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Why cities with high bicycling rates are safer for all road users

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ABSTRACT

Introduction: Despite bicycling being considered ten times more dangerous than driving, the evidence suggests that high-bicycling-mode-share cities are not only safer for bicyclists but for all road users. We look to understand what makes these cities safer. Are the safety differences related to 'safety-in-numbers' of bicyclists, or can they be better explained by built environment differences or the people that inhabit them?
Methods: Based on thirteen years of data from twelve large U.S. cities, we investigated over 17,000 fatalities and 77,000 severe injuries across nearly 8700 block groups via multilevel, longitudinal, negative binomial regression models. We hypothesize three pathways towards better road safety outcomes: i) travel behavior differences (e.g. 'safety-in-numbers' or shifts to 'safer' modes); ii) built environment differences (e.g. infrastructure that helps promote safer environments); and iii) socio-demographic/socio-economic differences (e.g. some cities may be populated by those with lower road safety risk).
Results: The results suggest that more bicyclists is not the reason these cities are safer for all road users. Better safety outcomes are instead associated with a greater prevalence of bike facilities – particularly protected and separated bike facilities – at the block group level and, more strongly so, across the overall city. Higher intersection density, which typically corresponds to more compact and lower-speed built environments, was strongly associated with better road safety outcomes for all road users. The variables representing gentrification also accounted for much of our explainable variation in safety outcomes.
Conclusions: This paper provides an evidence-based approach to building safer cities. While the policy implications of this work point to protected and separated bike infrastructure as part of the solution, we need to keep in mind that these approaches are complementary and should not be considered in isolation. Moreover, our results – particularly the safety disparities associated with gentrification – suggest equity issues and the need for future research.

1. Introduction

Bicycling as a fundamental mode of transportation is being reinvented in the United States. To begin with, Americans are becoming increasingly reliant on bicycling, as evidenced by the 51% increase in bicycling to work between 2010 and 2016 (ACS, 2018). At the same time, more and more U.S. cities are improving their bicycling infrastructure. For instance, the number of protected bike lanes in the U.S. has doubled every two years since 2009 (Peopleforbikes, 2018). Despite these changes, a recent bicycling safety report from the Organization for Economic Cooperation and Development (OECD) states that Americans still bicycle less than residents of the other 33 OECD countries and are among the most likely to die as bicyclists (OECD, 2013).

Just how dangerous is bicycling? Given the lack of exposure data and bicycling counts, this is a difficult question to answer

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definitively. An analysis using person-trips from the National Household Travel Survey as an exposure metric found that fatality and nonfatal injury rates for bicyclists were nearly twice the overall average, significantly higher than the rates for passenger vehicle, walking, or bus trips (Beck et al., 2007). Although research on the topic is limited, it can also be estimated in relative terms. For instance, 37,461 and 840 people were killed in motor vehicle and bicycle crashes in the U.S. in 2016, respectively (NHTSA, 2017a). Americans drove approximately 3.2 trillion miles in 2016, which equates to a fatality rate of 1.18 fatalities per 100 million VMT (vehicle miles traveled) (FHWA, 2017). Bicycling participation estimates range from less than 10% of Americans to more than 24% (NSGA, 2017; Mapes, 2009; Breakaway Research Group, 2015). The National Sporting Goods Association, for example, reports that 39.3 million Americans ride a bike at least once a year, which equates to about 12% of the population (NSGA, 2017). With 840 bicyclist fatalities, each of these 39.3 million bicyclists would have to bike more than 1,600 miles each year to be safer than those in motor vehicles. This would equate to 12% of Americans bicycling more than four miles every day of the year. This, however, is not a realistic level of bicycle exposure in the U.S. context given current travel patterns (Mapes, 2009). Even if we increased our assumption to 24% of the population, it would still equate to more than 800 miles of bicycling each year for more than 78 million people.

The finding that bicycling is more dangerous than other modes holds in other countries as well. In Great Britain, fatality risk is higher for bicyclists than for drivers (Mindell et al., 2012). However, while risk is higher for bicyclists themselves, motorized vehicles present a higher risk for third-party road users (Scholes et al., 2018). In France, the risk of being killed – based on both time spent traveling and the number of trips – was about 1.5 times higher for bicyclists than for car occupants (Bouaoun et al., 2015).

So despite the myriad health benefits of bicycling (Deenihan and Caulfield, 2014; Garrard, 2011; Marshall et al., 2015), research suggests that bicycling is significantly more dangerous than driving, and those looking to promote the health benefits of bicycling typically do so despite the known road safety risks (De Hartog et al., 2011). To be more specific, Pucher and Dijkstra approximated bicycling exposure from commute data and found that the per-mile fatality rate for drivers in the U.S. was approximately ten times lower than that for bicyclists (Pucher and Dijkstra, 2003). More recently, McAndrews et al. delved deeper into the data to derive mileage-based exposure metrics and estimated similar elevated risks for bicyclists (Mcandrews et al., 2013).

Transit, on the other hand, is a much safer mode of transportation than driving. Recent numbers suggest fewer than 0.06 fatalities per 100 million passenger transit miles traveled, which is approximately twenty times safer than driving (Politifact.Com, 2011). Based upon this difference between transit and automobile safety, it would stand to reason that cities with a high percentage of people traveling by transit would be safer than the typical automobile-based city. At the city level, this trend turns out to be the case. In an international study, Kenworthy and Laube concluded that cities with high transit use also tended to have lower overall fatality rates (Kenworthy and Laube, 2000). In the U.S. context, Litman found that residents of automobile-oriented cities had a traffic fatality rate five times that of those living in transit-oriented communities (Litman, 2009, 2013). One reason behind these results is that more transit use tends to also lower the overall amount of vehicle use. Another explanation is that transit use is higher in relatively dense metropolitan areas with urban form designed around relatively slow speeds, thus reducing the number of deaths of travelers by just about any mode.

Given these safety trends, one might conclude that high bicycling cities must be far more dangerous than either transit-based cities or automobile-based cities. However, cities with high levels of biking also have surprisingly good traffic safety records, and not just for bicyclists, but for all road users (Marshall and Garrick, 2011b). For instance, the U.S. city long with the greatest percentage of people bicycling to work – Davis, California – endured 28 road fatalities over a recent 20-year period, with 19 of those fatalities occurring on non-limited access streets and two involving bicyclists. These results equate to a road fatality rate of 2.3 per 100,000 residents. With the current per capita crash rate in the U.S. more than five times higher at 12.4 fatalities per 100,000 residents, it is easiest to discount Davis as an anomaly. Yet, Davis is not alone. Another U.S. city that has become renowned for its bicycling – Portland, Oregon – has concurrently improved its road safety record. Between 1990 and 2010, for example, Portland's bicycle mode share increased from 1.2% to 6.0%; over this same period, the overall road fatality rate in Portland dropped by 75% (City Of Portland Bureau Of Transportation, 2011). This is a relatively impressive safety record (4.5 fatalities per 100,000 residents) for a city of over 600,000 people and is comparable internationally to the countries reporting the lowest crash rates in the world such as the Netherlands (3.4 fatalities per 100,000 residents) (Marshall, 2018). Perhaps not coincidentally, the Netherlands also boasts a bicyclist mode share of nearly 30% (Heinen et al., 2013).

Examples such as Davis, Portland, and the Netherlands are often written off as outliers because their cultures of bicycling have been prevalent for decades. New York City, however, is a relative newcomer to the bicycling experiment, having installed over 600 lane miles of bike lanes since 2006 (New York City DOT, 2018). Since then, bicycling has more than doubled in New York City while traffic fatality rates dropped to the lowest numbers on record (Donohue, 2013; Miller, 2013). While these improvements cannot simply be attributed to increased levels of bicycling, these represent trends worthy of exploration.

A number of existing papers have studied the idea of bicyclist 'safety in numbers' where individual bicyclist risk drops with an increasing number of bicyclists (Ekman, 2006; Jacobsen, 2003; Jacobsen et al., 2015; Jensen, 2002; Nordback and Marshall, 2010; Nordback et al., 2014). The rationale most often given for this safety benefit is a shift in driver expectations and behavior based upon the perceived possibility of encountering a bicyclist. However, these studies only attempt to understand the difference in bicyclist safety. Fewer studies have investigated the safety effect of a high-bicycling-mode-share city on the safety of all road users (Marshall and Garrick, 2011b).

Despite conventional logic, the evidence continues to build that high bicycling places are not only safer for bicyclists but for all road users. Via a longitudinal 13-year analysis of 12 large U.S. cities, this research study seeks to understand what makes large cities with high bicycling rates safer for all road users. Do these safety trends have anything to do with safety in numbers, or can they be explained by other factors? Accordingly, we hypothesize three primary possibilities:

1. Travel behavior differences, such as bicyclist safety in numbers, and/or shifts to modes that are safer or may reduce exposure;
2. Built environment differences, such as bicycling infrastructure, that may help promote lower speed environments and safer streets; and
3. Socio-demographic and socio-economic differences, as cities become more populated by populations with generally lower

transportation injury risks.

The next section delves into the theory behind these possible explanations. We then describe the study in more detail along with the data collection efforts and statistical methodology. This is followed by our results and conclusions.

2. Theory

The pervasiveness of road deaths remains one of our most unrelenting public health failures. In fact, road fatalities purge more productive years of life than any other disease, including cancer and heart disease combined (Maxton and Wormald, 2004). Just last year alone, there were more than 40,000 road deaths in the U.S. and 1.25 million worldwide (National Safety Council, 2018). According to the Centers for Disease Control and Prevention, road fatalities are the number one cause of death for every U.S. age group from 5 through 24 (CDC, 2017). Traffic safety should be considered a public health priority (Ewing and Dumbaugh, 2009), and the seriousness of this issue, combined with the fact that progress in this area remains slow, suggests a need for a fundamentally different approach. This paper attempts to accomplish this via a comprehensive look at what may be influencing road safety outcomes. This section examines the existing literature related to the potential pathways for better road safety outcomes.

2.1. *Travel behavior differences*

There is considerable bicycling research focused on the 'safety in numbers' phenomenon. As far back as 1996, Ekman found a significant relationship between bicyclist exposure and conflict rate (Ekman, 2006). In this comprehensive Swedish study, Ekman's results suggest that the conflict rate for an individual bicyclist was higher when the number of bicyclists was low and that this conflict rate waned as the flow of bicyclists increased. In other words, the more bicyclists, the safer it is for each individual bicyclist. Pedestrians did not experience the same benefit in Ekman's study. In a 2002 study from Copenhagen, Jensen found that a 40% increase in bicycle kilometers traveled corresponded to a 50% decrease in seriously injured bicyclists (Jensen, 2002). In one of the first U.S. studies looking at this issue, Jacobsen investigated 68 California cities and showed that the individual chance of a bicyclist being struck by a car drops with more people bicycling (Jacobsen, 2003). Larger-scale, international studies soon began to support these results (Pucher and Dijkstra, 2003; Pucher and Buehler, 2008; Robinson, 2005; Yao and Loo, 2016). Similar results are now emanating from the research focused on developing safety performance functions (Nordback et al., 2014).

While these studies generally focus on bicyclist-related crash outcomes and not on all road users, they do begin to shed light on why cities with high bicycling might see improved road safety outcomes. Although not explicitly studied, most of these papers assert that high levels of bicycling may influence driver behavior. In other words, when the number of bicyclists increases to the point where drivers habitually expect to see bicyclists, drivers may be more likely to, for example, look over their shoulder for a bicyclist when making a right turn. It is possible that higher driver awareness lends itself to safer outcomes for other road users as well. It is also possible that high numbers of bicyclists may even act as traffic calming measure themselves. Speeding down a street is not as easy when there are bicyclists in the way. Whereas switching from driving to bicycling might lead to worse safety outcomes in conventional circumstances, this may not be the case in cities with high bicycling rates.

Since the statistics suggest that transit is on the order of twenty times safer than driving, it stands to reason that places with high transit usage might have lower road fatality rates (Kenworthy and Laube, 2000; Litman, 2009, 2013). The same can be said for cities with higher percentages of people that work from home. The ability to access one's job without exposing oneself to the dangers of the roads should, in theory, be safer than any conventional commute. In fact, the percentage of people working from home has grown more than walking, bicycling, or transit use over the last decade (ACS, 2018; Polzin, 2016). Yet, the contribution of this growing trend to road safety outcomes remains under-researched.

2.2. *Built environment differences*

A recent development to the built environment of U.S. cities has been the growth of bicycle-focused infrastructure. Does such bicycling infrastructure actually improve road safety outcomes? The majority of papers find that bicycle paths and lanes help reduce bicyclist fatalities (Pucher, 2001; Reynolds et al., 2009; Mulvaney et al., 2016). However as described in the introduction, the number of protected bike lanes – also known as cycle tracks – went from being almost non-existent in U.S. cities to doubling every other year since 2009 (Peopleforbikes, 2018). While there remains a relative lack of peer-reviewed safety research on protected bicycling infrastructure in the U.S. (Mulvaney et al., 2016), the results seem promising (Harris et al., 2013; Zangenehpour et al., 2016). It is worth pointing out, however, that most of these papers focus specifically on the safety of bicyclist; yet, it is conceivable that such bicycle infrastructure may also function as a traffic calming measure that reduces vehicle speeds and improves road safety outcomes for other road users as well (Marshall and Garrick, 2011b). In terms of the relationship between bike infrastructure and bicycling activity, separated infrastructure has been shown to increase bicycling rates and help reduce the bicycling gender gap (Garrard et al., 2008). Yet, the research remains mixed. For instance, a report by the University of Minnesota concludes that "the 'build it and they will come' theory is not universally applicable" when it comes to bike facilities (Douma and Cleaveland, 2008). Such results suggest that we should consider changes in bicycling rates separately from changes in bicycling infrastructure.

More generally in terms of the built environment, denser, more urban areas generally experience lower road fatality rates than more suburban or rural environments (EWING et al., 2003a, Dumbaugh, 2006; Dumbaugh and Rae, 2009; Marshall and Garrick, 2010b, 2011a; Ewing et al., 2014; Myers et al., 2013; Glaeser, 2011). For example, intersection density, which typically suggests a more compact and lower speed built environment, has been shown to be associated with more property damage only crashes but significantly fewer fatalities and severe injury crashes (Marshall and Garrick, 2011a). When accounting for the built environment in terms of population density, one study found that those living in rural zip codes suffered from vehicle occupant fatality rates approximately six times higher than those living in the most urban zip codes (Marshall and Ferenchak, 2017).

In an overview of the existing evidence on the subject of safety and the built environment, Ewing and Dumbaugh cite two main reasons for these road safety disparities: i) those living in urban areas generally drive less; and ii) urban areas tend to be designed to promote lower speeds (Ewing and Dumbaugh, 2009). In fact, speeding plays a role in more than 30% of fatal crashes in the U.S. (USDOT, 2014), and the preponderance of research suggests that lower speeds help reduce injury severity (Archer et al., 2008). For instance, a synthesis paper by Elvik concluded “that the relationship between speed and road safety is causal, not just statistical” (Elvik, 2005). A later paper by the same author estimated that eliminating speeding would reduce road fatalities by 25% to 33% (Elvik, 2012).

2.3. Socio-demographic and socio-economic differences

Gentrification – typically defined as the arrival of wealthier people, usually white, into an existing urban neighborhood and the coincident displacement of lower-income, usually non-white, residents – has become a persistent issue for U.S. cities (Grant, 2011; Maciag, 2015). In terms of road safety outcomes, income has proven to be significant in road safety outcomes, all other factors being held equal (Al-Lamki, 2010; Marshall and Ferenchak, 2017). With respect to socio-demographics, much of the literature suggests lower road fatality rates for non-Hispanic white populations (Schiff and Becker, 1996; Baker et al., 1998; Harper et al., 2000) while other papers found higher fatality rates for American Indian and Black populations (Mcandrews et al., 2013, Braver, 2003; Campos-Outcalt et al., 2003; Mayrose and Jehle, 2002). While the existing research struggles to explain why the transportation system is not equally safe for various demographic and economic groups, it stands to reason that we need to account for the shifting demographics and incomes of cities when trying to understand the road safety disparities.

In terms of age, the existing literature suggests that both younger drivers and older drivers have increased risks for collisions, injury crashes, and fatal crashes. For instance, younger drivers are more likely to speed and tend to underestimate risk (Stradling et al., 2003; Constantinou et al., 2011; Rhodes and Pivik, 2011; Hatfield and Fernandes, 2009; Machin and Sankey, 2008). Older drivers, on the other hand, tend to have slower reaction and processing times as well as decreased visual acuity (Clay et al., 2005; Horswill et al., 2008; Anstey et al., 2005).

3. Study overview, data, & methods

To answer these research questions, we carried out a longitudinal spatial analysis - gathering data for the same locations over a period of thirteen years - of road safety outcomes in cities with and without high-bicycling mode shares. This section overviews the study design, followed by the data collection efforts, and finishes by describing the statistical analysis.

With respect to site selection, the fundamental intent was to select cities across a spectrum of bicycling, bicycling infrastructure, and road safety outcomes. Hence, we first acquired city-level American Community Survey (ACS) data so that we could assess mode share longitudinally. We then supplemented the ACS data with the data behind the Alliance for Biking and Walking Benchmarking Report (Milne and Melin, 2014). This included, for the fifty most populous U.S. cities, city-level bicycling-related data such as mileage of bike facility by type, density of bike facility by type, and bicyclist fatalities per 10,000 bicycling commuters. The intent was to use this data get a better sense of these cities in terms of bicycling activity and the different types of bicycling infrastructure being installed. We also retrieved fatal crash data from the Fatality Analysis Reporting System (FARS) and calculated fatal crash rates by year for each city from 1990 onward.

As discussed above, we wanted to find cities that exhibited a broad range of road safety outcomes and bicycling rates as well as cities with varying degrees of investment in bicycle-specific infrastructure. Data availability was another important criterion (for instance, despite persistent attempts, we were unable to acquire non-fatal crash data from Baltimore). Based on our assessment of the

Table 1
City selection.

	Population	Fatal Crash Rate (fatalities per 100k pop.)			1990's to 2010's		Bike Mode Share				1990 to 2015	
		1990's	2000's	2010's	Δ Crash Rate	Percent Change	1990	2000	2010	2015	Δ Mode Share	Percent Change
Oklahoma City, OK	6,38,367	16.2	14.9	12.6	−3.6	−22.2%	0.1%	0.1%	0.2%	0.1%	0.0%	−28.1%
Memphis, TN	6,52,717	20.3	16.5	13.5	−6.8	−33.5%	0.1%	0.1%	0.2%	0.1%	0.0%	−25.3%
Kansas City, MO	481,420	18.3	15.3	13.6	−4.7	−25.8%	0.1%	0.1%	0.3%	0.1%	0.0%	−10.5%
Dallas, TX	1,317,929	16.5	13.6	11.2	−5.3	−32.2%	0.2%	0.1%	0.1%	0.2%	0.0%	29.5%
Houston, TX	2,303,482	14.0	13.1	11.2	−2.7	−19.5%	0.4%	0.5%	0.4%	0.5%	0.1%	42.3%
Austin, TX	947,890	12.0	11.2	8.4	−3.5	−29.5%	0.8%	0.9%	1.5%	1.3%	0.5%	67.2%
Chicago, IL	2,704,958	9.4	7.7	5.8	−3.6	−38.2%	0.3%	0.5%	1.3%	1.8%	1.5%	541.4%
Denver, CO	682,545	11.1	10.5	6.6	−4.5	−40.3%	0.9%	1.0%	2.3%	2.1%	1.2%	143.4%
Seattle, WA	704,352	11.6	5.6	4.6	−7.0	−60.6%	1.5%	1.9%	3.4%	4.0%	2.5%	163.8%
San Francisco, CA	864,816	8.9	6.2	4.5	−4.4	−49.3%	1.0%	2.0%	3.4%	4.3%	3.3%	348.1%
Minneapolis, MN	413,651	6.4	5.5	4.1	−2.3	−36.2%	1.6%	1.9%	4.1%	5.0%	3.4%	207.8%
Portland, OR	639,863	14.0	7.4	5.1	−8.9	−63.5%	1.2%	1.8%	6.1%	7.0%	5.8%	504.5%

Table 2
Descriptive Statistics (selected variables).

		Variable	Obs	Mean	SD	Min	Max
Dependent Variables							
	Block Group Level:	Fatal Crashes	112,918	0.15	0.51	0	29
	Block Group Level:	Fatal & Severe Injury Crashes	112,918	0.84	1.64	0	40
Population Variables							
	City Level:	Population *(in 1000s)*	156	942	705	383	2,896
	Block Group Level:	Population	112,918	1,479	576	0	13,362
Travel Behavior Variables							
Category 1	*City Level:*	Bicycle Mode Share to Work	156	1.52	1.52	0.11	7.01
	City Level:	Transit Mode Share to Work	156	10.90	9.51	0.53	32.67
	City Level:	Work from Home Modal Share	156	4.19	1.46	1.73	7.64
	Block Group Level:	Bicycle Mode Share to Work	112,918	1.06	2.51	0	62.40
	Block Group Level:	Transit Mode Share to Work	112,918	13.53	13.96	0	100
	Block Group Level:	Work from Home Modal Share	112,918	3.75	4.31	0	100
Built Environment Variables							
Category 2	*City Level:*	Density of Protected/Separated Bike Facilities *(100s of ft. per sq. mi.)*	156	30.8	30.8	0	111.6
	City Level:	Density of Bike Lanes *(100s of ft. per sq. mi.)*	156	29.3	35.8	0	135.8
	City Level:	Density of Sharrows *(100s of ft. per sq. mi.)*	156	41.5	106.3	0	588.3
	City Level:	Population Density *(pop. per sq. mi.)*	156	5,282	4,571	816	17,234
	City Level:	Intersection Density *(intersections per sq. mi.)*	12	181.0	97.8	53.0	396.0
	City Level:	Driving Speed Variable *(mph)*	12	27.8	6.2	18.0	40.1
	Block Group Level:	Density of Protected/Separated Bike Facilities *(100s of ft. per sq. mi.)*	112,918	61.8	1,717.2	0	144,085
	Block Group Level:	Density of Bike Lanes *(100s of ft. per sq. mi.)*	112,918	120.8	3,866.8	0	467,729
	Block Group Level:	Density of Sharrows *(100s of ft. per sq. mi.)*	112,918	24.2	877.0	0	149,120
	Block Group Level:	Population Density *(pop. per sq. mi.)*	112,918	14,361	21,538	0	1,412,671
	Block Group Level:	Intersection Density *(intersections per sq. mi.)*	8,686	338	220	0	1947
Socio-economic & Socio-demographic Variables							
Category 3	*City Level:*	Percent of Population Age 15 to 24	156	15.16	1.89	11.77	20.33
	City Level:	Percent of Population Age 65 or older	156	10.49	1.79	6.78	14.09
	City Level:	Percent of Population Identifying as White	156	60.19	13.42	28.81	81.28
	City Level:	Median Household Income *(in 1000s)*	156	46.01	8.92	32.29	77.52
	Block Group Level:	Percent of Population Age 15 to 24	112,918	14.22	7.31	0	100
	Block Group Level:	Percent of Population Age 65 or older	112,918	10.65	7.14	0	100
	Block Group Level:	Percent of Population Identifying as White	112,918	54.11	29.76	0	100
	Block Group Level:	Median Household Income *(in 1000s)*	112,918	49.60	28.90	0	291.12

bicycling infrastructure, fatality rates, and bicycle mode shares, we limited our study to twelve cities (primarily thanks to the arduous task of collecting the longitudinal data, particularly with respect to the bike infrastructure data and the non-fatal crash data, which is described later in this section). Table 1 displays the selected cities, ranked in order of bicycle mode share to work. The most recent bicycling mode shares range from almost negligible in a few cities to 7% in Portland. This table also presents fatal crash rates aggregated by decade. Road fatality rates range from 4.1 fatalities per 100,000 residents in Minneapolis to 13.6 per 100,000 residents in Kansas City. While all cities improved their road safety records over the years, bicycling rates dropped nearly 30% in Oklahoma City but increased by over 500% in Chicago.

We narrowed our study period down to 2000 through 2012 based on the availability of non-fatal crash data (we were particularly interested in severe injury crashes) and historic Google Earth satellite imagery, which was used to determine bike infrastructure installation periods. Since this paper focuses on large cities, it is important to point out that these results are not generalizable to smaller cities. The next sub-section focuses on the data collection efforts. Table 2 presents the descriptive statistics for the accumulated data.

3.1. Data

3.1.1. Crash data

The FARS database was created in the mid-1970s by the National Highway Traffic Safety Administration (NHTSA) to document all motor vehicle crashes resulting in a fatality (within 30 days of crash) on public roadways (NHTSA, 2017b). While the underlying FARS data is compiled from police crash reports and hospital reports separately by different states and multiple agencies, NHTSA staff cross-check all data before it enters the final database. For our time period of 2000 through 2012, we were able to geocode nearly all crashes occurring after 2001 using latitude and longitude information. The remaining fatal crashes were geocoded (using ESRI Online geocoding in combination with the online mapping services MapQuest and Google) to the highest degree of accuracy possible based on the location information provided by FARS. The location information for these crashes typically included the name of the street where the crash occurred and the nearest cross street, and such crashes were geocoded to the nearest intersection. Within this step, we tested a subset of geocoded crashes for accuracy or systematic errors and found no issues. In total, we were able to successfully geocode all of the approximately 17,000 fatal crash records.

We collected non-fatal crash data from each of the cities. Three cities (Denver, Minneapolis, and Portland) had the data already available in GIS format. Four other cites (Austin, Chicago, Dallas, and Houston) gave us spreadsheet data with latitude/longitude columns included. The data for the remaining cities had some coordinate data but mostly had to be geocoded in the same fashion that we used for the FARS data. Due to differences by city in terms of crash severity definitions, we separated the crash data into two groups: those that resulted in a severe injury and all other crashes. This process resulted in 77,456 severe injury crashes and 3,531,504 total crashes with a geocoding success rate of 97.9%.

Using GIS, each of the geocoded crashes was counted and summed at the Census block group level of geography. The Census block group is the unit of analysis for our study because it is the smallest geographic unit that has journey to work data available. Our twelve cities include 8,686 block groups (at an average of approximately 724 block groups per city), each with 13 years of data, for a total of 112,918 observations. According to the Census, a block group averages 250–500 housing units but varies in terms of area depending upon housing density.

It is worth pointing out that such aggregated Census data may be affected by the modifiable areal unit problem and that similar studies based on a different geographic unit may find different results (Spielman et al., 2014). Another potential limitation is the ecological fallacy, so we should be careful not to assume that relationships found at the group level also apply at the individual level (Kramer, 1983; Schwartz, 1994).

3.1.2. Census and American community survey data

In order to control for travel behavior changes, we collected journey-to-work Census data from the National Historical Geographic Information System (NHGIS) for the years 2000 and 2010 as well as ACS data for 2012 for both the city and block group level (Manson et al., 2017). Our variables of interest were bicycle mode share to work, transit mode share to work, and the work from home mode share. Driving mode share had a high inverse correlation with transit mode share and was not included in the analysis. For the sake of the longitudinal analysis, we interpolated between the Census and ACS years for each variable using the trend function in Microsoft Excel, which performs a linear least squares statistical regression. While annual data would have been preferred, such data was not available for these variables.

Akin to the travel behavior data, we collected socio-demographic and socio-economic changes – in terms of age, race/ethnicity, and income – from the Census and ACS. In terms of age, we developed several age-related variables based on categories that the literature suggests have the highest risk. We created variables identifying the percent of the population age 15 to 24 and the percent of the population age 65 or older, with the thinking being that places with a higher percentage of those age groups may have worse road safety outcomes, all things being equal. Our race/ethnicity variables were highly correlated with one another and could result in multicollinearity and biased estimators; as a result, we aggregated the data into a variable representing the percentage of non-Hispanic white residents. Income variables represented median household income in thousands of dollars.

3.1.3. Built environment data

With this research, we want to understand the influence that bike infrastructure might have on road safety outcomes. Although most of our cities managed bike infrastructure GIS layers, only Portland included the year each facility was built as an attribute. For our other cities, collecting longitudinal bike infrastructure proved to be relatively difficult and time consuming. The objective was to categorize and time stamp each piece of bike infrastructure in each city by type (i.e. protected/separated bike facilities, bike lanes, and shared lane markings or sharrows) and the year it was built. This required a combination of emails/phone calls with city planners and in-depth review of old bike maps and historic satellite imagery available in Google Earth. The goal was to be as accurate as possible given the data limitations, so most of this work was done manually and ended up being quite time consuming. When we compared our ability to discern bike infrastructure via Google Earth imagery against old bike maps, our results matched up well. During the Google Earth work, however, we noticed that some protected/separated cycle tracks, for instance, were previously bike lanes or sharrows. This led us to perform the same satellite imagery review for Portland as well. After categorizing and time stamping each piece of bike infrastructure based on Federal Highway Administration (FHWA) definitions, we calculated the cumulative length and density of each facility type for each year (FHWA, 2015).

To control for the impact of the built environment, we also sought out population density data. Population density has long been used as a measure of urban form and has been shown to be associated with fatal crash outcomes (Ewing and Dumbaugh, 2009; Marshall and Ferenchak, 2017; Ewing et al., 2014; Marshall and Garrick, 2010a; Tsai, 2005). Since boundaries sometimes change over time (such as when a city annexes new land), we wanted to be careful not to simply calculate population density based upon the most recent areas. Accordingly, we downloaded historic GIS shapefiles from NHGIS and calculated population density using time series population data and the shapefile from the nearest year.

We also collected cross-sectional intersection density data at the block group level, calculated as the number of intersections, including dead ends, per square mile (Marshall and Garrick, 2012). Intersection density is a measure of street network compactness or density (Marshall and Garrick, 2012) and has been shown to be associated with road safety outcomes (Marshall and Garrick, 2011a) as well as vehicle speed. Yokoo and Levinson (2016) used GPS data to study actual travel speeds in relation to street network variables and found long links to be conducive to higher speeds (Yokoo and Levinson, 2016). In order to gain a better sense of the impact of the built environment on vehicle speeds, we also collected data from an open source program called CitySpeed that aggregates an average driving speed in each city by mapping the distance and duration of over 1,000 routes in each city (Kleint, 2009). Based upon an origin-destination matrix determined by popular coffee shops and schools, this Python script then collects data for each origin-destination pair from the Google Maps API regarding average speed, distance, duration, number of turns, and the number of turns per mile. We collected data from the CitySpeed program for each of our cities and tested the city-level average driving speed result in the statistical analysis. The fact that speed data could not be collected at the block group level was a further limitation of the study.

3.2. Statistical methodology

This research tries to understand what makes high-bicycling-mode-share cities safer for all road users. The dependent variable for our analysis is a crash count. One common problem with road safety research relates to the handling of injury severity. For instance, some studies intermingle fatal crashes with minor injury crashes and property damage only crashes (Scheiner and Holz-Rau, 2011). Thus, a handful of property damage only crashes could outweigh one or two fatal crashes. We focus on fatalities and severe injuries in order to maintain an emphasis on road safety outcomes as a health impact.

Given that our dependent variable is count-based data, a typical linear regression model may not be appropriate because of the requirement that the dependent response variable be normally distributed (Long, 1997). Researchers, instead, frequently apply generalized linear models (GLM) when analyzing crash data because they can account for a non-normal distribution using a link function that relates the linear portion of the model to the mean of the dependent variable. Link functions allow the response variable to relate to the explanatory variables in a nonlinear way (Long, 1997).

Since our dependent variable is count data, we initially looked to a Poisson distribution (which is a discrete probability distribution intended to measure the rate of occurrence of some event) to see if it had the correct distributional properties, but since our data is considered over-dispersed (i.e. the variance in our response variables exceeds the mean), the negative binomial is more appropriate. The negative binomial model is a generalized version of the Poisson model that accounts for this over-dispersion by introducing a random stochastic component to the log-linear Poisson mean function relationship (Long, 1997; Noland and Quddus, 2004; Lord et al., 2005).

We conducted a longitudinal study, using time in years as a variable, since it can help provide insight into the potential causal factors underlying changes in transportation safety outcomes (Zhou et al., 2009). We also used a multilevel, hierarchical statistical approach. Multilevel statistical models have become standard practice for researchers conducting spatial health studies over the last two decades (Radenbush and Bruk, 2002; Subramanian et al., 2003; Burton et al., 2009; Healy, 2001; Li et al., 2005; Rundle et al., 2007). Multilevel models help account for spatial autocorrelation and the idea that block group-level outcomes in the same cities share the characteristics of those cities, which would infringe upon the independence assumption of typical statistical models (Ewing et al., 2003b). Since our data consists of road safety outcomes and possible explanatory factors on both the block group and city levels, we grouped those levels accordingly. For instance, when comparing a standard model against a multilevel model with bicycle mode share as the independent variable, we found higher bicycle mode share to be significantly associated with fewer fatalities in the standard model but non-significant when accounting for the multilevel nature of our data. This example reveals the importance of selecting the most appropriate model when trying to understand safety in our cities.

In developing our database, one consistent issue was high correlation among some of our variables. For instance, population density and transit mode share had a Pearson correlation coefficient of 0.95 at the city level, which suggests a very high positive correlation. The related statistical problem was that including such highly-correlated variables in the same model could result in multicollinearity and biased estimators. While we would normally omit one of the offending variables from the final statistical model to deal with this issue, one objective of this paper was to understand the relative influence of the possible pathways to road safety outcomes. To best assess these differences, we separated the pathways and initially tested each one separately against our dependent variables. The following and the left-hand portion of Table 2 indicates this structure:

- Category 1: Travel Behavior Data
- Category 2: Built Environment Data
- Category 3: Socio-demographic and Socio-economic Data

After presenting the results of each category, we combine them into final models. First stepping through the results category-by-category meant that we could eliminate non-significant variables found in the category models from the full models, which was useful in dealing with the multi-collinearity issues (see Appendix 1 for a correlation matrix). The model fit variables shown in the results tables include log-likelihood and Wald chi-square. While these fit statistics cannot be compared across models, we used them to help with final variable selection for the full models using Stata 15.

We account for exposure in all of our models with population data at the block group level. Population-based exposure metrics are considered a better measure of road safety as a health statistic and are common in studies that consider socio-demographic and socio-economic issues (Sewell et al., 1989; Gallaher et al., 1992; Schiff and Becker, 1996; Campos-Outcalt et al., 2003; Marshall and Ferenchak, 2017; Marshall and Garrick, 2010b). According to McAndrews et al., for example, outcomes based on population-based exposure reflect overall societal risk while those based on travel exposure (e.g. distance or time) reflect travel risk (Mcandrews et al., 2013).

4. Results

4.1. Category-by-category model results

As described in the statistical methodology section above, we initially developed statistical models for each data category individually. These results are presented first and include a fatality model followed by a fatal and severe injury model. If a variable in one of these models was determined to be non-significant in these category-by-category results, we were able to remove it from the corresponding full model. Every model controls for population at the block group level, and to ease interpretation of the resulting coefficients, all independent variables were standardized (for each variable, we subtracted the mean and divided by the standard deviation so that the standardized value represents the number of standard deviations above or below the mean and the resulting coefficients are more directly comparable). When dealing with multi-collinearity issues, we selected the presented models based upon model fit statistics. Akin to most crash studies, the results verify the dispersion parameters as significantly greater than zero and the data over-dispersed. This indicates that negative binomial model is more appropriate than the Poisson model. Since the city-level intercept is significantly different from zero, the hierarchical model is more appropriate.

4.1.1. Travel behavior results

In the fatality model shown in Table 3, bicycling mode share at both the city and block group level is non-significant. This suggests that factors other than bicycling mode share may better account for differences in fatal crash outcomes. In the fatal and severe injury model, bicycling mode share – at both the city and block group level – is significantly associated with worse safety outcomes. Overall, the results do not suggest a 'safety in numbers' effect when it comes to bicycling and road safety for all road users.

City-level transit mode share was non-significant in both models but associated with more crashes when measured at the block group level. While riding transit is generally considered to be safer than driving, transit usage requires additional time as a pedestrian, which could potentially explain the seemingly increased risk. This result may also speak to socio-demographic and socio-economic differences with respect to road safety risk. As the existing literature described above suggests, minority populations and lower income groups tend to be associated with additional crash risk, all other variables being held equal. At the same time, these populations have also been shown to have higher transit rates (Rosenbloom and Clifton, 1996). Since this first model does not include socio-demographic or socio-economic variables, it makes sense that higher transit usage at the block group level may be associated with worse safety outcomes despite per-mile transit being safer than driving. City-level work from home mode share was significant in the fatality model and associated with fewer crashes.

While the time variable is non-significant in this first fatality model, it is highly significant in all of the other models presented in this paper. The results are consistent and suggest fewer fatalities over time but additional severe injury crashes over time. This trend may be at least partially facilitated by safer vehicle designs, better emergency services, and – in some places – a trend toward safer and slower streets (Jones, 2002; Harris et al., 2002; Anderson et al., 2015).

4.1.2. Built environment results

In terms of bike infrastructure, the variables representing the density of protected/separated bike facilities and the density of standard bike lanes were highly correlated with one another at both the city and block group levels (Pearson correlation coefficients of 0.68 and 0.60, respectively). The results suggest that increased density of bike facilities (either protected/separated or standard bike lanes) is associated with fewer crashes across both severity levels. Since the model employing both the city and block group-level protected/separated bike facilities variables led to the strongest model fit statistics, Table 4 displays these results. The density of shared lane markings (road markings used to indicate a shared car/bicycle lane and more commonly known as sharrows) turned out to be non-significant.

Higher intersection density at the block group level, a measure of street network compactness and typically illustrative of slower speed streets, was associated with fewer road fatalities as well as fewer fatal and severe crashes. Population density suggested similar trends (i.e.

Table 3
Category 1 travel behavior negative binomial statistical models.

Variable	Fatal Crash Model			Fatal & Severe Injury Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	−1.9431	< .0001	0.1083	−1.2372	< .0001	0.2443
City Level Variables						
Bike Mode Share	–			0.2668	< .0001	0.0211
Transit Mode Share	–			–		
Work from Home Share	– 0.1422	0.001	0.0420	–		
Block Group Level Variables						
Population	0.1626	< .0001	0.0081	0.1692	< .0001	0.0051
Bike Mode Share	–			0.0284	< .0001	0.0069
Transit Mode Share	0.0938	< .0001	0.0133	0.1041	< .0001	0.0069
Work from Home Share	–			–		
Longitudinal Effects						
Time (years)	– 0.0002	0.968	0.0052	0.1226	< .0001	0.0019
Model Fit						
log of Dispersion Parameter	0.7388		0.0269	0.2870		0.0105
Hierarchical Effects: City Variance	0.1327		0.0568	0.7147		0.2937
Log-Likelihood	−49,078			−130,408		
Wald Chi-Square	554			8.791		
No. of Observations Used	112,918			112,918		
Number of Groups	12			12		

Table 4
Category 2 built environment negative binomial statistical models.

Variable	Fatal Crash Model			Fatal & Severe Injury Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	−1.9413	< .0001	0.0550	−1.2678	< .0001	0.1672
City Level Variables						
Population Density	–			–		
Density of Protected/Separated Bike Facilities	−0.2566	0.023	0.0425	−0.2317	< .0001	0.0622
Density of Standard Bike Lanes	–			–		
Density of Sharrows	–			–		
Driving Speed Variable	–			–		
Block Group Level Variables						
Population	0.1433	< .0001	0.0081	0.1549	< .0001	0.0051
Population Density	–			–		
Intersection Density	–0.2724	< .0001	0.0136	−0.1152	< .0001	0.0067
Density of Protected/Separated Bike Facilities	–0.0322	0.046	0.0161	−0.0300	< .0001	0.0078
Density of Standard Bike Lanes	–			–		
Density of Sharrows	–			–		
Longitudinal Effects						
Time (years)	–0.01123	< .0001	0.0026	0.14289	< .0001	0.0021
Model Fit						
log of Dispersion Parameter	0.69453		0.0273	0.28610		0.0105
Hierarchical Effects: City Variance	0.03238		0.0141	0.33349		0.1367
Log-Likelihood	−48,881			−1,30,470		
Wald Chi-Square	954			8744		
No. of Observations Used	1,12,918			1,12,918		
Number of Groups	12			12		

higher population density significantly associated with better road safety outcomes), but the variable was highly correlated with intersection density but with reduced model fit statistics. The cross-sectional, city-level speed variable was not significant in either model.

4.1.3. Category 3: socio-demographic and socio-economic results

With regard to race and income, the category 3 results in Table 5 generally support the literature findings. In terms of fatalities, the results suggest that, all things being held equal, we would expect fewer fatalities as block groups and cities gain higher proportions of white residents. Income results were similar, in that higher incomes were associated with better road safety outcomes, but income was highly correlated with the race variable, which resulted in the stronger models that are presented. The block-group race variable holds in the fatal and severe injury model as well but is non-significant at the city level.

In terms of age, cities with a higher percentage of the population older than 65 are significantly associated with fewer fatalities. The same can be said when looking at fatal and severe injuries with respect to the percent of the population older than 65 at the block group level. While older populations may have increased risk on a per-mile basis, they may also have lower exposure and reduced population-based crash rates. As for young people age 15 to 24, we find more young people at the block group level to be significantly associated with more fatal and severe injury crashes.

4.2. Full model results

This section combines all the significant variables found above into full statistical models. Table 6 presents the resulting statistical models, and the dispersion parameters indicate that the negative binomial model is appropriate. Table 7 presents the percent change in expected crash counts based upon changing the level of a single variable and holding all other variables at their mean value for the dataset. These values are mathematically the same as elasticity measures but easier to visualize and comprehend (Noland and Quddus, 2004). The reference values tend to be close to the mean of that variable, and the levels generally correspond with the standard deviation. To illustrate the logic of how Table 7 functions, consider the lower right box, which presents the expected crash outcomes at different levels of the variable representing the percent of the population age 65 or older. At the reference value, 10% of the block group population is age 65 or older. With all other variables held at their mean, we could expect 0.79 fatal/severe injury crashes per block group per year, which equates to a crash rate of 53.4 fatal/severe injury crashes per 100,000 residents annually. In a block group where 20% of the population is 65 or older, we would expect only 0.76 fatal/severe injury crashes per block group per year. This equates to a fatal/severe injury crash rate of 51.2 per 100,000 residents annually, a 4.2% decrease.

The remainder of this section describes the results based upon such expected crash rate differences.

4.2.1. Category 1: travel behavior results

When combining the three variable categories in the same models, nearly all the travel behavior variables lose their significance. This includes the transit variables that become non-significant when either the race or income variables are added. The remaining travel behavior variable is bicycling mode share at the block group level in the fatal/severe injury model. For a block group with 3%

Table 5
Category 3 socio-demographic & socio-economic negative binomial statistical models.

Variable	Fatal Crash Model			Fatal & Severe Injury Model		
	Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
Constant	−1.7543	< .0001	0.1238	−1.2508	< .0001	0.1772
City Level Variables						
Age: % of Population 15 to 24	–			–		
Age: % of Population 65 Plus	–0.1326	0.021	0.0576	–		
Race: % of Population White	–0.3069	< .0001	0.0910	–		
Median HH Income (1000's)	–			–		
Block Group Level Variables						
Population	0.1653	< .0001	0.0081	0.1583	< .0001	0.0051
Age: % of Population 15 to 24	–			0.0379	< .0001	0.0056
Age: % of Population 65 Plus	–			–0.0281	< .0001	0.0055
Race: % of Population White	–0.1644	< .0001	0.0099	–0.0999	< .0001	0.0055
Median HH Income (1000's)	–			–		
Longitudinal Effects						
Time (years)	–0.01578	< .0001	0.0024	0.13729	< .0001	0.0015
Model Fit						
log of Dispersion Parameter	0.72331		0.0270	0.28581		0.0105
Hierarchical Effects: City Variance	0.16877		0.0809	0.37527		0.1532
Log-Likelihood	−48,952			−1,30,380		
Wald Chi-Square	795			8893		
No. of Observations Used	1,12,918			1,12,918		
Number of Groups	12			12		

bike mode share compared to the reference value of 1.3%, this equates to 3.9% more fatal/severe injury crashes, holding all other variables at their mean. So, when we ask the question as to what makes high-bicycling-mode-share cities safer for all road users, the answer does not seem to be a 'safety in numbers' effect.

4.2.2. Category 2: built environment results

Though bike mode share did not explain much in terms of differences in safety outcomes, the infrastructure cities build for bicyclists played a more significant role. For example, with the variable representing the density of protected/separated bike facilities at the city level, the reference value of 25 equates to 2,500 linear feet of protected or separated bike facilities per square mile. At that density of protected/separated bike infrastructure, we would expect 0.14 fatalities and 0.79 fatal/severe injury crashes per block group per year. This equates to annual crash rates of 9.7 fatalities per 100,000 residents and 53.4 fatal/severe injury crashes per 100,000 residents. If we increase the density of protected/separated bike facilities to 5,000 linear feet per square mile (approximately 1 standard deviation increase), and holding all other variables at their mean value, we would expect 0.12 fatalities and 0.61 fatal/severe injury crashes per block group per year. With annual crash rates of 7.9 fatalities per 100,000 residents and 41.5 fatal/severe injury crashes per 100,000 residents, this suggests a nearly 18% drop in the fatal crash rate and more than a 22% drop in the fatal/severe injury crash rate. At the highest level of citywide protected/separated bike infrastructure, we would expect a 44% reduction in the fatal crash rate and more than 50% drop in the fatal/severe injury crash rate, all other variables held at their mean.

While a higher density of protected/separated bike facilities at the block group level is associated with fewer crashes in both models, the results suggest that bike infrastructure at the city level is more important. For instance, we would expect a little less than a 3% reduction in both fatalities and fatal/severe crashes when the density of protected/separated bike infrastructure increases from the mean reference level to approximately one standard deviation higher. We also tested the variables representing the density of standard bike lanes in place of the protected/separated bike facility variables, and even though both standard bike lane variables were significant in the category models, they interestingly become non-significant in the full models. This suggests that improved road safety for all road users is tied to the prevalence of protected/separated bike facilities much more so than the prevalence of standard bike lanes.

With the built environment results, we also found that higher intersection densities at the block group level correspond with fewer expected crashes across both severity levels when holding all other variables at their mean. Since intersection density has been shown to be an appropriate proxy for the level of urbanity, these results support the research showing that more urban neighborhoods have better safety outcomes (Marshall and Ferenchak, 2017; Ewing et al., 2014).

4.2.3. Category 3: socio-demographic and socio-economic results

For the variables representing gentrification and the changing demographics of a city or neighborhood, the results suggest fewer fatalities as a city or neighborhood becomes whiter. Median household income would have been similarly significant to the race variables, but the resulting models were not as strong. In terms of the city-level race variable, it was non-significant in the second model, but we would expect a 10% decrease in the fatality rate when a city changes from 50% to 60% white. The block group race variable had a similar effect in both models but to a lesser extent. As the neighborhood gentrifies and a greater percentage of white residents arrive, a jump from 50% to 60% white suggests an expected drop in fatalities of 5% and a drop in fatal and severe crashes of just over 3%. These results support studies that suggest changing demographics and economics can play a role in road safety

Table 6
Full negative binomial statistical models.

Category 1	Travel Behavior	Variable	Fatal Crash Model			Fatal & Severe Injury Model		
			Coefficient	p-value	S.E.	Coefficient	p-value	S.E.
		Constant	−1.8853	< .0001	0.0579	−1.2554	< .0001	0.1682
		City Level Variables						
		Bike Mode Share	–			–		
		Transit Mode Share	–			–		
		Work from Home Share	–			–		
		Block Group Level Variables						
		Bike Mode Share	–			0.0559	< .0001	0.0054
		Transit Mode Share	–			–		
		Work from Home Share	–			–		
Category 2	Built Environment	*City Level Variables*						
		Population Density	–			–		
		Driving Speed Variable	–			–		
		Density of Protected/Separated Bike Facilities	0.1939	< .0001	0.0436	0.2505	< .0001	0.0623
		Density of Standard Bike Lanes	–			–		
		Density of Sharrows	–			–		
		Block Group Level Variables						
		Population Density	–			–		
		Intersection Density	0.2715	< .0001	0.0137	0.1213	< .0001	0.0068
		Density of Protected/Separated Bike Facilities	0.0297	0.059	0.0158	0.0286	< .0001	0.0077
		Density of Standard Bike Lanes	–			–		
		Density of Sharrows	–			–		
Category 3	Demographics & SES	*City Level Variables*						
		Age: % of Population 15 to 24	–			–		
		Age: % of Population 65 Plus	–			–		
		Race: % of Population White	0.1255	0.041	0.0613	–		
		Median HH Income (1000's)	–			–		
		Block Group Level Variables						
		Population	0.1465	< .0001	0.0080	0.1521	< .0001	0.0051
		Age: % of Population 15 to 24	–			0.0389	< .0001	0.0056
		Age: % of Population 65 Plus	–			0.0307	< .0001	0.0055
		Race: % of Population White	0.1591	< .0001	0.0098	0.1002	< .0001	0.0056
		Median HH Income (1000's)	–			–		
		Longitudinal Effects						
		Time (years)	0.0130	< .0001	0.0026	0.1414	< .0001	0.0021
		Model Fit						
		log of Dispersion Parameter	0.6745		0.0275	0.2705		0.0105
		Hierarchical Effects: City	0.0315	< .0001	0.0181	0.3374	< .0001	0.1384
		Log-Likelihood	−48,741			−1,30,163		
		Wald Chi-Square	1219			9328		
		No. of Observations Used	1,12,918			1,12,918		
		Number of Groups	12			12		

outcomes (Mcandrews et al., 2013). They are also suggestive of equity disparities that deserve additional research.

In the full fatality model, the age variables become non-significant. The block group-level age subgroup variables, however, remain significant in the fatal/severe injury model while the city-level age variables both drop out. This suggests that city-level age distributions do not seem to be important factors in block group-level crash outcomes. In terms of block group-level age categories, an increase in those aged 15 to 24 from 10% to 15% of the block group population suggests an almost 3% increase in fatal/severe injury crashes. If the population of those aged 65 or older similarly increases from 10% to 15% of the block group population, we would expect a 2% decrease in fatal/severe injury crashes. These results may speak to the possibility of reduced travel exposure for those over 65 years old. In other words, their risk may be higher per mile of travel, but if they travel less, the result may be improved road safety outcomes.

5. Conclusions

What makes high-bicycling-mode-share cities so much safer than many of their counterparts? Our results suggest that more bicyclists on the road is not as important as the infrastructure we build for them. More specifically, our results suggest that improving bike infrastructure with more protected/separated bike facilities is significantly associated with fewer fatalities and better road safety outcomes for all road users. It stands to reason that such infrastructure may help improve bicyclist safety. Then again, our study finds protected/separated bike facilities significantly associated with better safety for all road users, so such infrastructure may have a traffic calming effect and facilitate safer speeds. Given our results, we also cannot ignore the possibility that the lower road safety risks of the people that tend to inhabit high-bicycling-mode-share cities also plays a role, as our variables representing gentrifying neighborhoods were also significant. This outcome may be indicative of inequity issues in need of additional research.

In terms of study limitations, it is important to understand that the relationship between safety outcomes and bicycling activity is quite complex and possibly bi-directional. Better safety outcomes – or at least the perception of better safety – can lead to increased

Table 7
Expected change in crash counts for full models.

	Fatality Model					Fatal & Severe Injury Model				
	Expected Crashes[a]	p-value	S.E.	Crash Rate[b]	Percent Change[c]	Expected Crashes[a]	p-value	S.E.	Crash Rate[b]	Percent Change[c]
Base Annual Expected Crash Outcomes/Crash Rates[a]	0.143	< .0001	0.0086	9.6	–	0.788	< .0001	0.1439	53.3	–
Category 1 - Travel Behavior Differences										
BG Level: Bicycling Mode Share to Work[d]										
0.0%						0.770	< .0001	0.1406	52.1	−2.8%
1.3% (reference value)						0.792	< .0001	0.1447	53.6	–
3.0%						0.823	< .0001	0.1503	55.6	3.9%
5.0%						0.860	< .0001	0.1572	58.2	8.6%
7.0%						0.899	< .0001	0.1646	60.8	13.5%
Category 2 - Built Environment Differences										
City Level: Protected/Separated Bike Facility Density *(in 100s of feet per sq. mi.)*										
0	0.174	< .0001	0.0135	11.8	21.6%	1.018	< .0001	0.2036	68.8	28.8%
25 (reference value)	0.143	< .0001	0.0086	9.7	–	0.790	< .0001	0.1443	53.4	–
50	0.117	< .0001	0.0084	7.9	−17.8%	0.614	< .0001	0.1142	41.5	−22.4%
100	0.079	< .0001	0.0112	5.4	−44.4%	0.370	< .0001	0.0913	25.0	−53.2%
BG Level: Protected/Separated Bike Facility Density *(in 100s of feet per sq. mi.)*										
60 (reference value)	0.143	< .0001	0.0085	9.6	–	0.788	< .0001	0.1437	53.3	–
1750	0.139	< .0001	0.0085	9.4	−2.8%	0.766	< .0001	0.1400	51.8	−2.7%
3500	0.134	< .0001	0.0091	9.1	−5.7%	0.744	< .0001	0.1363	50.3	−5.5%
7000	0.126	< .0001	0.0111	8.6	−11.3%	0.702	< .0001	0.1300	47.5	−10.9%
BG Level: Intersection Density										
81	0.196	< .0001	0.0120	13.3	19.5%	0.908	< .0001	0.1660	61.4	8.3%
144	0.181	< .0001	0.0110	12.3	10.5%	0.877	< .0001	0.1602	59.3	4.6%
225 (reference value)	0.164	< .0001	0.0099	11.1	–	0.839	< .0001	0.1532	56.7	–
324	0.145	< .0001	0.0087	9.8	−11.5%	0.794	< .0001	0.1450	53.7	−5.3%
Category 3 - Socio-economic/Socio-demographic Differences										
City Level: Percent of Population Identifying as White										
30%	0.185	< .0001	0.0309	12.5	22.4%					
40%	0.167	< .0001	0.0200	11.3	10.6%					
50% (reference value)	0.151	< .0001	0.0117	10.2	–					
60%	0.136	< .0001	0.0074	9.2	−9.6%					
70%	0.123	< .0001	0.0088	8.3	−18.3%					
BG Level: Percent of Population Identifying as White										
30%	0.162	< .0001	0.0098	11.0	11.3%	0.855	< .0001	0.1561	57.8	7.0%
40%	0.154	< .0001	0.0093	10.4	5.5%	0.826	< .0001	0.1509	55.9	3.4%
50% (reference value)	0.146	< .0001	0.0088	9.9	–	0.799	< .0001	0.1459	54.0	–
60%	0.138	< .0001	0.0083	9.3	−5.2%	0.773	< .0001	0.1411	52.2	−3.3%
70%	0.131	< .0001	0.0079	8.9	−10.1%	0.747	< .0001	0.1364	50.5	−6.5%
BG Level: Percent of Population Age 15 to 24										
0%						0.731	< .0001	0.1337	49.4	−5.2%
5%						0.750	< .0001	0.1371	50.7	−2.6%
10% (reference value)						0.771	< .0001	0.1407	52.1	–
15%						0.791	< .0001	0.1445	53.5	2.7%
20%						0.813	< .0001	0.1483	55.0	5.5%
BG Level: Percent of Population Age 65 Plus										
0%						0.825	< .0001	0.1508	55.8	4.4%
5%						0.808	< .0001	0.1475	54.6	2.2%
10% (reference value)						0.790	< .0001	0.0144	53.4	–
15%						0.774	< .0001	0.1412	52.3	−2.1%
20%						0.757	< .0001	0.1383	51.2	−4.2%

[a] Calculated using mean values for all other variables.
[b] Crash rates calculated per 100,000 block group residents.
[c] Percentage change from reference value when holding all other variables at their mean.

bicycling. Statistically, the related methodological problem is called endogeneity (Sweet, 2014). The issue is that this could create a situation where the error term in the statistical model is correlated with the variable representing bicycling activity, which could in turn violate the independence assumption and perhaps bias the model (Chatman and Noland, 2014; Duranton and Turner, 2011; Baum-Snow, 2007; Hymel, 2009; Sweet, 2011, 2014). Future studies should attempt to control for potential endogeneity issues. While our study was an extensive data collection project that included twelve large U.S. cities and thirteen years of data, more cities, in more countries, and more years of data would still have been preferable. At this point, the results should not be considered generalizable to other countries or smaller cities.

Taking a broader view, it is important to understand that the potential pathways for safer places are complementary and should not be considered in isolation. Compact street networks in many U.S. cities, for example, are typically representative of lower-speed urban environments with better bike facilities, increased traffic calming, and improved emergency response (Pucher and Dijkstra, 2000; Retting et al., 2003). Those looking towards trying to fulfill the promise of Vision Zero and the goal of zero fatalities or serious injuries on the roads – as opposed to the business-as-usual, whack-a-mole approach to road safety – are in need of evidence-based research. This paper helps fulfill this need and can inform cities in their effort toward a safer and healthier transportation system.

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Appendix 1. Correlation matrix

	Population	Bicycle Mode Share	Transit Mode Share	Work from Home Share	Bicycle Mode Share	Transit Mode Share	Work from Home Share	Separated Bike Facility Density
	BG:	C:	C:	C:	BG:	BG:	BG:	C:
BG: Population	1.00							
C: Bicycle Mode Share	−0.09	1.00						
C: Transit Mode Share	−0.05	0.39	1.00					
C: Work from Home Share	−0.12	0.84	0.33	1.00				
BG: Bicycle Mode Share	−0.07	0.45	0.15	0.37	1.00			
BG: Transit Mode Share	−0.06	0.27	0.72	0.23	0.15	1.00		
BG: Work from Home Share	−0.05	0.24	0.08	0.28	0.13	−0.01	1.00	
C: Separated Bike Facility Density	−0.06	0.78	0.33	0.58	0.34	0.23	0.17	1.00
C: Bike Lane Density	−0.07	0.79	0.64	0.70	0.35	0.46	0.19	0.52
C: Sharrows Density	−0.14	0.46	0.56	0.51	0.19	0.40	0.13	0.20
C: Population Density	−0.03	0.32	0.95	0.30	0.12	0.71	0.07	0.31
C: Intersection Density	−0.03	0.25	0.92	0.17	0.09	0.67	0.03	0.16
C: Driving Speed	−0.03	−0.48	−0.70	−0.52	−0.20	−0.50	−0.16	−0.42
BG: Separated Bike Facility Density	0.04	0.02	0.01	0.01	0.01	0.02	0.04	0.02
BG: Bike Lane Density	0.02	0.02	0.02	0.01	0.01	0.03	0.02	0.01
BG: Sharrows Density	0.00	0.03	0.03	0.03	0.01	0.04	0.01	0.01
BG: Population Density	0.11	0.09	0.42	0.06	0.07	0.43	0.02	0.10
BG: Intersection Density	−0.09	0.17	0.66	0.12	0.13	0.58	0.02	0.11
C: Age 15 to 24	0.04	−0.25	−0.27	−0.32	−0.11	−0.20	−0.08	−0.17
C: Age 65 or older	−0.06	0.28	0.48	0.27	0.11	0.35	0.06	0.24
C: Percent White	−0.01	0.53	−0.28	0.58	0.26	−0.21	0.17	0.42
C: Median Household Income	−0.10	0.67	0.51	0.85	0.28	0.36	0.24	0.52
BG: Age 15 to 24	0.11	−0.08	−0.06	−0.09	0.02	0.04	−0.18	−0.07
BG: Age 65 or older	−0.13	0.03	0.08	0.04	−0.09	−0.02	0.13	0.03
BG: Percent White	0.02	0.22	−0.12	0.24	0.19	−0.26	0.29	0.18
Median Household Income	−0.03	0.18	0.11	0.25	0.05	−0.11	0.36	0.15

	Bike Lane Density	Sharrows Density	Population Density	Intersection Density	Driving Speed	Separated Bike Facility Density	Bike Lane Density	Sharrows Density	Population Density
	C:	C:	C:	C:	C:	BG:	BG:	BG:	BG:
BG: Population									
C: Bicycle Mode Share									
C: Transit Mode Share									
C: Work from Home Share									
BG: Bicycle Mode Share									
BG: Transit Mode Share									
BG: Work from Home Share									
C: Separated Bike Facility Density									

C: Bike Lane Density	1.00								
C: Sharrows Density	0.67	1.00							
C: Population Density	0.60	0.54	1.00						
C: Intersection Density	0.51	0.47	0.88	1.00					
C: Driving Speed	−0.61	−0.41	−0.71	−0.66	1.00				
BG: Separated Bike Facility Density	0.01	0.00	0.00	0.01	−0.01	1.00			
BG: Bike Lane Density	0.03	0.02	0.02	0.02	−0.02	0.89	1.00		
BG: Sharrows Density	0.04	0.06	0.03	0.03	−0.02	0.69	0.87	1.00	
BG: Population Density	0.22	0.17	0.43	0.39	−0.30	0.02	0.03	0.03	1.00
BG: Intersection Density	0.41	0.37	0.64	0.66	−0.47	0.00	0.02	0.03	0.54
C: Age 15 to 24	−0.39	−0.29	−0.29	−0.03	0.30	0.00	0.00	−0.02	−0.12
C: Age 65 or older	0.41	0.34	0.48	0.20	−0.19	0.00	0.00	0.02	0.21
C: Percent White	0.17	−0.11	−0.36	−0.35	−0.01	0.01	0.00	−0.01	−0.17
C: Median Household Income	0.67	0.58	0.53	0.29	−0.53	0.00	0.01	0.04	0.16
BG: Age 15 to 24	−0.08	−0.06	−0.06	−0.01	0.08	0.01	0.00	0.00	0.02
BG: Age 65 or older	0.06	0.06	0.09	0.03	−0.03	0.00	−0.01	−0.01	0.00
BG: Percent White	0.06	−0.06	−0.15	−0.15	−0.03	0.01	0.00	0.00	−0.02
Median Household Income	0.17	0.14	0.12	0.05	−0.17	0.00	0.00	0.01	−0.04

	Intersection Density	Age 15 to 24	Age 65 or older	Percent White	Median Household Income	Age 15 to 24	Age 65 or older	Percent White	Median Household Income
	BG:	C:	C:	C:	C:	BG:	BG:	BG:	BG:
BG: Population									
C: Bicycle Mode Share									
C: Transit Mode Share									
C: Work from Home Share									
BG: Bicycle Mode Share									
BG: Transit Mode Share									
BG: Work from Home Share									
C: Separated Bike Facility Density									
C: Bike Lane Density									
C: Sharrows Density									
C: Population Density									
C: Intersection Density									
C: Driving Speed									
BG: Separated Bike Facility Density									
BG: Bike Lane Density									
BG: Sharrows Density									
BG: Population Density									
BG: Intersection Density	1.00								
C: Age 15 to 24	−0.19	1.00							
C: Age 65 or older	0.29	−0.82	1.00						
C: Percent White	−0.26	−0.07	−0.02	1.00					
C: Median Household Income	0.24	−0.43	0.46	0.28	1.00				
BG: Age 15 to 24	0.01	0.18	−0.15	−0.03	−0.11	1.00			
BG: Age 65 or older	−0.02	−0.16	0.19	−0.01	0.08	−0.38	1.00		
BG: Percent White	−0.09	−0.02	−0.04	0.40	0.11	−0.21	0.08	1.00	
Median Household Income	−0.03	−0.12	0.09	0.08	0.29	−0.36	0.16	0.53	1.00

C = City Level Variable; BG = Block Group Level Variable.

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