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16. ABSTRACT

With bicycle infrastructure and bicycling activity on the rise, it is more crucial than ever to understand bicycle crash risk as a function of roadway design and operational characteristics, as well as driver and bicyclist behavior. This report significantly advances that goal by compiling data from just under 500 sites in Los Angeles County. By associating count volumes, we are able to differentiate between high incidence / high risk sites and high incidence / low risk sites. The Researchers also analyze a suite of roadway design and operational characteristics, adjacent land uses, and socioeconomic variables, to examine correlations with crash risk. Data analyzed bicycle crash incidence and bicycle crash risk at 247 intersections and 816 roadway segments in Los Angeles County. Many locations with high crash incidence also have high bicycle ridership. The locations with the highest crash risk tend to have below-average bicycle ridership.

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Bicycle Crash Risk: How Does It Vary, and Why?

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Introduction

The Issue

Since 2006, there has been an upward trend in bicyclist fatalities, counter to the trend of decreasing automobile crashes. In California in 2011, bicycle fatalities were 4.1 percent of total crashes -- about twice the national average. During the years 2008-2010 there were 503,552 injury collisions in California, of which 35,934 involved bicycles (7.1 percent of the total). During that same three-year period, there were 9,216 roadway fatalities in California, of which 348 involved bicycles (3.8 percent of the total). Los Angeles County, with its relatively high number of cyclists, also had the highest percentage of collisions at nearly 31 percent of the total. Bicycle collisions are also known to be underreported; therefore, the injury level is likely higher than appears here.

Bicycle crashes constitute a disproportionate fraction of injuries and fatalities, but bicycle crash risk has been poorly understood due to a lack of exposure data. Information about bicycle crashes is readily available via the Statewide Integrated Traffic Records System (SWITRS). Until recently corresponding exposure data were not available, making the crash rate unknown. In the past five to six years, local agencies have begun to conduct more bicycle counts in a greater number of locations, and these counts have been assembled into various regional datasets. It is now possible to examine crash history throughout the Los Angeles region while accounting for spatial variation in bicycle usage.

Purpose of This Report

With bicycle infrastructure and bicycling activity on the rise, it is more crucial than ever to understand bicycle crash risk as a function of roadway design and operational characteristics, as well as driver and bicyclist behavior. This report significantly advances that goal by compiling data from just under 500 sites in Los Angeles County. By associating count volumes, we are able to differentiate between high incidence / high risk sites and high incidence / low risk sites. We also analyze a suite of roadway design and operational characteristics, adjacent land uses, and socioeconomic variables, to examine correlations with crash risk.

Bike Crash and Exposure Trends: Nationwide

The National Highway Traffic Safety Administration collects nationwide data about bicycle crashes that result in death. Since 2004, the share of bicyclist fatalities compared to all traffic fatalities has increased, and the rate of increase has grown. In 2013, 2.3 percent of traffic fatalities were bicyclists, while in 2004 only 1.7 percent were bicyclists. The total number of traffic fatalities have been declining, however, suggesting that driving is becoming safer faster than bicycling. Bicycling fatalities have remained largely static over the past decade. In 2013, 743 bicyclists were killed, while a recent high 786 bicyclists were killed in 2005 (National Center for Statistics and Analysis, 2013).

Determining crash trends using fatality data alone is not particularly useful without exposure data. If bicyclist fatalities increased from one year to the next, does that signal that streets became less safe for bicyclists, or does it mean that more bicyclists were on the road and the risk of crashes remained the same? Exposure data, or data about how many trips bicyclists are making, provide essential context to crash data trends. The National Household Travel Survey (NHTS), conducted periodically and most recently in 2001 and 2009, is a well-known source of nationwide bicycle exposure data. The NHTS found that the number of trips made by bicycle increased from 1.7 billion in 2001 to 4 billion in 2009 (U.S. Department of Transportation, 2009). Another common source for nationwide bicycle exposure data is the US Census' American Community Survey. The survey, conducted annually, supplements the decennial census and measures many aspects of life for American citizens, including their commutes. The 2014 ACS reports that 904,463 Americans were bike commuters, a 62 percent increase since 2000 (United States Census Bureau, 2014). The remarkable growth in the number of total trips and commute trips, combined with relatively static bicyclist fatality totals, suggest that the nationwide crash risk is declining.

Bike Crash and Exposure Trends: California and Los Angeles

California's Statewide Integrated Traffic Records System (SWITRS) is a statewide database of crash information and a common source for data on bicycle crashes in California. SWITRS data shows an increase in bicycle crashes per total population for both California and Los Angeles County between 2003 and 2012 (California Highway Patrol, 2015). Figure 1, below, further suggests that bicycling in Los Angeles County may be getting more dangerous than in California as a

whole. The data does not consider exposure, however, and an increase in bicycling may account for the increase in crashes. Figure 2 displays bicycle crashes per number of bicycle commuters. Using bicycle commuters provides a crude way to consider exposure and its relationship to crashes. The chart show that crashes are more static for commuters than for the total population and while risk is somewhat higher in Los Angeles County than statewide, there is no significant difference between 2003 and 2012.
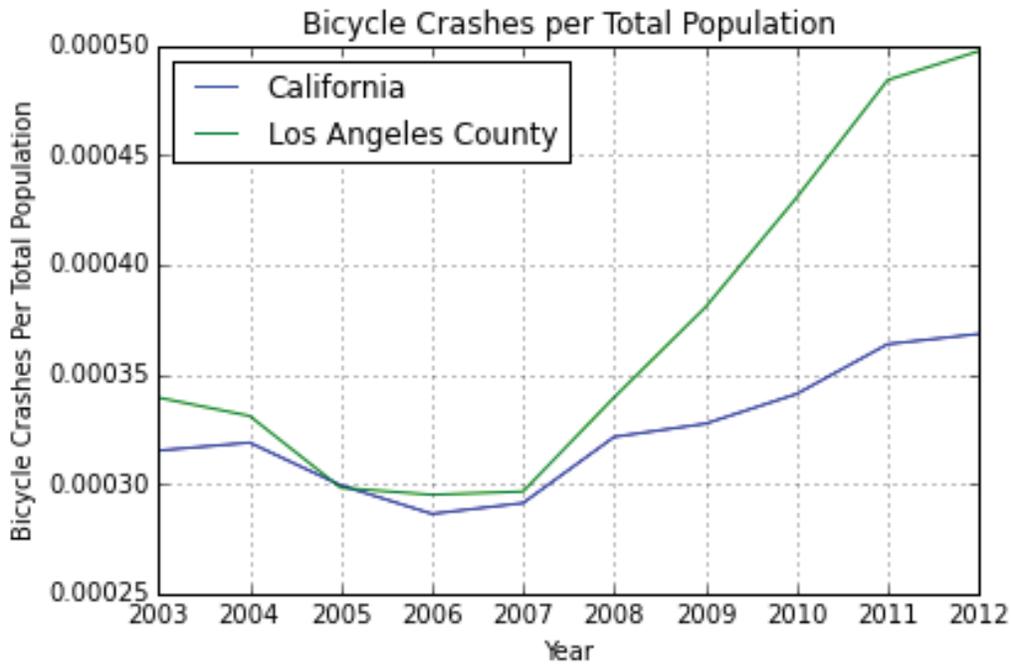
Figure 1. Bicycle crashes per total population.
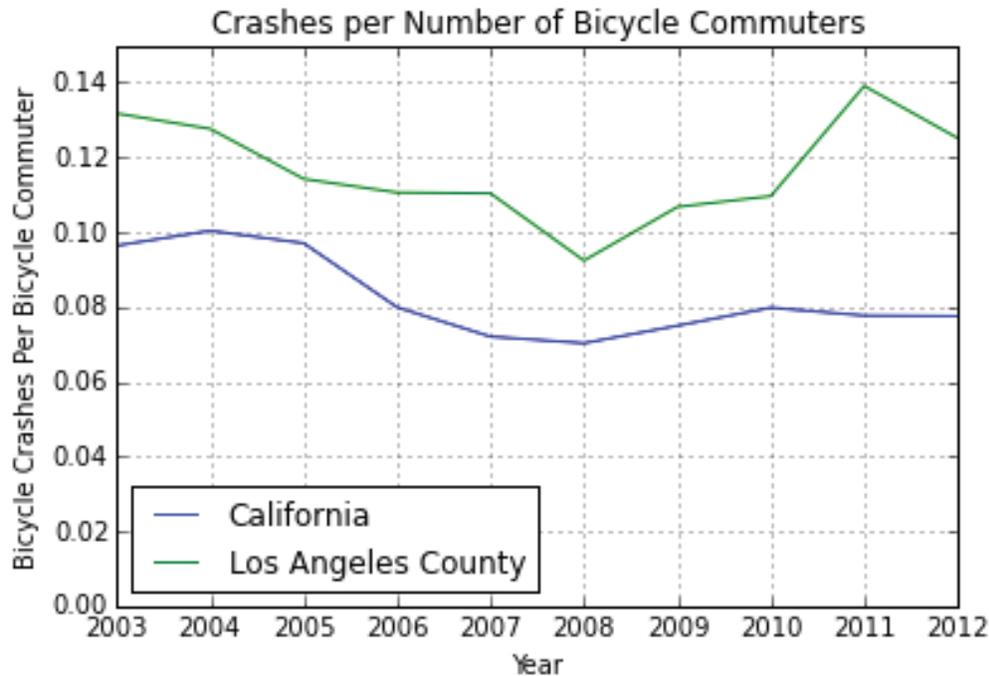
Figure 2. Crashes per number of bicycle commuters.

The ACS, a source for national bicycle exposure trends, can also be used at the State and local level. According to the 2014 ACS, 1.2 percent of Californians are bike commuters (United States Census Bureau, 2014). This is the fourth-highest bicycle commute percentage, behind Oregon, Colorado, and Montana. In the city of Los Angeles, 1.3 percent of residents are bike commuters. Of cities with populations over 1,000,000, Los Angeles is ranked fourth, behind Philadelphia, Chicago, and San Diego.

Most of the data used for this report was collected between 2009 and 2015, and bicycle exposure rates have likely changed in that period. Although anecdotal evidence suggests that cycling rates are on the rise, results from count data do not show a clear rise. Analysis of manual count sites in Los Angeles with longitudinal data shows that ridership increased 23 percent between 2009 and 2011 for both streets and off-street paths combined. Ridership then fell 11 percent between 2011 and 2013 and fell again 10 percent between 2013 and 2015. Notes on the 2013 and 2015 count days indicate that it was extremely hot, which may explain the decline. As stated above, the 2014 ACS found that 1.3 percent of Los Angeles County residents commute via bicycle. The 2009 ACS found that less than one percent (0.8%) of residents commuted via bicycle. This result, though calculating commute trips only, but over a more robust sample size, shows an increase in ridership.

The California Household Travel Survey is California's own survey about exposure and was most recently conducted from 2010 to 2012. The survey is the single largest household travel survey in the United States, with travel behavior information obtained from over 42,500 households, some of which provided GPS data. The survey counted both commute and non-commute bicycle trips and found that 1.5 percent of all trips in California are made by bicycle (California Department of Transportation, 2014). The survey also found that the average duration of bicycle trips was 18.2 minutes, longer than the average walking trip of 10.9 minutes and exactly the same as a driver in a car. The average bicycle trip was 1.5 miles, shorter than the average car trip of 5.6 miles.

Geography of Bicycle Crashes in Los Angeles, 2003-2014

Figure 3 depicts bicyclist-involved crashes in Los Angeles County that occurred in 2003-2014, the period of time for which geocoded crash data are available from SWITRS. There are large hot spots of crashes in Central, South, and West Los Angeles / Santa Monica. There are also pockets of many crashes in the San Fernando Valley, Pasadena, Pomona, and a few other miscellaneous areas.
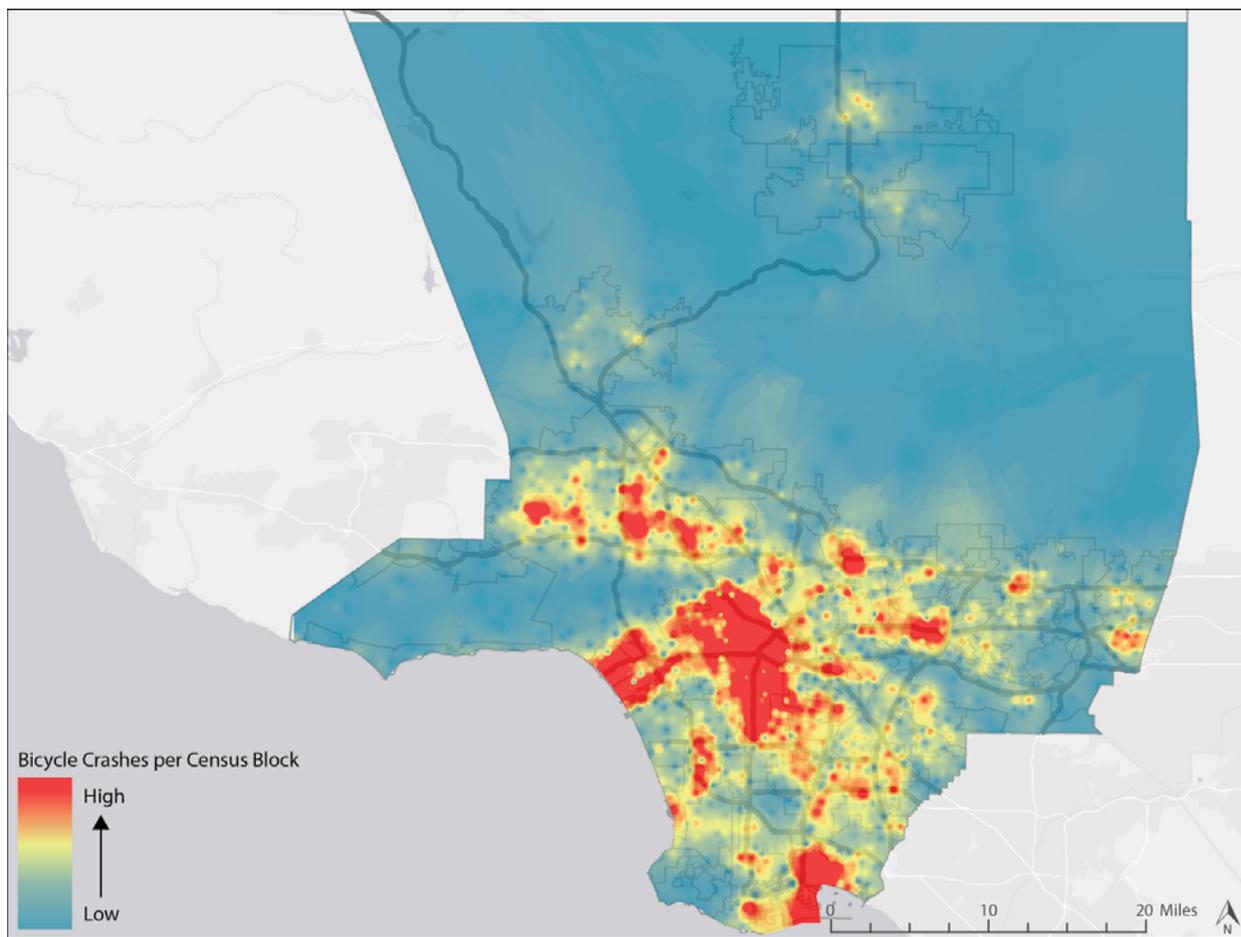
Figure 3. Heat map of bicyclist-involved crashes resulting in injury in Los Angeles County, 2003-2014 (Source: California Highway Patrol, SWITRS).

Literature Review

The body of literature on bicycle safety is increasing, as bicycling and bicycling safety improvements and facilities increase. Understanding the literature on the types of improvements that promote safety are important to analyzing and understanding risk, as is identifying the types of environments that may be tied to greater risk for bicyclists. This literature review presents research on the type of improvements that reduce risk, as well as types of roadway configuration that are associated with risk.

Bike infrastructure

Literature on the topic of bicycle safety and road infrastructure makes it clear that bicycle-specific facilities make cyclists safer. A review of 23 papers on the topic of transportation infrastructure and bicycle safety found that riding on roads with bicycle-specific facilities reduces the risk of crashes when compared to riding on roads without treatments or on the sidewalk (Reynolds, 2009). Bicycle facilities include on-road bike routes (bicycle boulevards), on-road marked bike lanes, off-road bike paths, and physically separated, on-street bike facilities (cycle tracks). Bicycle boulevards offer cyclists a quiet street alternative to busy arterial streets. They do not delineate separate space on the roadway for cyclists, but use signage, pavement markings, and traffic diverters to optimize the street for bicycle travel. A study of bicycle boulevards in Berkeley, California found lower collision rates for cyclists on bicycle boulevards than their parallel arterial routes (Minikel, 2012). Bike lanes separate cyclists from auto traffic on the same road using a painted line. Adding bicycle lanes to streets in New York City reduced the rate of bicycle-motor vehicle crashes along those routes (Chen, et. al., 2012). A study of Johnson County, Iowa found that bicycle-specific pavement markings (bike lanes and sharrows) and signage may reduce the number of bicycle-motor vehicle collisions (Hamann and Peek-Asa, 2013). Teschke, et. al. (2012) found that cyclists in bicycle lanes on major streets experienced half the injury risk as compared to cyclists on routes without bicycle infrastructure. Cyclists on cycle tracks had the lowest injury risk of all of the route types evaluated in that study, suggesting that separate facilities for cyclists results in a safer roadway. A study of Montreal cycle tracks by Lusk, et. al. (2011) found that more cyclists rode on cycle tracks than the study's reference streets and injury rates were lower for cyclists on cycle tracks.

Intersections

With many potential points of conflict, intersections pose some of the greatest threats to cyclist safety. Intersections vary considerably in their configurations, with turn lanes, intersection legs, medians, and traffic signals further complicating the act of safely navigating an intersection. Recent literature has attempted to determine the factors that improve and reduce cyclist safety at intersections. While bicycle lanes at mid-block locations were found to reduce injury risk, Strauss, et. al. (2013) found that the presence of bicycle facilities at intersections in Montreal was not statistically associated with injury frequency, though intersections with bicycle facilities did see higher cyclist volumes. The results showed that corridors with high cycling volumes had lower injury risk, lending some credence to the "safety in numbers" hypothesis. The study used a two-equation Bayesian model to study injury occurrence and bicycle activity as joint outcomes. The researchers used temporal and weather adjustment factors to obtain annual daily volumes from their manual counts.

In a study in Japan, Wang and Nihan (2004) found that a higher number of turning lanes and the presence of a wide median significantly increased the risk of bicycle-motor vehicle crashes. The study divided the data from 115 Tokyo intersections into crashes from through motor vehicle movements, right turn motor vehicle movements, and left turn motor vehicle movements. Independent explanatory variables including intersection location (central business district or not) and visual noise were tested using three negative binomial regression models.

Miranda-Moreno, et. al. (2011) tested different cyclist risk exposure measures in the context of intersections in central Montreal. The authors found that bicycle safety at signalized intersections is significantly affected by the amount of right-turn motor vehicle movements or right-turn conflicts. Unlike Wang and Nihan, this study did not find a statistically significant association between the presence of medians and crash risk.

Other non-infrastructure factors may also impact cyclist safety at intersections. A study of crashes in Ohio found that at intersections, variables increasing severe bicyclist injuries include: the cyclist not wearing a helmet, the driver being uninsured, collisions involving pickup trucks or vans, and collisions occurring at intersection on a horizontal curves with grades. The least severe injuries tend to occur when the front of the bicycle strikes the rear of the motor vehicle or the front of the motor vehicle strikes the rear of the bicycle (Moore, et. al., 2011).

Methodology

Introduction

This research focuses on observing and understanding how roadway dynamics affect bicycle crash risk. This study models bicycle crash risk at 481 locations in the Los Angeles area. These comprise 1,139 distinct units of analysis: 247 intersections and 816 distinct segments of roadway. While bicycle crashes have been studied in singular locations and along certain corridors, these studies have often lacked exposure data and have therefore been limited in their ability to draw conclusions. Similarly, where volume data has been available, it has generally been in limited locations related to certain changes in infrastructure. Few studies have examined a large enough dataset of both crashes and bicyclist volumes to draw larger conclusions about factors contributing to bicycle crash risk. In addition, not all studies apply methods to standardize manual bicycle counts by time, season, and occlusion.

The crux of our methodology is the association between crash incidence (count of crashes over a period of time at a location) and bicycle exposure (number of bicyclists passing through a location over a period of time). To calculate crash incidence, we employ California SWITRS data and precise spatial definitions of segments and intersections of streets. To calculate bicycle exposure, we employ a convenience sample of bicycle count data aggregated at bikecounts.luskin.ucla.edu, and employ a number of methods to standardize these data, which are collected via different technologies and methodologies, and over inconsistent time periods.

We associate crashes and count data to create two distinct, but similarly structured, databases, one for intersections and one for segments. Our datasets consist of those segments and intersections in LA County for which we have bicycle count data. We refer to intersections and segments generically as **sections** throughout this report. Because counts have been done using a variety of technologies and methodologies, significant data cleaning and summarizing was necessary to associate a measurement of bicycling activity to each section. We calculated multiple bicycling volume metrics. To associate crashes with each section, we take advantage of existing geocoded coordinates for bicycle crashes in LA County, and simply associate those crashes that geographically intersect with the section. Finally, in addition to crash history and bicycle count volumes, we also assembled a long list of potential explanatory variables as indicated by

the literature, including vehicle volumes, speed limits, demographics, and operational characteristics such as number of lanes, type of traffic control, and presence of right- and center-turn lanes.

The resulting databases enable descriptive analysis and statistical modeling of raw crash incidence (count of crashes over a period of time) as well as crash risk (crashes per bicyclist) as a function of well-established explanatory variables.

Crash Data

The crash data are from the California Highway Patrol's Statewide Integrated Traffic Records System (SWITRS) database, as downloaded from the Transportation Injury Mapping System (TIMS) at UC Berkeley's Safe Transportation Research and Education Center. SWITRS collects and standardizes data collected by local law enforcement at the scene of a collision, and includes crash location, time, whether the crash resulted in an injury or fatality, the modes of travel of the parties involved (e.g. pedestrian, bicycle, vehicle), and collision factors and fault as assigned at the scene, among other information. Our analysis is limited to bicyclist-involved crashes in Los Angeles County that resulted in injury or fatality and occurred in 2003-2014. The crash locations have been geocoded by SafeTREC. Note that only injury and fatality collisions are included in TIMS.

Limitations of SWITRS Data

An analysis of trauma center data conducted in San Francisco found significant underreporting in SWITRS (Lopez et al, 2012). About 26% of bicyclist trauma cases were not reported to SWITRS, and cyclist-only crashes were dramatically underreported, with only 50% of cyclist-only crashes reported to SWITRS.

SWITRS almost certainly underreports in Los Angeles County, and the San Francisco analysis provides a base hypothesis of how much. But underreporting in Los Angeles has not yet been directly studied. San Francisco General Hospital is the only Level 1 trauma center in the City and County of San Francisco, which greatly facilitates studying this issue in San Francisco. A similar analysis in Los Angeles County would need to compile data from multiple trauma centers and would be a significantly more difficult undertaking.

Still, the same comparative analysis found that SWITRS was by far the more comprehensive dataset. While our data certainly excludes some crashes and

probably excludes a significant proportion of cyclist-only crashes, it is the most complete known data source of cyclist-involved crashes.

Collecting and Compiling Count Data

The count data are a convenience sample of bicycle counts conducted in 2009-2015 by various agencies and organizations in Los Angeles County. The regional database at bikecounts.luskin.ucla.edu, administered and maintained by UCLA, allows for this data to be readily available and somewhat standardized. Location selection, date and time counted, and counting technology (manual vs. automated, and type of automated counter) are all determined by the agencies, who do the work of conducting the counts in the field and subsequently digitizing and uploading the count data. As a result, the sample is not random, nor is it stratified. Agencies probably select locations, dates, and times when they expect to observe high bicycle and pedestrian travel. For example, there is very little data on off-peak travel, and very little data on mountain highways. Many locations have multiple years of data, having been counted every year or every other year since 2009.

While the regional database contains over 1400 distinct locations of data, we filter for inclusion in our analysis only those locations at which at least six hours of counting have been conducted. We set this minimum standard for the duration of counting in order to assure some consistency in the validity of the resulting volume as an estimate of bicycling activity. About 500 count locations meet this criteria.

Most of the counts are manually conducted. Thirty of the sites had temporary automated counters installed. These were EcoCounter pneumatic tubes, owned by the Los Angeles County Department of Public Health (LACDPH) and loaned to cities receiving grants from LACDPH for bicycle and pedestrian planning and programs. Most of these automated counts took place in low-income suburbs due to the nature of LACDPH's granting programs. The length of time these tubes were installed varied from a minimum of 3 days to a maximum of 62 days. They were installed for a mean of 19 days.

Working in partnership with the Los Angeles County Bicycle Coalition, we were able to influence the selection of 14 additional sites (12 of which are listed further below in Table 1) in the City of Los Angeles for counting in September 2015. This allowed for the inclusion of a few sites that had very high crash incidence, but no corresponding bicycle volumes data. The final dataset consisted of 481 manual count locations and 30 automated counter locations.

Selecting New Sites for Manual Counts

To select new locations at which manual counts would take place in September 2015, we cross-referenced locations with high crash incidence with the locations of existing count data. Knowing that vehicle volumes are the crucial variable in modeling bicycle crashes, we also used vehicle volume data from the Los Angeles Department of Transportation (LADOT) and Los Angeles County to ensure that this information was available at any location we selected. (Unfortunately, later, upon closer inspection we threw out many of these vehicle volumes due to inconsistencies in the data, and our final analysis employs a different source of vehicle volume estimates, from the Southern California Association of Government's regional travel demand model).

Because it would be computationally prohibitive to associate crashes with sections of street for the entire County, we conduct a relatively crude, but effective GIS process to identify locations with large numbers of crashes. It was as follows:

1. Create a buffer, radius 50 feet, around each crash
2. Dissolve intersecting buffers to create contiguous shapes
3. Find the centroid of each contiguous shape
4. Count the crashes (bicyclist-involved, 2003-2013) within 150 feet of each centroid (see Figure 4)

Figure 4. Crashes clustered using 150 foot buffers. The tone of the buffer denotes the quantity of crashes within it. We identified this intersection as a high-crash location, and then counted bicyclists at it in 2015.

We found that this process generally created shapes that corresponded with corridors and intersections, with a few exceptions that we could treat manually.

The buffer analysis showed that many locations with high crash incidence were not included in the existing count data. Aiming to increase the range of values in our outcome variable, as well as the distribution of values within that range, we selected sites with high crash incidence. Table 1 shows 12 of the new locations added to the 2015 Los Angeles Bike and Pedestrian count, as led by the Los Angeles County Bicycle Coalition (LACBC). The City of Los Angeles also worked with LACBC to add about 28 locations to the 2015 count, and about half of these were chosen for their high combined bicycle and pedestrian crashes. Thus, LADOT's location selection also contributed positively to the expansion of our data set and to the addition of locations with greater crash incidence.

Number of Bike Crashes, 2003-2012	Streets (Primary / Secondary)	City	Existing Count Location?	New counts here?
	Table 1. Intersections Ranked by Crash History			
19	Vermont / 4th	Los Angeles		On Vermont (1)
16	Main / Ocean Park	Santa Monica	X	No
13	Reseda / Roscoe	Los Angeles		On Reseda (2) and on Roscoe (3)
12	Lincoln / Rose	Los Angeles		No
12	Lincoln / Washington	Los Angeles		On Lincoln (4)
11	Balboa / Victory	Los Angeles		On Balboa (5) and on Victory (6)
11	Jefferson / Vermont	Los Angeles	X	No
11	Vermont / Olympic	Los Angeles		On Vermont (7) and on Olympic (8)
10	Admiralty / Bali	Los Angeles		No
10	Harvard / Olympic	Los Angeles		No
10	Hoover / 30th	Los Angeles	X	No
10	Lankershim / Oxnard	Los Angeles		On Lankershim (9) and on Oxnard (10)
10	PCH / Sunset	Los Angeles		No
10	Sepulveda / Nordhoff	Los Angeles		On Sepulveda (11) and on Nordhoff (12)
10	Sunset / La Brea	Los Angeles		No

Table 1. Intersections ranked by crash history, with note where new counts were conducted at that intersection.

The 2015 Los Angeles Bike and Pedestrian count combined LACBC volunteers with UCLA student researchers funded by this project grant. In total, 138 locations were counted: 98 established locations that had been previously counted in 2009-2013, 14 new locations specifically chosen for this project, and 26 other new locations, some requested by LADOT because of high incidence of pedestrian and bicycle collisions. All volunteers were trained and used the Los

Angeles region's standard forms and methodology as documented at bikecounts.luskin.ucla.edu. More information on the count findings will be in LACBC's upcoming 2015 Bike Ped Count Report.

Defining "Quality" Counts

The Bike Data Clearinghouse contains over 1400 locations. The counts at these locations are all conducted by different organizations and agencies for different purposes. Some of the counts are very short in duration, and many have only a few hours of counting. Because bicycle volumes can be highly variable, the number of bicyclists observed over a short duration of time is weakly predictive of daily, monthly, or annual volumes. At the same time, order of magnitude differences in volumes can be observed with only a few hours of counting: Nordback, et al (2013) find estimation errors for annual volumes from a single error of counting that range from 54% for a single hour of counting to 15% with 4 weeks of continuous counting. So, we sought to define a minimum standard for the duration of counting that would strike a balance between 1) assuring some consistency in the validity of the resulting volume as an estimate of bicycling activity and 2) allowing for the inclusion of a fair portion of the region's data.

Any cut-off would be necessarily arbitrary, and longer duration of counting would always produce a more reliable measurement of bicycling activity. Variability in bicyclist volumes must be understood as a major source of error in our results.

For inclusion in our data set, we set a cut-off of six hours of counting per count site. The six hours could span multiple days, and even be spread across multiple years. There are 481 sites with six or more hours of counting, out of a total of just over 1400 count sites (Figure 5).
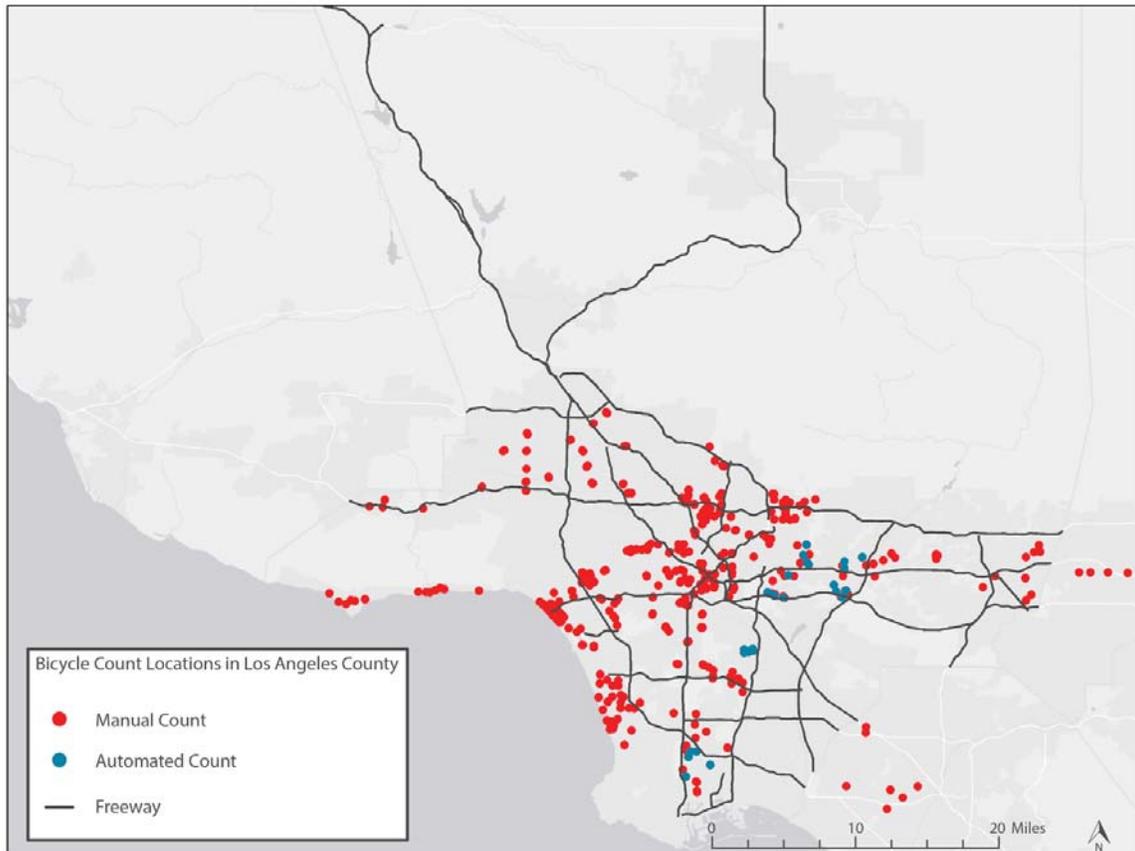
Figure 5. 481 locations throughout Los Angeles County containing six or more hours of bicyclist count data.

The following 12 maps show these locations in greater detail, with depictions of the sections that formed our units of analysis, along with the numbers of crashes that occurred at them in 2003-2014.
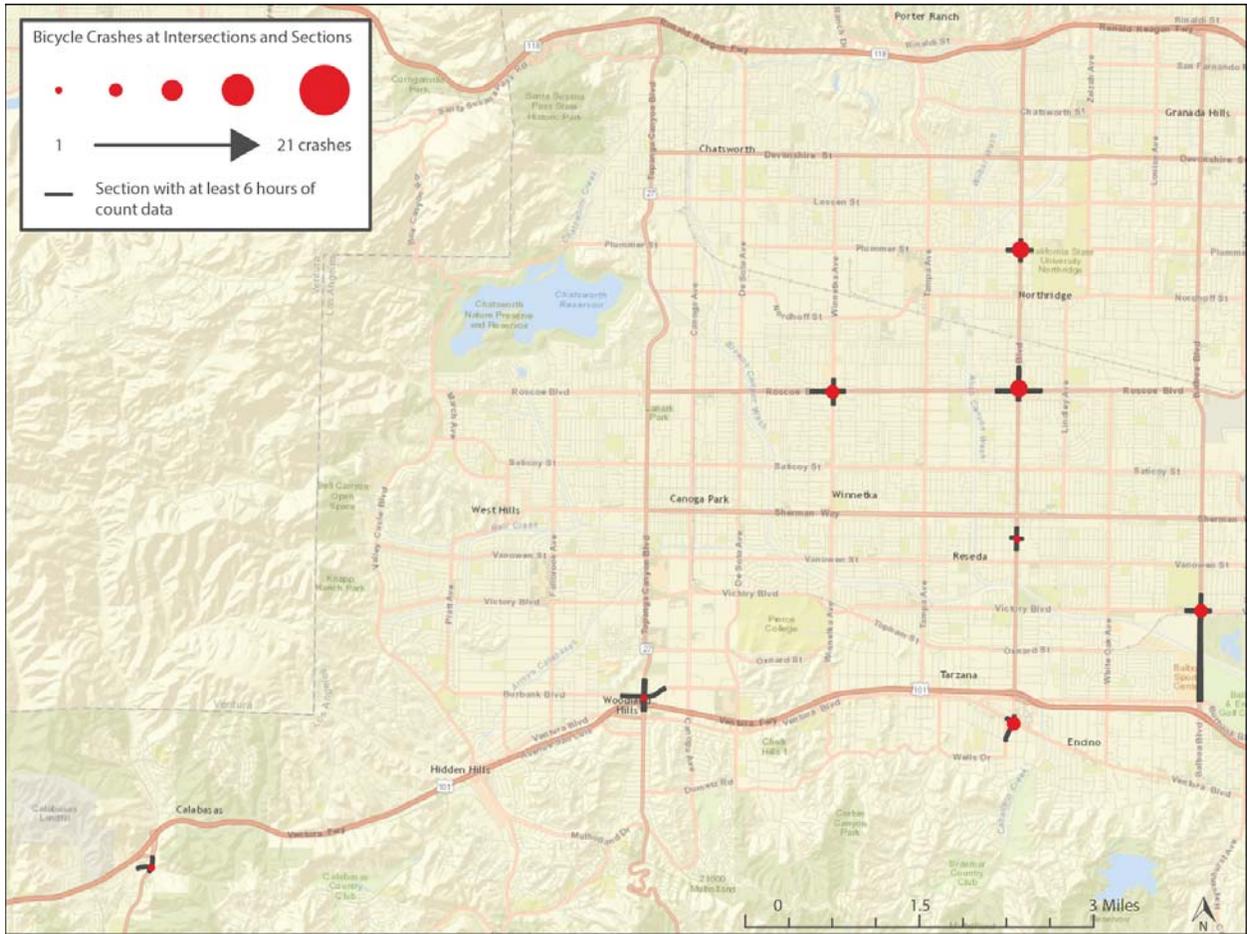
Figure 6. Sections in the West San Fernando Valley (1 of 12)
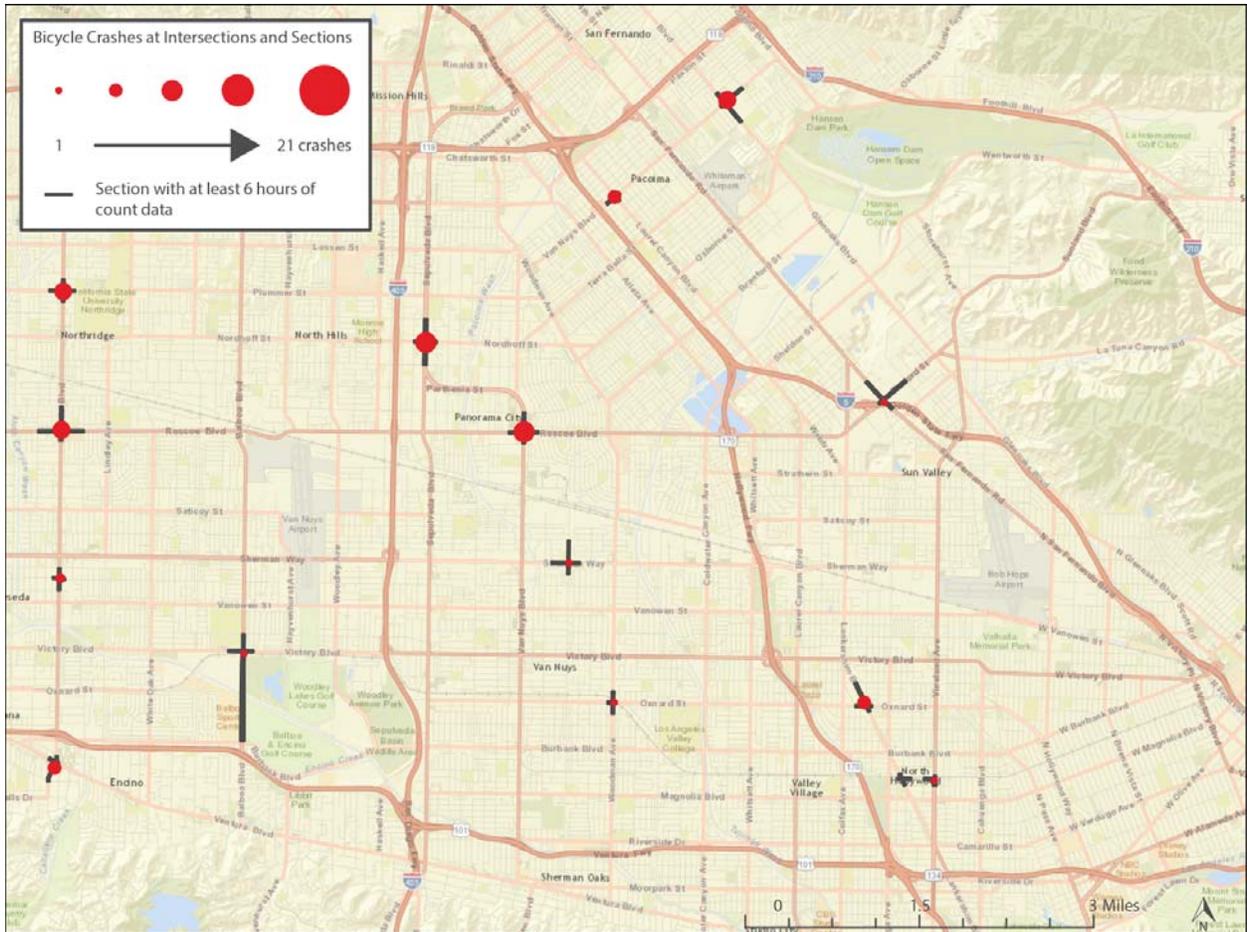
Figure 7. Sections in the Central San Fernando Valley (2 of 12).
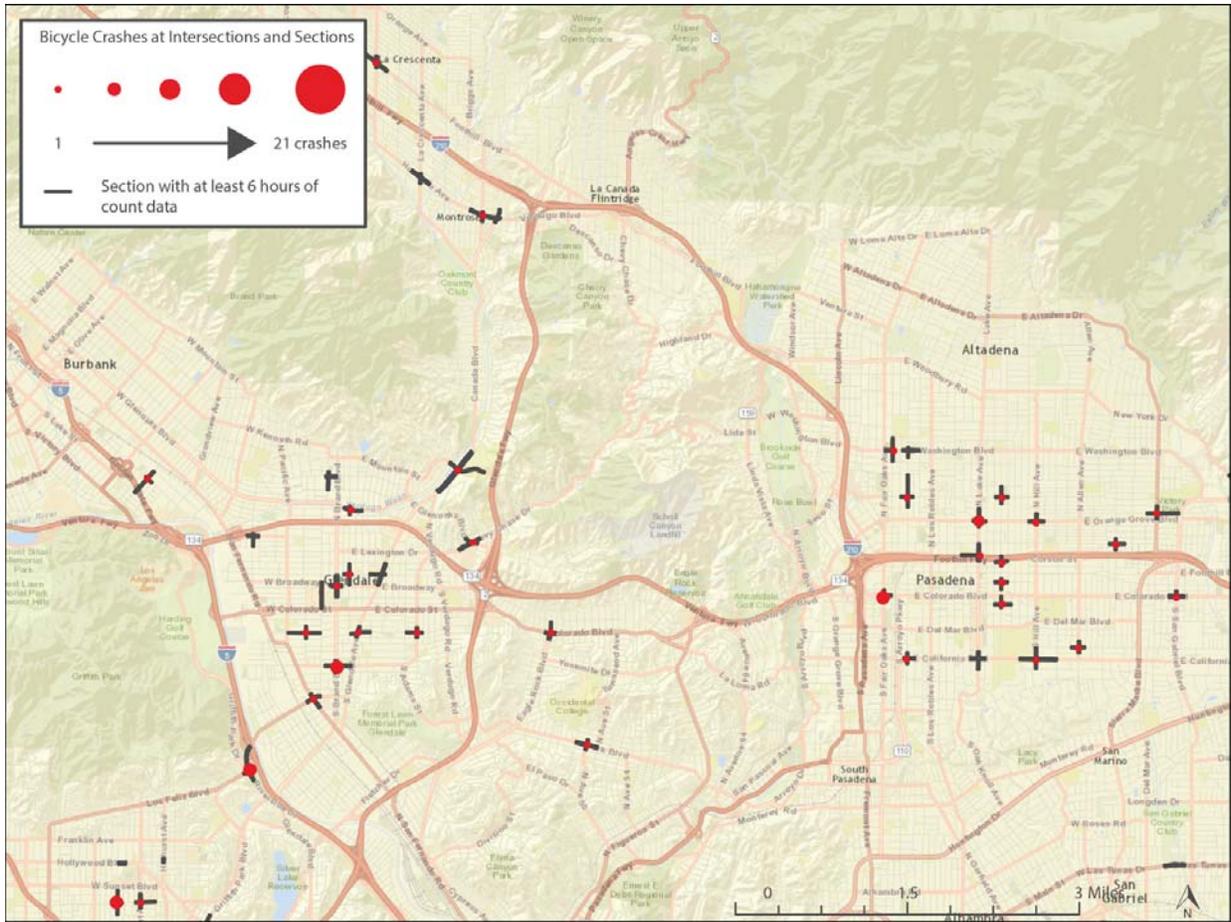
Figure 8. Sections in Burbank, Glendale, and Pasadena (3 of 12).
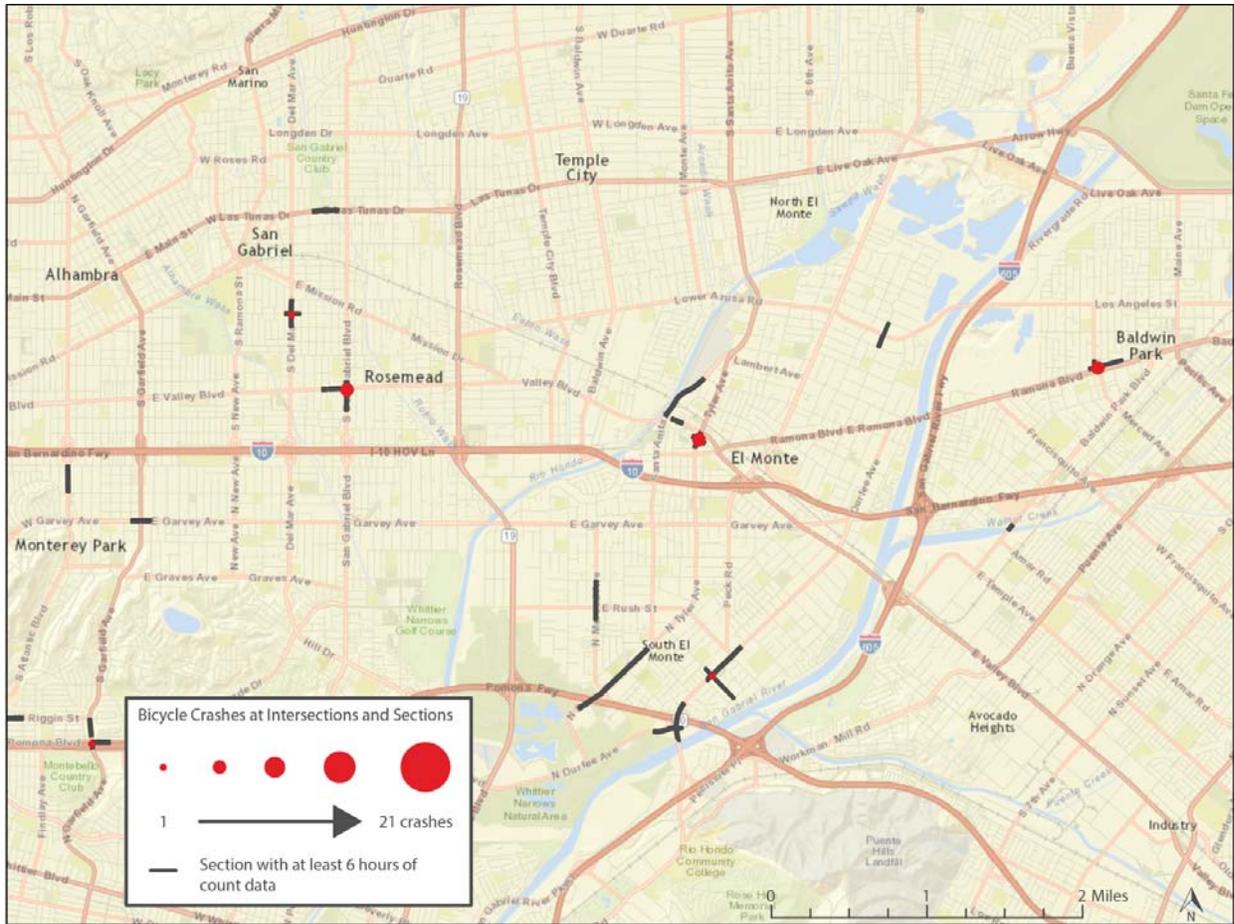
Figure 9. Sections in the West San Gabriel Valley (4 of 12).
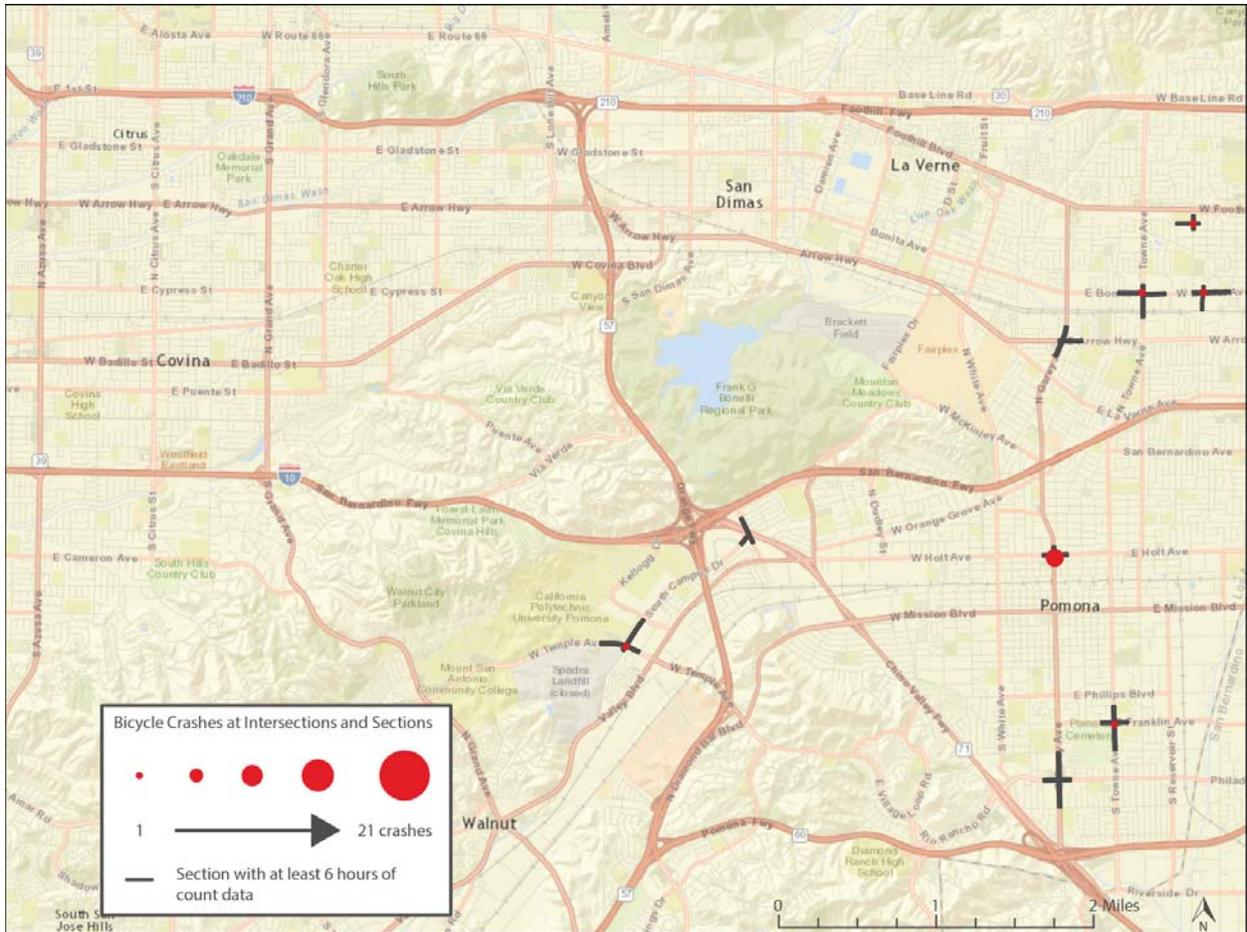
Figure 10. Sections in the East San Gabriel Valley (5 of 12).
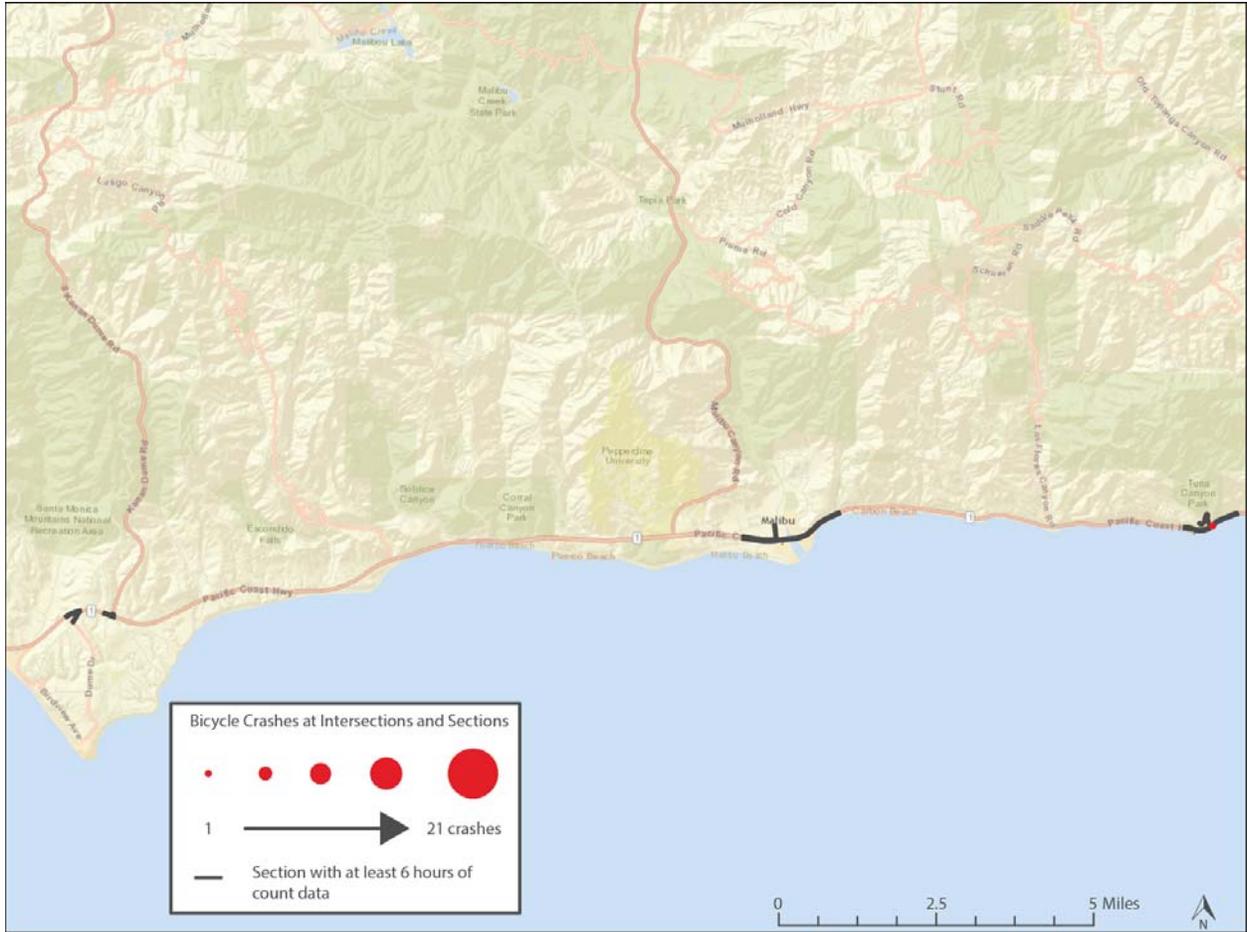
Figure 11. Sections in Malibu (6 of 12).
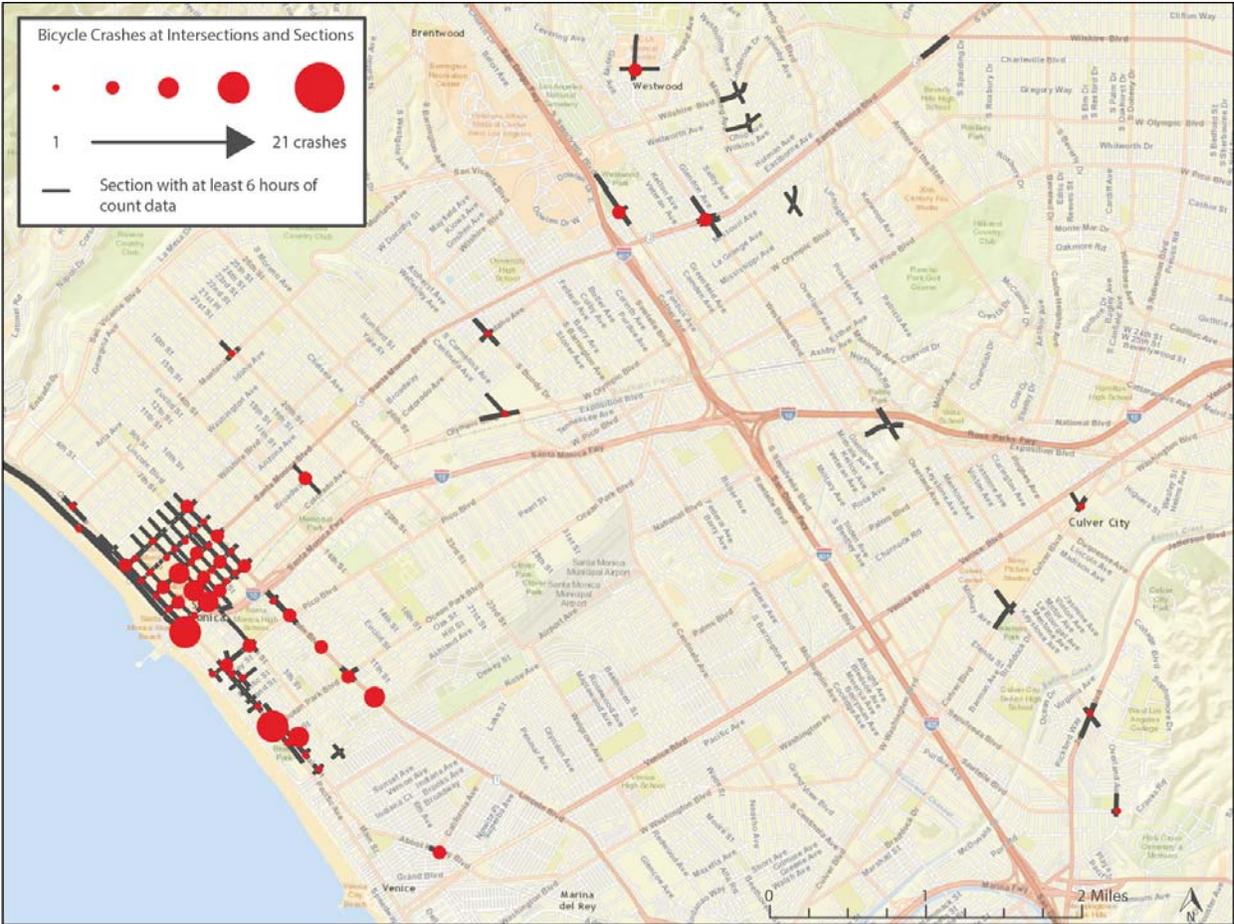
Figure 12. Sections in Santa Monica, West Los Angeles, and Culver City (7 of 12).
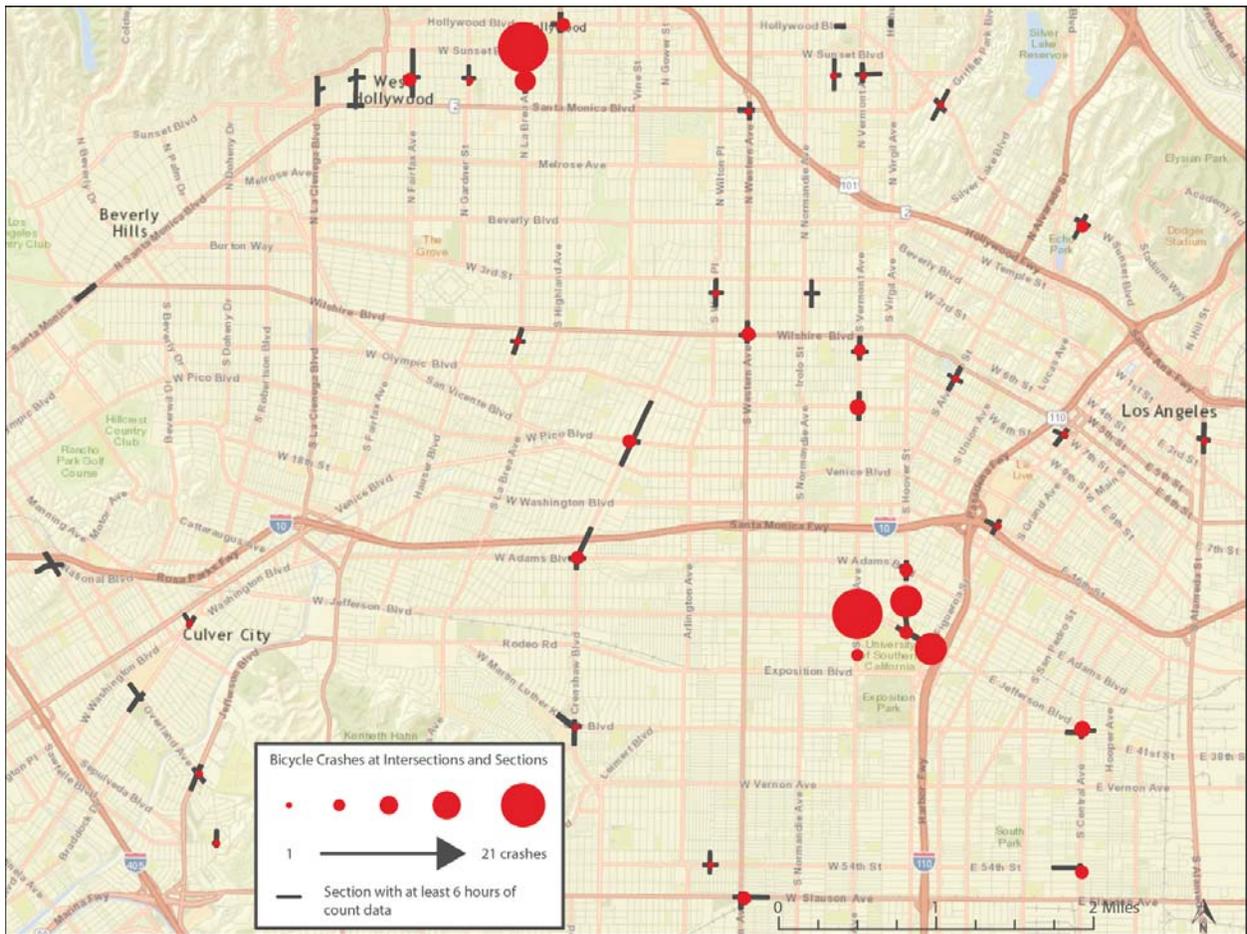
Figure 13. Sections in Central Los Angeles, as well as Culver City and South Los Angeles also visible (8 of 12).
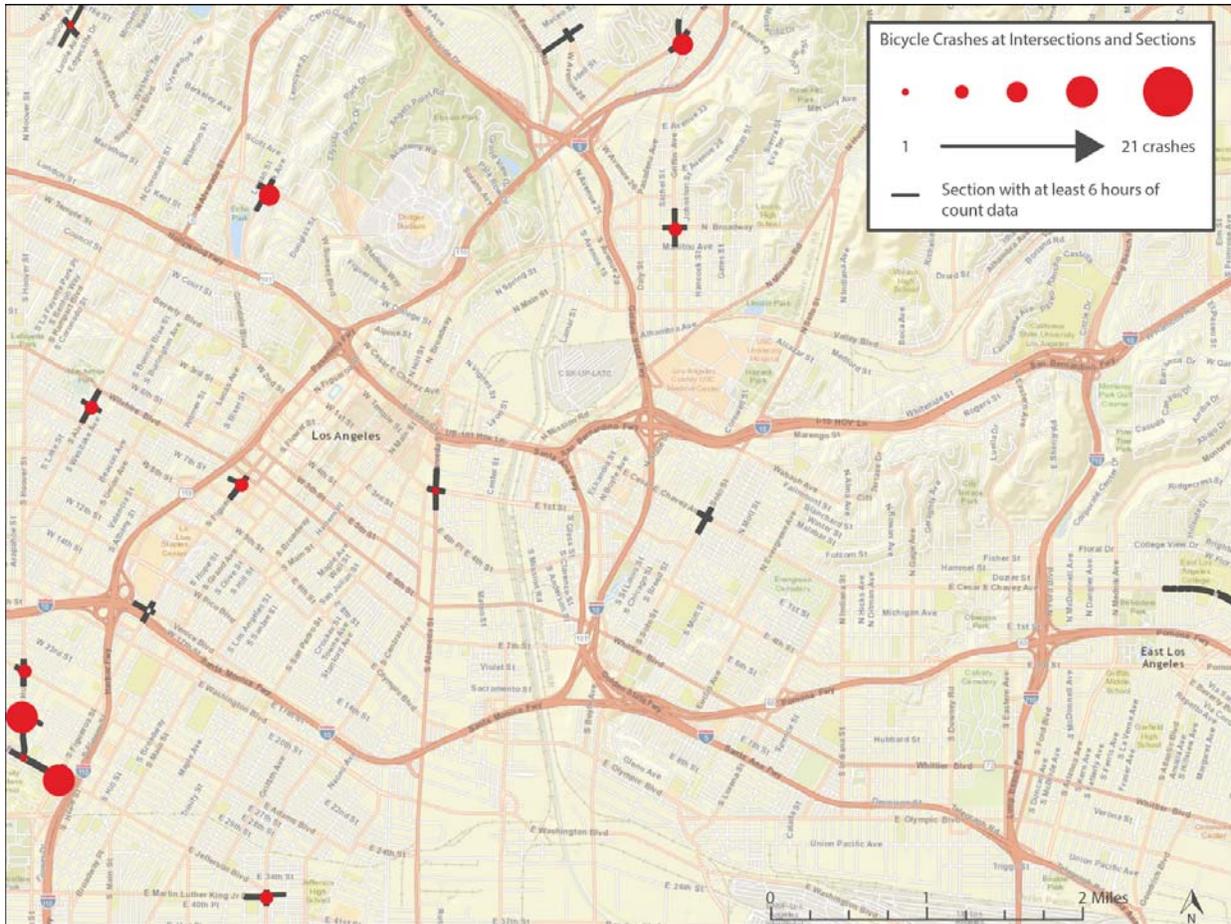
Figure 14. Sections in Downtown Los Angeles, East Los Angeles, and environs (9 of 12).
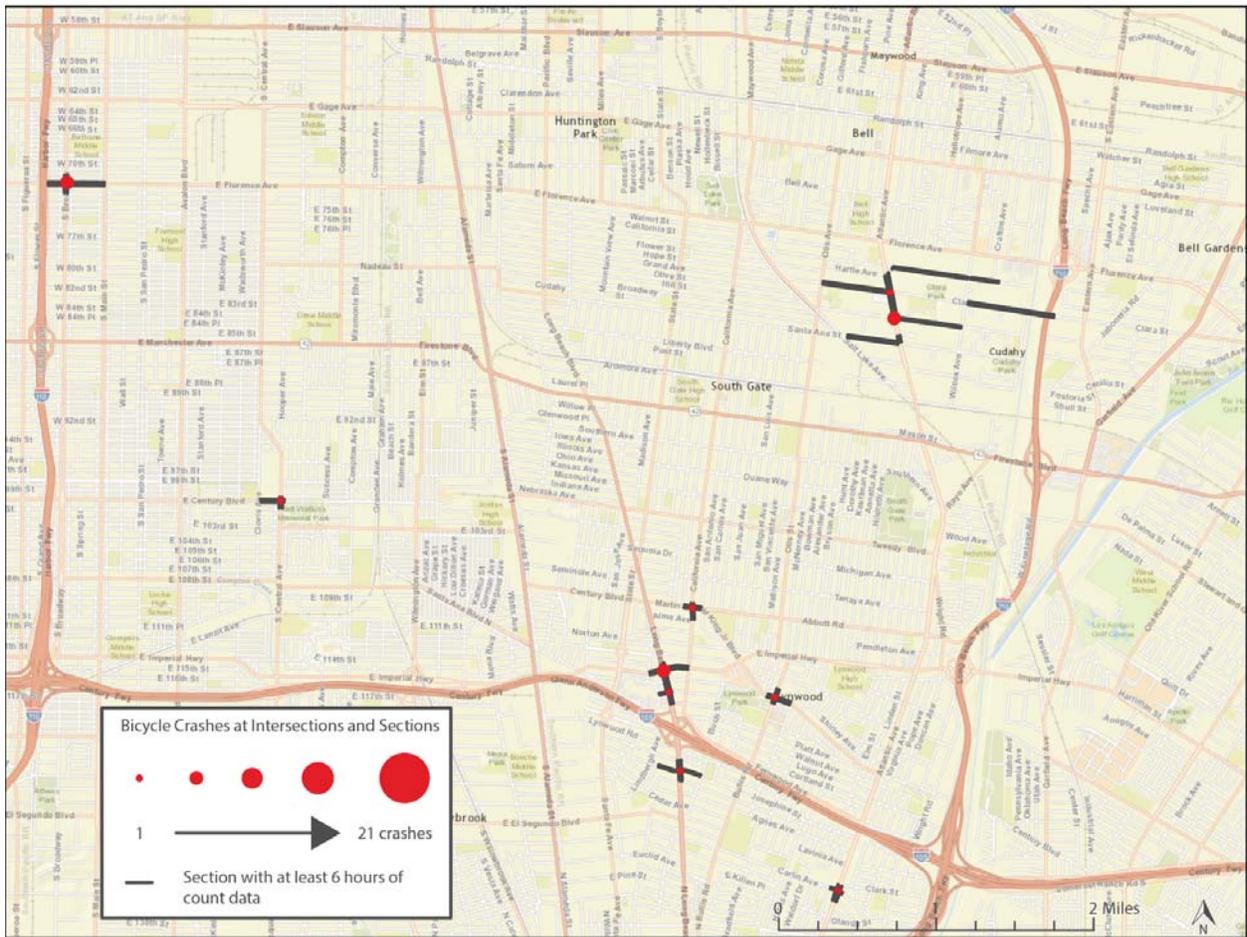
Figure 15. Sections in the Gateway Cities region, primarily Cudahy and Lynwood (10 of 12).
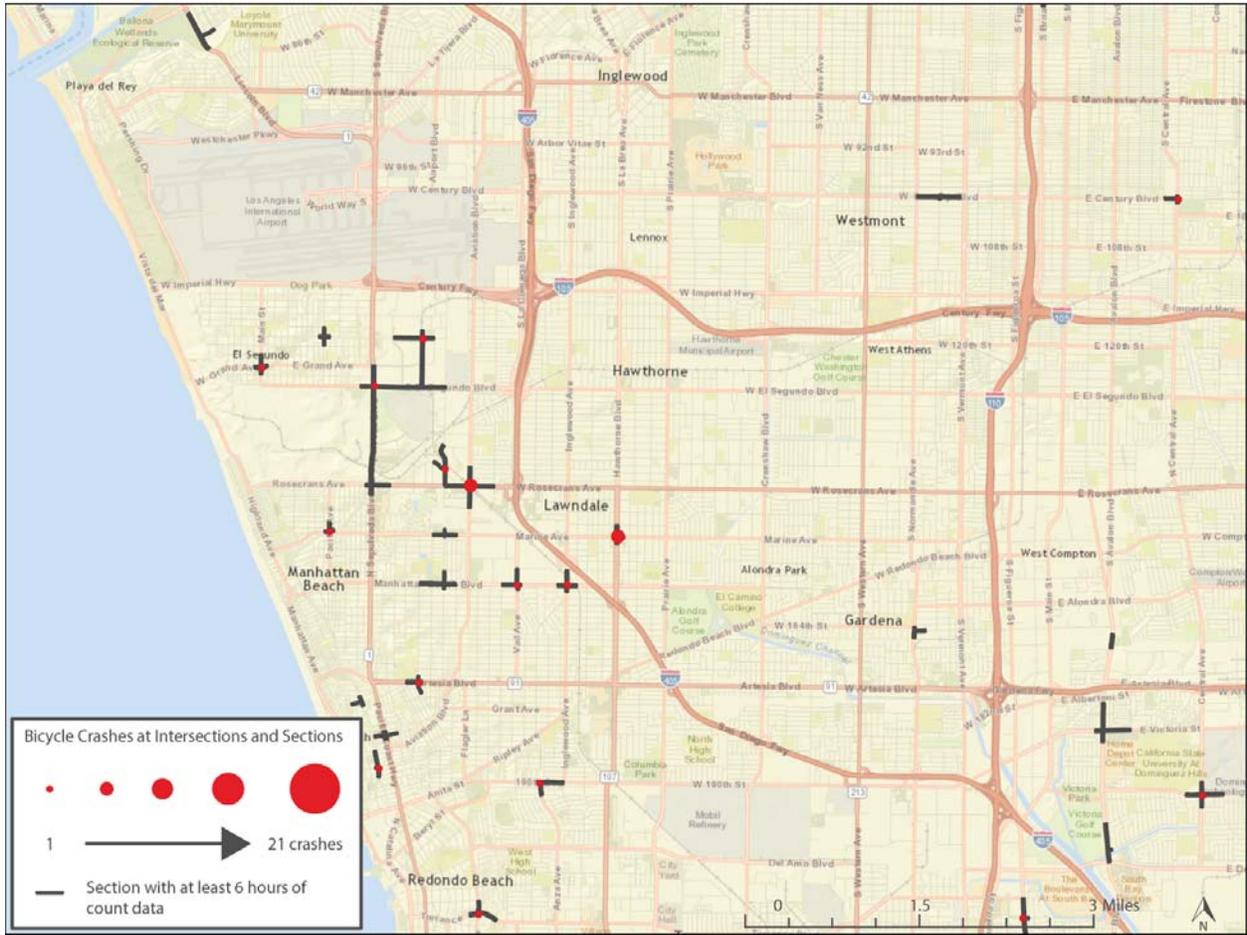
Figure 16. Sections in the South Bay Cities: El Segundo, Manhattan Beach, Hermosa Beach, Redondo Beach, and Carson (11 of 12).
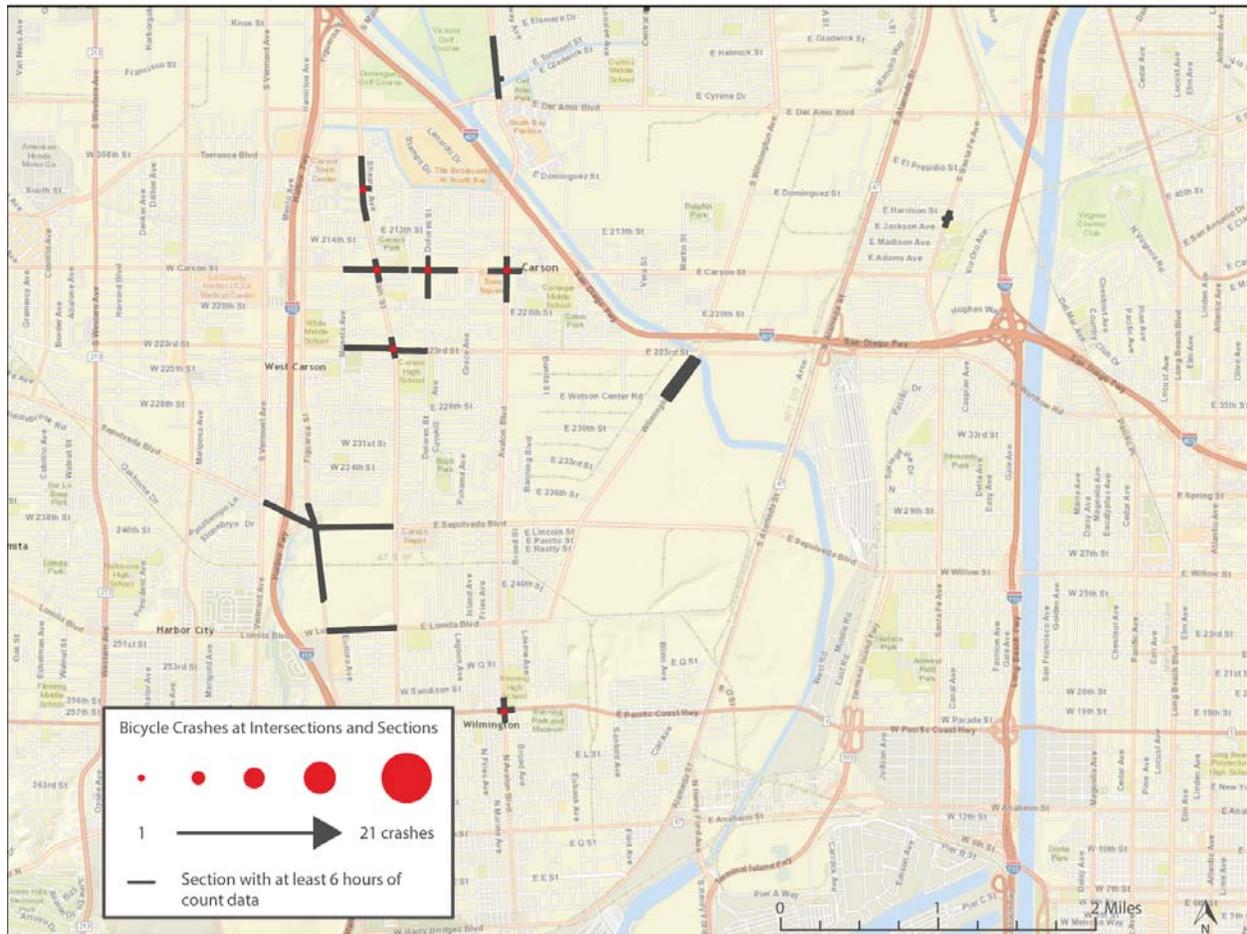
Figure 17. Sections in Carson, in the southern portion of the County (12 of 12).

Creating Roadway "Sections" to Associate Counts and Crashes

We differentiate between intersections and what we refer to in this report as segments - the portion of roadway between two intersections. The distinction is important: the roadway characteristics of segments are distinct from those of intersections, the causes and mechanisms of crashes are very different in segments and intersections, and bicycle crash incidence is much higher on intersections. For example, turning conflicts are a common cause of intersection crashes (e.g. the crash types commonly known as right-hook and left-hook), while being struck from behind is a common cause of a segment crash (McLeod and Murphy, 2014; Pai, 2011). Thus, we created unique study sections and categorized them as either an intersection or a segment. Formally, each section is a polygon in space. A segment section is the roadway spanning between two intersections. An intersection section radiates 62 feet out from the intersecting

point of two roadway centerlines. In the study, there are a total of 1,139 sections, composed of 247 intersections and 892 segments. See Appendix 2 for detailed methodology on creating study sections.

We joined crash data, census data, volumes, and the physical environment variables, to each section. Bicyclist count data is the most necessary variable, thus we only studied crash rates on sections that have quality location counts on or near them.

Figure 18. Four segment sections, one intersection section. With segment crashes (red), intersection crashes (purple), and count sites (pink).

Associating Sections with Count Locations

The bicyclist counts provide ridership data for the study sections. The bicycle data include data collected at screenlines and intersections, defined as follows:

A *screenline count* is conducted by counting every bicyclist who crosses an imaginary line drawn from curb to curb at the midblock portion of the street. Volume totals for each direction of travel are reported. Screenline counts may be conducted manually or with automated technology.

An *intersection count* is conducted by counting every bicyclist who passes through an intersection. Volume totals for each turning movement by intersection leg are reported. Alternatively, volume totals by entering leg or exiting leg are reported.

Table 2 describes the types of bicycle counts found in our database and the corresponding physical units of analysis for which they provide exposure data.

Table 2. Types of Bicycle Counts	
Type of Count	**Physical Unit of Analysis**
Screenline	Segment section
Intersection	Intersection section

Table 2. Types of bicycle counts and corresponding physical units of analysis.

Our basic assumption is that a count is a valid measurement of bicycle activity at the locations where it was conducted and at locations immediately adjacent to it. A count on a segment can be used to assign volumes to that segment and to the adjacent segment (e.g. the segment on the other side of the adjoining intersection). If two screenline segment counts are present, then they can be used to assign volumes to the intersection that is between them. A count on an intersection can be used to assign volumes to that intersection and all adjoining segments (but not the next intersection or the segment beyond).

If a count site is on a segment, that segment is included in the study. An adjacent segment (on the other side of the nearest intersection) is also regularly, but not always, included. We chose to include adjacent segments when there were paired with screenline counts at an intersection: we included the two segments directly counted as well as the other two segments that meet at the

intersection, as in Figure 19. With these paired screenline counts, we did not include the adjacent segments in the direction away from the intersection. We also included adjacent segments when there was a single screenline count in isolation.

Figure 19. Two screenline counts, located on segments. Each count informs the segment on which the count is located, as well as the segment directly on the other side of the intersection that is between them. Together, the counts inform the intersection.

If the count area includes paired screenline counts - defined as two count sites located on nearby segments that are perpendicular to each other - we included the intersection that is between the screenline count sites in the study. This is because intersections contain cross-traffic (for example, on a four-armed intersection, there are four directions of travel) and the two screenline count

sites are necessary to capture all ridership within the intersection. Thus, a four-way intersection that contains nearby screenline counts sites will generally have five sections in the study: the two segments with the count sites on them, the intersection, and the two segments that are on the other side of the intersection (Figure 19).

Count sites that are on intersections count bicyclists in every direction of travel. For adjacent segments, the relevant directional volumes are taken from the intersection count data. Thus, a four-way intersection that contains an intersection count will generally have five sections in the study: the intersection, as well as the four adjacent arms (Figure 20). The segment to the north is assigned north/south directional volumes; the segment to the east is assigned east/west directional volumes.
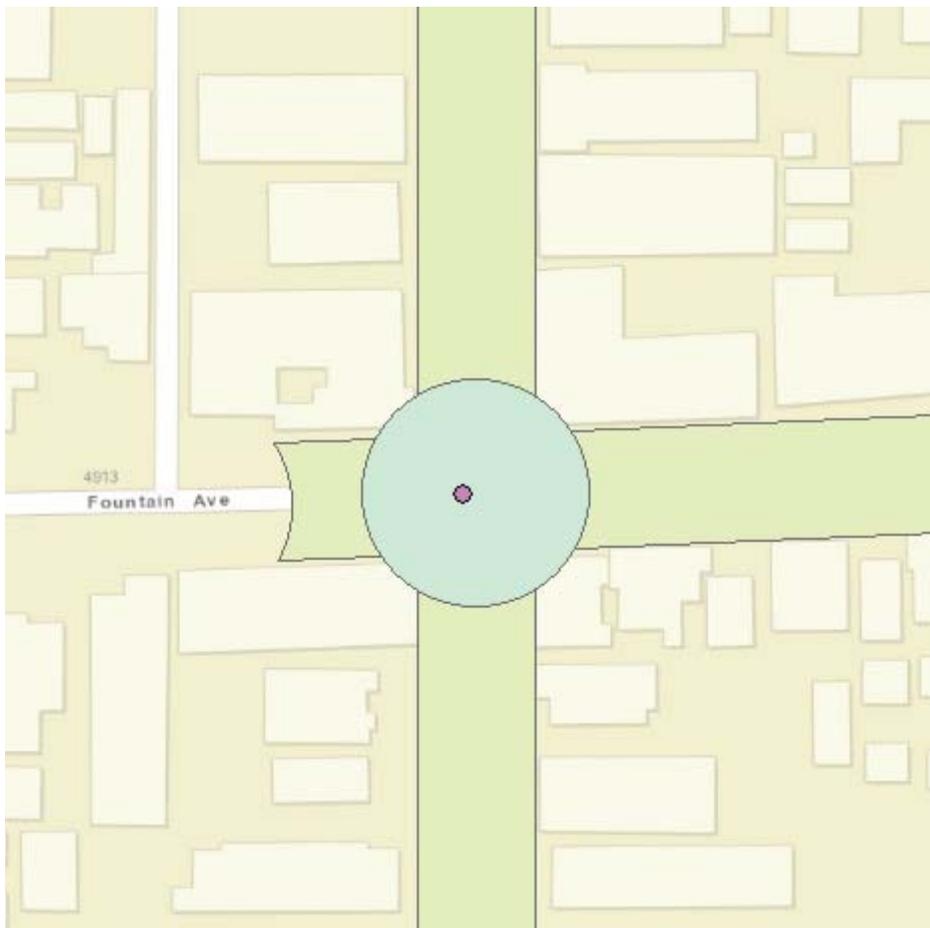
Figure 20. Bicyclist count located on an intersection. The count captured bicyclists passing through the intersection from four directions.

To summarize, the association between a count location and its corresponding segment or intersection could thus have one of the following six relationships (Table 3). These associations were encoded by visual inspection.

Table 3. Encoding Count Volumes to Sections	
Count's relationship to location	**Code (field in database)**
Intersection with direct volume measurement from an intersection count	INT_INT
Segment with direct volume measurement from a screenline count	SEG_SEG
Segments with volume measurement from the intersection they adjoin - typically four segments with a common intersection	SEG_ADJ_INT with required additional field SEG_ADJ_INT_DIR to encode the appropriate directions
Segment with volume measurement from an adjacent segment	SEG_ADJ_SEG
Intersection with volume measurement from paired screenline counts	INT_ADJ_SEG

Table 3. Encoding the relationship between count volumes data at a location and the segments and intersections surrounding it.

For more details on the database structure, see Appendix 3.

Sometimes there are multiple counts assigning volumes to a section. For example, there may be count sites located within an intersection and an adjacent segment. In these cases, we include data from each count, as further explained in the following.

Summarizing Section Volumes by Time Period

After assigning count locations to sections via the relationships in Table 5, we then calculate several alternative measures of bicycle exposure by summarizing count volumes for each section. Because counts are generally conducted for short durations of time, often across multiple dates and multiple years, and the choice of time periods is not necessarily consistent from location to location, we develop a series of summary rules and specifications as follows. These measures

seek to ensure consistency across locations, where count times and methods vary by location.

First note that the count data comes in three different "vintages": current, historical, and automated. "Current" are screenline (segment) counts that contain bicycle volumes for two directions of travel along a segment. The "current" counts have been conducted using standard methodologies codified by SCAG in 2011 and were digitized and uploaded via an interface bikecounts.luskin.ucla.edu, resulting in standard fields and field definitions. The "historical" vintage contains count data originally conducted via both screenline and intersection methods, which have been standardized into one table. Most of the historical counts are intersection counts with four directions of travel. "Automated" counts were conducted with devices on segments and contain two directions of travel. The tables for automated counts are much different than the other two vintages. In particular, it takes two tube counters to count a street, one on each side of the street. Given that automated sites do not count sidewalk riders, for the sake of consistency we have subtracted sidewalk riding from the manual counts.

Most of the data is of the "current" vintage, which begins in 2011. And most, but not all, of the data in the "current" vintage are counts that occurred 7-9AM on a weekday, 4-6PM on a weekday, and 11AM - 1PM on a weekend. Counts at a given location can span multiple dates over a period of years, and many locations have missing time periods. Overall, most of the data is from 2009-present. All of the data, regardless of vintage, is stored in 15-minute intervals in a SQL database which forms the back-end of bikecounts.luskin.ucla.edu. SQL queries implement both the time period summaries described here as well as the pulling of appropriate directional sums depending on whether the section is a segment or an intersection.

Because of temporal patterns of bicycle activity across the hours of the day, we are concerned not to compare volumes from different time periods. Because of the dominance of the 7-9AM weekday, 4-6PM weekday, and 11AM-1PM weekend time periods, we run queries to select only volumes conducted during these times. We refer to these as vol_AM, vol_PM, and vol_WKND respectively.

The query might return fewer than 8 15-minute intervals: for example, volumes for 8-9AM at a site, but 7-8 AM was not counted at that site. The query might also return many more than 8 intervals, if the site has been counted in multiple years.

Thus, we normalize all sums as follows:

$$\frac{\Sigma Volume}{Number\ of\ intervals/8}$$

This produces an expected two-hour volume. Note that this normalization implies the assumption that all times within each of the AM, PM, and WKND periods are equal. We treat a 7:15 volume exactly the same as an 8:45 volume. There is certainly within-period variation in volumes, but this simplifying assumption greatly facilitates the process.

We run one last query, seeking to incorporate all the volume data that exists for any given location. We refer to this as vol_ALL. This query takes the opposite approach to variation across hours of the day, and ignores it altogether. We sum all intervals counted at a location and normalize to a two-hour volume. This allows us to include a great number of miscellaneous intervals that would not be captured by vol_AM, vol_PM, or vol_WKND.

Finally, note that sections may intersect with more than one count location according to the relationships in Table 3. In these cases, we average the query results from each location.

See Appendix 3 for notes containing detailed descriptions of the count query methodology and documenting various exceptions and special cases.

Extrapolating Annual Volumes from Short-Duration Counts

It is problematic to compare one two hour count with another if the counts were taken at different times of the day or months of the year, or in radically different weather conditions. There are bicycle ridership patterns that are generally predictable associated with time of day, day of the week, month of the year (or season), and weather. To state an obvious example: ridership is typically lowest in the winter months where winter is associated with cold, rainy, and/or snowy weather. Bicycle commuters also tend to ride during the morning and evening rush hours, to give another example. The degree of difference in counts between winter and summer and rush hour and non-rush hour depends on the character of the area studied. One would expect a bigger gap between summer and winter ridership in Wisconsin, for example, as compared to Los Angeles. For this reason, it is important to create extrapolation factors in the same community as the short duration manual counts when possible. If it is not possible to create localized extrapolation factors, substitute factors should be used from locations with similar climates and commute patterns.

In addition to the time period sums described above, we also calculate a final measure of bicycle exposure, the annual volume. We extrapolate this volume using time-of-day and day-of-week patterns observed in the automated counter data. Extrapolation results are complete, but not included in this report due to time constraints. See Appendix 1 for a description of the factors used in extrapolating counts.

Calculating Exposure-Adjusted Crash Risk

Note that we are looking at 12 years of crashes (2003-2014) but most of the bicycling volumes data are from 2009-2015. Given the trends in commuters and the recent explosion in bicycle infrastructure in the region, it's likely that volumes were lower in 2003-2009 than they were in 2009-2015, but the 2009-2015 volumes are the best estimate we have of volumes at these locations in 2003-2014.

Collecting Potential Explanatory Variables

Our list of explanatory variables is primarily composed of variables which have already been identified by the literature to be correlated with crash incidence or crash risk. In addition, we collected a small number of additional built environment variables which we hypothesized might have an effect, and which were straightforward to visually evaluate using historical satellite imagery. Historical satellite imagery was accessed via Google Earth.

Table 4. List of Explanatory Variables			
Variable Name	**Variable Source**	**Measurement Definition**	**Applies to Segment, Intersection, or both?**
Intersection Type	Google Earth, DigitalGlobe	How is the intersection controlled? Signalized; two-way; four-way; roundabout	Intersection
Intersection Arms	Google Earth, DigitalGlobe	How many segment arms adjoin the intersection?	Intersection
Sidewalk Missing	Google Earth,	Is any leg of the	Both

	DigitalGlobe	intersection or side of the segment missing a sidewalk?	
Travel Lane Quantity	Google Earth, DigitalGlobe	How many general travel lanes are on the section? Exclude turn lanes, bus lanes, bike lanes, or parking area.	Both
Travel Lane Quantity Change	Google Earth, DigitalGlobe	Is a lane added or removed within the segment?	Segment
Dedicated Right Turn	Google Earth, DigitalGlobe	Is there a dedicated right turn lane in the segment?	Both
Center Turn Lane	Google Earth, DigitalGlobe	Is there a dedicated left turn lane in the segment?	Both
Road Width	Google Earth, DigitalGlobe	Curb to curb measurement of street width.	Segment
Intersection Width	Google Earth, DigitalGlobe	Length of the perimeter of the intersection.	Intersection
Rail Tracks	Google Earth, DigitalGlobe	Are there rail tracks within the section?	Both
Parking On Street	Google Earth, DigitalGlobe	Is there any on-street parking anywhere on the segment? Note if the parking is diagonal or perpendicular.	Segment
Crashes	SWITRS / SafeTREC (2003-2014)	How many bicyclist-involved crashes occurred in the section (2003-2014)?	Both
Street Type	CAMS, 2016	Roadway classification	Both
Driving Direction	CAMS, 2016	One-way or	Both

		two-way travel within section	
Bikeway Type	KPCC Data Team (2015) / LA County (2012)	What type of bikeway is in the section? Bike lane; bike route; shared-lane marking; none.	Both
Truck Route	Caltrans, 2011	Is the section part of a state truck route?	Both
Transit Stops	Metro, 2015	How many transit lines have a stop within the section?	Both
Rapid Bus Line	Metro, 2015	Is the section part of a Metro Rapid Bus route?	Both
Proximity to Ramp	CAMS	Is the section within 400 feet of a freeway ramp?	Both
Proximity to Hospital	LA County, 2016	Is the section within 400 feet of a hospital?	Both
Proximity to Park	LA County, 2016	Is the section within 400 feet of a park?	Both
Proximity to School	LA County, 2016	Is the section within 400 feet of a school?	Both
School Type	LA County, 2016	If the section is within 400 feet of a school, what kind of school is it?	Both
Income (Median)	US Census, ACS 2009-2014	Median income of block group that the section is within	Both
Housing Population	US Census, 2010	Total people living within block group	Both
Race - White	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both

Race - Hispanic	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - Black	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - American Indian	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - Asian	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - Pacific Islander	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - Other	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Race - Two or More	US Census, ACS 2009-2014	Percent of people living in block group, by race/ethnicity	Both
Journey to Work by Bicycle	US Census, ACS 2009-2014	Percent who bicycle to work (block group level)	Both
Age (Median)	US Census, ACS 2009-2014	Median age of those living within the section (block group level)	Both
Vehicles Available per Household	US Census, ACS 2009-2014	The mean quantity of vehicles available per household (block group level)	Both
Employment Sector	US Census, 2010	The quantity of jobs in the section (block level)	Both

Vehicle Volume	SCAG, 2003, 2008, 2012		Both
Speed Limit	Google Street View	Posted speed limit	Both
Bicyclist Volume	Various	Volume of bicyclists observed in a two hour period	Both

Table 4. Explanatory variables and their sources: roadway design and operational characteristics, adjacent land uses, and socioeconomic variables.

At times, the roadway data that inform the intersection variables are in conflict. For example, Street Type is determined by the CAMS centerline data, and since an intersection is defined as a point where two centerlines intersect, the intersection may contain two different street types. In that specific case, we assigned the higher roadway classification to the intersection. There are also examples where the segment data inform the values for intersections. For example, there are no travel lanes within intersections, so to obtain a value for the "Travel Lane Quantity" field, the values in all of the adjoining segments were summed.

Analysis

Using the resulting databases, we can now compare the intersections and segments with the highest crash incidence (count of crashes) with those with the highest crash risk (crashes per bicyclist). We also conduct a series of t-tests to find those independent variables which are associated with significant differences in crash incidence and crash risk.

Intersections

The following section is a descriptive analysis of crashes within intersections and our collected physical and socio-economic variables.

Crash Incidence

For the 247 intersections studied, the number of bike crashes ranged from zero to 21. About one-fourth of the intersections recorded no crashes with 44 percent recording one or fewer. Just 13 percent (33 intersections) recorded over five crashes. The average number of crashes per intersection is 2.8 with a standard deviation of 3.1 further indicating a skewed distribution.
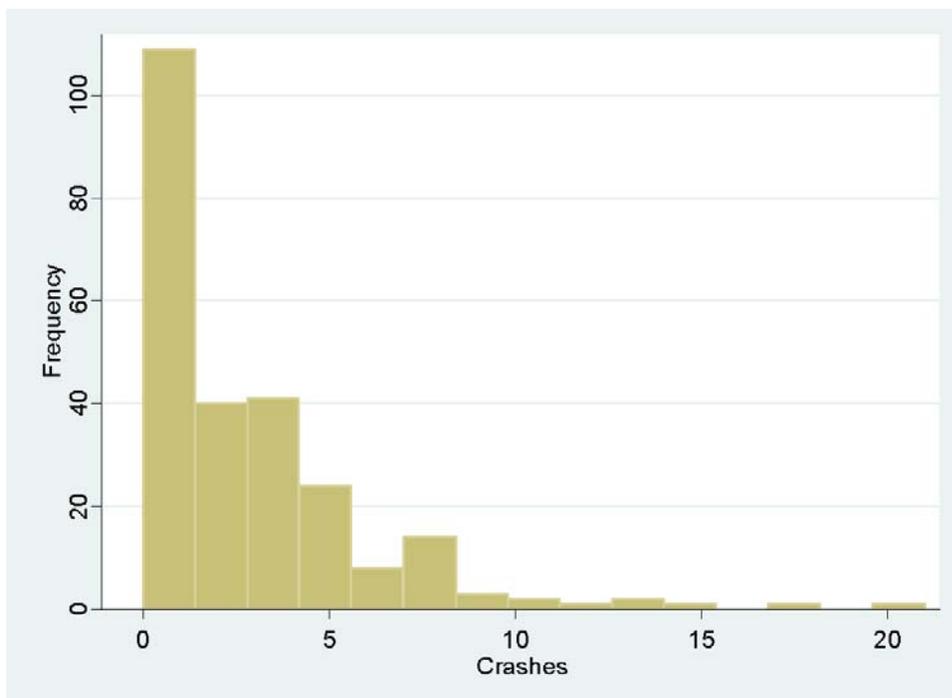
Figure 21. Frequency distribution of crashes on intersections.

Bike Ridership

Bike ridership counts were available for 232 intersections in the database. The count measure used in this analysis is vol_ALL, the average number of riders per two-hour period across all intervals counted. This appeared to be the most consistent measure out of vol_AM, vol_PM, vol_WKND, and vol_ALL. More work needs to be done to compare these time period summaries with each other, and with the extrapolated annual volumes. Average counts ranged from a low of about three riders to a high of 554 with an average of 58 riders per two-hour period (standard deviation of 64 riders). The histogram for bike counts also shows a skewed distribution with just a few high count intersections.
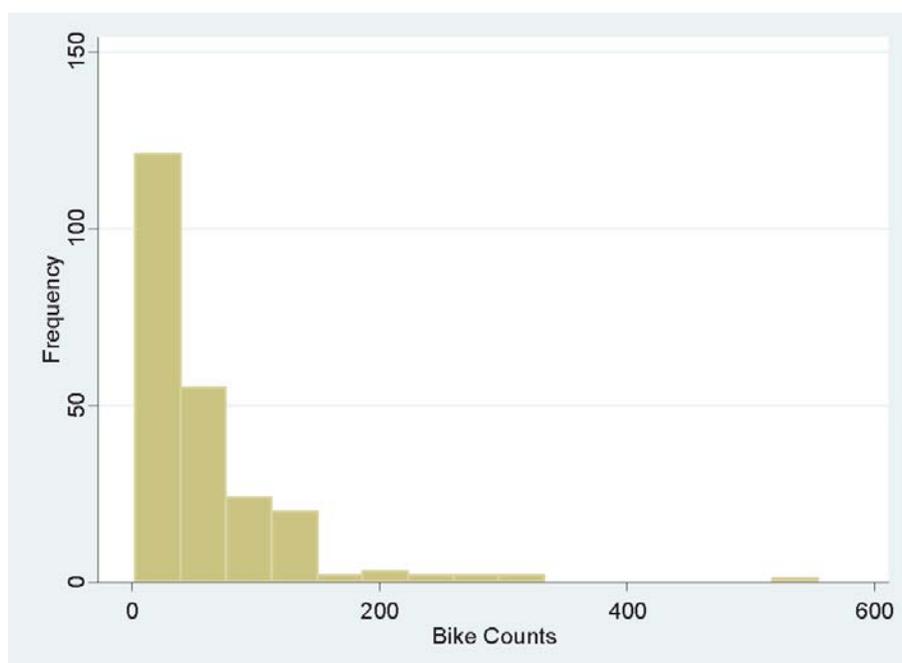
Figure 22. Frequency distribution of bike counts on intersections.

Using the bike counts, a crash rate measure was created. Table 5 lists the intersections with the highest number of crashes followed by a list of intersections with the highest crash rates. Most of the intersections with the highest numbers of crashes also have the most riders and thus lower crash rates. Just three of the intersections are on both lists. These three locations with high crash incidence *and* high crash risk are all intersections of two major arterials with relatively low bike ridership.

Intersections with Highest Number of Crashes

	Intersection	Crashes	Bike Count	Crash Rate	Right-Turn	Left-Turn	Primary Road	Bikeway	Bikeway Type	Transit Stops	BRT	Speed	Lanes
1	S Vermont Ave & W Jefferson Blvd	21	128.00	0.164	Y	Y	Y	Y	R	2	Y	35	8
2	N La Brea Ave & W Sunset Blvd	17	34.00	0.500	Y	Y	Y	N		3	N	35	11
3	Main St & Ocean Park Blvd	15	320.75	0.047	N	Y	N	Y	L	0	Y	35	4
4	S Vermont Ave & W Olympic Blvd	13	30.50	0.426	Y	Y	Y	N		6	Y	35	10
5	S Hoover St & W 30th St	13	554.00	0.023	N	Y	N	Y	L	0	N	35	6
6	Colorado Ave & Pacific Coast Hwy	12	324.33	0.037	Y	Y	Y	Y	L	4	Y	30	7
7	S Figueroa St & W Jefferson Blvd	11	115.00	0.096	Y	Y	Y	Y	R	4	N	35	9
8	Nordhoff St & Sepulveda Blvd	10	21.00	0.476	Y	Y	Y	Y	L	1	Y	35	10
9	Echo Park Ave & W Sunset Blvd	9	86.67	0.104	N	Y	Y	Y	L	3	Y	35	7
10	4th St & Colorado Ave	9	128.00	0.070	N	Y	N	N		0	N	30	6
11	E Ocean Ave & Pico Blvd	9	188.25	0.048	Y	Y	N	Y	L	0	Y	35	6

Intersections with Highest Crash Rates

	Intersection	Crashes	Bike Count	Crash Rate	Right-Turn	Left-Turn	Primary Road	Bikeway	Bikeway Type	Transit Stops	BRT	Speed	Lanes
1	Roscoe Blvd & Van Nuys Blvd	7	9.14	0.766	Y	Y	Y	N		0	Y	35	11
2	N La Brea Ave & W Sunset Blvd	17	34.00	0.500	Y	Y	Y	Y	R	2	Y	35	8
3	S Western Ave & W Slauson Ave	5	10.13	0.493	Y	Y	Y	N		2	Y	35	8
4	Nordhoff St & Sepulveda Blvd	10	21.00	0.476	Y	Y	Y	Y	L	1	Y	35	10
5	S Vermont Ave & W Olympic Blvd	13	30.50	0.426	Y	Y	Y	N		6	Y	35	10
6	Reseda Blvd & Roscoe Blvd	8	21.00	0.381	Y	Y	Y	Y	L	0	Y	35	10
7	Reseda Blvd & Ventura Blvd	4	11.00	0.364	Y	Y	N	Y	L	1	Y	35	8
8	Griffin Ave & N Broadway	6	17.00	0.353	Y	Y	N	N		0	N		7
9	Crenshaw Blvd & W Adams Blvd	6	18.00	0.333	N	Y	Y	N		0	Y	35	10
10	Oxnard St & Woodman Ave	3	9.33	0.321	N	Y	Y	Y	L	0	N	35	8
11	N Western Ave & Santa Monica Blvd	5	16.00	0.313	N	Y	Y	Y	L	0	N	35	8

Table 5. Intersections with highest number of crashes. Intersections with highest crash rates.

Physical and Socio-Economic Characteristics

A number of physical and socio-economic characteristics were gathered for each intersection to see what factors might influence bike crashes. The analysis below looks at the relationship between these variables and both crashes and crash rates.

Intersection Control (Signalized, Four-way Stop, and Two-way Stop)

Most of the intersections (90%) are signalized, and all but one of the top crash intersections listed above is signalized. Eight percent are four-way stops with just five two-way stops and one roundabout. The two-way stop intersections had a significantly higher average number of crashes (6 as compared to 2.8 for signalized intersections); however, the Vermont Avenue and Jefferson Boulevard intersection with the highest number of crashes (21) is a two-way stop, which pulls up the mean. Vermont Avenue and Jefferson Boulevard is also a high ridership area. T-test results (see Table 6) show that 4-way stops have a significantly lower average number of crashes than signalized intersections, however this difference is not statistically significant when considering ridership (i.e. difference in crash rates).

Physical Characteristics	Crash Counts				Crash Rates			
	n	Mean	St. Dev.	Sig.	n	Mean	St. Dev.	Sig.
All Intersections	247	2.78	3.11		232	0.076	0.106	
Type								
Signalized	222	2.84	2.95	0.01	210	0.078	0.109	ns
4-Way	19	1.16	1.83		18	0.044	0.065	
Intersection Arms								
4 or More	208	3.00	3.21	0.005	193	0.085	0.112	0.005
Less than 4	39	1.56	2.17		39	0.037	0.055	
Sidewalks Missing								
No	234	2.88	3.14	0.001	219	0.080	0.108	0.02
Yes	13	0.92	1.66		13	0.013	0.020	
Dedicated center-turn Lane								
Yes	199	3.13	3.30	0.0001	186	0.081	0.111	ns
No	48	1.33	1.46		46	0.058	0.082	
Dedicated Right Turn								
Yes	106	3.21	3.64	0.05	104	0.091	0.130	0.03
No	141	2.45	2.61		128	0.64	0.081	
Primary Road								
Yes	98	3.63	3.58	0.005	90	0.112	0.071	0.001
No	149	2.21	2.61		142	0.054	0.038	
Bikeway								
Yes	118	3.46	3.42	0.0005	118	0.075	0.092	ns
No	129	2.16	2.65		114	0.077	0.119	
Bikeway Type								
Lane	71	3.72	3.18	ns	69	0.087	0.108	0.03

Table 6. Intersection T-Test Results.

Intersection — T-test Results - Difference in Group Means

Route	45	3.04	3.81		43	0.053	0.051	
Transit Stops								
Yes	84	3.81	3.79	0.0005	79	0.107	0.124	0.003
No	163	2.25	2.54		153	0.061	0.093	
Rapid Bus Line								
Yes	78	4.36	3.58	0.0001	74	0.110	0.144	0.005
No	169	2.05	2.56		158	0.061	0.078	
NS Speed > 30 MPH								
Yes	75	4.29	3.68	0.05	70	0.127	0.149	0.01
No	45	3.09	3.80		42	0.060	0.96	
EW Speed > 30 MPH								
Yes	58	4.46	4.18	0.02	54	0.154	0.167	0.0001
No	64	3.11	2.44		61	0.056	0.070	
8 or More Lanes								
Yes	83	3.78	2.66	0.0001	76	0.136	0.148	0.0001
No	164	2.27	2.66		156	0.047	0.059	

Table 6. Intersection T-test results.

Intersection Arms

Most of the intersections (83%) have four arms. The 36 intersections with just three arms have a lower average number of crashes and crash rates (1.6 crashes/ 0.03 crash rate) than intersections with four arms (2.9 crashes/ 0.08 crash rate). The two intersections with five or more arms have the highest average number of crashes at 6 (Ocean Ave & Pico Blvd is one of these intersections). The difference in both crash rates and average number of crashes between intersections with four or more arms and those with less than four is statistically significant at the 0.005 level (see Table 6).

Sidewalks Missing

Only five percent (13) of the intersections have sidewalks missing. These intersections have a significantly lower average number of crashes (less than one) than the 234 intersections with sidewalks (average 2.9 crashes). This also holds true for crash rates (see t-test results). However, because of the small sample size for the "sidewalk missing" group and the fact that neither crash counts nor crash rates are normally distributed, this finding should be held with caution.

Dedicated Right and Center-Turn Lanes

Forty-three percent of intersections have dedicated right turn lanes and just over 80 percent have dedicated center-turn lanes. The average number of crashes per intersection was significantly higher in both cases – i.e. an average of 3.1 crashes for intersections with dedicated center-turn lanes versus 1.3 for intersections without dedicated center-turn lanes; and an average of 3.2 crashes for intersections with dedicated right turn lanes compared to 2.5 for intersections without right turn lanes.

Both t-tests show statistically significant differences in the average number of crashes. We can be a little more confident in these results since group sizes are larger. However, when looking at differences in crash rates, we see that while intersections with dedicated center-turn lanes have higher average crash rates, the difference is not statistically significant.

Road Type

Intersections are located across five road types as shown in the table below. Forty percent are primary roads with just 13 categorized as highways. Just over half are classified as minor (31%) and secondary roads (24%).

Table 7. Frequencies of Crashes on Intersections by Road Type			
Type	Frequency	Percent	Cumulative
Alley	1	0.40	0.40
Highway	13	5.26	5.67
Minor	76	30.77	36.44
Primary	98	39.68	76.11
Secondary	59	23.89	100.00
Total	247	100.00	

Table 7. Frequencies of crashes on intersections by road type.

The average number of crashes is highest for primary roads (3.6) and lowest for secondary roads (1.9 crashes per intersection). A T-test shows that primary roads have a significantly higher average number of crashes than non-primary roads (sig. 0.001). This also holds true for crash rates although rates are lowest for minor roads rather than secondary roads.

Bikeway

Almost half of the intersections (118) have a bikeway of some sort. Of these the majority are classified as bike lanes. There are just two bike paths. Intersections with a bikeway of any type have higher than average number of crashes (Lane, 3.7; Path, 3.5; Route, 3.4).

Table 8. Frequencies of Crashes on Intersections by Bikeway Type			
Bikeway Type	Frequency	Percent	Cumulative
Lane	71	60.17	60.17
Path	2	1.69	61.86
Route	45	38.14	100.00
Total	118	100.00	

Table 8. Frequencies of crashes on intersections by bikeway type.

As would be expected, bike ridership is higher for intersections where there is a bikeway (average ridership is 78 versus 39 for intersections without a bikeway). Thus it is not surprising that the t-test table shows there is no significant difference in average crash rates between intersections with a bikeway and those without. In fact the average crash rate is slightly higher for intersections without a bikeway.

Comparing type of bikeway within the set of intersections with a bikeway, we see that while the difference in average number of crashes between a lane and a route is not statistically significant; lanes have a significantly higher crash rate than routes.

Truck Route

Just 19 (less than 8 percent) of the intersections were on truck routes and the average number of crashes differed negligibly for these than those not on truck routes (2.6 crashes versus 2.8). Similar results hold for crash rates.

Transit Stops

There are transit stops on about one-third of the intersections (most of these have one to four stops with a high of eight stops at one intersection). The average number of bike crashes is significantly higher at intersections with transit stops (3.8 versus an average of 2.2 at intersections with no stops). Crash rates are also higher at intersections with transit stops.
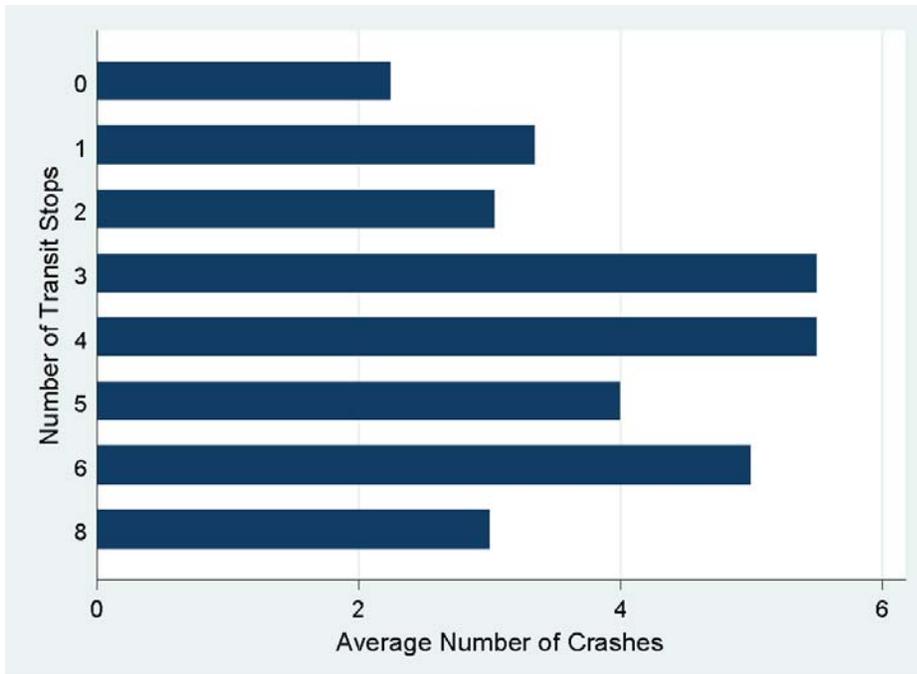
Figure 23: Average number of crashes near transit stops.
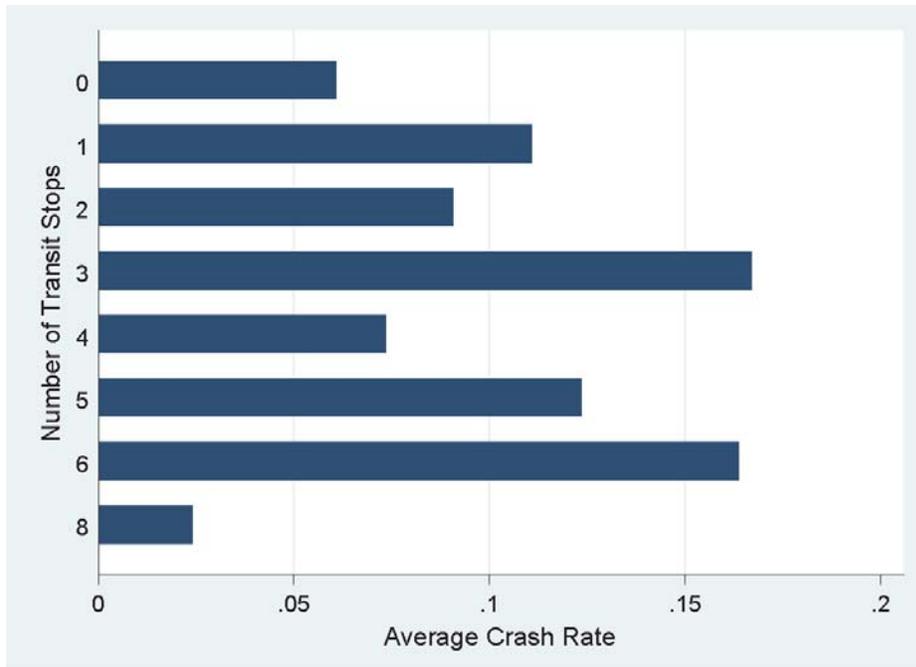
Figure 24: Average crash rates near transit stops.

Rapid Bus Line

Just over 30% of the intersections are on a Rapid Bus line (78). As with transit stops the average number of crashes (4.4) is significantly higher for these intersections than those not on a Rapid Bus line (average number of crashes is 2.0). This also holds for crash rates. It should be noted that Rapid Bus lines are more likely to be on a primary road which have been shown to be more likely to have bike crashes (half of the intersections with Rapid Bus lines are primary roads as compared to 35% of intersections without Rapid Bus lines). However, if we limit the sample to just intersections with Primary roads, we still see significant differences in both average number of crashes and crash rates between those with and without Rapid Bus lines.

Table 9. Frequencies of Crashes at Intersections Along Rapid Bus Lines				
	Rapid Bus Line	Primary Road		
		No	**Yes**	**Total**
Frequency	**No**	110	59	169
Percent		65.09	34.91	100
Cumulative		73.83	60.20	68.42
Frequency	**Yes**	39	39	78
Percent		50	50	100
Cumulative		26.17	39.80	31.58
Frequency	**Total**	149	98	247
Percent		60.32	39.68	100
Cumulative		100	100	100
		Pearson chi2(1) - 5.0766		Pr = 0.024

Table 9. Frequencies of crashes at intersections along rapid bus lines.

Table 10. Crash Counts and Rates at Intersections Along Rapid Bus Lines								
Primary Roads Only	Crash Counts				Crash Rates			
	n	**Mean**	**St. Dev.**	**Sig.**	**n**	**Mean**	**St. Dev.**	**Sig.**
Rapid Bus Line								
Yes	39	5.10	3.75	0.0004	36	0.162	0.172	0.005
No	59	2.66	3.13		54	0.078	0.098	

Table 10. Crash counts and crash rates at intersections along rapid bus lines.

Nearby Land Uses

Only 16 intersections are within 400 feet of a freeway ramp and these have a slightly lower than average number of crashes (2.2). Five intersections are close to a hospital and have a higher than average number of crashes (6.6). Being near a park (18 intersections) seems to make no difference in average number

of crashes. The impact of being within 400 feet of an educational institution (a total of 40 intersections) varies across institution type and is hard to discern due to the small numbers in each category. The five intersections classified as within 400 feet of a college or university have a higher than average number of crashes (4.2) and two of the highest crash intersections are located in the vicinity of USC but aren't categorized as close to an educational institution. But when considering number of riders, crash rate is not higher for intersections near college or university.

Speeds

Only about 60 percent of the intersections have speed recorded in the data so this is a limited independent variable at this point. For intersections with data, most recorded speeds of 25 mph to 40 mph. In general average number of crashes and average crash rates increased with speed and both are significantly higher for intersections with speed limits over 30 mph. Note, all but one of the top crash and crash rate intersections have a speed limit of 35.

Number of Lanes/Width

About 80% of the intersections had four to eight lanes with almost thirty percent six lane intersections. The third of the intersections with 8 or more lanes have a significantly higher average number of crashes (3.8) than intersections with less than eight lanes (2.3). This difference is significant at the 0.0001 level for both number of crashes and crash rates. Over half of primary roads are eight lanes or over as compared to just 18% of secondary and minor roads. While this might help explain the difference in crashes, limiting the sample to just primary roads again shows that the number of lanes still has a significant effect.

Table 11. Crash Counts and Rates at Intersections of Roads with Eight or More Lanes								
Primary Roads Only	Crash Counts				Crash Rates			
	n	Mean	St. Dev.	Sig.	n	Mean	St. Dev.	Sig.
8 or More Lanes								
Yes	53	4.57	4.15	0.0003	47	0.171	0.166	0.0001
No	45	2.53	2.37		43	0.046	0.044	

Table 11. Crash counts and crash rates at intersections of roads with eight or more lanes.

There is also a slight positive correlation between the number of crashes and number of lanes (0.25) and intersection width (0.17). These correlation coefficients are somewhat higher when looking at crash rates (0.36 for number of lanes and 0.2 for width) as shown in Table Y.

Vehicle Volumes

Vehicle volumes were estimated for about three-fourths of the intersections in the north-south direction or east-west direction or both. There is a weak positive correlation between vehicle volumes and number of crashes (0.26 for NS volumes and 0.17 for EW volumes) and a slightly higher correlation between volumes and crash rates (0.28 for NS volumes and 0.32 for EW volumes).

Census Variables

Looking at socio-economic characteristics based on census data for the intersection area, we see that only two variables are correlated with both number of crashes and crash rates: median income and median age. The average number of vehicles per household is also negatively correlated with average number of crashes while percent White has a negative correlation with crash rates and percent Hispanic a positive correlation with crash rates.

Correlations indicate we would expect lower number of crashes and crash rates in areas with higher income, higher median age, higher vehicle ownership and a higher white population. The converse is higher number of crashes and crash rates in poorer, non-white neighborhoods. Varying n in Table 12 are due to missing data for vehicle volumes and missing Census data for 4 intersections.

Table 12. Correlations Between Crashes and Select Variables						
Intersection	Correlations					
Physical Characteristics	Crash Counts			Crash Rates		
	n	**r**	**Sig.**	**n**	**r**	**Sig.**
No. of Lanes	247	0.253	0.0001	232	0.363	0.0001
Width	247	0.178	0.0050	232	0.203	0.0020
NS Vehicle Volume	190	0.256	0.0010	180	0.278	0.0002
EW Vehicle Volume	187	0.167	0.0500	180	0.323	0.0001
Socio-Economic Characteristics	Crash Counts			Crash Rates		
	n	**r**	**Sig.**	**n**	**r**	**Sig.**
Median Income	243	-0.272	0.0001	228	-0.211	0.0020
Median Age	243	-0.246	0.0001	228	-0.208	0.0020
Avg. No. of Vehicles	243	-0.207	0.0012	228	0.022	ns
Percent White	243	-0.110	ns	228	-0.314	0.0001
Percent Hispanic	243	0.111	ns	228	-0.287	0.0001

Table 12. Correlations between crashes and select variables.

Segments

The following section is a descriptive analysis of crashes within segment and our collected physical and socio-economic variables.

Crash Incidence

Of the 887 segments studied, 68 percent have no bike crashes and another 17 percent have just one crash. Only seven segments have over five crashes. The average number of crashes per segment is less than one (.61) with a standard deviation of 1.2 further indicating a skewed distribution similar to that for crash incidence at intersections.
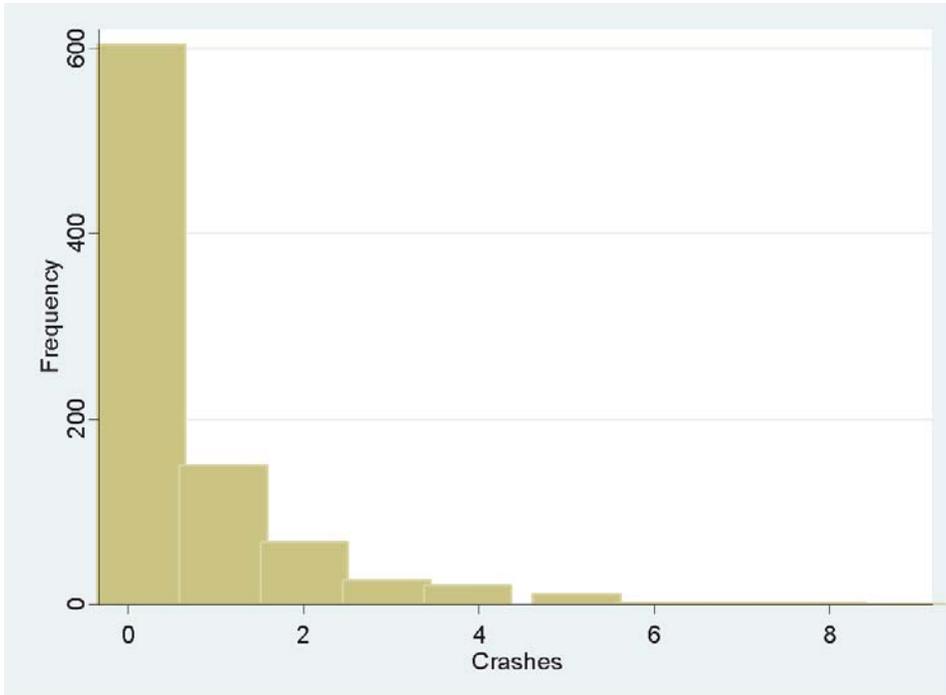
Figure 25. Frequency distribution of segment crashes per site.

Bike Ridership

Bike ridership counts were available for 816 segments in the database. The count measure used in the analysis is average number of riders per two-hour period. Average counts range from a low of less than one bike per two hour period to a high of about 300 riders. The average is 25 riders with a standard deviation of 32. The histogram for bike counts also shows a skewed distribution with just a few high count segments.
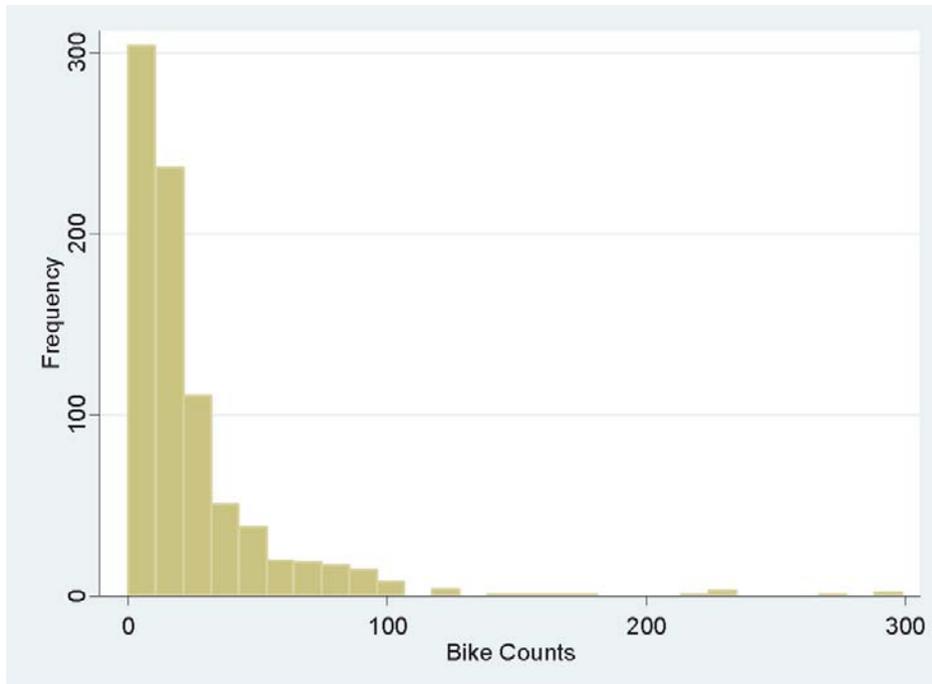
Figure 26. Frequency distribution of bike counts on segments.

Using the bike counts, a crash rate measure was created. Table 13 lists the top 10 segments with respect to the highest number of crashes followed by a list of segments with the highest crash rates (only segments with at least four crashes are included in this list). Half of the segments are on both lists. The other half with high numbers of crashes also have relatively high ridership counts and thus lower crash rates. The segment with the most crashes is on Westwood Blvd and since it is close to a university we can assume it is near UCLA. As with the high crash intersections close to USC, it has a moderately high bike ridership count and thus does not make the crash rate list.

Physical and Socio-Economic Characteristics

A number of physical and socio-economic characteristics were gathered for each segment to see what factors might influence bike crashes. The analysis below looks at the relationship between these variables and both crashes and crash rates.

Segments with Highest Number of Crashes

	Segment	Crashes	Bike Count	Crash Rate	Width > 62 ft.	3 Travel Lanes	Left Turn	Highway/Primary	Bikeway	Bikeway Type	Truck Route	Transit Stops	BRT Line	W > 20,000
1	Westwood Blvd	9	47.83	0.188	Y	N	Y	Y	Y	L	N	0	N	Y
2	E Ocean Ave	8	45.75	0.175	Y	N	Y	Y	Y	L	N	13	Y	N
3	Balboa Blvd	8	3.67	2.182	Y	Y	Y	Y	Y	P	N	4	Y	Y
4	Main St	7	94.00	0.074	N	N	Y	N	Y	L	N	0	Y	N
5	Main St	7	60.25	0.116	N	N	Y	Y	Y	L	N	0	Y	N
6	4th Ave	6	37.75	0.159	N	N	Y	N	Y	R	N	0	N	N
7	Sepulveda Blvd	6	6.33	0.947	Y	Y	Y	Y	N		N	4	Y	Y
8	Pacific Coast Hwy	5	2.50	2.000	Y	Y	Y	Y	N		Y	0	N	Y
9	Roscoe Blvd	5	2.80	1.786	Y	Y	Y	Y	N		N	3	N	Y
10	W Sepulveda Blvd	5	7.53	0.664	Y	Y	Y	Y	N		Y	0	Y	Y

Segments with Highest Crash Rates

	Segment	Crashes	Bike Count	Crash Rate	Width > 62 ft.	3 Travel Lanes	Left Turn	Highway/Primary	Bikeway	Bikeway Type	Truck Route	Transit Stops	BRT Line	W > 20,000
1	Oxnard St	1	0.33	3.000	N	N	Y	N	N		N	1	N	N
2	Pacific Coast Hwy	1	0.44	2.250	N	N	N	N	Y	R	Y	0	N	N
3	Balboa Blvd	8	3.67	2.182	Y	Y	Y	Y	Y	P	N	4	Y	Y
4	Pacific Coast Hwy	5	2.50	2.000	Y	Y	Y	Y	N		Y	0	N	Y
5	Roscoe Blvd	5	2.80	1.786	Y	Y	Y	Y	N		N	3	N	Y
6	Roscoe Blvd	4	2.80	1.429	Y	Y	Y	Y	N		N	1	N	N
7	W Slauson Ave	2	1.81	1.107	N	N	Y	Y	N		N	2	N	N
8	W Slauson Ave	2	1.81	1.107	Y	N	Y	Y	N		N	1	N	N
9	Sepulveda Blvd	6	6.33	0.947	Y	Y	Y	Y	N		N	4	Y	Y
10	Pacific Coast Hwy	2	2.50	0.800	Y	Y	Y	Y	N		Y	0	N	N

Table 13. Segments with highest number of crashes.

Road Width

Segments widths range from 20 feet to 160 feet with an average of 63 feet. The median and mean road width are essentially the same. There is a statistically significant difference in the average crash count for segments less than the median width (average is 0.43 crashes) versus segments with widths above the median (average is 0.80 crashes). This difference also holds for crash rates where the rate for segments with width over 62 is twice that for segments with width under the median (see Table 14).

Table 14. Segment T-Test Results								
Segment	T-test Results - Difference in Group Means							
	Crash Counts				Crash Rates			
Physical Characteristics	n	Mean	St. Dev.	Sig.	n	Mean	St. Dev.	Sig.
All Segments	887	0.61	1.19		816	0.059	0.215	
Road Width > Median (62 Ft)								
Yes	437	0.80	1.36	0.0001	400	0.080	0.225	0.004
No	450	0.43	0.98		416	0.039	0.203	
Travel Lanes = 3								
Yes	86	1.08	1.64	0.0001	82	0.189	0.431	0.0001
No	801	0.56	1.12		734	0.044	0.170	
dedicated center-turn Lane								
Yes	617	0.77	1.32	0.0001	575	0.071	0.232	0.005
No	269	0.26	0.71		241	0.031	0.166	
Highway or Primary Road								
Yes	472	0.88	1.38	0.0001	431	0.089	0.250	0.0001
No	415	0.31	0.84		385	0.025	0.163	
Bikeway								
Yes	271	0.89	1.56	0.0001	259	0.053	0.208	ns
No	616	0.49	0.96		557	0.062	0.219	
Bikeway Type								

Lane	148	1.11	1.72	0.001	142	0.048	0.093	ns
Route	117	0.56	1.14		112	0.040	0.219	
Truck Route								
Yes	55	1.18	1.39	0.0001	51	0.171	0.434	0.0001
No	832	0.57	1.17		765	0.051	0.190	
Transit Stops								
Yes	317	0.93	1.39	0.0001	295	0.103	0.289	0.0001
No	570	0.43	1.03		521	0.034	0.154	
Rapid Bus Line								
Yes	163	1.18	1.02	0.0001	152	0.089	0.219	0.03
No	724	0.48	1.64		664	0.052	0.214	
Vehicle Volume > 20,000								
Yes	102	1.21	1.55	0.0001	91	0.160	0.380	0.003
No	785	0.53	1.12		725	0.046	0.181	

Table 14. Segment T-test results.

Travel Lanes

Most of the segments are one or two lanes in each direction (82%) as shown in Figure 27. Figure 28 plots the average number of crashes for segments with different number of lanes and the third plots the average crash rate. While the average number of crashes is highest for segments with three lanes in each direction, an even more dramatic difference is seen for crash rates. The rate for three lane segments is more than twice that of other segments. Note the charts below show combined lanes in both directions per segment divided by two.
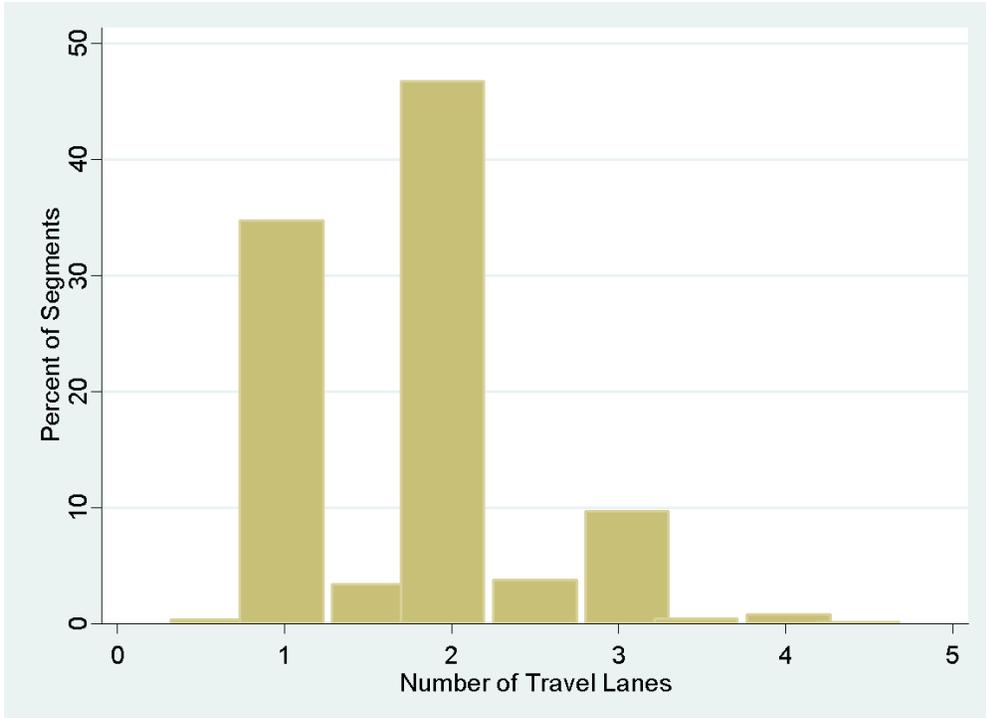
Figure 27. Frequency distribution of number of travel lanes per segment.
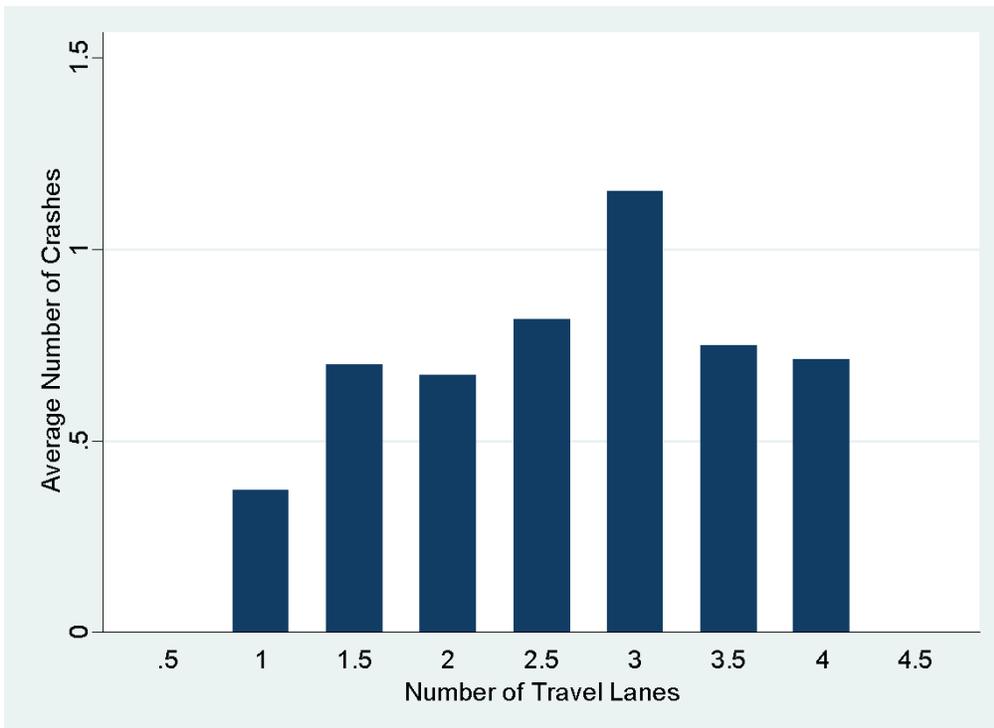
Figure 28. Average number of crashes based on number of travel lanes per segment.
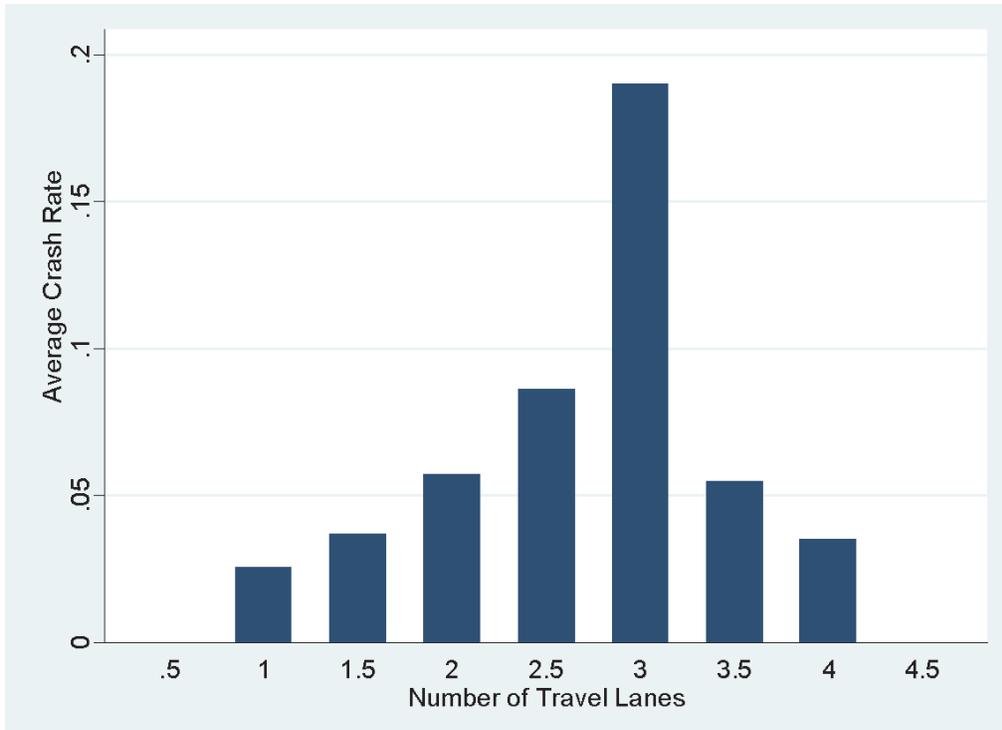
Figure 29. Average crash rates based on number of travel lanes per segment.

Sidewalks Missing

Less than 10 percent (55) of the segments have sidewalks missing. There is essentially no difference in the average number of crashes or crash rates between this group and segments with sidewalks.

Dedicated Right and Left Turns

One fourth of the segments have dedicated right turn lanes and there is little difference in the average number of crashes per segment or crash rate between those with right-turn lanes and segments without. A much higher proportion of segments has dedicated center-turn lanes (almost 70%) and the t-tests show (see Table 14) that there is a significantly higher average number of crashes per segment for these (0.77) than for segments without (0.26). This difference also holds for crash rates. dedicated center-turn lanes seems to be an important variable associated with bike safety. Segments with dedicated center-turn lanes are more likely to have three lanes than other segments. However, if we compare crashes or crash rates within the sub-group of 800 observations that are not three-lane, we still see a significant difference between segments with

left-turn lanes and those without. Segments with dedicated center-turn lanes are also much more likely to be greater than the median width (two-thirds have widths greater than the median versus just 13% of segments without a dedicated center-turn lane). However, again if we limit the analysis to just segments greater than the median width, we still see a significant difference in average number of crashes and average crash rate between segments with and without a left-turn lane. So, width of segments does not seem to explain why left hand turns contribute to bike crashes.

Table 15. Crash Counts and Rates for Segments With and Without dedicated center-turn Lanes								
Segment Width > Median (62 ft) Only	Crash Counts				Crash Rates			
	n	Mean	St. Dev.	Sig.	n	Mean	St. Dev.	Sig.
dedicated center-turn Lane								
Yes	401	0.84	1.38	0.001	366	0.086	0.239	0.0001
No	36	0.31	0.89		34	0.014	0.040	

Table 15. Crash counts and rates for segments with and without dedicated center-turn lanes.

Road Type

The distribution of segments across road types is similar to intersections, as shown in the table below. Almost half are primary roads with just five percent categorized as highways. The remaining is pretty evenly split between minor and secondary roads.

Table 16. Frequencies of Segment Crashes by Road Type			
Type	**Frequency**	**Percent**	**Cumulative**
Highway	46	5.19	5.19
Minor	229	25.82	31.00
Primary	426	40.03	79.03
Private Road	1	0.11	79.14
Secondary	185	20.86	100.00
Total	887	100.00	

Table 16. Frequencies of segment crashes by road type.

In contrast to intersections, average number of crashes is highest for highways (just over one) followed by primary roads (0.86). Secondary and minor road segments have the lowest average number of crashes (0.34 and 0.29 average crashes per intersection). A similar progression holds for crash rates. Table 17 shows that the difference in average number of crashes and crash rates between highways or primary roads and other road types is statistically significant.

Table 17. Crash Counts and Rates on Segments by Road Type						
Road Type	Crash Counts			Crash Rates		
	n	**Mean**	**St. Dev.**	**n**	**Mean**	**St. Dev.**
Highway	46	1.040	1.350	44	0.165	0.459
Primary	426	0.859	1.387	387	0.080	0.213
Secondary	185	0.335	0.888	178	0.033	0.228
Minor	229	0.288	0.792	206	0.019	0.067

Table 17. Crash counts and crash rates on segments by road type.

Further exploration of why dedicated center-turn lanes contribute to bike crashes shows that two-thirds of segments with these lanes are highway or primary roads as compared to just over 20% of segments without left-hand turn lanes. Limiting the analysis to just those segments classified as highway or primary roads, we see no significant difference in crashes or crash rate between segments with left-turn lanes and not. However, if we look just at segments on secondary or minor roads, we do see a significant difference in average number of crashes between segments with left-turn lanes and those without, although there is not a statistically significant difference for crash rates.

Table 18. Crash Counts and Rates on Segments With and Without dedicated center-turn Lanes								
Secondary or Minor Road Type Only	Crash Counts				Crash Rates			
	n	**Mean**	**St. Dev.**	**Sig.**	**n**	**Mean**	**St. Dev.**	**Sig.**
Dedicated Center-turn Lane								
Yes	205	0.500	1.070	0.0001	199	0.037	0.218	ns
No	209	0.124	0.443		185	0.014	0.062	

Table 18. Crash counts and crash rates on segments with and without dedicated center-turn lanes.

On-Street Parking

Almost 60 percent of the segments allow parallel parking on both sides of the street and another ten percent on one side. No parking is allowed on 30 percent of the segments.

Table 19. Frequencies of Crashes on Segments by On-Street Parking Type			
On-Street Parking	**Frequency**	**Percent**	**Cumulative**
Diagonal or Perpendicular	13	1.48	1.48
No	266	30.26	31.74
Other	12	1.37	33.11
Parallel	502	57.11	90.22
Parallel 1 Side	86	9.78	100.00
Total	879	100.00	

Table 19. Frequencies of crashes on segments by on-street parking type.

There is no difference in the average number of crashes between segments which allow parallel parking and those with no parking. The 13 segments which allow diagonal or perpendicular parking have an average number of crashes almost twice that of the other segments. However, average crash rate for this group is no different than the overall average. This is too small a group to test for statistical significance.

Driving Direction

All but one segment has two-way traffic.

Bikeway

Thirty percent of the segments (271) have a bikeway of some sort. While the average number of crashes is higher for segments with bikeways, crash rates are actually slightly lower due to higher ridership (see Table 20). The average number of riders per two hour period on segments with bikeways is 38 as compared to an average of just 19 riders on segments without bikeways.

Bikeways are split fairly evenly between bike lanes and bike routes. Sections with lanes or paths have a higher average number of crashes (Lane, 1.1; Path, 1.8) than sections with routes (0.56). However, crash rates do not differ between lanes and routes as lanes have a somewhat higher ridership than routes (average count for lanes is 42 riders compared to 34 for routes).

Table 20. Frequencies of Crashes on Segments by Bikeway Type			
Bikeway Type	**Frequency**	**Percent**	**Cumulative**
Lane	148	54.61	54.61
Path	6	2.21	56.83
Route	117	43.17	100.00
Total	271	100.00	

Table 20. Frequencies of crashes on segments by bikeway type.

Truck Route

Only six percent of the sections are on truck routes. However, different from intersections, these 55 segments have more than twice the average number of crashes as segments that are not on truck routes and three times the crash rates. Two-thirds of truck routes are Highways and another 20% are Primary roads, both of which have higher average crash counts and average crash rates. However, limiting the segments to just those that are Highways or Primary roads, segments that are truck routes still have significantly higher average crash counts and crash rates.

Transit Stops

There are transit stops on 35% of the segments (most of these serve one to four bus lines, with one serving as many as 13). The average number of bike crashes is significantly higher at segments with transit stops (0.93 versus an average of 0.43 at intersections with no stops). Crash rates also differ significantly by whether or not a segment has transit (see Table 14).

Rapid Bus Line

Eighteen percent of the segments are on a Rapid Bus line (163). As with transit stops the average number of crashes (1.2) is significantly higher than for those

segments not on a Rapid Bus line (average number of crashes is 0.48). This also holds true for crash rates (see Table 14).

Most Rapid Bus lines (83%) are on highways or primary roads which have higher crash measures. Limiting the analysis to just segments on Highways or Primary roads, segments with Rapid Bus lines still have a significantly higher number of crashes than segments without. However, there is no significant difference in crash rates.

Table 21. Crash Counts and Rates on Segments With and Without Rapid Bus Lines								
Highway/Primary Road Only	Crash Counts				Crash Rates			
	n	Mean	St. Dev.	Sig.	n	Mean	St. Dev.	Sig.
Rapid Bus Line								
Yes	136	1.23	1.64	0.001	126	0.103	0.238	ns
No	336	0.74	1.24		305	0.083	0.254	

Table 21. Crash counts and rates on segments with and without rapid bus lines.

Nearby Land Uses

Only eight percent of segments are within 400 feet of a freeway ramp (73) and while there are slightly higher average crash counts and crash rates for these segments, differences are not large enough to be statistically significant. Twenty-four segments are close to a hospital and have a significantly higher than average number of crashes (1.4) but not crash rates. Being near a park (65 segments) again has significantly higher average crash counts (0.83) but not crash rates. The impact of being within 400 feet of an educational institution (184 segments) also shows slightly higher crash counts and crash rates, which are in this case considered statistically significant due to a larger sample size. Specifically, the 25 segments near colleges and universities have a significantly higher average number of crashes (1.36 versus 0.59 for other segments). However when considering ridership counts, there is not a significant difference in crash rates. Average number of riders in segments near a college or university is 61 per two hour period versus just 24 for segments not near a college or university.
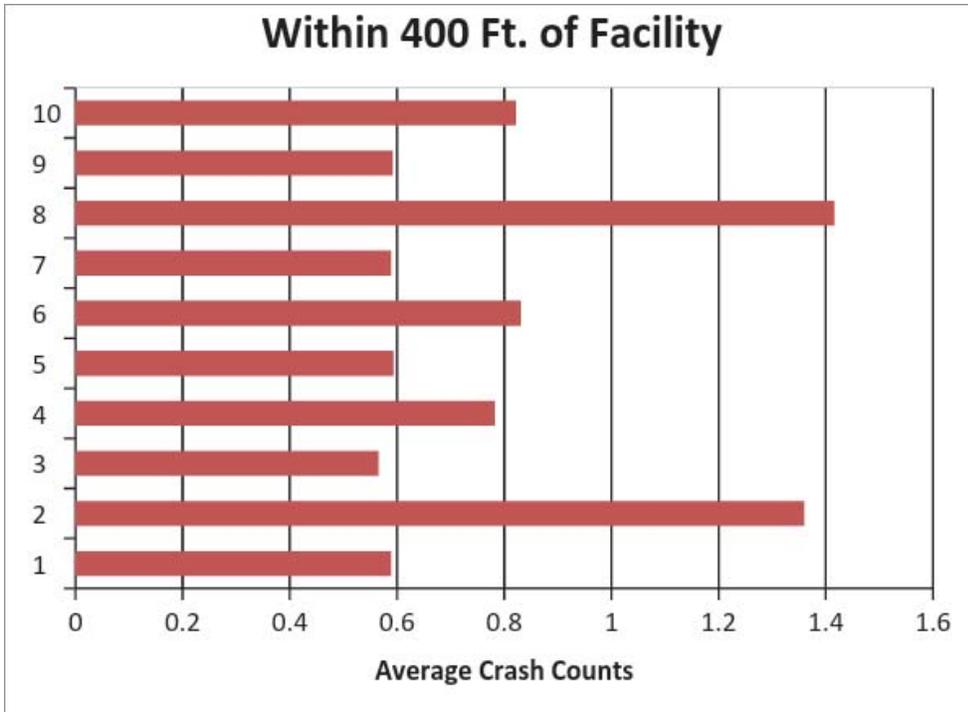
Figure 30. Average crash counts on segments within 400 feet of a facility.
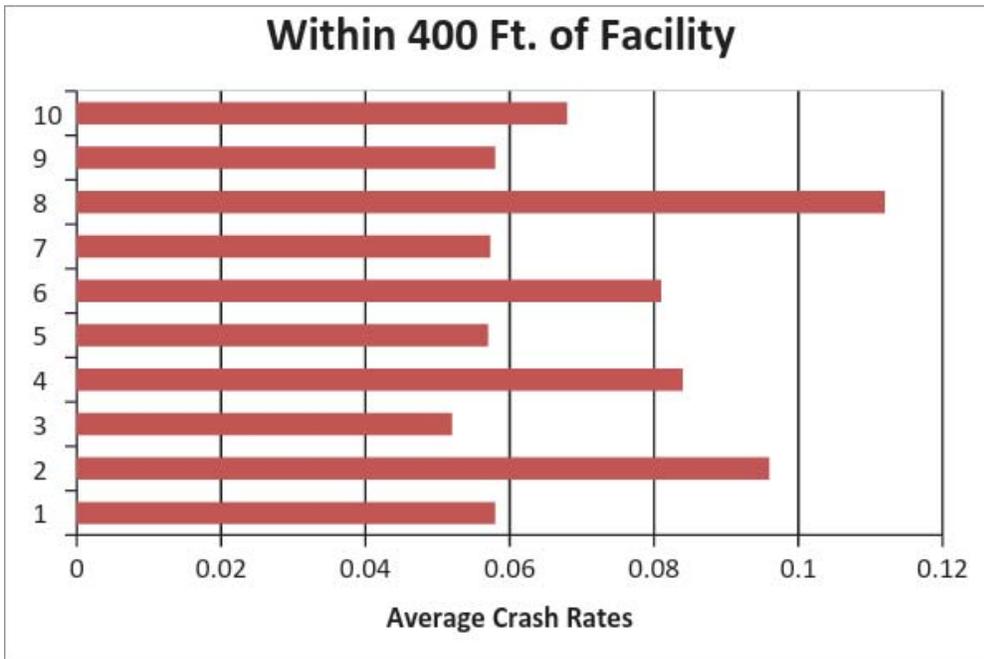
Figure 31. Average crash rates on segments within 400 feet of a facility.

Speeds

Almost 60 percent of the segments do not have speed limits recorded in the data, so this is not a viable independent variable at this point. The remainder recorded speeds of 25 mph to 40 mph. For those segments with recorded speeds there is no clear pattern of increasing average crash counts or crash rates with increasing speeds.

Vehicle Volumes

Estimated vehicle volumes are available for most of the segments (84%). Figure 32, below, shows volumes are fairly evenly distributed across segments up to about 20,000 vehicles. Just over 10 percent of the segments have volumes from 20,000 vehicles to a maximum of about 46,000 vehicles.
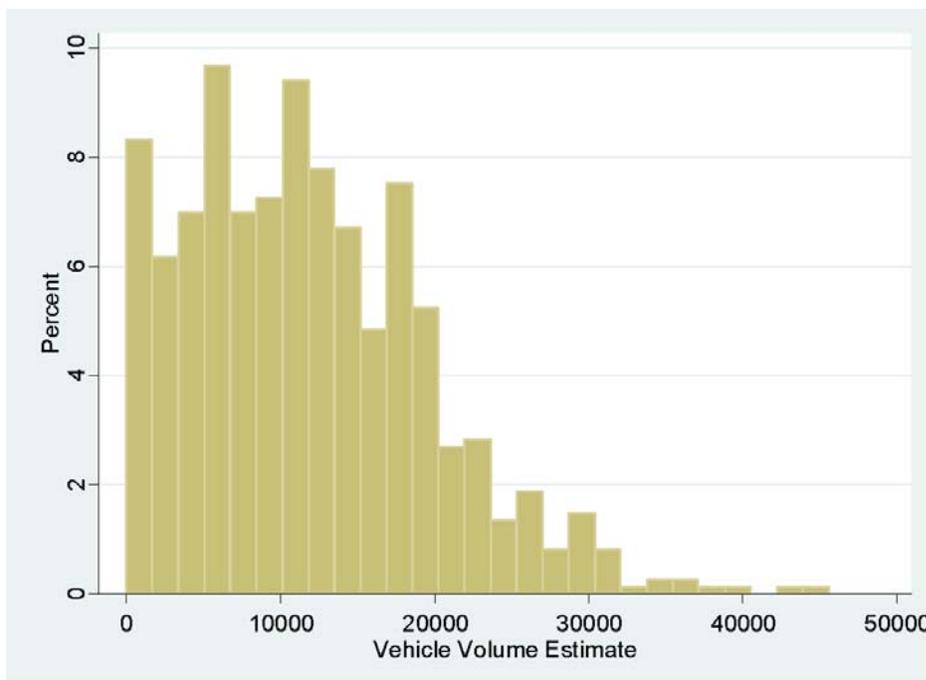
Figure 32. Frequency distribution of segments by vehicle volume.

Segments with vehicle volumes over 20,000 have significantly higher average crash counts and crash rates (see Table 14). This is also true if we look at segments with volumes over the median of about 10,000 vehicles. There is a

small but significant correlation between vehicle volume and average number of crashes (r = 0.25) and average crash rates (r = 0.22).

Census Variables

There is no correlation between any of the socio-economic variables available in the census for areas surrounding each segment and average number of crashes or average crash rate. This differs for intersections where small but significant correlations were found with a few socio-economic variables.

Conclusion

Summary of Findings

We analyzed bicycle crash incidence and bicycle crash risk at 247 intersections and 816 roadway segments in Los Angeles County. Many locations with high crash incidence also have high bicycle ridership. The locations with the highest crash risk tend to have below-average bicycle ridership.

Intersections

For intersections, our analysis finds that the following variables are associated with greater crash incidence *and* greater crash risk: dedicated right turn lanes, classification as a primary roadway, existence of transit stops, high vehicle speeds, and having more than 8 lanes (combined across the two intersecting roadways). The difference in crash incidence and crash risk associated with each of these variables was of roughly the same magnitude: about 1.5-2X more crashes or crashes / cyclist with the variable present.

For some variables, a crash risk analysis reveals a different story than crash incidence alone would tell. Bikeways are associated with more crashes, but when ridership is taken into account, bikeways and non-bikeways have nearly identical crash risk. Curiously, dedicated center-turn lanes at intersections follow the same pattern: they are associated with more crashes, but when ridership is taken into account dedicated center-turn lanes are not associated with greater crash risk. For vehicle speeds, accounting for crash risk increases both the magnitude of the difference and its significance. Vehicle speeds above 30 mph are associated with about 30-40% greater crashes, but about 200-300% high crash risk per cyclist.

We find that number of lanes, combined roadway width, and vehicle volumes all have significant correlations with both crash incidence and crash risk, but that when ridership is taken into account, the significance of these variables is more clear and the magnitude of their apparent effect is stronger. For socioeconomic characteristics, the picture is somewhat more murky. Income, age, and vehicle ownership are all negatively correlated with crash incidence, but ethnicity and race measures are not. When considering crash risk, however, race variables are notably correlated. The percentage of the population that is white is negatively correlated with crash risk and the percentage of the population that is Hispanic is positively correlated. The correlation with income and age is weaker for crash risk, and vehicle ownership is not correlated with crash risk. This

suggests that income, age, and vehicle ownership might be proxy variables for bicycle ridership, and that when ridership is measured directly we can observe more clearly the correlations between crash risk and race.

Segments

For segments, our analysis finds that the following variables are associated with greater crash incidence *and* greater crash risk: roadway widths greater than 62 feet, three travel lanes in each direction, the presence of a dedicated center-turn lane, classification as a truck route, the presence of transit stops in general and rapid transit stops in particular, and vehicle volumes. The difference in crash incidence and crash risk associated with each of these variables was of roughly the same magnitude: about 1.5-2X more crashes or crashes / cyclist with the variable present.

Again, we find that accounting for bicycle ridership reveals a slightly different story than crash incidence alone would tell, although this is less so the case for segments than it is for intersections. Being classified as a highway or primary road is associated with more crashes; this difference is even more stark when considering crash risk per cyclist. Vehicle volumes above 20,000 vehicles per day are associated with more crashes, and this difference is even more stark when considering crash risk. Notably, as with intersections, bikeways are associated with more crashes, but this difference disappears when considering crash risk per cyclist. Also quite notable is the fact that segments near colleges and universities have much higher numbers of crashes but also very high ridership, leading to crash rates on par with the median of the sample.

Policy Implications

Keep Building Bike Lanes

The results reinforce previous findings that bike lanes are an effective safety intervention, and that greater numbers of cyclists leads to cyclist safety. For policymakers, this lends support to a continued program of bicycle infrastructure construction and encouraging bicycle riding. Further, this finding is consistent with the literature.

Be Wary of Crashes as a Prioritization Metric

Because many locations with high crash incidence also have high bicycle ridership, and the locations with the highest crash risk tend to have

below-average bicycle ridership, there are real implications for safety prioritization efforts currently taking place in many cities as part of Vision Zero efforts. Crash incidence as a prioritization metric will tend to point cities toward high ridership corridors where risk per cyclist is actually quite low. It will tend to imply the need for additional safety treatments or programs where bike lanes, themselves an effective safety treatment, already exist. It seems reasonable to argue that the lower-hanging fruit in terms of safety interventions is where ridership is moderate but risk is high. In other words, at the margin, additional safety treatments or programmatic interventions in high ridership, low risk corridors are likely to be less effective than implementing bike lanes in moderate ridership corridors with high crash risk. In the absence of systematic counting programs, cities can begin by conducting counts at locations with high crash incidence, allowing planners to distinguish between high risk / moderate volume sites and low risk / high volume sites.

Bicycle Boulevards are Promising

Many of the variables that we found to be associated with greater crash incidence and greater crash risk are features of major highways and primary roads: higher speeds, more lanes, the presence of transit stops and rapid transit service, higher vehicle volumes. We were not able to directly consider bicycle boulevards in our analysis because there are very few of them currently in Los Angeles County. But because bicycle boulevards are on quiet, neighborhood roads, which tend to be absent of most of the aforementioned features, they are likely to have low crash risk.

Crash Risk Cannot be Understood without Bicycle Count Data

Crash risk cannot be understood without some measurement of bicycle activity. This project validates the added value of aggregating count data into regional, state, and federal databases. These allow for larger datasets and for the posing of deeper questions. Local, regional, and state agencies should prioritize collection of volume data.

It is non-trivial to associate count and crash locations, which are typically represented in a geographic information system as points in space, with segment and intersections of street, which are typically represented as lines. The GIS processes we used to create sections which facilitate this association can be very valuable to any large agency, like a state Department of Transportation, a regional or County government, or even a large city, that needs systematic methods to analyze bicycle (or pedestrian or vehicle) safety.

The Importance of Ethnicity and Race

Accounting for ridership reveals a negative relationship (r=-0.314) between the crashes per cyclist on a segment and the percentage of people who are white in the Census block group around that segment. Likewise, there is a positive relationship (r = 0.287) between crash risk and the percentage of people who are Latino. While these relationships existed in the same direction for crash incidence, they were much weaker and not statistically significant (r = -.110 and r = .111 respectively). Many advocates are currently focused on place-based racial disparities in bicycle access and safety. This analysis suggests that those disparities are more clearly revealed when ridership is directly measured.

Directions for Future Research

This analysis is one of the first to incorporate directly measured bicycle volumes for a large number of intersections and segments. The mechanics of creating the data set were arduous and consumed much of the grant period. Obviously, much more work will be necessary to better understand the dynamics that are suggested by our early results.

A next step would be to better analyze the representativeness of our dataset, providing a better understanding of whether these segments and intersections encompass the variation that can be found in Los Angeles County across neighborhoods, roadway types, crash incidence, and other variables.

The data we employed can be improved. Our dataset excluded sidewalk riding volumes, but the data we do have on sidewalk riding shows that it can be a significant portion of the total ridership at any given location, particularly where there are no bicycle lanes and vehicle traffic is heavy and fast. An immediate next step would be to rerun the analysis on that subset of locations that do have sidewalk riding data. This is a large subset, on the order of 60-80% of our locations. Similarly, we can improve our measurement of cycling activity by better accounting for time of day and day of week factors. We have done significant work toward this, creating extrapolated annual volumes for each location in our data set. We next need to rerun the analysis using this improved measure.

Along similar lines, another next step would be to consider subsets of the crash history, whereas we currently consider 2003-2014. Although smaller subsets would be even more skewed and would contain even more sites with no crashes,

this would allow for more accurate measurement of the crash history at sites with recently installed bikeways.

There is great opportunity for more sophisticated modeling approaches. The skewed distributions (as well as the literature) suggest that negative binomial and Poisson models hold promise. The large numbers of locations with zero crashes in our data set suggest that a two-step model that first models whether there are any crashes at a location -- known as a zero-inflated model -- holds promise.

Finally, continued expansion of the set of locations with bicycle count data, and systematic selection of these sites, would expand the variation within the dataset and thus our ability to better understand the effects of variables like signalization, bicycle boulevards, and others that are not represented by many of the sites in our current dataset.

Appendices

Appendix 1. Extrapolation Factors

The importance of using extrapolation factors to compare exposure data is clear, but there is still little consensus on best practices for developing them in the bicycle and pedestrian safety literature. The Federal Highway Administration's Office of Highway Policy Information published its most recent *Traffic Monitoring Guide* (TMG) in 2013, which provides some guidance on the topic but its authors acknowledge more needs to be done to achieve a true consensus. The TMG identifies five possible factors that may be applied to short duration manual counts. They are listed below, along with a description of how this research project addresses each.

1. Time of day and 2. Day of week

This study uses automated count data from 26 locations around the Los Angeles area to calculate time of day and day of week temporal extrapolation factors. We averaged the automated counts to create a composite factor that accounts for many different location types and conditions. Each location recorded at least a week of data. The automated counts occurred during all seasons in 2013 and 2014.

According to NCHRP Report 797, land use factors are sometimes applied to account for count volume differences associated with uses such as schools, shopping malls, and other locations that are busy at specific times. The report acknowledged that land use factors are more commonly applied to pedestrian counts, as it is harder to link bicycle traffic to adjacent land uses when many bicyclists are merely passing through. Therefore, we did not separate our individual automated count locations by land use type but instead opted for one citywide average.

3. Month/season of year

We did not have access to automated count locations in the Los Angeles area with more than one year of counts, therefore monthly factors could not be generated. We substituted Los Angeles monthly factors for Bay Area monthly

factors at three locations. The automated count locations were located in Oakland, Dublin, and Emeryville. While monthly factors derived from Los Angeles counts would have been ideal, the Bay Area climate and location in California were a good fit when compared to other substitute automated count locations throughout the United States. The factors include two years (2012 and 2013) of counts in urban Oakland and one year each on off-street trails serving urban locations (Dublin and Emeryville in 2014 and 2012, respectively).

4. Occlusion

Occlusion occurs when an automated sensor undercounts cyclists that pass by the sensor at the same time. The sensor registers two cyclists as one. This project relied on EcoCounter's pneumatic tube counters to collect count data. NCHRP Project 07-19, on the topic of automated counters, recommends a simple multiplicative factor to address the occlusion issue with automated counters. The same report conducted field testing on a variety of automated counter method and developed factors for use in projects such as this one. The report recommends applying a factor of 1.135 to all automated counts using pneumatic tubes (Ryus, et al. 2014). This factor will not be applied to manual counts, but instead to any exposure data that uses automated counts and the temporal factors described above.

5. Weather

Due to the dry conditions in Los Angeles, both from the climate and a historically-extreme drought, and the amount of days and hours we aggregated to produce the extrapolation factors, no extrapolation factors for weather were created. Los Angeles' climate is classified as Mediterranean, and the area receives somewhat less rainfall than typical regions with the same climate classification. Most of Los Angeles' rain comes in the winter and spring; summers tend to be extremely dry. Over the past few years, Los Angeles has been experiencing drought conditions, and the 2015-2016 El Nino, expected to bring welcomed rainfall, proved disappointing (Pydynowski 2016). Volunteers collecting bicycle and pedestrian data manually for this project confirm the recent dry conditions in the area. Of the over 2,000 manual count sessions, volunteers indicated it was raining only seven times.

The automated counters perform their task rain or shine, but the extrapolation factors that use the automated data use an average automated counts to smooth out any low counts that could occur do to rain. The monthly and day of the week temporal factors from the Bay Area used the average of four or five days to create the factor, while the hourly factors from the Los Angeles Area used the

average of 28 to 34 of the same hours. Any one of those hours may have been rainy, but their impact on the hourly average would be small.

Rain isn't the only weather that may influence a bicyclists decision to ride. A study of automated counters and pedestrians found that fewer people walked when it was cloudy, as well as when it was cool or hot (Schneider, et al. 2009). The researchers evaluated windy conditions but found no clear effect on pedestrian volumes. Bicyclists are similarly exposed to the elements and may choose not to ride when it is extremely hot or cold. Los Angeles' Mediterranean climate minimizes seasonal variations in temperature. Los Angeles' hottest month is August, with a daily mean temperature of 74.3 degrees Fahrenheit. Its coldest month, December, as a daily mean temperature of 57.6 degrees Fahrenheit. Both temperatures are conducive to outdoor activities such as riding a bicycle. Los Angeles can get uncomfortably hot in the summer, however. Our month-of-the-year counts, though from the Bay Area of California, do reflect some variation in ridership that may be due to cyclists responding to extreme hot or cold temperatures. We did not adjust the hourly or daily factors to account for a particularly hot or cold day captured by an automated counter.

Appendix 2. Creating Roadway Sections to Associate Crashes

In order to associate a particular segment or intersection with the variables, we first had to physically define the segments and intersections. To do this, we used the Los Angeles County Countywide Address Management System (CAMS) centerline data to create street buffers. We removed all freeways and ramps. We found that when using a uniform buffer size, the buffers tended to overlap (especially at intersections with adjoining streets at acute angles). Thus, we used City of Los Angeles sources to determine the widths of the buffers based on the street type field (Fehr & Peers, 2010).

Standard Street Widths by Type:

Highway: 120ft
Primary: 100ft
Secondary: 90ft
Minor: 64ft
Alley: 24ft

From here, we manually spot-checked the sections. Some streets with medians have two centerlines (one for each direction of travel). This results in two distinct section buffers. Thus, intersecting section buffers were merged.

An intersection was defined as the point at which centerlines intersect. From those points, we drew a buffer with a 62 foot radius (two feet larger than our largest street width). We then erased any overlapping buffers. The result is distinct intersections and segments.

On blocks that contain multiple T-intersections (for example, small neighborhood streets connecting to a collector street), the segments can be quite short. In general, we removed these uncontrolled intersections from the study.

If a crash physically intersects with a section, it is counted as having occurred within that section. Thus, the size of our intersection buffers determines if a crash occurred within an intersection.

SWITRS data provides an alternative tag for whether or not a crash occurs in an intersection, the 'INTERSECT_' variable, which classifies a crash as having occurred in an intersection as reported by the reporting officer. After lengthy visual inspection, we found their measurement methods too strict. The CHP defines a crash as "within an intersection" as follows:

"An intersection is the area located within the prolongations of the lateral curb lines, or, if none, the lateral boundary lines of the roadways of two highways that join one another at approximately right angles. It is also the area within which vehicles traveling upon different highways joining at any other angle may come in conflict. When the distance along a roadway between two areas meeting these criteria is less than 10 meters (33 feet), the two areas and the roadway connecting them are considered to be parts of a single intersection." [CHP's 555 Traffic Collision Report form]

But "within an intersection" can be interpreted more broadly. SafeTREC also includes street segments close to the intersection: "Traditionally, for bicycle and pedestrian counts SafeTREC has included anyone crossing within 50 feet of an intersection." For our definition, we drew a uniform intersection with a 62 foot radius from each intersection center point, and then relied on the SafeTREC geocoding of the SWITRS data to determine if a crash is within our drawn intersection. Our mapped intersections are of a uniform size, although the physical sizes of the intersections depend on the width of the adjoining streets. We cannot then define our intersection crashes as always being "within x feet of the intersection." Instead, we can state that intersection crashes are in close proximity, or completely within, the intersection. Our justification is that creating

the sections was the first step in developing the dataset, and those mapped sections were used to assign the physical roadway characteristics to each one. Thus we created a standard intersection that was no smaller than the largest street buffer. Intersection-like conflicts, such as turning lanes and merges, can extend more than or less than 60 feet from the intersection of the centerlines, depending on the roadway design and geometry. Additionally, we found some inconsistencies in the geocoding (for example, a crash that is tagged as occurring 50 feet from an intersection, and another crash occurring 62 feet from an intersection, are not always spatially located 10 feet apart from one another). Thus, we consider our larger intersection buffers to provide a grace space around the intersections.

Appendix 3. Count Query Methodology

For these SQL queries, we first filter out any location that has fewer than 24 15-minute intervals (which equates to six hours of total counting). There are many locations in the database that have only 2-4 hours of counts and this filters those out. We refer to these locations with 24 or more intervals as "quality locations."

Location ID is the main identifier we use to reference count data. Each section was manually tagged with Location IDs, which were stored within one of six columns in the dataset based on the section's spatial relationship to the count location (Table 3). The queries that result in associations between count volumes and sections are based on these six columns. The queries read the Location ID values, reference the count volume tables for the given count location IDs, and return various sums of the volumes.

Further details on the queries are as follows.
- All queries are left outer joins meaning the resulting output includes all sections even if the location reports no count data.
- For automated counts, we include wrong-way riding (WWR) where WWR is defined as going against the flow of vehicle traffic. Automated counts have 8 possible flows, 2 in each direction on each side facing the road and 2 in each direction facing the sidewalk. Since the data is so granular, we can separate out sidewalk riding and exclude them from the analysis. This is different from manual counts where sidewalk riding is a subset of all volume and must be subtracted.
- For automated counts, an incomplete is defined as missing any of the 4 directions/flows. For manual counts, incomplete is defined as having fewer than 8 intervals in AM, PM, WKND (since there are 8 15-minute intervals during a 2 hour block)

- For automated counts, we are only including periods that contain all 4 flows
- For automated counts, since there is a longer counting period, we are returning a date range rather a comma separated list of dates
- We normalize counts (ALL, AM, PM, WKND) like so for each section:

$$\frac{\Sigma Volume}{Number\ of\ intervals/8}$$

There are further rules specific to the nature of the count-section relationship, as encoded by the five fields INT_INT, INT_ADJ_SEG, SEG_SEG, SEG_ADJ_SEG, and SEG_ADJ_INT, discussed as follows.

INT_INT
- Intersection counts only exist in the historical vintage.

INT_ADJ_SEG
- Since we are building an intersection count (with four directions) using 2 screenline count locations (2 directions each - N/S and E/W) perpendicular to each other, we are only counting complete pairs (i.e. dates and time of the intervals match across the two count locations). Disregard incomplete pairs as if not existing.
- We are requiring that automated counts have exactly 4 flows. After applying this requirement in SQL, there are no rows that satisfy this. Without the flow requirement, we would have had 3 automated sections, not counting the hybrid automated/screenline section.
- For mixed segments (manual and automated count dates/times overlap), keep the automated segments since they have counts for longer time periods rather than a snapshot of one day
- For instances where we are averaging more than 1 segment for each direction in an intersection we run the pairs separately and sum and normalize. However, if we use the same Section ID, this would cause a many to many join, particularly when we have multiple dates for each segment. Therefore we need to differentiate the sections as if they were different sections altogether. We use the negative Section ID. This can be seen in the RAW table. After the query output we change the Section ID back to its non-negative value so that we can sum and normalize as usual.
- SEG 3272: Location IDs 1180, 1181, 1182, 1183
    - Pair 1181 + 1182
    - Pair 1180 + 1183
- SEG 2144: Location IDs 1190, 1191, 1192
    - Pair 1190 + 1191
    - Pair 1190 + 1192
    - Averaged the 2 pairs
- SEG 8543: Location IDs 767, 774, 769

- - Pair 767 + 774
  - - Pair 769 + 774
  - - Averaged the 2 pairs
- - SEG 5364: Location IDs 1054, 1057, 1226
  - - Removed 1054 since 1226 is automated

- - No counts:
  - - SEG 2380
    - - Location ID 1233 (Single LOC)
  - - SEG 5471 (different days)
    - - Location ID 1025
    - - Location ID 1204 (AUTOMATED)
  - - SEG 6947 (no matching dates/times)
    - - Location ID 1214
    - - Location ID 1215
  - - SEG 3065 (1217 counts peds)
    - - Location ID 1217
    - - Location ID 1218
  - - SEG 3091 (1217 counts peds)
    - - Location ID 1217
    - - Location ID 1218

SEG_SEG
- - Automated Counts: Query segments with fewer than 4 flows and exclude from results
  - - No counts (SEG_SEG):
    - - SEG 14316
      - - Only 1 direction counted (flows 89, 90)
      - - Missing flows 85, 86 (DPH_B03)
    - - Segments with fewer than 4 flows
      - - 11448
      - - 12291
      - - 12449
      - - 13015
      - - 14316
      - - 14513
      - - 14520
      - - 14718

SEG_ADJ_SEG
- - No counts:
  - - SEG 14317
    - - Only has 2 flows. Ignore

- Segments with fewer than 4 flows
    - 12292
    - 12296
    - 12456
    - 13013
    - 13014
    - 13016
    - 14317
    - 14512
    - 14515
    - 14717

SEG_ADJ_INT
- There are instances of automated count locations mistaken for intersection counts. Data was not queried for these section IDs but were still included in the output:
    - Section_ID   Seg_Adj_Int
    - 11243   1232
    - 12690   1214
    - 12692   1214
    - 14255   1236
    - 14256   1236
    - 18368   1214
    - 21064   1213
    - 23390   1214
    - 27491   1232
    - 30029   1213

Four Additional Combination Queries
- SEG_SEG__SEG_ADJ_INT
- SEG_SEG__SEG_ADJ_SEG
- INT_INT__INT_ADJ_SEG
- SEG_ADJ_SEG__SEG_ADJ_INT

Each of these four queries combine a pair of primary queries in cases where a Section ID falls under more than one type of relationship. In those cases we take counts from both primary queries and average them so that we have a larger sample size. In order to do this, we must take the original non concatenated data because we want to avoid aggregating dates that are already concatenated. Using the lookup function on a table containing Section ID's that appear in both primary queries (LOOKUP), we attempt to find matching Section ID's in our primary query result tables (e.g. SEG_SEG and SEG_ADJ_INT). Then,

we combine the outputs from the queries into one (COMBINED) and treat this is a new query where we sort by Section ID, then date and time, and filter by LOCATION CHANGE_KEEP = TRUE.

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