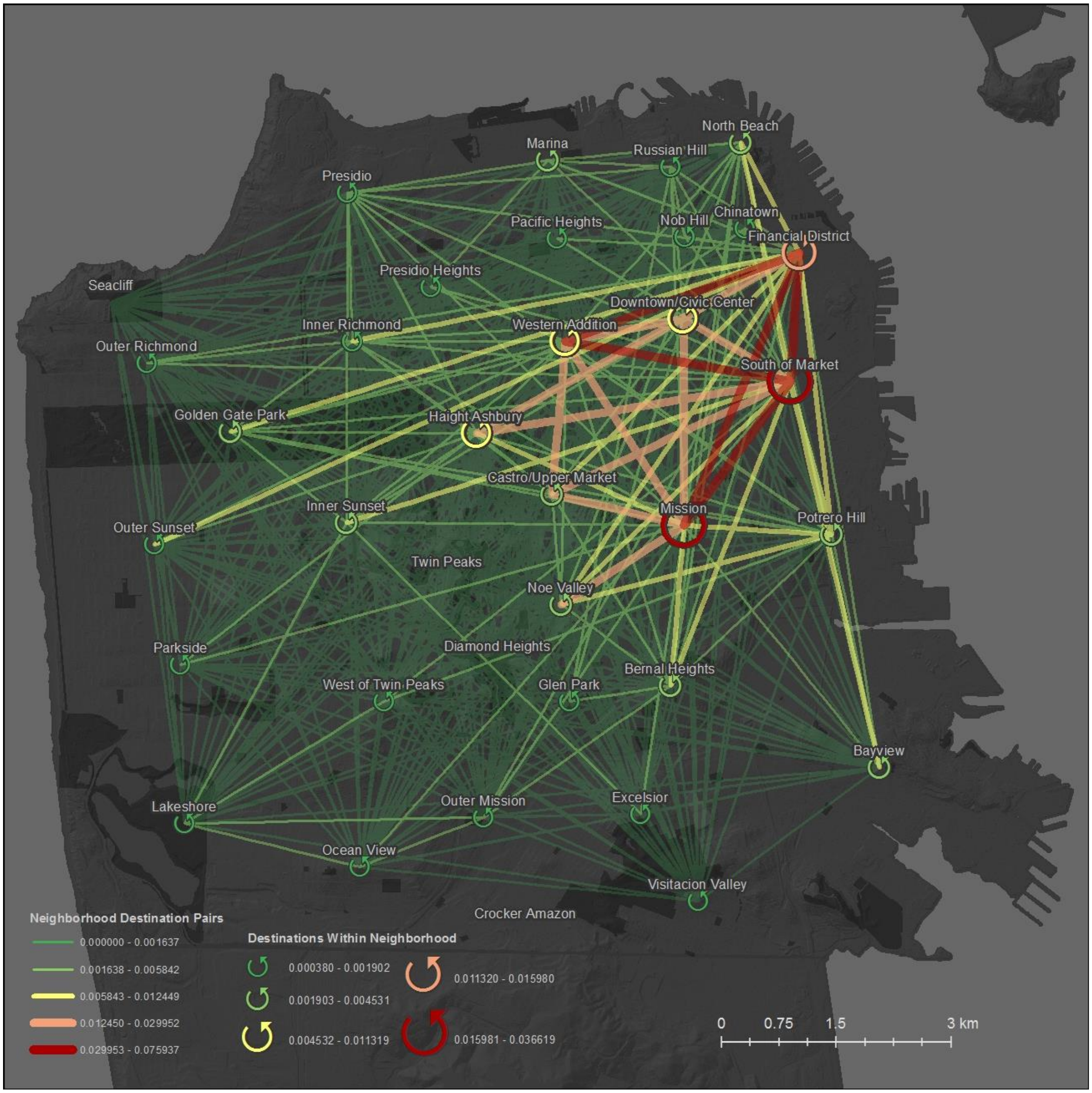


Figure 3.4. Weighted trip distribution for all trip types. Reprinted from "Bicyclist behavior in San Francisco: a before-and-after study of the impact of infrastructure investments," by Fitch et al. (2016a). National Center for Sustainable Transportation Research Report.

3.6.2 Network data

Both the Davis and San Francisco network geometry come from city GIS sources (City of Davis and San Francisco County Transportation Authority (SFCTA), respectively). The Davis network is undirected (one link for two directions of traffic) while the San Francisco network is directed (two links on top of each other in opposing directions represent two directions of traffic roads). Because one-way streets are rare in Davis, I made no attempt to monitor wrong-way riding. In San Francisco one-way streets are more common. Because the network is directed, I kept the network constrained by direction but created "wrong-way" links to allow bicyclists to ride in illegal directions based on evidence that wrong-way riding was significant in San Francisco (Hood et al., 2011). However, visualization of a random sample of routes with wrong-way riding suggested in many cases it was unlikely the participant really rode the wrong way (i.e. 4 lanes of opposing one-way traffic indicates they probably rode on the sidewalk or walked their bike). Also, much wrong-way riding occurred at the end of trips, again suggesting sidewalk riding or walking. The uncertainty about how much of that wrong-way riding was really in the street indicates a problem for interpretability of a wrong-way riding. In addition, generating alternative routes with wrong-way links resulted in unrealistic bicycling routes (see section 3.6.4.1).

I manually edited the road networks for both cities to ensure they were topologically correct and all recorded routes roughly aligned with existing network links (adding links as necessary). The most common edit in the Davis network was adding links in and around the UC Davis campus. In the San Francisco network, geometry edits were few, but mostly included fixing dangling nodes and adjusting intersections to better represent bicyclist stopping and turning movements (e.g. for three-way signals with a parallel off-street path, I connected the path to the signal node to represent possible turning movements).

Network attribute data for Davis was based on two prior studies of bicycling to elementary school (see Fitch et al. (2016b, 2016c)) and include number of lanes, posted speed limit, presence and width of bike lanes, and presence of on-street parking. Network attributes for San Francisco were based on GIS data from San Francisco Municipal Transportation Agency (SFMTA) bikeway GIS layer and manual review of historical Google Maps Streetview data (See Appendix A from Fitch et al. (2016a)).

Some important variables were not available for these networks, most notably road specific vehicle volumes and speeds. I use approximated vehicle capacity (vehicles per hour) reported by SFCTA based on road classification and neighborhood which should be sufficient to describe a combination of general traffic volume and speed.

3.6.3 Preprocessing routes

The Davis route data included paper based surveys of drawn routes and web-map surveys. For the paper surveys where participants mapped their most common route to and from UC Davis, I manually selected the network links most likely used on the drawn route, and saved each route. For the online survey where participants used google maps to draw their route, I exported the vector data from the

Survey Gizmo API and loaded it into a GIS. Because the geometry of the exported data did not match the current GIS network with link attributes, I used the following algorithm to match the routes to the network:

1) Convert each polyline (route) into a series of points spaced 10 feet apart along the polyline.
2) Calculate the nearest node (intersection) in the network for each point and select all nodes for all points.
3) Select all network links that touch the selected nodes.
4) Solve the shortest path from the origin to destination on the selected network links. If path simulation fails (because of a break in the network), go back to step 2 and calculate the nearest two nodes and repeat steps 3 and 4 until all paths can be simulated.

Because the raw route geometry was a close match to the network geometry, the first iteration of the algorithm captured most routes. All route simulation was successful after three algorithm iterations. I visually compared each resulting route to the raw route geometry to ensure the success of the algorithm.

The San Francisco data required much more intensive preprocessing. Following the consolidation of GPS data, I removed trips with the same origin and destination and used a data cleaning algorithm to remove noisy GPS points loosely based on Wolf et al. (2014a, 2014b). In some cases, the removal of GPS points resulted in the removal of routes, and the removal of routes resulted in the removal of participants. This process diminished the sample to 589 participants with 8,352 total destination-oriented bicycle routes. The cleaning algorithm excludes GPS points based on the following criteria:

1. Instantaneous speed was unreasonably large (>16 m/s) or negative
2. Acceleration was unreasonably large (> 1 m/s^2)
3. Calculated speed from consecutive GPS points was unreasonably large (>50 m/s) (set very high due to poor accuracy)
4. Difference between instantaneous and calculated speed was unreasonably large (>40 m/s) (set very high due to poor accuracy)
5. Distance between consecutive GPS points was large (> 150 m)(empirically justified by sporadic GPS positions within a short time interval)
6. Horizontal accuracy of GPS was large (>200 m)

To determine the links (and thus bicycle facilities) used on each route, I matched GPS points to the GIS road network (known as map matching). Map matching is a necessary step because while GPS is accurate, it is imprecise due to technology limitations and environmental conditions (e.g. satellite obstructions, nearby cell towers, etc.). On the other hand, the GIS network is both accurate and precise, so matching GPS points to the network ensures accurate and precise routing.

I designed and implemented a map-matching algorithm that deterministically assigns network links to each trip given the GPS points recorded. The algorithm uses horizontal accuracy of GPS locations, distance between GPS locations and near network links, headings of consecutive GPS locations, headings of near links, and connectivity of trip routes (using network topology) to weight links for their likely match to each GPS point. I sum the weights for each link, and generate a least cost path (based on maximizing link weight) to determine the final links used in each route. The map-matching algorithm also acts as a secondary data cleaning procedure by removing routes which (1) have the same start and end location, (2) have very sparse GPS data, and (3) have an unreasonably short distance (e.g. one block). This algorithm is only successful for destination-oriented travel (e.g. not round trips) because the least cost path between adjacent start and end locations is the adjacent link, not the traversed round trip path. The most important assumptions regarding the algorithm are:

1) Only the links within the horizontal accuracy of a GPS point are considered (I call this the *link set* for each GPS point). When no links within that horizontal accuracy exist, a search for links in consecutive 30 meter buffers is used until at least one link is found.
2) The weights for matching a GPS point to a link in the link set is:

$$\left(\frac{\frac{1}{d^2}}{\sum_i \frac{1}{d^2}}\right)\left(\frac{\frac{1}{(180\ -\ ||Hg-Hl|\ -\ 180\,|)}}{\sum_i \frac{1}{(180\ -\ ||Hg-Hl|\ -\ 180\,|)}}\right)$$

   Where d is the Euclidean distance between GPS point and link, Hg is the GPS heading, Hl is the link heading, and subscript i is each link in the link set. The resulting weight is an equal inverse square distance and inverse degrees difference in heading between a given GPS point and nearby network links.
3) Routes with the same start and end location, distance < 200 meters (as measured from the diagonal of the bounding box (envelope) of GPS points), or fewer than four GPS points per km I discarded.
4) If the combined link sets for each route do not result in a connected network (topographically correct), I split the route into the two longest topographically correct stretches and generate a two-part route. Through visual inspection, I found this method to cover the spatial domain of most trips without having to make assumptions where GPS data was sparse or had great positional uncertainty. The downside to this approach is that the length of these two-part trips systematically under represents those trip lengths, while the upside being a more precise measurement of road characteristics as percentages of path lengths.

3.6.4 Analysis

3.6.4.1 Simulating alternative routes

It is natural to treat observed bicycling routes (like other observed travel routes) as discrete choices out of a suite of alternative paths. Because people can choose alternative paths, knowing characteristics of chosen routes are not enough to make inferences about those characteristics' influence on routing decisions. However, in route choice problems the suite of available routes is often unknown. The most basic comparison is between the shortest and chosen route. We might assume that any additional distance ridden to the destination is due to route characteristics. Implicitly this also assumes that bicyclists prefer the shortest route if it is also the most suitable. However, bicyclist route choice is more realistically a choice between alternative routes, where each route has a series of characteristics (other than distance or time), most importantly characteristics relating to perceived safety (i.e. comfort) and exertion (Ehrgott et al., 2012). Many techniques to generate plausible alternative routes exist. I use the method proposed by Broach et al. (2010) because it was successfully applied to similar data and showed improvement over other methods. Recently, a method that doesn't require simulating alternative routes has been used to model bicyclist route choice (Zimmermann et al., 2017). This method considers route choice as an iterative decision process where each intersection in a route is a new choice. Results from this one study are consistent with other path-based bicyclist route choice model results in describing the influence of road attributes on route choice (Zimmermann et al., 2017). Although the benefits of an iterative model are clear, the behavioral realism of that type of model is questionable given people are not likely to make decisions at every intersection. Perhaps the most behaviorally accurate way to model route choices is somewhere in between these approaches. For example, at least one study had participants indicate when they made routing decisions along a route (Kang and Fricker, 2013). Nonetheless, without information about where people make decisions along a route, this framework is limiting.

The Broach et al. (2010) algorithm generates paths by optimizing one road attribute[6] over a range of distance weightings, and settling on an attribute-specific distance weight that generates routes of similar lengths to the observed chosen routes (in the aggregate to avoid generating routes too much like the chosen routes). I used this algorithm (see below) over a series of road attributes and distance weights. More formally, I considered a set of road attributes **L** (see Table 3.3), and a set of three distance weights **D** (see Table 3.3) representing the percentage of influence distance has on link cost compared to the road attribute. I chose the road attribute specific distance weights based on the same visual plots of Broach et al. (2010) (quantile-quantile plots describing the route detouring for observed v. simulated routes), but I include three different weights for each attribute representing simulated

[6] Often called a *label* in the route choice modeling literature (hence the use of **L**), but I use *attribute* because it is more descriptive.

routes that are slightly longer, slightly shorter, and similar in length to observed routes in the aggregate. The goal of this visual "calibration" is to ensure that the simulated alternative routes roughly detour similar amounts compared to the observed data across the sample. The alternative route simulation algorithm works as follows:

1) Define the cost for each network link based on distance only and call that the first network.
2) Define the cost for each network link by each road attribute and distance weight combination: $C_{ijk} = D_j * \delta_k + (1 - D_j) * L_i$
   Where C_{ijk} is the cost for one road attribute *i*, and one distance weight *j* on link *k*; δ is the link length, and D_j and L_i are distance weights and road attributes respectively. This results in **D*****L** + 1 unique networks for generating alternative routes.
3) Solve the least cost path for origin-destination pair on each of the networks and remove redundant paths resulting in a unique set of paths for each trip. This results in a minimum of 1 and maximum of **D*****L** + 1 alternative paths per trip.

I dropped some of the original road attributes if I could not simulate alternative routes of similar lengths to the chosen routes. Also, some of the distance weights were smaller than those reported by Broach et al. (2010) in Portland. I suspect this effect may be due to the prevalence of the road attributes along plausible paths (i.e. routing on some of the road attributes in San Francisco required unreasonably large detours for given origin-destination pairs). In San Francisco I also simulated 20 alternative routes using simple deviations of link cost by randomly inflating or deflating length using the lognormal route length (one of the methods used by Ghanayim and Bekhor (2018)). I used the same quantile-quantile plots to reduce the set of 20 to only those that created routes that matched the length of the chosen routes in the aggregate across the sample.

In San Francisco, route choice simulation resulted in a median of 10 alternative routes, while 90% of trips had a range of 6-17 alternatives. About 8% of routes were two-part (a gap in GPS data during the trip was large enough to warrant the breaking of the trip into two route segments ignoring the missing data, see section 3.6.3), and therefore had much larger choice sets (25-100) at the trip level because of all possible combinations of route labels and distance weights for each of the two parts. I constrained these choice sets by randomly sampling 25 alternatives to ensure that no more than 25 alternatives for each trip enter the model. In Davis, route simulation resulted in a median of 14 alternatives with 90% of trips having a range of 7-19 alternatives. In both datasets, I removed trips where no alternatives could be simulated (captive routes) resulting in a total of 740 route choices in Davis and 8,190 route choices in San Francisco. For each route choice I include the chosen alternative, the shortest path, and the suite of simulated alternatives from the method described above.

Table 3.3 Route Attributes (Labels) and Distance Weights

Location	Route Attribute (**L**)	Distance Weights (**D**)
Davis	Signals (minimize)	{0.3, 0.4, 0.5}
	Bike lane	{0.4, 0.5, 0.6}
	Bike lane without parking	{0.25, 0.375, 0.5}
	Wide bike lane	{0.4, 0.5, 0.6}
	Off-street path	{0.3, 0.4, 0.5}
	Commercial (min)	{0.15, 0.25, 0.35}
	25 mph roads	{0.3, 0.4, 0.5}
	Signals (minimize) × local roads	{0.15, 0.25, 0.35}
	Signals (minimize) × wide bike lane × 25 mph roads	{0.2, 0.3, 0.4}
San Francisco	Slope < 4%	{0.1, 0.125, 0.15}
	Bike routes	{0.4, 0.425, 0.45}
	Bike lanes	{0.35, 0.4, 0.45}
	Stop signs (minimize) × Bike lane	{0.275, 0.3, 0.325}
	Off-street path	{0.075, 0.1, 0.125}
	Signals (minimize)	{0.25, 0.3, 0.35}
	Stop signs (minimize)	{0.15, 0.2, 0.25}
	25 mph posted speed roads	{0.15, 0.2, 0.25}
	<600 vehicle per hour roads with bike lanes	{0.1, 0.15, 0.2}
	<300 vehicle per hour roads	{0.35, 0.375, 0.4}

Often route simulation success is measured by how well the simulated routes "cover" the chosen routes (i.e. the maximum overlap of alternative routes with the chosen route as a percent of chosen route length). The idea is that if the route simulation procedure is behaviorally representative of how people consider alternative routes, it should capture the chosen route. My simulated route coverage in Davis and San Francisco was unlike others reported in bicycling route choice studies. Davis route simulation succeeded in generating routes with most of the links in the chosen paths, but rarely exactly replicated the chosen paths. For example, 80% of the chosen paths were covered by at least 50% of a simulated alternative, while only 12% were covered 100% by an alternative. The low coverage for the 100% threshold is likely due to the very detailed path network on and around UC Davis campus. Not surprisingly, many alternative routes could not capture the detours on the intricate network of paths on campus. However, the relatively high coverage at 50% suggests the alternative routes are reasonable alternatives.

San Francisco route simulation was made more complicated by the fact that wrong-way riding occurred on many trips. As mentioned above I tested route simulation allowing wrong-way riding and restricting riding to the legal traffic direction. When comparing the chosen and shortest routes using the network that allowed wrong-way riding, route detours seemed excessive (24% on average). In addition, route choice models resulted in unreasonable parameters (not reported) based on prior bicycling route choice studies. When comparing the chosen and shortest routes using the network that restricted wrong-way riding, detour distances were more in line with prior bicyclist route choice studies (12% on average), as were route choice model results (reported below). However, using the one-way network resulted in the chosen route being shorter than the simulated shortest route in some cases (due to wrong-way riding). When examining the simulated alternative routes, the restricted (no wrong-way) routes showed better coverage of the chosen routes (16% of chosen routes 100% covered by a simulated alternative, and 67 % of chosen routes 50% covered by a simulated alternative) and seemed more reasonable from an individual trip perspective (i.e. no long stretches of wrong-way riding). Like the Davis case, the coverage of the chosen routes by the alternatives was worse at the 100% threshold compared to prior studies. Unlike Davis, the problem of poor coverage seems to be due to wrong-way riding and large detours that are either difficult to capture by the calibrated labeling method, or require further refinement of route attributes to increase coverage. The greater coverage of the method used by Hood et al. (2011) with San Francisco CycleTracks data is likely due to differences in preprocessing and route simulation methodology. Since generating routes that cover chosen routes depends on pre-processing of GPS data, it is possible that my procedures were not as strict for removing routes that were difficult to accurately match to the map, and thus posed difficulty in simulation.

While it would have been nice to have better coverage of the chosen paths by the alternatives, it isn't clear that it is necessary for generating plausible alternatives. Without surveys of people's alternative routes, we cannot validate any route simulation algorithm. Maps of route alternatives for the most part showed reasonable bicycling routes.

3.6.4.2 Modeling route choice

Like in many prior bicyclist routing studies (Broach et al., 2012; Hood et al., 2011; Menghini et al., 2010; Zimmermann et al., 2017), I chose to consider the route behavior of bicyclists as discrete choices and use a route choice model to make multivariable inferences. Because I take the approach to generate alternative routes to represent choice sets, the distance and attributes of those routes directly influence the inferences in the route choice model. Sensitivity analysis of route choice models to alternative suites of routes is likely a fruitful endeavor, but like so many methodological examinations, it is beyond the scope of this chapter. Past evidence is mixed on the magnitude of influence alternative route simulation has on resulting route choice model results (Broach et al., 2010; Ghanayim and Bekhor, 2018). Instead, I try to use conservative language to reflect the challenge of trying to make inferences with route choice models of predefined alternatives (choice sets) that cannot be validated.[7]

I chose predictor variables for the models that are route specific (e.g. proportion of bike lanes), trip specific (e.g. commute), and person specific (e.g. gender). I chose variables based on availability, prior evidence, and those that were not highly correlated with each other. Because many road attributes are highly correlated, some variables that have support in the literature I intentionally left out of the models. It was impossible to not consider some colinear variables (e.g. signals and stop signs were negatively correlated, and bike lane proportions on low and high capacity roads were positively correlated). However, the path size variable (see below) serves to partially correct predictor correlations. I list the variables I considered in the Davis and San Francisco models in Table 3.1. The variables in the San Francisco model most closely align with those of Broach et al (2012) which considers bicycling infrastructure as a component of the broader characteristics of a road (e.g. traffic volume and speed) rather than as independent features of the road (which they most certainly are not). For example, bicycle lanes are rarely found on local roads, only on collectors and arterials. The bicycling infrastructure variables in the Davis model are treated as independent features because no volume or speed data was available for the network. However, in Davis, volume and speeds are not as variable as in large cities. The innovative bicycling infrastructure (buffered and protected lanes) in San Francisco almost entirely occur on high capacity roads, so the effects of both buffered and protected bike lanes should be interpreted as buffered or protected bike lanes on high capacity roads.

I consider three main functional forms to model route choice. They are all variants of a multinomial logistic regression model with an added variable (path size) that describes the proportion of path overlap between each path and the alternative paths in the choice set (I use the original path size formulation (Appendix A)). Frejinger and Bierlaire (2006) offer a discussion of the path size variants and their pros and cons, and consider the original formulation reasonable. The path size variable weighs network links based on their proportion of overall route alternative length and their prevalence of occurring in the alternative routes. It is a measure of route overlap and thus route correlation. This is important because choices in a route choice set are not mutually exclusive like in most choice

[7] Another fruitful endeavor would be to survey people about the alternative routes they consider.

contexts. The three models are as follows: (1) multinomial logit[8], (2) multilevel multinomial logit (varying effects by person), and (3) multilevel multinomial logit (varying effects by person and person-level predictors) (see Appendix A for specific model equations). The first model is most similar to many past bicycling route choice studies (Broach et al., 2012; Chen et al., 2016; Ghanayim and Bekhor, 2018; Hood et al., 2011). The multilevel models are most similar to those used by Ghanayim and Bekhor (2018) to model bicyclist route choice. The main distinction between model forms 2 and 3 from Ghanayim and Bekhor (2018) is that I estimate varying effects for all route attributes, whereas Ghanayim and Bekhor (2018) estimated an individual specific constant. Because I am interested in the individual variation in the influence of road attributes, model forms 2 and 3 help to make inferences about individual heterogeneity with respect to road attributes.

I 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. In addition, estimating large varying effects models is possible through Markov-chain Monte Carlo (MCMC) simulation of posterior probabilities. In all models I use so called *weakly informative* prior probabilities to guard against overfitting (Gelman, 2006) (see Appendix A for specific priors). Through the R statistical package *Rstan* as an interface for the probabilistic statistical programming language Stan, I used the No-U-Turn (NUTS) sampler, a form of Hamiltonian MCMC to estimate the models (Stan Development Team, 2017).

I 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 are on the deviance scale and can be 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).

[8] Often called the path size logit model. This name implies that the model structure is different from a normal multinomial logit, but in most cases the model structure is the same. In some cases a parameter in the path size term is estimated in the model (see example in Frejinger and Bierlaire (2006)), and in this case the path size logit is distinct from the normal linear in parameters formulation of the multinomial logit in the discrete choice literature. The main peculiarities with path-based route choice models is that the decision alternatives vary for every choice, and the alternatives have no formal categorical label.

3.7 Results and discussion

3.7.1 Route diversion in Davis and San Francisco

In Davis, most bicyclists do not pick very circuitous routes. Nearly everyone (99%) in the sample chose a route that was less than 50% longer than the shortest path, and 83% diverted less than a quarter mile (Figure 3.5). The median detouring in Davis was only 5% further than the shortest route. The directness of the bicycling routes in Davis is probably a function of them being usual commute routes and there being plentiful bicycling infrastructure on and off UC Davis campus. In addition, Davis is a small town, thus bicycling commute distances are short (μ=2.2, σ =0.9 miles). They nonetheless fall somewhere between past bicyclist route studies (e.g. means of 0.6 miles in Zurich (Menghini et al., 2010), 3.6 in San Francisco (Hood et al., 2011), and 4.5 in Portland (Broach et al., 2012)). Perhaps because distances are short (short absolute length trips have fewer alternative routes that are similar length to the shortest route) compared to other bicyclist route data, detour ratios (actual/shortest distance) are less than other studies. For example, Broach et al. (2012) showed 50% of trips having less than a 10% increase in length in Portland, while the Davis data shows 78% of trips for the same 10% increase, more in line with 75% of trips in Vancouver, Canada (Winters et al., 2010). Conversely, the distance (and time) spent detouring a half mile trip by 100% is quite short which might indicate a willingness to detour at much greater ratios for short trips if the environment along the shortest route wasn't considered suitable.

Perhaps a fairer comparison to past bicycling route choice studies is the data from San Francisco. The sample I use in San Francisco has an average route length of 2.7 miles with standard deviation of 1.9 miles. These route distances are shorter on average than the trips analyzed by Hood et al. (2011) with just the early phase of CycleTracks participants in San Francisco. The shorter estimated trip length may be due to differences in pre-processing: I didn't interpolate chosen routes with very poor GPS accuracy (I broke the route into sub-segments which systematically underestimates trip length, see methods section 3.6.3 above), but also probably due to difference in the samples. CycleTracks experienced complete turnover in users from 2009 to 2013 (only one user recorded routes in both 2009 and 2013). Detouring proportions in San Francisco are considerably larger than in Davis. The median detouring length was just about a third of a mile with only 59% of participants detouring less than a quarter mile, compared to the 83% in Davis. Detouring as a percentage of route length for San Francisco commuters was also considerably longer than in Davis (Figure 3.5). Although the detouring in San Francisco seems large compared to Davis, the detour ratios in San Francisco are consistent with other bicycling route choice studies in large cities (mean of 12% further than the shortest path).

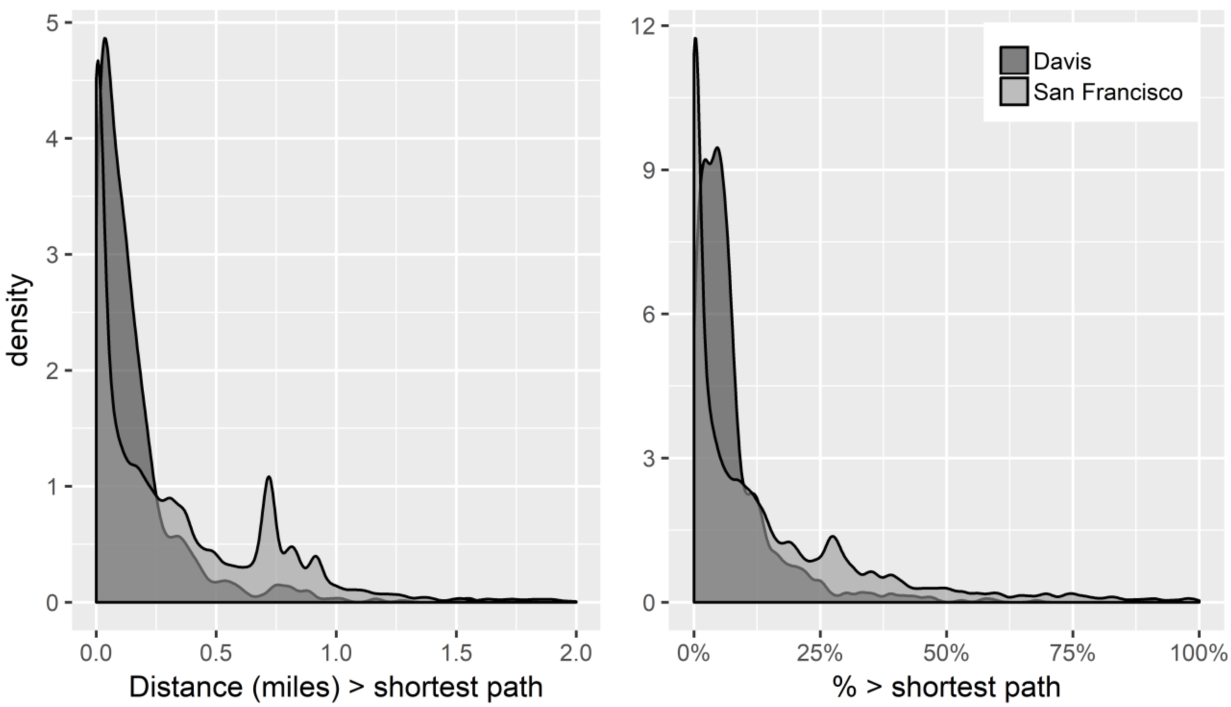


Figure 3.5 Density plots of differences in chosen route distance compared to shortest route in Davis (all trips) and San Francisco (commute and school trips).

3.7.2 Road attributes

In Davis, road attribute differences between chosen and shortest routes are surprisingly similar. Figure 3.6 shows the density of differences between chosen and shortest routes for each road attribute. Most densities have modes near 0 for a few reasons. First, if the attribute didn't exist on either the chosen or shortest route then the difference is 0. Second, if the chosen route was very similar or the same as the shortest route, the attribute difference would be 0. The differences between the left and right tails of the density plots indicate any systematic difference between chosen and shortest routes. Some tails in the density plots indicate a preference for bike lanes, off-street paths, and 25 mph posted speed roads but these differences are not as dramatic as might be expected. Davis is indeed a unique bicycling environment such that the shortest routes can look very similar to chosen routes based on aggregated (link-additive) road attributes. The difference between chosen and shortest routes that matter for routing decisions may be subtler than the current data show. Perhaps the clearest difference between chosen and shortest routes in Davis is the proportion of mixed traffic (no bicycling facilities) roads with greater than two lanes (one lane in each direction). In Davis, four lane arterial roads are rare (only three exist on plausible routes to UC Davis). However, shortest routes have a much larger proportion of these few arterials compared to chosen routes. In Davis, off-street paths parallel two of the three major arterials and most people choose to take those paths, so to some extent, the two variables are reciprocal.

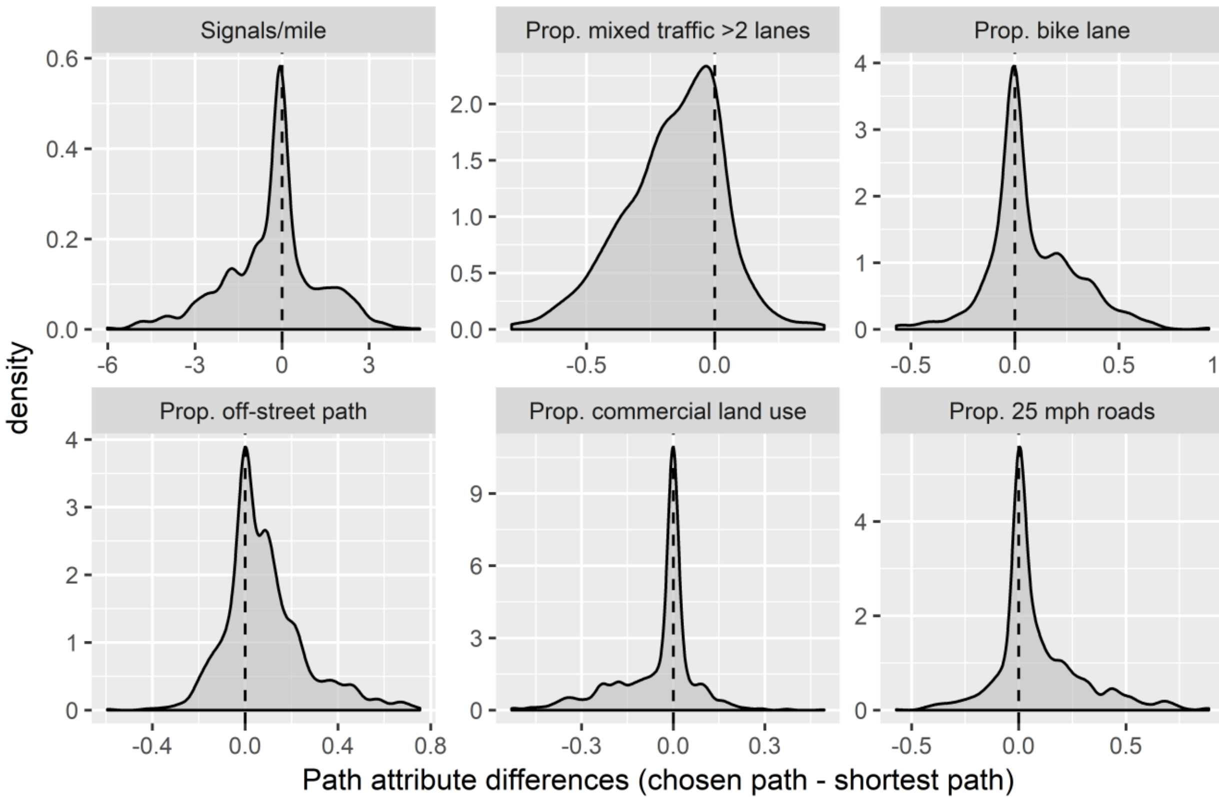


Figure 3.6 Density plots of differences between chosen and shortest path route attributes in Davis. Variables are proportions of route length or counts/length.

The comparison of chosen and shortest routes in San Francisco show some clear differences by road attributes (Figure 3.7). Greater proportions of chosen routes have shallow slopes (<4% up-slope) compared to shortest routes. Because very few chosen routes include even moderately steep slopes, I chose the steep slope class of >4% to ensure some riding on steep slopes. Signed bike routes seem to be used in similar proportions on chosen and shortest routes, with perhaps slightly more use on chosen routes (right tail density in Figure 3.7). However, given that bicycle routes are widespread in San Francisco, it is telling that this effect isn't more visible.[9] Conventional bike lanes account for larger proportions of chosen compared to shortest routes, especially when vehicle capacity is large (> 600

[9] Most of the bicycle routes in San Francisco during this data collection were signed routes. Throughout the study period, innovative shared lane markings became prevalent. Unfortunately, because the network data doesn't have specific install dates for infrastructure, it was difficult to determine when CycleTracks participants were riding on traditional signed bicycle routes, or newly marked shared lanes (sharrows painted on the lane). This means, without extensive effort by SFMTA to extract dates from plan drawings, we won't be able to tell if these features cause changes in route behavior.

vehicles per hour). Since most bike lanes in San Francisco are on roads that move a lot of cars, the differences between bike lane proportions from low and high capacity roads is likely based on availability. High capacity roads without bike lanes account for less proportion of chosen routes suggesting that the bike lanes cause some route detour. Slightly longer right tails in the density plots of Figure 3.7 suggest people are detouring for buffered bike lanes, protected bike lanes, and off-street paths. However, the negligible proportions of chosen and shortest routes on these bicycling facilities makes it difficult to tell. Surprisingly, number of traffic signals per mile seems to be consistent on chosen and shortest routes, although stop signs look to be avoided.

Figures 3.6 and 3.7 both show that road attribute differences between chosen and shortest paths are most often negligible (i.e. nearly every density curve has a statistical mode near 0). However, the tails of the density plots suggest that on the margin, proportions of road attributes likely matter. For example, even though the differences between the proportion of route with steep slopes (> 4% upslope) for the chosen versus shortest routes are most often 0, when they do differ, chosen paths are more likely to have less proportion of steep slopes as indicated by the bump in the negative side of the density plot (Figure 3.7). Figures 3.6 and 3.7 also highlight a major limitation with respect to using aggregated path attributes. For example, since evidence suggests that protected bike lanes have large effects on bicycling volume (Monsere et al., 2014), perhaps proportions of this type of infrastructure do not adequately capture their importance for comfort and safety. It is possible that these rare (small proportion of route) facilities are great connectors of comfortable bicycling environments. Much like the discussion in Mekuria et al. (2012), protected bike lanes may be connecting "islands" of low traffic stress roads. If this is the case, aggregate link-sum attributes are not appropriate because perhaps only a very short protected bike lane that connects "islands" of comfortable bicycling environments would be needed to have a dramatic effect on route choice. This problem also relates to the behavior mechanism for choosing routes. Many attributes we typically consider as proportions may instead have threshold type effects on behavior. For example, we might expect people to use simple heuristics like "I won't take that route because it has a large hill". This is different from "I won't take that route because 10% of the route has an uphill gradient greater than 4%". Although % rise is a more objective and accurate measure of slope than "large hill", a linear effect doesn't capture the decision heuristic. Instead, what we might try to do is consider a threshold percent that someone would consider the route to have a "large hill" both in gradient and length. Thresholds could be as simple as presence or absence of road attributes (e.g. a major arterial with large vehicular volumes and no bike lanes may be no-way no-how for most prospective bicyclists, not even 1% of a route), or they may be a tipping point where the utility of a certain infrastructure type is realized once the attribute reaches a certain proportion or certain length. Future methodological explorations into estimating threshold effects may be fruitful.

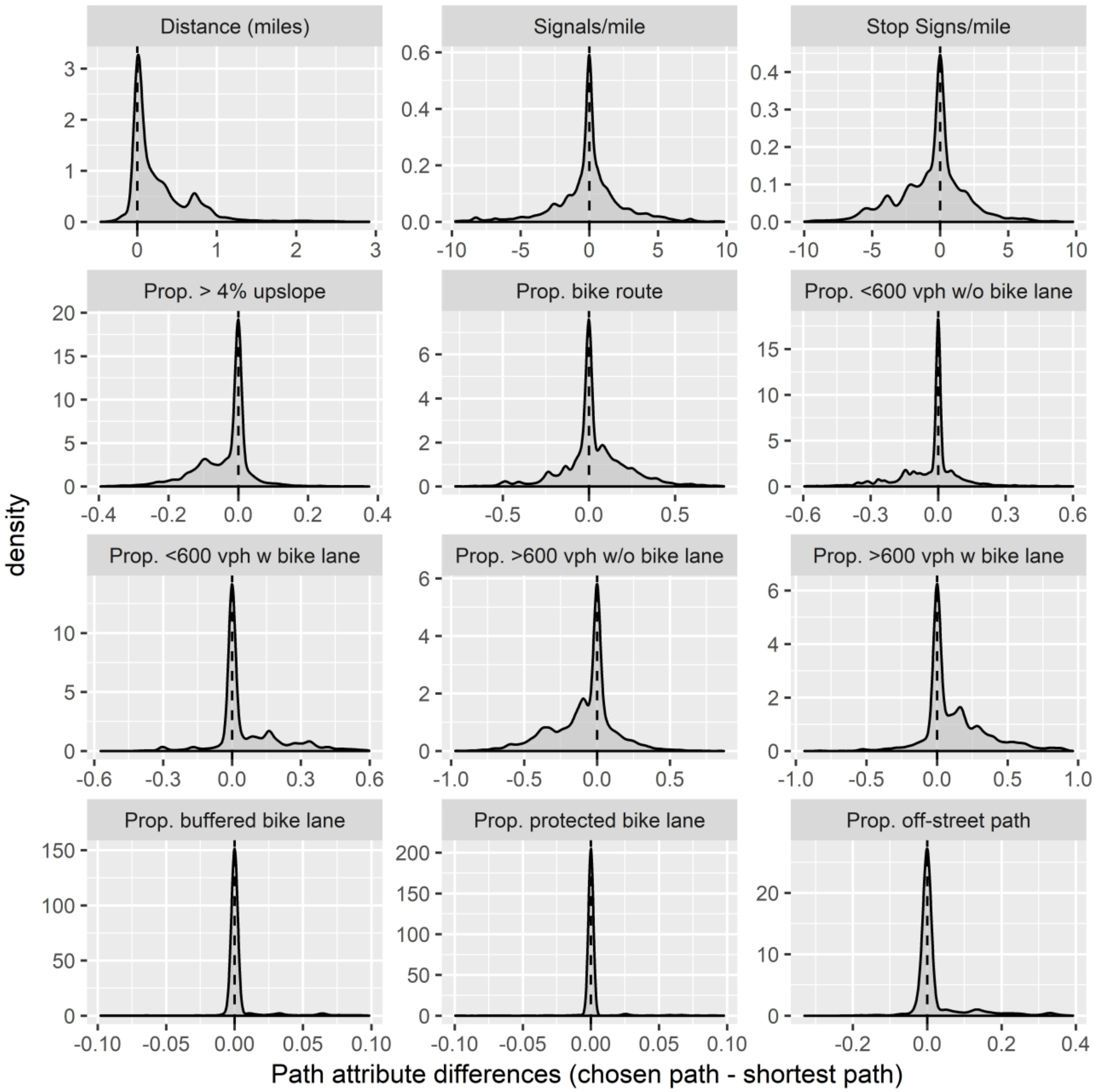


Figure 3.7 Density plots of differences between chosen and shortest path route attributes in San Francisco. Variables are proportions of route length or counts/length.

Even if some road attributes are more meaningfully threshold effects, it may be safe to assume that estimating effects as proportions of routes can still inform bicyclist route behavior. In Figure 3.8 I plot the expected distance tradeoff based on marginal rates of substitution (MRS)[10] for each road attribute for the Davis data as estimated by model 1.[11] The somewhat awkward distance percentages attempt to relate road attributes to a distance equivalent. Positive distance percentages can be interpreted as the amount of additional distance felt for the change in proportion of the attribute of interest. For example, according to model 1, an average person in Davis is willing to choose a 10% longer route with no proportion of mixed-traffic two-lane roads compared to a route with 20% mixed-traffic two-lane roads. Negative distance percentages can be interpreted as the reduction in distance the proportion of the attribute of interest is worth. For example, according to model 1, an average person in Davis is willing to choose a 10% longer route with 30% of that route on off-street paths compared to a route with no off-street paths. Distance equivalents can be used to inform policy decisions about the necessary density of road attributes for bicycling. Unfortunately, the two Davis examples of average distance equivalents are very uncertain. The uncertainty is so large that we can't confidently identify a reliable direction of effect let alone a consistent distance equivalent for bike lanes, off-street paths, or mixed traffic lanes (see shaded grey intervals spanning 0 in Figure 3.8). However, the wide range in uncertainty suggests that proportions of bike lanes and off-street paths could indeed have large distance equivalents, we just cannot tell from this data.

Bike lane effects in Davis are for the most part also low traffic volume and low vehicle speed effects, so it is surprising we don't see a more confident estimate. I considered a few alternative link-level interaction variables for bike lanes in Davis (e.g. bike lane and low posted speed, >6 ft wide bike lanes, bike lanes without on-street parking), only to come to similarly inconclusive MRS. One explanation for these inconclusive results could be that alternative route simulation found too many similar paths. In Davis, because bicycle lanes and paths are ubiquitous, alternative paths with varying road environments are hard to find. In a very counterintuitive sense, these unclear results may be indicative of such good surrounding bicycling environments that bicyclists are choosing one among many similarly adequate routes. Perhaps, like the chosen versus shortest path statistics indicated, the route choices in Davis are based on more subtle road features than were available for this study (i.e.

[10] Calculated as $e^{(B_j/B_{\log miles})} - 1$ for Model 1. For San Francisco Model 2, interaction terms are included in the ratio when appropriate. For the varying effect models, I calculate individual level MRS based on sampling the posteriors of the person level effects for the San Francisco participants who recorded more than 3 trips. Since the Davis participants provided no more than two routes, I don't plot their individual effects because they are imprecisely estimated. However, Gelman and Hill (2007) still advise using varying effects as a tool to help understand group level (person) variation (σ).
[11] I provide results and discussion of better predicting models later in this and the next section. The point of examining the influence of the simpler models is that they are what are commonly reported in other bicycling route choice studies (so for comparison), and because they help show how added complexity changes model inference.

pavement condition, bike specific signals, etc.).

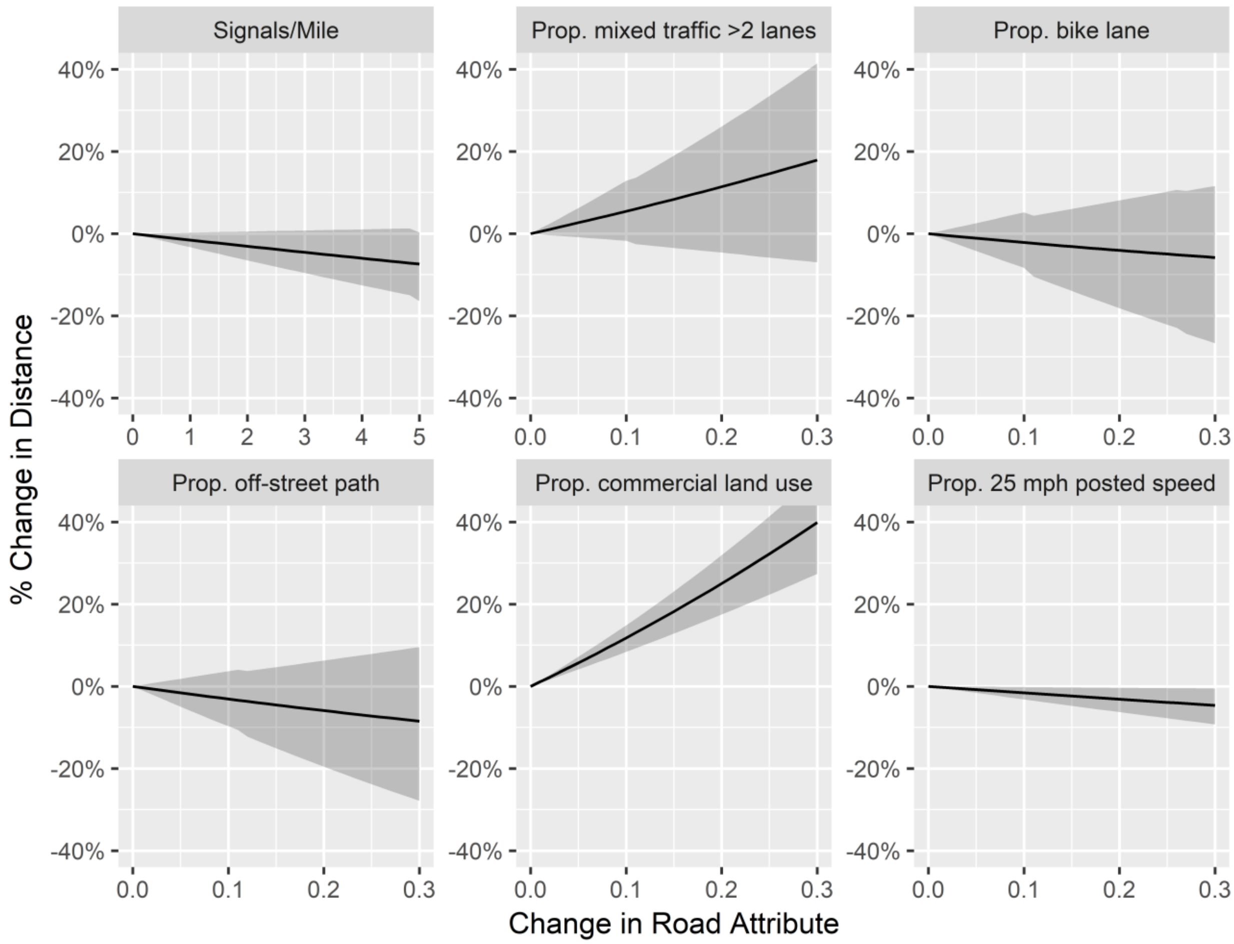


Figure 3.8 Road attribute and distance tradeoff in Davis calculated based on the mean marginal rates of substitution (MRS). The black line represents the mean MRS, and grey shadow represents the 90% highest posterior density interval (HPDI) MRS estimated from model 1.

With this sample in Davis we can be confident that signals and low speed roads have negative MRS, although their slopes (magnitude of effect) are small. The effect of signals is counterintuitive, but negligible because of the small magnitude. It may be that stop signs are being avoided since they tend to have a negative correlation with number of traffic signals along routes. Unfortunately, stop sign data was not available for Davis. The only strong effect in the model is the impact of proportion of route through commercial land use zones (e.g. offices, shops, restaurants), which suggest people are willing to take long detours to avoid. In Davis, the commercial land that intersects travel routes to UC Davis is primarily the downtown core (adjacent to the UC Davis campus on the east), but also includes some commercial land on the north side of UC Davis. The downtown core has many stop signs, so that may be one reason for avoiding commercial land. It may also be that interacting with parking cars is a deterrent since commercial land has greater parking turnover. Stated preference research on bicyclist route choice indicates that people prefer bicycling on roads with no on-street parking (Sener et al., 2009). However, this effect is also a bit surprising because of the sheer number of bicyclists choosing paths through downtown Davis (Figure 1). While commercial land use has a strong average effect of causing detours around it, it also has the widest person level heterogeneity among all the road attributes (σ= 5.5-6.2, see Appendix B for other parameter summaries). This heterogeneity suggests that some people in Davis are either indifferent to riding through commercial land, or perhaps even detour to go through it. Although the survey was designed to capture usual route to campus (without intermediate stops), it may be that some people reported routes to campus where they stop for other errands along the way.

Uncertain effects of road attributes on route choice in Davis contrasts with many certain effects of different road attributes in San Francisco (Figure 3.9). San Francisco Model 2 predicts extremely large willingness to detour for avoiding up-slopes and for bicycling on bike lanes, buffered bike lanes, protected bike lanes and off-street paths.[12] A person's willingness to detour for different bike infrastructure in San Francisco follows a very intuitive hierarchy of small detours for bike routes, larger detours for bike lanes, and very large detours for buffered bike lanes, protected bike lanes, and off-street paths. The MRS for these attributes vary slightly by trip purpose with exercise trips having larger distance equivalents for bike infrastructure. Figure 3.9 shows a counterintuitive result of people on exercise trips being willing to detour further than commuters to avoid hills. However, mean parameter values (Appendix B) indicate that this effect is likely due to distance not being near the deterrent for picking a route when exercising, since the interaction of exercise trip and proportion > 4% upslope is positive on average (μ=1.856, σ=1.662). The difference in slope effects by trip type is a reminder that interpreting MRS can be challenging because we can't determine whether differences in MRS are due to differences in the attribute of interest or distance. This challenge only increases if we begin to examine individual level heterogeneity in route choice.

[12] Like the Davis model results above, better predicting models for San Francisco are presented in subsequent sections, so the curves from Figure 3.9 are used as a comparison not conclusion.

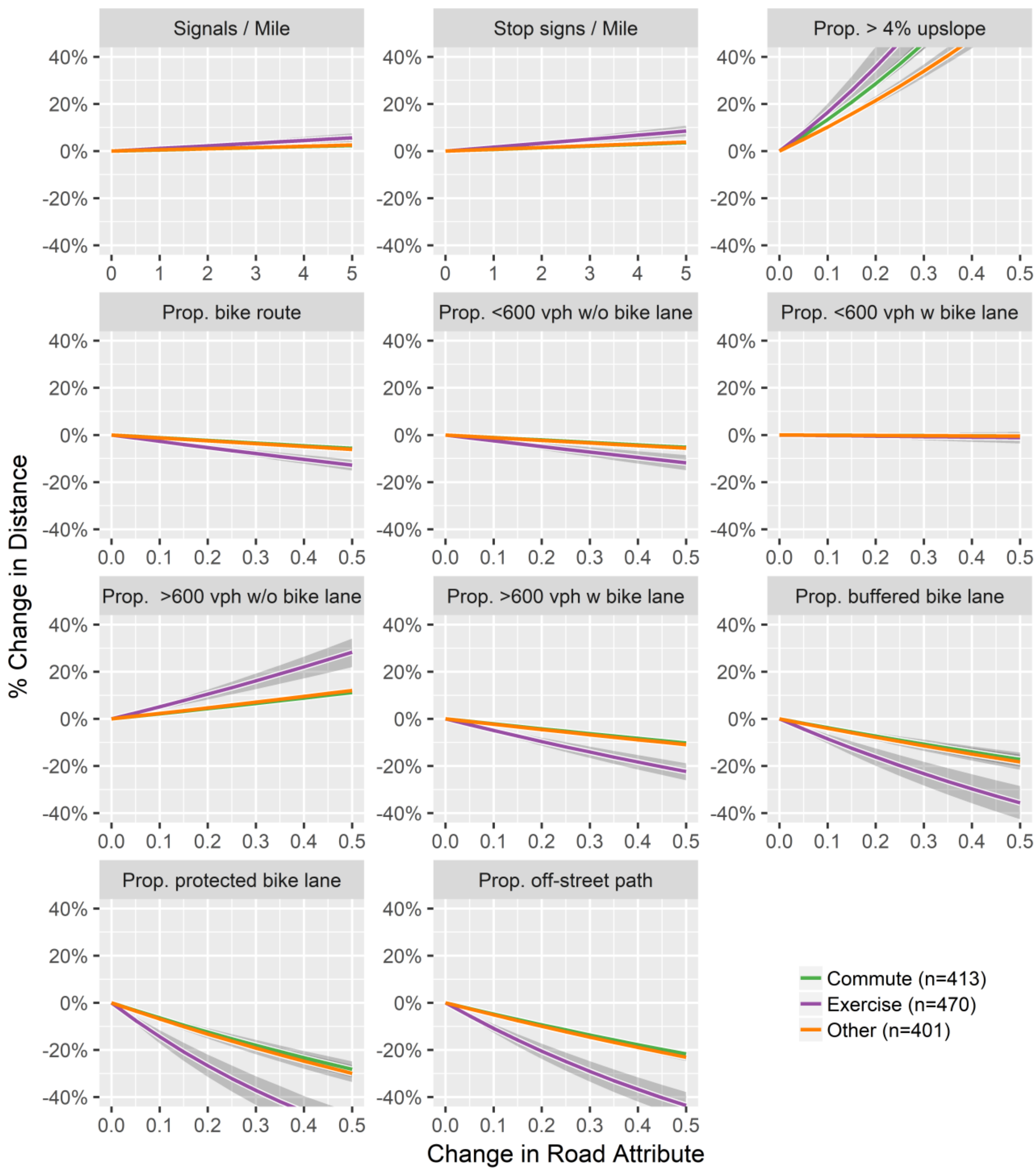


Figure 3.9 Road attribute and distance tradeoff in San Francisco calculated based on the mean marginal rates of substitution (MRS). The black line represents the mean MRS, and grey shadow represents the 90% highest posterior density interval (HPDI) MRS estimated from model 1.

3.7.3 Heterogeneity in the distance tradeoff for road attributes

These above results do not account for heterogeneity in route choice decision making, but instead assume that all people have the same substitution patterns between road attributes and distance. However, model prediction is improved when including varying effects by person and person level covariates are added (i.e. large drops in information criteria, see Appendix B). Because prediction improves, we are likely missing valuable information about route choice behavior without considering person level heterogeneity. Person level heterogeneity also helps highlight non-average route choice behavior which may help us infer the importance of road attributes for prospective bicyclists who are likely to be more conservative in their willingness to detour than average existing bicyclists.

In the Davis models, variation in the influence of road attributes between people is described by the scale parameters (σ) in Models 2 and 3 (see Appendix B for parameter summaries). Because the predictor variables are mostly on the same scale (i.e. proportions of route), the scale parameters describe the relative magnitude of heterogeneity between variables. However, it is difficult to translate these parameters into meaningful statements about distance tradeoffs (which are more important for policy). Considering the Davis data does not have large enough within person samples to estimate individual effects precisely, we can instead look at groups of individuals to get a better sense for heterogeneity. Figure 3.10 shows four classes of people based on gender, student status, and two survey responses: one to a question on comfort bicycling on an arterial with no bike lane, and one on bicycling ability. These classes were specifically selected to be maximally different from each other to demonstrate heterogeneity in the sample. Model 3 predicts some widely different rates of substitution for these different classes of people. For example, each of the four groups falls outside the 90% highest posterior interval for the mean substitution rate from Model 1 for at least 2 of the 6 road attributes.[13] Since the form of Model 1 most closely aligns with the logit models employed in past route choice studies, Figure 3.10 also acts as a caution for drawing inferences from models that ignore individual heterogeneity.

The most notable class might be the low comfort, low ability, female, students (*n*=41). They show great aversion to traffic signals, mixed travel lanes, and counterintuitively to low posted speed roads. They show strong effects of proportion of off-street paths, but little to no effects of bike lanes. Alternatively, the high comfort, high ability, male, non-students (*n*=22) show the strongest influence of bike lanes, affinity with low posted speed roads, and aversion to commercial land. Some of these class differences are hard to explain. For example, why do high comfort, high ability, male, non-students have such a strong aversion to traveling through commercial land? Possibly, this effect

[13] Of course, Model 1 doesn't allow for person level variation in the slopes, so this might not be that unexpected.

represents a difference between travel distance and travel time. Although travel distance and time tend to be highly correlated (Broach et al., 2012), in Davis where routes are short, distance may not be an accurate representation of travel time (the ultimate cost for travel). If traveling through commercial land results in a relatively similar distances but longer travel times, then high comfort, high ability, male, non-students may not have a particularly special aversion to riding through commercial land after all. Further research into the difference between travel distance and time at different distances is likely to improve our understanding of the true distance tradeoff for route attributes. One more interesting finding is the particularly strong moderating effect of being a student. Students are less likely to detour on average (negative moderating effect) and less likely to choose routes with large proportions of low speed roads (negative moderating effect) (Appendix B). This result perhaps relates to knowledge of the city. Students are often new to the city and often change residences from year to year. They may not detour as much as non-students because they don't have the same time to learn alternative routes. The other moderating effects of students are quite uncertain.

In the San Francisco case, person level parameters are estimated with much greater precision because most participants recorded multiple routes. In this case, person level MRS can give an even better indication of the heterogeneity in the sample (see Figure 3.11). In San Francisco, the person level variation is quite dramatic. Every route attribute has at least a few people who exhibit the opposite direction of effect from the average. Opposing direction of effects for individual MRS have been observed in other cases, but they are usually rare and deemed insignificant (Sillano and de Dios Ortúzar, 2005). In the case of Figure 3.11, many of the person-level curves showing the opposite direction of effect from the average are imprecisely estimated. Plotting the uncertainty for individual effects proved too distracting to the main story that individual differences matter, but we should be skeptical of some of those very deviant curves.

Considering that the average effects of road attributes are estimated with great certainty in the simple model (Model 1) (see shaded regions in Figure 3.9), the person level heterogeneity shows that many people just don't behave like the average person. Person-level variation also seems to washout the moderating effects of trip type on route attributes. Comparing the colored lines from Figure 3.9 and 3.11, the differences between average effects for exercise trips are much more similar to commute and other trips when person-level heterogeneity is captured. In addition, the average effects of buffered bike lanes, protected bike lanes, and off-street paths are reduced in general (flattening of the curves in Figure 3.11). This reduction in these average effects indicates that CycleTracks users who recorded many routes had stronger preferences for these attributes. The reason is that prior to Model 3, all 8,190 route choices were considered independent. The behavior of heavy CycleTracks users was overrepresented as a result. In Model 3, the varying effects by person ensure that the behavior of heavy CycleTracks users don't unfairly dominate inference (McElreath, 2015).

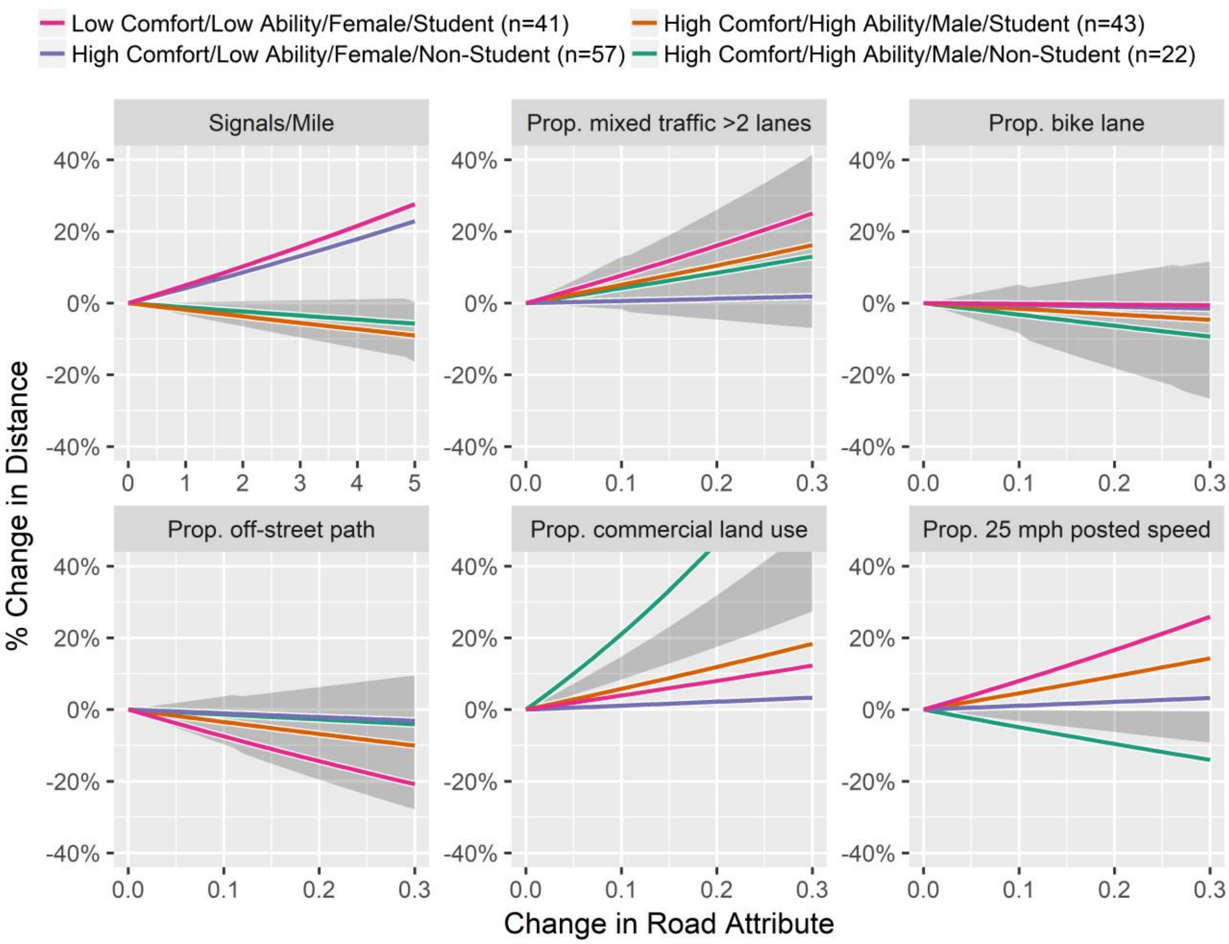


Figure 3.10 Road attribute and distance tradeoff calculated based on the mean marginal rates of substitution (MRS) by four classes of participants in Davis. The solid lines represent the mean MRS by class from model 3, and grey shadow represents the 90% highest posterior density interval (HPDI) MRS estimated from model 1.

The San Francisco model results suggest that most bicyclists avoid high vehicle capacity roads without bike lanes, and choose routes with more bike lanes, buffered bike lane, protected bike lanes, and off-street paths. The influence of bike routes and bike lanes along low capacity routes are less strong, but for the most part people still detour for them. For example, compared to a route with no buffered bike lanes, only 11% of people are willing to ride an additional 10% further if an alternative route had 20% buffered bike lanes, while 89% would add that same distance if the alternative had 50% buffered bike lanes. Similarly, compared to a route with no protected bike lanes only 11% of people are willing to ride an additional 10% further if an alternative had 20% protected bike lanes, while 99% would add that same distance if the alternative had 50% protected bike lanes. The individual level substitutions for off-street paths are similar to protected bike lanes when they occur on half of the route. These substitution patterns suggest that an order of magnitude larger proportions of these facilities (currently routes in San Francisco have very small proportions of buffered bike lanes, protected bike lanes, and off-street paths, see Table 3.2) may be needed to encourage more bicycling.

3.8 Planning implications and future research

It is hard to know the williness of bicyclists to detour. Variation in average detour rates from other studies and these two cases suggest local context is likely to matter. Estimates currently range from about 8% to 18% on average (Ghanayim and Bekhor, 2018). However, some San Francisco bicyclists are willing to detour much further to ride in prefereable environments as evidenced by the heterogeneity in marginal rates of substitution (Figure 3.11). It is probably safe to assume that prospective bicyclists are equal or less willing to detour than existing bicyclists. Perhaps the Davis results might best be used as a guide for willingness to detour since they are most likely to reflect prospective bicyclists in other cities. This would indicate that we should attempt to plan for people to have a comfortable route to their destination within 5-8% of the shortest route (the median and mean detouring rates in Davis). Even this goal may only help encourage short trips (less than 3 miles) since the trips in Davis are so short.

In terms of identifying prefered road attributes, the Davis data is ambiguous, but the San Francisco data clearly shows that bicyclists are willing to detour further for off-street paths and protected bike lanes compared to bike routes and conventional bike lanes. However because of avilability, bike lanes and routes are still the predominantly used facilities on most trips by most riders. Futhermore, only 11% of trips were able to avoid high capacity arterials with no bike lanes altogether. Given the overwhelming attempt to avoid these roads by most bicyclists, improvements to these roads are most likely worthwile investments. Although the way they might be improved is heavily context dependent, if we consider two potential classes of improvements (conventional bike lane[14] and protected bike lane), you would need about 2.4 times as many miles of conventional bike lanes compared to protected bike lanes to provide the same value to the average bicyclist in this San Francisco sample.

[14] Buffered bike lanes show very similar rates of substitution with conventional bike lanes.

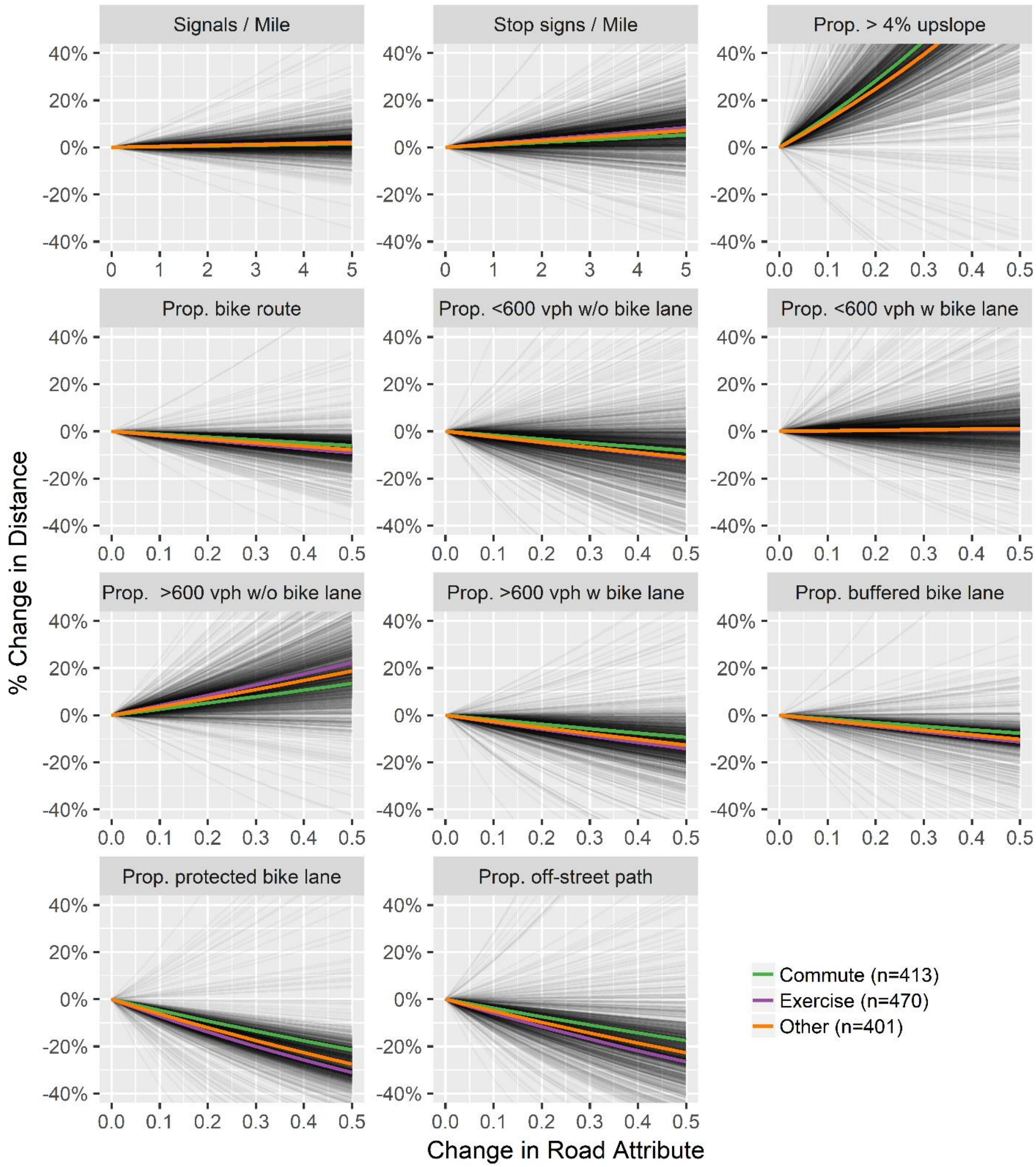


Figure 3.11 Road attribute and distance tradeoff calculated based on the person specific mean marginal rates of substitution (MRS) in San Francisco. The thin lines represent individual mean MRS estimated from model 3. People with less than 3 trips are absent from plot because of imprecise estimates. The thick colored lines represent the trip type mean tradeoff.

It isn't quite clear what this means for the necessary densities of these facilities. The relative rates of substitution suggest protected bike lanes just don't have to be near as dense as conventional bike lanes.

But at the same time, protected bike lanes (or off-street paths) may be crucial for providing comfortable bicycling access for more people, so they might need to be very dense if cities want to provide comfortable access within minor detours. More research is needed that focuses on the specific question of necessary density of bicycling infrastructure.

Future research is also needed to identify infrastructure thresholds for prospective bicyclists. In addition, the road environment is really a large interaction between lots of attributes. No one attribute influences route choice independently. This study, as well as the study by Broach et al. (2012), explored the specific interactions of traffic and bike lanes. In Portland, the effect of large traffic volumes seemed to wash out any effect of bike lanes, but the same was not found in San Francisco. This may be partially due to the definitions of traffic (I used capacity estimates based on road class and neighborhood), but also may be due to differences in regional bicycling behavior. In both cases, results showed that interactions matter. Further interactions are needed in the model to properly describe which road environments are most likely to encourage more bicycling. In addition, we need to find better ways of incorporating route choice model results into bike planning tools (Lowry et al., 2016).

3.9 Conclusions

By combining evidence of bicycling route choice behavior from two distinct bicycling populations in two distinct environments, we can see that heterogeneity in route behavior is strong. This heterogeneity has important policy ramifications. More conservative effects than those from average existing bicyclists should probably be used for policy. The largely inconclusive nature of the Davis results is unfortunate. I intended the Davis sample to be a better representation of prospective bicyclists in other places, and so more conclusive marginal rates of substitution for them would have provided stronger evidence for what we might expect changes to the road environment might have on encouraging more bicycling. At the same time, the inconclusive nature of the Davis data may be telling of the need for many alternative plausible routes to destinations that can accommodate the variety of preferences for the population. The evidence that bicycling infrastructure matters for existing San Franciscan bicyclists is overwhelming. Interestingly, even with small proportions of routes with innovative investments (buffered and protected lanes), we can observe confidently strong effects on route choice. This supports the conclusion that these new bike infrastructures should play a key role for the future of bicycling in big cities.

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Appendix A. Model Equations

For calculating the correlation among routes (path size) in a given choice set, I use the following equation:

$$PS_{in} = \sum_{a \in \Gamma_i} \frac{l_a}{L_i} \frac{1}{\sum_{j \in C_n} \delta_{aj}}$$

Where Γ_i are the links in alternative *i*, l_a is the length of link *a*, L_i is the length of alternative *i*, and δ_{aj} equals 1 if *j* includes link *a*. This measure defines a reduction in weight (length) for a given link's contribution to the path based on the proportion of paths in the choice set with that link. The log transformed path size variable is included in all models to reduce the bias of strongly correlated alternatives for each person for each choice set.

The following are the equations describing the three route choice models:

<u>Model 1: Multinomial Logit</u>

$$y_i \sim Multinomial\ Logit(U_{ijk})$$

$$U_{ijk} = X_{jk}B$$

Priors:

$$B \sim \text{Normal}(0 , 3)$$

<u>Model 3: Multilevel Multinomial Logit with varying effects by person</u>

$$y_i \sim Multinomial\ Logit(U_{ijk})$$

$$U_{ijk} = X_{jk}B_i$$

$$B_i \sim \text{MVNormal}(B , \Sigma_B)$$

$$\Sigma_B = \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_p \end{pmatrix}$$

Priors:

$$B \sim \text{Normal}(0 , 3)$$

$$\sigma_{person} \sim \text{Half Normal}(0 , 1)$$

<u>Model 3: Multilevel Multinomial Logit with varying effects by person and person level predictors</u>

$$y_i \sim Multinomial\ Logit(U_{ijk})$$

$$U_{ijk} = X_{jk}B_i$$

$$B_i \sim \text{MVNormal}(B + X2_i G , \Sigma_B)$$

$$\Sigma_B = \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_p \end{pmatrix}$$

Priors:

$$G \sim \text{Normal}(\ 0\ ,3\ )$$
$$\sigma_{person} \sim \text{Half Normal}(\ 0\ ,1\ )$$

Where y_i is the travel route for person *i* from 1 to N; U_{ijk} is the utility of choice alternative *j* in choice situation *k* for each person. The number of non-matching simulated routes determines the *j* alternatives in each choice set from 1 to J, and the number of trips each person recorded determines the number of choice situations *k* from 1 to K. X_{jk} is the NJK × P matrix of P route level predictors and B is a vector of route level regression parameters, length P. In the varying effects models B_i are individual specific effects centered around the respective mean parameter B and have independent standard deviations σ_p (diagonal covariance). Although a full covariance model is advantageous for handling correlations, comparisons for subsets of the Davis data suggested the B_i parameters were very similar with unstructured and diagonal covariance terms. Therefore, I adopted with simpler model form. Keeping the varying effects independent also has two practical effects: (1) reduced computational time, (2) marginal rates of substitution are easy to calculate from parameter ratios.

In model 3, $X2_i$ is the N × L matrix of L person level predictors and G is the L × P matrix of parameters for the person level regression acting as moderators for the route level predictions. I follow general guidance on selecting priors to reduce overfitting (McElreath, 2015) by selecting weakly regularizing priors on B based on existing bicycling route choice evidence (Normal with σ=3), and half-Normal with smaller variance (σ=1) for the scale parameters of individual effects. These priors still allow considerable individual variation but act to restrain the model from estimating unreasonable person level effects, especially given most participants recorded less than 5 routes. I estimate all models with four Markov chains of 2,000 iterations each (1,000 iterations of warmup). I determined model convergence based on the Gelman-Rubin statistic (<1.01), lack of divergent transitions, lack of transitions hitting the maximum tree-depth, and estimated fraction of missing information above 0.3, all of which are reported by RStan.

Appendix B Model Parameter Summaries

Table 3.B1 Model parameter summaries for Davis

Description		Parameter	Model 1 mean	Model 1 sd	Model 1 n eff.	Model 2 mean	Model 2 sd	Model 2 n eff.	Model 3 mean	Model 3 sd	Model 3 n eff.
	log miles	B_1	-4.243	0.538	3398	-4.924	0.695	4000	-2.802	1.321	2340
	log path size	B_2	0.953	0.110	3258	1.301	0.168	4000	1.914	0.426	1660
	Signals/mile	B_3	0.065	0.044	2754	0.085	0.050	4000	0.055	0.127	1692
	Prop. mixed traffic two lanes	B_4	-2.190	1.737	1854	-2.743	1.729	2963	-1.821	1.746	1669
	Prop. bike lane	B_5	0.940	1.728	1854	1.150	1.719	3045	1.442	1.726	1614
	Prop. off-street path	B_6	1.340	1.732	1852	1.572	1.724	3018	0.626	1.762	1697
	Prop. commercial	B_7	-4.658	0.512	3368	-6.540	0.770	4000	-7.525	1.444	1770
	Prop. 25 mph posted speed	B_8	0.661	0.376	2618	0.672	0.435	4000	2.069	0.986	1927
Varying effects by person (standard deviations)	log miles	σ_1				2.376	1.237	991	2.413	1.348	569
	log path size	σ_2				2.060	0.242	1366	2.101	0.245	1197
	Signals/mile	σ_3				0.070	0.050	1264	0.074	0.054	1058
	Prop. mixed traffic two lanes	σ_4				1.506	0.792	559	1.533	0.806	418
	Prop. bike lane	σ_5				0.296	0.227	2369	0.326	0.249	1286
	Prop. off-street path	σ_6				0.323	0.250	2733	0.350	0.270	2069
	Prop. commercial	σ_7				5.472	1.006	1201	6.154	1.047	1037
	Prop. 25 mph posted speed	σ_8				0.609	0.456	1462	0.633	0.452	1100
log miles ×	female	G [1,1]							-0.886	1.235	3074
	student	G [1,2]							-3.767	1.240	3159
	low comfort	G [1,3]							0.469	1.307	2929
	low ability	G [1,4]							2.127	1.675	4000
log path size ×	female	G [2,1]							0.281	0.340	2366
	student	G [2,2]							-1.014	0.354	2061
	low comfort	G [2,3]							-0.067	0.368	1933
	low ability	G [2,4]							-0.101	0.538	2715
Signals/mile ×	female	G [3,1]							-0.073	0.111	2774
	student	G [3,2]							0.070	0.111	2461
	low comfort	G [3,3]							0.051	0.112	1721

		low ability	G [3,4]			-0.264	0.175	3352
Prop. mixed traffic two lanes	×	female	G [4,1]			0.816	1.793	1462
		student	G [4,2]			-1.650	1.774	1610
		low comfort	G [4,3]			-0.456	1.805	1456
		low ability	G [4,4]			-0.757	1.913	1913
Prop. bike lane	×	female	G [5,1]			-0.245	1.752	1408
		student	G [5,2]			0.086	1.747	1584
		low comfort	G [5,3]			0.029	1.776	1480
		low ability	G [5,4]			-0.512	1.872	1764
Prop. off-street path	×	female	G [6,1]			-0.511	1.786	1407
		student	G [6,2]			1.485	1.766	1612
		low comfort	G [6,3]			0.474	1.802	1496
		low ability	G [6,4]			1.285	1.914	1812
Prop. commercial	×	female	G [7,1]			0.629	1.307	2383
		student	G [7,2]			0.878	1.341	2801
		low comfort	G [7,3]			-0.651	1.307	2591
		low ability	G [7,4]			1.276	1.878	4000
Prop. 25 mph posted speed	×	female	G [8,1]			0.144	0.934	2695
		student	G [8,2]			-3.333	0.930	2684
		low comfort	G [8,3]			0.995	0.960	1945
		low ability	G [8,4]			-1.786	1.430	4000
n				740	740		740	
Approximated leave-one-out cross validation information criteria (LOOIC) and standard error				3192.9 (43.1)	3040.8 (47.0)		3014.5 (48.5)	
Widely applicable information criteria (WAIC) and standard error				3192.9 (43.1)	3040.8 (47.0)		3014.5 (48.5)	

Table 3.B2 Model parameter summaries for San Francisco

		Model 1			Model 2			Model 3			Model 4		
Description	Parameter	mean	sd	*n* eff.	mean	sd	*n* eff.	mean	sd	*n* eff.	mean	sd	*n* eff.
log miles	B_1	-8.953	0.154	4000	-8.865	0.250	3834	-11.276	0.518	1790	-11.085	0.588	2889
exercise ×log miles	B_{14}				4.770	0.466	4000	4.499	0.891	3085	4.955	1.094	4000
commute ×log miles	B_{16}				-0.651	0.283	4000	-2.747	0.692	2440	-2.536	0.768	3022
log path size	B_2	2.210	0.034	4000	2.220	0.033	4000	2.640	0.108	1440	2.382	0.124	2096
Signals /mile	B_3	-0.044	0.008	4000	-0.044	0.008	4000	-0.047	0.021	2696	-0.011	0.024	3265
Stop signs/mile	B_4	-0.068	0.008	3832	-0.066	0.008	4000	-0.166	0.025	1813	-0.150	0.028	2184
Prop. > 4% upslope	B_5	-10.479	0.250	4000	-8.611	0.387	3806	-12.541	0.779	2334	-11.487	0.854	4000
exercise ×Prop. > 4% upslope	B_{15}				2.413	0.911	4000	1.918	1.414	4000	1.856	1.662	4000
commute ×Prop. > 4% upslope	B_{17}				-3.346	0.489	4000	-6.039	1.024	3241	-4.722	1.080	4000
Prop. bike route	B_6	1.139	0.071	4000	1.113	0.070	4000	1.894	0.182	2201	1.902	0.222	3285
Prop. <600 vph w/o bike lane	B_7	1.024	0.147	4000	1.020	0.145	4000	2.652	0.426	2006	2.700	0.485	2447
Prop. <600 vph w bike lane	B_8	0.004	0.121	3279	0.094	0.124	4000	-0.417	0.393	2216	0.059	0.421	2915
Prop. >600 vph w/o bike lane	B_9	-2.011	0.110	3880	-2.018	0.111	4000	-3.982	0.322	1993	-3.890	0.363	2639
Prop. >600 vph w bike lane	B_{10}	2.095	0.101	3153	2.052	0.102	4000	3.129	0.303	1966	2.666	0.336	2946
Prop. buffered bike lane	B_{11}	3.461	0.424	4000	3.591	0.417	4000	2.462	1.017	2695	2.788	0.934	4000
Prop. protected bike lane	B_{12}	6.270	0.518	4000	6.309	0.528	4000	7.413	1.211	3060	6.733	1.319	4000
Prop. Off-street path	B_{13}	4.624	0.190	4000	4.653	0.196	4000	6.087	0.595	2366	5.753	0.659	3673
Varying Effect Std. Dev.: log miles	σ_1							4.911	0.441	1259	4.625	0.472	1750
Varying Effect Std. Dev.: exercise ×log miles	σ_{14}							3.563	0.885	1163	3.022	1.022	1195
Varying Effect Std. Dev.: commute ×log miles	σ_{16}							6.366	0.530	1969	5.687	0.547	2222
Varying Effect Std. Dev.: log path size	σ_2							1.586	0.108	1480	1.446	0.117	1651
Varying Effect Std. Dev.: Signals /mile	σ_3							0.215	0.022	1169	0.205	0.023	1747
Varying Effect Std. Dev.: Stop signs/mile	σ_4							0.311	0.023	1312	0.282	0.025	1892
Varying Effect Std. Dev.: Prop. > 4% upslope	σ_5							6.619	0.609	1559	6.048	0.653	1641

	exercise × Prop. > 4% upslope	σ_{15}	0.839	0.628	4000	0.829	0.613	4000
	commute × Prop. > 4% upslope	σ_{17}	5.580	0.859	1416	3.887	1.110	690
	Prop. bike route	σ_6	2.073	0.204	1155	2.056	0.231	1597
	Prop. <600 vph w/o bike lane	σ_7	5.012	0.365	2006	4.712	0.398	1963
	Prop. <600 vph w bike lane	σ_8	4.467	0.335	1298	3.612	0.348	2028
	Prop. >600 vph w/o bike lane	σ_9	3.799	0.277	1649	3.549	0.304	1849
	Prop. >600 vph w bike lane	σ_{10}	3.359	0.255	1657	2.726	0.257	2010
	Prop. buffered bike lane	σ_{11}	4.922	0.763	2687	2.438	0.978	1354
	Prop. protected bike lane	σ_{12}	6.040	0.689	3126	5.563	0.709	4000
	Prop. Off-street path	σ_{13}	5.992	0.513	2045	5.173	0.584	2577
	log miles	G_1				0.742	1.234	4000
	exercise × log miles	G_{14}				-0.321	1.936	4000
	commute × log miles	G_{16}				1.746	1.626	4000
	log path size	G_2				-0.087	0.298	2963
	Signals /mile	G_3				-0.053	0.062	4000
	Stop signs/mile	G_4				-0.088	0.073	3271
	Prop. > 4% upslope	G_5				-2.165	1.686	4000
	exercise × Prop. > 4% upslope	G_{15}				3.019	2.408	4000
Female ×	commute × Prop. > 4% upslope	G_{17}				-2.633	2.131	4000
	Prop. bike route	G_6				-0.372	0.546	4000
	Prop. <600 vph w/o bike lane	G_7				-0.707	1.165	4000
	Prop. <600 vph w bike lane	G_8				-0.796	0.985	4000
	Prop. >600 vph w/o bike lane	G_9				-0.487	0.879	4000
	Prop. >600 vph w bike lane	G_{10}				0.453	0.799	4000

Prop. buffered bike lane	G_{11}				4.529	1.956	4000
Prop. protected bike lane	G_{12}				-0.389	2.184	4000
Prop. Off-street path	G_{13}				0.432	1.471	4000
	n	8,190	8,190	8,190	5,407		
Approximated leave-one-out cross validation information criteria (LOOIC) and standard error *		31682.4 (211.3)	31542.3 (209.2)	21752.6 (239.8)	16013.8 (186.1)		
Widely applicable information criteria (WAIC) and standard error *		31682.4 (211.3)	31542.3 (209.2)	21434.6 (236.9)	15813.9 (184.1)		

*Some diagnostic errors in the estimates of WAIC and LOOIC suggest out-of-sample prediction estimates can be improved with brute force cross-validation which is not feasible with these sample sizes. Note that model 4 has a reduced sample size so its LOOIC and WAIC are not comparable to the other models.

4 Bicycling attitudes and the road environment, and their relation to usual travel mode to school in teenagers

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. Considering that teenage travel may have important implications for the formation of habits that shape adult travel behavior, research on the determinants of teen active travel to school is needed. Using data from a large cross-sectional survey of students at three high schools in Northern California, I present evidence linking travel to school with bicycling attitudes and with road environments on plausible paths to school. Results suggests the relationship between attitudes and bicycling are stronger than the relationship between road environments and bicycling. Student perceived social pressure to bicycle has a particularly strong association with bicycling. Hypothetical intervention scenarios suggest that with improvement of road environments for walking and bicycling, shorter distances to school, and more positive bicycling attitudes, students would walk and bicycle to school at substantially greater rates. This chapter is based partially on work presented at the 14th International Conference on Travel Behavior Research in Windsor, UK (2015) and the Transportation Research Board 96th Annual Conference (2016) (Fitch and Handy. *Mode choice to high school: evidence from Northern California*).

4.1 Introduction

Adolescence is arguably one of the most dynamic and formative stages in the development of peoples' travel preferences and habits. Teenagers are granted more freedom to travel by 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 make is their daily travel to and from school. Therefore, a steady decline in active travel to school in the US is 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 by improving conditions for active travel or change attitudes toward active travel by education and encouragement. Evaluations of these strategies have largely focused on primary and not high schools. The road environment and attitudes, and their relation to teens' active travel decisions are important gaps in the literature. Improving our knowledge of these factors should make planning strategies more effective at increasing the number of teenagers who walk and bicycle, potentially forming lasting habits into adulthood.

4.2 Travel to school: conceptual framework

Conceptually, 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) interact with their children's constraints and preferences. Furthermore, it is likely that as children become more independent, this joint-choice and potentially joint-travel outcome changes (Mitra, 2013). Travel to school is repeated and mandatory and is therefore likely to follow routine or habitual behaviors. However, 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.

Pairing utility theory with psychological and ecological theory, as presented in Chapter 1, may be a useful way to examine this complex relationship. However, obtaining data on all the specific variables identified by complex conceptual models is challenging. In addition, travel constraints and preferences may be downstream effects of other household decisions (e.g. residential location choice) suggesting more complex causal links with travel mode choice. For all these reasons, understanding the variables most strongly associated with school travel are an important first step for determining what to measure over time to assess causal relationships.

4.3 Travel to school: empirical evidence

Although growing concerns over the decline in active travel to school have 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. 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). Furthermore, car access is heavily dependent on familial economic status. In many cases a lack of teen driving is due to economic restraints, not the choosing of an alternative mode. 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 increase even as teen licensing rates decline.

The urban environment is thought to influence the choice to walk or bicycle to school. 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. I.e. fewer students live within reasonable walking and bicycling distance to their local high school as they do 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 a part of a broader challenge of increasing sustainable travel in cities with decades of planning for low-density communities with segregated land uses.

In addition to distance, evidence suggests that aggregate urban characteristics like residential density and street connectivity both increase 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 contradict the positive relationship between aggregate urban characteristics and active travel to school. Mitra (2013) reviewed 42 studies on school travel (only 6 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 variables are indirect aggregate measures of the urban environment at the school level and in theory have less of a direct impact on any individual student's specific environment to and from school.

Studies that focus on individual route-based environments rather than general environments (e.g. around a school) 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. In theory, and with some empirical support, individual route-based measures of the urban environment more strongly influence active travel, compared to non-route-based measures (Broach, 2016; Handy et al., 2002); however, very little evidence exists for teen travel to school.

Specific aspects of the urban environment that promote bicycling are less clear since many studies of active travel to school don't separate bicycling and walking behavior, muting the unique factors that influence the choice to walk *or* bicycle to school (McDonald, 2008). In one study, aggregate bike facility density was associated with increased teen travel for social and recreation activities, although it is unclear if this travel was by bicycle (Sener and Bhat, 2012). Evidence from bicycling research beyond school travel would suggest that perceived safe and comfortable access to school (e.g. bike lanes, separated paths, limited traffic, slow traffic), along with trip end facilities would be important factors (Pucher et al., 2010).

The attitudes and perceptions of both students and parents about bicycling have also been shown to affect mode choice (Dill and McNeil, 2013; Driller and Handy, 2013; McDonald, 2012). In a 2009 survey of high school students in Davis, CA, parental encouragement and students' comfort riding a bike were found to 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 an extensive survey of teen travel to school in Cyprus (Kamargianni and Polydoropoulou, 2013). Interestingly, both studies show that students use travel modes like those of their parents suggesting 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 mode safety are likely to influence travel mode decisions given 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 teen chauffeuring 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 which should negatively correlate with chauffeuring. Instead, the positive correlation seems to imply that (1) parents that 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.

Adding to the complexity of school travel, teen travel to and from school may not be as habitual as commuting to and from work for adults. Evidence from qualitative research shows considerable variation in teens travel to school in northern England (Walker et al., 2009). For example, teens choose routes and modes based social context (e.g. bullying), noxious smells, and scheduling logistics (e.g. picking up a friend on a bike) (Walker et al., 2009). Evidence from Japan suggests that variability in directness and travel mode is greater for the from-school rather than the to-school journey (Alemu and Tsutsumi, 2011). This variability in travel is consistent with evidence from the US that many children and teens do not return home immediately after school and instead engage in out of home activities (Paleti et al., 2011). Nonetheless, because of the frequency of school travel for teenagers, it remains the most likely travel pattern to instill habitual mode choice behavior.

4.4 Objective

The recent evidence shows that both attitudes (of parents and students) and the built environment to some degree influence teen travel to school. However, given the limited evidence, the magnitude of these relationships are uncertain. In this study, I examine usual mode choice to high school and focus specifically on the magnitude of these relationships. I explore the road environment with regards to walking and bicycling, and bicycling attitudes of students regarding their travel environment and influence of parents and peers. Because I use cross-sectional data, I cannot draw causal inferences. Nonetheless associational evidence is important for establishing the likely magnitudes of relationships between variables which can help improve conceptual models of teen travel, and focus future longitudinal studies for evaluating causal relationships.

4.5 Methods

4.5.1 Study Setting and Survey Data

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

Sequoia and Tamalpais High 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 schools differ in their socio-demographics, surrounding topography, and bicycling infrastructure. Mill Valley (where Tamalpais High is located) has the highest median income ($167,561) and Redwood City the lowest ($88,525), according to the U.S. Census, but all three have median incomes above the state average. Mill Valley also has considerable topography compared to the other communities, and most of the bicycling infrastructure is geared towards recreational use. Redwood City notably differs from the other communities in its comparatively larger percentage of Hispanic population, while Davis has a comparatively larger Asian population (US Census Bureau, 2012). The survey results show that the three schools are strikingly similar with respect to driver's licensing, distance to school, and student demographics, although the percentage of Hispanic and Asian students differs.

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 household income), and nearest cross street to home (see Appendix C for the survey instrument). The survey was designed by Susan Handy and Kristin Lovejoy to explore numerous facets of teen travel including bicycling and driver's licensing.

In analyzing the data, I grouped some of these responses for ease of analysis. For example, travel modes of skateboard, motorcycle, and train were so small so they were added to walk, drive, and bus, respectively. A few nonsense responses (e.g. travel via "hot air balloon" or "teleport") were treated as missing data. Also, I 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 scale from *Strongly Disagree* to *Strongly Agree*, and focused on perceptions and preferences about travel to school, particularly bicycling. The focus on bicycling was by design to examine the largest mode distinction between the three schools.

Since the surveys were administered in class, and 83% of classrooms participated, a large number of surveys were collected: 3,076 total surveys (Davis = 1,227 (71% of enrolled), Sequoia = 1,088 (54% of enrolled), Tamalpais = 761 (62% of enrolled)). Although participation was high, many students chose to skip some key questions. Case-wise deletion the sample was nearly halved. Most of this reduction was due to missing home cross streets or difficulty geocoding home cross streets, but data on parent education and some attitudinal statements was also often missing. Because of this I imputed missing data using multiple imputation by chained equations from the R statistical package MICE (Van Buuren and Groothuis-Oudshoorn, 2011).[1] I imputed five datasets through five iterations each, retained only the records with surveyed (not imputed) dependent variables (n = 2814)[2], ran each statistical model (see section 4.5.4 below) on each of the five datasets, and pooled the results for each model.

4.5.2 Defining bicycling attitudes

Likert items were designed to explore the attitudinal and perceptive 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. I reversed the scales of items with expected negative correlation with bicycling to make composite scores meaningful and for ease of item comparison. Importantly, I treat the items as exploratory measures of psychological constructs because they have not been normed in a rigorous manner. Because the items are exploratory, I chose to compare three methods of analysis in estimating bicycling attitudes as a kind of methodological sensitivity check on the relationship between bicycling attitudes and travel mode choice.

First, I assumed each Likert item represented an independent attitudinal construct, and included each directly in a statistical model (see section 4.5.4 below). The advantage of this approach is the ease of interpretation and the ability to distinguish more detailed attitudinal constructs (e.g. the difference between social pressure from parents and peers). The disadvantage being the reliability (and perhaps construct validity) of single item constructs is unknowable (i.e. no inter-item correlation).

The second and third approach both started with repeated stand-alone exploratory factor analyses

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[1] I 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). Chained equations for the Likert variables were restricted 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, I assumed the student lived beyond a reasonable walking/bicycling distance and removed walking and bicycling from those student's choice set.

[2] Removing records with an imputed dependent variable post imputation is thought to improve 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)).

(EFA)[3] and visualizations of Likert item correlations to search for groupings of items for bicycling attitude constructs. The goal was to map Likert items to constructs that were theoretically meaningful and to ensure items were primarily associated with a single construct (i.e. little to no "cross loading" in EFA). The outcomes from the EFA led me to define four factors each representing an attitudinal construct (I had a priori defined three factors based loosely on social ecological domains, but there were some serious cross loadings in the three variable EFA), and exclude two items that had very weak loadings in the four-factor model. Besides these contributions from EFA, the grouping of Likert items into four attitudinal constructs about bicycling (*Enjoyment, Self-image, Social pressure,* and *Environment* (Table 4.1)) was loosely based on the three levels of a social ecological model (interpersonal, social, environmental) (Sallis et al., 2006). I did not use factor scores generated from the EFA analyses for further modeling. The decision to not use factor scores was based on the challenge of defending all the decisions that go into an EFA (Fabrigar et al., 1999), on the inability of classic EFA to provide uncertainty in factor scores, and because a confirmatory approach has been suggested to be more dependable for making inferences when a theoretical basis exists (Costello and Osborne, 2005). After using EFA to improve the grouping of items (Table 4.1), I created two versions of these four factors (the second and third approaches to measuring bicycling attitudes). The first version (second attitude estimation approach) is a simple *composite* (or *formative* or *sum scores*) approach because the factor is formed by summing Likert items. That is, the factor includes both the common (shared) and unique variance among the items. In this way, each item is integral to the formation of the factor because it can contribute something that no other item can. The advantage of this approach is the ease in interpretation, while the disadvantage is that each Likert item gets equal weight in the formation of each factor. The equal weight assumption means differences in interpretation of Likert items by participants are not accounted for (known as "interpretational confounding") (Rhemtulla et al., 2015). For ease of discussion I refer to the constructs, also known as latent variables, estimated through simple summation of Likert items as *composite attitudes*.

The second version (third attitude estimation approach) is commonly called *reflective* measurement (this is the traditional and dominant approach to measuring latent variables in psychology) (Bainter and Bollen, 2014). Only the shared variance of the Likert items is extracted when estimating factors

[3] I estimated classic EFA models with a polychoric correlation matrix (appropriate for ordered Likert data) and an oblique transformation ("oblimin"), because it allows for factor correlation (Costello and Osborne, 2005; Fabrigar et al., 1999), on a variety of Likert items (10-15 total) thought to have bearing on bicycling attitudes. I examined EFA solutions of 3, 4, and 5 latent factors using the psych package in R (Revelle, 2016).

representing latent variables. I conducted reflective measurement by estimating an ordinal latent variable model (appropriate for ordered Likert data) akin to confirmatory factor analysis (see Appendix A for model equations). The advantage of this approach is the estimation of parameters representing the influence of each factor on each Likert item (I refer to the constructs estimated this way as *reflective attitudes*). The disadvantage of this approach is the assumption that only the shared variance of the Likert items reflects the attitudinal constructs. In addition, some Likert items arguably do not reflect a unidimensional construct but instead form parts of a multidimensional construct (see Table 4.1 for exact items). For example, the construct *Social pressure* may not be one unified construct, but instead parents, peers, and community may represent distinct sources of social pressure and norms. Lastly, the phrasing of the Likert items varies (e.g. the statement about parental pressure to bicycle is direct, while peer pressure statements are indirect (to try and minimize social desirability bias)), which may limit the items' ability to measure unidimensional constructs.

Table 4.1 Bicycling attitudinal constructs and their respective Likert items

Likert statement	Attitude	Reliability (α)*
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

* Cronbach's $\alpha = \frac{k\bar{c}}{\bar{v}+(k-1)\bar{c}}$ where k is the number of items, $\bar{c}$ is the mean item covariance, and $\bar{v}$ is the mean item variance.

4.5.3 Road Characteristics and Walking and Bicycling Environments

In addition to the in-class survey, I added several road attributes to a Geographic Information System (GIS) to describe the bicycling and walking environments in each community. The attributes include the number of travel lanes, speed limit, median presence, bike lane width, on-street parking, parking width, and signalized intersections. These attributes were obtained from local city GIS files, OpenStreetMap data, and through visual inspection of Google's Street View imagery using 2013 data when available.

I summarized the road environment through route-based instead of areal measures (e.g. buffers around trip ends, in this case home and school) because areal 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 was unavailable, I simulated plausible routes. I did this by using the same route choice set generation algorithm used in Chapter 3 based on Broach et al. (2010). Because the procedure differs slightly from that used in Chapter 3, I explain it below (with some slight repetition from Chapter 3.6.4.1).

The algorithm optimizes one road attribute[4] over a range of distance weightings. The purpose of including a range of distances is to be able to generate paths that tradeoff distance for the purpose of walking or bicycling in a specific environment (e.g. road with a bike lane). I used this algorithm (see below) over a series of road attributes and then summarized each road attribute by using an inverse distance squared weighted average of all generated paths per student. The inverse distance weighted average effectively treats shorter paths as more likely to be chosen and therefore more likely that the road environment will be experienced when walking or bicycling to school. More formally, I considered a set of road attributes **L** = {street crossings, traffic signals, two-lane roads, bike lane, bike lane without on-street parking, wide bike lane (≥14ft along parking or ≥ 6 ft not along parking), off-street paths, percent slope, adjacent to commercial land use, speed limit less than 25 mph, BLTS[5] level 1, BLTS level 2, BLTS level 3}, and a set of distance weights representing the percentage of influence distance has on edge cost compared to the road attribute **D** = {0.95, 0.9, 0.75, 0.5}. I then:

- Define the cost for each network edge based on distance only and call that the first network.
- Define the cost for each network edge by each road attribute and distance weight combination:
  $C_{ijk} = D_j * \delta_k + \left(1 - D_j\right) * L_i$
  Where C_{ijk} is the cost for one road attribute *i*, and one distance weight *j* on edge *k*; δ is the edge length, and D_j and L_i are distance weights and road attributes respectively. This results in 53 unique networks (4 distance weights * 13 road characteristics + 1 network based only on distance) for each school.
- 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.
- For each student, calculate inverse squared distance weighted road attributes based on the

[4] Often called a *label* in the route choice modeling literature (hence the use of **L**), but I use *road attribute* because it is more concrete.
[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).

relative length of each path compared to the alternative paths. The distance weight effectively gives attributes of shorter paths more weight because they are more likely to be taken by the student (see Figure 4.1 below for a visual example). The equation for one student *s* and one road attribute *i* is:

$$L_{si}{}^{*} = \sum_{p} L_{spi} \times \left(\frac{\left(\frac{1}{\delta_p / \left(\sum_p \delta_p\right)^2} \right)}{\sum_p \left(\frac{1}{\delta_p / \left(\sum_p \delta_p\right)^2} \right)} \right)$$

Where δ_p is the distance for the path *p*, and $\sum \delta_p$ is the sum of all the path distances. An $L_{si}{}^{*}$ statistic exists for every student *s* and road attribute *i*.

For example, assume a student has three paths (A, B, C) with lengths 0.6, 0.5, 1.0 miles and percentage bike lane along those paths 50, 30, and 80% respectively (Figure 1). Using the equation in step 5 above, each path gets a statistic that represents the distance weighted bike lane percentage. This ensures that short paths are given greater weight than longer paths when summarizing the road environment. In Figure 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 value of 51% bike lane (18% + 13% + 2%). This represents a distance-weighted bike lane percent based on plausible paths to school. We estimate these plausible path road environment variables prior to and independent from the following models of travel behavior.

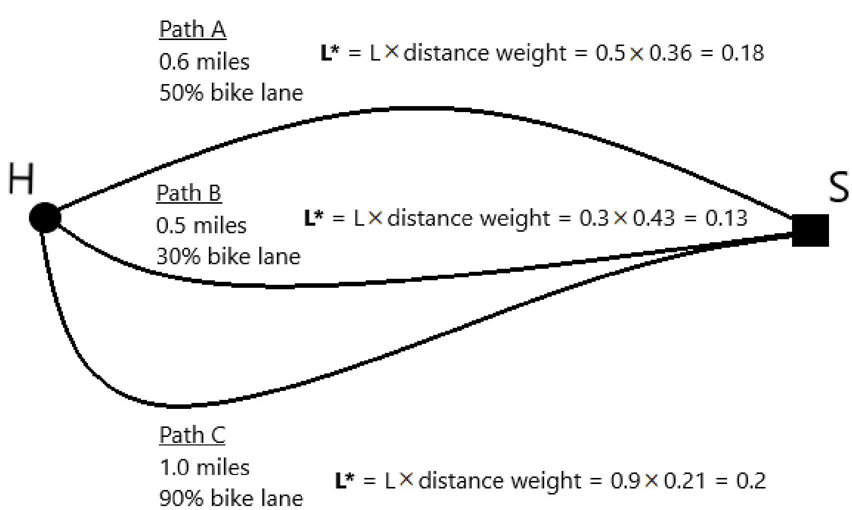

Figure 4.1 Diagram of three home to school paths for one student and the resulting distance weighted statistics for each path based on percentage of bike lane along each path.

I estimate these plausible path road environment variables prior to and independent from the following models of travel behavior.

4.5.4 Model Development and Analysis of Behavior

Along with bivariate summary statistics, I 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 4.2 for model descriptions). I specified the models by selecting variables that have prior evidence for influencing teen mode choice. Socio-demographic and travel constraint type variables are in all models (Table 4.2), road environment variables in models 3 and 7, and attitudes in models 4 through 7. I constrained the models such that the travel mode categories were dependent on the realistic choices available to each student (see Appendix A for model equations, although for clarity I ignore the varying choice sets in the notation). In this application, it is appropriate to constrain mode choices (often termed a "varying choice set" model) because some students are not licensed to drive or live beyond a reasonable distance to walk or bicycle to school (i.e. these options are not in their individual choice sets).

I use three approaches to examine the relationship between student attitudes and high school mode choice (see section 4.5.2). In the composite attitude models, attitudes are measured data like any other independent variable and so they enter the regression models as linear in parameters; thus, the model form of the base model (Table 4.2) is unchanged. The reflective attitude model (ordinal latent variable) is jointly estimated with the categorical model (for mode choice). In the transportation literature, the combination of a latent variable and discrete choice model (a categorical regression is one of many discrete choice models) is often called an integrated choice and latent variable model (ICLV) or a hybrid choice model (HCM). These models have been used to evaluate the influence of latent variables in the economic framework of utility maximization (Ben-Akiva et al., 2002; Kim et al., 2014), and recently have been used to jointly model teenage attitudes and travel behavior (Kamargianni et al., 2015, 2014; 2014 (2)). The common argument for these complex models is improved statistical efficiency (i.e. improved standard errors), and the ability to jointly measure latent variables and travel outcomes. However, there is an ongoing debate about the utility of such models (Vij and Walker, 2016). The only other added complexity in the modeling is a varying intercept by school because of the clustered nature of the data. This is a common approach in statistics to relax model assumptions (Train, 2009) and improve inference (Gelman and Hill, 2007).

Table 4.2 Model descriptions

Model Name	Predictor variables and constraints*
(1) Base	Distance, age, gender, parent bachelor's degree or higher, not White or Asian, parking access, driver's license (constraint for drive choice), live in town (constraint for walk/skate and bike choices)
(2) School	Base model with varying intercept for school by alternative
(3) Road Environment	School 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%)
(4) Attitude as Likert items	Road Environment model with attitudes as raw Likert items
(5) Attitude (Composite)	School model with equal weighted item sums for four factors (Enjoyment, Self-image, Social pressure, Environment)(see Table 4.1)
(6) Attitude (Reflective)	School model with four factors estimated by an ordinal latent variable model (Enjoyment, Self-image, Social pressure, Environment)(see Table 4.1)
(7) Full model (with Composite attitudes)	Road Environment model with composite attitudes (combination of models 3 and 5)

* All variables are individual specific with alternative varying parameters.

I 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. In addition, the integrated choice and latent variable model has no closed form and must be estimated through simulation. Although most applications in the transportation literature continue to use some form of maximum likelihood, there are cases of Bayesian estimation (Daziano, 2010). In all models I use so called *weakly informative* prior probabilities to guard against overfitting (Gelman, 2006) (see Appendix A for model equations and specific priors). Through the R statistical package *Rstan* as an interface for the probabilistic statistical programming language Stan, I used the No-U-Turn (NUTS) sampler, a form of Hamiltonian Markov chain Monte Carlo (MCMC) to estimate the models (Stan Development Team, 2017).

Because I imputed missing data prior to model estimation instead of treating the missing data as parameters in a traditional Bayesian multiple imputation, I 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, I pooled all 15 chains (3 chains * 5 datasets) to assess the full uncertainty across all imputations.

I use in-sample predictions[6] of mode choice of each of the 5 datasets and pool the results to assess model performance. I 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 are on the deviance scale and can be 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).

4.6 Results and Discussion

4.6.1 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 (Figure 4.2). 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 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 Section 4.6.4-4.6.6.

A form of car travel (e.g. single occupancy vehicle, carpool, parent drives, etc.) is the dominant mode to school for teenagers at all three schools, and the share of active modes declines by age (Figure 4.2). This is good evidence that these schools are at least similar to many suburban located high schools 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 (Figure 4.2). This is especially true in Davis, where bicycling declines precipitously as it is presumably replaced by driving.

Mode to school varies by parent education, race, and student driver's licensure (Table 4.3). Parent

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

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. access to their own car). However, higher parent education is also associated with more bicycling (Table 4.3). Similarly, White and Asian students drive and bicycle at greater rates compared to other ethnicities suggesting possibly another surrogate for income, perhaps a cultural difference, or maybe a spurious relationship given the greater percent of Asian students in Davis (e.g. 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 driver's license holding students. Although the percentage of the sample is small for students with a driver's license who don't drive to school, it is suggestive that licensure has a larger impact on decreasing chauffeuring than it does on decreasing walking/bicycling which is consistent with other reports of licensure impacting teen travel (McDonald et al., 2015).

Travel mode is fairly consistent across genders. The only clear difference is that females bicycle less and are chauffeured more than males (Table 4.3). This gender difference (chauffeured substituting for bicycling) is less pronounced in Davis, with 41% of bicyclists who are female, compared to 24% and 21% at Sequoia and Tamalpais, respectively. In the following sections I focus on how the road environment and bicycling attitudes explain these differences through multivariable analyses.

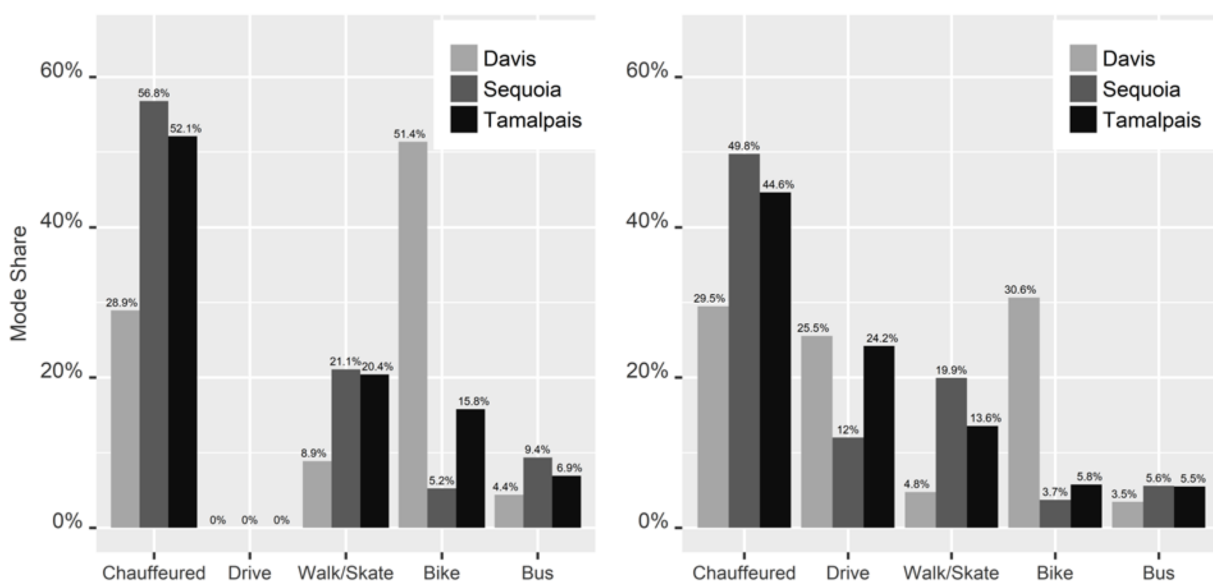

Figure 4.2 Self-reported most common travel mode to school: mode to high school (left), mode to middle school (right).

Table 4.3 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

4.6.2 Statistical model evaluation

I present model estimation results and parameter summaries in Appendix B. Before addressing the primary research questions which involve drawing inferences from model parameters, I evaluate the success of each model through model comparisons. The predictive success of the models varies dramatically by travel mode. In comparing the models, clear improvements are seen in predictive abilities as models are expanded in complexity. Figure 4.3 shows two "confusion" plots of the in-sample mode choice predictions using the base and full model. 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). Predictions from the other models (not shown) have accuracies in between these two example plots. Most prominent in Figure 4.3 is the misclassification of students who were bussed to school. Most of those students are misclassified as having been chauffeured. This is not surprising given that there is no variable representing household income (only surrogates), which is known to correlate (negatively) with bussing to primary school (McDonald, 2008). Nor are there measures of attitudes pertaining to bussing or variables about bussing availability in the models. Although not included in the model, the survey had a single Likert item "I like riding the bus". But even that doesn't have a strong correlation with bussing, perhaps because those that ride the bus do so out of necessity. Similarly walk/skate is often confused for chauffeured which is 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.

Model prediction is improved when road environment and attitudinal variables are included, especially in the classification of bike (the focus of the study) and marginally so for walk/skate. The inclusion of bicycling attitudes is where the bulk of the prediction improvement is made. This is also the case when estimating out-of-sample prediction (Table 4.4). Estimated out-of-sample prediction results suggest the road environment variables offer only about half of the improvement gained from the attitude variables (Figure 4.4). However, when both attitudes and road environment variables are included, their combined influence is additive resulting in the best performing model (Figure 4.4).

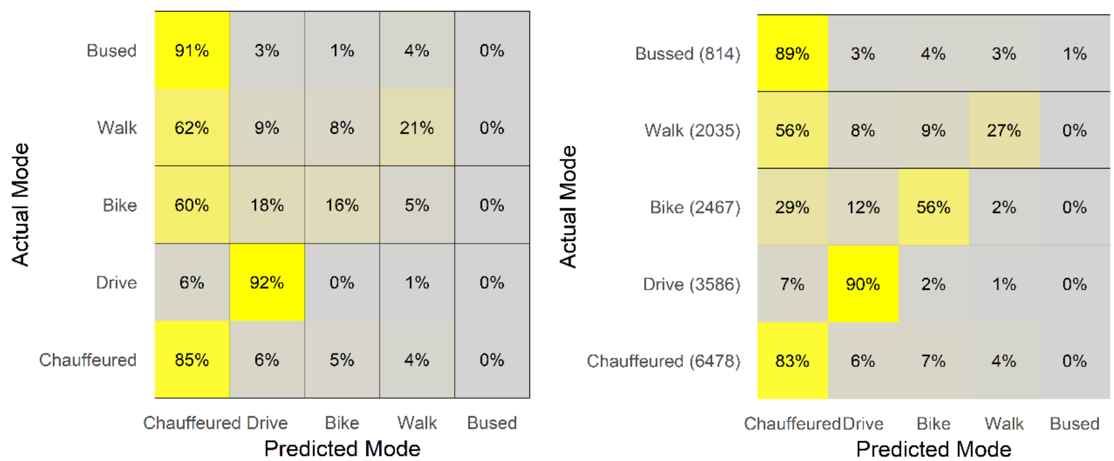

Figure 4.3 Confusion plots for base model 1 (left) and full model 7 (right). Numbers and color gradient represent percent matching classification.

TABLE 4.4 Estimated Out-of-Sample Prediction through Information Criteria

	LOOIC*	(se)	p_{LOO}	(se)	WAIC*	(se)	p_{WAIC}	(se)
(7) Full (Attitude Composite and Road Environment)	4551.2	(94.1)	150.0	(9.3)	4566.7	(95.0)	157.7	(10.5)
(4) Attitude Likert	4645.3	(105.8)	180.5	(22.3)	4746.8	(131.7)	231.3	(43.5)
(5) Attitude Composite	4752.5	(107.3)	178.5	(24.6)	4855.4	(135.3)	230.0	(46.5)
(6) Attitude Reflective[7]	4770.2	(107.1)	448.9	(27.5)	4826.4	(133.3)	477.0	(46.9)
(3) Road Environment	4881.4	(92.6)	156.2	(9.3)	4897.1	(93.5)	164.0	(10.5)
(2) School	5100.9	(104.7)	183.9	(23.6)	5199.7	(131.2)	233.3	(44.6)
(1) Base	5475.8	(104.6)	177.6	(25.6)	5589.7	(137.4)	234.6	(49.8)

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

[7] Both WAIC and LOOIC estimates had diagnostic warnings suggesting their instability in assessing model 6 suggesting they may be poor estimates of out-of-sample prediction.

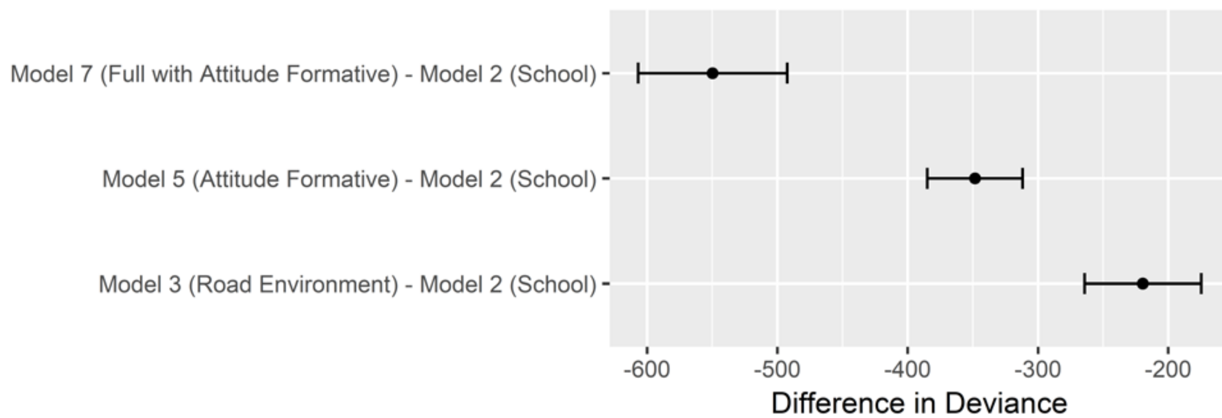

Figure 4.4 Mean and standard errors of differences in deviance as calculated by LOOIC. These model comparisons illustrate the improvement (decrease in deviance) in model performance by adding road environment, attitudes, and both road environment and attitude variables.

4.6.3 Attitudes about bicycling

Some Likert items had strong within-school consensus and between-school differences. For example, unlike Sequoia and Tamalpais students, Davis students have consensus that they are comfortable bicycling on a busy street, have a safe route to bicycling to school, and that people in their community bicycle (not shown). Because the survey is cross-sectional, it is unclear whether the school environment and travel behavior of students are causing these different perceptions about bicycling or the reverse. What is clear is there is both more bicycling and more favorable perceptions about bicycling in Davis.

The relationship between Likert item response and travel mode is further explained through parameter values in Model 4 (Figure 4.5). 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 (Figure 4.5). 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 living too far to bicycle was negatively associated with bicycling (not perceptions of hilliness and safety). This is surprising because other evidence 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 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, clear differences in the relationship between the items and bicycling exist (Figure 4.5). 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 perception of bicycling in student's community and their bicycling to school. Collinearity of predictors is not the cause for this result given correlations are never stronger than r = 0.33. Perhaps the negative relationship is another indication of the major difference between the schools (i.e. most Davis students strongly agree 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). However, given that Model 4 is already conditional on school, this explanation is insufficient. Adding to the confusion, the bivariate relationship between bicycling and this item ("lots of people bicycle in my community") shows a slightly positive relationship (r = 0.22). This suggests that something about socio-demographics and school cause the community bicycling item and student bicycling relationship to flip (given Model 4 is conditional on socio-demographics). One thing is clear, the contributions of parent, peer, and community pressures to bicycle are likely unequal. Given I estimate peer and community pressures from indirectly worded Likert items, it would be prudent to verify these specific results in future studies, perhaps with an additional comparison with more directly worded items.

Some attitude results from single Likert items in this study (from Model 4) 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) isn't ideal (they used a binary bicycling/not bicycling model instead of multinomial 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 4 (see Appendix B for parameter means) gives odds ratios of 1.2 and 2.0 for those same items. This suggests that perhaps attitudes about bicycling have a consistent association with bicycling independent of the urban context. However, we should be cautious in drawing conclusions that the attitude/bicycling relationship will always be consistent across urban contexts for two reasons. First, like Emond and Handy (2012) I assume the category responses on the five-point Likert scale are interval (i.e. equal interval between each category), even though this may hide nuanced differences between student responses. For example, the difference between *neutral* and *agree* for statements about the perceived bicycling environment may be different for Davis and Sequoia students given that they are exposed to very different bicycling environments. Second, measuring attitudinal constructs from a single Likert item is prone to poor construct validity. Measuring a construct with one item holds the strong assumption that interpretation of that item is completely consistent between subjects and that the item fully represents a construct. For these reasons, I compare alternative estimates of bicycling attitudes.

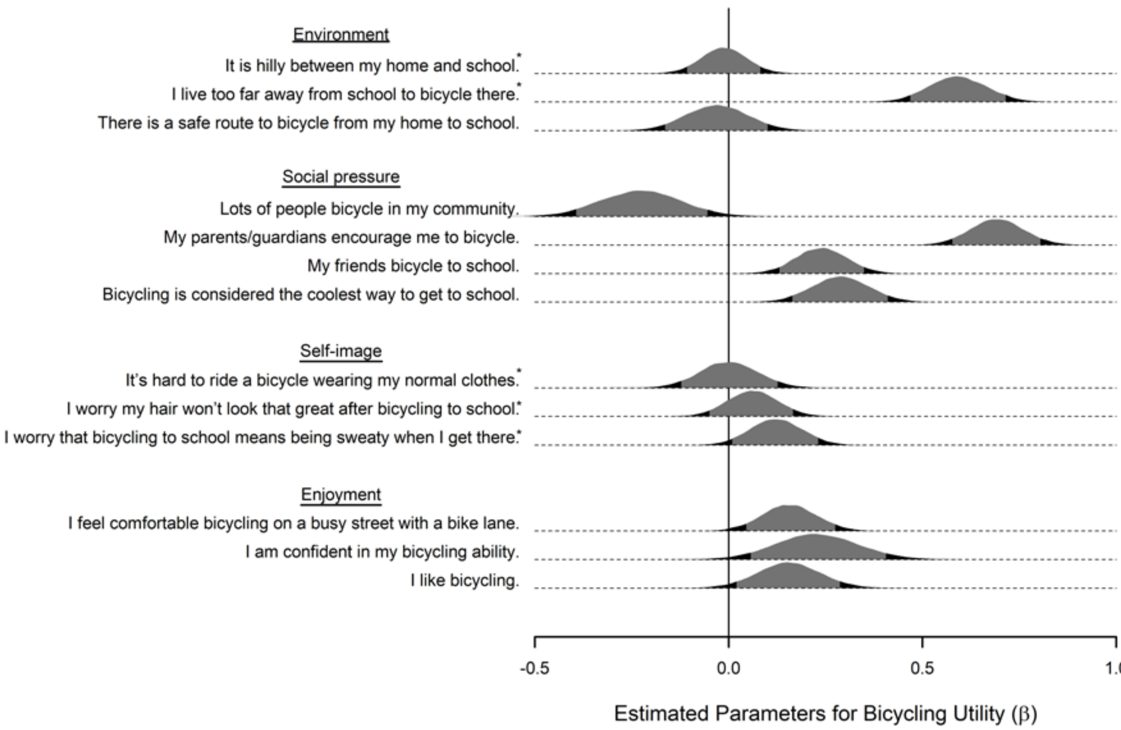

Figure 4.5 Posterior distributions of parameters reflecting the association between each Likert item and bicycling to school compared to being chauffeured conditional on the other variables specified in model 4. Likert variables are treated as interval (hence the assumption that the difference between Likert categories are equal). A unit increase in a Likert variable is equivalent to the difference between, for example, "neutral" and "agree" or "agree" and "strongly agree". The grey portions of the posterior densities for the parameters are the 90 % highest probability density intervals (HDPIs). Reversed scales reported for * items to allow composites of items worded in the positive and negative, and to allow clear comparison between composites.

I created composite bicycling attitudes prior to multivariable modeling because they are simple sums of Likert items. These attitudes were on average most positive for Davis students and most negative for Sequoia students (Table 4.5). It was expected that the Davis students would have the most positive attitudes about bicycling due to the high bicycling mode share. 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 (Figure 4.1), but could also be associated with recreational bicycling (Tamalpais High has the only mountain bike team amongst these schools). In addition, the composite attitudes and travel mode association is stronger than the composite attitude and school association (Table 4.5). This suggests that the composite attitudes are not just a reflection of bicycling culture in Davis, but instead generalizable factors across schools.

Table 4.5 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

To compare the composite and reflective bicycling attitudes I extracted the posterior latent variable estimates from Model 6. The composite and reflective attitudes are moderately correlated: *Enjoyment* (r = 0.74), *Self-Image* (r = 0.74), *Social Pressure* (r = 0.71), *Environment* (r = 0.58), when considering the full uncertainty of the reflective bicycling attitudes. The correlations are much stronger: *Enjoyment* (r = 0.86), *Self-Image* (r = 0.96), *Social Pressure* (r = 0.86), *Environment* (r = 0.74), when considering only the mean estimate of the reflective attitudes. This suggests that the two approaches are measuring similar constructs. The differences between the approaches are a function of the difference between the common (reflective) and combined common and unique (composite) item variance, and the estimated uncertainty in the shared item variance for the reflective estimates. The "loading" parameters of the reflective attitudes (Figure 4.6) describe more specifically the differences between the composite and reflective approaches. This is because the composite attitudes have essentially equal "loading" since they are simple sum scores.[8] For the reflective attitudes, the loadings indicate that *Environment* is predominantly about perceived distance and safety, and less about hilliness; *Social pressure* is more

[8] composite scores can be weighted, but in this case they are not.

influenced by perceptions of parents and community, less so by peers; *Self-image* is more about appearance of hair and sweatiness, and less about the barrier of students not being able to wear the clothes they want when bicycling; *Enjoyment* is nearly equally determined by comfort, confidence, and liking bicycling.

Although the composite and reflective attitudes are correlated, they have considerably different associations with bicycling in the mode choice models (Figure 4.7). The composite attitudes all have confidently positive associations with bicycling compared to being chauffeured, while the uncertainty in the reflective attitudes suggest that only *Social pressure* has a confident positive association with bicycling. The large scale of the posterior distributions for the reflective attitudes and the fact that *Enjoyment* is confidently negative are counterintuitive results. The negative effect of *Enjoyment* is likely due to the correlation between *Enjoyment* and *Social Pressure* (r = 0.87) leading to the so called "suppression effect" in regression (Friedman and Wall, 2005). The composite scores for *Enjoyment* and *Social Pressure* exhibit a much weaker correlation (r = 0.46) which may be why the results from Models 5 and 6 differ (Figure 4.7). In other specifications for Model 6 where only one latent variable was estimated at a time (not shown), the posterior distributions for the parameters more closely resemble the posteriors from the composite attitudes in Model 5 (i.e. no negative effects, and smaller posterior scales). The potential for suppression and the inconsistent results for restricted specifications of Model 6 indicates a clear problem for interpreting the latent variable regression parameters in Model 6 (Figure 4.7). Does *Social Pressure* really have an order of magnitude stronger association with bicycling than *Environment* and *Self-image*? Model 5 suggests possibly a relationship that is twice as strong (doubling of the odds ratio), while Model 6 suggests something substantially greater and more uncertain (OR difference of 10-250). The most conservative inference to make about Model 6 is that *Enjoyment* and *Social Pressure* are not separable using the reflective approach described in section 4.5.4, therefore their marginal effects are untrustworthy. This does not mean the constructs are not unique (in theory they are), just that estimates in Model 6 are highly suspect. With this said, these results suggest the need for further research into the operationalization (specification and estimation) of attitudinal constructs in the context of travel behavior models. I chose to expand Model 5 and not Model 6 for the reasons already alluded to and summarized here: (1) Likert items had some cross-loadings during exploratory factor analysis which suggest that the attitudinal constructs are not fully separable, (2) Likert item phrasing may be more indicative of multidimensional constructs in which a composite model is more appropriate, and (3) evidence for suppression due to high collinearity between *Enjoyment* and *Social Pressure* make interpretability of the reflective attitudes difficult.

Model 5 most closely corresponds with expected associations between attitudes and bicycling. In addition, the results highlight the magnitude of differences between attitudinal construct associations with bicycling. For example, students with one standard deviation above the average of *Social Pressure* to bicycle are three times more likely to bike compared to being chauffeured, whereas students who report self-image is unaffected by bicycling (*Self-image*) are less than 1.5 times more likely to bike compared to being chauffeured. This suggests that some bicycling attitudes are more important than others, specifically *Social Pressure* and perceptions of the road environment (*Environment*).

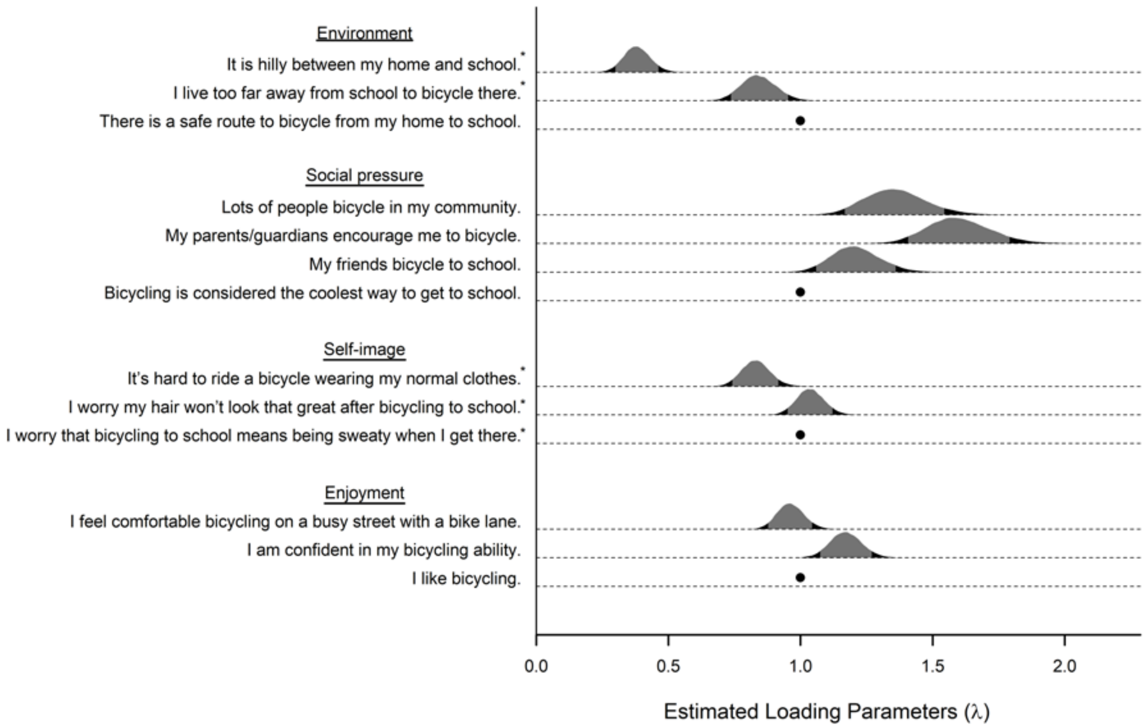

Figure 4.6 Posterior distributions of parameters reflecting the item loadings for each latent variable (reflective attitudes) conditional on the other variables specified in model 6. Dots represent parameters constrained to 1.0 for identifiability, and grey portions of the posterior densities for the other parameters are the 90 % highest probability density intervals (HDPIs). Items with * indicate the scale has been reversed prior to inclusion in the latent variable model.

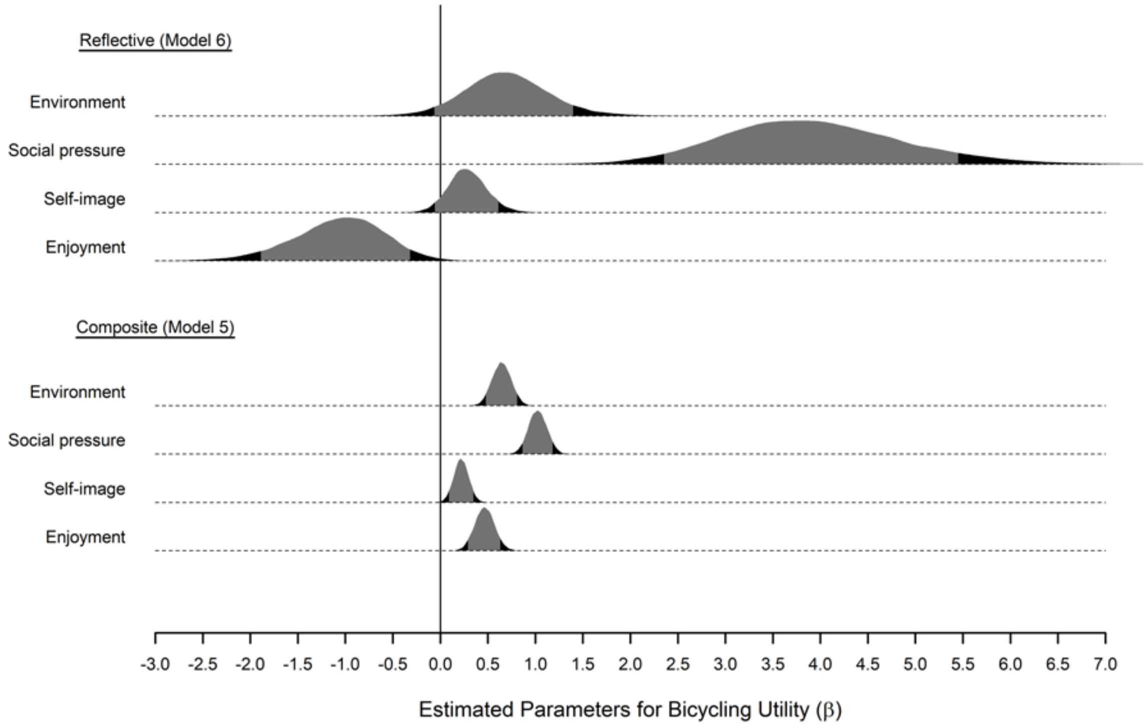

Figure 4.7 Posterior distributions of parameters reflecting the association between attitudes and biking to school compared to being chauffeured conditional on the other variables specified in models 5 and 6. The grey portions of the posterior densities for the parameters are the 90 % highest probability density intervals (HDPIs).

4.6.4 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. Figure 4.8 shows the distribution (grey "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. Figure 4.8 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. Sequoia and Tamalpais paths 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. The steepness of the terrain around Tamalpais (even though it is downward sloping toward the school) probably acts as a strong barrier for bicycling to school. Because most students travel by the same mode to and from school, it is likely that the positive slope on the return trip is the deterrent for bicycling at Tamalpais.

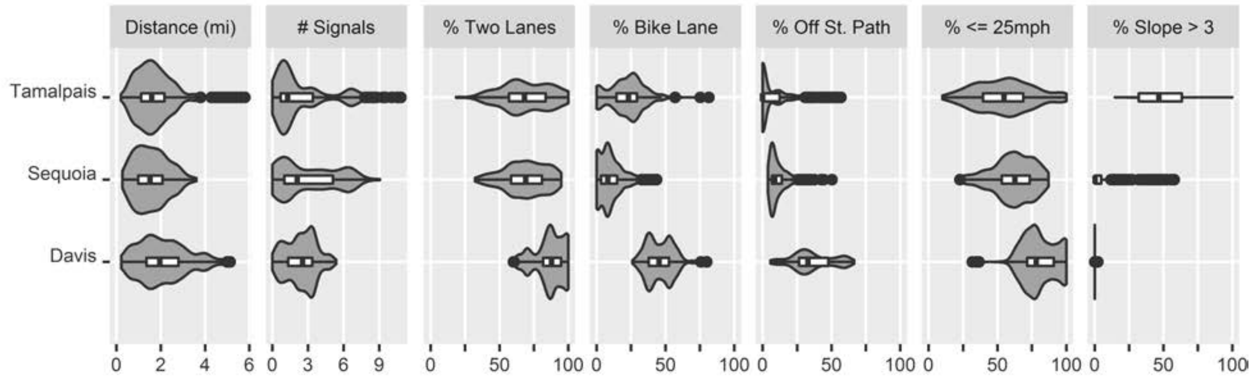

Figure 4.8 Bivariate box and violin plots of distance weighted road environment variables along plausible paths to school by school.

Differences in road environment variables by mode are more moderate compared to differences by school (Figure 4.8 and 4.9). Distances are clearly shortest for walk/skate, and therefore number of traffic signals are fewest. Compared to other modes, percent of two lane roads, bike lanes, off street paths and slow speed roads are marginally greater for students who bicycle, and marginally less for those who walk/skate. This suggests that students may be walking when the road environment is not conducive for safe bicycling. It also suggests that for students who travel by the other travel modes (bussed, chauffeured, and drive), their paths to school are likely more stressful and less comfortable for bicycling. This is especially true considering that each of these variables (besides distance and slope) contribute to a different aspect of comfort and safety, and students who don't bicycle tend to have lower levels of these features along plausible paths to school.

The marginal effects of each road environment variable on walking and bicycling are best represented by the posterior densities of the parameters in Models 3 and 7 (see Figure 4.10 for Model 7 estimates). There are several noteworthy observations about Figure 4.10, starting with the 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 the use of mean percentages for each road environment variable along plausible paths to school. Had there been 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. Slow-speed roads have a more uncertain influence on walking since two lane and low speed limit roads do not align in their effects. 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 is evident from Figure 4.10 where the walk/skate group has the lowest percent two lane and low speed limit roads in their plausible paths. The dependence of the results on the actual choices students have is important because the model has a greatly simplified view of each student's plausible paths. If walkers don't 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 it is theoretically sound that 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 Figure 4.10 as well. For bicycling, the influence of distance is clearly negative, but less so than for walking.

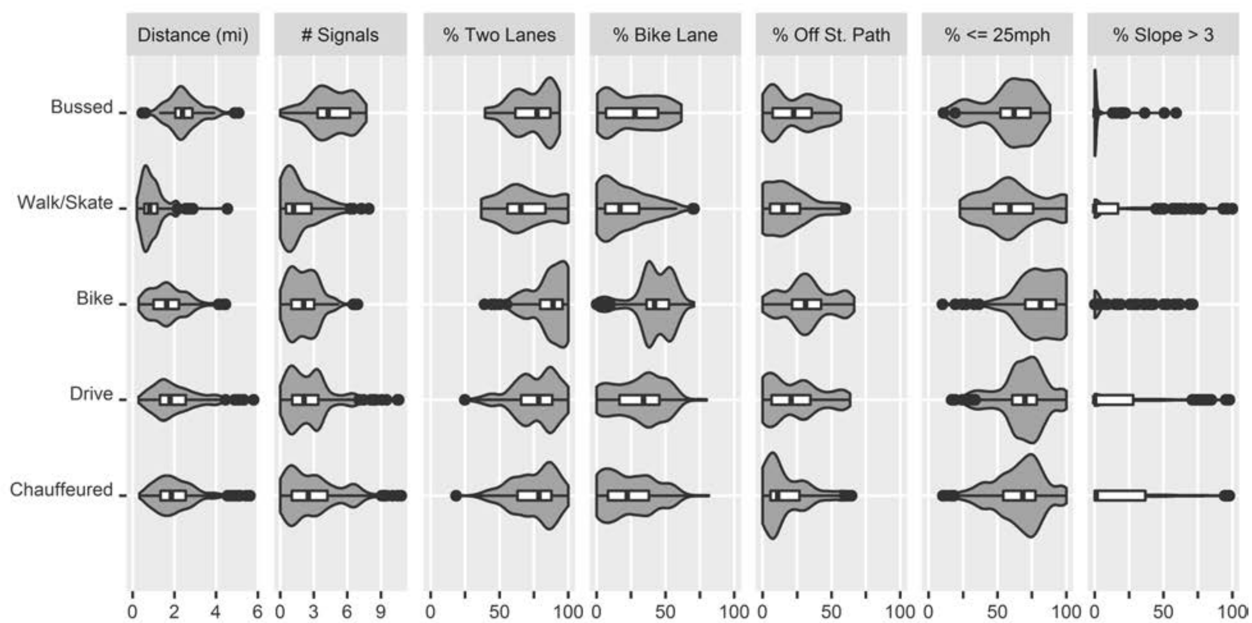

Figure 4.9 Bivariate box and violin plots of distance weighted road environment variables along plausible paths to school by travel mode.

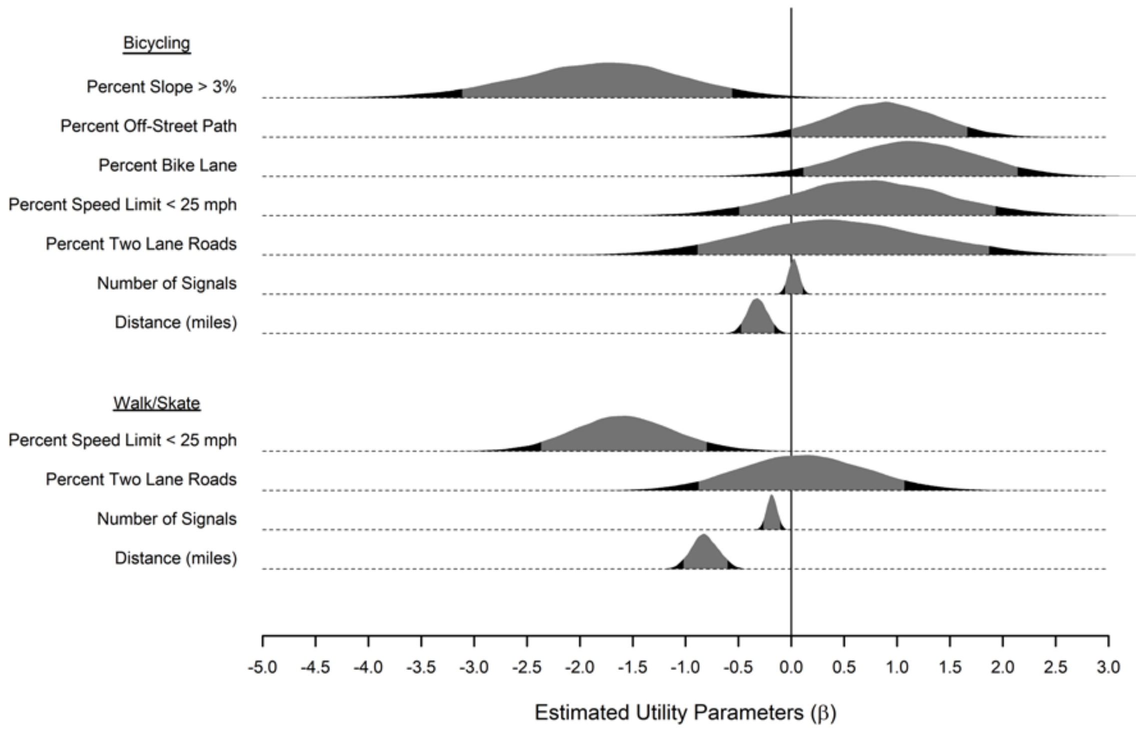

Figure 4.10 Posterior distributions of parameters reflecting the association between road environment variables for both walking and bicycling to school compared to being chauffeured conditional on the other variables specified in model 7. The grey portions of the posterior densities for the parameters are the 90 % highest probability density intervals (HDPIs).

4.6.5 Road characteristics in relation to perceived environment

Correlations between hilliness and distance to school estimated based on network data (road environment variables) and based on survey responses (Likert response variables) are moderate (*r* ~0.4-0.5). This correlation suggests a reasonable alignment between objective and subjective measures of the road environment. The lack of a stronger correlation may be due to differences in perception among students, but it is also likely due to the imprecise way I generate the road environment variables (i.e. data on actual paths was not surveyed). Likert responses about safe bicycling access have much weaker correlations with road environment measures (e.g. percent bike lanes, low speed roads, etc.) (*r* ~ 0.01-0.12). This suggests that some important road variables could be missing that influence students' perceived safety. It could also be that interactions of road measures need to be considered when testing their correlation with perceived road safety.

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

Both the road environment and bicycling attitudes have thus far been examined in association with travel mode, but the magnitude of their relationships with travel mode has been difficult to assess since the predictor variables are on different scales and the coefficients are on the log-odds scale. From model comparisons, we see that bicycling attitudes are nearly twice as strong predictors of mode choice compared to the road environment (Table 4.4). However, it isn't clear what that means in terms of numbers of students choosing to walk or bicycle to school. To better understand the magnitude of these relationships, I use counterfactual predictions of travel mode based on differences in road environments and attitudes. This does not assume a causal model (i.e. the question is not: how does changing the road environment for student X, change the likelihood of student X bicycling?). Instead, it is: considering hypothetical cohorts of students (e.g. a future class) with varying road conditions and bicycling attitudes, what is their mode share? In this way, we can see the associations on the outcome scale 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 often used when modeling with cross-sectional data and latent variables. I use this 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.

I assume the simulated students resemble the sampled students by leaving unchanged all variables (see Table 4.6 base scenario). Then I 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 4.6). 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. Figure 4.11 shows the predicted probabilities for all 6 scenarios (Table 4.6). 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 (9 p.p.) and walking (10 p.p.), with predominantly fewer students being chauffeured (-16 p.p.). The lack of strong negative difference in drive (-3 p.p.) for this scenario suggests that even when distances are short and environments are conducive for 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 (15 p.p.) and a large negative difference in chauffeured (-11 p.p.). This result suggests that attitudes have a stronger influence on bicycling than do distance and road environment variables (also supported by model comparisons in section 4.6.2). However, this result is complicated by the fact that the *Environment* attitude represents students' perceived bicycling environment. While the correlation between this attitude and objective measures of the road environment is weak, this attitude may be capturing other attributes of the road environment that make for safe and comfortable bicycling that are not objectively measured. This is all to say that there is no clear distinction between attitudes and environmental variables, even though these results suggest that attitudes are more powerful predictors of bicycling.

The last scenario, which combines 20% improvements in attitudes, road environments, and distance, shows that bicycling can see a positive difference of nearly 29 p.p. compared to the baseline scenario. This result suggests there is little overlap between the road environment/bicycling and attitude/bicycling relationships (as defined in this study). The "effects" of improving the road environment and attitudes seem to be nearly additive on bicycling (also supported by model comparisons in section 4.6.2). 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 when distances to school were reduced. This suggests that improvements to the road environment that benefit both bicycling and walking will likely only influence bicycling. It isn't until students live much closer to school that students will consider walking. A major caveat to this inference is that this analysis lacked good objective data on walking 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 estimate from the model (Figure 4.11). This is likely because I restricted the choice set for students based on driver's licensure and access to a car. One might argue that these variables are bidirectionally causal (i.e. a student who wants to drive to school will acquire a license to drive just as a student who acquires a license to drive will do so because they want to drive to school). However, it is more likely that the licensure/drive to school relationship is a hierarchical decision process where the decision to get a license is caused by many other factors besides the trip to school. In this view, licensure acts as a prior decision and therefore a constraint on driving to school (as I've modeled it). What is more interesting about the driving predictions is how little they differ across scenarios (Figure 4.11). This 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 4.6 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.)

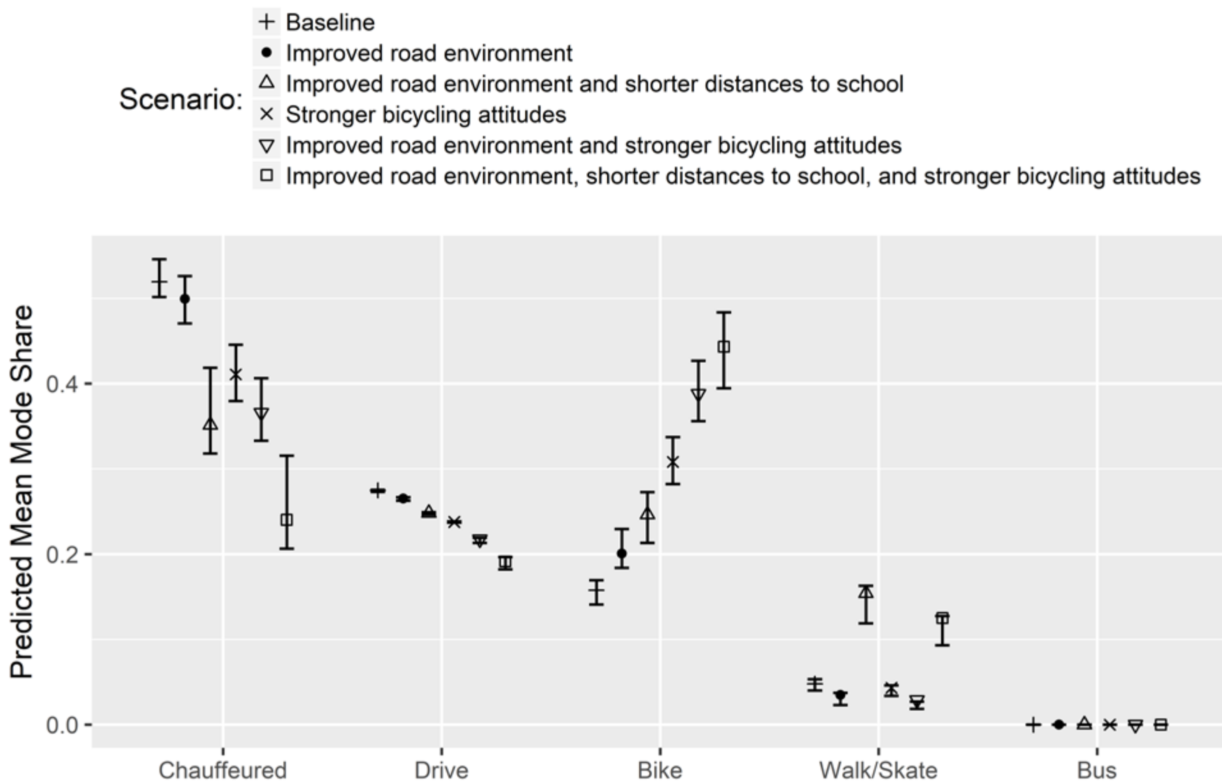

Figure 4.11 Predicted travel mode shares to school (mean and 90% HPDI) by scenario.

4.7 Conclusions

Bicycling studies in Davis, CA can allow unique insights into bicycling behavior (because bicycling is a normal travel mode), but they lack the ability to generalize 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 the bicycling of teenagers that generalizes beyond Davis. Nonetheless, these three schools only represent "suburban" style communities with large shares of teens with car access, and any attempt to generalize to dense urban or rural environments where car availability differs is likely to fail. Considering the prevalence of "suburban" high schools, plenty of environments exist where these results should generalize.

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 bidirectionally causal (e.g. attitudes, driver's licensure). This makes inference challenging. Nonetheless, the evidence we have replicates many associations between socio-demographics and teen travel (See Appendix B 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.

The strongest attitudinal associations with bicycling are social. Whether social pressure is unidimensional or multidimensional (e.g. distinct parent, peer, and community), next to providing safer and more comfortable bicycling environments (as measured both objectively and subjectively), social pressure may be the most influential variable/s for bicycling to school. However, these associations are only in the context of having reasonable travel distances. This is also true of the relationship between the road environment and walking to school. When distances to school are long, attitudes and road environments have weak associations with walking and bicycling to school. The problem of distance is complex because it not only relates to the siting of schools, residential density, and freedom of school choice, but it relates to residential location decisions of families, which are driven by socio-economics and nuanced attitudes and preferences.

What do these results say about potential interventions to increase walking and bicycling to high school? The cross-sectional nature of the data limits conclusions that changing the road environment and attitudes will result in changes in current student behavior. However, the 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 can successfully improve the road environment for future students. In addition, given that school choice may be inadvertently driven more by social status than school quality (Holland and Holme, 2002), in many cases it is possible that high quality schools are closer to home than many parents think. Educating parents about the specific strengths and programs at local schools may help encourage local school attendance. This of course depends on the ability of a local school to compete with neighboring schools. When a school is unable to retain residents, they might consider the specific needs and desires of residents for school reform. School choice is a complex process that in many cases likely precedes travel mode choice. The existence of magnet schools (e.g. schools which attract students from across the district because they have a program not offered elsewhere) and the consolidation of school campuses pose a significant challenge to getting teens to actively travel to school. Nonetheless, in general, increasing local attendance should reduce travel distances resulting in greater walking and bicycling to school. 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 attitudinal constructs (e.g. social pressure) may have more theoretically straightforward causal chains from attitude to behavior (i.e. a student is likely to agree there is a social pressure for them to bicycle before they begin bicycling, not after they begin bicycling).

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 policies should begin by evaluating improvements to road environments along plausible paths, promotions of local attendance, and programs to generate social pressure to walk and bicycle. In addition, because the attitude/behavior relationship may be stronger in the opposite direction, programs nudging behavior directly (e.g. foot-in-the-door type techniques (Burger, 1999)) may also prove successful.

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Appendix A. Model Equations

Model 6 is presented below in its general form. Each of the prior models are slight variations in predictor variables which can be seen in the parameter results (Appendix B). The discrete choice component of the models is as follows:

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

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

$$\alpha_{j,school[i]} = \tilde{\alpha}_{j,school[i]} * \sigma_j$$

Priors:

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

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

$$(\gamma_{11}, \dots, \gamma_{mj}) \sim Normal(0\ ,2)$$

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

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

Where y_i is the travel mode choice for person *i*; U_{ij} is the utility of choice alternative *j* for each person (note: this is equivalent to the classic formulation of utility ("representative utility" and error components) in that the error components are inherent in the sampling of all parameters); α_j is the alternative specific constant; $\alpha_{j,school[i]}$ is the alternative specific constant that varies by school, indexed by person (varying intercept), and is scaled by σ_j, the alternative specific school standard deviation (I scale the varying intercept by the standard deviation to improve sampling. This is known as the non-centered parameterization (McElreath, 2015)); $\tilde{\alpha}_{j,school[i]}$ is the unscaled varying intercept; $\sum_{m=1}^{M} \beta_{mj} X_{mi}$ are alternative specific regression coefficients (β_{mj}) for variables (X_{mi}) for number of variables M; $\sum_{w=1}^{W} \gamma_{wj} \eta_{wi}$ are the alternative specific regression coefficients (γ_{wj}) for the latent variables (η_{wi}) for number of latent variables W. When dropping subscript *i* for clarity, the categorical logit sampling statement 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 the situation of students living beyond a reasonable walking and bicycling distance (which I define as off the GIS network for which I had coded road environment variables), a varying choice set model is appropriate. This entails a reduction of *J* for students living beyond the GIS network. In addition, students who do not have any form of driver's license cannot legally drive and so drive is not considered in their choice set[9]. To avoid making the notation more confusing, I have not included this in the above model. However, I do limit the choice set (*J*) to one of four based on home location and reported driver's license (see Appendix C for Stan code). The sets are: {chauffeured, bussed}; {chauffeured, drive, bus}; {chauffeured, bike, walk, bus}, {chauffeured, drive, bike, walk, bus}

The latent variable regression term ($\sum_{w=1}^{W} \gamma_{wj} \eta_{wi}$) only exists for model 6 which jointly estimates the above model with the following latent variable model:

$$
\begin{aligned}
\mathrm{I}_{ri} &\sim \text{Ordered Logit}(\phi_{ri}, \tau_{rt}) \\
\phi_{ri} &= \lambda_r(\eta_{wi}) \\
\eta_{wi} &= \left(\begin{pmatrix} \sigma_{\eta_1} & & \\ & \ddots & \\ & & \sigma_{\eta_w} \end{pmatrix} (L)(\tilde{\eta}_{wi}) \right)^{\boldsymbol{T}}
\end{aligned}
$$

Priors:

$$
\begin{aligned}
(\lambda_1, \dots, \lambda_n) &\sim HalfNormal(0\,, 1) \\
\tilde{\eta}_{iw} &\sim \text{Normal}(\,0\,, 1\,) \\
\mathrm{LL}^T &\sim \text{LkjCorr}(2) \\
(\sigma_{\eta_1}, \dots, \sigma_{\eta_w}) &\sim HalfStudentT(3, 0\,, 2)
\end{aligned}
$$

Where I_{ri} are the Likert responses for item *r* for person *i*; ϕ_{ri} are the linear models describing the relationship between items and latent variables; τ_{rt} are the threshold (cutpoint) parameters where t indexes the item specific categorical boundaries from 1 to 4 (i.e. four thresholds for Likert items with five response categories); λ_r are the coefficients describing the item influence on the latent variable (loading); η_{wi} are the latent variables (indexed by *w*) which are the product of the diagonal standard deviations for each latent variable $(\sigma_{\eta_1}, \dots, \sigma_{\eta_w})$, the Cholesky factor (*w* x *w*) matrix (L) of the latent variable correlation matrix $(\Omega = LL^T)$, and the unscaled latent variables $(\tilde{\eta}_{wi})$. The η_{wi} term is the

[9] One student reported having no form of license but indicated they drove to school. In that case, drive was considered in that student's choice set.

multivariate version of the non-centered parameterization used in the choice model above through re-parameterization of the correlation matrix Ω as Cholesky factors L (both strategies recommended by the Stan Development Team (2017)). This parameterization removes the latent variable standard deviations and correlations out of the prior which improves the efficiency and stability of sampling. Priors for λ and $\tilde{\eta}$ set the scale for the loadings and latent variables, while priors for LL^T and σ are weakly regularizing. When dropping item subscript *r* and person subscript *i* for clarity, the ordered logit sampling statement implies the probability of each category is:

$$\Pr(y = c) = \left(\frac{e^{\phi - \tau_{t-1}}}{1 + e^{\phi - \tau_{t-1}}}\right) - \left(\frac{e^{\phi - \tau_t}}{1 + e^{\phi - \tau_t}}\right)$$

Where *c* is the chosen ordered category. Parameter constraints are needed to identify the latent variable model. I follow the guidance of Lee and Song (2012) and set the first λ for each latent variable to 1, and fix the threshold endpoints τ_{r1} and τ_{r4} at the cumulative proportion of responses in the data below each threshold on the logit scale. I set the thresholds on the logit scale instead of the unit normal scale as suggested by Lee and Song (2012) because the ordered logit samples much faster than ordered probit in Stan version 2.16.2. To ensure the threshold constraints didn't have undue effect on the model parameters of interest, thresholds set on the unit normal scale were compared with those generated from another structural equation model (SEM) software lavaan (Rosseel, 2012). Lavaan, like other frequentist SEM software such as Mplus, uses the "delta" parameterization to identify latent variables from ordinal indicators. The comparison confirmed that the Lee and Song (2012) method of fixed threshold end points generated posterior means that exactly replicated the point estimated thresholds computed from Lavaan. This ensured the constraints aligned with more traditional and recognizable latent variable model implementations

Appendix B. Model Estimation and Parameter Summaries

All seven 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, with the exception of the threshold parameters in Model 6 (e.g. $\tau[1,2]$ and $\tau[1,3]$). Those start values were constrained between the fixed endpoints (e.g. $\tau[1,1]$ and $\tau[1,4]$) and constrained to be ordered (e.g. $\tau[1,2] < \tau[1,3]$). 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), the step size (adapt_delta) was increased from the default 0.8 to 0.99 for all models. In addition, to improve sampling efficiency, the treedepth was increased from the default 10 to 18 after warnings that sampling was terminating prematurely. Changing these tuning parameters ensured the sampler never exceeded the treedepth nor reported divergences (see bottom of Table 4.B1).

Table 4.B1 summarizes the model parameters by their posterior mean, standard deviation (sd) which represent the marginal influence and confidence 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. Model 6 includes a series of different types of parameters related to the ordinal latent variable model (see Appendix A). Also summarized are parameter specific diagnostics: estimated number of effective samples (n_{eff}) (e.g. efficiency), and potential scale reduction factor ($\hat{R}$) (e.g. MCMC convergence) (Gelman et al., 2013, pp. 285–286). Runtime and minimum Bayesian Fraction of Missing Information (BFMI) are reported for each model to assess computational efficiency and the sufficiency of the sampler to explore the full joint distribution. BFMIs above 0.2 are thought to provide adequate exploration of the target distribution (based on current Stan warnings).

Table 4.B1 Parameter estimates, effective samples, and convergence diagnostics.

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	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]	1.04	(0.41)	4306	0.89	(0.47)	3806	1.09	(0.47)	3722	0.84	(0.47)	3566	0.80	(0.47)	4169	0.93	(0.49)	4889	1.03	(0.48)	3911
α[bike]	-0.42	(0.16)	3551	-0.44	(0.94)	2339	-1.58	(0.90)	2608	-8.86	(1.16)	2692	-1.62	(0.74)	2645	-2.09	(0.93)	2486	-2.39	(0.80)	3446
α[walk]	0.04	(0.21)	3727	-0.10	(0.45)	2142	1.44	(0.42)	2879	-0.08	(0.47)	1887	-0.08	(0.49)	1843	-0.10	(0.46)	2588	1.47	(0.41)	3401
α[bus]	-2.40	(0.22)	3708	-2.39	(0.53)	2195	-2.40	(0.56)	2185	-2.39	(0.55)	1849	-2.39	(0.55)	2254	-2.40	(0.53)	2560	-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	0.29	(0.33)	3216	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	1.36	(0.68)	4235	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	0.58	(0.43)	2729	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	0.69	(0.48)	2948	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	0.06	(0.27)	3686	-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	-0.08	(0.28)	2800	-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	0.01	(0.27)	2540	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	1.33	(0.88)	2530	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	-0.68	(0.89)	3517	-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	-0.70	(0.89)	2801	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	-0.35	(0.43)	2475	-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	0.11	(0.42)	2516	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	0.26	(0.42)	3509	-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	0.05	(0.50)	2834	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	-0.43	(0.50)	2482	-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	(0.51)	2492	0.37	(0.52)	2063

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
Categorical Regression Parameters																					
Distance (miles)[drive]	0.13	(0.05)	6000	0.13	(0.05)	6000	0.10	(0.05)	6000	0.13	(0.06)	6000	0.14	(0.05)	6000	0.13	(0.06)	6000	0.10	(0.05)	6000
Distance (miles)[bike]	-0.19	(0.04)	6000	-0.32	(0.06)	6000	-0.46	(0.08)	5591	-0.10	(0.06)	6000	-0.16	(0.06)	6000	-0.22	(0.08)	6000	-0.32	(0.10)	5863
Distance (miles)[walk]	-0.59	(0.10)	5849	-0.56	(0.10)	6000	-0.83	(0.13)	6000	-0.56	(0.10)	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	0.06	(0.03)	6000	0.06	(0.03)	6000
Age (fractional yrs)[drive]	0.36	(0.14)	6000	0.26	(0.14)	6000	0.28	(0.14)	6000	0.20	(0.14)	6000	0.21	(0.14)	6000	0.20	(0.15)	6000	0.21	(0.14)	6000
Age (fractional yrs)[bike]	0.37	(0.06)	6000	0.10	(0.07)	6000	0.08	(0.07)	6000	0.24	(0.08)	6000	0.24	(0.08)	6000	0.20	(0.10)	6000	0.19	(0.08)	6000
Age (fractional yrs)[walk]	0.16	(0.06)	6000	0.19	(0.06)	6000	0.14	(0.06)	6000	0.19	(0.06)	6000	0.19	(0.06)	6000	0.19	(0.06)	6000	0.14	(0.06)	6000
Age (fractional yrs)[bus]	0.25	(0.09)	6000	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	0.24	(0.09)	6000
Female[drive]	0.12	(0.18)	6000	0.08	(0.18)	6000	0.07	(0.18)	6000	0.05	(0.18)	6000	0.10	(0.18)	6000	0.02	(0.20)	6000	0.06	(0.18)	6000
Female[bike]	-0.77	(0.12)	6000	-0.93	(0.13)	6000	-0.95	(0.14)	6000	-0.50	(0.17)	6000	-0.46	(0.16)	6000	-0.64	(0.20)	6000	-0.45	(0.16)	6000
Female[walk]	-0.24	(0.13)	6000	-0.21	(0.13)	6000	-0.20	(0.13)	6000	-0.22	(0.13)	6000	-0.22	(0.13)	6000	-0.22	(0.13)	6000	-0.21	(0.13)	6000
Female[bus]	-0.06	(0.18)	6000	-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	-0.05	(0.18)	6000
ParentHighEducation [drive]	0.00	(0.21)	6000	-0.03	(0.22)	6000	-0.05	(0.22)	6000	0.01	(0.22)	6000	-0.02	(0.22)	6000	0.00	(0.23)	6000	-0.04	(0.22)	6000
ParentHighEducation [bike]	0.87	(0.14)	4556	0.45	(0.15)	6000	0.47	(0.15)	6000	0.35	(0.18)	6000	0.32	(0.17)	6000	0.35	(0.22)	6000	0.33	(0.17)	6000
ParentHighEducation [walk]	-0.31	(0.14)	5796	-0.25	(0.15)	6000	-0.27	(0.15)	6000	-0.25	(0.15)	6000	-0.25	(0.15)	6000	-0.25	(0.15)	6000	-0.28	(0.16)	6000
ParentHighEducation [bus]	-0.78	(0.22)	6000	-0.91	(0.23)	6000	-0.91	(0.23)	6000	-0.90	(0.23)	6000	-0.90	(0.23)	6000	-0.90	(0.22)	6000	-0.90	(0.23)	6000
Non-White or Asian[drive]	-0.64	(0.26)	6000	-0.59	(0.27)	6000	-0.54	(0.26)	6000	-0.62	(0.26)	6000	-0.60	(0.26)	6000	-0.75	(0.27)	6000	-0.58	(0.26)	6000
Non-White or Asian[bike]	-0.85	(0.17)	6000	-0.66	(0.18)	6000	-0.63	(0.19)	6000	-0.28	(0.21)	6000	-0.43	(0.20)	6000	-0.58	(0.26)	6000	-0.41	(0.21)	6000
Non-White or Asian[walk]	0.49	(0.14)	5400	0.50	(0.16)	6000	0.65	(0.16)	6000	0.50	(0.16)	6000	0.50	(0.16)	6000	0.50	(0.16)	6000	0.65	(0.16)	6000

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
Non-White or Asian[bus]	0.80	(0.20)	4791	1.06	(0.22)	6000	1.07	(0.22)	6000	1.05	(0.22)	6000	1.05	(0.22)	6000	1.05	(0.23)	6000	1.06	(0.23)	6000
On-campus Parking[drive]	0.34	(0.41)	4790	0.62	(0.41)	5603	0.56	(0.42)	5341	0.72	(0.42)	5601	0.69	(0.42)	5681	0.77	(0.42)	5749	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									

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
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	-1.08	(0.49)	801	0.50	(0.10)	6000
Self-image[bike]													0.22	(0.08)	6000	0.29	(0.21)	924	0.23	(0.08)	6000
Social Pressure[bike]													1.03	(0.10)	6000	3.93	(0.95)	852	1.00	(0.10)	6000
Environment[bike]													0.65	(0.10)	6000	0.70	(0.45)	628	0.55	(0.11)	6000
Item Loadings																					
λ_1 (Environment)																0.38	(0.05)	2537			
λ_2 (Environment)																0.84	(0.07)	2051			
λ_3 (Environment)																1.00	-	-			

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
λ_4 (Social Pressure)																1.36	(0.12)	2590			
λ_5 (Social Pressure)																1.60	(0.12)	2677			
λ_6 (Social Pressure)																1.21	(0.09)	3445			
λ_7 (Social Pressure)																1.00	-	-			
λ_8 (Self-image)																0.83	(0.05)	3696			
λ_9 (Self-image)																1.04	(0.05)	5513			
λ_{10} (Self-image)																1.00	-	-			
λ_{11} (Enjoyment)																0.96	(0.05)	4963			
λ_{12} (Enjoyment)																1.17	(0.06)	4744			
λ_{13} (Enjoyment)																1.00	-	-			
Reflective Attitude Scales																					
$\sigma_{\text{attitudes}}$[enjoyment]																1.23	(0.05)	2882			
$\sigma_{\text{attitudes}}$[self-image]																1.26	(0.05)	2518			
$\sigma_{\text{attitudes}}$[social pressure]																0.72	(0.05)	2191			
$\sigma_{\text{attitudes}}$[environment]																1.16	(0.05)	3024			
Reflective Attitude Correlations																					
Ω[enjoyment, self-image]																0.28	(0.03)	1650			
Ω[enjoyment, social pressure]																0.87	(0.02)	782			
Ω[enjoyment, environment]																0.75	(0.04)	821			
Ω[self-image, social pressure]																0.13	(0.04)	3063			
Ω[self-image, environment]																0.49	(0.04)	2302			

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
Ω[social pressure, environment]																0.70	(0.04)	868			
Free Thresholds																					
τ[1,2]																-1.56	(0.04)	6000			
τ[1,3]																-0.17	(0.03)	6000			
τ[2,2]																-2.26	(0.04)	6000			
τ[2,3]																-1.31	(0.04)	6000			
τ[3,2]																-0.85	(0.03)	6000			
τ[3,3]																0.06	(0.03)	6000			
τ[4,2]																-0.73	(0.03)	6000			
τ[4,3]																0.35	(0.03)	6000			
τ[5,2]																-0.93	(0.03)	6000			
τ[5,3]																0.04	(0.03)	6000			
τ[6,2]																-1.77	(0.04)	6000			
τ[6,3]																-0.61	(0.03)	6000			
τ[7,2]																0.83	(0.04)	6000			
τ[7,3]																3.07	(0.05)	6000			
τ[8,2]																-0.23	(0.03)	6000			
τ[8,3]																0.88	(0.03)	6000			
τ[9,2]																-0.27	(0.03)	6000			
τ[9,3]																0.93	(0.03)	6000			
τ[10,2]																-2.37	(0.05)	6000			
τ[10,3]																-0.86	(0.04)	6000			
τ[11,2]																-1.34	(0.03)	6000			
τ[11,3]																-0.33	(0.03)	6000			
τ[12,2]																-1.11	(0.03)	6000			
τ[12,3]																-0.44	(0.03)	6000			
τ[13,2]																-0.96	(0.03)	6000			
τ[13,3]																-0.29	(0.03)	6000			

	Model 1 (Base)			Model 2 (School)			Model 3 (Road Environment)			Model 4 (Attitudes Likert)			Model 5 (Attitude Composite)			Model 6 (Attitude Reflective)			Model 7 (Full Composite)		
	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}	mean	sd	n_{eff}
15 parallel chains runtime (hrs)		0.78			3.40			5.22			4.75			3.08			33.40			5.29	
Divergent iteration ratio		0.00			0.00			0.00			0.00			0.00			0.00			0.00	
Treedepth exceeded ratio		0.00			0.00			0.00			0.00			0.00			0.00			0.00	
Minimum BFMI		0.93			0.82			0.86			0.86			0.84			0.49			0.89	

Appendix C. Survey Instrument

UC Davis Survey on Travel to High School

We are collecting data about how high school students get to and from school. This study is being directed by Professor Susan Handy of the Institute of Transportation Studies at the University of California Davis.

The survey should take at most 10 minutes to complete. Your participation is completely voluntary, and you are not required to finish the survey, but we hope that you will answer each question on both pages. All of your responses will be completely confidential. No one will know which survey is yours. There are no direct benefits or compensation for participating, but by answering the survey you will help us understand the choices that high school students make about getting to school. The results can help your school and city in addressing transportation issues faced by students.

If you have any questions, please contact Professor Susan Handy (slhandy@ucdavis.edu), her assistant Kristin Lovejoy (klovejoy@ucdavis.edu), or the UC Davis Internal Review Board (916-703-9151). Your school will receive a summary of the survey results, but you may also request a personal copy be sent to you. -- *Thank you for your assistance!*

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1. What grade are you in? □ 9th □ 10th □ 11th □ 12th

2. What is your gender? □ Male □ Female

3. How do you usually get to school? (check one)
   □ I bicycle □ A friend drives me □ I drive myself
   □ I walk □ A family member drives me □ I take the bus
   □ I skateboard □ Another parent drives me □ Other: ____________

4. When do you usually arrive at school? (check one)
   □ For activities before 1st period □ For 1st period □ After 1st period

5. How many days in the school week do you currently participate in after-school activities at school?
   □ 5 □4 □3 □2 □1 □ Rarely/never

6. How many days in the school week do you currently participate in after-school activities somewhere else?
   □ 5 □4 □3 □2 □1 □ Rarely/never

7. How do you usually get home after school? (check one)
   □ I bicycle □ A friend drives me □ I drive myself
   □ I walk □ A family member drives me □ I take the bus
   □ I skateboard □ Another parent drives me □ Other: ____________

8. How did you usually get to middle school? (check one)
   □ I bicycled □ A family member drove me □ I took the bus
   □ I walked □ Another parent drove me □ Other: ____________
   □ I skateboarded

9. Do you currently own or have regular access to a functioning bicycle? □ No □ Yes

10. How often do you ride your bicycle to places other than school? (check one)
    □ Every day □ Most days of the week □ A few days a week □ Once a week or less □ Never

11. Do you have a cell phone? □ No □ Yes, but not a smartphone □ Yes, a smartphone with a data plan

12. How often do you use a cell phone, texting, email, instant messaging, or other electronic communications to arrange transportation with someone? (*Examples*: find a ride; arrange to take the bus with a friend; tell

your parents about a change in plans related to transportation, etc.) (check one)

□ Every day □ Most days of the week □ A few days a week □ Once a week or less □ Never

13. What is your birth date? Month born: _________________ Year born: _________

14. What is the most recent driver's license/permit you have obtained? (check one)

□ Provisional license □ Driver learner's permit – ***SKIP TO THE NEXT PAGE***
□ Regular driver's license □ I do not have a license or permit – ***SKIP TO THE NEXT PAGE***

If you have a license:

a. When did you get your license? Month: ________________ Year: _________
b. Do you have regular access to a car? □ No □ Yes
c. Do you pay for your own gasoline? □ No □ Yes

15. Please tell us whether you agree or disagree with the following.

		Strongly Disagree		Neutral		Strongly Agree
a.	I like being physically active.	□1	□ 2	□3	□4	□5
b.	Lots of people bicycle in my community.	□1	□ 2	□3	□4	□5
c.	I like bicycling.	□1	□ 2	□3	□4	□5
d.	I am confident in my bicycling ability.	□1	□ 2	□3	□4	□5
e.	I have a physical condition that makes it hard to bicycle.	□1	□ 2	□3	□4	□5
f.	Bicycling is my usual way of getting around town.	□1	□ 2	□3	□4	□5
g.	I like being driven places.	□1	□ 2	□3	□4	□5
h.	My parents/guardians encourage me to bicycle.	□1	□ 2	□3	□4	□5
i.	I worry about my bicycle getting stolen.	□1	□ 2	□3	□4	□5
j.	I feel comfortable getting places on my own.	□1	□ 2	□3	□4	□5
k.	Protecting the environment is important to me.	□1	□ 2	□3	□4	□5
l.	I like riding the bus.	□1	□ 2	□3	□4	□5
m.	My parents/guardians allow me to go places on my own.	□1	□ 2	□3	□4	□5
n.	I can rely on my parents/guardians to drive me places.	□1	□ 2	□3	□4	□5
o.	I need a car to do the things I like to do.	□1	□ 2	□3	□4	□5
p.	It's hard to ride a bicycle wearing my normal clothes.	□1	□ 2	□3	□4	□5
q.	I feel comfortable bicycling on a busy street with a bike lane.	□1	□ 2	□3	□4	□5
r.	I don't like to bicycle when the weather is bad.	□1	□ 2	□3	□4	□5
s.	One or both of my parents/guardians bicycle frequently.	□1	□ 2	□3	□4	□5
t.	I hate wearing a bicycle helmet.	□1	□ 2	□3	□4	□5
u.	I am always rushed to get ready in the morning.	□1	□ 2	□3	□4	□5
v.	The traffic congestion getting in and out of school is a major hassle.	□1	□ 2	□3	□4	□5
w.	I have lots of stuff to carry to school.	□1	□ 2	□3	□4	□5
x.	Going to/from school with friends rather than alone is a priority.	□1	□ 2	□3	□4	□5
y.	Bicycling is considered the coolest way to get to school.	□1	□ 2	□3	□4	□5
z.	There is a safe route to bicycle from my home to school.	□1	□ 2	□3	□4	□5
aa.	My friends bicycle to school.	□1	□ 2	□3	□4	□5
bb.	I live too far away from school to bicycle there.	□1	□ 2	□3	□4	□5
cc.	I worry that bicycling to school means being sweaty when I get there.	□1	□ 2	□3	□4	□5
dd.	I worry my hair won't look that great after bicycling to school.	□1	□ 2	□3	□4	□5
ee.	Driving is considered the coolest way to get to school.	□1	□ 2	□3	□4	□5
ff.	It is hilly between my home and school.	□1	□ 2	□3	□4	□5
gg.	The bicycle parking areas at my school are easy to use.	□1	□ 2	□3	□4	□5
hh.	I often go off-campus for lunch.	□1	□ 2	□3	□4	□5

16. How would you describe your race/ethnicity? (Check all that apply)

□ American Indian/ Native American □ Asian □ Hispanic/Latino □ White / Caucasian
□ Black/African American □ Pacific Islander □ Other

17. What is the highest level of education completed by whichever parent/guardian has the most education?
□ Some High School □ Some College □ Bachelor Degree □ Other
□ High School □ Associate Degree □ Advanced Degree □ Don't know

18. Do you live with your parents/guardians in one home, or split your time at different homes of separated parents?
□ I live in one place □ I live at more than one place

19. Do you have siblings who currently live with you? □ No □ Yes, older one(s) □ Yes, younger one(s)

20. What is the nearest intersection to your home? (This is to give us an idea of how far away from school you live. If you live at more than one place, answer for wherever you spend more time.)

____________________ and __________________ in ____________________, CA
(street name) (nearest cross street) (city)

5 Conclusions

In this dissertation I use a variety of data and methods to examine the relationship between road environments and bicycling attitudes and behaviors. Cities and regions are now faced with the difficult decision of what type of environmental interventions are needed to make bicycling safe and attractive. Although planning is a deliberative and collaborative process, clear guidance from research can provide a foundation to support this process. Current use of bicycling research and data in the planning process show that sophistication and specialization are increasing. It is now more common than ever for cities to utilize GIS data, travel and crash statistics, community surveys, and even models of demand to plan for bicycling (City of Long Beach Department of Development Services and Department of Public Works, 2016; Hondorp et al., 2013; Wyant and Harris, 2016). Although large cities provide more sophistication in their bicycling plans, even very small communities use surveys and other data to prioritize investments (Del Norte Local Transportation Commission, 2017). Private consultants advertise their proprietary tools and models designed specifically for bicycling (Fehr and Peers, n.d.; Toole Design Group, n.d.), and Federal guidelines for prioritizing investments for bicycling are provided through the ActiveTrans Priority Tool (Lagerwey et al., 2015). Most of these tools and methods rely on generalizations from research to provide guidance for where and how to invest. Although the studies in this dissertation do not create or improve existing tools directly, they provide valuable insight for planning and policy.

Planning for stress-free bicycling environments offers an intuitive approach for improving safety and encouraging more bicycling. This is because stress associated with bicycling in car traffic determines perceived safety and can reflect many people's willingness to bicycle. Although the term "stress" has been used in prior bicycling studies (Furth, 2008; Sorton and Walsh, 1994) and is commonly used in practice thanks to the report by Mekuria et al. (2012), we still do not have a good understanding of bicyclist stress and its connection to behavior. Results from Chapter 2 suggest that even when measuring stress precisely through high-frequency heart rate variability, the relationship between road environments and bicycling stress is hard to establish. In that study, the local road with low car volume and speed was the only environment where participants were relaxed. Contrasts of more subtle road features of trafficked roads showed stress and perceptions of safety and comfort did not always align. For example, perceived safety and comfort were consistently greater for minor arterials and collectors with bike lanes compared to the major arterial with no bike lane. However, differences in stress for the same road environments were uncertain, although on average in the same direction as the survey measures. Most surprising was the inability of stress or perceived safety and comfort to differentiate to road environments with large differences in car traffic. The two-lane (with center turn lane) minor arterial with about 10,000 cars a day and the collector with a buffered bike lane and about 2,000 cars a day showed similar results across all measures of stress, anxiety, safety, and comfort. The lack of clear differences in stress for the subtle road features may indicate that to improve bicyclist stress, low car volumes and speeds are necessary. Indirectly, this indicates that bicyclists in Davis are willing to put up with some stress because most of them have to spend some time bicycling on collectors and minor arterials with bike lanes. Future explorations of bicyclist stress are warranted, with particular focus on differentiating environments with moderate and heavy car traffic with varying bicycling facilities.

The Chapter 2 stress results suggest local planning should consider designs that allow bicycling access by low car speed routes as a top priority. The challenge in North America is the ubiquitous nature of major arterial roads as the conduits to activity locations with few local road alternatives. Even the speeds of cars on most local roads in the US may be too fast for prospective bicyclists. Without investment in completely separated/protected bicycling facilities or low speed road connectivity, environmental stress is likely to limit the appeal of bicycling.

Alternatives to completely separated facilities and minimally trafficked local roads are of course possible, but until governments decide to prioritize safety over speed (like the Netherlands has done (Schepers et al., 2014)), mixed travel lanes and high-speed roads with on-street bike facilities are likely to continue to result in poor safety and remain a primary barrier for bicycling as a normal mode of travel. In the US, more support has been gained for trying to separate bikes and cars than from slowing cars down. Some exceptions exist such as the bicycle boulevards in Portland, Oregon, and Berkeley, California; however, even these examples allow cars to drive at faster speeds than those in the Netherlands. The vast majority of North American cities use bike lanes and now buffered and protected bike lanes to improve bicycling safety and encourage more bicycling. Evidence from Chapter 3 in San Francisco suggests that these investments cause changes in existing bicyclist route behavior. Coupled with evidence that both perceived and objective measures of safety improve with bicycling facilities (Reynolds et al., 2009; Teschke et al., 2012), we can be confident that bicycle infrastructure is increasing bicyclist safety. Specifically, off-street paths and protected lanes offer a considerable effect on route detouring compared to conventional bike lanes. Given that bicycling rates correlate with infrastructure investments (Dill et al., 2013) and existing bicyclists detour for new infrastructure, we can also be fairly confident that investment in infrastructure is causing more bicycling.[1] Although some planning tools currently assume threshold effects for willingness to ride (Mekuria et al., 2012), more empirical evidence is needed to determine realistic thresholds. This is especially true in light of the evidence from Chapter 2 that low speed and volume roads may be one clear way to reduce environmental stress.[2]

Results from Chapter 3 on bicyclist route choice also suggest it is important that bicycling facilities are available within minimal detours from people's shortest travel routes. The amount of bicycling infrastructure correlates with aggregate rates of bicycling (Schoner and Levinson, 2014), but the necessary density of bicycling networks for supporting bicycling for the mases is uncertain. Route detouring in Davis is some of the smallest reported in North America (similar to that of Winters et al. (2010)). Considering the high bicycling mode share in Davis, necessary densities of facilities may need to approach Davis levels for cities to support large shares of bicycling. At the same time, key road attributes in Davis showed highly uncertain effects on individual route detouring. I took the uncertainty in the Davis data to indicate that contexts of ubiquitous supportive bicycling environments may mask the influence of individual road attributes and/or more detailed attributes (e.g. bike signals, pavement conditions) may be needed. However, further research is needed to confirm this hypothesis.

One of the key methodological contributions of Chapter 3 is the modeling of individual level marginal rates of substitution for road attributes. In both Davis and San Francisco, large scale individual heterogeneity demonstrates the challenge for providing a bicycling network that uniformly works for everyone. In Davis, predicted marginal rates of substitutions for a low comfort, low ability, female student group showed strong effects of off-street paths and little to no effect for bike lanes. The same was not true of the high comfort, high ability, male non-students. Identifying interventions that target a specific social group may be efficacious for increasing bicycling rates (e.g. bicyclist typologies (Damant-Sirois et al., 2014; Dill and McNeil, 2013)), but caution should be employed to ensure interventions are equitable and lasting. Although I studied a more homogenous and experienced cohort in San Francisco, their route behavior clearly demonstrated that protected bike lanes and off-street paths are more valuable than conventional bike lanes. The vast majority of individual level marginal rates of substitution showed this pattern. Without growth of protected lanes, bicycling rates

[1] Self-selection is still not well accounted for, but is unlikely to explain the large growth in bicycling.
[2] Although protected lanes were not evaluated in Chapter 2, one road had a buffered lane which was inconclusive in alleviating stress.

are sure to stagnate in many cities.

Examining the stress, perceived safety and comfort, and routing behavior of bicyclists offers key insights into supportive road environments for bicycling. However, they don't directly indicate how those environments influence the decision to bicycle in the first place. Only limited evidence shows the road attributes related to routing behavior and mode choice behavior may be consistent (Broach and Dill, 2016). Evidence from Chapter 4 of teen travel to school shows that indeed characteristics along plausible routes to school have a strong influence on the decision to bike. Surprisingly, bike lanes show a slightly stronger effect on mode choice to school than off-street paths. This may be due to the prevalence of these facilities across the three school enrollment areas. Other road environment characteristics (e.g. % two-lane and low posted speed roads) showed uncertain effects on bicycling possibly due to large variation in volume and speed of cars on two lane, 25 mph posted speed roads.

One of the key methodological contributions from Chapter 4 was the representation of road environment variables along plausible paths to school. In the past, researchers have relied on areal measures (e.g. buffers around trip ends, in this case home and school) of the urban environment to predict travel mode choice. However, areal measures include information that is irrelevant at the trip level and may miss important information along the route (Broach, 2016). Path summarized variables have the advantage of a clear causal mechanism for influencing bicycling. Nonetheless, in Chapter 4, paths to school are unknown, so I could not validate the generated plausible routes. Future research on chosen route attributes for school travel would be needed to confirm the effects observed in Chapter 4, and may provide more precise estimates of the effects of specific attributes like bike lanes and off-street paths.

A second methodological contribution of Chapter 4 was the comparison of statistical techniques for estimating the influence of personal level attitude variables on mode choice to school. The first method uses each Likert type survey response as an independent variable in the bicycling utility equation. The second approach was a sum of Likert items thought to represent important latent variables for bicycling to school. The third method was a factor analytic approach to estimating the latent variables themselves through the same Likert items while jointly modeling mode choice. Muñoz et al. (2016) document a growing interest in integrated latent variable and choice models of bicycling. They suggest the joint models 'properly' deal with psychological latent variables. However, the results in Chapter 4 suggest that adoption of joint models can result in unintelligible results when estimating correlated latent variables. In the Chapter 4 case, strongly correlated latent variables resulted in unrealistic effects compared to the simple sum-score approach. Because I did not conduct validity and reliability testing of the attitudinal constructs (which is general rare in bicycling research), most of the attitudinal work is exploratory and demands further testing. Probably more important than advancing statistical techniques is the design of the questionnaires to accurately and consistently reflect bicycling attitudes. Future research in this vein may be fruitful.

Using the mode choice models from Chapter 4 I showed that social pressure to bicycle to school had an even stronger effect on mode choice than the road environment variables. Results also suggest that the combination of improved road environments and social pressure to bicycle have the potential to dramatically increase bicycling rates for teens to high school. Whether this result can generalize population wide in large cities remains to be seen. In addition, it isn't clear if interventions aimed at increasing the social pressure to walk and bike would work. Perhaps long-term driving disincentives and active travel incentives can indirectly create a social pressure over time. Future evaluation of both changes to road environments in tandem with incentives and programs at specific destinations like schools or large employment centers can help us understand the bidirectional relationship between attitudes and travel and generate more efficacious policy.

This dissertation adds to the quickly growing literature on the relationship between road environments and bicycling behavior. It also offers some methodological explorations that help describe these relationships and at the same time complicate them by suggesting new research questions. It is well understood by researchers, planners, and the public that the road environment is an integral part of the bicycling experience. Sacrifices may need to be made to provide safe and attractive environments for bicycling. With clear policy goals for reducing emissions, increasing public health, improving equity, the transportation sector is ripe for overhaul. A no more efficient and less impactful travel mode exists to satisfy these goals than bicycling. The current wave of enthusiasm for clean, automated vehicles will no doubt have an impact on our travel behavior and our environmental sustainability in the future. However, solely car based futures all hold much higher potentials for counterproductive outcomes. For example, automated cars may induce greater car travel (Harb et al., 2018). Success of electric vehicles in curbing emissions relies on the transition from traditional to renewable energy sources. This is likely to happen slowly given proved reserves of traditional sources are vast (US Energy Information Administration, 2018). Finally, a car dominant future is likely to maintain or even decrease current levels of physical activity maintaining the global pandemic of non-communicable disease (Sallis et al., 2016).

We are more likely to meet our sustainability goals if future travel is truly multimodal. The recent rise in bicycling as well as non-traditional travel forms such as shared cars, bikes and scooters suggest some people are willing to change behavior. Planning for a future where bicycling and other forms of active travel are the norm for everyday short journeys will require dramatic changes to our current transportation networks and land use. I hope this dissertation serves to support current policy decisions aimed at improving urban environments for bicycling and I hope it will incite more investigations into how changes to the environment might influence bicycling and other active travel behaviors.

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