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Bicycle infrastructure and the incidence rate of crashes with cars: A case-control study with Strava data in Atlanta

Michael D. Garber[a,b,c,*], **Kari E. Watkins**[d], **W. Dana Flanders**[a,e], **Michael R. Kramer**[a], **R.L. Felipe Lobelo**[f], **Stephen J. Mooney**[g,h], **David J. Ederer**[i], **Lauren E. McCullough**[a]

[a]Department of Epidemiology, Rollins School of Public Health, Emory University, Atlanta, GA, USA

[b]Department of Environmental and Radiological Health Sciences, Colorado State University, Fort Collins, CO, USA

[c]Herbert Wertheim School of Public Health and Human Longevity Science & Scripps Institution of Oceanography, UC San Diego, San Diego, CA, USA

[d]Civil and Environmental Engineering, University of California, Davis, Davis, CA, USA

[e]Department of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, Atlanta, GA, USA

[f]Hubert Department of Global Health, Rollins School of Public Health, Emory University, Atlanta, GA, USA

[g]Department of Epidemiology, University of Washington School of Public Health, USA

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[*]Corresponding author. Environmental Health Building, 1681 Campus Delivery, Fort Collins, CO, 80523-1681, USA. michael.garber@colostate.edu (M.D. Garber).

Author contributions
Conceptualization: MDG, KEW, WDF, MRK, FL, LEM.
Data curation: MDG, KEW, WDF, MRK, FL, LEM, DE.
Formal analysis: MDG, KEW, WDF, MRK, LEM.
Funding acquisition: MDG, KEW, WDF, MRK, FL, LEM.
Investigation: MDG, KEW, WDF, LEM.
Methodology: MDG, KEW, WDF, LEM, SJM.
Project administration: MDG, KEW, WDF, MRK, FL, LEM.
Resources: MDG, KEW, WDF, MRK, LEM, FL.
Software: MDG, WDF.
Supervision: WDF, KEW, LEM, MRK, FL.
Validation: MDG, KEW, WDF, MRK, FL, LEM.
Visualization: MDG.
Roles/Writing - original draft: MDG.
Roles/Writing - review & editing: MDG, KEW, WDF, MRK, FL, LEM, SJM, DE.

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We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.
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Appendix A. Supplementary data
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[h]Harborview Injury Prevention & Research Center, University of Washington, Seattle, WA, USA

[i]Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA, USA

Abstract

Introduction: Bicycling has individual and collective health benefits. Safety concerns are a deterrent to bicycling. Incomplete data on bicycling volumes has limited epidemiologic research investigating safety impacts of bicycle infrastructure, such as protected bike lanes.

Methods: In this case-control study, set in Atlanta, Georgia, USA between 2016–10-01 and 2018–08-31, we estimated the incidence rate of police-reported crashes between bicyclists and motor vehicles (n = 124) on several types of infrastructure (off-street paved trails, protected bike lanes, buffered bike lanes, conventional bike lanes, and sharrows) per distance ridden and per intersection entered. To estimate underlying bicycling (the control series), we used a sample of high-resolution bicycling data from Strava, an app, combined with data from 15 on-the-ground bicycle counters to adjust for possible selection bias in the Strava data. We used model-based standardization to estimate effects of treatment on the treated.

Results: After adjustment for selection bias and confounding, estimated ratio effects on segments (excluding intersections) with protected bike lanes (incidence rate ratio [IRR] = 0.5 [95% confidence interval: 0.0, 2.5]) and buffered bike lanes (IRR = 0 [0,0]) were below 1, but were above 1 on conventional bike lanes (IRR = 2.8 [1.2, 6.0]) and near null on sharrows (IRR = 1.1 [0.2, 2.9]). Per intersection entry, estimated ratio effects were above 1 for entries originating from protected bike lanes (incidence proportion ratio [IPR] = 3.0 [0.0, 10.8]), buffered bike lanes (IPR = 16.2 [0.0, 53.1]), and conventional bike lanes (IPR = 3.2 [1.8, 6.0]), and were near 1 and below 1, respectively, for those originating from sharrows (IPR = 0.9 [0.2, 2.1]) and off-street paved trails (IPR = 0.7 [0.0, 2.9]).

Conclusions: Protected bike lanes and buffered bike lanes had estimated protective effects on segments between intersections but estimated harmful effects at intersections. Conventional bike lanes had estimated harmful effects along segments and at intersections.

Keywords

Bicycle infrastructure; Strava; Case-control studies; Bicycling safety; Atlanta; Georgia; Causal inference

1. Introduction

Bicycling is beneficial for communities (Pucher and Buehler, 2017; Garrard et al., 2021; Götschi et al., 2016). It is a form of physical activity (Bauman et al., 2011), which has several physiologic benefits (Piercy et al., 2018). The broader community also benefits from less air pollution (Neves and Brand, 2019), greenhouse-gas emissions (Brand et al., 2021), and noise (Laverty et al., 2021), as well as more equitable street-space allocation (Creutzig et al., 2020). Bicycling as a mode of transportation is nevertheless rare in the U.S., comprising about 1% of daily trips (Buehler et al., 2021). Perhaps the primary barrier to bicycling is the concern that it is unsafe, specifically fear of motor-vehicle-bike collisions and of motor-vehicle traffic in general (de Souza et al., 2014; Winters et al., 2011; Fowler et al., 2017; Aldred et al., 2017). Although individual health benefits from bicycling can outweigh risks (Garrard et al., 2021; Götschi et al., 2016), safety concerns are warranted (Buehler et al., 2021). Per trip, bicyclists have a higher risk of both fatality and nonfatal traffic injury than do car occupants in many settings (Feleke et al., 2018; Scholes et al., 2018; Beck et al., 2007; Bouaoun et al., 2015). The U.S. fatality rate per bicycle-distance traveled has risen over the past decade. The estimated rate of 6 fatalities per 100 million kilometers cycled is about 6 times that of many Western European countries (Buehler et al., 2021; Buehler and Pucher, 2021; Elvik et al., 2021). For every bicycling fatality in the U.S., there are at least 130 injuries (Bicycle Safety | Transportation Safety, 2022), and even crashes without an injury to the bicyclist can deter future bicycling (Lee et al., 2015; Aldred, 2016), with consequent individual and community harms.

U.S. municipalities have been installing bicycling-specific infrastructure aiming to make bicycling more appealing and safer (Furth et al., 2021; McLeod et al., 2018). The role of infrastructure on bicycling safety has been extensively investigated (Furth et al., 2021; Mulvaney et al., 2015; Reynolds et al., 2009; DiGioia et al., 2017; Thomas and De Robertis, 2013; Kondo et al., 2018; Morrison et al., 2019; Cicchino et al., 2020; Ling et al., 2020; Buehler and Dill, 2016; Marqués and Hernandez-Herrador, 2017), but research has mixed results and limitations. One persistent limitation has been difficulty gathering information on the volume of bicycling at risk of a crash (Mulvaney et al., 2015; DiGioia et al., 2017; Thomas and De Robertis, 2013; Vanparijs et al., 2015). Count data with high spatial and temporal resolution at specific locations have been used in research on bicycle infrastructure for over a decade (Lusk et al., 2011, 2013), but these data are often available for a small number of locations over a limited period. As a result, fundamental epidemiologic measures like the incidence rate of crashes per distance bicycled are rarely estimated for multiple infrastructure types (Mulvaney et al., 2015; Reynolds et al., 2009).

To measure bicycling with high resolution over a broader spatial and temporal extent, researchers have begun using bicycling data measured by mobile devices (Lee and Sener, 2020a, 2020b; Nelson et al., 2020; Saad et al., 2019). For example, data from Strava, an app used to track and share bike rides and other activities (Lee and Sener, 2020a), have been used in bicycle-safety research in England (Adams and Aldred, 2020; Aldred et al., 2018) and North America (Saad et al., 2019; Ferster et al., 2021). Research suggests Strava data comprise between 5% and 15% of total bicycling volume in cities (Lee and Sener, 2020a; Fischer et al., 2020; Garber et al., 2022a) and that Strava data correlate highly with on-the-ground bicycling counts in urban areas (Lee and Sener, 2020a; Nelson et al., 2020). However, Strava-using bicyclists may be disproportionately enthusiastic bicyclists, and, among Strava-using bicyclists, leisure rides may be more likely to be recorded in the app compared with utilitarian rides (Garber et al., 2019; Alattar et al., 2021). Researchers have developed methods to address these potential biases (Garber et al., 2019; Roy et al., 2019; Nelson et al., 2021; Dadashova and Griffin, 2020) and have shown that certain summary measures calculated from mobile-device-generated data can be unbiased under plausible assumptions even if the sample is not entirely representativeness of the population (Garber et al., 2021, 2022b). Bicycling safety research using high-resolution app data to measure bicycling at risk of a crash while incorporating such bias-adjustment methods nevertheless remains scarce.

Another gap in knowledge pertains to geographic location. The Southeastern U.S. is underrepresented in research on bicycling safety despite having a comparatively unsafe transportation environment (McLeod et al., 2018; Smart Growth America, 2021). Nine of the ten most dangerous U.S. states for bicycling are in the South (McLeod et al., 2018), yet much of North American bicycle-safety research has occurred in northern cities like Vancouver (Winters et al., 2016; Teschke et al., 2012, 2017; Harris et al., 2013; Winters and Teschke, 2010), Portland (Cicchino et al., 2020; Broach et al., 2012; Deliali et al., 2022), Minneapolis (Winters et al., 2016; Krizek et al., 2009), Montreal (Lusk et al., 2011; Winters et al., 2016), and Toronto (Ling et al., 2020; Teschke et al., 2012; Harris et al., 2013; Zangenehpour et al., 2016). Compared with a prototypical city in the Southeastern U.S., these northern cities tend to have denser built environments with higher connectivity (Winters et al., 2016; Boeing, 2018; Ewing and Hamidi, 2014). Research in these locations may therefore not generalize to the Southeast.

In this case-control study, we have two objectives. First, we estimate the incidence rate of crashes between bicyclists and motor vehicles per bicycle-distance ridden along with the incidence proportion of crashes per intersection entered in Atlanta, Georgia between 2016 and 10–01 and 2018–08-31 on five types of bicycle infrastructure: off-street paved trails, protected bike lanes, buffered bike lanes, conventional bike lanes, and shared-travel lanes. Second, we compare these incidence rates and incidence proportions on each type of infrastructure with no infrastructure using ratios. We first estimate unadjusted ratios and, secondarily, estimate effects of treatment on the treated using model-based standardization. Throughout the analysis, we measure bicycling at risk of a crash using high-resolution app-generated bicycling data and adjust for potential selection bias in this app-based sample via inverse-probability-of-selection weighting using a validation sample of on-the-ground bicycling counts.

2. Methods

2.1. Study setting

The study examined a 23-month period, 2016–10-01 to 2018–08-31, in an 8.85-km radius around the intersection of Ponce de Leon Ave NE and Monroe Dr NE (Fig. 1) in Atlanta, Georgia, USA. Atlanta's population is about 500,000 residents with 6 million in its metropolitan area. The city has a mild winter climate amenable to bicycling. Like other U.S. cities (McLeod et al., 2018), the City of Atlanta has been expanding its bicycling infrastructure (Garber et al., 2022a; City of Atlanta, 2018; Atlanta Beltline Annual Report, 2018; City of Atlanta, 2017). Compared with other cities of similar size, the Atlanta area has low levels of street connectivity (Boeing, 2018) and high levels of sprawl (Ewing and Hamidi, 2014). The study area also includes part of the City of Decatur, which has a population of about 25,000 and a dense and walkable downtown. At the time of this study, an estimated 0.8% of people commuted by bicycle in the region, and about two thirds of commuters drove to work alone in a private automobile (McLeod et al., 2018).

2.2. Characteristics of segments

Roadway and path segments are the principal spatial unit on which data in this study are summarized. A segment is a stretch of roadway or path, often between two intersections. We downloaded segment data from OpenStreetMap (Padgham et al., 2020). Excluding interstate highways and dirt trails, we began with 65,599 segments.

2.2.1. Bicycle infrastructure on segments—The treatment of interest is bicycle infrastructure. The most common type of bicycle infrastructure in U.S. cities is the conventional bike lane (McLeod et al., 2018), a paint-demarcated lane designating space for bicyclists to ride parallel to motor-vehicle traffic without a buffer or physical separation. Protected bike lanes, also called cycle-tracks (Lusk et al., 2011, 2013), use a curb-like barrier, parked cars, bollard posts, or flex posts to physically separate the bicycle lane from motorized traffic (Furth et al., 2021; DiGioia et al., 2017; NACTO, 2017). Buffered bike lanes include extra space between the motor-vehicle lane and the bicycle lane but do not include a physical barrier (DiGioia et al., 2017). Shared-lane markings, also called sharrows, use pavement markings to indicate a shared-lane environment between bicyclists and motor vehicles. They are often accompanied by signs stating that “bicyclists may use the full lane.” Finally, off-street paved trails are physically separated from roadways and are intended for use by people walking, riding a bicycle, rolling a wheelchair, or using other modes of light individual transit (DiGioia et al., 2017). Off-street paved trails often do not follow the road network (Buehler and Dill, 2016). eFig. 1.1 shows examples of these infrastructure types in Atlanta.

We gathered longitudinal data on bicycle infrastructure using several sources. Guided by work by Ferster and colleagues (Ferster et al., 2020) and the *Bicycle* page on the OpenStreetMap wiki (Bicycle, 2022), we used combinations of the *cycleway*, *path*, *highway*, and *footway* tags in OpenStreetMap as a first pass to classify bicycle infrastructure. OpenStreetMap does not always correctly classify the presence of or differences between bicycle infrastructure, so we used additional local data sources to classify infrastructure, including reports from the City and other local organizations (City of Atlanta, 2018; Atlanta Beltline Annual Report, 2018; City of Atlanta, 2017; Atlanta Beltline Annual Report, 2017; PATH Trails, 2017; Metro Atlanta Bicycle Facility Inventory, 2014). We inspected and, as needed, corrected bicycle infrastructure using date-stamped Google Street View imagery. Of the segments with infrastructure (n = 3, 422) in the analysis sample, some changed infrastructure status during the study period (n = 217, 6%), so we created a longitudinal dataset in which we noted the infrastructure’s opening date and classified infrastructure status by segment-month (n, segment-months in analysis sample = 396,374; exclusions described below). R code detailing these decisions is available online: https://github.com/michaeldgarber/diss/blob/main/scripts/2_wrangle_basemap.R. Fig. 1 maps the bicycle infrastructure in the study area.

2.2.2. Potential confounders—We considered three possible confounders in the estimate of effect of infrastructure on crash incidence: roadway type, area-level population density, and area-level household income. Roadway segments were classified as trunk, primary, secondary, tertiary, residential, or service or unclassified by the OpenStreetMap definition (Highways - OpenStreetMap Wiki, 2022). Roadway type is strongly associated with motor-vehicle volume in this study (eAppendix 3), and motor-vehicle volume may confound the association between infrastructure presence and crash incidence. Motor-vehicle volume was not consistently available over all segments in the study area, so we used roadway type as a proxy (Mooney et al., 2016).

Area-level population density and household income each may be associated with both the decision to install infrastructure and crash incidence (Hirsch et al., 2017; Barajas, 2018). We retrieved these variables at the census-tract level from the 2015–2019 5-year American Community Survey.

2.2.3. Segment exclusions—We excluded service and unclassified roadways because the service classification was inconsistently used by OpenStreetMap over the study area and because there was no infrastructure on these roadway types, yielding an analysis sample of 23,002 segments and 396,374 segment-months.

2.3. Intersections

Intersections are high-risk locations for bicycle crashes (Morrison et al., 2019; Harris et al., 2013; Strauss et al., 2013). As have others (Kondo et al., 2018; Morrison et al., 2019; Deliali et al., 2022), we separated crashes at intersections from those occurring elsewhere. We defined intersections as points where two or more roadways of type trunk, primary, secondary, tertiary, or residential meet one another or where at least one roadway of those types meets an off-street paved trail. This process yielded 7,136 intersections and 172,267 intersection-months. R code to create intersections is available online (https://github.com/michaeldgarber/diss/blob/main/scripts/2_1_basemap_generate_intersections.R), as is an interactive map of resulting intersections (eFig. 1.4).

2.4. Crashes

Police-reported crashes (n = 129) involving at least one bicyclist and at least one motor vehicle (hereafter, "crashes") in the study area and timeframe were obtained from the Georgia Department of Transportation. Using their latitude and longitude coordinates and date, we assigned crashes to a segment-month and thus to that segment-month's infrastructure status and other characteristics. Crashes occurring at intersections were assigned the infrastructure type and roadway type of the street segment on which the bicyclist entered the intersection in that month according to the police report. We also reviewed the narrative remarks and diagram of each crash report to correct, as needed, the crash location, whether the crash occurred at an intersection, and the crash's injury status (definition in eAppendix 2). In accordance with our protocol with Emory University Institutional Review Board, we excluded three crashes involving a bicyclist 17 years old or younger. We additionally excluded two crashes because they originated from service roadways, which were excluded as stated above, resulting in 124 included crashes.

2.5. Analysis

2.5.1. Bicycling measures

2.5.1.1. Bicycling data sources: Strava and stationary counters (ZELT).: To measure the at-risk experience giving rise to crashes, we estimated bicycle-distance ridden on segment-months and the number of intersection entries at intersection-months using two data sources. As a note on terminology, the amount of bicycling at risk of a crash, measured as distance traveled or otherwise, is often referred to as *exposure* in bicycle-safety research (Vanparijs et al., 2015; Ferster et al., 2021). We avoid this term because in epidemiology, exposure commonly refers to the treatment or condition of etiologic interest, which is bicycle infrastructure here. The main source for these measures was Strava, a GPS-based mobile application used to track and share bike rides and other activities (Lee and Sener, 2020a). As described previously (Garber et al., 2021, 2022a), these data included about 300,000 rides contributed by about 10, 000 unique people over the study period. To protect user privacy, Strava summarized the data by segment rather than by individual, reporting the number of times, $n_{i,t}$, a segment i was ridden upon in either direction in month t by a bicyclist using Strava on that ride.

Previous research in Atlanta suggests that Strava-using bicyclists may use infrastructure differently than the broader bicycling population (Garber et al., 2019), possibly leading to selection bias if not addressed. Both to adjust for this potential selection bias and to estimate absolute measures of occurrence (incidence rates and incidence proportions, defined below), we estimated all rides (i.e., not just those reported in Strava) occurring on each segment-month using data from 15 stationary bicycle-counting monitors (manufacturer: Eco-Counter® Urban ZELT) installed on off-street paved trails (Atlanta Beltline Trail Counts, 2022) and roadways (City of Atlanta, 2017) (eAppendix 2). Given their reported high accuracy (Tin et al., 2012), we assume the counters capture all rides on their segment–month. The number of rides reported by ZELT, $N_{i,t}$, was available for 197 segment–months. In these segment-months, we calculated the proportion of $N_{i,t}$ reported in Strava on segment i in month t (the sampling fraction, $f_{i,t}$) by dividing the number in Strava by the corresponding number from ZELT, $f_{i,t} = \frac{n_{i,t}}{N_{i,t}}$.

2.5.1.2. Bicycle-distance: Strava-reported and inverse-probability-of-selection weighted.: To estimate $f_{i,t}$ on all segment-months, we fit an event-trial logistic regression model in the 197 segment–months with ZELT data. Similar to previous work (Garber et al., 2021, 2022a), predictor variables include the number of Strava-reported rides on a segment–month, the proportion thereof classified as a commute, the presence of an off-street paved trail, and the time-period. eAppendix 2 has more details. To estimate the total number of times a segment was ridden in a month, $N_{i,t}$, we inverse-probability-of-selection weighted (IPSW) $n_{i,t}$, multiplying $n_{i,t}$ by the inverse of $\hat{f}_{i,t}$: $\widehat{N}_{i,t} = n_{i,j} * \frac{1}{\hat{f}_{i,t}}$. We truncated $\hat{f}_{i,t}$ at 0.02 and 0.5 to avoid extremely large or implausible weights.

We then calculated bicycle–distance ridden for both the Strava-reported and IPSW bicycling measures. Strava-reported bicycle–distance on segment i during month t, $d_{i,t}$ is the product of $n_{i,t}$ and the centerline length, L_i, of segment $i: d_{i,t} = n_{i,t} * L_i$. Analogously, estimated IPSW bicycle–distance on segment i during month t is $\widehat{D}_{i,t} = \widehat{N}_{i,t} * L_i$.

We denote six levels of infrastructure treatment, $A_{ij}, a = 1, 2, 3, 4, 5$, or 0, for off-street paved trails, protected bike lanes, buffered bike lanes, conventional bike lanes, sharrows, and no infrastructure, respectively. If $I_{t,a}$ denotes the number of segments in month t with infrastructure a, then total Strava-reported bicycle-distance on infrastructure type a during the study, d_a, is the sum of $d_{i,t}$ over corresponding segments and months: $d_a = \sum_{t=1}^{t=23} \sum_{i=1}^{i=I_{t,a}} d_{i,t}$. The corresponding total estimated IPSW bicycle-distance on infrastructure type a, $\widehat{D}_a$, is analogously, $\widehat{D}_a = \sum_{t=1}^{t=23} \sum_{i=1}^{i=I_{t,a}} \widehat{D}_{i,t}$.

2.5.1.3. Intersection entries.: An intersection entry occurs when a bicyclist enters an intersection and is thus at risk of a crash at the intersection. To estimate the number of intersection entries, we first enumerated the number of segments of infrastructure type a in month t comprising intersection j, denoted $I_{j,t,a}$. For example, if intersection j is a four-way intersection with a conventional bike lane (a = 4) along one of the intersecting roadways (i.e., two segments) in month 23 and no infrastructure on the perpendicular roadway, then $I_{j,t=23,a=4} = 2$, and $I_{j,t=23,a=0} = 2$. With this framework, we estimated the total number of Strava-reported entries, x_a, entering intersections from infrastructure type a over all segments, intersections, and months: $x_a = \sum_{t=1}^{t=23} \sum_{j=1}^{i=J} \sum_{i=1}^{i=I_{j,t,a}} \frac{n_{i,t}}{2}$. We divide $n_{i,t}$ by 2 because $n_{i,t}$ is the number of times a Strava-using bicyclist rode in either direction on segment i in month t. This calculation assumes bicyclists continue from one segment to the next and do not stop and turn around on the same segment before entering the intersection. Analogously, the total number of estimated IPSW entries from infrastructure type a, denoted $\widehat{X}_a$, is computed as $\widehat{X}_a = \sum_{t=1}^{t=23} \sum_{j=1}^{i=J} \sum_{i=1}^{i=I_{j,t,a}} \frac{\widehat{N}_{i,t}}{2}$.

2.5.2. Study design, measures of occurrence, and measures of association—

This study is a case-control study in that we gathered a series of cases and a sample of the measure of the at-risk experience giving rise to those cases (Garber et al., 2021; Rothman et al., 2008). The purpose of the controls in a case-control study is to serve as a sample of the measure of the experience at risk of the outcome in the corresponding hypothetical cohort study (Rothman et al., 2008), implying both treated and untreated units can be represented among the controls. In this study, bicycle-distance ridden throughout the study area—both where infrastructure is present and absent—as reported by Strava serves as that sample. This framework, using a sample of an aggregated measure to estimate the distribution of the measure of the experience at risk of an outcome in a hypothetical cohort study, has been previously described (Garber et al., 2021). Discrete controls (e.g., specific streets) are not sampled.

We nevertheless estimate absolute incidence rates and incidence proportions as if the study were a cohort study (Wacholder, 1996) by estimating overall bicycle-distance ridden via IPSW, as described above. We use the term *incidence rate* (IR) for the number of crashes per bicycle-distance ridden, as this measure is not a proportion (e.g., it could exceed 1), and the denominator, bicycle-distance, is akin to person-time, aligning with the usual use of *incidence rate* in epidemiology (Lash and Rothman, 2021). We use *incidence proportion* (IP) to describe the measure of crashes per intersection entry because the quantity is a proportion (bounded by 0 and 1) and can be considered an estimate of risk (for additional discussion, please see p. 54 (Lash and Rothman, 2021)). The estimated IR among bicycle-distance ridden on infrastructure a is $\widehat{IR}_a = \frac{Y_{D,a}}{\widehat{D}_a}$, where $Y_{D,a}$ denotes the number of crashes among bicycle-distance ridden on segments outside of intersections on infrastructure type a The estimated IP among intersection entries from infrastructure type a is $\widehat{IP}_a = \frac{Y_{X,a}}{\widehat{X}_a}$, where $Y_{X,a}$ denotes the corresponding number among intersection entries.

Following the at-risk-measure sampling method (Garber et al., 2021), we estimate ratio measures—the incidence rate ratio (IRR) and incidence proportion ratio (IPR), respectively—using both the Strava-reported and estimated IPSW bicycling measures as the at-risk measure to assess the susceptibility to selection bias of the ratio measure estimated from the Strava-reported sample. The estimated IRR comparing infrastructure type a with a = 0 using Strava-reported bicycle-distance as the measure of the at-risk experience, denoted $\widehat{IRR}_{d,a}$, is $\widehat{IRR}_{d,a} = \frac{\frac{Y_{D,a}}{d_a}}{\frac{Y_{D,0}}{d_0}}$. The corresponding ratio measure among intersection entries is $\widehat{IPR}_{x,a}$; $\widehat{IPR}_{x,a} = \frac{\frac{Y_{X,a}}{x_a}}{\frac{Y_{X,0}}{x_0}}$. The analogous ratio measures using the estimated IPSW bicycle-distance and number of intersection entries, respectively, are $\widehat{IRR}_{D,a} = \frac{\widehat{IR}_a}{\widehat{IR}_0}$ and $\widehat{IPR}_{X,a} = \frac{\widehat{IP}_a}{\widehat{IP}_0}$.

2.5.3. Estimating effects of treatment on the treated—

In addition to estimating unadjusted IRRs and IPRs for descriptive purposes, we estimate the effect of infrastructure where it was installed. Using R for generality to represent both IR and IP, the ratio effect of treatment on the treated is $\frac{R^{A = a \neq 0} \mid A = a \neq 0}{R^{A = 0} \mid A = a \neq 0}$, following notation for potential outcomes (Hernán and Robins, 2020). The quantity, $R^{A = a \neq 0} \mid A = a \neq 0$, denotes the IR or IP where infrastructure type a really was present (denoted by the condition notation, $\mid A = a \neq 0$) had it been present (denoted by the superscript, $A = a \neq 0$), while $R^{A = 0} \mid A = a \neq 0$ denotes the IR or IP where infrastructure a was present had it been absent. Assuming counterfactual consistency (VanderWeele, 2009), $R^{A = a \neq 0} \mid A = a \neq 0$ is observable, so the observed outcome, $R \mid A = a \neq 0$, can be substituted for the potential outcome, $R^{A = a \neq 0} \mid A = a \neq 0$. We thus estimate the quantity $R^{A = 0} \mid A = a \neq 0$, the IR or IP where infrastructure a was present had it been absent.

We use model-based standardization to estimate the counterfactual expected IR or IP in the treated had they been untreated. As such, our method can be viewed as a variation of the parametric g-formula (Hernán and Robins, 2020). Specifically, we first fit a Poisson regression in the no-infrastructure ("untreated") group, modeling the number of crashes as a function of roadway type, population density (quintiles), and household income (quintiles). We fit separate models for crashes on segments and at intersections. In each model, we include the logarithm of the corresponding denominator (i.e., bicycle-distance for the IR on segments and number of intersection entries for the IP among intersection entries) as an offset (Frome and Checkoway, 1985). We then use this model to predict the counterfactual number of crashes in each treated group had they not been treated based on that treated group's empirical distribution of the variables in the model. "Had they not been treated" is implied by the model because the model is fit in observations without infrastructure. As in other counterfactual prediction methods, the predicted counterfactual values can be viewed as out-of-sample missing data (Xu, 2017). Predicting out-of-sample counterfactual values using a model fit in the untreated data is well-suited for this study because the number of untreated observations is large relative to the number of observations in each treated group. Next, we estimate $R^{A=0} \mid A = a \neq 0$ on each infrastructure type by dividing the predicted number of counterfactual crashes by the corresponding denominator. We finally calculate adjusted IRRs and IPRs by substituting the predicted counterfactual IRs and IPs in the ratio's referent category, e.g., $\widehat{IRR}_{causal,\,D,\,a} = \frac{\widehat{IR}_a}{IR^{a-0}\widehat{\mid A = a \neq 0}}$, where $\widehat{IRR}_{causal,\,D,\,a}$ is an estimate of the causal IRR using the IPSW bicycle-distance.

2.5.4. Uncertainty—We used bootstrapping to estimate uncertainty arising from sampling variability in the crashes and, for applicable measures, in the sampling-fraction regression model, as detailed in eAppendix 5. Confidence intervals for all measures are their empirical 2.5th and 97.5th percentiles over 1,000 replicates of the analysis (Efron and Hastie, 2016). We do not report confidence intervals for Strava-reported ridership, as we consider this sample constant once drawn for this time period and place.

2.5.5. Sensitivity analyses—In sensitivity analyses, we considered the impact of two potential threats to validity. First, police data may under-report crashes between bicyclists and motor-vehicles (Winters and Branion-Calles, 2017; Juhra et al., 2012), which could lead to selection bias in relative measures if under-reporting differed by infrastructure. Estimates exist for the overall proportion of crashes between bicyclists and motor vehicles reported by police (e.g., about half (Winters and Branion-Calles, 2017)), but we could not find estimates of this proportion stratified by infrastructure type nor did we have estimates from our study. We thus consider the hypothetical impact of differential crash reporting by infrastructure type (eAppendix 6). Second, we calculate e-values to assess the strength of residual or unmeasured confounding needed for estimated ratio effect measures to be 1 (VanderWeele et al., 2017)

2.5.6. Code sharing and ethics statement—R code that we can share publicly has been noted in the text, and the repository is available here: https://github.com/michaeldgarber/diss. Ethical aspects of the study were approved by Emory University Institutional Review Board (IRB00105514). The study includes aggregated and de-identified data from Strava Metro.

3. Results

3.1. Incidence rates among bicycle-distance ridden and incidence proportions among intersection entries

We estimated that about 336,000,000 (95% CI: 266,000,000, 380,000,000) bicycle-kilometers were ridden over the course of the study and that 9.2% (8.2%, 11.7%) of that bicycle-distance was reported by Strava (Table 1). The overall estimated IR was 3.7 (3.0, 4.9) crashes per million kilometers ridden (value not shown in a table), when including crashes both at intersections and along segments (N = 124). Among the 48 (35, 62) crashes occurring on segments outside of intersections (Table 1), the overall estimated IR was 1.4 (1.1, 2.0) crashes per million bicycle-kilometers and was highest on conventional bike lanes (5.0 [2.7, 8.2]) and shared-travel lanes (1.9 [0.4, 4.0]) and lowest on off-street paved trails and buffered bike lanes (both 0 [0,0]).

Most of the 76 (59, 94) crashes occurring at intersections (Table 2) originated from roadways where no infrastructure was present (n = 41 [29, 54]) or with a conventional bike lane (n = 23 [14, 33]). On a per-entry basis, the 3 crashes each originating from protected bike lanes and buffered bike lanes resulted in relatively high estimated incidence proportions per million entries, respectively, 0.73 (0.00, 1.80) and 3.64 (0.00, 8.97), compared with the overall estimated IP of 0.38 (0.28, 0.52) crashes per million entries.

3.2. Incidence rate ratios and incidence proportion ratios

Compared with no infrastructure, the estimated IRR among bicycle-distance ridden on segments adjusted for Strava use but not confounding (Table 3) was highest for conventional bike lanes (3.7 [1.3, 4.0]) and sharrows (1.4 [0.2, 2.0]), lowest for off-street paved trails and buffered bike lanes (both 0.0 [0.0, 0.0]), and was about 1 for protected bike lanes (1.1 [0.0, 2.5]). Adjustment for confounding attenuated all nonzero IRRs. The estimated IRR decreased but remained above 1 for conventional bike lanes (2.8 [1.2, 6.0], became about 1 for sharrows (1.1 [0.2, 2.9]), and changed to the protective direction for protected bike lanes (0.5 [0.0, 2.5]). This last result states that the IR on protected bike lanes was half as high as it would have been had the same segments not had protected bike lanes, assuming no residual confounding, residual selection bias, or misclassification.

Among intersection entries, the estimated IPR adjusted for Strava use but not confounding (Table 4) was above 1 for those originating from protected bike lanes (2.6 [0.0, 5.9]), buffered bike lanes (13.1 [0.0, 29.3]), and conventional bike lanes (3.8 [2.0, 5.4]), was about 1 for entries from sharrows (0.9 [0.2, 1.7]), and was less than 1 for entries originating from off-street paved trails 0.5 (0.0, 1.9). Additional adjustment for confounding had a mixed impact on the IPRs, as the estimated IPR rose for entries originating from protected bike lanes (3.0 [0.0, 10.8]) and buffered bike lanes (16.2 [0.0, 53.1], decreased for conventional bike lanes (3.2 [1.8, 6.0]), and did not change for sharrows (0.9 [0.2, 2.1]).

Adjustment for Strava use had a mixed impact on the IRRs and IPRs. Estimated ratio measures involving protected bike lanes decreased (e.g., IRR, adjustment for confounding but not Strava use = 0.7 [0.0, 3.4] vs. IRR, adjustment for confounding and Strava use = 0.5 [0.0, 2.5]; Table 3) because the estimated sampling fraction (6.8% [5.3%, 10.1%]) was lower than where infrastructure was absent (9.6% [8.3%, 12.2%]; Table 1). That is, we estimated that Strava-using bicyclists were relatively less likely to use protected bike lanes. Failure to adjust for this would have under-estimated the denominator of the IR on protected bike lanes, biasing the IR upward and the corresponding IRR up and towards the null. In contrast, estimated ratio measures involving conventional bike lanes slightly rose (e.g., IRR, adjusted for confounding, from 2.6 [1.2, 5.5] to 2.8 [1.2, 6.0]; Table 3) because the estimated sampling fraction was higher (10.8% [8.8%, 13.6%]) than where infrastructure was absent.

3.3. Injury

To facilitate comparison with other studies on bicycling safety, we present analyses for the subset of crashes resulting in injury to the bicyclist in eTable 4.1. Overall, 67% (52%, 80%) of crashes on segments and 71% (60%, 81%) of crashes at intersections resulted in an injury.

3.4. Sensitivity analyses

Assuming police data missed 54% of all crashes (Winters and Branion-Calles, 2017), 145 crashes would have been unreported. If these 145 crashes were distributed such that the proportion of reported crashes was twice as high where there was infrastructure than where there was not, then many of the estimated IRRs and IPRs above 1 would remain above 1 (eAppendix 6). For example, the adjusted IPR among intersection entries from conventional bike lanes would change to 1.6 (0.9, 3.0). Notably, even if all un-reported crashes at intersections originated from roadways without infrastructure, the adjusted IPR among entries from buffered bike lanes would be 5.1 (0.0, 16.7).

E-values (eTable 7.1) show that unmeasured or residual confounding would have to be rather strong to nullify many of the estimated adjusted IRRs and IPRs that were greater than 1. For example, to nullify the estimated adjusted IPR among intersection entries originating from conventional bike lanes, it would take a confounder associated with the treatment and outcome of size 5.9 (95% CI: 2.9, 11.5) on the ratio scale.

4. Discussion

Using a combination of Strava data and on-the-ground counters to measure bicycling, we estimated the incidence rate of crashes between motor vehicles and bicyclists on various types of bicycle infrastructure per distance ridden along segments and per intersection entered in Atlanta, Georgia, USA. After adjustment for both selection bias due to the mobile-device-generated sample and confounding, we estimated that protected bike lanes and buffered bike lanes each had a protective effect on crash incidence along segments between intersections but that conventional bike lanes had a strong harmful effect and that sharrows had a near-null effect in the harmful direction. At intersections, we estimated that protected bike lanes, buffered bike lanes, and conventional bike lanes each had a harmful effect on crash incidence, that off-street paved trails had a small beneficial impact, and that sharrows had a near-null effect in the protective direction. Results should be interpreted with their sampling variability in mind, as the number of crashes was small, and consequently, confidence intervals were wide with many including the null, but as discussed below, plausible explanations exist for why some of the infrastructure, as it was installed and managed in Atlanta, may have increased risk, especially at intersections.

4.1. Absolute incidence rates

Our overall estimated incidence rate of 3.7 (3.0, 4.8) crashes, including those on segments and at intersections, per million kilometers ridden is comparable to estimates of the same outcome from the U.S. (2.3; (Lusk et al., 2013) several protected bike lanes), Montreal, Canada (10.5; protected bike lanes (Lusk et al., 2011)), and Seville, Spain (1.2; using their assumption of 5 km per trip (Marqués and Hernández-Herrador, 2017)). Infrastructure is frequently studied in bicycling-safety research, but reporting of absolute estimates of incidence rates on infrastructure types is less common. Our combination of crash data with inverse-probability-weighted Strava (or other app-derived) data could be a useful framework for future studies estimating absolute incidence rates and incidence proportions, especially as data on crashes become more complete through open-data platforms (Costa et al., 2022) or crowdsourcing (Fischer et al., 2020; Jestico et al., 2017).

4.2. Relative safety of bicycle infrastructure in context

Our study contributes to the mixed results of research on the relative safety of types of bicycle infrastructure (Mulvaney et al., 2015; Reynolds et al., 2009; DiGioia et al., 2017; Thomas and De Robertis, 2013; Buehler and Dill, 2016; Deliali et al., 2022). Off-street paved trails are frequently excluded from analyses of crashes between bicyclists and motor vehicles because motor vehicles are prohibited from traveling on trails (Reynolds et al., 2009). Although uncommon, cars occasionally travel on off-street paved trails (e.g., Reinmann, 2022), so our results are evidence that in Atlanta during this time period, the IRR per bicycle-distance traveled was indeed estimated to be zero, as expected. The analysis of intersection entries originating from off-street paved trails is perhaps more useful, as there was one crash originating from an off-street paved trail in this study. Per intersection entry, however, the adjusted IPR of 0.7 (0.0, 2.9) suggests paved trails had a small protective effect, a promising finding given other research observing that crashes were more common at intersections with trails (Jestico et al., 2017). This result is particularly important in Atlanta because off-street paved trails support such a large share of the bicycling volume (an estimated 21% of bicycle-distance ridden despite 3% of paved rideable area; Table 1).

It is encouraging that protected bike lanes had an estimated protective effect along segments between intersections (adjusted IRR = 0.5 [0.0, 2.5]), as expected, but the relatively high IPR among intersection entries (adjusted IPR = 3.0 [0.0, 10.8]) warrants concern. This pattern—a beneficial effect between intersections but a potentially harmful effect at intersections—has similarities with a recent study from Portland, which also used app-generated bicycling data (from a separate app) to estimate underlying bicycle ridership (Deliali et al., 2022). Other recent research observed mixed results of protected bike lanes, finding that their relative safety depended on their level of protection (Cicchino et al., 2020).

We propose possible reasons for the high IPR among intersection entries from protected bike lanes in this study. First, all protected bike lanes in this study were two-way protected bike lanes on one side of the roadway with two opposing lanes for bicyclists. A concern with these two-way protected bike lanes are that they can add complexity at intersections (Furth et al., 2021; Thomas and De Robertis, 2013). This concern may have been especially pertinent in Atlanta given how uncommon protected bike lanes were during the study period (total length between 3.5 km and 5.0 km), so drivers may not have expected them. On the other hand, per lane-kilometer, protected bike lanes were ridden the most of any of the infrastructure (Table 1), so, theoretically, drivers may have become accustomed to this high bicycling volume. This result is evidence against the so-called safety-in-numbers hypothesis (Elvik and Bjørnskau, 2017). As another possible explanation for their relative lack of safety at intersections in this study, some protected bike lanes were frequently blocked by parked cars, taxis, and delivery activity (Reddit user, 2021). Bicyclists may thus have had to swerve into the motor-vehicle lane, a possibly unsafe maneuver, or not use the lane at all. Finally, protected bike lanes varied in their level of protection in this study, both between lanes (concrete curb vs. flexible bollards) and within the same lane. On at least one bollard-protected lane, bollards were frequently knocked down by cars (eFig. 8.1). These potential explanations could be explored empirically in future research.

The literature on conventional bike lanes is extensive, and our study is not the first to suggest that conventional bike lanes may not improve safety (DiGioia et al., 2017; Jensen, 2008). In contrast with our results, a study from Charlotte, North Carolina, a city of comparable size and transportation environment, observed that conventional bike lanes were associated with a lower incidence of crashes (Pulugurtha and Thakur, 2015). Authors of that study measured incidence in terms of motor-vehicle distance traveled rather than bicycle-distance traveled as in this study. Two recent studies have assessed the safety of conventional bike lanes while accounting for a proxy of bicycle-distance traveled (Kondo et al., 2018; Morrison et al., 2019). In some sub-comparisons, conventional bike lanes had an estimated IRR above 1 consistent with our results, but at intersections, results from both studies suggested conventional bike lanes had a lower risk of crash (Kondo et al., 2018; Morrison et al., 2019), contrary to our results.

Design guidance (NACTO, 2017) by the National Association of City Transportation Officials (NACTO) referenced by the City of Atlanta (Atlanta Department of Transportation, 2022) advises that buffered and conventional bike lanes be placed along roadways with motor-vehicle speeds less than 25 mph (40 km/h), either one motor-vehicle lane in each direction or a single one-way lane, and low motor-vehicle volume. The guidance specifically states that either conventional or buffered bike lanes are appropriate where Annual Average Daily Traffic (AADT) is up to 3,000 and that buffered bike lanes are appropriate where AADT is up to 6,000 (NACTO, 2017). Several buffered and conventional bike lanes in the study area fail on all counts, which may partly explain the high estimated IPR at intersections with buffered bike lanes, and the high estimated ratio measures on both segments and intersections with conventional bike lanes. For example, Ponce De Leon Ave NE has a 1.6-km buffered bike lane, a posted speed limit of 35 mph, two motor-vehicle lanes in each direction (eFig. 8.2), and motor-vehicle volumes five times higher than NACTO guidance (AADT of 30,800 in 2017 [eAppendix 3]). Another example is Peachtree Rd NE, a section of which has a conventional bike lane, three motor-vehicle lanes in each direction (eFig. 8.3), a posted speed limit of 35 mph, and motor-vehicle volumes 15 times higher than levels NACTO advises where conventional bike lanes are present (45,900 in 2017; eAppendix 3).

Finally, our results agree with both street-level and ecologic studies finding a null or slightly harmful effect of sharrows on crash risk (Furth et al., 2021; Cicchino et al., 2020).

4.3. Limitations

This study has limitations. Our use of police-reported crashes probably biased the absolute estimated IRs and IPs downward. However, assuming that police missed 54% of crashes (Winters and Branion-Calles, 2017), our bias analysis shows that under-reporting must have been considerably more prevalent where infrastructure was absent for many of the estimated ratio measures above 1 to be attenuated to 1. Some of the estimated IRR or IPR mathematically cannot be attenuated to 1 solely due to under-reporting assuming 54% of crashes were not reported (eTable 6.2).

Residual selection bias in the estimate of bicycling due to use of Strava data also may have threatened validity, as our model to estimate overall bicycling from Strava data and the on-the-ground counters was fit in a small number of counter-months (n = 197). This potential bias is most concerning for measures of absolute incidence, as those measures could be biased even if the estimated sampling fraction were biased non-differentially. For the estimated ratio measures (IRRs and IPRs) to be biased, however, bias in the estimated sampling fractions would have to differ by infrastructure type. That we estimated different sampling fractions on each infrastructure type (Tables 1 and 2) leads us to believe this is not true. Our comparison of ratio measures with and without adjustment for Strava use (Tables 3 and 4) shows that not adjusting for Strava use would have biased the ratio measures in different directions depending on the infrastructure type, illustrating the importance of estimating infrastructure-specific bias parameters to adjust for selection bias (Garber et al., 2019).

Residual confounding may also threaten validity in effect estimates. E-values showed that residual or unmeasured confounding would have to be rather strong for many of the estimated ratio measures above 1 to be 1. Finally, the small number of crashes hindered the precision of our estimates and raises the possibility that the conclusions are due to random error.

4.4. Conclusions

In summary, results from this study suggest protected bike lanes and buffered bike lanes had their expected protective effect on segments between intersections but that additional strategies may be needed to improve the safety of these types of infrastructure at intersections (NACTO, 2019). The estimated harmful effect of conventional bike lanes on crash incidence both between and at intersections is concerning given their ubiquity. Future research might empirically examine specific factors contributing to these findings in Atlanta, such as inconsistent protection within protected bike lanes or a potential mismatch between on-road infrastructure and its roadway environment with respect to motor vehicle volume and speed.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability

Our data-use agreement with Strava prohibits us from sharing code that handles Strava Metro data. In addition, details of each bicycle crash are considered sensitive information that may reveal individual identity. We thus do not share code that directly handles Strava Metro data or crash data. However, in a public Github repository (https://github.com/michaeldgarber/diss), we have posted code that prepares data on the street segments and intersections.

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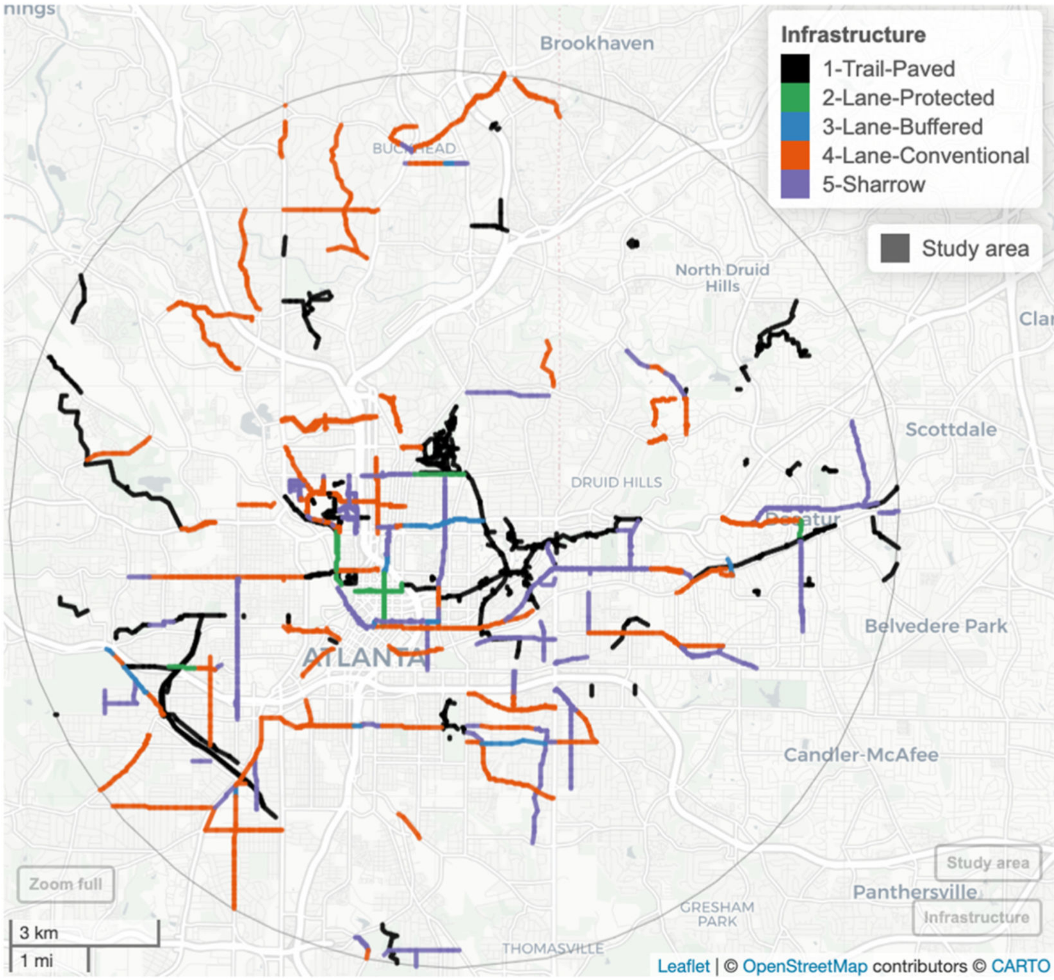

Fig. 1.

Bicycle infrastructure present in August 2018 in the 8.85-km radius around the intersection of Ponce de Leon Ave NE and Monroe Dr NE in Atlanta, GA. An interactive version of this map is available here: https://michaeldgarber.github.io/diss/atl-bike-infra-201808.

Table 1

The length of roadways and paths included in study; the amount of bicycle-distance ridden, both Strava-reported and estimated via inverse-probability-of-selection weighting; and the incidence rate of crashes (N, crashes = 48) occurring on segments excluding intersections among estimated bicycle-distance, stratified by infrastructure type and potential confounders, 2016-10-01 to 2018-08-31.

	Total length of roadways or paths (km)[a]	Strava-reported bicycle-distance, 100k b-km	Estimated (IPSW) bicycle-distance, 100k b-km (95% CI)	Estimated sampling fraction (95% CI)	Estimated (IPSW) bicycle-distance (b-km) per length (km) of roadway or path per month, mean (95% CI)	Number of crashes on segments excluding those at intersections (95% CI)	Incidence rate, crashes per 1M estimated (IPSW) b-km (95% CI)
Total	2,405.7 (2,402.4; 2,412.0)	31.0	336 (266, 380)	9.2% (8.2%, 11.7%)	607 (480, 686)	48 (35, 62)	1.4 (1.1, 2.0)
Infrastructure type							
Off-street paved trail	63.6 (60.0; 70.9)	4.7	70 (40, 81)	6.8% (5.8%, 11.7%)	4,704 (2,723; 5,502)	0 (0, 0)	0.0 (0.0, 0.0)
Protected bike lane	5.0 (3.5; 5.0)	0.5	7 (5, 9)	6.8% (5.3%, 10.1%)	6,762 (4,532; 8,595)	1 (0, 3)	1.4 (0.0, 5.1)
Buffered bike lane	2.8 (2.8; 5.3)	0.1	1 (1, 2)	10.2% (8.1%, 13.4%)	1,614 (1,213; 2,018)	0 (0, 0)	0.0 (0.0, 0.0)
Conventional bike lane	71.2 (70.4; 77.9)	3.2	30 (24, 36)	10.8% (8.8%, 13.6%)	1,791 (1,413; 2,187)	15 (8, 23)	5.0 (2.7, 8.2)
Shared-travel lane	48.0 (47.2; 52.7)	2.4	21 (17, 25)	11.5% (9.6%, 14.4%)	1,806 (1,440; 2,154)	4 (1, 8)	1.9 (0.4, 4.0)
No infrastructure	2,216.0 (2,200.2; 2,217.7)	20.1	208 (164, 243)	9.6% (8.3%, 12.2%)	409 (322; 478)	28 (18, 39)	1.4 (0.8, 2.1)
Roadway type							
Trunk or primary	103	2.4	22 (18, 25)	11.0% (9.4%, 13.4%)	917 (750;1,069)	3 (0, 7)	1.4 (0.0, 3.1)
Secondary	261	6.5	71 (54, 84)	9.1% (7.7%, 12.0%)	1,185 (897; 1,400)	25 (16, 35)	3.5 (2.2, 5.5)
Tertiary	228	6.7	57 (47, 69)	11.6% (9.6%, 14.1%)	1,095 (900; 1,326)	12 (6, 19)	2.1 (1.0, 3.5)
Residential	1,754	10.8	118 (92, 136)	9.2% (8.0%, 11.8%)	292 (228; 338)	8 (3, 14)	0.7 (0.3, 1.3)
Population density (residents per km^2), census tract							
0, 1,170	582	4.6	40 (33, 47)	11.6% (9.7%, 14.0%)	296 (247, 355)	6 (2, 11)	1.5 (0.5, 2.8)
1,171–1,760	718	6.1	64 (51, 76)	9.5% (8.0%, 11.9%)	385 (308, 457)	9 (4, 15)	1.4 (0.6, 2.6)
1,761–2,170	459	5.3	53 (42, 63)	10.0% (8.4%, 12.7%)	506 (400, 600)	4 (1, 8)	0.8 (0.2, 1.5)
2,171–3,450	456	7.7	77 (61, 90)	10.0% (8.6%, 12.6%)	733 (584, 858)	14 (7, 22)	1.8 (0.9, 3.0)
3,451–1,000,000	191	2.6	34 (25, 40)	7.6% (6.5%, 10.6%)	786 (563, 924)	15 (8, 23)	4.4 (2.2, 7.5)
Median household income (USD), census tract							
\$12,500–\$32,000	450	2.0	28 (20, 32)	7.1% (6.2%, 10.1%)	273 (191, 312)	18 (10, 27)	6.4 (3.4, 10.6)
\$32,001–\$50,800	322	1.9	24 (17, 29)	7.5% (6.4%, 10.8%)	330 (231, 387)	1 (0, 3)	0.4 (0.0, 1.5)

	Total length of roadways or paths (km)[a]	Strava-reported bicycle-distance, 100k b-km	Estimated (IPSW) bicycle-distance, 100k b-km (95% CI)	Estimated sampling fraction (95% CI)	Estimated (IPSW) bicycle-distance (b-km) per length (km) of roadway or path per month, mean (95% CI)	Number of crashes on segments excluding those at intersections (95% CI)	Incidence rate, crashes per 1M estimated (IPSW) b-km (95% CI)
\$50,801–\$73,900	496	4.6	55 (41, 64)	8.4% (7.1%, 11.4%)	480 (354, 562)	7 (3, 13)	1.3 (0.5, 2.5)
\$73,901–\$103,000	573	7.7	76 (61, 90)	10.2% (8.6%, 12.8%)	574 (458, 681)	11 (5, 17)	1.4 (0.6, 2.4)
\$103,001–\$209,000	558	10.1	84 (71, 102)	12.1% (10.0%, 14.3%)	655 (551, 793)	11 (5, 17)	1.3 (0.6, 2.1)

Abbreviations: k, thousand; b-km, bicycle-kilometers; IPSW, inverse-probability-of-selection weighted; CI, confidence interval; M, million.

[a] The amount of infrastructure changed over the study period, so we report the median length (minimum, maximum).

Table 2

The number of intersection entries, both Strava-reported and estimated via inverse-probability-of-selection weighting, and the incidence proportion of crashes (N, crashes = 76) among estimated entries, stratified by infrastructure type and potential confounders, 2016-10-01 to 2018-08-31.

Attribute	Strava-reported intersection entries, 100k entries	Estimated (IPSW) intersection entries, 100k entries (95% CI)	Estimated sampling fraction (95% CI)	Number of crashes at intersections (95% CI)	Incidence proportion, crashes per 1M estimated (IPSW) entries (95% CI)
Total	198.7	2,002 (1,591; 2,318)	9.9% (8.6%, 12.5%)	76 (59, 94)	0.38 (0.28, 0.52)
Infrastructure type[a]					
Off-street paved trail	5.1	66 (38; 77)	7.8% (6.6%, 13.4%)	1 (0, 3)	0.15 (0.00, 0.60)
Protected bike lane	2.9	41 (29; 53)	7.1% (5.5%, 10.0%)	3 (0, 7)	0.73 (0.00, 1.80)
Buffered bike lane	0.8	8 (6; 10)	10.2% (8.0%, 14.2%)	3 (0, 7)	3.64 (0.00, 8.97)
Conventional bike lane	23.9	219 (171; 262)	10.9% (9.1%, 14.0%)	23 (14, 33)	1.05 (0.62, 1.65)
Shared-travel lane	23.6	196 (157; 238)	12.0% (9.9%, 15.0%)	5 (1, 10)	0.25 (0.05, 0.52)
No infrastructure	142.3	1,472 (1,160; 1,709)	9.7% (8.3%, 12.3%)	41 (29, 54)	0.28 (0.20, 0.41)
Roadway type					
Trunk or primary	20.2	186 (151; 214)	10.9% (9.4%, 13.4%)	8 (3, 14)	0.43 (0.15, 0.77)
Secondary	53.5	578 (444; 677)	9.2% (7.9%, 12.1%)	26 (17, 37)	0.45 (0.29, 0.72)
Tertiary	53.8	443 (364; 537)	12.2% (10.0%, 14.8%)	24 (14, 35)	0.54 (0.30, 0.83)
Residential	71.1	795 (620; 903)	8.9% (7.9%, 11.5%)	18 (10, 27)	0.23 (0.12, 0.37)
Population density (residents per km^2), census tract					
0, 1170	24.1	215 (179; 259)	11.2% (9.3%, 13.5%)	6 (2, 11)	0.28 (0.08, 0.53)
1171 −1760	41.3	426 (340; 509)	9.7% (8.1%, 12.2%)	8 (3, 14)	0.19 (0.07, 0.35)
1761–2170	38.3	363 (289; 436)	10.5% (8.8%, 13.2%)	16 (9, 24)	0.44 (0.23, 0.73)
2171–3450	72.3	703 (557; 826)	10.3% (8.7%, 13.0%)	19 (11, 28)	0.27 (0.15, 0.42)
3451–1,000,000	22.8	295 (210; 349)	7.7% (6.5%, 10.8%)	27 (17, 38)	0.91 (0.58, 1.47)
Median household income (USD), census tract					
$12,500–$32,000	16.3	228 (167; 261)	7.1% (6.2%, 9.8%)	27 (17, 38)	1.18 (0.75, 1.89)
$32,001–$50,800	13.2	168 (125; 195)	7.8% (6.8%, 10.6%)	9 (4, 15)	0.54 (0.23, 1.05)
$50,801–$73,900	34.4	396 (309; 460)	8.7% (7.5%, 11.1%)	11 (5, 19)	0.28 (0.13, 0.51)
$73,901–$103,000	59.9	592 (481; 690)	10.1% (8.7%, 12.5%)	19 (11, 27)	0.32 (0.18, 0.49)
$103,001–$209,000	74.8	618 (517; 735)	12.1% (10.2%, 14.5%)	10 (4, 17)	0.16 (0.07, 0.28)

Abbreviations: k, thousand; IPSW, inverse-probability-of-selection weighted; CI, confidence interval; M, million.

[a]From which bicyclist entered intersection.

Table 3

Incidence rate ratios (IRRs) comparing the incidence rates of crashes (N, crashes = 48) occurring on segments excluding intersections.

	Compared to segments without infrastructure segments; no confounding adjustment		Estimated effects: adjusted for roadway type, area-level population density and household income[a]	
Infrastructure type	**IRR, at-risk measure: Strava-reported bicycle-distance (95% CI)**	**IRR, at-risk measure: estimated (IPSW) bicycle-distance adjusted for Strava use (95% CI)**	**IRR, at-risk measure: Strava-reported bicycle-distance (95% CI)**	**IRR, at-risk measure: estimated (IPSW) bicycle-distance adjusted for Strava use (95% CI)**
Off-street paved trail	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	N/R	N/R
Protected bike lane	1.5 (0.0, 3.5)	1.1 (0.0, 2.5)	0.7 (0.0, 3.4)	0.5 (0.0, 2.5)
Buffered bike lane	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)
Conventional bike lane	3.3 (1.3, 3.9)	3.7 (1.3, 4.0)	2.6 (1.2, 5.5)	2.8 (1.2, 6.0)
Shared-travel lane	1.2 (0.2, 1.8)	1.4 (0.2, 2.0)	1.1 (0.2, 2.9)	1.1 (0.2, 2.9)
No infrastructure	Referent	Referent	N/A	N/A

Abbreviations: IRR, incidence rate ratio; CI, confidence interval; IPSW, inverse-probability-of-selection weighted; N/R, not reported; N/A, not applicable.

[a]Estimated effect of treatment on the treated via model-based standardization. Please see text for additional details.

Table 4

Incidence proportion ratios (IPRs) comparing the incidence proportions of crashes (N, crashes = 76) occurring among intersection entries.

	Compared to entries without infrastructure; no confounding adjustment		Estimated effects: adjusted for roadway type, area-level population density and household income[b]	
Infrastructure type[a]	**IPR, at-risk measure: Strava-reported number of entries (95% CI)**	**IPR, at-risk measure: estimated (IPSW) number of entries adjusted for Strava use (95% CI)**	**IPR, at-risk measure: Strava-reported number of entries (95% CI)**	**IPR, at-risk measure: estimated (IPSW) number of entries adjusted for Strava use (95% CI)**
Off-street paved trail	0.7 (0.0, 2.1)	0.5 (0.0, 1.9)	0.8 (0.0, 2.9)	0.7 (0.0, 2.9)
Protected bike lane	3.6 (0.0, 8.5)	2.6 (0.0, 5.9)	4.1 (0.0, 15.0)	3.0 (0.0, 10.8)
Buffered bike lane	12.5 (0.0, 29.8)	13.1 (0.0, 29.3)	15.5 (0.0, 47.3)	16.2 (0.0, 53.1)
Conventional bike lane	3.3 (2.1, 4.9)	3.8 (2.0, 5.4)	2.8 (1.6, 5.3)	3.2 (1.8, 6.0)
Shared-travel lane	0.7 (0.2, 1.5)	0.9 (0.2, 1.7)	0.9 (0.2, 2.0)	0.9 (0.2, 2.1)
No infrastructure	Referent	Referent	N/A	N/A

Abbreviations: IPR, incidence proportion ratio; CI, confidence interval; IPSW, inverse-probability-of-selection weighting; N/A, not applicable.

[a] From which bicyclist entered intersection.

[b] Estimated effect of treatment on the treated via model-based standardization. Please see text for additional details.