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Safe Routes to Play? Pedestrian and Bicyclist Crashes Near Parks in Los Angeles

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Abstract

Background—Areas near parks may present active travelers with higher risks than in other areas due to the confluence of more pedestrians and bicyclists, younger travelers, and the potential for increased traffic volumes. These risks may be amplified in low-income and minority neighborhoods due to generally higher rates of active travel or lack of safety infrastructure. This paper examines active travel crashes near parks and builds on existing research around disparities in park access and extends research from the Safe Routes to School and Safe Routes to Transit movements to parks.

Methods—We utilized the Green Visions Parks coverage, encompassing Los Angeles County and several other cities in the LA Metropolitan area. We used negative binomial regression modeling techniques and ten years of geolocated pedestrian and bicyclist crash data to assess the number of active travel injuries within a quarter mile (~400 m) buffer around parks. We controlled for differential exposures to active travel using travel survey data and Bayesian smoothing models.

Results—Of 1,311,736 parties involved in 608,530 crashes, there were 896,359 injuries and 7317 fatalities. The number of active travel crash injuries is higher within a quarter-mile of a park, with a ratio of 1.52 per 100,000 residents, compared to areas outside that buffer. This higher rate near parks is amplified in neighborhoods with high proportions of minority and low-income residents. Higher traffic levels are highly predictive of active travel crash injuries.

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Conclusions—Planners should consider the higher risks of active travel near parks and the socioeconomic modification of these risks. Additional traffic calming and safety infrastructure may be needed to provide safe routes to parks.

Keywords

Parks; Active travel; Crash risk; GIS

1. Introduction

Walking, jogging, and bicycling, can reduce the risk of cardiovascular disease, diabetes, breast and colon cancer, dementia, and depression (Woodcock et al., 2009). Walking and biking for transportation can assist in meeting recommended physical activity and with reducing burdens caused by motor vehicles (de Nazelle et al., 2011; Sanders et al., 2012). As such, there have been increased efforts to promote active and multimodal transportation.

Safe Routes to School and Safe Routes to Transit encourage physical activity and reduce the risks faced by pedestrians and cyclists accessing important public spaces (Safe Routes to School, 2012; Ragland et al., 2014; Weinzimmer et al., 2015). Parks, like schools and transit, are valuable public amenities that should be accessible for pedestrians and bicyclists (hereafter active travelers). Active travelers tend to be more vulnerable to motor vehicle crashes and subsequent injuries (Cooper et al., 2008; Beck et al., 2007; Grembek, 2012). Parks are places that tend to be relatively free from conflict with motor vehicle traffic and, therefore, may be safer in terms of traffic safety and exposure to air pollution, which may also make it more comfortable and pleasant for physical activity (Su et al., 2011). Ensuring that people have “Safe Routes to Play” could encourage physical activity and provide safe, equitable access to parks for pedestrians and bicyclists.

Neighborhoods surrounding parks could pose a higher risk of crash injury or death as it may be an area that attracts more vulnerable road users. Areas near parks may host more young active travelers. Children suffer pedestrian injuries at a higher rate than the adult population (American Academy of Pediatrics, 2009). Child pedestrian injuries tend to occur while playing or walking to destinations (Karsch et al., 2012). In some situations, children are more likely to walk or bicycle to a neighborhood park than other destinations in an area (Pont et al., 2009).

Moreover, active travelers, in general, are more vulnerable without the appropriate infrastructure. Parks in urban areas might be surrounded by high capacity roads and parks with recreation facilities may attract higher volumes of motor vehicle traffic, thereby, increasing the exposure of active travelers in the neighborhood to traffic (Byrne and Sipe, 2010). It is also reasonable to conjecture that there may be a spatial-temporal relationship between active travel by children and adults as well as motor vehicle trips around parks. An after-school soccer tournament, for example, is likely to draw large numbers of neighborhood walkers or bicyclists and regional traffic simultaneously. Much like school zones, motor vehicle and active travel conflict may be greater certain days and times.

Research also suggests an elevated risk of crash injury for pedestrians and cyclists in low-income and minority neighborhoods (Laflamme and Diderichsen, 2000; Durkin et al., 1994). Higher active travel rates and greater motor vehicle volumes are important components of crash risk in any neighborhood. People may walk more in lower income neighborhoods. Pedestrian crashes tend to be negatively associated with income and walking trips negatively associated with income (Karsch et al., 2012). Low-income and minority neighborhoods have more vehicle kilometers traveled (Gunier et al., 2003), which increases the risk to pedestrians and bicyclists (Houston et al., 2004). In Montreal, pedestrian and cyclist injuries are heightened in low-income neighborhoods, but this association is attenuated after accounting for higher numbers of pedestrians and cyclists exposed to greater volumes of motor vehicle traffic (Morency et al., 2012).

Parks in low-income or minority neighborhoods also have a higher proportion of people to park-acres and may be more congested (Sister et al., 2010). Parks with a higher potential for congestion may have more active travelers and motor vehicles converging on the same space. Therefore, the risks may be heightened in park areas and, in particular, low income or minority park areas.

To our knowledge, there is no existing research comparing the active travel crashes near public parks and in other areas. In Southern California, many people live within a quarter-mile (ten to fifteen minute) walk or bicycle ride of a public park and the Mediterranean climate allows for year-round outdoor physical activity (Su et al., 2011). This study examines active travel crashes near parks in Southern California by comparing crashes occurring within one-quarter mile of a park to crashes outside that buffer. We separately look at crashes near parks in low-income and minority neighborhoods, where rates of active travel and infrastructure provision may differ from the rest of the region. We control for exposure to active travel as well as exposure to traffic using travel survey data and estimated vehicle kilometers traveled.

2. Objectives

In this context, we sought to address the following research objectives:

1. To determine if pedestrian and bicyclist crash injuries occur at higher rates in park-adjacent neighborhoods compared to the rest of the Los Angeles study area.
2. To identify if demographic characteristics predict crash injuries for active travelers after controlling for population, motor vehicle traffic, and the rate of active trips.
3. To assess if there is an amplified effect of park proximity for active crash injuries in low-income and minority neighborhoods after controlling for population and the rate of active trips.

We hypothesized that the number of crash injuries for pedestrians and bicyclists would be elevated near parks. We further hypothesized that the number of crash injuries in park-adjacent neighborhoods with a high proportion of low-income and minority residents would

be significantly higher than park-adjacent neighborhoods in less disadvantaged neighborhoods.

3. Data and methods

3.1. Overview

The risk of injury to active travelers is influenced by the behavior of drivers, pedestrians, and cyclists traveling there as well as any risks that may stem from the built environment (e.g., pedestrian facilities, traffic calming devices). Two places with similar physical features and traffic volumes may see different levels of active travel and therefore have different absolute numbers of crash injury and fatality but similar rates. We used estimates of active travel and vehicle traffic kilometers traveled within each census tract of our study area to better isolate the effects of park proximity, race/ethnicity, and income on active travel crash injuries.

3.2. Study area and network buffer

We studied the area in the Green Visions Plan for 21st Century Southern California (GVP). The GVP encompasses most of Los Angeles county and parts of Orange and Ventura counties; it includes five watersheds: Los Angeles River, Calleguas Creek, Santa Clara River, San Gabriel River, and the Santa Monica Bay. The GVP area contains 1672 parks. We removed three large parks in the northern part of the study area that are not representative of urban parks (Angeles National Forest, Los Padres National Forest, and Vasquez Rocks Park) leaving 1669 parks. Parks in the GVP area were identified using a combination of field audits, available government digital maps, and private sector resources (see Sister et al., 2010 for details).

The GVP covers 2303 census tracts. We restricted the study area to those census tracts with reported travel survey data that could be used to estimate differential active travel exposure. The travel survey data is described below. Four additional census tracts within the GVP area were excluded from analysis for having zero residential population. The final analysis included 2249 census tracts covering 6097 km². Fig. 1 shows the study area and the 1669 parks in the Green Vision Plan.

We designated areas within one-quarter mile (or 402 m) of a park along the road network as park-adjacent. A quarter-mile network buffer is widely used in the urban park literature to define areas proximate to a park (e.g. Dill, 2004; Sister et al., 2010; Su et al., 2011; Wolch et al., 2005). A quarter-mile also represents approximately a ten to fifteen minute walk or a short bicycle ride for children and adults accessing a park from their homes. The GVP parks and the quarter-mile network buffer were created using ESRI's ArcGIS and data from the ESRI Business Analyst (ESRI) and TeleAtlas Dynamap 2000. Fig. 2 shows a quarter-mile network buffer around the Burns Park in Los Angeles. The buffer forms an irregular boundary around the park because it follows the road network.

Park and park adjacent areas account for approximately 18% of the study area (Parks cover 10.7% and the non-park area within the quarter-mile network buffer around parks covers 7.6%).

3.3. Sociodemographic data

We utilize U.S. Census 2000 data to align with our study data. The 2249 census tracts in the study area include 10,694,153 residents. We estimated the poverty level in each census tract using counts of households under the U.S. federal poverty level. The racial and ethnic composition of each census tract is from ESRI's Business Analyst, including counts of Hispanics, non-Hispanic Whites, Blacks, and Asians, and other races based on census counts. We assumed an even distribution of socioeconomic traits throughout the census tract. For example, a census tract of 100 Hispanic residents with 20% of its land area falling within a park buffer was assumed to have 20 Hispanic residents living within one-quarter mile of a park.

3.4. Crash data

We analyzed pedestrian and bicyclist crash injuries and fatalities (hereafter "active crash injuries") that were reported in the Statewide Integrated Traffic Reporting System (SWITRS) between 2000 and 2009. The SWITRS database is produced and maintained by the California Highway Patrol and includes all police-reported fatal and injury collisions that occur on California's state highways and public roads. The Safe Transportation Research and Education Center at the University of California, Berkeley, geolocated these collisions in a GIS shape file (Bigham et al., 2009; Safe Transportation Research and Education Center, 2012). We used this layer to determine which crashes occurred within our quarter-mile network buffer.

The SWITRS dataset includes 608,530 crashes from all types of travel that occurred within the study area between 2000 and 2009. Some crashes resulted in no injuries or fatalities, or injury to only some of the parties involved. Out of 1,311,736 parties involved in these crashes, there were 896,359 injuries and 7317 fatalities (representing approximately 31% of the traffic injuries and fatalities for the State of California during the same time period).

Among active travelers there were 88,745 injuries and 2361 deaths. Most active crashes involved more than one party (for example a pedestrian and a driver), with some crashes involving multiple parties and victims (i.e. pedestrians, cyclists, and motor vehicle occupants). Most pedestrians and bicyclists involved in a crash reported in the SWITRS database were injured or killed. Some 260 injuries to active travelers could not be geocoded and were not included in the final analysis. Since we are interested in the risk of crash injury and property damage only crashes are frequently underreported to the database, we included only injuries and fatalities in our analysis. Most of these involved at least one motor vehicle.

The SWITRS crash reports from 2002 to 2009 include the race of each party involved in a crash. Party race is recorded as White, Hispanic, Black, Asian, Other, or Missing. All parties involved in an active crash in 2000 and 2001 are missing race data. Active crashes occurring between 2002 and 2009 have party race or ethnicity reported (n=63,230). For descriptive analyses comparing active travel and injury patterns, analyses of SWITRS data were restricted to 2002–2009. Rates by race were also restricted to 2002–2009 SWITRS data. Other analyses that do not include injured party's race utilize the full 10-year period.

3.5. Travel survey

The proportion of active travel trips in each census tract was estimated using the 2001 Travel and Congestion Survey conducted by the Southern California Association of Governments (SCAG, 2003). The SCAG survey collected travel diaries from 16,506 households in Southern California with a response rate of 38%. Over half of the study households (n=9135) were located within the GVP study area. Our analysis includes only the 2249 census tracts with a residential population and at least one recorded trip ending at a destination within the tract.

The SCAG survey captures all types of trips for any purpose. The proportion of active travel trips across all census tracts is 9.61%, meaning 9.61% of surveyed trips terminating within one of the study census tracts were walking or cycling trips. The median proportion of active travel trips across census tracts was 5.0%. The proportion varied from 0% in 826 tracts to 100% in 3 of the tracts.

The SCAG travel survey (Fig. 3) did not contain enough observations to estimate directly the proportion of active travel trips in each census tract. We smoothed the estimate of the proportion of active travel trips across the study area using empirical Bayes (Fig. 4) and spatial empirical Bayes methods included in the GeoDa geostatistical program (Anselin, 2011). The empirical Bayes adjustment estimates the proportion of active travel trips within each census tract using a combination of the regional average and the surveyed estimate within the tract. The surveyed proportion of active travel trips is adjusted by the regional rate based on the number of observations in each census tract. As the number of surveyed trips increases, the observed proportion is given greater weight. The spatial empirical Bayes estimate adjusts the surveyed proportion according to the number of surveyed trips and the proportion of active travel in contiguous census tracts using the queen criterion, meaning tracts that shared a border or a corner.

Adjusting the data using the spatial empirical Bayes method produced several estimates of zero in census tracts near the edges of the study area. The empirical Bayes method estimated rates in all census tracts, and we used these rates for the final analysis. A sensitivity analysis of the spatial adjustment, the raw SCAG proportion, and the proportion of active travel among commuters sampled in the 2000 U.S. Census found the choice of estimates has little effect on the final outcome. They are included in Appendix A2.

3.6. Vehicle kilometers traveled

We estimated vehicle kilometers traveled within each census tract using traffic volume and road network lengths within each tract both inside and outside the network buffer. Traffic counts were estimated using statewide traffic count data from 1987 to 2005 provided by Tele Atlas and mapped onto the ESRI Dynamap 2000 base map (Spatial Insights, Inc.). Tele Atlas compiled municipal counts to estimate annual average daily traffic on 2.04% of the road network in California.

These counts were sorted into seven categories by road feature classification code (FCC) including primary road with limited access; primary road without limited access; secondary and connecting road; local, neighborhood, or rural road; vehicle trail; road ramp; and

bicycle, pedestrian trail, or driveway. The median traffic count from each road type was assigned to the matching roads in the study area and mapped onto the ESRI Dynamap 2000 base map. We estimated vehicle kilometers traveled by multiplying the estimated volume by the road segment lengths within the park buffer and outside the park buffer.

The models included vehicle kilometers traveled on primary and secondary roads classified as FCC A20-A39 (roads classified as US and State highways, principal and minor arterials, and residential roads), but excluded freeways and limited access roads unlikely to have active travelers. We also excluded local and neighborhood roads that see highly variable levels of traffic and for which the estimates may not be reliable. A sensitivity analysis including FCC A15-A39, A15-A49, and A20-A49 showed similar results (see Appendix A1 for the results and definitions of the road types).

We also conducted a sensitivity analysis where the data were modeled using local kriging models (Beckerman, 2014). Through other research, we developed a local kriging-type estimator capable of providing prediction estimates on a network/graph-like structure, i.e., a road network. It leverages the measureable autocorrelation structure along the network to create an unbiased estimator. The program was coded in Python 2.7 and makes use of the Networkx package (Hagberg et al., 2008). Networkx is a Python software package that is used to read, manipulate and analyze network data. For this application, the package was used to read in shapefile data on roads and determine its connectivity structure. Beta testing on the fully developed code has shown the program to be capable of estimating on large networks (~ 500,000 links). A network of this size would represent all major roads and highways (excluding freeways) in the State of California. Additionally, the algorithm has a v-fold cross-validation procedure that is used to get a reliable estimate of the prediction error. Testing has shown the kriging procedure to work well and provide reasonable estimates with our traffic examples with a v-fold cross-validation showing good predictive accuracy ($R^2 \sim 60\%$). For these traffic data, we used the kriging model to interpolate across the A3 and A4 (major roads), and we used the High Performance Monitoring System data, based on actual counts, for the A1 restricted access highways and A2 state highways. The data cover a smaller spatial extent of our study area, so these are used as corroborative sensitivity estimates.

3.7. Predicting active crash injuries inside and outside the park buffer using negative binomial regression

We used paired negative binomial regression models to compare the effects of race/ethnicity and poverty on the number of active crash injuries inside and outside the buffer. Traffic crashes are overdispersed, meaning the variance exceeds the mean. The negative binomial regression model is more appropriate for these data than a standard Poisson model (Gardner et al., 1995). The first set of models uses active crash injuries over a ten-year period as the dependent variable and the independent variables are counts of Hispanic, Black, Asian, and other minority populations normalized to every 100 residents, which is within the distribution of data in the tracts. The second pair of models uses the count of residents in poverty normalized to every 100 persons as the independent variable. Poverty and race/ethnicity are included in separate models due to collinearity between poverty and

Hispanicity. Both models include an estimate of vehicle kilometers traveled on major non-freeway roads normalized by 40,000, which is approximately the mean VKT at the census tract level. Both models also include an offset equal to the population in the area multiplied by the proportion of active travel trips smoothed by the empirical Bayes method. Simply put, we estimated the effects of VKT, race/ethnicity, and poverty on the number of active crash injuries near parks while controlling for surveyed active travel in the census tract.

$Y_{i,j}$ is the predicted count of active crash injuries over a 10 year period with i defined as 1 for areas within a quarter mile of a park and 2 for areas outside a park or the quarter-mile buffer in census tract j . The offset in both pairs is $\log(\% \text{Active Trips} * \text{Population}_{i,j})$. The model for race/ethnicity is specified as follows:

$$\log(Y_{i,j}) = \beta_0 + \beta_1 * \text{VKT}_{i,j} + \beta_2 * \text{CountHispanic}_{i,j} + \beta_3 * \text{CountBlack}_{i,j} + \beta_4 * \text{CountAsian}_{i,j} + \beta_5 * \text{CountOther}_{i,j} + \log(\% \text{Active Trips} * \text{Population}_{i,j})$$

The model for poverty is specified as follows:

$$\log(Y_{i,j}) = \beta_0 + \beta_1 * \text{VKT}_{i,j} + \beta_2 * \text{CountInPoverty}_{i,j} + \log(\% \text{ActiveTrips} * \text{Population}_{i,j})$$

The coefficients for each independent variable can be compared within each pair of models to see if the effect size for similar variables varies based on whether the crashes are within or outside the park buffer. The method used to compare coefficients is the random effects Q-test first described by Cochran (1954). The Q-test tells whether the difference in effect size of the variable of interest between park-adjacent and non-park adjacent models is significant at the 95% level (see Su et al. (2011) for a similar application of the Q-test).

4. Results

4.1. Sociodemographic data

The proportion of the population within each racial or ethnic group is similar inside and outside the quarter-mile park buffer. When examined across the entire study area, racial and ethnic groups live within a quarter-mile of a park in similar proportions to their share of the regional population. Whites are somewhat more likely to live near parks than minorities and Hispanics and households in poverty are less likely to live near parks than non-Hispanic and wealthier households. Table 1 shows the estimated number of residents across the study area in racial/ethnic, income, and age categories.

4.2. Active crash results

Among all parties involved in a crash in the study area, active parties were more likely to be injured or killed than motor vehicle drivers and passengers (not shown). Pedestrians and bicyclists represent 7.0% of all parties involved in a crash and 10.1% of all parties who were injured or killed (not shown). The number of active parties injured or killed in a crash (pedestrian or bicyclist) ranged from a high of 9536 in 2000 to a low of 8717 in 2005 (not shown).

Minority pedestrians and cyclists make up a larger proportion of the active crash parties (not shown) than their share of the study area population (Table 1). Among the crashes for which the race of the active traveler was documented, 27.0% of the active parties were non-Hispanic White and 73.0% were racial/ethnic minorities. This contrasts with the sociodemographic makeup of the study area recorded in the 2000 Census, when 33.33% of the population was non-Hispanic White while the remaining 66.67% of the population was not White.

The percent of children ages 0–17 involved in an active crash (29.92%) is slightly higher than the percent of children in the population of the study area (27.86%). Children are much more likely to be injured than killed in an active crash. Thirty percent of active travelers injured are children, while only 10.56% of those killed are between ages 0 and 17. This pattern reverses for senior citizens ages 65 and older, who account for 7.82% of injuries, 29.09% of fatal crashes and 9.86% of the study area population.

The rate of active crash injuries is estimated per 100,000 residents per year for different sociodemographic groups within and outside the quarter-mile network buffer (Table 2). Injury rates are highest among Black and Hispanic residents and lowest among Asians. The total number of active crash injuries in park adjacent areas is more than 50% higher than in areas farther away from parks. The increased rate of injuries within a quarter-mile network buffer of a park is found among all races, with a rate ratio ranging from 1.40 among Blacks to 1.70 among non-Hispanic Whites.

4.3. SCAG travel survey results

Hispanic, Black, and other minority residents are more likely to report active travel trips than non-Hispanic White and Asian respondents. Table 3 shows the number of respondents in each racial/ ethnic category and their reported active travel trips. Active travel is less common among non-Hispanic White and Asian respondents than it is among Hispanic, Black, and other minority respondents.

4.4. Vehicle kilometers traveled results

Primary and secondary roads are more likely to be found near parks than outside the park buffer (Table 4). Fifteen percent of primary and secondary roadway kilometers (excluding freeways and residential roads) and 14.93% of vehicle kilometers traveled on these roads are within the quarter-mile park buffer, while only 7.6% of the study area land falls in this space. In other words, the roads in the park buffer carry more traffic than the average in the entire study area. The combined length of primary and secondary roads both in parks and within the park buffer account for 18.88% of the road network, which is similar to the 18.3% share of land area covered by parks and the park buffer.

4.5. Negative binomial regression predicting active crash injuries for the within and outside the quarter-mile network buffer area

Dividing the study area into areas within the quarter-mile network buffer and outside the buffer reveals differences in the effects of race/ethnicity and poverty. The coefficients for traffic remain positive and strongly predictive of the number of active crash injuries. In areas

inside the park buffer, active crash injuries are more frequent in areas with higher counts of Hispanic and other minority residents as well as those in poverty. The results of the negative binomial regression analysis of paired models are found in Table 5.

The impact of proximity to parks is shown by the difference between coefficients from the two models. The significance of this difference at the 95% level was evaluated using Cochran's Q-test (Table 5). The prediction coefficients for traffic and the count of Hispanics, other minority residents, and residents in poverty in a census tract are significantly different between the in-buffer and out-of-buffer areas. There is an amplified effect of park proximity on crashes in areas with more Hispanic, other minority residents, and households in poverty.

The incidence rate ratios in Table 6 show the change in number of active crash injuries if a census tract's sociodemographic profile changed by 100 people in the stated sociodemographic variable or 40,000 VKT (about 25,000 vehicle miles traveled; approximately the mean VKT at the census tract-level). If the number of Hispanic residents within a quarter mile of a park increased by 100, the expected number of active crash injuries within that quarter-mile buffer would increase by about 8.9%. Similarly, if we compared two within-buffer areas in two different census tracts and one had 100 more Hispanics, the model predicts 8.9% more active crash injuries. If the VKT in the quarter-mile buffer increased by 40,000, then the expected number of active crash injuries would increase by over 70 times (95% CI=50–98), while similar changes to census tracts outside the buffer would yield a relatively precise 2-fold increase (IRR=2.3, 95% CI=2.1–2.4).

We conducted sensitivity analyses using the network kriging estimates of traffic (see Tables A4-1 and A4-2). While the results are not directly comparable due to the difference in the size of spatial domain, we see results that are largely consistent with the main modeling results using the less refined estimates of traffic. Specifically, in areas inside the park buffer, active crash injuries are more frequent in areas with higher counts of Hispanic and other minority residents as well as those in poverty. There remains an amplified effect of park proximity on crashes in areas with more Hispanic, other minority residents, and households in poverty (Table A4-1). Using the network kriging estimates (Table A4-2), the IRRs for VKT are elevated but smaller than the IRRs in Table 6 (inside buffer: IRR=1.15, 95% CI=1.11–1.19; and outside buffer: IRR=1.02, 95% CI=1.02–1.03).

In summary, those areas within a quarter-mile of parks have a higher injury rate than areas away from parks. A higher proportion of Hispanics, other minority residents, or households in poverty within a quarter-mile of parks, further amplifies this effect.

5. Discussion

In the Los Angeles region, pedestrians and bicyclists lack “safe routes to play.” This research shows that pedestrians and bicyclists are injured or killed at much higher rates in park-adjacent neighborhoods than in areas farther away from parks, with a ratio per 100,000 population of 1.52. Furthermore, after adjusting for active travel, there is an amplified effect of park proximity on active crash injuries in low-income, Hispanic, Black, and other minority neighborhoods.

To our knowledge, this is the first study to compare the traffic safety of park adjacent locations to other locations. Safe routes to parks may be important for park access and for promoting physical activity. Higher traffic speed routes to parks have been found to be associated with less park use (Kaczynski et al., 2014). This is noteworthy because park access and park proximity are associated with physical activity among youth and adults (Babey et al., 2013; Kaczynski et al., 2009; National Recreation and Park Association, 2015). Parks and places with green space are important for physical activity and health. Lachowycz and Jones (2011) found 33 studies showing a positive or potential association between green space and physical activity in a literature review of evidence linking green space and reduced obesity. Children in California who were exposed to green spaces for more than twenty minutes a day were more than five times as likely to engage in moderate to vigorous physical activity compared to children who were exposed to no green spaces (Almanza et al., 2011). Parks are also associated with lower body mass in children. A longitudinal study of children in southern California found that improved access to parks and recreational programming is associated with reduced obesity (Wolch et al., 2010). Among adolescents in Minneapolis and Saint Paul, lower access to parks was associated with a higher body mass index (Wall et al., 2012).

The benefits and opportunities provided by parks and active transportation, however, are not evenly shared. Parks in low income communities may have less supervision and programming (Cohen et al., 2012). Residents of disadvantaged neighborhoods and communities of color may face more congested parks and less access to recreation facilities (Sister et al., 2010). Visitors to the parks that are located in poor and minority neighborhoods have higher exposure to and inhalation of criteria air pollutants compared to those visiting parks in wealthier and whiter neighborhoods (Su et al., 2011). Active travelers in poor and minority neighborhoods face a higher risk of crash injury (Laflamme and Diderichsen, 2000), and this may extend to areas surrounding neighborhood parks.

The results from the present study shows that active travel injury rates are higher in park adjacent areas than those areas away from parks. Traffic has a highly significant effect on active crash injuries both within and outside the quarter-mile park buffer. The effect of motor vehicle traffic, however, near parks is more pronounced. The results also show that there are additional risks in low-income and minority neighborhoods that are not accounted for by changes in VKT.

Furthermore, sensitivity analyses of active crash injuries using different methods to estimate active travel and sensitivity analyses using VKT estimates from different modeled estimates and road classifications show similarly significant and positive differences in the prediction coefficient for Hispanic neighborhoods, neighborhoods with people of color, and neighborhoods with many households in poverty when comparing areas near parks to those away from parks. Disadvantaged neighborhoods may have less traffic safety infrastructure, which could explain part of the effect modification from low-income, Hispanic, and other minority residents.

5.1. Implications and future research

Parks with recreational facilities and sports fields can serve as destinations for motor vehicle traffic and can act to attract pedestrians, bicyclists, and motor vehicles onto the same streets at the same time of day, potentially increasing exposure to active travelers. Dumbaugh and Li (2011) argue that when crashes are systematically linked with characteristics of the built environment, rather than being the result of purely random error, and they require an active intervention beyond VKT reduction. These areas may need special attention from planners and further research into the potential causes of the disparities in risk.

Like school zones, park adjacent areas may be places where active travel conflict is more likely. There is research to suggest that Safe Routes to School and Transit programs, that have funded safety improvements, have observed some benefits in safety and encouraged active travel (Ragland et al., 2014; Weinzimmer et al., 2015). To ensure there is the appropriate level of service and access for active travelers, safe routes to parks could be addressed through policy, planning, and coordination. Through examples from the National Cooperative Highway Research Program, recreational trips to parks could be monetized to enable transportation investment. In terms of planning, some master plans in California are proposing an integrated pedestrian and bicycle system to improve access to work, schools, and parks through the provision of facilities and increased connectivity and multimodal paths (Sanders et al., 2012). More dense street connectivity has been associated with park use (Kaczynski et al., 2014). Connectivity might also be addressed through networks that connect public amenities by identifying places that have sidewalks and crossing improvements and streets with transit routes (Sanders et al., 2012). Additional research is needed to investigate potential causes for the higher risks to active travelers near parks and the modification by underlying demographics. Traffic is a strong predictor of crashes near parks, and the measure of traffic near parks is higher than in other areas of the region. Still, the crash risk remains higher near parks even after controlling for motor vehicle traffic. Future research might examine the infrastructure in these communities and behaviors of road users traveling through these communities. In addition, volumes may be higher by day of week and time of day. Active travel exposure data are often difficult to obtain. Future research might include temporally detailed exposure data.

5.2. Limitations

Collisions occurring at specific locations were aggregated to the neighborhood-level. Neighborhoods were operationalized using census tracts. Census tracts tend to be small but can vary in size. Therefore, the amount of conflict space (e.g. roadway miles, intersections, driveways) may vary by census tract. We addressed this by accounting for population and traffic volumes; however, the geographic scale may still matter. In general, pedestrian collisions tend to be clustered. Analyzing these data at larger scales, may diminish associations with some contributing factors.

6. Conclusion

Park access and active travel are both potential ways to increase physical activity levels in children and adults, yet residents of low income neighborhoods and communities of color

face increased risk of injury or death due to traffic crashes. More research is needed on how to ensure that all urban dwellers have a “Safe Route to Play.”

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Appendix A1. Sensitivity analysis of estimating VKT using various road classifications

The following tables show the regression coefficient differences from within and outside the quarter-mile network buffer after adjusting for VKT on various types of roads. The final analysis uses VKT on roads classified as FCC 20–39. This excludes freeways, which are unlikely to have active travelers, and residential streets, which have unreliable traffic volume estimates.

See Tables A1-1, A1-2 and A1-3.

Table A1-1

Significance of the difference between regression coefficients with VKT estimated on roads classified FCC A15-A39.¹

Model using EB rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	8.83E-04	132.17	<0.001 **
	Black	3.94E-04	24.63	<0.001 **
	Asian	5.80E-05	0.06	0.081
	Other	1.19E-02	791.52	<0.001 **
	Traffic on A15-A39 Roads	6.25E-05	151.46	<0.001 **
Poverty	Poverty	2.51E-03	2664.43	<0.001 **
	Traffic on A15-A39 Roads	6.79E-05	158.11	<0.001 **

* indicates significance at the 95% level.

** indicates significance at the 99% level.

¹ Includes collectors that distribute traffic, US and state highways, and principal and minor arterials.

Table A1-2

Significance of the difference between regression coefficients with VKT estimated on roads classified FCC A20-A49.²

Model using EB rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	8.48E-04	253.26	<0.001 **
	Black	2.22E-04	4.49	0.0341
	Asian	-8.85E-05	0.18	0.673
	Other	3.38E-03	23.89	<0.001 **
	Traffic on A20-A49 Roads	7.46E-05	45.17	<0.001 **
Poverty	Poverty	1.95E-03	104.16	<0.001 **
	Traffic on A20-A49 Roads	7.53E-05	41.42	<0.001 **

* indicates significance at the 95% level.

** indicates significance at the 99% level.

² Includes US and state highways, principal and minor arterials, and private roads.

Table A1-3

Significance of the difference between regression coefficients with VKT estimated on roads classified FCC A15-A49.³

Model using EB Rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	8.60E-04	133.74	<0.001 **
	Black	3.58E-04	18.18	<0.001 **
	Asian	-6.00E-07	0.00	0.998
	Other	6.49E-03	167.11	<0.001 **
	Traffic on A15-A49 Roads	5.23E-05	144.28	<0.001 **
Poverty	Poverty	2.20E-03	800.11	<0.001 **

Model using EB Rate	Variable	Coefficient difference	Q	p-value
	Traffic on A15–A49 Roads	5.68E–05	150.34	<0.001 ^{**}

* indicates significance at the 95% level.

** indicates significance at the 99% level.

³ Includes collectors that distribute traffic, US and state highways, principal and minor arterials, and private roads.

Appendix A2. Sensitivity analysis of various estimates of active travel

This study used an estimate of active travel calculated using an empirical Bayes smoothing method on the raw rate of surveyed trips that were taken on foot or bicycle. The following maps show: 1) the active rate of travel using the SCAG data as surveyed; 2) SCAG data as adjusted using empirical Bayes (used in the final models); 3) SCAG data implementing spatial empirical Bayes; and 4) using reported commute mode from the 2000 U.S. Census. The tables below that show the regression coefficient differences and their significance tested with Cochran's Q-test.

The SCAG survey captures the mode share for all trip types combined, while the U.S. Census only asks about commute trips. If active travel trips form a greater share of local errands and recreational trips than they do work trips, the regional active travel rate will be higher than the active travel rate for commutes. In the SCAG survey, an individual who drove to work and home, then walked to the local park and home would have taken four trips: two driving and two walking.

The U.S. Census commute data represents less than 20% of all trips (United States Census Bureau, 2009). Journeys to work likely include a lower proportion of active travel than all trips. In Minneapolis, the 2000 Census found that 6.6% of residents walked to work and 1.9% rode a bicycle. In the same year, the Twin Cities Metropolitan Council's Travel Behavior Inventory found that among Minneapolis residents, 13.6% of trips were walking and 4.5% of trips were on a bicycle (City of Minneapolis, 2012). In Los Angeles the SCAG survey shows similarly higher rates of active travel among all trips than the U.S. Census reports for commutes.

The method used in this paper, to geographically locate a trip, relies on the trip destination census tract. A round-trip drive between census tracts counts as one driving trip in each tract. A round-trip walk to the park in the same census tract counts as two walking trips in that tract.

See Tables A2-1, A2-2 and A2-3.

Table A2-1

Significance of the difference between regression coefficients with the exposure set as an estimate of active travel smoothed with the spatial empirical Bayes method times the census tract population.

Model using SEB Rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	7.98E-04	321.44	<0.001**
	Black	2.17E-04	4.80	0.028
	Asian	1.85E-04	2.43	0.119
	Other	9.58E-03	15,558.00	<0.001**
	Traffic on A20–A39 Roads	8.50E-05	14.40	<0.001**
Poverty	Poverty	2.11E-03	601.24	<0.001**
	Traffic on A20–A39 Roads	8.91E-05	15.14	<0.001**

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Table A2-2

Significance of the difference between regression coefficients with the exposure set as the proportion of surveyed trips that were active times the census tract population.

Model using SCAG rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	6.88E-04	19.73	<0.001**
	Black	3.14E-04	8.94	0.003*
	Asian	8.00E-07	0.00	0.997
	Other	1.16E-02	478.32	<0.001**
	Traffic on A20–A39 Roads	8.87E-05	10.56	<0.001**
Poverty	Poverty	1.89E-03	2677.87	<0.001**
	Traffic on A20–A39 Roads	9.40E-05	11.03	<0.001**

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Table A2-3

Significance of the difference between regression coefficients with the exposure set as the proportion of active commute trips reported in the 2000 U.S. Census times the census tract population.

Model using census rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	5.89E-04	35.09	<0.000**
	Black	8.80E-04	6.88	0.009**
	Asian	5.53E-04	2119.72	<0.001**
	Other	1.12E-02	2828.55	<0.001**
	Traffic on A20–A39 Roads	7.19E-05	86.69	<0.001**
Poverty	Poverty	2.12E-03	744.10	<0.001**

Model using census rate	Variable	Coefficient difference	Q	p-value
	Traffic on A20–A39 Roads	8.83E-05	156.09	<0.001**

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Appendix A3. Sensitivity analysis of the choice of offset

The active crash injury rate is provided by subtracting the offset element from the dependent variable, $\log(Y_{i,j})$. For example, the model with race/ethnicity would yield the following equation:

$$\begin{aligned}
 Y_{i,j} / (\% \text{ActiveTrips} * \text{Population}_{i,j}) = & \exp(\beta_0 \\
 & + \beta_1 * \text{VKT}_{i,j} \\
 & + \beta_2 * \text{CountHispanic}_{i,j} \\
 & + \beta_3 * \text{CountBlack}_{i,j} \\
 & + \beta_4 * \text{CountAsian}_{i,j} \\
 & + \beta_5 * \text{CountOther}_{i,j})
 \end{aligned}$$

The offset term in the negative binomial regression model can be estimated in several ways. In our final analysis we specified the offset as the empirical Bayes-smoothed active rate of travel times the population in each census tract. This gave an offset that estimated the relative number of active trips in a census tract based on the SCAG travel survey and the number of people residing in the tract. The following two tables show the resulting coefficient differences and their significance tested with Cochran's Q-test for two alternative offsets. The first is the mean active crash injury rate (total active crash injuries from 2000 to 2009 per capita) across the entire study area, which is 0.00849763. The second alternative offset is the expected active crash injury number, which was calculated as the study-wide crash rate per capita over a ten year period times the population in each census tract.

See Tables A3-1 and A3-2.

Table A3-1

Significance of the difference between regression coefficients with the offset defined as the active crash injury rate (0.00849763).

Model using EB Rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	1.12E-03	176.73	<0.000**
	Black	4.46E-04	4.18	0.041*
	Asian	2.29E-04	1.18	0.277
	Other	8.59E-03	44.13	<0.001**
	Traffic on A20–A39 Roads	8.18E-05	461.32	<0.001**
Poverty	Poverty	3.02E-03	228.94	<0.001**
	Traffic on A20–A39 Roads	8.31E-05	488.48	<0.001**

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Table A3-2

Significance of the difference between regression coefficients with the offset defined as the expected number of active crash injuries (census tract population times the active crash injury rate).

Model using EB rate	Variable	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	1.12E-03	176.73	<0.000**
	Black	4.46E-04	4.18	0.041*
	Asian	2.29E-04	1.18	0.277
	Other	8.59E-03	44.13	<0.001**
	Traffic on A20–A39 Roads	8.18E-05	461.32	<0.001**
Poverty	Poverty	3.02E-03	228.94	<0.001**
	Traffic on A20–A39 Roads	8.31E-05	488.48	<0.001**

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Appendix A4. Sensitivity analysis of estimating VKT using Network Kriging Methods

The following tables include VKT estimated from kriging. For these traffic data, we used the kriging model to interpolate across the A3 and A4 (major roads), and we used the High Performance Monitoring System data, based on actual counts, for the A1 restricted access highways and A2 state highways.

See Tables A4-1 and A4-2.

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Fig. 1.
Study area with Green Vision Plan parks, 2249 census tracts in Los Angeles.

Fig. 2.
Burns park and surrounding quarter-mile buffer.

Fig. 3.
SCAG Surveyed active travel rate in Los Angeles.

Fig. 4.
SCAG surveyed active travel rate adjusted using empirical Bayes in Los Angeles.

Population within the study area estimated within and outside a quarter-mile park buffer in 2249 census tracts in Los Angeles, US Census 2000.

Table 1

Variable	Within a quarter-mile of a park				Outside a quarter-mile of a park			
	Percent	Count	Mean ^a	Median ^a	Percent	Count	Mean ^a	Median ^a
Population	100.00%	1,534,699	682	401	100.00%	9,159,454	4073	3954
Hispanic	42.91%	658,602	293	92	43.56%	3,989,696	1774	1350
White (non-Hispanic)	33.92%	520,643	231	50	33.22%	3,042,971	1353	1052
Asian	11.23%	172,378	77	19	11.95%	1,094,173	467	280
Black	8.92%	136,922	61	8	8.24%	754,649	336	100
Other	3.01%	46,154	21	9	3.03%	277,965	124	104
In Poverty	17.62%	270,416	120	38	16.36%	1,498,811	666	505
Age 0–17	27.47%	421,592	187	102	27.93%	2,558,274	1138	1050
Age 18–64	62.68%	962,002	428	247	62.20%	5,697,389	2533	2436
Age 65+	9.85%	151,106	67	36	9.87%	903,792	402	352

^aPer census tract.

Table 2

Yearly pedestrian and bicyclist-involved injury crashes per 100,000 population^a in 2249 census tracts in Los Angeles.

	Active crashes	Active crashes within a quarter-mile of a park	Active crashes outside a quarter-mile of a park	Ratio of within buffer to outside buffer
Total	87.2	122.9	81.1	1.52
Hispanic	92.2	128.5	88.0	1.46
White, non-Hispanic	59.9	95.6	56.4	1.70
Black	125.3	173.9	124.2	1.40
Asian	25.8	39.1	24.8	1.58
Age 0–17	89.3	131.3	84.8	1.55
Age 18–64	82.5	117.6	78.9	1.49
Age 65+	70.4	107.7	66.4	1.62

^aThe rate of total crashes per 100,000 population per year is based on crash data from 2000 to 2009 and population counts from the 2000 Census. The rate for the four racial groups is based on crash data from 2002 to 2009 and population counts from the 2000 Census. Population inside and outside the quarter-mile network buffer is estimated by multiplying the population by the proportion of non-park land area inside and outside the buffer within each census tract.

SCAG travel survey responses and distribution of active trips by race/ethnicity in 2249 census tracts in Los Angeles, SCAG, 2003.

Table 3

SCAG respondents	Count of respondents	Percent of respondents	Count of trips	Count of active trips	Percent of trips that are active
Total Respondents	10,050	100%	74,374	7098	9.54%
Hispanic	2060	20.50%	17,275	3126	18.10%
White (non-Hispanic)	5961	59.31%	42,763	2787	6.52%
Black	684	6.81%	4578	430	9.39%
Asian	552	5.49%	4158	257	6.18%
Other	274	2.73%	1882	157	8.34%
Race Missing	519	5.16%	3718	341	9.17%

Table 4

Vehicle kilometers traveled on roads classified FCC A20-A39^a in 2249 census tracts in Los Angeles.

	Road kilometers	Road percent of total	VKT (millions)	VKT percent of total	Percent of land area in study area
Study area (Total)	8149	100.00%	90.4	100.00%	100.0%
Park area	310	3.80%	3.4	3.76%	10.7%
Non-park area in the quarter-mile network buffer	1229	15.08%	13.5	14.93%	7.6%
Non-park area outside the quarter-mile network buffer	6609	81.10%	73.5	81.31%	81.7%
Parks and quarter-mile network buffer combined	1539	18.88%	16.9	18.69%	18.3%

^aIncludes US and state highways and principal and minor arterials. Excludes freeways and limited access and residential roads.

Table 5

Negative binomial regression analyses for within and outside the quarter-mile network park buffer using sociodemographic counts normalized to 100 persons and VKT normalized to 40,000 and Q-test of significant difference between coefficients in 2249 census tracts in Los Angeles.

Model	Variable	Within a quarter-mile of a park				Outside a quarter-mile of a park				Difference		
		Coefficient	Standard error	p-value		Coefficient	Standard error	p-value		Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	0.085	0.009	<0.001**		-0.004	0.002	0.021*		0.089	97.382	<0.001**
	Black	0.041	0.021	0.057		0.012	0.004	0.001**		0.029	1.734	0.188
	Asian	-0.014	0.023	0.548		-0.019	0.004	<0.001**		0.005	0.044	0.834
	Other	0.957	0.148	<0.001**		-0.050	0.021	0.016*		1.007	44.623	<0.001**
	VKT	4.261	0.163	<0.001**		0.828	0.032	<0.001**		3.432	410.810	<0.001**
Poverty	Constant	- 5.232	0.053	<0.001**		- 2.695	0.053	<0.001**				
	Poverty	0.254	0.020	<0.001**		0.022	0.004	<0.001**		0.232	126.778	<0.001**
	VKT	4.459	0.168	<0.001**		0.870	0.033	<0.001**		3.588	424.103	<0.001**
	Constant	- 5.082	0.049	<0.001**		- 3.051	0.046	<0.001**				

* indicates significance at the 95% level.

** indicates significance at the 99% level.

Table 6

Incidence rate ratios within and outside the quarter-mile network buffer using sociodemographic counts normalized to 100 persons and VKT normalized to 40,000 in 2249 census tracts in Los Angeles.

Model	Variable	Within a quarter-mile of a park				Outside a quarter-mile of a park			
		Incidence rate ratio	Standard Error	95% Confidence interval lower bound	95% Confidence interval upper bound	Incidence rate ratio	Standard error	95% Confidence interval lower bound	95% Confidence interval upper bound
Race/ethnicity	Hispanic	1.089 *	0.010	1.070	1.108	0.996 *	0.002	0.994	0.999
	Black	1.042	0.022	0.999	1.086	1.012 *	0.004	1.005	1.019
	Asian	0.986	0.023	0.943	1.032	0.981 *	0.004	0.975	0.988
	Other	2.603 *	0.385	1.948	3.480	0.951 *	0.020	0.913	0.991
	VKT	70.855 *	11.543	51.486	97.509	2.290 *	0.074	2.149	2.440
Poverty	Poverty	1.289 *	0.026	1.240	1.340	1.022 *	0.004	1.014	1.030
	VKT	86.373 *	14.483	62.179	119.981	2.388 *	0.079	2.237	2.548

* indicates significance at the 95% level.

Table A4-1

Negative binomial regression analyses for within and outside the quarter-mile network park buffer using sociodemographic counts normalized to 100 persons and VKT (interpolated from kriging) normalized to 40,000 and Q-test of significant difference between coefficients in 2249 census tracts in Los Angeles.

Model	Variable	Within a quarter-mile of a park			Outside a quarter-mile of a park			Difference		
		Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient difference	Q	p-value
Race/ethnicity	Hispanic	0.0165	0.0049	<0.001	0.0071	0.0014	<0.001	-0.0054	<0.001	
	Black	0.0127	0.0141	0.37	0.0001	0.0032	0.98	0.0007	0.38	
	Asian	-0.0003	0.0002	0.07	-0.0002	0.0000	<0.001	-0.0002	0.44	
	Other	0.4063	0.0898	<0.001	0.0141	0.0220	0.52	0.0364	<0.001	
	VKT	0.1406	0.0168	<0.001	0.0211	0.0018	<0.001	0.0224	<0.001	
Poverty	Constant	3.5553	0.0500	<0.001	3.8540	0.0475	<0.001			
	Poverty	0.0585	0.0101	<0.001	-0.0032	0.0036	0.39	0.0039	<0.001	
	VKT	0.1524	0.0158	<0.001	0.0215	0.0018	<0.001	0.0231	<0.001	
	Constant	3.6187	0.0448	<0.001	3.6794	0.0377	<0.001			

Table A4-2

Incidence rate ratios within and outside the quarter-mile network buffer using sociodemographic counts normalized to 100 persons and VKT (interpolated from kriging) normalized to 40,000 in 2249 census tracts in Los Angeles.

Model	Variable	Within a quarter-mile of a park				Outside a quarter-mile of a park			
		Incidence rate ratio	Standard error	95% Confidence interval lower bound	95% Confidence interval upper bound	Incidence rate ratio	Standard error	95% Confidence interval lower bound	95% Confidence interval upper bound
Race/ethnicity	Hispanic	1.017 *	0.005	1.007	1.026	0.993 *	0.001	0.990	0.996
	Black	1.013	0.014	0.985	1.041	1.000	0.003	0.994	1.006
	Asian	1.000	0.000	0.999	1.000	1.000	0.000	1.000	1.000
	Other	1.501 *	0.135	1.237	1.765	1.014	0.022	0.970	1.058
Poverty	VKT	1.151 *	0.019	1.113	1.189	1.021 *	0.002	1.018	1.025
	Poverty	1.060 *	0.011	1.039	1.081	0.997	0.004	0.990	1.004
	VKT	1.165 *	0.018	1.128	1.201	1.022 *	0.002	1.018	1.025

* indicates significance at the 95% level.