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Traffic safety for all road users: A paired comparison study of small & mid-sized U.S. cities with high/low bicycling rates

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ABSTRACT

Cities with high levels of bicycling tend to be some of the safest cities for all road users. This paper investigates *why* this relationship exists for fourteen small and mid-sized cities across the U.S. (seven with high bicycling rates and seven paired comparison cities) using ten years of data and hierarchical negative binomial regression models. Findings confirm that higher-bicycling cities are significantly associated with better overall road safety outcomes. In terms of mode choice differences, pedestrian 'safety in numbers' as well as reduced driving activity had a positive impact on pedestrian safety. Results from hierarchical negative binomial regressions also suggest that more compact cities were significantly associated with better road safety outcomes for all road users. In terms of socio-demographic and socio-economic factors, the results reveal equity concerns with areas with lower incomes and more non-White residents seeing more overall road fatalities.

1. Introduction

Boulder, CO, Corvallis, OR, and Davis, CA, are biking enclaves with 2019 bike commute mode shares of 9.9%, 11.1%, and 17.5%, respectively, versus a national average of 0.4% for all United States (U.S.) cities. Even though these three cities accommodate relatively high numbers of bicyclists, their streets are also relatively safe. This safety is not just for bicyclists but extends to all road users. Between 2015 and 2019, overall traffic fatality rates per 100,000 residents in these three cities were 2.1, 2.8, and 1.4, respectively, versus a national average of 11.3 for all U.S. cities over the same period.

For an individual, bicycling is conventionally considered to be a relatively unsafe travel behavior. For instance, Beck et al. (2007) found that fatal and non-fatal injury rates (per person-trip) for bicyclists were nearly twice the overall road user average and significantly higher than rates for passenger vehicle, walking, or bus trips. Thus, one might assume that more of an unsafe travel behavior might lead to worse overall road safety.

Nevertheless, a developing body of knowledge suggests that the relationship between increased bicycling activity and improved traffic safety outcomes is not a coincidence. Cities with high bicycling rates tend to be safer for both bicyclists (Elvik and Bjørnskau, 2017; Jacobsen, 2003; Nordback et al., 2014) as well as all road users (Marshall and Garrick, 2011a; Marshall and Ferenchak, 2019). Past research has found that the mechanisms behind improved traffic safety outcomes for the bicyclists may include more visibility and awareness of the bicyclists and more laws and regulations protective of people bicycling (Elvik, 2017; Fyhri et al., 2017; Jacobsen et al., 2015), while physical differences in the built environment such as more bicycle infrastructure may be related to improved traffic safety outcomes for all road users in large high-bicycling cities (Marshall and Ferenchak, 2019). In this study, we investigate small and mid-sized cities to see if these relationships hold and determine what factors are related to better road safety outcomes.

To answer these questions, we investigated 14 small and mid-sized U.S. cities with populations between 50,000 and 200,000 residents. We first selected seven cities with high rates of bicycle commuting, which we designated as our high-bicycling cities. We then paired each of the high-bicycling cities with a paired comparison city that had low or average rates of bicycle commuting but similar characteristics in terms of overall population, regional location, and/or proximity to a major university or large city. We detail the specifics of the city selection process later in the paper.

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In terms of trying to understand the factors associated with better safety, we examined factors across three categories: mode choice, built environment, and socio-demographic/socio-economic status. Mode choice, for instance, may impact traffic safety by shifting travelers away from unsafe modes, by decreasing overall exposure, or by enabling "safety in numbers" for vulnerable road users (which is further detailed in Section 2). The built environment may impact traffic safety by enabling safer street environments, likely through lower traffic speeds. With this effort, we collected bike facility data by facility type (e.g., protected bike lane, buffered bike lane, standard bike lane, shared lane marking, or off-road trail) and longitudinally noted the installation month of each bike facility in each study city. Socio-demographics and socio-economic status may impact traffic safety due to the increased risk of certain populations (such as older populations who are more susceptible to blunt force trauma or teenagers and young adults who are more likely to engage in risky behavior). We then explored which, if any, of these characteristics were most strongly related to traffic safety outcomes by analyzing block groups that were also grouped on the city level through hierarchical negative binomial regressions.

The next section assesses the existing literature. We then delve deeper into the city selection process and the 10 years of longitudinal data collected for each of the 14 cities. This is followed by a description of our statistical analysis and a step-by-step assessment of our results for each of the safety factors. Lastly, we discuss the implications of this work.

2. Literature review

2.1. *Traffic safety in cities with high levels of non-driving travel modes*

A strain of research has developed suggesting that cities with high levels of public transit activity are safer than their peers. Stimpson et al. (2014) found that increased mass transit miles traveled per capita over 29 years for 100 U.S. cities was associated with lower traffic fatality rates in those cities. A similar trend was found by Litman in a 2014 international study (Litman, 2014). However, public transit is a relatively safe mode of travel, with fatality rates for car occupants being 15 times greater than for transit users (Savage, 2013). Therefore, it is fairly intuitive that more of a safe travel mode would make a city safer.

On a per mile basis, biking is a relatively unsafe mode of travel. Yet, past research suggests that cities with higher levels of bicycling also have better traffic safety outcomes for both bicyclists themselves (Elvik, 2017; Fyhri et al., 2017; Jacobsen, 2003; Jacobsen et al., 2015) and other road users as well (Marshall and Ferenchak, 2019; Marshall and Garrick, 2011a). The research as to *why* cities with higher levels of bicycling are safer for bicyclists suggests that societies with more bicycling have more laws and regulations protective of people bicycling (as well as more adherence of those laws and regulations) and that road users are more aware of the presence of bicyclists (Elvik, 2017). Interestingly, safety in numbers has been found to be stronger when there are fewer bicyclists (Jacobsen et al., 2015), possibly because of the influx of inexperienced and risk-taking bicyclists dampens the bicyclist safety in numbers effect (Fyhri et al., 2017). This current paper builds upon that past work to understand the mechanisms behind why cities with high levels of bicycling are not only safer for bicyclists, but for all road users.

2.2. *Potential factors associated with traffic safety*

We explore three factors that may be associated with traffic safety identified in past research: 1) mode choice (how people travel within their cities); 2) built environment (the physical makeup of the cities); and 3) socio-demographic/socio-economic characteristics of the residents of the cities (who is living in the cities).

2.2.1. *Mode choice*

The first category that we explored was directly related to the research question at hand: mode choice. Might the bicyclists themselves in the high-bicycling cities correlate with better safety outcomes? Or maybe these cities with higher rates of bicycling also have higher rates of transit usage or lower rates of driving that are playing an important role?

2.2.1.1. Bicycle mode share. Bicyclist safety in numbers has been internationally established by past research and shows that as more people bike, the chance that an individual bicyclist will be struck by a car decreases (Elvik and Bjørnskau, 2017; Jacobsen, 2003; Nordback et al., 2014). It has been hypothesized that the reason that bicyclists in areas with high bicycling activity are at a decreased risk of being struck is because drivers are more aware of their presence or because built environments that lend themselves to more biking also lend themselves to safer driving. By exploring whether levels of biking activity are related to safety outcomes in our small and mid-size cities, we may be able to see whether 'safety in numbers' plays an important role.

Interestingly, better safety outcomes in large high-bicycling U.S. cities were *not* strongly related to levels of bicycling, which suggests that safety in numbers and the bicyclists themselves were not the critical factor for better safety outcomes, although this result could have been because any variation in safety outcomes overwhelmed the safety in numbers phenomena (Marshall and Ferenchak, 2019).

2.2.1.2. Pedestrian mode share. Safety in numbers has been established for pedestrians as well, with pedestrian crashes increasing more slowly than pedestrian activity levels (Elvik and Bjørnskau, 2017; Jacobsen, 2003). However, we were not able to find research exploring the relationship between pedestrian activity and safety for all road user types on the city level. Thus, it is worth further exploring different modes of travel in relation to traffic safety outcomes. Improved safety outcomes may be related to bicyclist or pedestrian safety in numbers, increased exposure for safe modes, or decreased exposure for unsafe modes.

2.2.2. *Built environment*

In terms of the built environment, we explored land use (Section 2.2.2.1) and physical transportation systems (Section 2.2.2.2), both of which past research has linked with traffic safety outcomes (Ferenchak, 2020; Kim, Brunner, and Yamashita, 2006; Miranda-Moreno, Morency, and El-Geneidy, 2011; Pulugurtha et al., 2013; Ukkusuri et al., 2012).

2.2.2.1. Land use. Urban sprawl has been linked with higher total and pedestrian crash rates (Ewing et al., 2003; Ewing et al., 2016). The authors credited worse safety outcomes in sprawling areas to higher traffic speeds and greater vehicle miles driven. Similarly, it has been hypothesized that the better traffic safety outcomes in denser areas may be a result of lower motor vehicle activity and speeds (Chen, 2015; Chen and Shen, 2016; Dumbaugh and Rae, 2009). As developments become denser, there is a higher likelihood that road users will opt to walk, bike, or take transit, thereby lowering motor vehicle exposure and lowering the risk of a motor vehicle collision. For motor vehicle trips that occur in dense developments, trip lengths are likely shorter and therefore do not require high vehicle speeds. The relationship between population density and traffic safety appears to be dependent upon the geographic scale of analysis, as population density was found to be negatively associated with collisions on the block group level but positively associated on the TAZ and zip code level when using vehicle miles travelled (VMT) as exposure (Xu et al., 2018).

While we would have liked to further explore specific types of land use, obtaining updated land use data in GIS format for fourteen relatively small cities across the U.S. was difficult and would have required significant assumptions to make the cities' categorizations comparable. We instead used population density as a proxy for land use development. Population density has long been used as a general representation for unsustainable development such as suburban sprawl and has been used in safety research (Brueckner and Fansler, 1983; Ewing, 1997; Ewing, Schieber, and Zegeer, 2003; Lindsay and Willis, 1974; Marshall and Ferenchak, 2017). Areas in England with lower population densities were associated with increased traffic fatalities (Noland and Quddus, 2004). Similarly, areas in San Antonio and Philadelphia with higher population densities were found to experience fewer overall collisions, injuries, and fatalities (Dumbaugh and Rae, 2009; Guerra et al., 2019).

2.2.2.2. Transportation systems. We wanted to analyze two aspects of our study cities' transportation systems: large-scale network configurations and small-scale street design elements.

Similar to the land use discussion above, denser street networks have been linked with lower vehicle miles driven – and therefore lower overall exposure – as trips are shorter and people are more likely to switch to alternative modes of transportation. Denser street networks have also been linked with lower vehicles speeds because of more frequent intersections (Ewing et al., 2020). Operationalizing this concept, denser street networks with higher intersection counts per area have been found to correlate with fewer motor vehicle collisions across all severity levels while accounting for exposure (Marshall and Garrick, 2010; Marshall and Garrick, 2011b). Higher intersection counts per road length correlated with lower pedestrian mortality rates (Mohan et al., 2017) and fewer collisions for pedestrians and bicyclists (Zhang et al., 2015). Past research has postulated that the negative relationship between street network density and traffic collisions is driven by higher-density areas' lower vehicle speeds and travel decisions such as the use of non-vehicular modes (Marshall and Garrick, 2011b).

On the street design level, past research correlated bike facilities – and especially protected and separated bike facilities – with improved traffic safety outcomes (DiGioia et al., 2017). It has been postulated that bike facilities may be correlated with improved traffic safety outcomes because of their traffic calming effects. On the other hand, not all bike facilities are created equal. For example, past research has found that block groups and intersections that have shared lane markings (or sharrows) are less safe for bicyclists (Ferenchak and Marshall, 2019a; Harris et al., 2013). Therefore, we sought to analyze each type of bike facility separately.

We would have also liked to explore other street design characteristics that have been found to relate to traffic safety outcomes such as number of lanes, posted speed limits, and lane widths (Ferenchak and Marshall, 2019b; Ferenchak and Marshall, 2019c; Manuel et al., 2014; Potts et al., 2007). However, obtaining street-level design information for all our study cities proved too cumbersome for the wide geographic range of the current analysis.

2.2.3. Socio-demographics and socio-economic status

A population's socio-demographic or economic status may impact their traffic safety risk because of either the built environment in which they live (e.g., possible underinvestment in lower-income neighborhoods) and/or their mobility options (e.g., less access to an automobile means a higher probability of being a vulnerable road user). For instance, with poverty in the U.S. over recent decades migrating from inner cities to suburbs, over half of the people living below the poverty line in the U.S. now reside in suburbs (Ferenchak and Abadi, 2021). These lower-income individuals often have limited transportation options but must navigate built environments designed exclusively for the automobile, presenting heightened risk to these lower-income populations. Other research has identified that different socio-demographic and socio-economic populations have access to different amounts and types of bike infrastructure (Ferenchak and Marshall, 2021). Having access to less safe infrastructure could impact safety outcomes. In addition to differences in the built environment, populations of varying demographics and economic status have been shown to experience more or less aggressive behavior from drivers (Goddard et al., 2015).

These built environment and behavioral factors have been found to translate into adverse traffic safety outcomes. Prior studies have generally shown that Black, Hispanic, lower-socio-economic, and lower-education populations are at higher risk of traffic fatalities and injuries, although those associations may be surrogates for other underlying factors such as inequitable street safety or policing (Braver, 2003; Campos-Outcalt et al., 2003; Harper et al., 2000; Marshall and Ferenchak, 2017; McAndrews et al., 2013; Schiff and Becker, 1996). At the same time, past studies have linked bicycling to gentrification, suggesting that bicycling may lead to more White, higher-income, and higher-education populations (and possibly better traffic safety outcomes) (Flanagan et al., 2016; Stehlin, 2015; Stein, 2011). While we do not want to explore or substantiate the possible link between gentrification and bicycling activity and/or bicycling facilities with this paper, we do want to understand pertinent related equity factors such as race/ethnicity, income, and age that have been shown to be related to road safety.

The current work contributes to the body of knowledge on road safety of high-driving cities by examining from a bicycling perspective, specifically examining small and mid-size cities, analyzing on multiple levels, and statistically accounting for all pertinent factors detailed above.

3. City selection

To understand whether small and mid-size cities with high rates of bicycling are safer than their peers, we sought to first identify what we termed "high-bicycling" cities and then identify paired comparison cities. For every city in the U.S. with between 50,000 and 200,000 residents, we obtained city-level 2019 American Community Survey (ACS) 5-year estimates on bicycle commute mode share. While we would have liked to explore the prevalence of bike facilities during our city selection process, most of the cities did not have updated bike facility data readily available. We therefore used our bicycle commute mode share data to first identify small and mid-size cities that could be considered high-bicycling cities. With this, we sought high-bicycling cities that had both high levels of bike commute mode share (i.e., greater than triple the national average of 0.5%). The population and bicycle commute mode share criteria left us with 28 possible high-bicycling cities. Next, each high-bicycling city needed a logical paired comparison city that had significantly lower levels of bike commute mode share (less than half of its high-bicycling city) but with similar population (within 15% of each other), geographic location (same or adjoining census region), terrain, climate, and function (such as both cities housing a major university or being just outside a major city). Since many of the possible high-bicycling cities did not have logical comparison cities, our final city selection resulted in 7 high-bicycling cities and 7 paired comparison cities (Table 1). We then generated bike facility data for those cities and their paired comparisons (see more details in Section 4.2).

We examined all block groups that were completely within the cities' place boundaries as provided by the U.S. Census Bureau. The study covered ten years of data (2010–2019). This study period allowed us to use consistent geographies as 2010 block group boundaries were unchanged throughout the study years. The study included 659 block groups: 305 block groups in the high-bicycling cities and 354 in the paired comparison cities.

4. Data

4.1. Traffic safety data

For our traffic safety outcome variable, we chose to analyze fatalities because we wanted to explore the most serious traffic safety outcomes. Furthermore, we were not able to analyze motor vehicle collisions resulting in non-fatal injuries because of inconsistent data reporting across the study cities, availability issues, and changing injury severity definitions with the release of the 5th edition of the Model Minimum

Table 1
City Selection and City-Level Descriptive Statistics. Cities paired in order (e.g., Boulder to Norman; Cambridge to Alexandria; etc.).

High-Bicycling Cities	Population (2019)	Population Density[1]	Total Fatal Rate[2]	Bicycle Fatal Rate[3]	Bike Commute Share (2019)	SOV Commute Share (2019)	Density Bike Lanes[4]	Density Trails[4]	Density Sharrows[4]	Intersection Density[5]
Boulder, CO	106,392	3.9	1.8	0.2	9.9%	50.8%	34.7%	20.5%	0.0%	94.5
Cambridge, MA	116,632	16.4	1.8	0.8	7.7%	26.8%	25.8%	5.1%	2.5%	208.4
Pasadena, CA	141,258	6.1	5.1	3.0	1.8%	69.9%	8.7%	0.0%	4.9%	111.0
Iowa City, IA	74,950	2.9	2.4	0.0	3.6%	58.9%	1.4%	9.3%	6.5%	92.8
New Haven, CT	130,331	6.8	8.1	1.1	3.1%	58.7%	10.5%	1.8%	20.7%	79.6
Portland, ME	66,595	3.1	3.8	0.0	2.2%	65.6%	8.8%	1.6%	5.5%	136.4
Passaic, NJ	70,019	21.6	2.0	0.0	0.6%	48.1%	1.2%	0.0%	1.5%	126.8
Paired Comparison Cities										
Norman, OK	122,837	0.6	5.7	2.0	1.6%	80.3%	5.4%	3.3%	0.0%	78.3
Alexandria, VA	157,613	10.4	2.2	0.0	1.3%	59.3%	7.9%	4.2%	10.9%	118.4
Fullerton, CA	139,611	6.2	4.9	6.2	0.7%	79.5%	16.2%	1.3%	0.0%	101.7
Eau Claire, WI	68,187	2.0	2.9	2.1	1.3%	80.8%	0.9%	13.8%	0.0%	101.6
Columbia, SC	133,273	1.0	12.2	11.9	0.5%	64.1%	1.4%	0.1%	0.2%	115.2
Youngstown, OH	64,783	1.9	11.0	47.6	0.1%	74.7%	0.9%	0.0%	0.0%	84.7
East Orange, NJ	64,374	16.4	2.5	0.0	0.2%	56.9%	0.0%	0.4%	0.0%	97.3

Note: 1) 1000 residents per square mile of land; 2) 2010-2019 fatalities per 10,000 population; 3) 2010-2019 bicyclist fatalities per 1000 bicycle commuters; 4) % road lane miles; 5) intersections per square mile.

Uniform Crash Criteria (MMUCC) in 2017. We originally sought to run statistical models on three separate analyses: total, pedestrian, and bicycle fatalities. However, because sample sizes for bicycle fatalities were too low in our small and mid-size cities, we only analyzed total and pedestrian fatalities.

Motor vehicle fatality data was available nationwide through FARS, which captures all motor vehicle collisions on public roads in the U.S. that resulted in a fatality within 30 days of the collision (Table 2). Fatal collisions between 2010 and 2019 were counted for each block group using spatial joins in GIS. Because roadways are often chosen as block group boundaries, collisions frequently lie along the edge of two adjoining block groups. In which block group should we count such a collision? Not counting the collision would provide us with an incomplete picture of safety, while counting the collision in only one block group would bias our analysis (Tresidder, 2005). Therefore, we applied 30-foot buffers to all block groups and counted boundary collisions in all adjoining block groups. Because of this method, the fatality data cannot be aggregated from the block group level.

Table 2
Variables and Block Group Descriptive Statistics.

Variable	Mean	SD	Min	Max
Safety Variables				
Total Fatal Collisions *(2010-2019)*	0.7	1.1	0	7
Pedestrian Fatal Collisions *(2010-2019)*	0.2	0.6	0	5
Bicycle Fatal Collisions *(2010-2019)*	0.0	0.2	0	1
Population Variables				
Population *(residents)*	1258.1	646.4	48	4744
Mode Choice Variables				
Bicycle Mode Share to Work *(%)*	2.8	4.6	0	35.5
Transit Mode Share to Work *(%)*	10.3	12.1	0	75.0
SOV Mode Share to Work *(%)*	62.2	21.3	1.1	100
Built Environment Variables				
Density of Bike Lanes *(% road lane miles)*	9.9	15.9	0	105.0
Density of Trails *(% road lane miles)*	3.7	12.2	0	123.2
Density of Sharrows *(% road lane miles)*	4.4	11.9	0	88.4
Intersection Density *(intersections per sq. mi.)*	109.9	68.1	4.1	860.4
Population Density *(1000 pop. Per sq. mi. of land)*	12.8	11.9	0.1	72.1
Socio-Demographic and Socio-Economic Variables				
Population Identifying as White *(%)*	60.6	27.2	0	100
Median Household Income *(in 1000 s)*	64.2	43.1	0	248.2
Median Age *(years)*	35.4	9.0	16.7	76.4

4.2. Built environment data

As described in Section 2.2.2.1, past traffic safety research has frequently used population density as a land use proxy. Higher population density has been linked with improved safety outcomes because of shorter trips resulting in lower levels of exposure and lower vehicle speeds. To calculate population density, we divided each block group's 2019 ACS 5-year estimate of population by each block group's area of land.

As described in Section 2.2.2.2., denser street networks have been linked with lower vehicle miles driven and lower vehicles speeds (Ewing et al., 2020). We obtained data representing street network density from the U.S. Environmental Protection Agency's Smart Location Database in the form of intersection density on the block group level.

Bike facility data proved more difficult to compile. Although some of our cities provided bike facility GIS layers, many cities did not have them available. Even when GIS layers were available, many were outdated or did not include shared lane markings. A single coder therefore updated all bike networks for all cities in 2019. This required a combination of emails/phone calls with city planners, an in-depth review of bike maps, as well as reviewing facilities documented in Google Maps and Google Street View. We originally differentiated between protected, buffered, and standard bike lanes, off road trails, and shared lanes markings as defined by the American Association of State Highway and Transportation Officials' (AASHTO) *Guide for the Development of Bicycle Facilities* (AASHTO, 2012), but because of limited prevalence of protected and buffered bike lanes in the small and mid-size cities, we grouped facilities into three categories: 1) bike lanes (including protected, buffered, and standard), 2) off-road trails, and 3) shared lane markings. Shared lane markings are pavement markings consisting of a bicycle with two chevrons above it, with the chevrons designating the desired direction of travel for the bicyclist (AASHTO, 2012). Shared lane markings are specified to be 112 in. in length by 40 in. in width and are often used when road designers wish to provide more guidance than signage can provide but where it has been deemed that not enough space is available for a designated bike lane (AASHTO, 2012).

We calculated the cumulative length of each facility type in each block group using spatial joins in GIS. A 30-foot buffer allowed facilities that formed the boundary of two block groups to be counted for both, thereby avoiding edge issues. Bike facilities that were present on both sides of a road were counted twice, while bike facilities on one side were counted once. We normalized these bike facility measurements by dividing the length of bike facilities in each block group by the total length of roadway for that respective block group. Our bike facility metric was therefore the proportion of centerline miles that had a bike facility installed. Roadway data was provided by the United States Geological Survey (USGS) National Transportation Dataset (NTD) in GIS polyline format. The California dataset provided by USGS was last updated in April 2019 and the dataset containing all the other cities was last updated in May 2020.

4.3. Socio-demographic/socio-economic data

Prior studies have generally shown that Black, Hispanic, lower-socio-economic, and lower-education populations are at higher risk of traffic fatalities and injuries because of differences in built environment and/or travel behavior (Braver, 2003; Campos-Outcalt et al., 2003; Harper et al., 2000; Marshall and Ferenchak, 2017; McAndrews et al., 2013; Schiff and Becker, 1996). A population's age may relate to traffic safety outcomes because of higher levels of risk in younger populations or older populations being more vulnerable to injury. Accordingly, the 2019 ACS 5-year estimates also provided block group-level data on percent of population identifying as non-Hispanic White, median household income, and median age.

5. Methods

We first sought to understand whether small and mid-size high-bicycling cities are in fact safer for all road users, pedestrians, and bicyclists. Then, we identified important determinants of those differences in safety outcomes.

5.1. Are high-bicycling cities safer?

Since the study cities and block groups varied in size, we sought to account for the level of exposure in our geographies. Exposure is a measure of risk experienced in the roadway environment, typically quantified in either the number of persons, distance travelled, or time spent in the transportation system. Population-based exposure metrics allow road safety to be studied as a public health issue and are common in studies that consider socio-demographic and socio-economic factors (Sewell et al., 1989; Gallaher et al., 1992; Schiff and Becker, 1996; Campos-Outcalt et al., 2003; Marshall and Ferenchak, 2017; Marshall and Garrick, 2010). Outcomes based on population-based exposure reflect overall societal risk while those based on travel exposure (e.g., distance or time) reflect travel risk (Ferenchak and Marshall, 2020a; McAndrews et al., 2013).

We accounted for exposure for overall traffic fatalities (all modes) with population data on the block group level. For each block group, we divided the total number of roadway fatalities by the total number of residents. This allowed us to explore how safe the residents of each block group were, as opposed to how safe it was for them to drive. In other words, the results of this paper reflect the safety of living in a city versus the safety of driving in that city.

Since not all residents regularly walk or bike on public roads, population-based exposure metrics are less accurate for measuring active transportation safety. We therefore accounted for active transportation exposure using commute mode share data from the Census (for instance, the number of bike fatalities per bike commuter), which is a more accurate reflection of the prevalence of those activities and therefore a more accurate reflection of the safety of those activities. However, not all pedestrians and bicyclists are commuting, so this metric should be considered as an exposure proxy.

We then analyzed fatality rates for all road users (using population as exposure), pedestrians, and bicyclists (using walking and biking commuters as exposure) using 95% confidence intervals that compared the means of our high-bicycling block group sample to the means of our paired comparison block group sample. This allowed us to identify whether high-bicycling cities were safer for all road users relative to their paired comparisons.

5.2. Statistical analysis

We next wanted to understand which possible determinants were significantly related to any identified safety differences. What made those living, working, and playing in a block group or city safer?

To answer this research question, we employed negative binomial regressions. Negative binomial regressions are often used in traffic safety research as injury counts are frequently over-dispersed, as our data was. Given the structure of our study, we used hierarchical negative binomial regressions to account for spatial autocorrelation in our analyses. While we gathered data on the block group level, it may be that block groups within one city share characteristics of that city, which would spatially violate the assumption of independence that underlies most statistical models. We therefore ran a multi-level model so that we could distinguish between block group and city level factors and outcomes.

The dependent variable in our statistical models was fatalities. We included results for all traffic fatalities and pedestrian fatalities in this paper. We did not create statistical models for bicyclist fatalities because of low sample sizes. To account for exposure, we controlled for population in the total fatalities model and the number of pedestrian commuters in the pedestrian fatality model.

Independent variables were selected from our three possible factors as detailed above. We standardized each independent variable by converting every value to a Z-score. This is done by subtracting the mean from each observed value and dividing by the standard deviation for that variable. The Z-score is therefore a measure of standard deviations above or below the mean, which allows for the strength of disparate variables to be compared.

When selecting our independent variables, we ran into multicollinearity issues where variables were correlated with each other, which would again violate the independence assumption. For instance, there was a strong negative correlation between transit commute mode share and single-occupancy vehicle commute mode share. We therefore first built hierarchical negative binomial regressions for each possible factor separately and identified any non-significant variables or, if two variables were highly correlated, the weakest variables. We dropped these variables from the full models that simultaneously accounted for variables related to all three factors.

6. Results

6.1. Are high-bicycling cities safer than paired comparison cities?

There were 719 total fatal collisions, 192 fatal pedestrian collisions, and 22 fatal bicycle collisions in the study cities between 2010 and 2019. Paired comparison cities had 61.4% more total traffic fatalities and 40% more pedestrian fatalities (both statistically significant at 95% confidence). The high-bicycling and paired comparison cities had the same number of bicyclist fatalities.

If paired comparison cities had more residents or pedestrians, we might expect the results above. Controlling for the exposure to risk helps us better understand the relative safety of the study cities. After accounting for exposure, fatality rates were higher in paired comparison cities for all modes studied. Total traffic fatality rates (per 10,000 population) were 57.3% higher in paired comparison cities (Fig. 1). However, the paired comparison cities also had relatively high variability,

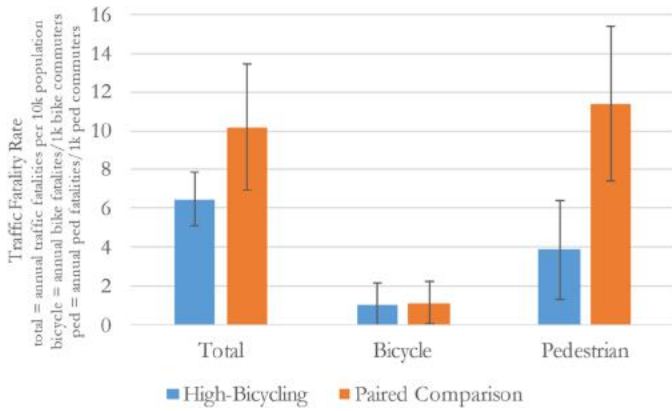

Fig. 1. Means and 95% Confidence Intervals of Fatality Rates by Block Groups (total = annual traffic fatalities per 10k population; bicycle = annual bicycle fatalities per 1k bicycle commuters; pedestrian = annual pedestrian fatalities per 1k pedestrian commuters).

leading to a lack of statistical significance.

The bicycle fatality rates should be interpreted with caution due to low sample sizes (Fig. 1). There were only 22 bicycle fatalities in the fourteen study cities over the ten years of the study. A lack of bicycle fatalities does not necessarily signal safe conditions, as it may be a sign that conditions are so inhospitable to bicyclists, there is no bike activity and therefore no bicyclists to be struck (Ferenchak and Marshall, 2020b; Nevelsteen et al., 2012; Schneider et al., 2004). It is difficult to assess bicyclist safety in the 75.0% of study block groups that had no bicycle fatalities and fewer than 50 bicycle commuters. More research is needed to better understand bicyclist-specific safety.

Pedestrian commuters and fatalities were prevalent enough to obtain statistically significant results (Fig. 1). Pedestrian fatalities in paired comparison cities were 193.8% higher than in high-bicycling cities, and the difference was statistically significant at 95% confidence. If lower traffic speeds and fewer vehicle trips play a role in improved safety for small and mid-size high-bicycling cities as is the case in large cities, we would expect those traffic safety benefits to be especially reflected in vulnerable road user outcomes (Marshall and Ferenchak, 2019).

6.2. Category-by-category model results

Which variables are related to lower fatality rates? The results below are from our hierarchical negative binomial regressions. To avoid multicollinearity, we first developed category-specific statistical models that individually explore our three possible factors: mode share, built environment, and socio-demographic/socio-economic status. For each category, we developed two separate models: one model for all traffic fatalities and one model for pedestrian fatalities. This allowed us to remove non-significant variables and variables that introduced multicollinearity when we developed our full statistical models in Section 6.3. Every total fatality model controlled for population and every pedestrian fatality model controlled for the number of pedestrian commuters. To allow for the comparison of coefficients, we standardized all variables using Z-scores by subtracting each observed value by the mean of that variable and dividing by the standard deviation. Each variable's coefficient therefore represents standard deviations above or below the mean, which can be compared to other variables' coefficients.

6.2.1. Mode choice category results

For all traffic fatalities, mode choice variables were only significant on the block group level (Table 3). The negative coefficients can be interpreted as showing that block groups with higher levels of bike, pedestrian, and transit commuting had fewer traffic fatalities after controlling for exposure with population. These results suggest that for all road users, there may be a 'safety in numbers' effect in that more bicyclists and pedestrians on the streets improves overall safety (Elvik and Bjørnskau, 2017; Jacobsen, 2003; Nordback et al., 2014).

There is evidence of pedestrian 'safety in numbers' when examining pedestrian fatalities. The negative coefficients on both the city and block group levels indicate that areas with many pedestrians experience significantly fewer pedestrian fatalities. Additionally, cities with higher levels of single-occupancy vehicle commute mode share were found to have more pedestrian fatalities (Table 3). This resonates with previous research that found that less driving – as opposed to high shares of other travel modes – was the best predictor of improved safety outcomes (Stimpson et al., 2014).

6.2.2. Built environment category results

For both pedestrian fatalities and all road user fatalities, population density was the strongest built environment variable on both the city and block group levels (Table 4). The negative coefficient is interpreted as higher population densities correlating with fewer fatalities. These results are expected because – as detailed in the literature review – denser built environments have been linked with shorter trips (and therefore less exposure), slower vehicle speeds, and less driving (Ewing et al., 2020; Marshall and Garrick, 2010). Because intersection density, which is typically positively related to population density, also had a statistically significant negative relationships with fatalities, we decided to keep both population density and intersection density in our final statistical models.

The relationship between traffic fatalities and bike facilities was relatively weak (Table 4). Sharrows were significant for all traffic fatalities on the city level while trails were significant for all fatalities and pedestrian fatalities on the block group level. Both relationships were negative meaning that higher levels of sharrows and trails were correlated with fewer fatalities. Bike lanes were not significant for any category. We therefore left the trails and sharrows variables in our final models but removed the bike lane variable. However, the bike facility results should be interpreted with caution as sample sizes were low. For

Table 3
Category 1 Mode Choice Negative Binomial Models (95% confidence in bold).

Variable	All Fatalities Model			Pedestrian Fatalities Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	**-8.509**	**< 0.001**	**0.265**	**-9.698**	**< 0.001**	**0.396**
City Level Variables						
Bike Mode Share	-0.108	0.265	0.097	-0.217	0.206	0.172
Pedestrian Mode Share	-0.189	0.106	0.117	**-1.472**	**< 0.001**	**0.269**
SOV Mode Share	-0.065	0.680	0.157	**0.515**	**0.046**	**0.300**
Transit Mode Share	-0.018	0.889	0.132	0.242	0.290	0.229
Block Group Level Variables						
Bike Mode Share	**-0.304**	**0.002**	**0.101**	**-0.419**	**0.013**	**0.168**
Pedestrian Mode Share	**-0.257**	**0.042**	**0.126**	**-1.670**	**< 0.001**	**0.282**
SOV Mode Share	-0.139	0.400	0.165	0.258	0.394	0.303
Transit Mode Share	**-0.279**	**0.021**	**0.120**	-0.040	0.845	0.206

Table 4
Category 2 Built Environment Negative Binomial Models (95% confidence in bold).

Variable	All Fatalities Model			Pedestrian Fatalities Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	**-8.191**	**< 0.001**	**0.271**	**-8.456**	**< 0.001**	**0.435**
City Level Variables						
Population Density	**-0.470**	**< 0.001**	**0.110**	**-0.484**	**0.014**	**0.198**
Intersection Density	**-0.209**	**0.042**	**0.101**	-0.137	0.431	0.174
Density of Bike Lanes	0.114	0.182	0.086	0.126	0.472	0.176
Density of Trails	0.082	0.284	0.077	-0.027	0.874	0.172
Density of Sharrows	**-0.175**	**0.045**	**0.087**	-0.120	0.459	0.162
Block Group Level Variables						
Population Density	**-0.572**	**< 0.001**	**0.093**	**-0.919**	**< 0.001**	**0.176**
Intersection Density	**-0.346**	**< 0.001**	**0.098**	**-0.570**	**0.001**	**0.175**
Density of Bike Lanes	0.025	0.735	0.074	-0.096	0.516	0.148
Density of Trails	**-0.178**	**0.030**	**0.082**	**-0.569**	**0.001**	**0.178**
Density of Sharrows	-0.051	0.502	0.076	-0.013	0.924	0.142

example, 53.5% of study block groups had no bike lanes, 78.3% of study block groups had no trails, and 79.1% of study block groups had no sharrows. The weak results that we obtained may not be so much a reflection of a lack of relationship between bike facilities and traffic safety, but more a reflection of the lack of facilities.

6.2.3. Socio-demographic/socio-economic category results

For all road user fatalities, income was the strongest socio-economic status (SES) variable on both the city and block group levels. The negative coefficients mean that areas with lower incomes had more fatalities, which could be related to underinvestment or imprudent investments in those neighborhoods or behavioral differences such as unsafe driving behaviors or higher prevalence of vulnerable road users (Table 5). Areas with older residents and more non-White residents experienced more fatalities, although those relationships were not as strong as income. These relationships reveal equity issues and may be because older residents to be more vulnerable to injury when involved in a crash and non-White populations are likely exposed to the same factors listed above for lower-income neighborhoods (i.e., underinvestment or imprudent investments or behavioral differences such as unsafe driving behaviors or higher prevalence of vulnerable road users in their neighborhoods).

For pedestrian fatalities, all the relationships detailed above were in the same direction, but age and race/ethnicity became much stronger variables. This suggests that the equity issues identified above for all road users are more acute for pedestrians.

6.3. Full model results

Which variables remain significant after controlling for all other variables? As with the individual category models, we standardized each independent variable with Z-scores in our final holistic negative binomial regressions. We controlled for population in our total fatality model and controlled for pedestrian commuters in our pedestrian fatality model. Because the bike lane variable was not significant in the category models, we removed that variable from our final models. To confirm this decision, we tested the bike lane variable in our final models, and it remained non-significant.

6.3.1. Mode choice full results

Bike mode share did not reach statistical significance for either type of fatality or for either level that was studied, a result similar to what was found in large U.S. cities (Marshall and Ferenchak, 2019). (Table 6). We interpret these results with caution given the small sample sizes of bicyclist commuters in these small and mid-size cities and suggest that future work might explore bicyclist 'safety in numbers' in cities with high enough bicyclist activity to appropriately detect the possible phenomenon. It would also be interesting to examine bike fatalities in future work to understand if bicyclist 'safety in numbers' exists for bicyclist safety, but the number of bike fatalities was too low for the small and mid-size cities studied in this paper to garner any meaningful results.

While bicyclist 'safety in numbers' was not apparent in our analysis, pedestrian 'safety in numbers' seems to be strongly present. Cities and block groups with more pedestrian commuting had significantly lower pedestrian fatality rates. While pedestrian 'safety in numbers' appears to be impacting pedestrian safety, there is no significant evidence that it is extending to overall road user safety.

SOV mode share continued to be significantly and positively related to pedestrian fatalities, with cities with higher levels of SOV mode share having more pedestrian fatalities (Table 6). Promoting mode shift to non-driving modes may therefore be an effective means of improving the safety of vulnerable road users.

6.3.2. Built environment full results

The density of the built environment was one of the strongest variables in the full models, with denser built environments being associated with better safety outcomes (Table 6). Population density was the strongest variable for total fatalities and was the third strongest variable for pedestrian fatalities. Intersection density also reached significance for total fatalities but was slightly weaker than population density.

Table 5
Category 3 Socio-Demographic/Socio-Economic Negative Binomial Models (95% confidence in bold).

Variable	All Fatalities Model			Pedestrian Fatalities Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	**-8.218**	**< 0.001**	**0.261**	**-8.222**	**< 0.001**	**0.439**
City Level Variables						
Age	**0.238**	**< 0.001**	**0.071**	**0.527**	**< 0.001**	**0.151**
Income	**-0.240**	**0.019**	**0.102**	-0.382	0.060	0.203
White	-0.128	0.192	0.098	-0.391	0.059	0.207
Block Group Level Variables						
Age	**0.343**	**< 0.001**	**0.074**	**0.831**	**< 0.001**	**0.147**
Income	**-0.432**	**< 0.001**	**0.090**	**-0.464**	**0.007**	**0.173**
White	**-0.295**	**< 0.001**	**0.073**	**-0.866**	**< 0.001**	**0.146**

Table 6
Full Negative Binomial Models (95% confidence in bold).

Variable	All Fatalities Model			Pedestrian Fatalities Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	**-7.810**	**< 0.001**	**0.287**	**-8.773**	**< 0.001**	**0.414**
Category 1 Mode Choice						
City Level Variables						
Bike Mode Share	-0.063	0.506	0.095	-0.048	0.770	0.165
Pedestrian Mode Share	-0.152	0.190	0.116	**-1.464**	**< 0.001**	**0.262**
SOV Mode Share	-0.086	0.571	0.152	**0.574**	**0.043**	**0.284**
Transit Mode Share	-0.047	0.706	0.126	0.148	0.478	0.209
Block Group Level						
Bike Mode Share	-0.061	0.517	0.094	-0.101	0.516	0.156
Pedestrian Mode Share	-0.114	0.336	0.119	**-1.532**	**< 0.001**	**0.263**
SOV Mode Share	-0.091	0.555	0.154	0.349	0.205	0.276
Transit Mode Share	-0.164	0.160	0.117	0.037	0.847	0.192
Category 2 Built Environment						
City Level Variables						
Population Density	**-0.611**	**< 0.001**	**0.120**	**-0.643**	**< 0.001**	**0.186**
Intersection Density	**-0.214**	**0.029**	**0.098**	-0.067	0.664	0.154
Density of Trails	0.077	0.293	0.073	0.102	0.352	0.110
Density of Sharrows	-0.165	0.053	0.085	0.049	0.709	0.130
Block Group Level Variables						
Population Density	**-0.586**	**< 0.001**	**0.100**	**-0.554**	**< 0.001**	**0.156**
Intersection Density	**-0.208**	**0.025**	**0.093**	-0.027	0.852	0.147
Density of Trails	-0.030	0.686	0.075	0.095	0.375	0.107
Density of Sharrows	-0.023	0.761	0.076	0.068	0.558	0.117
Category 3 Demographic & SES						
City Level Variables						
Age	0.104	0.155	0.073	0.159	0.226	0.131
Income	**-0.428**	**< 0.001**	**0.107**	**-0.772**	**< 0.001**	**0.197**
White	-0.131	0.185	0.099	-0.286	0.101	0.175
Block Group Level Variables						
Age	0.117	0.123	0.076	0.207	0.112	0.130
Income	**-0.357**	**< 0.001**	**0.089**	**-0.619**	**< 0.001**	**0.164**
White	**-0.397**	**< 0.001**	**0.082**	**-0.490**	**< 0.001**	**0.137**

While no bike facility variables were significantly related to safety outcomes, the bike facilities results should be interpreted with caution because of the lack of bike facilities in the study cities.

6.3.3. *Socio-demographic/socio-economic full results*

There appears to be an equity component to the results, with income being an especially strong determinant of safety outcomes (Table 6). Income was the second strongest determinant of both overall fatalities and pedestrian fatalities. The negative relationship signifies that areas with higher incomes had fewer fatalities.

Race/ ethnicity was also significant on the block group level, with non-White block groups being associated with more overall and pedestrian fatalities. Age was not significant in any of the models.

More research is needed to understand the underlying mechanisms behind these equity issues. Why are low-income and non-White neighborhoods more susceptible to traffic fatalities? It is particularly worrisome that the equity issues appear to be strongest for vulnerable road users.

7. Discussion

Findings suggest that high-bicycling small and mid-size cities are safer than their peers in terms of total and pedestrian fatality rates. While we would assume that they would also be safer for bicyclists, sample sizes were too small and exposure data was lacking, precluding a definitive conclusion on bicyclist safety.

Why are small and mid-size high-bicycling cities safer than their peers? It is important to note that the results of this work are exploratory and not confirmatory evidence of causality. First considering mode choice, the results suggest that to improve the safety of their streets, and especially for vulnerable road users, small and mid-size cities might focus on promoting alternatives to driving. There was strong evidence of pedestrian 'safety in numbers' identified, with cities and block groups with higher levels of pedestrian commuting experiencing lower pedestrian fatality rates. While bicyclists 'safety in numbers' was not detected in this current paper, past research has established the phenomenon and future research specific to bicyclist safety in areas with larger sample sizes and more robust bicycling activity data would be better suited to further identify and define such relationships (Elvik, 2017; Elvik and Bjørnskau, 2017; Jacobsen, 2003; Jacobsen et al., 2015).

There was also evidence that lower levels of driving were associated with improved pedestrian safety. This finding resonates with past research that similarly found that it was not so much the proliferation of any one non-driving mode that improved traffic safety, but instead the lower levels of driving that correlated most strongly with decreased traffic fatality rates (Stimpson et al., 2014). While we did not directly explore non-physical changes such as travel demand management in breaking auto-dependence with this work, future work might explore and this relationship with safety outcomes.

Secondly considering the built environment, one of the principal findings of this work is the importance of a high-density built environment in terms of both land use and street networks when pursuing traffic safety improvements. Such high-density built environments are likely associated with shorter trips, lower vehicle speeds, and less vehicle miles travelled, thereby resulting in the traffic safety improvements identified in this paper, although future work will be needed to verify these underlying mechanisms.

Thirdly considering socio-demographic and socio-economic factors, the results suggest that lower-income and non-White neighborhoods are especially susceptible to traffic fatalities. These findings represent significant equity issues, with vulnerable road users being especially susceptible. As cities pursue densification and mode shift, they should ensure that all populations have access to the safety improvements incurred.

Future work that continues to explore the complex nature and interconnectedness of the relationships identified above would provide further contributions to the body of knowledge on the connection between bicycling and traffic safety. For instance, a positive feedback loop may be formed when cities with fewer cars are more appealing for bicyclists and pedestrians, with corresponding increases in cycling and walking leading to still fewer cars. With these reductions in cars, all road users may become safer. Similarly, because denser cities may enable people to walk and cycle more due to increased access, does the density of the city (and lower vehicle speeds necessitated by smaller block sizes and smaller and busier streets) correlate with improved safety or is that density a proxy for the underlying mode shift away from cars? In the overall statistical model of this paper, the built environment factors were the strongest, suggesting that the urban form itself may be more important than who is on the streets, although future work could continue to elucidate this relationship. These ideas may call into question the fundamentals of bicycling safety in numbers. Are cyclists safer in places with more cyclists or are there more cyclists present in places that are safe for cyclists?

How can we leverage these findings to improve traffic safety? The results of this work align with past research that has shown that the most fundamental approach to reducing motor vehicle crashes is by reducing motor vehicle exposure, namely by providing alternative mobility options. This multimodal perspective has been shown to be effective for Vision Zero cities (Ferenchak, 2022) and has been placed at the top of the Safe Systems Pyramid, ranking above other approaches such as engineering controls and administrative controls (Ederer et al., 2023). The results of the current paper further suggest that the approaches to this multimodality may be multifaceted. Planners may play an important role through the promotion of safe and livable densification through policies such as infill, urban growth boundaries, and transit-oriented development. Engineers can further enhance that multimodality through road and multimodal network connectivity and densification and by providing safe and comfortable facilities for non-motorized modes of transportation (although the bicycle infrastructure variable was not significant in the current work, likely because of small sample sizes). While not tested in this research, it would also be reasonable to expect other policies aimed at promoting multimodality such as transportation demand management (TDM) might also be a practical approach to improved traffic safety through multimodality as past research has suggested as much (Litman and Fitzroy, 2018; Pirdavani et al., 2013).

8. Conclusions

If cities wish to improve their traffic safety outcomes, they should first and foremost plan and design for the convenience and safety of those not using a personal automobile as findings from this paper have identified 1) that small and mid-size cities with higher bicycling activity are significantly associated with better overall road safety outcomes and 2) evidence of pedestrian ‘safety in numbers’. A key approach to this focus on non-automobile modes appears to be higher density land use development and transportation networks, which are likely linked to fewer vehicle trips and lower vehicle speeds. Because results revealed that areas with lower incomes and more non-White residents experience more overall road fatalities, equity issues must also be addressed to ensure all residents have access to safety benefits.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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