Active Exposure:
Using collision data in lieu of traffic counts to evaluate risk for active transportation users

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PROFESSIONAL REPORT

Submitted in partial satisfaction of the requirements for the degree

of

MASTER OF CITY PLANNING

in the

Department of City and Regional Planning

of the

UNIVERSITY OF CALIFORNIA, BERKELEY

APPROVED

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Date: Fall 2021

1. Introduction

Vulnerable road users, like pedestrians and bicyclists, are more likely to be involved in traffic collisions than road users in motor vehicles (NHTSA, 2015). Traffic safety for these vulnerable road users affects everyone: regardless of one's primary mode of transportation, everyone is a pedestrian[1] for part of their trip (NHTSA, 2013). Improving road safety for vulnerable road users is critical to improving traffic safety. However, road safety does not affect everyone equally. People of color are disproportionately affected by pedestrian and bicycle collisions (Coughenour et al., 2017; Barajas, 2018). Improving pedestrian and bicycle road safety can help to mitigate existing inequities in our transportation network.

Measurements of traffic safety typically rely on an exposure value in order to convert the number of collisions into an exposure rate (often by the number of trips, distance, or time traveled). In order to determine these exposure values for motor vehicles, robust models are used; however, few models exist at the local level to forecast pedestrian and bicycle travel on specific road segments, making it hard to measure local pedestrian and bicycle risk by exposure. Furthermore, while there are some bicycle and pedestrian counts collected by local governments or advocacy groups for specific intersections or on road segments, they do not allow for easy comparison of traffic safety across demographic groups. In order to better understand factors that contribute to bicycle and pedestrian collisions, we can examine collision data. Although we may not have an exposure risk of walking or bicycling, we can examine the relative conditions of the situations collisions occur under and the types of neighborhoods collisions more frequently occur in.

Historically, disadvantaged groups are disproportionately represented in bicycle collisions (Barajas, 2018). In order to better understand factors that contribute to bicycle and pedestrian collisions, we can explore collision data and the variables in it. By controlling for the neighborhoods the collisions take place in, we can discern whether there are different trends in crash data between different demographic neighborhoods. Note, this is not a measurement of risk for demographic groups, because cyclists travel through many different census tracts on a journey. Understanding these trends can be useful in deciding which countermeasures to implement though. Furthermore, we can use collision data to understand if there are areas that see higher rates of collisions that cite specific infrastructure-related problems, like bad road quality or bad lighting. We can also examine the race of the victim, as that is included in the collision data. We can map the collisions to the census tract level to better understand what neighborhoods are likely to see more collisions.

While it is not novel to use this data when determining infrastructure-based solutions, as agencies do use collision data to understand the collision patterns when deciding where and how to improve their infrastructure, this paper adds to the literature in two ways. First, it proposes a methodology of specifically examining collisions that cite bad road quality, bad lighting, bad weather, or whether collisions occur in intersections, to

[1] The National Highway Traffic Safety Administration (NHTSA) defines a pedestrian as "any person on foot, walking, running, jogging, hiking in a wheelchair, sitting, or lying down" (NHTSA, 2013).

understand where infrastructure-based countermeasures or investment can be directed to prevent future collisions. Second, while many authors explore the relationships between neighborhood income and transportation investment, transportation investment and collisions, and neighborhood income and collisions, this paper explores the three-way relationship by examining the correlation between infrastructure-related collisions and income.

This paper uses the nine-county San Francisco Bay Area as a case geography. Though there are limitations to using such a large case geography, it is used to explore trends in the data.

2. Methodology

This section details the data sources and data analysis methods used and provides a summary of the data.

2.1 Data Sources

This section details the data sources used for the analysis.

Collision Data

This analysis uses data from the Transportation Injury Mapping System (TIMS), a database maintained by Safe Transportation Research and Education Center (SafeTREC) at U.C., Berkeley (SafeTREC, 2020). TIMS applies a methodology to clean and geocode data from California Statewide Integrated Traffic Records System (SWITRS), a database of police traffic records. Using TIMS, all of the pedestrian and bicycle collision records were acquired for the nine county San Francisco Bay Area region for the ten-year period between January 1, 2009, and December 31, 2018. The nine counties that make up the San Francisco Bay Area are Alameda County, Contra Costa County, Marin County, Napa County, San Francisco County, San Mateo County, Santa Clara County, Solano County, and Sonoma County. These nine counties span over 6,900 square miles and 7.74 million people (2019 ACS). Figure 1 shows the population, population density, and share of the total Bay Area population of each county.

Figure 1: Descriptive statistics of the nine counties that make up the San Francisco Bay Area.

County	Population		Land Mass	Population Density
	N	%	(sq mi)	(per sq mi)
Santa Clara	1,927,852	24.9%	1,290	1,494.46
Alameda	1,671,329	21.6%	739	2,261.61
Contra Costa	1,153,526	14.9%	716	1,611.07
San Francisco	881,549	11.4%	47	18,808.38
San Mateo	766,573	9.9%	448	1,711.10
Sonoma	494,336	6.4%	1,576	313.66
Solano	447,643	5.8%	822	544.58
Marin	258,826	3.3%	520	497.74
Napa	137,744	1.8%	748	184.15
Total	**7,739,378**	**100%**	**6,906**	**1,120.70**

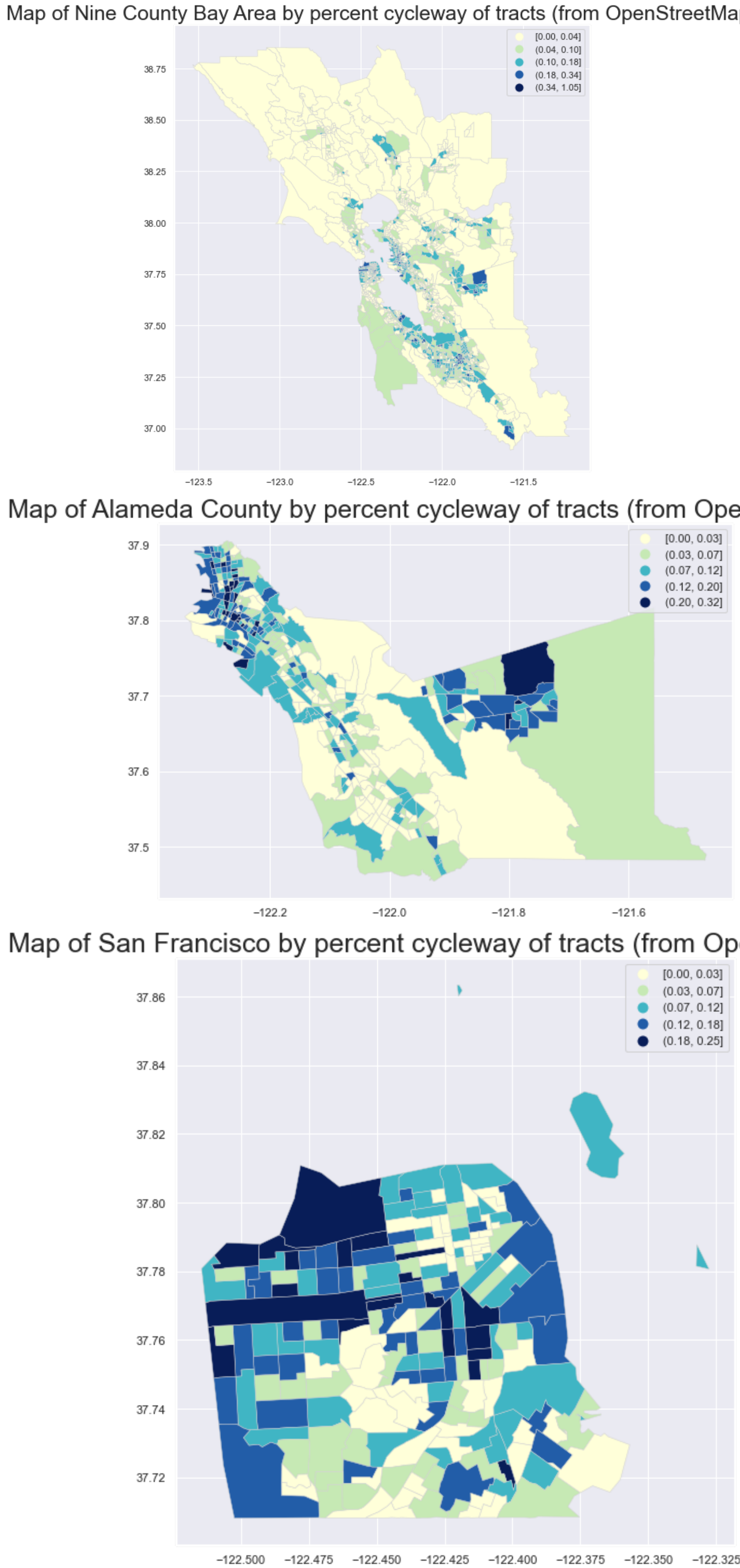
TIMS data includes the coordinates of the location at which the collision occurred, along with variables related to the cause of the collision, the infrastructure and facility where the collision took place, and the parties involved. This analysis uses demographic data (race/ethnicity and gender), collision severity (categorized into four discrete categories), and other environmental and party characteristics. TIMS data details whether or not the incident occurred at an intersection. TIMS's "lighting" variable, which identifies the lighting on the facility when the collision occurred, was recategorized to represent whether the street was well lit ("daylight" and "dark [with] street lights") or whether it was not well lit ("dawn or dusk," "dark no street lights," "dark street lights not functioning," or no data included). TIMS's "weather" variable was recategorized to represent whether the weather was clear ("clear") or not ("cloudy," "foggy," "rainy," "windy," "snowy," or "other"). TIMS's "road conditions" variable was recategorized to represent whether the road was under normal conditions ("no unusual condition" and "not stated"[2]), or abnormal conditions ("holes, deep ruts," "loose material on roadway," "obstruction on roadway," "construction or repair zone," "reduced roadway width," "flooded," or "other").

American Community Survey (ACS)
The United States Census Bureau conducts the American Community Survey (ACS) annually to collect geospatial sociodemographic data. This analysis uses ACS data to understand who is being affected by traffic collisions.

Bicycle Infrastructure Investment and Percent Cycleway
Open Street Maps, a collaborative, open, geodatabase includes streets that are tagged as "Bicycle Routes." These include "Bike lanes, sharrows, multi-use trails, dedicated cycleways and … desire paths" (OpenStreetMaps, 2021). Using Open Street Maps, the ratio of total road length of streets tagged as bicycle routes to the total distance of all roads was calculated for each census tract in the nine counties. This ratio was used as a proxy for infrastructure investment in active transportation. Figure 2a shows a map of the nine-county Bay Area colored by percent of cycleway by census tract; Figure 2b shows the data for the City and County of San Francisco; and Figure 2c shows the data for Alameda County. This data is used to understand the relationship between infrastructure investment and collisions that cite specific infrastructure-related issues.

[2] It was assumed that if abnormal road conditions affected the collision it would have been included on the police report.

Figure 2: Maps of percent cycleeway of tracts from OpenStreetMap



2.2 Data Discussion

Of the 300,084 collisions in all nine counties, 29,963 (10%) involved a pedestrian and 28,500 (9.5%) involved a bicycle. Figure 3 shows the distribution of total collisions, pedestrian collisions, and bicycle collisions by county. The counties are presented in descending order by number of active transportation collisions. The percentages are calculated from the total number of collisions of that type (by column). Santa Clara and Alameda had the highest proportion of collisions over the ten-year period. San Francisco County saw the highest rate of overall active-transportation and pedestrian-related collisions, while Santa Clara County saw the highest rate of collisions involving a pedestrian. Figure 4 shows the distribution of active-transportation-related collisions by county. San Francisco saw the highest rate of pedestrian and bicycle collisions, Santa Clara County saw the second highest rate of bicycle-involved collisions, and Marin saw the second highest rate of pedestrian-involved collisions.

Figure 3: Table of collisions by county and mode involved.

County	All Collisions		Active Collisions		Ped Collisions		Bicycle Collisions	
	N	%	N	%	N	%	N	%
San Francisco	36,387	12.1%	14,019	24.0%	8,338	27.8%	5,681	19.9%
Alameda	71,504	23.8%	13,607	23.3%	7,238	24.2%	6,369	22.3%
Santa Clara	71,799	23.9%	12,882	22.0%	5,526	18.4%	7,356	25.8%
Contra Costa	35,472	11.8%	4,993	8.5%	2,658	8.9%	2,335	8.2%
San Mateo	26,992	9.0%	4,913	8.4%	2,510	8.4%	2,403	8.4%
Sonoma	22,425	7.5%	2,961	5.1%	1,307	4.4%	1,654	5.8%
Marin	10,903	3.6%	2,225	3.8%	1,220	4.1%	1,005	3.5%
Solano	18,242	6.1%	2,029	3.5%	797	2.7%	1,232	4.3%
Napa	7,110	2.4%	834	1.4%	369	1.2%	465	1.6%
Total	**300,834**	**1**	**58,463**	**1**	**29,963**	**1**	**28,500**	**1**

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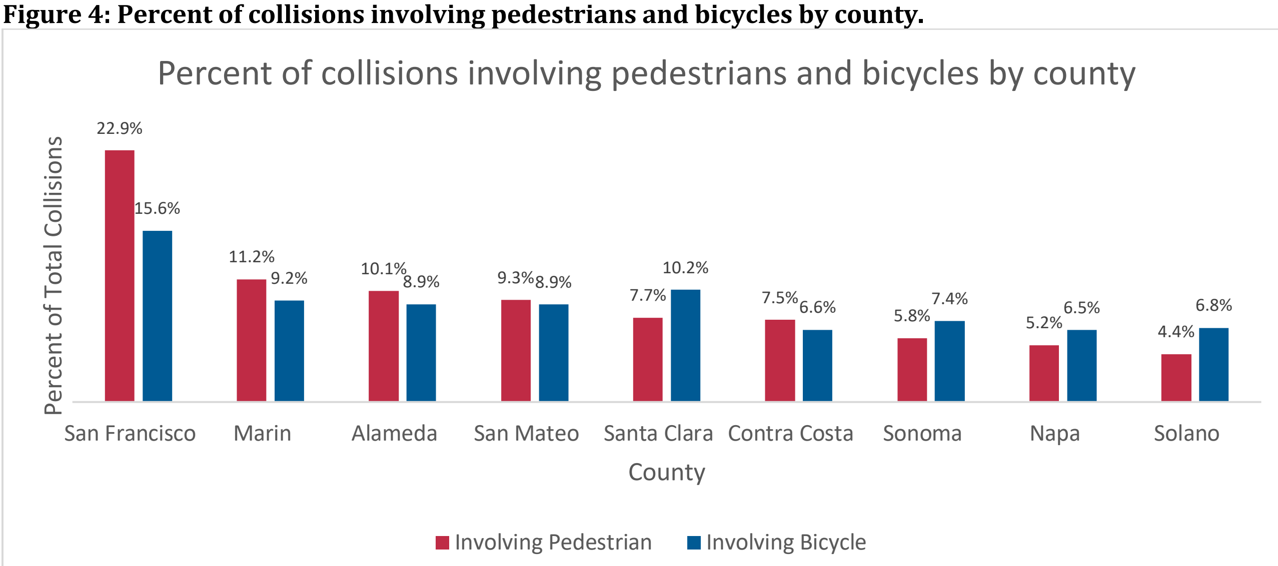
Figure 4: Percent of collisions involving pedestrians and bicycles by county.



There were 1,515 fatal collisions (2.6%) and 30,940 collisions (52.9%) that resulted in a severe or visible injury; slightly under half of all collisions (44.5%) resulted in a complaint of pain. While more than half of all collisions (52.7%) occurred at an intersection, 6,062 collisions (7.3%) occurred on a street that was not well lit. Most collisions (83.9%)

occurred while the weather was clear, however this is likely due to the geographic location and climate of the San Francisco Bay Area. A small percent of collision reports (3%) accounting for 3,662 collisions cited abnormal road conditions. 61.9% involved a male; 39.8% of victims were reported to be White, 10.9% Black, 19.2% Hispanic, and 9.7% Asian. Because the data is ultimately from individual police records of collisions, it has limitations and biases. One such limitation is that the race reported is at the discretion of the reporting officer.

Figure 5: Descriptive statistics of TIMS collision data.

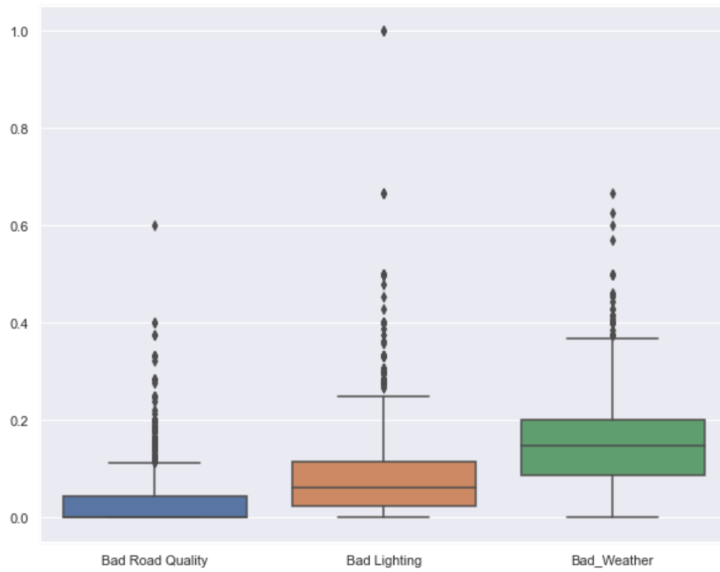
Descriptive Characteristics		
Total Number of Active Transportation Collisions	58,463	
Number of Pedestrian Collisions	29,963	9.95%
Number of Bicycle Collisions	28,500	9.47%
Demographic Characteristics		
Total Number of People (victims)	64,771	
Race/Ethnicity	**N**	**%**
White	25,776	39.8%
Black	7,035	10.9%
Hispanic	12,416	19.2%
Asian	6,281	9.7%
Other/Unknown	13,263	25.7%
Sex	**N**	**%**
Male	36,160	61.9%
Female	19,280	33.0%
Other/Unknown	3,023	5.2%
Collision and Infrastructure Characteristics		
Collision Severity	**N**	**%**
Complaint of Pain	26,008	44.5%
Visible Injury	24,674	42.2%
Severe Injury	6,266	10.7%
Fatal	1,515	2.6%
Environmental Characteristics	**N**	**%**
Collision occurred at an intersection	29,795	52.7%
Street was well lit	52,401	92.7%
Weather was clear	47,398	83.9%
Road conditions were normal	54,801	97.0%
Collisions Per Census Tract	**Mean**	**SD**
Number of collisions per tract	35.8	46.1
Number of severe collisions per tract	4.7	5.7
Number of collisions on abnormal roads per tract	1.1	2.2

2.3 Data Analysis

After the data is cleaned and recoded, collisions are mapped onto the Census Tract that they occur in using the coordinates of the collision. The total number of active transportation collisions, the number of collisions involving bicycles, and the number of collisions involving pedestrians are counted in each tract. For each of the three categories, the number of collisions that cite bad road quality, bad lighting, bad weather, and that occur in an intersection are also counted in each tract. Using these counts, the percent of collisions that cite bad road quality, bad lighting, bad weather, and that occur in an intersection are calculated for each tract.

Figure 6 shows the distribution of the percent of collisions in each census tract that cite bad road quality, bad lighting, and bad weather. Each data point is a census tract. All three distributions are right skewed, meaning that the minimum and median are closer together than the median and the maximum, and all three distributions have outliers: these tracts see high rates of collisions that cite these infrastructure-related issues. While the median percent of collisions that cite bad road quality is close to zero, the median percent of collisions that cite bad lighting is below 10%, and the median percent of collisions that cite bad weather is closer to 20%.

Figure 6: Distribution of the percent of collisions in each tract that cite infrastructure-related issues.



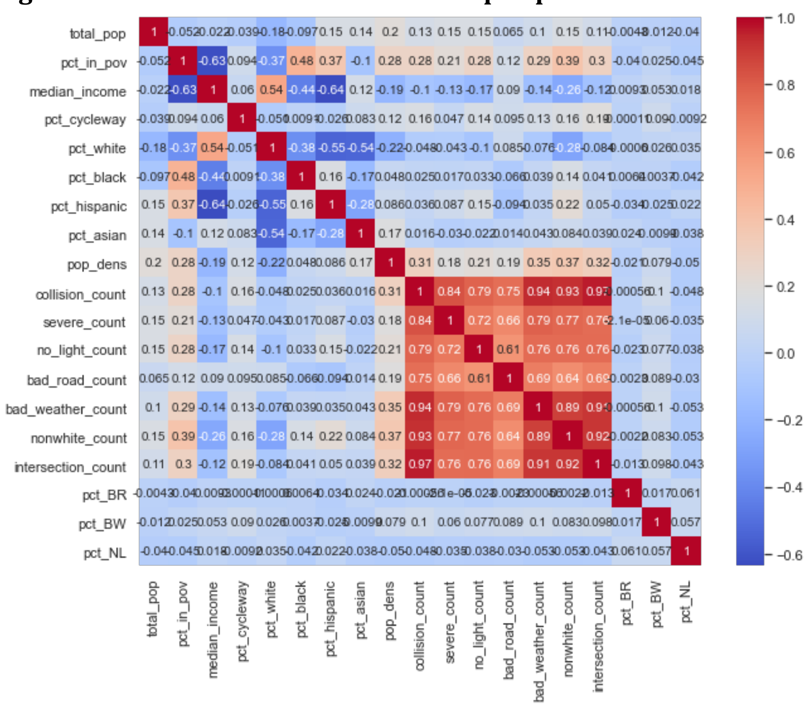
These collision counts for each of the 1581 tracts are combined with the ACS data at the tract level and the percent cycleway for each tract. For each of the three categories (all active transportation collisions, pedestrian collisions, and bicycle collisions), the correlation between every variable is computed. Figure 6 shows each variable, its mean and standard deviation, and a description.

Figure 7: Descriptive statistics of each variable used for analysis.

variable	description	mean	std
ACS data			
total_pop	total population of tract	4,855.03	1,876.41
pct_in_pov	percent of residents in tract living below the poverty level	9.49%	7.78%
median_income	median income of the tract ($2019)	$122,633.28	$52,187.33
pct_white	percent of residents in tract who are non-hispanic white	41.30%	23.41%
pct_black	percent of residents in tract who are non-Hispanic Black	6.15%	8.73%
pct_hispanic	percent of residents in tract who are Hispanic	22.60%	17.42%
pct_asian	percent of residents in tract who are non-Hispanic Asian	24.57%	19.48%
pop_dens	population density of the tract	38,910.49	42,946.26
TIMS data			
collision_count	number of collisions in the tract	35.81	46.12
severe_count	number of severe collisions in the tract	4.75	5.70
no_light_count	number of collisions that cite a lack of lighting in the tract	2.61	3.29
bad_road_count	number of collisions that cite bad roads in the tract	1.10	2.19
bad_weather_count	number of collisions that cite bad weather in the tract	5.78	8.34
nonwhite_count	number of collisions involving a non-white victim in the tract	17.92	23.48
intersection_count	number of collisions that occur in an intersection in the tract	16.93	24.48
pct_BR	percent of collisions that cite bad roads	3.11%	5.38%
pct_BW	percent of collisions that cite bad weather	14.86%	9.75%
pct_NL	percent of collisions that cite bad lighting	8.32%	9.19%
OpenStreetMaps data			
pct_cycleway	percent of road distance that is labeled as a "cycleway" in each tract	7.04%	6.83%

The pairwise correlation coefficients for each of the variables listed in Figure 7 are shown in a heatmap in Figure 8. Note that the significance is not shown in this table. Not all correlation results are statistically significant. The following results section discusses meaningful and significant relationships.

Figure 8: Correlation coefficient heatmap of pairwise correlation for each variable listed in Figure 6.



3. Results

This section explores the correlation between the total number of collisions and the number of collisions that cite specific factors in a tract with socio-demographic characteristics or infrastructure-related investment of the tract.

Severe Collisions and those that cite bad infrastructure:
There are strong positive correlations between the number of collisions in a tract and the counts of specific types of collisions. This indicates that tracts that see more collisions are more likely to see collisions that are severe, cite a lack of lighting, bad road quality, or bad weather, or occur at intersections. While this is not a surprising finding, it is important to acknowledge. Additionally, there is a strong correlation between the count of severe collisions and the count of collisions that cite bad roads, a lack of lighting, bad weather, and occurring at an intersection. Many cities in this region have committed to Vision Zero, including San Francisco, San Jose, Berkeley, Alameda, and Fremont. Vision Zero is a commitment to reaching zero traffic-related deaths and serious injuries. Improving these factors that are related to severe collisions is necessary to reach this goal.

Percent Cycleway in Tract
The percent of roads in tract that are tagged as a "cycleway" ("percent cycleway") is used as a proxy to represent infrastructure investment in a neighborhood. There is a positive correlation between the percent cycleway and population density of a tract (0.12), which indicates that the denser the tract, the more likely it is to have bicycle infrastructure investment.

While there is a positive correlation between the number of collisions in a tract and the percent cycleway (0.16), there is a weaker correlation between the number of collisions in a tract that cite bad lighting (0.14) and the number of collisions that cite bad weather (0.13) with the percent cycleway in that tract, meaning as the percent cycleway increases, the tract is less likely to see collisions that specifically cite these two infrastructure-related causes. There is a slightly stronger correlation between the percent cycleway and the number of collisions at an intersection (0.19), which could indicate that when there is bicycle infrastructure investment, collisions are less likely to happen on this infrastructure, and because fewer collisions are happening on the roads themselves, a higher proportion of these collisions are occurring in intersections. Nevertheless, it indicates the importance of not overlooking investing in intersection treatments or countermeasures when implementing street improvement projects.

There is a weak positive correlation between the percent cycleway and the two income-related metrics (median income and percent of residents in poverty), and a slightly negative correlation between the percent cycleway and percent of residents who are white. This may be because often infrastructure investment occurs in dense downtown areas that are often less white, and wealthier, whiter, and less dense areas may not have streets tagged as bicycle routes.

Population Density

Population density has a positive correlation with the percent of residents in poverty (0.28) and a negative correlation with the median income of the tract (-0.19). There is a strong positive correlation between the number of collisions in a tract with the tract's population density (0.31). There are weaker positive correlations between census tract population density and the number of severe collisions per tract (0.18), number of collisions that cite a lack of lighting per tract (0.21), and the number of collisions that cite bad road quality per tract (0.19). However, there is a stronger correlation between census tract's population density and the number of collisions that cite bad weather (0.35), the number of collisions with non-white victims (0.37), and the number of collisions that occur at intersections (0.32). This indicates that although denser tracts see higher rates of collisions, they are less often severe, and they less often cite bad road quality or bad lighting. However, they are more likely to involve a non-white victim and are more likely to occur at intersections.

Median Income:

When considering all tracts in the nine-county Bay Area, median income is negatively correlated with the total number of active-transportation related collisions in a tract with a correlation coefficient of -0.10. Median income has a stronger negative correlation with severe collisions (-0.13) and collisions that cite bad lighting (-0.17). This indicates that not only do tracts with higher household income see fewer active transportation-related collisions, but also that collisions that do occur in these tracts are more severe and more often related to a lack of adequate road lighting. There is also a slightly stronger negative correlation between median income and the number of collisions that occur at the intersection (-0.12), meaning tracts with lower incomes see higher rates of collisions at intersections than those with higher incomes. Median income also has a strong negative correlation with the number of collisions with non-white victims (-0.26), which indicates that as median income of the tract rises, the tract sees fewer collisions with non-white victims, makes sense given the correlation between income and race.

The relationship between pedestrian collisions and median income follows a similar trend. Median income of a tract has a negative correlation of -0.2 with the number of pedestrian collisions in a tract. Median income has a stronger negative correlation with severe collisions (-0.24), collisions that cite bad lighting (-0.23), and collisions with non-white victims (-0.3). These trends hold when accounting for exposure: normalizing the number of pedestrian collisions in a tract by the population of that tract.

When controlling for the population of a tract, there is still a negative correlation between the number of pedestrian collisions and median income of the tract (-0.13). There is a stronger negative correlation between median income of the tract and collisions normalized by population of the tract that cite bad lighting (-0.15), bad weather (-0.14), collisions with non-white victims (-0.18), and collisions at the intersection (-0.14). Although many bicycle and pedestrian collisions occur to cyclists/pedestrians in tracts they are moving through, the residents of the tract are (1) more likely to be involved in collisions in their tract and (2) live in proximity to the collisions, so by normalizing by the number of people in that tract we provide a proxy of the number of collisions near a person's residence.

Percent in Poverty
When considering all tracts in the nine-county Bay Area, the percent of residents in a tract in poverty is positively correlated with the total number of active-transportation related collisions in a tract with a correlation coefficient of 0.28. Percent of residents in a tract in poverty has the same correlation with the number of collisions that cite bad lighting (0.28). There is also a slightly stronger correlation between the percent of residents in poverty and the number of collisions in a tract that cite bad weather (0.29), meaning tracts with higher rates of residents in poverty see higher rates of collisions due to bad weather than those tracts with fewer residents in poverty. There is also a strong correlation between the percent of residents in poverty in a tract and the number of collisions with non-white victims (0.39), which makes sense given the correlation between income and race. There is also a slightly stronger correlation between the percent of residents in poverty and the number of collisions at an intersection (0.3) than the total number of collisions.

There is a positive correlation between the number of bicycle collisions per tract and the percent of residents that live in poverty (0.18). There is an even stronger negative correlation between percent of residents that live in poverty and bicycle collisions that cite bad weather (0.2) and bicycle collisions that occur at the intersection (0.23). This indicates that tracts with higher proportions of residents in poverty see higher rates of collisions due to bad weather and at intersections, beyond the increase in collisions that the tracts already see.

Despite there being a positive correlation between percent of residents that live in poverty and the total number of pedestrian collisions (0.33), there is a negative correlation between the percent of residents that live in poverty and the number of collisions that occur at intersections (-0.17). This would indicate that tracts with higher proportions of residents in poverty are more likely to see pedestrian collisions but less likely for those collisions to occur at the intersections. Intuitively, this could be related to the fact that the percent of residents in poverty is positively correlated with population density (0.28), and these pedestrian collisions could be occurring in denser urban areas where pedestrians are more likely to cross the street mid-block (FHWA, 2021). However, this may also be caused by the nature of the dataset where reporting officers decide not to answer all questions. A limitation of the data is that the analysis is occurring across the nine-county Bay Area, which is almost 7,000 square miles and over 7.7 million residents.

4. Discussion

By exploring maps of the rates of collisions that cite specific infrastructure-related issues, planners and policy makers can determine where funding an increased investment could be directed. Figure 9 shows three maps: the percent of collisions that cite bad light quality, the percent of collisions that cite bad road quality, and the percent of collisions that cite bad weather in San Francisco. These maps identify tracts that could benefit from repaving, increased lighting, or weather-related countermeasures, for example. They show that the Southeast corner of the city and the Dogpatch have high rates of collisions that cite bad lighting and bad road quality, while the Northeast corner of the city has high rates of collisions that cite bad lighting, bad road quality, and bad weather.

Figure 9: Maps of collisions that cite infrastructure-related issues in San Francisco.

5. Conclusions

This analysis shows that both census tract median income and the percent of residents in poverty not only have a strong correlation with the number of collisions in a tract, but they are more likely to see more severe collisions and collisions that cite infrastructure-related issues. This analysis also shows that infrastructure investment as measured by the percent of the road that is tagged as a cycleway was correlated with fewer collisions that cited bad lighting and bad weather, meaning this investment could be a factor in reducing the likelihood of collisions. Furthermore, it was shown that collisions that cite bad road quality, bad lighting, and bad weather are more likely to result in a severe or fatal injury. While this analysis does not examine local hotspots, it can be used to understand where investment could make the roadway safer.

6. Limitations and Future Work

Because the data is ultimately from individual police records of collisions, it has limitations and biases. Among other reasons, it is limited because it does not include data for collisions that are not reported to the police. Because each record is reported by an officer, it is subject to their biases; for example, the reported race is at the discretion of the reporting officer. Furthermore, it is important to understand that this analysis does not account for any exposure risk of walking or bicycling, but rather examines relative conditions of the situation a collision occurred under, given a collision. Although the analysis can illuminate characteristics of where collisions are occurring, it cannot discern who is involved in these collisions. Although each collision is one too many, in general, collisions are sparse, and especially at small geographies like individual census tracts, it can be hard to discern meaningful differences in the data. Further analysis that controls for rates of pedestrians and cyclists would be helpful in understanding the relationships between income, race, and collisions that cite bad road infrastructure that are normalized in the traditional traffic safety approach.

This analysis was conducted at the regional scale and does not try to draw specific local conclusions and discern specific areas in need of investment. The conclusions section details ways this analysis could be used at the local level to discern areas in need of investment due to bad road quality or a lack of lighting. This paper does not try to supplement other planning methods and it is important to still conduct adequate community engagement to understand what types of infrastructure investment communities want to see, as it differs by residents.

7. Acknowledgements

Funding for this project was provided by UC Berkeley Safe Transportation and Research Education Center (SafeTREC) and the Collaborative Sciences Center for Road Safety (CSCRS), a U.S. Department of Transportation-funded National University Transportation Center led by the University of North Carolina at Chapel Hill's Highway Safety Research Center.

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