Street Noise Relationship to Bicycling Road User Safety

December 2018 | Final Report

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Abstract

Vulnerable road users, such as bicyclists, experience road noise directly. This study explored the relationship between bicycle crash risk and street-level road noise as measured in Austin, Texas and the Washington, D.C. metropolitan area, in addition to other factors. Construction and validation of a method to measure noise directly using consumer-accessible tools supports additional studies as well as potential public crowdsourcing applications for urban planning. Results from the two case sites were mixed. Street noise, as measured on our chosen routes, was not a consistent predictor of bicycle crash risk. However, our model explained over 87% of the variation in crash risk in the Washington, D.C. metropolitan area route, considering infrastructure, nearby bicycle commute mode share, and street noise. Findings from the two routes using our modeling approaches are not exhaustive, but rather an initial exploration of these relationships to support further work on the role of street noise in planning for safety.

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Introduction

Street noise can have significant impacts on transportation system users, with the impacts varying by location and transportation mode. In 2017, the U.S. Department of Transportation released the National Transportation Noise Map, finding that 97% of the U.S. population experiences transportation-related noise of 50 decibels, and "less than one-tenth of a percent of the population could potentially experience noise levels of 80 decibels or more, equivalent to the noise level of a garbage disposal" (*1*). However, the role of noise experienced on the street and its relationship to transportation system safety is not well understood, particularly from the perspectives of vulnerable road users.

This study is the first known exploration of street noise as experienced by bicyclists, relating noise levels to bicycle-automobile collision rates and other factors. The project team developed an approach using consumer grade, handlebar-mounted smartphones with an app that consistently recorded noise levels and GPS locations spanning suburban to downtown routes in Austin, TX, and the Washington, D.C. metropolitan (metro) area. Initial results from the cities were mixed, and methods are documented to support related studies in other contexts. This study is exploratory rather than exhaustive—additional route sites, changes to data collection protocol, and additional statistical analysis may reveal different findings. This report includes a brief review of previous work, detailed documentation of methods, review of results in the two locations, including limitations, and potential implications for research and practice.

Background

The application of street noise data for assessing safety may be a useful way to build on well-developed research topics, such as characterizing street-level noise, crowdsourcing of bicycle safety, and crowdsourcing of noise data. The research team searched for literature on these topics, focusing on academic papers published between 2013 and 2017, using the Transport Research International Documentation (TRID) database. Then, key papers were reviewed for cited prior research, and Google Scholar was queried to identify later related works. This section generally follows review advice specific to transportation research (*2*), and the following sections describe the findings of each topic pertinent to the present study. A list of applicable literature is provided in Appendix A: Related Research.

Street-Level Noise

Transportation's impact on noise levels is well-documented, particularly through assessment of impacts from proximity to airports (*3*). However, the role of motorized vehicles in street-level noise has only received a large number of empirical studies in the last decade. Recognizing the potential for physical and psychological harm due to road noise, acoustic researchers have deployed various noise sensing technologies to assess impacts. Though reference-quality noise sensors are too expensive to deploy in a large urban configuration, researchers have found that high-quality sensors can be designed for urban environments (*4*), and personal smartphones may also help increase the scale of data in urban areas (*5*).

Crowdsourcing Bicycle Safety

Transportation agencies at all levels generally lack the data to support safety analysis specific to bicycling. Crash data are often reported as raw counts, and cannot be evaluated as risks related to exposure in a manner similar to motorized modes due to a lack of traffic volume data (*6*). Further, minor crashes and near misses often go un-reported, and do not show up in police and transportation agency databases (*7*, *8*). Researchers, private developers, and transportation agencies now use crowdsourcing approaches to mitigate these problems.

Early approaches to use smartphones with GPS to record bicycle trips functioned similarly to purpose-made traffic surveys—they required users to download a specific app, and necessitated starting the app before every ride in addition to answering questions about trips (*9*, *10*). Phone-based tools proved crowdsourcing of high-quality bicycle data was feasible, but as they did not have a built-in method to promote use, they subsequently had difficulty recruiting more than a few hundred users even in large cities. Subsequent phone-based tools leveraged design simplicity and user-focused information to encourage broad participation. Currently, the most widely-known crowdsourced bicycle volume data product is Strava Metro, which anonymizes and aggregates bicycle trips recorded using the Strava smartphone application (*11*). Researchers have found moderate to good correlations between Strava data and actual bicycle volumes in different contexts (*12*–*14*). However, the app is designed to serve fitness-oriented bicyclists, who might only choose to post select rides that they wish to record or share online, further biasing traffic volume results (*15*, *16*). Ride Report is a new approach to automatic sensing of bicycle trips with smartphones, which it does by running in the background, using accelerometer data to detect bicycle trips (*17*). Following a detected ride, Ride Report prompts riders to provide a one-button rating of the route. These ratings are aggregated to provide an additional bicycle comfort rating for transportation planning. Several pilot projects to use crowdsourced bicycle volume data to improve safety planning are underway, but do not yet have conclusive answers as to how useful the results are in practice.

Unreported bicycle collisions and near-misses also are a blind-spot for transportation safety. Researchers have developed a platform called BikeMaps, which encourages users to input these missing data through either a smartphone app or an online platform (*8*). Initial studies of deployments of several applications in Canada and the United States show promise for detailed evaluation of bicycling routes, such as off-street, shared-use paths, which often lack traditional collision data collected by transportation agencies (*18*–*20*). Crowdsourcing transportation system data offers potential for improving transportation safety processes and outcomes.

Crowdsourcing Noise Data

Transportation systems' vast geographies and challenging outdoor environments pose a challenge for noise data collection. Researchers and app developers are taking advantage of existing sensors on personal smartphones, with the advantage of tremendous scalability combined with mobile use spanning geographic contexts (*21*). However, the accuracy of measurements can vary according to the make and model of the mobile device. Additionally, apps' algorithms interpret sensed noise in varying ways (*21–24*). App developers have since calibrated sound level measurement for common smartphones and have provided guidance for community sensing, contributing to the level of precision possible for crowdsourced noise data (*22*, *25*, *26*). Studies have shown the usefulness of crowdsourcing for mapping noise levels in urban environments, leading to the development of urban noise as a performance measure provided by engaged citizens (*27*, *28*).

Environmental noise levels are typically measured as sound pressure levels expressed using *equivalent continuous sound level*, denoted as $L_{\mathrm{eq}T}$, taken over a time interval (T). The frequency of sound matters, as do time and pressure, since human hearing responds differently based on frequency. Sound regulations "almost universally call for *A-weighting* of sound frequencies to be used…[as] expressed in dB(A)" (*29*), which sums sound levels from a range of frequencies, emphasizing human-audible frequencies (*30*). "Typically absolute noise levels found along highways range from 60–80 dB(A)," which interferes with normal conversation, and can cause annoyance and discomfort (*30*, *31*). Though professional sound equipment provides the most accurate and consistent measurements, this study emphasizes the potential for leveraging existing smartphone technology, which might be used on a large scale for monitoring noise levels.

The sheer act of engaging the public with crowdsourcing can lead to other benefits, such as increasing awareness about the impact of environmental noise, fostering social learning, and potential political engagement to improve conditions (*32*, *33*).

This brief summary of research shows the importance of urban noise to health, the value of crowdsourced data for safety planning, and approaches to leveraging the public as noise sensors. To date, no research has combined these issues to determine the relationship between street-level noise levels and bicycle crash rates.

Bicycle Safety Factors

Research shows strong relationships between bicycle safety and infrastructure in addition to mode share levels of bicycling. Several studies show improved safety odds on smaller streets and bicycle-specific infrastructure, such as low-traffic roads (*34*), protected bike lanes (*35*), and separated paths (*36*). Additionally, evidence for the safety-in-numbers hypothesis suggests the sheer volume of bicyclists may reduce risk, perhaps because motorists expect to see bicyclists on routes with many bikers (*37*, *38*). National-level studies align with these factors, suggesting design conditions can improve the safety and total volume of bicycling (*39*). However, no research that we are aware of associates bicycle safety risk with street-level noise.

Research Questions

Recent research has identified population-level relationships between the built environment and bicycle crashes as well as methods to estimate bicycle volumes from limited counts. Despite these advancements, few studies have connected these methods to analyze safety at a sub-block level, and none have considered the role of noise as a variable that may be related to bicyclist safety.

This leads to two questions, which we evaluated through fieldwork in Austin, Texas, and the Washington, D.C. metro area:

1. What is the relationship between street-level noise and crash rates for bicyclists?

2. What street and land use variables are associated with high and low street-level noise rates?

For the first research question, we hypothesized the following:

$H_{1.1}$ – Street level noise increase is positively associated with crash risk.

$H_{1.2}$ – Street network classification (trunk highway = 1, off-street path = 4) is negatively related to crash risk.

$H_{1.3}$ – Bicycle mode share is negatively related to crash risk.

For the second research question, we hypothesized the following:

$H_{2.1}$ – Street network classification (trunk highway = 1, off-street path = 4) is negatively related to street noise.

$H_{2.2}$ – Motorized traffic volume is positively associated with street noise.

$H_{2.3}$ – Nearby employment densities are positively associated with street noise.

Method

This study method included 1) preliminary testing that established feasibility of the study; 2) development of a process to validate the noise data collection process; 3) collection and preparation of geographic information system (GIS) data; and 4) analysis of street noise and environmental variables.

Preliminary Testing

Preliminary testing was performed in Austin, Texas, during February, 2017. The lead author collected over 13,000 street-level noise data points using a tested smartphone app (*22, 25*) running on a bicycle-mounted iPhone. Results from this preliminary test showed a moderate, positive relationship of noise to nearby bicycle crashes over the period 2007–2015. Spatially weighted ordinary least squares regression Lagrange Multiplier (LM) diagnostics were significant (Robust LM error 36.8, $p < 0.001$), suggesting use of a spatial error regression model. Spatial error regression modeling showed a possible link between street-level noise as experienced on a bicycle and proximity to serious bicycle crash locations ($R^2 = 0.53$). This preliminary analysis suggested a relationship, but standardization of crash data by bicycle volume and inclusion of other explanatory variables were needed to further describe and evaluate the relationship between street noise and vulnerable road user safety.

Noise Data Collection

This project includes data from two study sites: Austin, Texas and the Washington, D.C. metro area. These two sites were chosen based on three factors: 1) proximity to researchers and anticipated students for bicycle route data collection, 2) availability of crash data of sufficient quality and quantity for statistical testing, and 3) available explanatory GIS data.

The Noisetube platform was developed to crowdsource decibel ratings for many different places and specific purposes, but there are no consistency or quality assurances for the crowdsourced data. Smartphones could be carried in a pocket or recording measurements could be made from inside a building or vehicle without this information being recorded. Existing noise data quantities are also insufficient for statistical testing for this purpose, even if their collection method was consistent. This study collected data using the same protocol, with a smartphone mounted on a bicycle handlebar, and the bike ridden as though on a normal bicycling trip.

Data collection routes were planned to balance a broad representation of urban and suburban contexts in each city, a variety of transportation functional classes, and practicality and safety for the riders. Figure 1 shows the routes in Austin (TX) and the Washington, D.C. metro area, including parts of Alexandria and Arlington (VA).

Figure 1. Noise data collection routes in Austin (TX) at left, and the Washington, D.C. metro area at right.

Data were downloaded from the Noisetube platform in JSON format and converted to CSV format for analysis in statistical and GIS software. Datasets from multiple rides were merged together, retaining a time stamp, GPS location, and decibel rating for each measurement.

Validation of Noise Data Collection

We used two methods to validate the process for collecting street-level noise levels. First, we compared collected data to the U.S. National Road Noise Inventory (*1*). Next, we compared smartphone-collected noise levels with a reference-quality noise meter.

The U.S. National Road Noise Inventory is a GIS dataset that uses Average Annual Daily Traffic (AADT) values from the Federal Highway Administration's Highway Performance Monitoring System (HPMS) with acoustical algorithms from the Traffic Noise Model (TNM). Typical noise levels on arterial streets range between 50 and 70 dB(A), slightly lower than the levels we recorded using smartphones, as shown in Figure 2. The variance meets expectations, since the National Road Noise Inventory only includes noise created by surface transportation, while local measurements include other ambient noise sources.

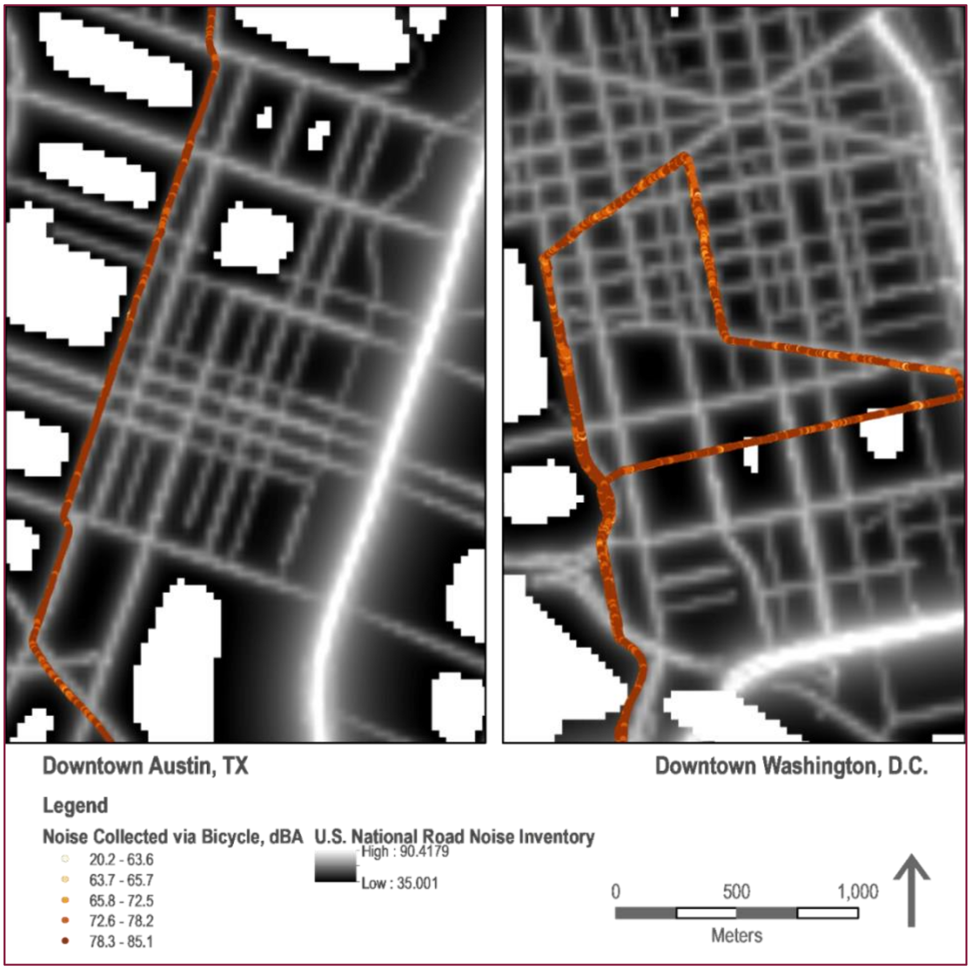

Figure 2. Noise collected via bicycle and from the U.S. National Road Noise Inventory in downtown Austin (TX) and the Washington, D.C. metro area.

A total of 27 photos were examined, with each photo containing a pair of street noise measurements. In each photo, one measurement was made with a handheld noise meter, and one measurement was made with a smartphone app. Figure 3 presents a typical example.

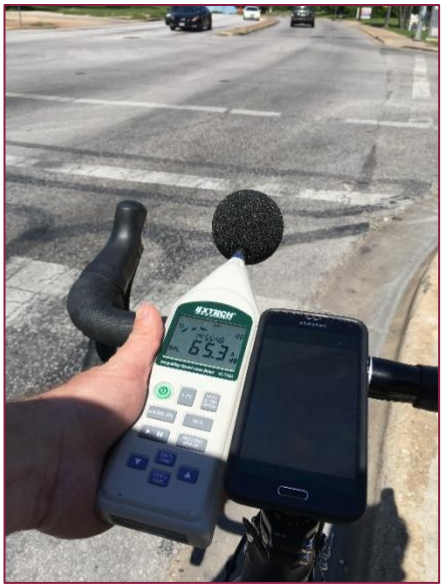

Figure 3. Street noise measurement with reference noise meter and bicycle-mounted smartphone.

Of the 27 photos, 11 (approximately 41%) yielded legible results. The remaining 59% were illegible due to sun glare on the screen, shadow on the screen, or the photo being out of focus.

The 11 legible photos yielded handheld noise meter readings and smartphone app readings. Data was imported into SPSS Statistics software and descriptive statistics are presented in Table 1. The smartphone reading was consistently higher at each location, resulting in higher mean and median values estimated by the smartphone app.

Table 1. Noise Data Validation Readings, db(A)

Statistic	Handheld Noise Meter	Smartphone App
Mean	63.00	69.80
Standard Error	2.27	2.15
Median	64.80	72.00
Minimum Value	50.60	58.00
Maximum Value	72.50	77.00
Standard Deviation	7.52	7.14
Range	21.90	19.00

Figure 4 presents a scatter plot of noise value intercepts for each of the 11 sites. The plot suggests a high degree of collinearity, confirmed by the significant correlation test (Kendall rank correlation = 0.881, $\alpha = 0.01$).

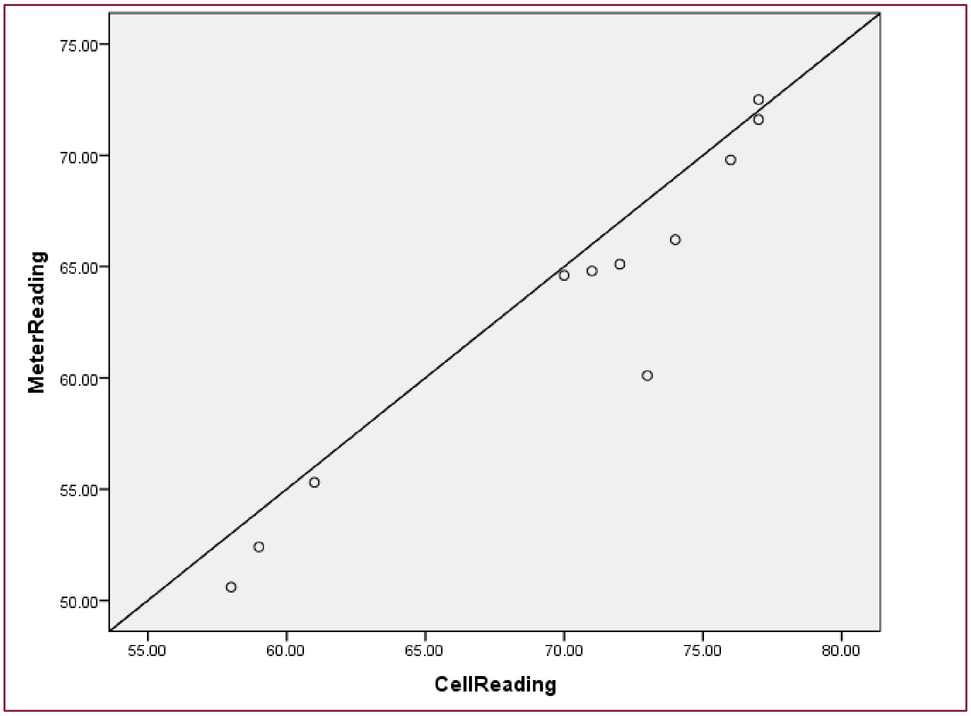

Figure 4. Scatter plot of cell reading/meter reading intercepts for each of the 11 sites.

Because 1) both noise readings essentially acted as "matched pairs," 2) both were estimated using a continuous scale (A-weighted decibels), 3) neither of the estimates being compared followed a normal distribution, and 4) the distribution of the differences between the two estimates was approximately symmetrical, a decision was made to use the Wilcoxon signed-rank test. The median smartphone reading was 7.2 dB(A) higher, a statistically significant amount ($Z = -2.937$, $p = 0.003$).

The difference may be at least partially explained by the foam wind muffler on the reference sound meter. It is plausible that the unprotected smartphone microphone may record noise levels more similarly to how a human ear experiences road noises, including wind, but this study did not explore the issue further. The overall consistency between meters suggests smartphones may be useful for evaluating relative ranges of noise levels in studies like this one, but may require further controls for other research needs.

GIS Data Collection and Preparation

The following explanatory GIS data was obtained from local transportation agencies for both the Austin, TX and the Washington, D.C. metro area regions: bicycle crashes, street volumes, speed limits, number of lanes, and bicycle infrastructure. In addition, the Environmental Protection Agency's Smart Location Database provided comparable factors between the regions (*41*).

We cleaned the route network layer so that it only included road and path segments where bicyclists collected noise data for each city. We removed parallel network lines on arterial streets and freeways that had separate linework for different directions, or main lanes versus frontage roads. We found no research evaluating the spatial accuracy of crash data, but we expect accuracy similar to consumer-grade GPS or address geolocators—likely between 10 and 20 meters (33–66 ft.) from the actual location. This variability could result in mis-attributing crashes to a nearby link, including intersecting streets. However, our choices of bicycle routes for data collection may moderate this potential effect, since the routes could be more often aligned with the population's choices, and therefore the crash locations. We selected only crashes within 20 meters (66 ft.) of the centerline of our route network, which prevented mis-attribution of crashes from further distances to the routes. Using a spatial join, we summed the number of crashes based on which route segment they were closest to. Calculating actual risk requires consideration of the length of a route segment in addition to the volume of bicycling at each location.

Data on transportation infrastructure specific to bicycling is inconsistent between jurisdictions. However, Open Street Map does include a functional system variable ranging in this dataset from the largest highway: "trunk," to "primary," "secondary," and "tertiary," then off-street "path." We converted these to ordinal number variables 1–5, respectively, for analysis.

Modeling Bicycle Volume to Control for Crash Risk

Direct modeling of noise levels with collision frequency would not control for overall bicycle volumes. Since on-street counts of bicycle traffic are not available for every segment, a direct-demand model provides a reasonable estimate to normalize crash frequencies. We used a national database of bicycle traffic counts (including data from ~20 metropolitan areas) to generate predictions for bicycle traffic at every street segment in Washington, D.C., Arlington, VA, Alexandria, VA, and Austin, TX.

The methods of processing count data, tabulating independent variables, and building the base-case models were documented in detail in the following report: *Multi-City, National Scale Direct-Demand Models of Peak-Period Bicycle and Pedestrian Traffic* (*42*).

We estimated spatial predictions of bicycle and pedestrian traffic volumes in the Washington, D.C. metro area and Austin, TX for every street segment. We used ArcGIS to create midpoints of all road segments for Washington, D.C., Arlington, VA, Alexandria, VA, and Austin, TX. We then applied models from the systematic hold-out cross validation models to predict traffic volumes at these locations. To illustrate this, Figure 5 shows predictions for one afternoon of peak-period counts in 2016 (the last year of count data) on a typical fall day (77 degrees Fahrenheit and no rain).

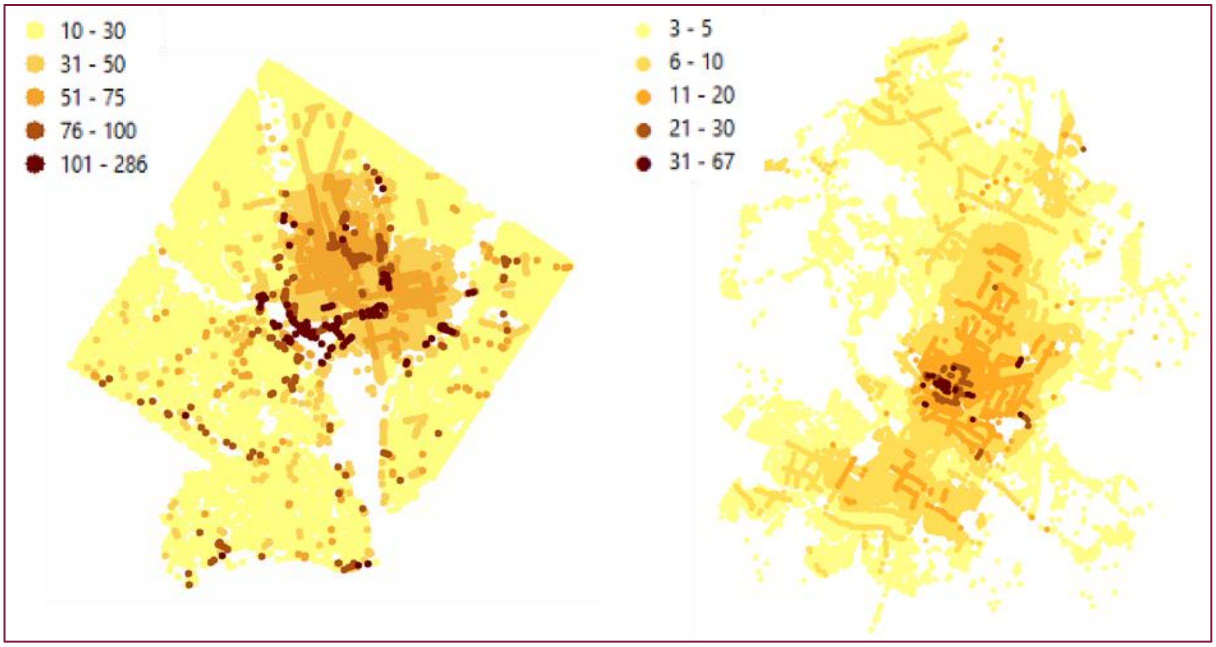

Figure 5. Bicycle traffic prediction (2-hr. afternoon peak) maps of the Washington, D.C. metro area (left) and Austin, TX (right).

Conversion of the predictions for one 2-hour period of peak afternoon bicycle traffic to annual traffic predictions required applying adjustment factors to estimate traffic for a full day, and then a year. Adjustment factors for bicycle trail traffic in Austin for afternoon peak hour traffic (7% of daily traffic) were similar to national averages recorded in the National Bicycle and Pedestrian Documentation Project documentation (*13*), so this factor was used for both cities (7% of daily traffic multiplied by 2 hours = 14% of daily traffic).

$$ADB, Average\ Daily\ Bicyclists = \frac{2{-}hr\ PM\ peak\ Volume}{2hr\ adustment\ factor\ (0.14)} \quad (1)$$

To estimate annual bicycle traffic, the number of average daily bicyclists was multiplied by 30.5 for a monthly volume, then we assumed a monthly volume would be 8% of annual trips, based again on National Bicycle and Pedestrian Documentation Project documentation (*43*).

$$AAB, Average\ Annual\ Bicyclists = \frac{Average\ Daily\ Bicyclists \times 30.5}{monthly\ adjustment\ factor\ (0.08)} \quad (2)$$

Next, we calculated the number of kilometers bicycled in a year per network segment by dividing the length of each segment in meters by 1,000 then multiplying by the number of average daily bicyclists.

$$ABKT, Annual\ Bicycle\ Kilometers\ Traveled = \frac{segment\ length\ in\ meters}{1{,}000} \times AAB \quad (3)$$

Crash risk was calculated as the number of crashes per year divided by 100,000 annual bicycle kilometers traveled.

$$Annual\ Crashes\ per\ 100{,}000\ BKT = \frac{crashes}{years\ of\ crash\ data} \Big/ \frac{ABKT}{100{,}000} \quad (4)$$

To summarize, we estimated the number of average annual bicyclists by starting with modeled 2-hour afternoon peak volumes in the fall, divided by 0.14 to get average daily bicyclists; multiplying by 30.5 to approximate a monthly volume; and dividing by a monthly adjustment factor of 0.08. Next, we estimated bicycle kilometers traveled on each network segment by multiplying the length of each segment by average annual bicyclists (AAB). Finally, we calculated crash risk by dividing crashes per year by bicycle 100,000 kilometers (62,137 mi.) traveled for each segment, as shown in Figure 6. On the Austin noise data collection route, the average risk was 19.7 (st. dev. 33.1) bicycle crashes per 100,000 bicycle kilometers traveled. On the Washington, D.C. metro area route, crash risk was 11.4 (st. dev. 36.2) bicycle crashes per 100,000 bicycle kilometers traveled.

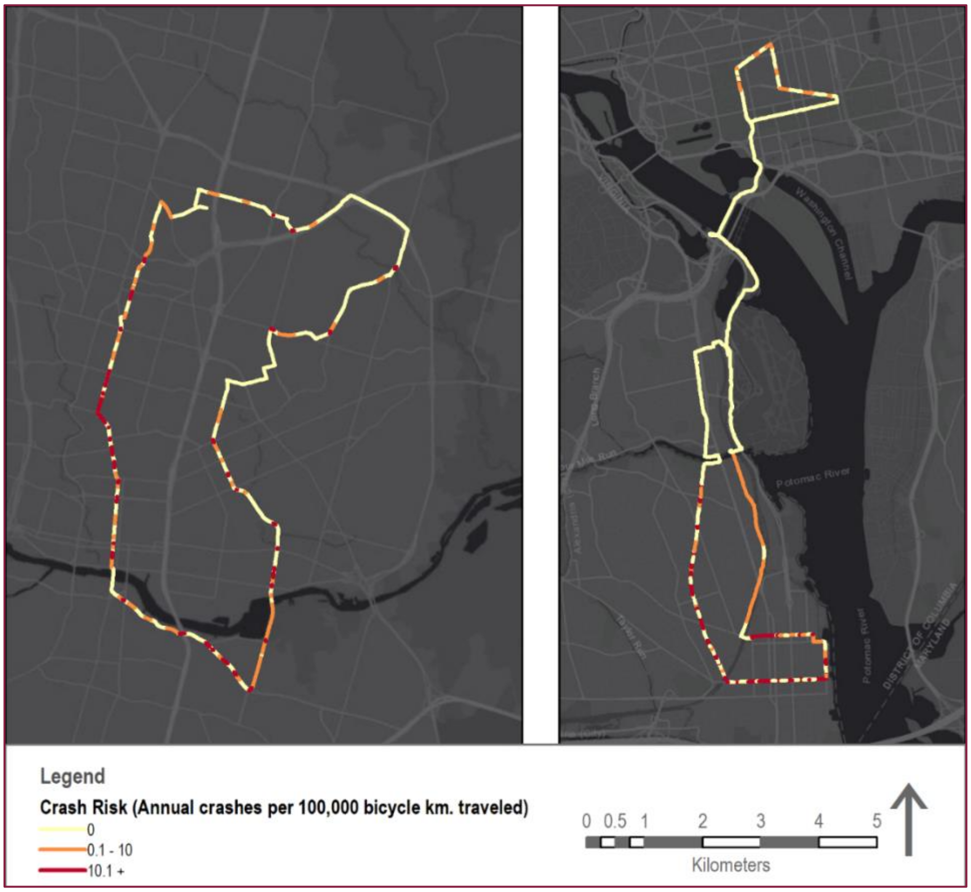

Figure 6. Bicycle crash risk (annual crashes per 100,000 bicycle kilometers, or 62,137 mi., traveled) along noise data collection routes in Austin, TX at left, and the Washington, D.C. metro area at right.

Analysis of Street Noise and Environmental Variables

Descriptive statistics of collected crash and noise data were computed to support comparison of the data collection effort and data characteristics of each site, including mean and standard deviations. Histograms of crash and noise data at both sites were graphed.

Inferential statistics were used to evaluate the extent of the relationship between street noise and bicycles. An independent sample *t*-test between the two cities provided a broad characterization of differences between sampled noise and crash data at each site. Ordinary least squares regression using spatial interaction diagnostics determined models for understanding the relationship between noise data and crashes at each testing site.

Results

Noise

Street-level noise results from both regions showed variation between and along the routes. We measured the overall differences with a two-tailed *t*-test assuming unequal variances. On average, the Austin route was louder, as measured in db(A) ($M = 79.1$), than the Washington, D.C. metro area ($M = 78.5$), $t(587) = 3.74$, $p < 0.001$. However, the maps of street-level noise in Figure 7 show the loudest areas in red in Austin along state highway 290 at the northern stretch of the route, and in the Washington, D.C. metro area crossing the Potomac River on the path paralleling I-395.

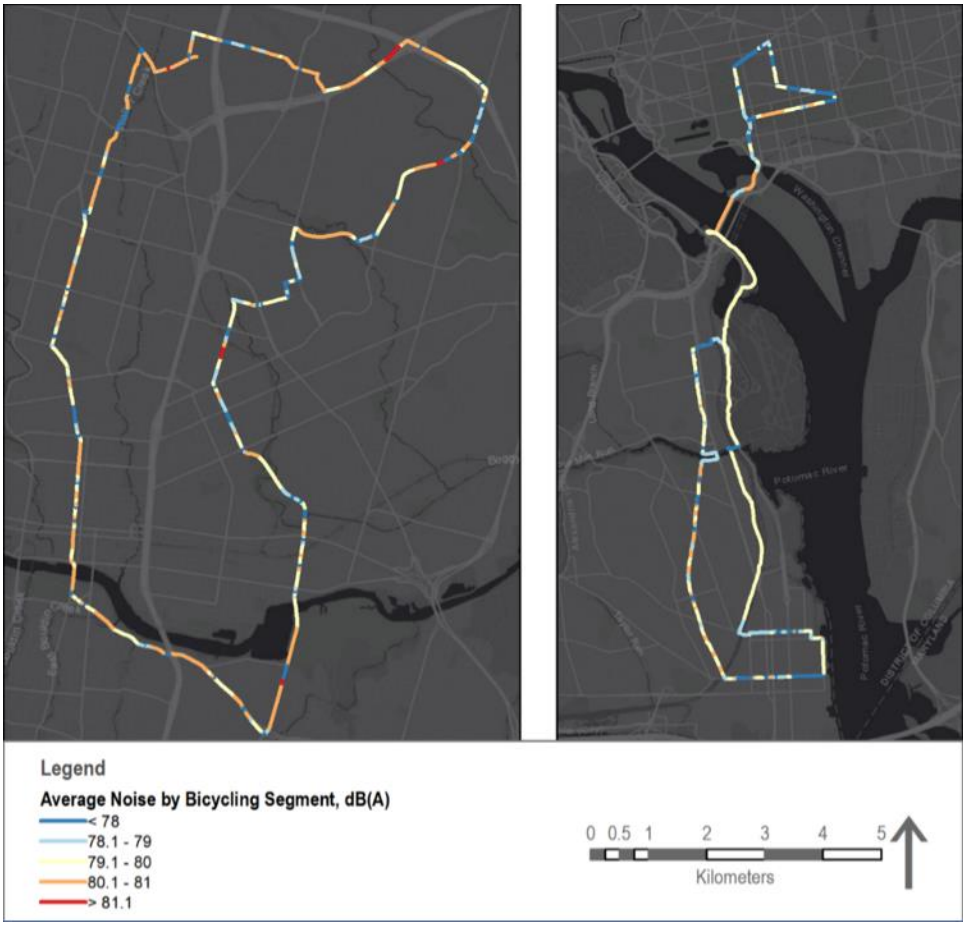

Figure 7. Average noise recorded by bicyclists along routes in Austin, TX (SH 290) at left, and the Washington, D.C. (I-395) metro area at right.

Descriptive results in Table 2 show that the Austin route included a wider range of noise levels along its 425 segments, with a minimum of 68 db(A), but low-range noise levels were more widespread in the Washington, D.C. metro area.

Table 2. Noise Data Descriptive Statistics, Averaged by Network Segment, db(A)

Statistic	Austin (TX) *N* segments = 425	Capitol Area (DC) *N* segments = 280
Mean	79.10	78.55
Standard Error	0.09	0.11
Median	79.72	79.26
Minimum Value	68.04	71.41
Maximum Value	81.82	81.02
Standard Deviation	1.88	1.92
Range	13.77	9.61

Histograms in Figures 8 and 9 show similar skewness in the cities' street-level noise levels. Both distributions are skewed to the right, which reflects the fact that the scale is logarithmic—halving the sound power results in a 3-decibel drop. Accordingly, very few measurement areas in this study were consistently louder than 80 dB(A).

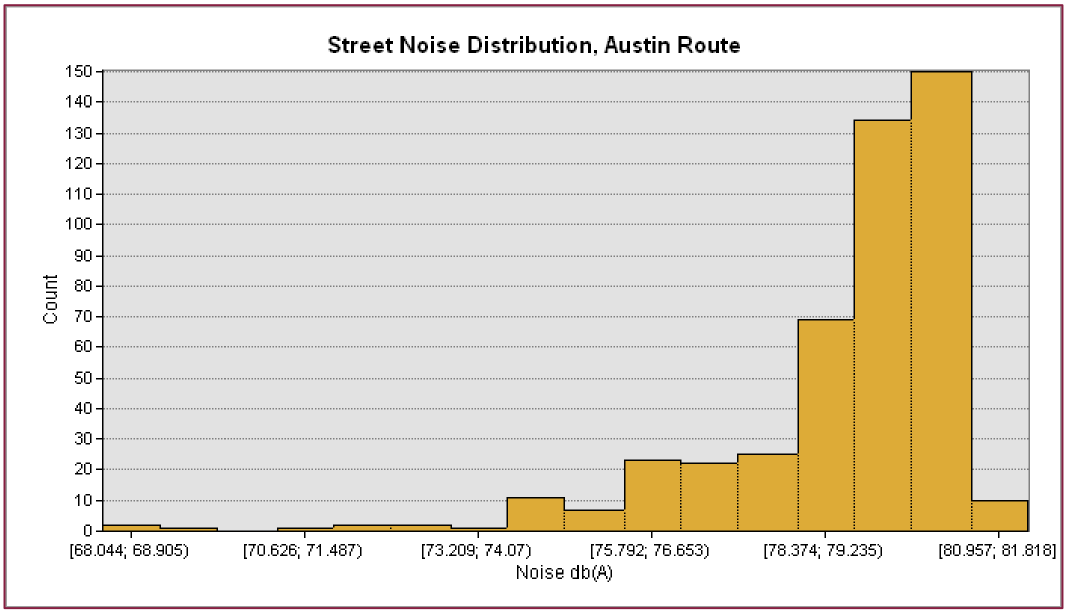

Figure 8. Histogram of average noise recorded by bicyclists along route in Austin, TX.

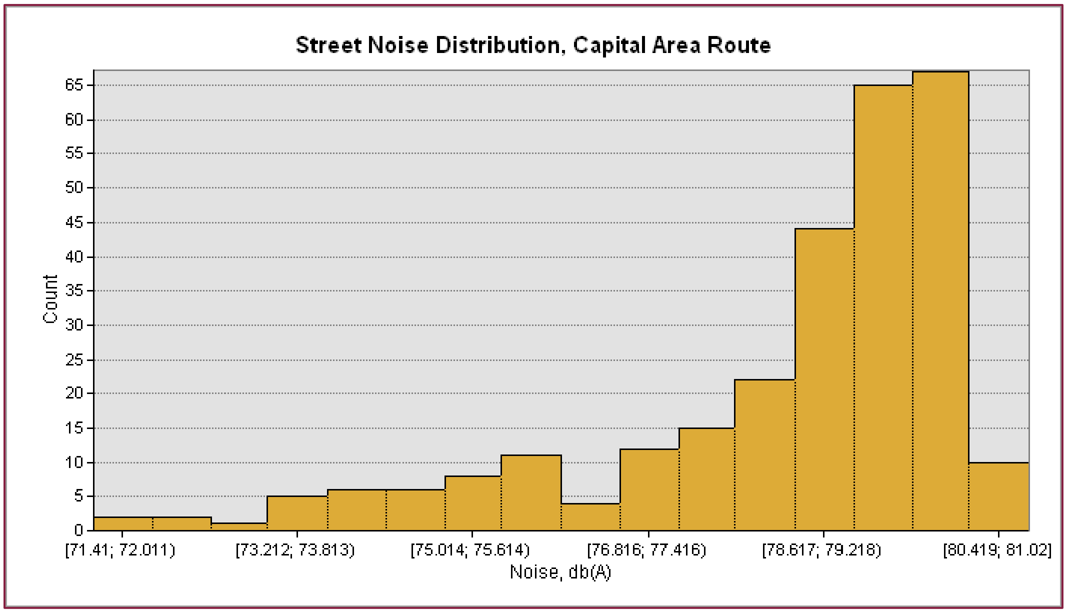

Figure 9. Histogram of average noise recorded by bicyclists along route in the Washington, D.C. metro area.

Crashes

Based on bicycle collision data from 2010–2017 (data in Alexandria, VA is from 2011–2016), we found relatively similar risks in Figure 6, normalized by modeled bicycle traffic volumes. When viewed on a per-kilometer basis, however, as in Table 3, the Washington, D.C. metro area had over three times as many crashes (M = 46.9) as Austin (M = 13.9), $t(328) = -3.7$, p <0.001. Both regions had some intersections with very high crash rates, with a maximum of over 600 and 1,200 bicycle crashes per kilometer in Austin and the Washington, D.C. metro area, respectively.

Both areas had long stretches of noise data collection routes with zero bicycle crashes in recent years—this could be because the areas are relatively safe or because these routes were largely avoided by bicyclists. This shows the importance of considering crash risk in terms of absolute numbers, per network distance, and per bicycle distance traveled.

Table 3. Bicycle Collision Descriptive Statistics, per Kilometer of Route Network

Statistic	Austin, TX *N* segments = 425	Washington, D.C. metro area *N* segments = 280
Mean	13.86	46.90
Standard Error	2.54	8.58
Median	0.00	0.00
Minimum Value	0.00	0.00
Maximum Value	655.74	1280.64
Standard Deviation	52.46	143.60
Range	655.74	1280.64

Multivariate Analysis

To test interactions of street noise and other variables on crash rates, we performed ordinary least squares (OLS) regression with tests of spatial dependence. Starting with hypothesized interaction of crash rates with street noise levels ($H_{1.1}$ = positive relationship), functional system class ($H_{1.2}$ = negative relationship), and bicycle mode share ($H_{1.3}$ = negative relationship), we found conflicting results. Similarly, further testing with street network classification ($H_{2.1}$), motorized traffic volume ($H_{2.2}$), and employment densities ($H_{2.3}$) differed between the sites.

Crash Risk in Austin, Texas

Regression of factors to explain variation in crash risk (annual crashes per 100,000 bicycle kilometers, or 62,137 mi. traveled) showed limited interaction. To evaluate spatial dependence, we spatially weighted the dataset using a single-order Queen configuration. None of the tests for spatial dependence were significant, as shown in Table 4 (Moran's $I = 0.91$, $p = 0.36$), including both spatial lag (LM = 0.28, $p = 0.60$), and spatial error (LM = 0.46, $p = 0.50$). Accordingly, we used a classic configuration of OLS, which explained very little of the variation in bicycle crash risk in Austin ($R^2 = 0.04$, AIC = 828.62). In our initial Austin model, none of the factors we hypothesized to predict crash risk met a 95% confidence level ($p < 0.05$), including street noise ($H_{1.1}$), functional system class ($H_{1.2}$), or bicycle mode share ($H_{1.3}$).

Table 4. Crash Risk Factors in Austin (TX)

Variable	Coefficient	Standard Error	t-Statistic	Probability
Constant	194.374	103.931	1.87023	0.06470
db(A)	-2.22284	1.29899	-1.71122	0.09049
Functional System	-2.77613	2.73011	-1.01686	0.31195
Bicycle Mode Share within 1,000 meters (0.62 mi.)	1442.89	2699.17	0.534569	0.59426

Crash Risk in the Washington, D.C. Metro Area

Using the same approach for spatial weighting—a single-order Queen configuration—showed that crash risk in the Washington, D.C. metro area dataset had significant spatial dependence (Moran's $I = -8.8$, $p < 0.001$) for both lag (LM = 37.7, $p < 0.001$) and error (LM = 76.80, $p < 0.001$). Therefore, we relied on the spatial error model with maximum likelihood estimation, which also included a Lambda spatial error term as shown in Table 5. Regression with the percent bicycle commuting and functional system classification were positive and significant ($p < 0.05$), while average dB(A) did not meet this threshold ($H_{1.1}$). This model explained most of the variation of bicycle crash risk in the Washington, D.C. metro area ($R^2 = 0.87$, AIC = 323.83).

Table 5. Crash Risk Factors in the Washington, D.C. Metro Area

Variable	Coefficient	Standard Error	z-value	Probability
Constant	10.4867	5.89581	1.77868	0.07529
db(A)	-0.138902	0.0751648	-1.84797	0.06461
Functional System	0.392085*	0.196294	1.99744	0.04578
Bicycle Mode Share within 1,000 meters (0.62 mi.)	0.000841779*	3.2222e-005	26.1244	<0.00001
Lambda	-0.870142	0.0738285	-11.786	<0.00001

Results of the street noise models did not meet a 95% probability threshold of association with crash risk in either city ($H_{1.1}$), though the direction of association was negative, as hypothesized. Street functional system classification was similarly not significant in Austin ($H_{1.2}$) but was positively associated with street noise in the Washington, D.C. metro area. Bicycle mode share, as an indicator of the safety-in-numbers concept ($H_{1.3}$), showed no significant association in Austin, but a positive correlation in the Washington, D.C. metro area.

Street Noise Factors in Austin, Texas

Again, none of the diagnostics for spatial dependence in Austin met significance criteria, suggesting use of a classic OLS regression model. Table 6 shows that none of the hypothesized factors met a 95% confidence threshold ($R^2 = 0.06$, AIC = 355.06), though functional system did have a non-significant negative association with street noise ($H_{2.1}$).

Table 6. Street Noise Factors in Austin (TX)

Variable	Coefficient	Standard Error	t-Statistic	Probability
Constant	79.5824	0.40509	196.456	0.00000
Functional System	-0.353532	0.214821	-1.64571	0.10331
Speed Limit	0.0013676	0.0136468	0.100214	0.92040
Employment within 300 meters (984 ft.)	7.60083e-005	7.40105e-005	1.02699	0.30718

Street Noise Factors in the Washington, D.C. Metro Area

Diagnostics for spatial dependency of street noise in the Washington, D.C. metro area route suggest the need for a model incorporating spatial error (Moran's $I = 4.66$, $p < 0.001$; LM lag = 21.70, $p < 0.001$; LM error = 18.82, $p < 0.001$).

Running a spatial error model with maximum likelihood estimation on the spatially weighted factors explained less than a quarter of the variation in street-level noise ($R^2 = 0.21$, AIC = 1,110.69). Table 7 shows that only employment density was a significant predictor of street noise in the Washington, D.C. metro area route ($H_{2.3}$), though with a counter-intuitive negative association.

Table 7. Street Noise Factors in the Washington, D.C. Metro Area

Variable	Coefficient	Standard Error	z-value	Probability
Constant	78.7982	0.367142	214.626	0.00000
Functional System	0.0510698	0.101366	0.503818	0.61439
Speed Limit	-0.00540134	0.0155835	-0.346607	0.72889
Employment within 300 meters (984 ft.)	-9.86176e-005*	2.50405e-005	-3.93833	0.00008
Lambda	0.364174	0.0725581	5.01907	0.00000

Discussion

Limitations and Differences Between City Models

This study involved several steps of data collection, traffic volume estimation, gathering of local GIS data, and analysis. Though we were able to control the final step, each of the previous tasks involved differences between our comparison sites.

First, the route choices in the Washington, D.C. metro area included off-street paths, whereas the Austin route was all on-street. This choice prioritized the safety of our data collection team over comparability of sites. While this difference restricts the comparability of our two models, it extends the usefulness of our results for people interested in the effects of local infrastructure on noise and safety. Though we used the same equipment configuration in each city, and validated it against reference sound equipment, the chosen routes do not represent the full extent of environmental variation in either city. Both bicycle noise data collectors reported seeing lower immediate sound levels when the bicycle was at very low speeds or stopped. This suggests that bicycle speed may be an important factor in street noise measured with smartphones that lack a wind buffer device, such as a foam muffler as used on dedicated microphones. Related to this issue, environmental wind might increase detected street noise, and can be expected to fluctuate not only with hourly weather conditions, but with micro-environmental situations, such as street trees, open fields, or tall buildings causing urban wind tunnels. Each of the wind factors may relate to detected street noise, but still are part of the whole variation of noise as experienced by a bicyclist in actual street conditions. Continuation of this study with additional routes in the same cities, or additional cities, with or without noise mufflers or controlling for local wind speeds, can be expected to produce different results.

Second, we used the same traffic volume estimation model in each city, but only the Washington, D.C. metro area was calibrated with local counts. Though local counts existed in Austin, they were recorded at fewer locations for longer durations. Since the direct-demand model developed in a previous study is specific to having short-duration counts in many locations, we decided to apply this model to Austin without local calibration rather than develop another model that might further limit the comparability of cities. This means that the Austin model may not accurately estimate exposure risk, and that later refinement of the input traffic volume estimates could produce different results.

Third, variations in local GIS data quality and completeness can influence analysis results. Incorporation of additional environmental factors may improve modeled explanation of crash risk and street noise. Our hypothesized factors varied in each city for each model and suggest other factors could be identified to improve understanding of the association between street noise and bicycle crash rates.

We used the same analysis steps in each city, however. Running ordinary least squares regression with spatial diagnostics for each city directed us to make adjustments to the final models for this report, but the magnitude of relationships stayed the same between variants in our models. Limitations of data collection, traffic volume estimates, and local GIS data likely impact the comparability and generalizability of the results.

Crash Risk Factors

Our hypothesized relationship of street noise, network functional class, and bicycle mode share showed mixed results between the cities. Though not significant in Austin, functional system and bicycle mode share were significant in the Washington, D.C. metro area. This could be due to variations in the built environment and culture of the cities, in addition to our specific choice of sampling routes.

Specific to the Washington, D.C. metro area, our findings provided further support for two key bicycle safety issues. The first is that providing infrastructure for bicycling, such as separated paths and connected residential streets, is associated with lower crash risk. The second is support for the safety-in-numbers hypothesis. Areas with a higher bicycle commuting mode share also had lower crash risk. Both findings from the D.C. metro area support efforts to plan and develop infrastructure to support bicycling, but our findings in Austin suggest that local contexts impact the results.

Street Noise Factors

In the Washington, D.C. metro area, only employment densities significantly predicted street noise, and the direction of association was the opposite of our hypothesis. This could result from reduced traffic speeds in urban areas, and/or perhaps from street trees and other landscape elements that influence street noise, which were not directly considered in this study.

Route choice makes a difference in street noise experienced by bicyclists. In Austin, functional system—infrastructure ranging from highways to separated paths—had the predicted negative relationship with street noise, but was outside a 95% threshold for statistical confidence. The route in the D.C. metro area included separated paths that ran parallel to highways, so this context of relatively noisy paths may not relate to many other areas. In reality, people who bicycle choose routes based on a wide variety of factors, and street noise may play a secondary role to perceived safety.

Conclusions and Recommendations

As the first known exploration of the relationship between street noise and vulnerable road user safety, this study provides a transferable method for further study. Evidence from the two noise data collection routes in this study show counter-intuitive results regarding safety—we did not find street noise to have a positive relationship with crash risk after controlling for other factors. However, given the limitations recognized and described previously in the Discussion section, we do not consider these results conclusive. Accordingly, we recommend the following recommendations and next steps:

1. **Investigate the causal factors of reduced crash risk.** Evidence from the Washington, D.C. metro area showed infrastructure and existing bicycle mode share are strong predictors of reduced risk. However, causal analysis of planning and engineering decisions requires methods less often used in transportation, such as cross-case and mixed-method designs.
2. **Conduct studies of different routes in other cities and roadway conditions.** Additional studies could extend and/or counter findings from this study.
3. **Employ different statistical methods.** Different methods should be used with the existing dataset provided on the Dataverse[1]. Techniques such as combining data with cities coded as a binary variable may produce different results.
4. **Adapt this method for participatory transportation planning.** Our review of previous research showed that street noise impacts communities, even if our immediate results were inconclusive regarding bicycle crash risk. The method could be helpful as part of local urban studies for different planning purposes, and validation of our off-the-shelf approach supports data collection by non-professionals.

Additional Products

This section provides an overview of the products from this study related to education and workforce development, technology transfer, and data products. Check the project website (https://www.vtti.vt.edu/utc/safe-d/index.php/projects/street-noise-relationship-to-vulnerable-road-user-safety/) for updates.

Education and Workforce Development Products

This study included student participation in data collection and traffic modeling through Virginia Tech, and the research team is developing course materials at university and professional levels.

[1] The Dataverse includes georeferenced noise readings for this study, available from https://doi.org/10.15787/VTT1/5LWJTV.

Dr. Buehler is developing a lecture for fall 2018, and Dr. Hankey is preparing a lecture for spring 2019. The research team will share slides for professional audiences online as well.

Technology Transfer Products

Following publication of this report, the project team is developing a paper for review and potential presentation through the Transportation Research Board Annual Meeting and later publication through a peer-reviewed journal; dissemination of the report via social media in cooperation with TTI; and is planning plan a webinar based on study results in further cooperation with the Safe-D UTC.

Safe-D has asked if we will make the noise collection platform and data public. The platform is a publicly available app. We are also happy to work with Safe-D to share our data. Completion date: as advised by Safe-D.

Data Products

Datasets from noise data collection and explanatory variables are available on the Safe-D Dataverse. The noise data collection platform itself is already public: http://www.noisetube.net.

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Appendix

Appendix A: Related Research

Table A-1. Related Research

Topic	Author	Year	Geographical Area
Street-level noise	Nijland & van Wee (*44*)	2005	Europe
Street-level noise	Boogaard et al. (*45*)	2009	The Netherlands
Street-level noise	Gidlöf-Gunnarsson & Öhrström (*46*)	2010	Sweden
Crowdsourcing noise data	Maisonneuve, Stevens & Ochab (*22*)	2010	Paris, France
Street-level noise	Botteldooren, Dekoninck & Gillis (*47*)	2011	Gent, Belgium
Crowdsourcing noise data	Dekoninck, Botteldooren & Panis (*23*)	2012	Gent, Belgium
Street-level noise	Bell & Galatioto (*4*)	2013	Europe
Crowdsourcing noise data	D'Hondt (*25*)	2013	Antwerp, Belgium
Street-level noise	Zuo, et al. (*48*)	2013	Toronto, Canada
Crowdsourcing noise data	Kardous & Shaw (*21*)	2014	United States (lab measurements)
Crowdsourcing noise data	Drosatos et al. (*27*)	2014	Antwerp, Belgium
Street-level noise	McAlexander, Gershon & Neitzel (*49*)	2015	New York City
Street-level noise	Dekoninck, et al. (*50*)	2015	India & Belgium

Street-level noise	Dekoninck, Botteldooren & Panis (*51*)	2015	Ghent, Belgium
Crowdsourcing noise data	Radicchi, Henckel & Memmel (*26*)	2016	Germany
Crowdsourcing noise data	Leao & Izadpahani (*52*)	2016	Victoria, Australia
Street-level noise	Apparicio et al. (*53*)	2016	Montreal, Canda
Street-level noise	Alsina-Pagès (*54*)	2016	n/a (conceptual)
Street-level noise	Kang et al. (*55*)	2016	n/a (conceptual)
Crowdsourcing noise data	Park (*56*)	2017	New York City
Crowdsourcing noise data	Aumond et al. (*24*)	2017	Paris
Street-level noise	Mydlarz, Salamon & Bello (*5*)	2017	New York City
Crowdsourcing noise data	Jennett et al. (*57*)	2017	London
Street-level noise	Seidman et al. (*58*)	2017	United States (lab measurements)
Crowdsourcing noise data	Droumeva (*32*)	2017	Global
Street-level noise	Li, Feng & Wu (*59*)	2017	China
Crowdsourcing noise data	Li, Liu & Haklay (*28*)	2018	Global