Not All Crashes Are Created Equal: Associations between the Built Environment and Disparities in Bicycle Collisions

Abstract

Historically disadvantaged populations are disproportionately represented in bicycle crashes. Previous research has found that Black and Hispanic bicyclists, and areas with higher populations of non-White residents, lower median income, and high poverty experience bicycle crashes more frequently than others. Although existing research has explored the role of socioeconomic status and the built environment in predicting crash frequency, few scholars have studied how those factors account for the disparities along racial and ethnic lines. Using a database of 7,088 bicycle crashes over a three-year period in the San Francisco Bay Area, this study examines the influence of socioeconomic, transportation, and land use characteristics as potential causes of differences in bicycle crash occurrences among racial and ethnic groups in the San Francisco Bay Area. While areas of high poverty and high land-use intensity are associated with higher numbers of bicycle crashes overall, lower-traffic streets and bicycle infrastructure do not affect the frequency of crashes involving Black and Hispanic cyclists.

Black bicyclists have a disproportionate risk of being involved in a crash in poor urban neighborhoods, controlling for other factors. These findings draw attention to the need for planners to consider how socioeconomic difference and vulnerability at the neighborhood level play a role in safety.

Keywords: Bicycling, Safety, Socioeconomic disparities

Introduction

Safety concerns often prevent people from bicycling or add significant burden to the experience (Dill & Voros, 2007; Winters, Davidson, Kao, & Teschke, 2011; Sanders, 2015). On the whole, bicyclists are disproportionately at risk of traffic fatalities on a per-trip basis compared to other road users. In 2012, 2% of all traffic fatalities and injuries involved bicyclists, while only 1% of trips were made by bicycle (Federal Highway Administration, 2009; National Highway Traffic Safety Administration, 2016). These incidents are not equally distributed in the population. During the five-year period from 1999 to 2003, Hispanic and Black bicyclists were overrepresented in bicycle crashes compared to the population (Knoblauch, Seifert, & Murphy, 2004). Differences in fatalities are even more stark. Approximately 38% of bicycle fatalities involved Hispanic victims in 2010, while only 16% of the US population was Hispanic (National Highway Traffic Safety Administration [NHTSA], 2016). Without controlling for exposure, these figures strongly suggest disparities among who falls victim to bicycle crashes.

Although scholars have explored the role of socioeconomic characteristics and the built environment in predicting numbers and rates of bicycle crashes, research has not examined how differences in those factors may explain the disparities in the racial and ethnic diversity found in aggregate statistics. Put another way, are differences in measurable features of the built environment like land use and transportation infrastructure responsible for higher rates of bicycle crash occurrences among racial and ethnic minorities? Or are factors proxied by neighborhood socioeconomic status more significantly associated with those differences? Using the San Francisco Bay Area as a case study, this research analyzes these environmental differences by comparing a set of identical statistical models for different racial or ethnic groups. I hypothesize that because Black and Hispanic or Latino cyclists are more likely to live in neighborhoods with poorer conditions for cycling, such as more vehicle traffic and lower quality bicycle infrastructure, they are more at risk for getting into a crash. But once controlling for those differences, the risk disparity should no longer be evident.

The remainder of this article begins by reviewing the literature on factors that are correlated with bicycle crashes and potential sources of disparities in crash rates among various population groups. The following section describes the Statewide Integrated Traffic Reporting System (SWITRS), a statewide source of traffic crash data, and the explanatory and control variables used in the statistical models. The article then proceeds to describe the methods and the data analysis, and concludes with a summary and discussion with implications for practice. A key limitation to this study concerns the exposure estimates used during data analysis. Exposure measures activity and reflects the baseline likelihood that an individual will experience a crash per trip or distance traveled. Estimates of risk across population groups in any safety study depend on accurate estimates of exposure, but those estimates are difficult to generate for total cycling activity at a neighborhood level across a metropolitan area because of data unavailability. This study uses a set of modeled bicycle-kilometers traveled as the exposure levels (see Data and Methods), but readers should be aware that uncertainties in these estimates could magnify or diminish the findings of crash disparities.

Literature review

Crash factors

Several studies have found evidence of disparities in the rates of bicycle crashes among different racial and ethnic groups. One of the first to examine the topic found that bicycle crashes in Miami–Dade County, Florida were associated with high-poverty neighborhoods, and that

Black children were involved in crashes at higher rates than other victims (Epperson, 1995). Researchers analyzed 2004 National Highway Traffic Safety Administration (NHTSA) Fatal Accident Reporting System (FARS) to find that Hispanics were more likely to be killed in bicycle crashes in urban areas versus rural areas than either Blacks or non-Hispanic Whites. Hispanic and Black bicyclists were more likely to be killed on urban arterial roadways with more than one lane in each direction. They were also more likely to be killed in crashes at night than White bicyclists. The Centers for Disease Control data the authors analyzed also showed higher cyclist death rates per 100,000 people for Hispanics and Blacks than Whites (Knoblauch et al., 2004). More recent data from 2013 confirm many of these trends still hold (NHTSA, 2016).

Some disparities in bicycle crash frequencies result from neighborhood socioeconomic factors. In general, areas of lower socioeconomic status tend to have more bicycle crashes. Scholars have linked increased occurrence of bicycle crashes to analysis zones with a greater Hispanic or non-White population (C. Chen, Lin, & Loo, 2012; Delmelle, Thill, & Ha, 2012), lower educational attainment (Delmelle et al., 2012), and higher poverty, lower income, or lower economic output (Yu, 2014; McArthur, Savolainen, & Gates, 2014; Noland & Quddus, 2004; Siddiqui, Abdel-Aty, & Choi, 2012; Epperson, 1995). A study on immigrant vulnerability to pedestrian and bicycle crashes found that census tracts in New York City with higher recent immigrant populations were associated with more crashes of both types (C. Chen et al., 2012).

Vision Zero, the program under cities seek to eliminate traffic deaths through data-driven strategies, has prompted planners to closely analyze patterns of crashes. Cities such as San Francisco, Chicago, and Philadelphia have found a disproportionate share of traffic injuries occur in neighborhoods with high poverty and high shares of people of color (City and County of San Francisco, 2015; City of Chicago, 2017; City of Philadelphia, 2017). However, other academic research has found no association between socioeconomic characteristics and frequency of bicycle crashes (P. Chen, 2015; Lee, Abdel-Aty, & Jiang, 2015). Areal studies cannot be used to assess the disparities in individual risk, however, without violating the ecological fallacy that assumes area-wide characteristics apply to individual riders.

More evidence is available for the link between bicycle crashes and neighborhood factors, such as population and employment density, and the built environment, such as land use, transportation facilities, and bikeway characteristics. Disaggregate studies have generally found dedicated bicycle infrastructure, such as cycle tracks, bike lanes, or bike boulevards, to be safer than streets without bicycle infrastructure (Rodgers, 1997; Reynolds, Harris, Teschke, Cripton, & Winters, 2009; Minikel, 2012; Teschke et al., 2012; Hamann & Peek-Asa, 2013; Vandenbulcke, Thomas, & Int Panis, 2014). But aggregate studies have not found a conclusive relationship between bikeways and bicycle crashes in an analysis zone (Yu, 2014) or have not reported their findings, if they examined such variables. Scholars have found other transportation infrastructure, including more high-speed and high-volume roads—or fewer low-speed roads—to be associated with more bicycle crashes (Noland & Quddus, 2004; Delmelle et al., 2012; Siddiqui et al., 2012; Lee et al., 2015). However, there is an inconclusive relationship between frequency of bicycle crashes and intersection density (Noland & Quddus 2004; C. Chen et al., 2012; Gladhill & Monsere, 2012; Siddiqui et al., 2012; Yu, 2014; D. Kim & Kim, 2015; P. Chen, 2015), population density (Delmelle et al., 2012; Siddiqui et al., 2012; McArthur, Savolainen, & Gates, 2014; Yu, 2014; Lee et al., 2015), and employment (Siddiqui et al., 2012; P. Chen, 2015). Research has not developed a clear consensus on individual land use and crash frequency, but at least one study has found a higher degree of mixed land use in a traffic analysis zone to be associated with more bicycle crashes (P. Chen, 2015).

Possible sources of disparities

A number of rationales explain why lower-income areas and their residents may be more at risk for bicycle crashes. First, neighborhoods with lower socioeconomic status are more likely to be in the core of metropolitan areas. The danger of urban bicycling results from interactions with motor vehicles, particularly those traveling at high rates of speed (Jacobsen & Rutter, 2012). More arterial traffic and a higher likelihood of land use mixes all contribute to more opportunities to encounter cars on the road in core areas, compared to typically wealthier and suburban areas (see previous section).[1]

Second, socioeconomically disadvantaged neighborhoods are historically less likely to have access to bicycle infrastructure (see, for example, Prelog 2015). Multiple studies suggest bicycle infrastructure is associated with more bicycling (Buehler & Pucher, 2012; Dill & Carr, 2003; Heinen, van Wee, & Maat, 2010) and lower risk of collisions (Reynolds et al., 2009; Hamann & Peek-Asa, 2013). Comparative international analysis also associates higher bicyclist safety with investment in bicycle infrastructure and policies to prioritize cycling (Pucher, Dill, & Handy, 2010; Pucher & Buehler, 2006). However, in the United States, areas of lower socioeconomic status may be less likely to implement bicycle infrastructure projects (Cradock et al., 2009). Lower income communities and communities of color have even viewed new investment in bicycle infrastructure with suspicion, associating it with gentrification and historic neglect of their neighborhoods (Stein, 2011; Lubitow & Miller, 2013; Golub, Hoffman, Lugo, & Sandoval, 2016). Finally, some have argued that new immigrants are particularly susceptible to bicycle crash risks because of cultural and language barriers (C. Chen et al., 2012). To counter

[1] Note that this does not address casual influences on injury severity, which may indeed be lower in central city areas where there are fewer opportunities to drive with excess speed.

such risks, organizations such as NHTSA publish materials in Spanish aimed at increasing safety among newcomers to the United States.

To summarize, neighborhoods or other geographic areas of higher socioeconomic disadvantage are associated with greater numbers of bicycle crashes. These areas may be riskier to bicycle in because they tend to be more centrally located, are denser, and have higher potential for vehicle-bicycle interactions. Planning processes in historically marginalized communities have also left many neighborhoods lacking infrastructure, placing individuals at a greater risk of getting into a bicycle crash per distance traveled. And some in those neighborhoods, like immigrants who speak languages other than English, may be at greater individual risk. Furthermore, the relationship between transportation, land use, and crash frequency per zone is murky at best. But there are few studies that link those patterns, and there is little in the literature that explores whether these patterns are causes of disparities in frequency of crashes across racial and ethnic groups. This study aims to address the gap in the literature by exploring whether neighborhood factors and the built environment account for these disparities.

Data and methods

Crash data

Counts of bicycle crashes per census tract serve as the dependent variables in the multivariate models that follow. Bicycle crash data come from California Statewide Integrated Traffic Reporting System (SWITRS), a statewide database managed by the California Highway Patrol that contains all vehicle, bicycle, and pedestrian incidents reported to police departments in California. I selected records from the most recent three-year period for which data were available at the beginning of this study (2011–2013). The Safe Transportation Research and

Education Center (SafeTREC) creates a geocoded version of the SWITRS database used for this analysis (SafeTREC, 2016). I analyzed crashes that occurred in the core San Francisco Bay Area counties of Alameda, Contra Costa, San Francisco, San Mateo, and Santa Clara, which encompass the three largest cities and over 80 percent of the population in the region.

The SWITRS database contains a variety of information about the time and location of each incident, the types of vehicles involved, crash severity and causes, and some characteristics of the parties involved in each crash. Sex, age, and race are the only demographic attributes available about the parties involved. Because the goal of this research is to understand disparate influences on crash outcomes by socioeconomic status, I use the race variable as the marker of crash victim identification. SWITRS classifies race as White, Black, Hispanic, Asian, and Other. In the set of models that follow, the independent variables are identical. However, every model is fit with a different dependent variable: one set for the total number of bicycle crashes per census tract, and one each for the number of bicycle crashes involving White, Black, Hispanic, and Asian victims per tract.

It is important to note the limitation of working with police-reported crash data for this analysis. Previous research has explored the extent to which bicycle crashes are underreported by comparing hospital records to police records and found that the number of incidents reported in police records can range from 10% to 50% of the total number of incidents as compared to hospital records (Stutts, Williamson, Whitley, & Sheldon, 1990; Juhra et al., 2012). Furthermore, scholars have found evidence of differences in reporting rates by race. In San Francisco, injured African American pedestrians treated at one hospital were roughly half as likely as Whites to have had a police report taken (Sciortino, Vassar, Radetsky, & Knudson, 2005). Nevertheless, using the SWITRS database allows for analysis of standardized information that spans multiple jurisdictions and provides a minimum value and relative frequency of crash incidents.

Independent variables

The literature review provided a starting point for the relevant independent and control variables. I compiled data from the five-county region from multiple sources (Table 1). I aggregated all variables to the census tract level. Socioeconomic characteristics are from the American Community Survey (ACS) five-year estimates. Multiple studies have shown that indicators of higher levels socioeconomic disadvantage are correlated with higher numbers of bicycle crashes (see Literature Review). Variables selected for this study include those that measure race and ethnicity, poverty, median household income, car ownership, educational attainment, and limited English proficiency. Population density and employment density, which imply more opportunities for interaction, are also included as control variables. Note that while the US Census relies on self-reporting to identify race and ethnicity, police departments do not necessarily report race in the same manner. Therefore, although race and ethnicity data should be comparable between the crash dataset and the Census data, they are not the same.

Roadway functional classification provided by the California Department of Transportation serves as a proxy for traffic levels. Ideally, the models would account for number of vehicles directly by including average vehicle volumes or zonal Annual Average Daily Traffic counts. However, those data were not available. I computed the density of roadway length per unit area by functional classification to normalize for the size of the census tract. Because cyclists are most likely to get into a crash at intersections, models include density of non-freeway intersections. The models also include the link-to-node ratio per tract—a measure of connectivity—to account for ease of bicycle travel.

The Metropolitan Transportation Commission (MTC), the regional metropolitan planning organization, provided bicycle facility data in three classifications: bike paths on a separate right-of-way (Class 1), bike lanes (Class 2), and bike routes on shared roadways (Class 3). At the time of the data used for this study, there were few cycle tracks or separated bike lanes, and bicycle boulevards were treated as Class 3 bikeways despite being qualitatively different from other bicycle routes. I computed both density of facility length and facility presence per census tract. As discussed previously, there is no conclusive evidence on the relationship between bicycle infrastructure and crash frequency, though there is positive correlation between bicycle infrastructure and cycling levels, which could increase the total number of bicycle crashes but lower the per-person risk.

The Association of Bay Area Governments (ABAG) provided land use data. I computed the proportion of six land-use types present in each tract: single-family residential, multifamily residential, retail, industrial, office, and other non-residential land use (including mixed use parcels). I also calculated the land use mix per tract using an entropy index, where 0 indicates a tract with only one land-use type and 1 indicates a perfectly evenly distribution of land uses in the tract. Areas with more mixed land uses may be associated with greater numbers of crashes.

Table 1: Summary statistics for variables tested in crash models

Variable	Units	Mean (SD) per tract	Source (vintage)
Bicycle crash data			
Number of crashes	N/A	5.6 (7.8)	SWITRS/SafeTREC (2011–2013)
White victims		3.0 (5.1)	
Hispanic victims		1.1 (2.0)	
Black victims		0.5 (1.2)	
Asian victims		0.5 (1.1)	
Exposure			
Bicycling activity	km	750 (296)	Salon and Handy (2014)
Socioeconomic characteristics			
Non-Hispanic white	%	40.3 (23.1)	ACS (2009–2013)
Asian	%	25.6 (18.6)	
Hispanic	%	22.5 (18.0)	
Black	%	7.0 (10.4)	
Proportion in poverty	%	11.0 (9.3)	ACS (2009–2013)
Median income	2013 $	86,958 (37,971)	ACS (2009–2013)
Proportion without vehicle	%	10.4 (13.6)	ACS (2009–2013)
Proportion college graduates	%	9.2 (8.0)	ACS (2009–2013)
Proportion speak English less than "very well"	%	18.7 (12.8)	ACS (2009–2013)
Population density	ppl/ha	44.4 (50.3)	ACS (2009–2013)
Employment density	ppl/ha	20.2 (74.7)	LODES (2012)
Land use characteristics			
Single family residential	%	54.7 (28.5)	ABAG (2011)
Multifamily residential	%	14.8 (17.5)	
Retail	%	6.1 (8.1)	
Industrial	%	5.3 (12.8)	
Office	%	4.4 (7.2)	
Land use mix index[2]	N/A	0.37 (0.16)	Author's calculations
Transportation characteristics			
Intersection density	int/ha	0.6 (0.4)	Caltrans (2015) / Author's calculations
Link-to-node ratio	links/node	1.6 (0.3)	Caltrans (2015) / Author's calculations
Class 1 bikeway density	km/ha	0.003 (0.007)	MTC (2012)
Class 2 bikeway density		0.013 (0.017)	
Class 3 bikeway density		0.013 (0.020)	
Highway/freeway density	km/ha	0.011 (0.020)	Caltrans (2015) functional classification
Principal arterial density		0.018 (0.022)	
Minor arterial density		0.019 (0.020)	
Collector density		0.015 (0.016)	
Local road density		0.106 (0.045)	

[2] Land use mix (entropy) is an index of similarity of land uses in a Census tract, where 0 indicates a single land use in a tract and 1 is an equal mix of all land-use types considered. Entropy is calculated as: $-1 * \sum[p_i \ln p_i]/\ln k$,

Data aggregation

I aggregated all data to census tracts. Studies that analyze area-wide factors on traffic safety have variously aggregated data to traffic analysis zones (Siddiqui et al., 2012), census tracts (Chakravarthy, Anderson, Ludlow, Lotifpour, & Vaca, 2012; Wier, Weintraub, Humphreys, Seto, & Bhatia, 2009), block groups (Noland, Klein, & Tulach, 2013), and uniform spatial grids (Gladhill & Monsere, 2012; K. Kim, Pant, & Yamashita 2010). Disaggregate studies on traffic safety analyze data at the intersection or street segment level, sometimes buffering around the crash sites to gather environmental information about what might cause a bicycle crash at that particular site. Because the premise of this study is how differences in social and environmental factors across the region may lead to disparities in numbers of crashes and crash rates, disaggregate analytical techniques are inappropriate.

Census tracts are an appropriate unit of analysis for several reasons. They provide a consistent neighborhood geography across the region. They are designed to be relatively homogeneous units in terms of socioeconomic characteristics, which helps minimize variation within tracts and maximize variation between. In contrast, traffic analysis zones are too large to capture influences on bicycle trips as they are originally designed to reflect characteristics of motor vehicle travel rather than socioeconomic and built environment influences on smaller scales of travel. ACS estimates are less consistent (i.e. have higher margins of error) at the block group level and contain too few bicyclists to be meaningful for analysis. After removing census tracts without land area, population, and reported land uses, 1,289 remained for further analysis.

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where p_i = the proportion of land use i in the tract, and k = the number of land uses considered (in this case, six: the five listed plus a category for other non-residential uses) (Cervero & Duncan, 2003).

Exposure

Estimates of bicycle activity to account for exposure levels are difficult to generate. In some cities, bicycle count data is robust. But count locations are far from universal and strategies for expanding count estimates to areal units are not well defined. The US Census reports journey to work estimates, but work trips compose a small fraction of all trips (approximately 17% in the study area), and tract level estimates have large margins of error. Similarly, although the National Household Travel Survey (NHTS) and the California Household Travel Survey (CHTS) have comprehensive coverage, census tract figures are not reliable because there are few—if any—responses per tract. While using either travel survey directly could be appropriate for exposure data when estimating regional environmental influences on bicycle crashes, there is simply not enough bicycle trip data to estimate neighborhood-level effects. Salon and Handy (2014) estimated bicycle activity in census tracts across California using a combination of age and gender variables, neighborhood types, and trip data from NHTS and CHTS. I use the NHTS-based bicycle-miles traveled (converted to kilometers) from that data source as exposure in this study.

Methods

Two sets of models form the basis for analysis in this study. The first tests the relative explanatory power of three categories of independent variables on the total number of bicycle crashes per census tract. The purpose was to understand the role of neighborhood factors, transportation infrastructure, and land use on the frequency of bicycle crashes. The second set of models uses identical independent variables, but the dependent variable for each model in the set is the number of bicycle crashes for a different racial category. The purpose was to understand how variables associated with bicycle crashes vary across racial and ethnic groups. All models use the estimated bicycle-kilometers traveled as descried above as the exposure variable.[3] Count data of rare events such as bicycle collisions typically follow a Poisson or negative binomial distribution. Both model types frequently provide the basis for analytical techniques in crash-frequency research (Lord & Mannering, 2010). Poisson models assume that the mean equals the variance in the dependent variable. The negative binomial model adds a parameter to the Poisson model that accounts for overdispersion in the data; that is, for when the variance of the counts is greater than the mean. Because the variance in crash frequency was significantly greater than the mean, I chose negative binomial models to best represent the data distribution.

Significant spatial autocorrelation, which indicates an unobserved spatial process that explains some of the patterns discovered in a model, may produce biased coefficients. Furthermore, research exploring the relationship between zonal characteristics and crash frequency has found better model fits when accounting for spatial dependence of the data (Quddus, 2008; Siddiqui et al., 2012; Noland et al., 2013). To test the necessity of accounting for spatial autocorrelation, I fit the full model via maximum likelihood and computed the Moran's I statistic on the data and the residuals. The test reported statistically significant evidence of spatial autocorrelation. There is no tractable procedure that uses maximum likelihood estimation to account for spatial autocorrelation in count models. Thus, I estimated the set of models using spatial Bayesian conditional autoregressive (CAR) estimation similar to previous research on social and environmental influences on crash frequency (Noland et al., 2013). Census tract spatial weights follow a simple binary weighting scheme. I estimated the models as random-

[3] In models that include a count variable as the dependent variable, it is possible to include the exposure variable as an offset if it represents the maximum count possible. I included the exposure variable as a control, or independent, variable, since it does not represent a possible maximum of crash occurrences.

intercept multilevel models for another level of spatial control, fitting census tract variables in the first level and the county as the second level (Huang & Abdel-Aty, 2010; Dupont et al., 2013).

Bayesian statistical methods use repeated sampling to update estimates of the prior distribution of events, converging on a posterior probability given the supplied data. I estimated the models using the brms package in R, which uses the Stan program for the backend computational algorithm (Stan Development Team, 2016). Each model reached convergence with four chains and 4,000 iterations after a warm-up period of 1,000 iterations.

Prior to fitting the models, I tested variables in the dataset for multicollinearity issues. Poverty was significantly correlated with the log of median income (0.81), and population density was significantly correlated with vehicle ownership (0.76). I removed the latter variable in those pairs from the models. Limited English proficiency was significantly negatively correlated with the proportion of the White population (-0.82), but was not highly correlated with the other racial and ethnic variables so I retained both variables for model testing. Intersection density was correlated with the density of local roadways (0.76), but because the two variables together represent different built environments—for example, a highly-gridded street network versus a suburban subdivision—I also retained both. No other variables were highly multicollinear so as to warrant removing from the models at the outset.

Results

Data summary

Over the three-year period, there were 7,088 bicycle crashes in the five-county study area. On average, there were 5.6 crashes per census tract with substantial variance in the number of occurrences across the region (Table 1). Although 85% of census tracts had at least one crash, the density of bicycle crashes varied according to intensity of activity in the area (Figure 1). Bicycle crashes were most concentrated in the eastern half of San Francisco, which contains the central business district and several of the city's denser residential neighborhoods. In the East Bay, which includes Alameda and Contra Costa Counties, crashes clustered near the University of California's Berkeley campus and major transportation corridors between Berkeley and Oakland. Bicycle crashes in other areas were more dispersed, with some concentrations in downtown San Jose and in other suburban population centers. A significantly smaller share of the region's crashes occurred in Contra Costa County compared to its population, while San Francisco had a significantly greater share of crashes.

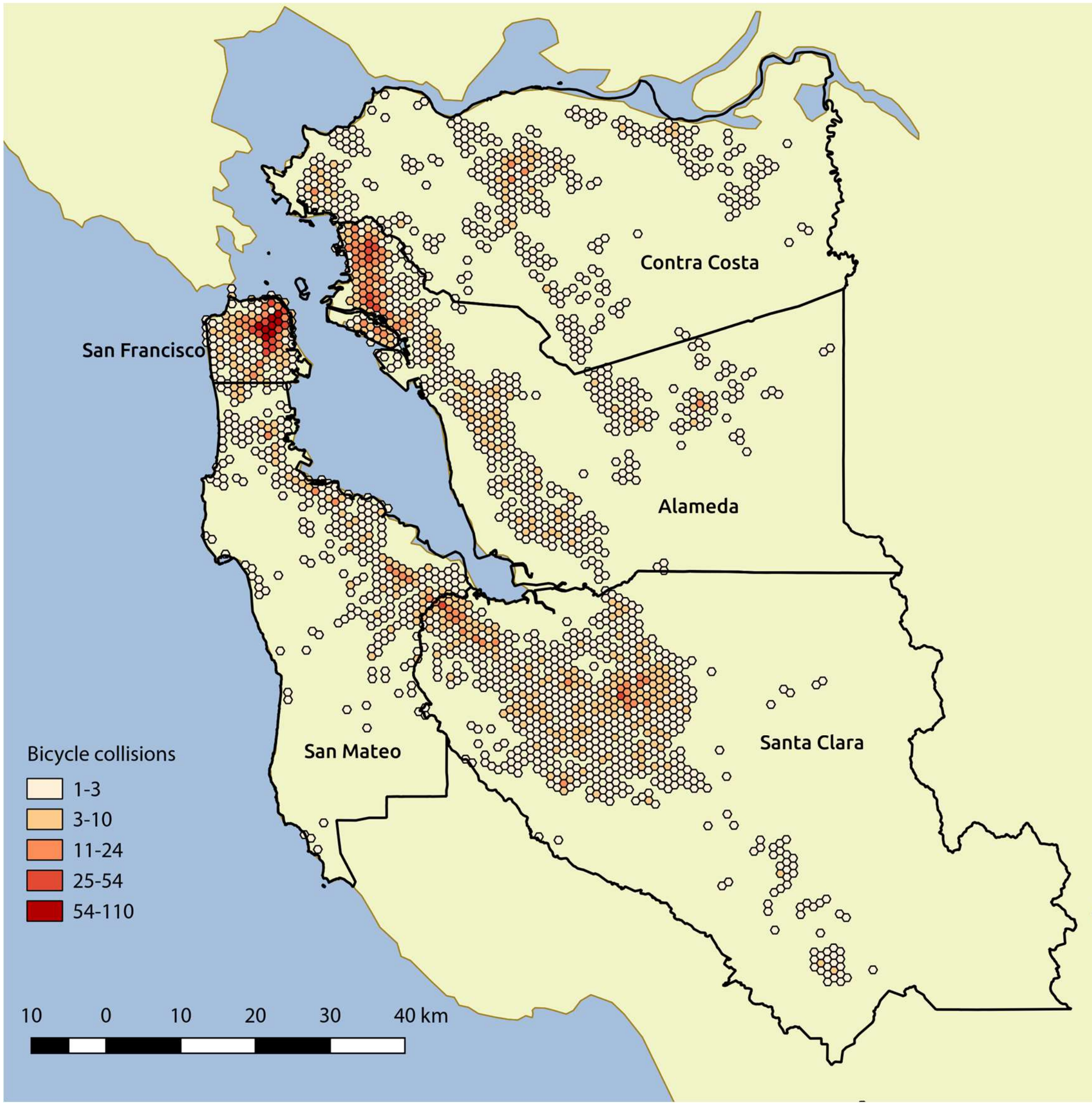

Figure 1: Density of bicycle collisions per 1 km hexagonal grid. (Study area outlined in black.)

In absolute numbers, bicycle crashes were more likely to involve White victims than other racial or ethnic groups (Table 2). Over half of all bicycle crashes in the region involved Whites, while they were only 39% of the population. However, on a per-capita and per-distance basis, Black bicyclists faced the greatest chance of being in a crash—they were far overrepresented among crash victims compared to other racial and ethnic groups. Despite forming the smallest share of the population, they were involved in the most crashes per person and per distance traveled, at a rate nearly eight times that of White cyclists. Hispanic cyclists were involved in bicycle crashes proportional to their share of the population, but at a rate 2.5 times greater than White cyclists per distance traveled. Asian cyclists were involved in the fewest number of crashes and at the lowest rates per capita and per distance.

Table 2: Bicycle crash statistics by race/ethnicity

Race/ethnicity	Population	Bicycle crashes	Crashes per million people	Crashes per million km (annualized) [a]
White	39%	52%	1,590	3.5
Asian	27%	9%	409	1.4
Hispanic	24%	21%	1,039	9.0
Black	6.4%	9%	1,675	27.6

[a] Distance traveled is calculated using NHTS annualized weighted data for the two study-region MSAs

Bivariate comparisons suggest that some of higher risk of crash for cyclists in historically disadvantaged neighborhoods could result from inequities in infrastructure provision (Table 3). On average, census tracts that had at least one separated bike path or bike route, and lacked a freeway or a major arterial road had a higher proportion of White residents. In contrast, census tracts with bicycle infrastructure tended to house lower proportions of people of color and have lower rates of poverty and limited-English proficiency. Census tracts with freeways were home to higher proportions of the Black and Hispanic population, while those with major arterials had more Hispanic, Asian, poor, and limited-English-proficient residents.

Table 3: Average population percentage per census tract by presence of transportation infrastructure

	Bike paths (Class 1)			Bike lanes (Class 2)			Bike routes (Class 3)			Freeway/ expressway			Major arterials		
	No	**Yes**	**p-value**	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**	**No**	**Yes**	**p-value**
White	**38.5**	**44.1**	< 0.001	40.2	40.3	0.926	**38.4**	**41.5**	0.020	**42.7**	**37.0**	< 0.001	**46.6**	**38.9**	< 0.001
Black	**8.0**	**5.0**	< 0.001	**8.5**	**6.3**	0.001	6.7	7.3	0.286	**6.5**	**7.7**	0.040	6.7	7.1	0.597
Hispanic	22.5	22.4	0.890	23.4	22.0	0.214	**24.7**	**21.1**	< 0.001	**20.8**	**24.6**	< 0.001	**19.2**	**23.2**	0.003
Asian	**26.4**	**23.7**	0.010	**23.4**	**26.7**	0.002	25.9	25.3	0.588	25.3	25.9	0.617	**22.7**	**26.2**	0.009
Poverty	**11.7**	**9.5**	< 0.001	**12.2**	**10.4**	0.001	11.4	10.7	0.211	11.4	10.5	0.074	**9.1**	**11.4**	< 0.001
LEP	**19.5**	**16.9**	< 0.001	**19.8**	**18.2**	0.040	**19.6**	**18.1**	0.042	18.2	19.4	0.103	**15.8**	**19.3**	< 0.001

Notes: LEP = limited-English proficient. *Yes* indicates census tracts that have that type of infrastructure, *no* indicates those that do not. P-value from two sample t-tests. Bold values indicate statistically significant differences ($p < 0.05$).

Analysis

Population, transportation, and land use characteristics

In the first set of models, each group of the hypothesized crash causes was entered individually into its own model, before adding all the variables to a grand model (Table 4). In general, neighborhood markers of socioeconomic disadvantage were associated with a higher number of crashes per census tract. The first model controlled only for neighborhood socioeconomic characteristics. Because most crashes involved White victims, a higher proportion of White residents in the neighborhood was associated with a greater number of crashes. However, census tracts with higher levels of poverty and higher proportions of limited-English-proficient speakers also experienced more bicycle crashes. Over the study area, an increase of the poverty rate of one percentage point was associated with a 3.7% increase in the number of bicycle crashes, while an equivalent increase in the limited English proficient population was associated with a 1.4% increase in bicycle crashes. These findings are consistent with research reviewed earlier that finds relationships between neighborhood disadvantage and higher crash frequency. Educational attainment was not significantly associated with the number of crashes. Population density was negatively associated with crash frequency, but employment density was positively associated with crash frequency, suggesting a greater impact of daytime activity on safe cycling activity. Note that in this and in all subsequent models, the county serves as the second level in the random-intercept multilevel models. There is significant variation in the number of crashes between counties. In the first model, the intra-class correlation coefficient indicates that the county accounts for about 37% of the variation in the number of bicycle crashes. Exposure was also included in each of the models, and the signs are in the expected direction. The effect was small but positive; for every increase in the distance traveled by bicycle in kilometers, the number of crashes increased by 0.1%.

The second model contained the set of transportation infrastructure variables as independent variables. The model was substantially stronger than the population-only model and reduced by over half the amount of variation explained by county differences alone. More large surface streets meant to carry significant volumes of traffic were associated with substantially more bicycle crashes. In two equally sized census tracts, an additional kilometer of principal and minor arterials would be associated with an increase in the incidence of crashes by nearly five times and over double, respectively. (This relationship was true for the unnormalized variables as well—i.e., total length per census tract—though the magnitudes of the effects were smaller.) Conversely, census tracts with more local roads per unit area were significantly safer. A higher density of freeways was also associated with a substantially smaller number of bicycle crashes, likely because bicycles are not permitted to travel on these roads and they create connectivity barriers for non-motorized travel throughout the rest of the neighborhood. Consistent with the literature, neighborhoods with more intersections and higher proportions of four-way intersections were also prone to more crashes.

Cyclists will ride where there is bicycle infrastructure. Thus, compared to neighborhoods without infrastructure, neighborhoods with more bikeways should have higher incidences of crashes, though the type of infrastructure may mitigate the severity and relative frequency of crashes. The model predicted just this relationship. There were significantly more bicycle crashes in neighborhoods with greater densities of Class 2 bicycle lanes and Class 3 bicycle routes. Because the 95% credible intervals of the two coefficients overlap, it is not possible to claim a significant difference between the two, but the model suggests that bicycle routes were associated with a lower incidence of crashes. The density of Class 1 separately bike lanes was not associated with the frequency of crashes.

The third model tested the association of land use with bicycle crashes. Although the strength of the model was similar to the transportation infrastructure model, fewer variables were significantly associated with the number of crashes. Higher proportions of office land use were associated with more crashes per census tract, likely for similar reasons as employment density. A higher land use mix was also associated with a greater number of crashes. None of the other land use variables tested had a significant association with bicycle crashes. The land use model was an improvement over the first, socioeconomic model, but not over the transportation infrastructure model.

The fourth model in the set tested each group of independent variables together. Model fit statistics indicate an improvement over each of the prior three models. The relationships of most of the variables with frequency of bicycle crashes remained the same when controlling for socioeconomic status, transportation infrastructure, and land use simultaneously. However, some coefficients changed in magnitude or became insignificant—primarily those in the transportation infrastructure category. In the population category, employment density became insignificant, suggesting that other transportation or land use characteristics associated with higher job concentrations have more explanatory power. Although the poverty rate in a census tract was still positively associated with bicycle crashes, the strength of the relationship reduced by about one third. The density of freeways and minor arterials were no longer significantly associated with crashes, suggesting these relationships were also associated with other neighborhood factors. For the same reasons, the magnitude of the coefficient for local roads reduced by about half, though a greater density of local roads was still associated with fewer bicycle crashes. None of the land use variables changed in significance, though the magnitudes of the office and land-use mix coefficients both decreased.

Crashes by race and ethnicity

The second set of models uses the same of predictors from the fourth model above to analyze crash frequency by race or ethnicity. These models test whether neighborhood socioeconomics, transportation infrastructure, and land use act in different ways on how many cyclists of different races and ethnicities got into crashes (Table 5). In other words, through these models, is it possible to identify neighborhood inequities that bicycle safety planning needs to address? To enable better comparisons, I retained all variables initially hypothesized to have an association with crash frequency regardless of whether the credible interval for each coefficient overlapped zero.

Because over half the crashes in the study area involved White cyclists, most of the same variables that were associated with crash frequency in the complete, all-crash model were also associated with the frequency of crashes involving White victims, though some magnitudes changed. However, fewer variables were significantly associated with the crash frequency involving victims of other races and ethnicities. Notably, none of the variables that were negatively associated with crash frequency in the total crash model or the White victim model were associated with crash frequency in the other models. For example, a higher density of local streets in a census tract was associated with fewer bicycle crashes involving White victims and fewer bicycle crashes overall. But local roads had no effect on crash frequency for Black or Hispanic cyclists, which was a significant difference from the coefficients in the other models. (For Asian cyclists, the magnitude of the coefficient on local roads was similar to that in the total crash model, but the credible interval overlapped zero, so it is not possible to say with 95% certainty that there is an effect or a difference.)

Some other differences between the models were significant as well. The relationship between neighborhood disadvantage and crash frequency was not equally strong across the models. Neighborhoods with higher poverty were likely to have higher numbers of bicycle crashes involving White and Black victims but not Hispanic and Asian victims, and limited English proficiency was not a significant predictor in any of the racial group models. An increase of 1 km of principal arterials in equivalently sized census tracts yielded incidence rates over three times greater for Black cyclists and nearly twice as great for Hispanic cyclists compared to White cyclists. Minor arterials were also associated with higher numbers of Hispanic-involved bicycle crashes, but not for any other racial or ethnic category. Bicycle infrastructure was not associated with the number of Hispanic-involved crashes, while increases in Class 2 bicycle lanes were associated with incidence rates of crashes substantially greater for Asian cyclists compared to others.

As with the total crash model, few of the land use characteristics were significantly associated with bicycle crashes in the second set of models. More office land use was associated with a greater number of crashes for White and Asian cyclists but not for any other group, more retail predicted more Hispanic-involved crashes, and more industrial land use had a negative effect on crash frequency of Asian cyclists. The effect of land-use mix was consistent across all models, however; a more equally distributed mix of land uses was associated with a greater number of crashes, regardless of racial or ethnic group.

Table 4: Association between population, transportation, and land use characteristics and total number of bicycle crashes

	Population		**Transportation**		**Land use**		**All variables**	
	Estimate	**95% credible interval**	**Estimate**	**95% credible interval**	**Estimate**	**95% credible interval**	**Estimate**	**95% credible interval**
Intercept	-0.661		-0.243	(-0.771, 0.279)	0.303	(-0.285, 0.902)	-2.273	(-2.969, -1.572)
Exposure (bkt)	**0.001**	(0.001, 0.001)	0.001	(0, 0.001)	0.001	(0, 0.001)	**0.001**	(0.001, 0.001)
% White	**0.022**	(0.017, 0.026)					**0.024**	(0.02, 0.028)
% in poverty	**0.036**	(0.028, 0.045)					**0.025**	(0.017, 0.032)
% college-educated	0.003	(-0.005, 0.011)					0.002	(-0.005, 0.008)
% limited-English	**0.014**	(0.006, 0.023)					**0.017**	(0.01, 0.025)
Population density	-0.002	(-0.004, 0)					0	(-0.002, 0.002)
Employment density	**0.003**	(0.002, 0.004)					0	(-0.001, 0)
Freeway (km per ha)			**-0.3219**	(-6.053, -0.359)			-1.116	(-3.796, 1.558)
Principal arterial (km per ha)			**5.917**	(2.345, 9.437)			**6.04**	(2.608, 9.625)
Minor arterial (km per ha)			**4.684**	(1.187, 8.12)			1.612	(-2.015, 5.194)
Collector streets (km per ha)			-2.566	(-6.438, 1.323)			-3.895	(-7.849, 0.082)
Local streets (km per ha)			**-7.402**	(-9.843, -4.943)			**-4.224**	(-6.936, -1.53)
Class 1 bikeways (km per ha)			3.535	(-4.013, 11.181)			0.685	(-6.27, 7.716)
Class 2 bikeways (km per ha)			**7.106**	(4.018, 10.277)			**7.362**	(4.537, 10.215)
Class 3 bikeways (km per ha)			**4.781**	(1.626, 7.983)			**4.983**	(2.11, 7.88)
Intersection density (per ha)			**0.89**	(0.492, 1.283)			**0.414**	(0.028, 0.8)
% four-way intersections			**0.742**	(0.539, 0.942)			**0.452**	(0.249, 0.656)
% Single-family residential					-0.003	(-0.007, 0)	0.001	(-0.003, 0.005)
% Multifamily residential					0.001	(-0.004, 0.005)	-0.001	(-0.006, 0.004)
% Retail					0.006	(-0.002, 0.014)	0.004	(-0.004, 0.012)
% Office					**0.022**	(0.014, 0.03)	**0.015**	(0.008, 0.023)
% Industrial					-0.003	(-0.009, 0.002)	0.002	(-0.003, 0.007)
Land-use mix (entropy)					**1.996**	(1.547, 2.456)	**1.444**	(1.014, 1.869)

County								
sd(Intercept)	0.6	(0.236, 1.623)	0.326	(0.121, 0.911)	0.443	(0.169, 1.23)	0.396	(0.154, 1.062)
ICC	0.37		0.135		0.228		0.185	
Autocorrelation								
car	0.893	(0.546, 0.997)	0.855	(0.633, 0.975)	0.722	(0.321, 0.964)	0.734	(0.37, 0.954)
sdcar	0.908	(0.56, 1.381)	1.165	(0.822, 1.558)	1.21	(0.807, 1.602)	1.098	(0.749, 1.51)
Theta	1.903	(1.516, 2.643)	2.905	(2.021, 4.92)	2.905	(1.991, 4.835)	4.996	(2.778, 11.573)
WAIC	6854		6688		6688		6427	
Bayesian R^2	0.5		0.56		0.51		0.656	

Note: Bold values indicate coefficients of independent variables where the 95% credible interval does not cross zero ("statistically significant").

Table 5: Associations between neighborhood characteristics and crash frequencies, by race or ethnicity

	White		Black		Hispanic		Asian	
	Estimate	**95% credible interval**	**Estimate**	**95% credible interval**	**Estimate**	**95% credible interval**	**Estimate**	**95% credible interval**
Intercept	-3.566	(-4.415, -2.699)	-4.731	(-5.963, -3.55)	-3.35	(-4.36, -2.376)	-2.695	(-4.278, -1.05)
Exposure (bkt)	0.001	(0, 0.001)	**0.001**	(0.001, 0.001)	**0.001**	(0.001, 0.001)	0	(0, 0.001)
% Same race	**0.039**	(0.034, 0.045)	**0.025**	(0.014, 0.035)	**0.031**	(0.025, 0.037)	**0.014**	(0.006, 0.021)
% in poverty	**0.019**	(0.01, 0.029)	**0.021**	(0.005, 0.036)	0.004	(-0.009, 0.016)	-0.004	(-0.022, 0.014)
% college-educated	0.008	(0, 0.015)	-0.001	(-0.015, 0.013)	0.002	(-0.009, 0.014)	**0.016**	(0.002, 0.029)
% limited-English	0.007	(-0.002, 0.017)	0.01	(0, 0.021)	-0.003	(-0.012, 0.006)	-0.01	(-0.024, 0.003)
Population density	0.001	(-0.001, 0.003)	-0.001	(-0.004, 0.003)	-0.002	(-0.005, 0.001)	-0.002	(-0.006, 0.002)
Employment density	0	(-0.001, 0.001)	0	(-0.001, 0.001)	0	(-0.001, 0.001)	0	(-0.001, 0.001)
Freeway (km per ha)	-0.612	(-3.814, 2.622)	1.094	(-3.608, 5.676)	1.236	(-2.972, 5.301)	-4.071	(-9.717, 1.518)
Principal arterial (km per ha)	**4.421**	(0.44, 8.49)	**10.241**	(3.899, 16.441)	**9.592**	(3.702, 15.483)	2.831	(-4.273, 10.086)
Minor arterial (km per ha)	-0.404	(-4.752, 3.791)	6.12	(-0.402, 12.711)	**8.49**	(2.512, 14.458)	-0.79	(-8.643, 6.833)
Collector streets (km per ha)	**-7.39**	(-12.124, -2.664)	2.21	(-5.666, 9.837)	0.002	(-6.592, 6.643)	-2.11	(-11.023, 6.769)
Local streets (km per ha)	**-7.712**	(-10.911, -4.521)	1.701	(-3.914, 7.205)	0.584	(-4.003, 5.306)	-4.519	(-10.376, 1.334)
Class 1 bikeways (km per ha)	-0.289	(-8.651, 8.068)	-0.444	(-16.893, 15.221)	5.532	(-6.106, 16.921)	11.148	(-3.379, 25.249)
Class 2 bikeways (km per ha)	**7.747**	(4.31, 11.151)	**7.478**	(2.225, 12.745)	3.259	(-1.182, 7.703)	**16.587**	(11.049, 22.06)
Class 3 bikeways (km per ha)	**4.984**	(1.644, 8.455)	4.347	(-1.123, 9.804)	1.822	(-2.917, 6.534)	3.05	(-3.191, 9.157)
Intersection density (per ha)	**0.868**	(0.42, 1.32)	0.171	(-0.544, 0.887)	-0.118	(-0.77, 0.523)	0.205	(-0.622, 1.016)
% four-way intersections	**0.565**	(0.322, 0.812)	0.369	(-0.032, 0.767)	0.169	(-0.154, 0.492)	0.337	(-0.082, 0.759)
% Single-family residential	0.001	(-0.004, 0.005)	-0.003	(-0.012, 0.005)	0.002	(-0.005, 0.009)	0.001	(-0.008, 0.01)
% Multifamily residential	-0.001	(-0.007, 0.005)	-0.006	(-0.017, 0.004)	0.002	(-0.007, 0.011)	-0.003	(-0.014, 0.008)
% Retail	-0.001	(-0.01, 0.008)	0.006	(-0.009, 0.02)	**0.018**	(0.007, 0.03)	-0.005	(-0.021, 0.011)
% Office	**0.017**	(0.008, 0.025)	0.002	(-0.015, 0.018)	0.009	(-0.004, 0.021)	**0.017**	(0.002, 0.031)
% Industrial	0.003	(-0.003, 0.01)	0.003	(-0.007, 0.014)	0.008	(0, 0.016)	**-0.015**	(-0.027, -0.004)
Land-use mix (entropy)	**1.552**	(1.045, 2.055)	**1.939**	(1.008, 2.868)	**1.567**	(0.869, 2.28)	**1.28**	(0.353, 2.207)

County								
sd(Intercept)	0.435	(0.151, 1.24)	0.582	(0.189, 1.635)	0.547	(0.209, 1.497)	1.225	(0.472, 3.3)
ICC	0.234		0.335		0.304		0.679	
Autocorrelation								
car	0.533	(0.144, 0.844)	0.695	(0.113, 0.971)	0.273	(0.012, 0.681)	0.968	(0.848, 0.999)
sdcar	1.431	(0.988, 1.797)	1.253	(0.686, 1.751)	1.497	(0.935, 1.949)	1.058	(0.596, 1.547)
Theta	16.445		18.739		11.095		1.983	
WAIC	4711		1985		3171		2215	
Bayesian R^2	0.758		0.586		0.622		0.431	

Notes: Bold values indicate coefficients of independent variables where the 95% credible interval does not cross zero ("statistically significant"). WAIC should not be directly compared between models as a goodness of fit, though the Bayesian R^2 may be compared.

Discussion and conclusions

The goal of the analysis in this paper was to identify what accounts for potential disparities in bicycle crash occurrences across racial and ethnic groups. In the case of the central core of the San Francisco Bay Area, disparities are greatest for Black cyclists: they are a minority of the population, but represent the majority of bicycle crashes per person and per estimated distance bicycled. And vulnerable neighborhoods, measured by poverty and English-proficiency rates, also experienced a greater number of bicycle crashes, holding all else equal. To return to the hypothesis posed in the introduction, I find a residual risk to cyclists in person-of-color neighborhoods.

By and large, transportation infrastructure, land use, and socioeconomic characteristics influenced the prevalence of bicycle crashes in census tracts in expected ways for all crashes and by group. The model results also indicate that not every variable is equally explanatory of crashes across all population groups involved. In general, heavier traffic as proxied by arterial roadways in areas of high activity predicted more bicycle crashes per kilometer cycled. But for Black and Hispanic cyclists, those effects were particularly pronounced and not mitigated by lower-traffic roads. There were significant correlations between the proportion of a racial or ethnic group in a census tract and the number of crashes involving that racial or ethnic group—in both bivariate comparisons and the multivariate models—suggesting a qualitatively negative difference in roadway infrastructure between majority person-of-color neighborhoods and majority White neighborhoods.

That bicycle infrastructure is associated with a greater number of crashes is not surprising if we consider it as an indicator of where cyclists are expected to be. (Bicycle crashes cannot occur where there are no cyclists.) Thus, the positive relationship with crash frequency should not be construed as an *individual* risk or the relative risk of riding on the same roadway without bicycle provisions. Notably, the safest type of infrastructure was that on fully separate rights-of-way. But as with some of the roadway characteristics, magnitudes and relationships of the bicycle infrastructure coefficients were not equivalent across the models, indicating real differences in the effects. For Hispanic cyclists, unlike for other groups, no type of bicycle infrastructure was significantly associated with crash frequency. This could indicate a behavioral difference, whereby Hispanic cyclists are less likely to use designated bicycle infrastructure out of habit or necessity.

These findings draw attention to the need for planners to consider how socioeconomic difference and vulnerability play a role in safety. Microscale analysis will identify which roadway characteristics contribute to a crash-prone corridor or area. Many current efforts in practice do just this by using data-driven approaches to identify hotspots and risk areas in their goals to eliminate traffic fatalities (e.g. City and County of San Francisco, 2015; City of Los Angeles, 2015). But as suggested earlier, improvements may not have the same effects for everyone even when using population characteristics to prioritize projects. A holistic planning approach might consider the role of neighborhood factors and drivers of travel behavior in assessing how to address safety for diverse groups.

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