Development of Crash Modification Factors for Bicycle Treatments at Intersections

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FOREWORD

The research documented in this report was conducted as part of the Federal Highway Administration's (FHWA) Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS). FHWA established this PFS in 2005 to conduct research on the effectiveness of safety improvements identified by the National Cooperative Highway Research Program *Report 500* guides as part of the implementation of the American Association of State Highway and Transportation Officials' Strategic Highway Safety Plan. ELCSI-PFS studies provide a crash modification factor and benefit–cost economic analysis for each targeted safety strategy identified as a priority by member States of the PFS.

This report documents the safety effectiveness of bicycle treatments at urban intersection locations in Virginia and Texas. This study included bicycle lanes, extension lines, through bicycle lanes, buffered bicycle lanes, and chevron pavement markings along the intersections. The evaluation considered the total number of vehicular crashes, including those resulting in fatality and injury. The analysis found statistically significant crash reduction for separated bicycle lanes in certain, but not all, contexts. These study results may be of interest to roadway safety professionals, State and local engineers, and planners responsible for the design and operation of facilities that may benefit from bicycle lane installations.

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Director, Office of Safety and Operations
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16. Abstract
This research developed crash modification factors (CMFs) for bicycle treatments at urban intersections in the United States. The treatments evaluated were the presence of bicycle lanes, extension lines, through bicycle lanes, buffered bicycle lanes, and chevrons along the intersections. The research team compiled and analyzed safety data from Virginia and Texas. The evaluation considered the total number of vehicular crashes, including those crashes resulting in fatality and injury. Safety data collection focused on locations with available bicycle traffic data, or where direct demand models were applicable, and at intersections where bicycle intersection countermeasures were sufficient to conduct a statistical analysis. The research team included bicycle traffic volume counts as a key factor in the analysis, similar to how average annual daily traffic accounts for motor vehicle exposure. For the Virginia study sites, the research team developed estimates of average daily bicycle traffic using actual bicycle counts. For the Texas sites, the bicycle volume estimates were based on direct demand models developed by team members for this evaluation. The analysis found that having separated bicycle lanes and providing a mixing zone between bicyclists and motor vehicles at intersection approaches was associated with reductions in total, fatal and injury, and non-weather-related crashes in Texas. Other evaluations that considered bicycle and vehicular traffic volume, traffic control devices, and other geometric design features yielded CMFs that were not statistically significant. For the economic evaluations, benefit–cost ratios for the two identified treatments were estimated as low as 5.9 when additional right of way was assumed, and up to 113.3 otherwise. Results indicate that these treatments are economically feasible.

17. Key Words
Safety, crash modification factor, CMF, bicycle lanes

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APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or “metric ton”)	Mg (or “t”)
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or “t”)	megagrams (or “metric ton”)	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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LIST OF ABBREVIATIONS

AADT	annual average daily traffic
AASHTO	America Association of State Highway and Transportation Officials
ADBT	average daily bicycle traffic
B/C	benefit–cost
BL	bicycle lane
CMF	crash modification factor
DCMF	Development of Crash Modification Factors
DOT	department of transportation
ELCSI-PFS	Evaluation of Low-Cost Safety Improvements Pooled Fund Study
FHWA	Federal Highway Administration
FI	fatal and injury
GIS	geographic information systems
GLM	generalized linear model
GLMM	generalized linear mixed model
LTL	left-turn lane
MUTCD	*Manual on Uniform Traffic Control Devices*
MV	motor vehicle
NACTO	National Association of City Transportation Officials
ROW	right of way
RTL	right-turn lane
SBL	separated bicycle lane
Std Dev	standard deviation
PS	propensity score
PSM	propensity score matching
PSW	propensity score weighting
SPF	safety performance function
VDOT	Virginia Department of Transportation
Vpd	vehicles per day
VSL	value of a statistical life

EXECUTIVE SUMMARY

The Federal Highway Administration's (FHWA) Development of Crash Modification Factors (DCMF) Program was established in 2012 to address highway safety research needs and evaluating new and innovative safety strategies (improvements) by developing reliable quantitative estimates of their effectiveness in reducing crashes (FHWA 2022a).

The ultimate goal of the FHWA DCMF Program is to save lives by identifying new safety strategies that effectively reduce crashes and promote these strategies for nationwide installation by providing measures of their safety effectiveness through the development of crash modification factors (CMFs) and benefit–cost (B/C) ratios through research. State departments of transportation (DOTs) and other transportation agencies need to have objective measures for safety effectiveness and B/C ratios before investing in new strategies for statewide safety improvements.

The Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS) functions under the DCMF Program (FHWA 2022b). Forty-one State DOTs are members of the ELCSI-PFS and provided technical feedback on high-priority research needs for safety improvements to the FHWA DCMF Program. These States implement new and unproven safety improvements to facilitate ELCSI-PFS evaluations. This project evaluated bicycle treatments at urban intersections. The ELCSI-PFS Technical Advisory Committee selected this evaluation as one of the priorities within its purview.

This evaluation assessed the potential safety improvements of various intersection geometric and traffic control device treatments to reduce crashes with regard to total vehicular crashes, fatal and injury (FI) vehicular crashes, and bicycle-specific crash frequencies. The intent was to develop CMFs and B/C ratios for each safety improvement. Practitioners can use the CMFs and B/C ratios for decisionmaking in the project development and safety planning processes.

In this study, the assessment focused on various strategies to accommodate bicycle lanes on the approaches, as well as other pavement markings on the intersection box, such as extension lines, colored crossing markings, and chevrons. The research team obtained geometric, traffic, and crash data at treated locations in Virginia and Texas. The limited availability of bicycle volume data to estimate average daily bicycle traffic (ADBT) was a controlling factor in the feasibility of developing a before–after study with a sufficiently large sample size. Ultimately, this research evaluated the bicycle treatments using a cross-sectional design. The modeling approach used generalized linear models and generalized linear mixed models. The evaluation included untreated sites (i.e., without bicycle treatments) with similar characteristics to sites with the intervention, so a contrast between treated and comparison sites could be made. This approach yields an unbiased estimate of a shift in safety performance associated with the treatments. The research team developed and applied propensity score (PS) weights to support causal inference while correcting for imbalances in the covariates (Banihashemi 2016; Li, Morgan, and Zaslavsky 2018). These methods are supported by the statistical literature regarding applicability in causal effects estimation problems, as is the case in this study (Imai and Ratkovic 2015; Vermeulen and Vansteelandt 2015).

The study included locations for which bicycle traffic volume estimates were available or could be made available, as volume was expected to be an influential variable affecting bicycle crashes, similar to how annual average daily traffic accounts for motor vehicle exposure. In the case of Virginia, the research team developed ADBT estimates using actual bicycle counts. In the case of Texas, the bicycle volume estimates were based on direct demand models developed for this purpose. CMF estimates for total and non-weather-related crashes in Texas were statistically significant for the application of separated bicycle lanes at intersections (0.552 and 0.456 CMFs, respectively). A CMF of 0.571 for FI crashes was estimated when a mixing zone between bicycle and two motor vehicle movements at intersection approaches was present. For other evaluations, results were statistically insignificant. The economic evaluation used the statistically significant CMF as the best available estimate of a hypothesized benefit of the two treatments of interest. The evaluation found that when these treatments are added at intersections, the construction and maintenance costs are notably smaller than the expected benefit. The B/C ratio estimates varied from 5.9 up to 113.3, depending on the assumptions implied in the cost estimates. Overall, results indicated the economic feasibility of the assessed treatments.

CHAPTER 1. INTRODUCTION

A large proportion of crashes between bicyclists and motor vehicles (MV) occur at intersections. Bicycle lanes (BLs) are travel lanes dedicated to bicyclists along a street. The presence of bicycle treatments at intersections can help raise awareness among motorists that these vulnerable users are present and that they should be alert. To provide additional accommodation for bicycles, a BL, when present, is commonly placed on the left of MV right-turn lanes (RTLs).

Developing crash modification factors (CMFs) for a particular treatment relies on a sufficient number of sites with the treatment and a sufficient number of bicycle crashes to assess any changes due to the treatment. This study overcame these challenges by considering several intersection approach configurations when BLs are present on the major approaches.

LITERATURE REVIEW

This section presents a summary of the relevant literature on safety effectiveness of bicycle configurations at intersections.

It has been well documented that a significant number of crashes between bicycles and MVs occur at intersections. In 2017, the National Association of City Transportation Officials (NACTO) estimated that 43 percent of urban bicyclist fatalities occurred at intersections (NACTO 2019). BLs are the most common bicycle facility in use in the United States, and most jurisdictions are familiar with their design and application, as described in the *Manual on Uniform Traffic Control Devices* (*MUTCD*) and the *American Association of State Highway and Transportation Officials (AASHTO) Guide for the Development of Bicycle Facilities* (FHWA 2012; AASHTO Task Force on Geometric Design 2012).

Bicycle crashes at signalized intersections are linked to the average daily bicycle volume (Reynolds et al. 2009). Because of this connection between crashes and exposure, an increase in ridership could lead to an increase in bicycle crashes at newly implemented BL locations, especially at locations with separated bicycle lanes (SBLs), which are BLs physically shielded from the main MV lanes (Dill and Carr 2003; Bryant, Deutsch, and Goodno 2016).

Intersection Geometric Design and User Expectations

Past work has recommended that construction of cycling facilities should not create a false sense of safety (Høye 2017; Arvidson 2012). Many urban intersections are designed with visibility of bicyclists and their expected interaction with MVs. The goal of these design strategies is to provide bicyclists and other users a higher level of safety. Documented intersection designs with safety and operational benefits include bicycle boxes (figure 7), BLs to the left of RTLs, and raised bikeways that are continuous across side road crossings or minor street crossings (Klassen, Basyouny, and Islam 2014).

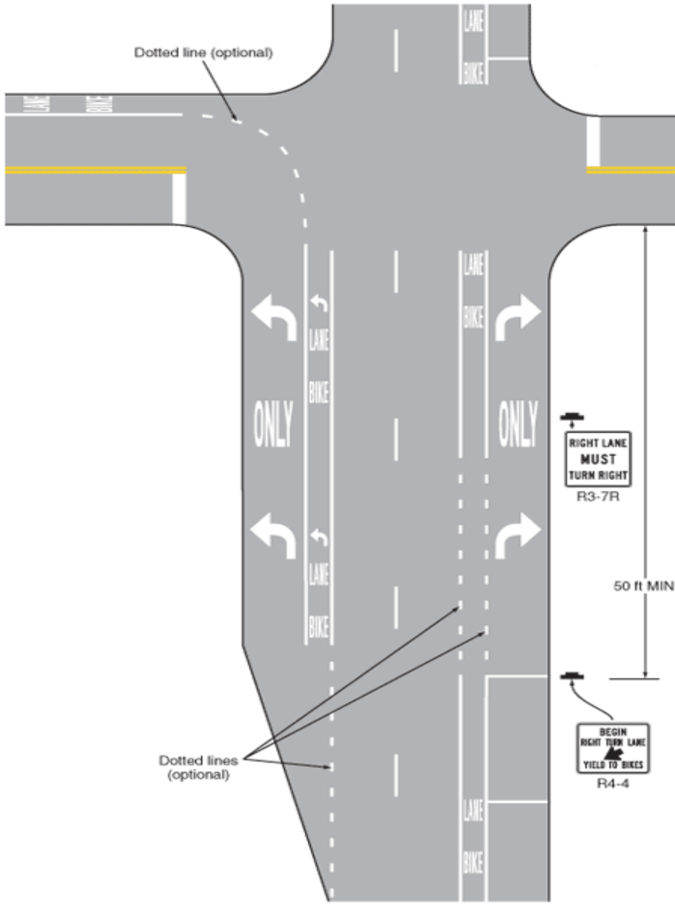
According to Høye (2017), an important concern with bicycles at intersections is that they might not be conspicuous to motorists. Another concern is that MV drivers may potentially assume that bicyclists in BLs must give way to MVs, regardless of the actual priority rules. Other safety concerns in the vicinity of intersections include poor sight conditions, the proximity to—and level of—MV parking, and the effective separation from pedestrian areas (Høye 2017). Intersections will experience increased bicycle–MV conflicts when bicyclists and motorists lack a good understanding of each other's intended behavior. Forty percent of cyclists reported being in a near collision on the BL (Arvidson 2012).

According to one study, the main design considerations to improve BL safety for users approaching and moving through an intersection are as follows (Bryant, Deutsch, and Goodno 2016):

- On-street parking setbacks.
- Lateral deflection.
- Mixing zones.
- Bicycle signs and signals.
- Conflict zone treatments.

A detailed review of six crashes involving bicyclists showed that five of them occurred when drivers crossed the BLs to enter an alley when a bicycle was present; similarly, one crash occurred when a vehicle exited an alley and crossed a BL when a bicycle was present (Bryant, Deutsch, and Goodno 2016). In their examination of the prevalent conditions during these crashes, Bryant, Deutsch and Goodno (2016) pointed to the need for better visibility and proposed potential strategies, such as eliminating on-street parking or providing parking setbacks at alley entrances and exits. Lateral deflection—an alignment deviation of the travel way to better position bicycles to be easily viewed by motorists—has an added benefit of increasing bicyclists' awareness of all cross-traffic modes at intersections. However, providing lateral deflection can be problematic if the number of alignment shifts becomes excessive.

An AASHTO guideline indicates that some cities have exceeded the prescribed minimum recommended dimensions for bicycle facilities, resulting in increased comfort and safety for bicyclists (AASHTO Task Force on Geometric Design 2012). A potential safety concern for cyclists at intersections is the conflict with right-turning MVs, and a geometric design decision on BL placement must be made at intersections featuring RTLs. To provide additional accommodation for bicycles, an alternative is to place a BL on the left of the RTL, as shown in figure 1. Alternatives designs are also available, including dissolving the BL into a mixing zone in the area immediately upstream of the stop bar.



Source: FHWA.

Figure 1. Illustration. Intersection with BL, left-turn lane, and RTL (FHWA 2012).

The *Urban Bikeway Design Guide* by NACTO (2014) provides design guidelines for treating BLs and turn lanes. In some situations, where a through travel lane becomes an RTL, bicyclists need to move laterally to weave across the travel lane. The BL along the curb is commonly dropped, and another small BL segment—often referred to as “keyway” or “pocket”—is introduced on the left side of the RTL, just upstream of the stop bar.

A good design provides bicyclists with the opportunity to reposition themselves to avoid conflicts with turning MVs. The NACTO (2014) *Urban Bikeway Design Guide* offers detailed guidance on intersection design treatments that reduce vehicle-bike and vehicle-pedestrian conflicts. These treatments include conventional BL designs, buffered BLs, and SBLs.

Lane Designs at Intersections

Buffered BLs are conventional BLs paired with a designated buffer space separating the BL from the adjacent MV travel lane and/or parking lane. The buffer provides greater distance between MVs and bicycles and creates space for a bicycle to pass another bicycle without encroaching into the adjacent MV travel lane. Figure 2 shows an example of a buffered BL design, and figure 3 shows an SBL, which includes vertical elements, such as plastic pylons, inside the buffer.

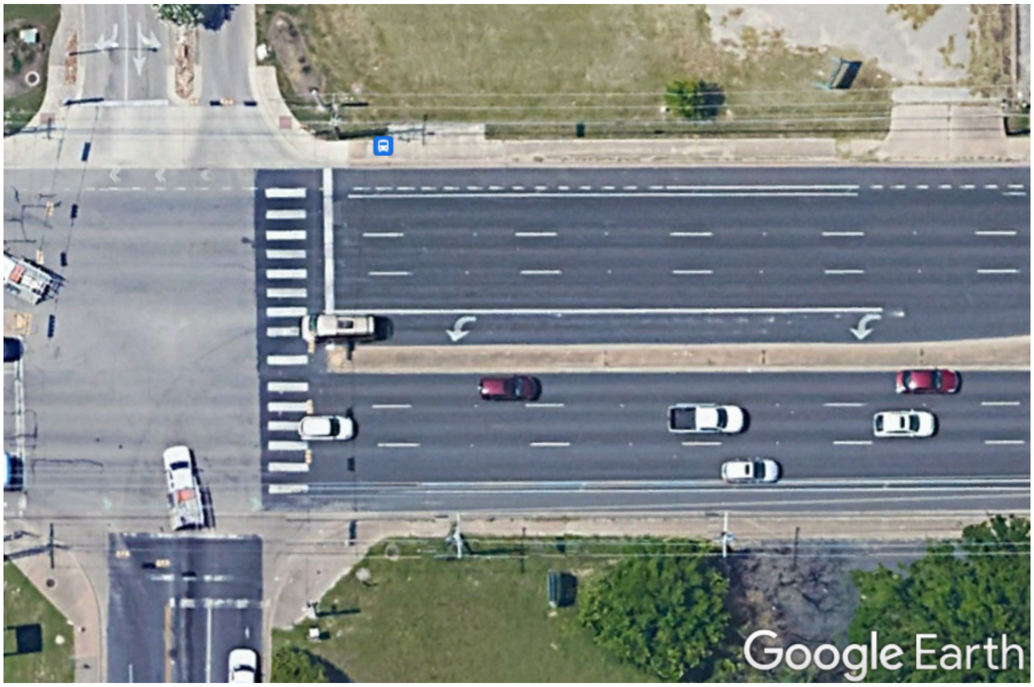


Figure 2. Map. Sample buffered BL design at intersections.

Figure 3. Map. Sample SBL design between intersections.

BL Evaluations

This section summarizes past evaluations of the safety performance of BL treatments at intersections.

Studies have showed that BLs increase perceived safety by bicyclists who feel less safe cycling among mixed traffic because they fear being sideswiped (Rasmussen and Rosenkilde 2007; Ng, Debnath, and Heesch 2017). According to a study conducted by researchers at Portland State University, bicyclists felt the risk was lower in buffered BLs, and nearly 9 of 10 cyclists preferred a buffered BL to a standard lane at intersections (Monsere, McNeil, and Dill 2011). Bicyclist perception of safety appears to be more heavily influenced by the volume of turning MV traffic rather than the prevalence of wrong maneuvers of turning MVs at these locations (Monsere et al. 2015).

Flügel et al. (2015) found a perceived safety gain at urban environments from a stated preference survey for separate bicycle facilities (bike paths) where bicycle interactions with motorized traffic are restricted. Another study found that the introduction of cycling tracks (i.e., BLs) was not perceived by the participants of the survey to bring a significant overall change in the number of bicycle-related crashes (Elvik et al. 2009).

At locations with bicycle traffic, the use of signs prohibiting certain turning movements may be warranted (Hunter, Thomas, and Stutts 2006). Approximately 70 percent of bicyclists indicated that installing BLs improved their sense of safety, and 45 percent of the motorists also felt that driver behavior was safer and calmer when a BL is present. In the study by Hunter, Thomas, and Stutts (2006), 41 percent of cyclists stated that they had been involved in a near collision with pedestrians at intersections before the installation of a BL.

Cherry, Hill, and Xiong (2012) simulated three intersections in VISSIM® using real-world data (Planung Transport Verkehr 2022). They then developed measures quantifying the conflict between bicycles and right-turning automobiles in China. The authors proposed layouts that introduced separate lanes for through bikes to eliminate prolonged conflicts that occur when bicycles and MVs share a lane. Delays and queue lengths were studied, and mixed results were obtained, depending on the configuration. The study suggested that a small barrier be installed between the RTL and the through BL to ensure compliance. This configuration moved the conflict point upstream from the intersection where bike and car traffic densities are lower (Cherry, Hill, and Xiong 2012).

At buffered BLs without an RTL, motorists' turning actions became inconsistent, posing a risk to both cyclists and other motorists. More than one-third of cyclists reported being involved in a near collision with a right-turning vehicle, and four respondents (3 percent) were involved in an actual collision with a right-turning vehicle in the buffered BL (Monsere, McNeil, and Dill 2011).

Madsen and Lahrmann (2017) compared five intersection layouts based on video data to evaluate reaction-based conflicts. This study suggested that ending the BL upstream of the intersection, as well as the presence of a narrow BL next to a shared lane for straight and right-turning MVs, is less safe for cyclists than a BL marked with solid lines next to a shared lane for straight and right-turning MVs. The low number of conflicts observed, however, suggests that the amount of data may not have been sufficient to make generalizable conclusions (Madsen and Lahrmann 2017).

Monsere et al. (2015) conducted a comprehensive evaluation of intersection designs for SBL in Oregon. The study used 78 h of video data that showed 6,082 bicyclists and 7,574 turning MVs. Results from this study indicated that the amount of weaving conflict in the mixing zone tended to be similar across treatments, but a semiprotected through BL (skip pattern of extension lines with green pavement markings on the approach) may be associated with fewer conflicts in the mixing zone of the design.

Bicycle Intersection Crash Characteristics

Carter et al. (2006) developed macrolevel pedestrian and bicycle intersection safety indexes that would allow engineers, planners, and other practitioners to use known intersection characteristics to proactively prioritize crosswalks and other intersection countermeasures for pedestrian and bicycle safety. The study sites were in Gainesville, FL (19 sites); Philadelphia, PA (21 sites); Portland, OR (13 sites); and Eugene, OR (14 sites). The characteristics evaluated by these researchers included traffic speed (high and low); traffic volumes (high and low); number of traffic lanes (two lanes and three or more lanes); bike facilities (BLs, wide curb lanes, etc.); RTL design (shared or exclusive); and left-turn lane (LTL) design (shared or exclusive). Crash data, behavioral data (conflicts and avoidance maneuvers), and subjective intersection ratings were analyzed. Statistical models for the average left-turn, right-turn, and through ratings were developed using regression analyses. Bicycle crashes were found to increase with increasing major street traffic volume, higher main street speed limits, presence of turning vehicle traffic, cross-street traffic volume, number and presence of RTLs on main street approach, presence of a traffic signal at an intersection, on-street parking on main street approach, number of traffic lanes for bicyclists to cross to make a right (or left) turn, and presence of a BL.

Based on a Bayesian meta-analysis of 20 studies that evaluated the effectiveness of different bicycle facilities at road junctions in Scandinavia, Garder, Leden, and Thedeen (1994) estimated that introducing a BL at an intersection may increase the risk of crashing with a vehicle by about 40 percent. Their Bayesian methodology study includes the prior opinion of experts (that the introduction of the BL would increase the risk by about 20 percent on average), the opinion of interviewed cyclists (that the risk would decrease by about 20 percent), and the evidence of past studies. Those percentages refer to continuing the BL through the intersection. The authors recommend terminating the BL some distance before the intersections or switching the path to the left of an RTL (Garder, Leden, and Thedeen 1994).

The literature shows mixed findings concerning the benefits of BLs arriving at intersections. Rasmussen and Rosenkilde (2007) and Loveday (2000) argue that the construction of BLs at intersections in Copenhagen increased collisions by 18 percent. However, other studies offer evidence that BLs reduce the number of injury collisions (Turner, Binder, and Roozenburg 2009). Herrstedt et al. (1994) recommended the elimination of BLs 20–30 m before signalized intersections and forcing road users to drive or ride closer to each other to improve the visibility of cyclists. The study determined that a truncated BL followed by an RTL in which cyclists merged with the right-turning MVs was safer. The study showed no difference in the number of cyclist crashes, whereas moped riders experienced significantly fewer right-hook and left-hook crashes (turning vehicle against straight-going bicycles) compared to a full-length BL. This recommendation is aligned with the recommendations by Garder, Leden, and Thedeen (1994).

Another study in Kentucky used partial proportional odds models to evaluate the injury severity among bicyclists at unsignalized intersections (Wang, Lu, and Lu 2015). The authors coded the injury severity on a four-point scale: slight injury, non-incapacitating injury, incapacitating injury, or fatality. Older (age > 55 yr) drivers and bicyclists and child (age < 16 yr) bicyclists were more likely to be severely injured. Uncontrolled intersections, foggy and rainy weather, inadequate use of lights in dark conditions, heavier vehicles, and wet road surfaces were also linked with increased injury severity. Stop-controlled intersections, one-lane approaches, helmet usage, and lower speed limits were associated with decreased injury severity.

Thomas and DeRobertis (2013) reported that one-way BLs are generally safer at intersections than two-way lanes. Additionally, the authors argued that properly signed and demarked, new BLs on busy streets should result in fewer collisions and injuries. When controlled for exposure and including all collision types, building one-way bicycle lanes was estimated to result in reduced injury severity, even when intersection specific treatments are not employed.

Ma et al. (2010) conducted longitudinal analyses of signalized intersections and road segments to understand the influence of a variety of factors on crash occurrences at signalized intersections. The study used generalized estimating equations. Barriers that separated bikeways from roadways on minor roads were found to be significantly linked to reduced severe crash risk (Ma et al. 2010).

Safety of Through BLs

Through BLs are BLs at signalized intersections to the left of the MV RTL (also called through-BLs), as shown next to the RTL in figure 1. The objective of this treatment is to replace the dangerous conflicts between the right-turning MVs and bicycles going straight ahead with less hazardous merging situations in front of the intersection. A study was conducted in Oslo, Norway to determine the safety impacts of this type of cycle lanes, but a crash analysis could not be conducted due to the small number of occurrences. However, analysis of conflicts involving cyclists at six intersections showed that intersections with central approach lanes have more conflicts than those without this design. However, the measure seemed to improve the mobility and perceived safety at intersections (Sørensen 2010). In contrast, work by Schepers et al. (2011) showed that the crash probability (as opposed to conflict frequency) seems to be reduced when BL approaches at the intersection are deflected between 2 and 5 m away from the main travel lanes.

Consistent with Sorensen’s (2010) assessment of increased perceived safety, a survey in Australia showed preference among bicyclists for keeping exclusive BLs to the right of LTLs (analogous to exclusive BL to the left of RTLs in the United States) (Daff and Barton 2010). Nearly 100 intersections in Melbourne, Australia, were then configured that way.

Safety of Shared Bicycle/MV Lanes at Intersections

By combining vehicle turn lanes and BLs at signalized intersections, motorists are encouraged to turn at a lower speed by yielding to bicycles. These combined lanes could guide bicycles to travel with slower traffic by maintaining comfort and priority when BLs are discontinued (NACTO 2014).

The mixing zone technique is a strategy that merges the left-turn MV lane and the BL into a single 16- to 18-ft lane, creating a weaving condition—where MVs cross the bike lane (BL)—that slows both modes and could increase safety. However, undue delays may occur. Bryant, Deutsch, and Goodno (2016) reported a high incidence of violations (41 percent of all bicyclists) at an intersection in Washington when the protected left turns for bicycles were eliminated because of this treatment, resulting in traffic queuing and higher intersection delay, which then contributed to more signal violations. Because of the issue observed with high left-turning volumes, the study then recommended bike movements not be separated from left-turning movements at locations where the hourly left-turning volume exceeds 250 vehicles per hour (Bryant, Deutsch, and Goodno 2016).

Summary of Literature on BL Treatments at Intersections

The safety and bicycle operational characteristics at intersections are significantly impacted by the intersection design. Sight conditions, on-street parking setbacks, and the separation of BLs are some of the most important safety features to be considered at intersections (Høye 2017; Bryant, Deutsch, and Goodno 2016; Arvidson 2012). The AASHTO task force on geometric design and the NACTO urban bikeway design guide provide design guidelines for combined BLs and turn lanes, as well as safety central approach designs (AASHTO 2013; NACTO 2014).

In general, studies show that BLs tend to increase bicyclists' perceived safety (Rasmussen and Rosenkilde 2007; Monsere, McNeil, and Dill 2011; Elvik et al. 2009; Hunter, Thomas, and Stutts 2006). Some studies show conflict reductions for both bicycles and vehicles associated with familiarity of the design (Philips et al. 2011). Installing bicycle signals was found to increase compliance with intended cross-path areas for right-turning MVs (Rahimi, Kojima, and Kubota 2013). Signage indicating the presence of bicycles was found to correlate with decreased chances of severe collisions involving bicyclists at intersections (Klassen, Basyouny, and Islam 2014). Although BLs improve the mobility and perceived safety at intersections, some research also points to increased conflicts at intersections (Sørensen 2010).

Regarding crashes, some studies found no changes in risk at intersections after the installation of bicycle facilities (Harris et al. 2013). However, other studies have reached opposite conclusions. For example, Garder, Leden, and Thedeen (1994) found that the risk of crashing with a vehicle increases by about 40 percent when BLs are part of the intersection design. They recommend terminating the BL some distance before the intersections or switching the bicycle path to the left of an RTL, effectively applying a central approaching lane BL. A truncated BL followed by an RTL in which cyclists merged with the right-turning MVs was found beneficial (Herrstedt et al. 1994).

In general, crash-based studies offer mixed results regarding the effectiveness of different strategies to manage BLs at intersections. Sundstrom, Quinn, and Weld (2019) found that SBLs reduced the rate of crashes per bicyclist by an average of 30 percent. One-way BLs were observed to be generally safer at intersections than two-way lanes when effective intersection treatments are employed. When controlled for exposure and including all collision types, building one-way BLs was found to reduce injury severity compared with not employing these intersection treatments (Thomas and DeRobertis 2013). Crash probability was reduced when the BL approaches were deflected between 2 and 5 m away from the main MV lanes (Schepers et al. 2011). However, Rasmussen and Rosenkilde (2007) and Loveday (2000) found an 18-percent increase in associated with the construction of BLs at intersections in Copenhagen.

Traffic Control Devices for Bicycles at Intersections

Part 9 of the *MUTCD* addresses signs, markings, channelizing devices, and signals for bicycle facilities (FHWA 2012). Five different marking treatments at intersections are described: crossing markings, chevrons on the BLs through the intersection, two-phase left-turn markings, bike boxes, and bicycle through lane markings. Each of these treatments has been evaluated previously for bicycle and motorist compliance and comprehension, in addition to safety, as measured through surrogate measures such as conflicts (Ohlms and Kweon 2018; Casello et al. 2017; Dill, Monsere, and McNeil 2012; Loskorn et al. 2013).

Chevrons and Extension Lines

Agencies have used various strategies to clearly mark the path for bicyclists through intersections. These markings also help raise motorist awareness of the possible presence of bicyclists in the intersection. Figure 4 shows intersection chevron pavement markings. This intersection also has white crossing markings showing the BL path through the intersection. Some jurisdictions also use color in these crossing markings, as shown in figure 5, as allowed in *MUTCD* Section 9C.03 (FHWA 2012). Extension lines on the intersection box are also referred to as “cross-bike markings” (e.g., NACTO 2019). One study of motorist yielding in Portland (Appiah 2021) assessed the effect of green crossing markings on motorist yielding behavior before and after their installation. The study found through video analysis that motorists yielding to bicyclists increased after the installation of these markings.

Figure 4. Map. Sample intersection with extension lines and chevrons.

Figure 5. Map. Sample intersection with extension lines and colored crossing markings.

Two-Phase-Turn Queue Box

Left turns for bicyclists pose a specific quandary—where is the best place to position them? On the approach to the intersection, a left-turning bicyclist can choose to cross left through lanes to reach a dedicated vehicle LTL or execute the left turn in two phases by first crossing through the intersection then turning 90 degrees to cross the through lane (figure 6).

Figure 6. Map. Sample intersection with two-phase-turn queue box for bicycles.

Two-phase-turn queue boxes indicate the location where a left-turning bicyclist should wait, which is on the far side of the intersection, before proceeding with the left turn. Ohlms and Kweon (2018) assessed compliance and conflicts at several intersections before and after the installation of bike boxes and two-phase-turn queue boxes. Their matched-pair analysis showed mixed results, with some bicyclists not using the markings correctly and traffic violations increasing for some approaches.

Another assessment of two-phase-turn boxes was completed in Toronto and showed that 70 percent of bicyclists used the boxes properly and legally executed their turns (Casello et al. 2017).

Bike Box

Figure 7 shows an example of a bike box using colored pavement marking material. Dill, Monsere, and McNeil (2012) analyzed video of bicyclist behavior around intersections with bike boxes in Portland. They found that 73 percent of bicyclists used the bike boxes correctly, whereas 27 percent of queued motorists encroached on the bike box markings. A study conducted in Austin, TX, in 2010 showed that only 15 to 25 percent of bicyclists used the boxes as intended (Loskorn et al. 2013).

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Figure 7. Map. Sample intersection with bike box on the bottom approach.

Through BL

Right-turning MVs can pose a threat to through bicyclists at traditional intersection designs. A resulting crash of this type is often called a "right-hook" crash. Bike through lanes demarcate a continuation of a BL through the intersection queuing area by extending the BL to the left of a dedicated RTL, as shown in figure 8.

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Figure 8. Map. Sample intersection with keyway bike through lane (to the left of RTL).

Figure 9 shows an example of a different strategy to treat a BL in the approach: a combined lane for through or right-turn movements that mixes with the BL, which continues, marked by dashed lines, into the mixing area on the approach to the intersection. Drivers are expected to pull close to the curb when making a right-turn, resulting in a mixing zone for motorists and bicyclists.

Figure 9. Map. Sample intersection with mixing zone for a BL, MV through lane, and right-turn movements.

Keyways at through BLs allow bicyclists to position themselves in a conspicuous space before proceeding through, drawing attention to their intended movement to motorists in adjacent lanes (NACTO 2014).

CHAPTER 2. STUDY DESIGN AND STATISTICAL METHODOLOGY

Before full data collection efforts are undertaken, exploring the proposed statistical methodology to determine data requirements and identifying suitable datasets that can be used to conduct this analysis are necessary. This chapter reviews the study design, and chapter 3 introduces the data sources and variables explored for analysis.

Two basic designs for observational studies are frequently used in safety evaluations:

- Cross sectional.
- Before and after.

A strong study design can significantly boost the quality of the results by carefully accounting for other influential variables, in addition to the variable of interest. Closely examining all potential data sources, their characteristics, and available data elements is critical. Ideally, this step should precede any data acquisition/collection and consider the needs of the analysis phase.

Initially in this study, the research team identified potential data sources from which to gather key data elements available for evaluating each improvement. Specifically, sources for safety relevant variables, such as vehicle and bicycle exposure, were identified to be critical for a robust evaluation. Observational designs are needed in safety evaluations since randomization is not possible and randomized comparison group experiments are not feasible. Good observational studies rely on data from both treated and nontreated sites in a manner consistent with control group experiments. A cross-sectional data analysis that does not include a matching or comparison group, and for which the sample is not the entire population, is considered an inferior preexperimental design and is sometimes called a static group comparison (Campbell and Stanley 1966). Likewise, if the before–after data are analyzed without any comparison group, the design quality (one-group pretest–posttest design) is negatively affected. These types of preexperimental designs have a higher potential for biased results. Therefore, this study initially targeted a quasi-experimental design to the extent possible, such as the nonequivalent comparison group (or comparison group) design or a control series design (e.g., Campbell and Stanley 1966; Campbell and Russo 1999). However, in the case of evaluating the tradeoff of bicycle treatments at intersections versus the absence of these treatments, obtaining before–after data from multiple jurisdictions proved to be infeasible after potential data sources were reviewed. Key variables to include in the study would be bicycle and MV volumes as these two variables represent exposure to the crash generation process. The research team developed a database for cross-sectional analysis with data collected at locations with available exposure data. The research team used PS weighting (PSW) methods to minimize imbalances between covariates when evaluating the safety effectiveness of various treatments. More details about these adjustment types are provided in the following section.

STATISTICAL METHODS IN THE DATA MANAGEMENT PROCESS

The research team examined a variety of data sources identified in the preliminary stages of this research. One goal of this effort was to select candidate sites for study while balancing the features of treated and comparison sites. This database development approach is consistent with the selected cross-sectional study design.

The data management stage used for this study required the research team to examine multiple data sources, collect candidate data, identify data supplemental sources, integrate variables from multiple sources, and prepare the data for the statistical analyses.

Data Extraction and Integration

The research team used geographic information systems (GIS) tools (Esri™ 2019) to prepare, filter, and combine multiple datasets containing geolocation (typically in shapefile format). GIS tools allow the manipulation, combination, and display of data for different types of information, including crashes, road infrastructure, traffic volume, census tract, and land use, among others.

Data Balancing

Data-matching and -balancing methods are used to assist causal inference that quantifies the impact of a treatment on a response variable. The main principle behind this effort is to identify untreated locations that are similar in their covariates to the treated locations so that the contrast by the response variable implicitly controls for differences due to other covariates that could have an impact on the response variable. The matching of treated and comparison sites is based on the covariates identified to "covary" with the treatment variable. A good, balanced dataset is one in which the means of the covariates are almost identical, carrying the implication that any observed differences between the treatment and comparison groups in the response variable are due to the effect of treatment. The crashes on the selected untreated locations are then used as a proxy to estimate the counterfactual crashes on the treated locations—that is, the crash frequency that would have been observed if the treatment had not been applied. The quality of the matched dataset can be increased by matching one treated site with several comparison sites. The epidemiology literature recommends selecting between two and four control units per one treated unit (see Linden and Samuels 2013).

PS Methods

More analytical approaches to guide the data-matching phase are based on PS. Under this framework, the PS of the treatment cases and their corresponding control cases are estimated and compared. The PS is a metric of similarity between covariates from the cases and can be estimated using parametric or nonparametric tools, such as logistic regression or random forest analysis (Sasidharan and Donnell 2013; Jovanis and Gross 2007; Guo and Fraser 2015). For example, a treatment of a through BL has a propensity to be applied on roadways with dedicated RTLs for vehicles.

In the case of binary logistic regression as a basis for PS estimation, figure 10 shows the definition of the conditional probability of a site receiving treatment *T*.

$$P(T_i|X_i) = \frac{e^{a_i x_i}}{1 + e^{a_i x_i}}$$

Figure 10. Equation. PS definition as logistic function of covariates.

Where:

$P(T_i|X_i)$ = the PS denoting the probability of the ith site receiving the treatment T.

T_i = the treatment status of the site i, which takes binary values $\{0,1\}$.

X_i = a vector of covariates that covary with the treatment presence.

α_i = the vector of coefficients through the binary logistic regression.

In a balanced sample, the distribution of PS is expected to be similar for treated sites ($P(T_A|X_A)$) and comparison sites ($P(T_B|X_B)$). An examination of these differences at various stages of data collection can be used to direct collection of data at additional comparison sites to improve the balance in the dataset.

An alternative to PS matching (PSM) is PSW. Under this approach, the PS remains the basis to balance two or more partitions of the data by the variable of interest (i.e., treatment or control). In contrast with PSM, balance is achieved by defining appropriate weights for each unit of analysis so they represent an underlying target population of sites. The data are weighted based on the probabilities of being in either the control or treatment group, and the selection of the weights defines the target population (Olmos and Govindasamy 2015). If all weights are equal, then the dataset is implied to be a simple random sample from a population of sites. That pool of sites is then implicitly defined as the target population. However, through the use of appropriate weights, more flexible definitions of the target population are possible, as can be found in the statistical literature (Olmos and Govindasamy 2015). In some cases, defining a theoretical population that is most suitable for inference makes sense. The definition of the weights also determines quantities that can be estimated, including the average treatment effect, the average treatment effect among the treated cases, the average treatment effect among the control cases, and the average treatment effect among the evenly matchable cases.

STUDY DESIGN

Since the study design is cross sectional, team members collected and assembled a cross-sectional database for estimating the CMFs of interest (intersection treatments). During data collection, comparison sites were sought and included to strengthen the design. Data collection required some metric that represented bicycle exposure so bicycle traffic could be included in the estimation of exposure. Ideally, this metric would be a direct bicyclist volume count, which was the case for some, but not all, sites. In cases where such a direct metric was not available, direct demand estimates of bicyclist volumes from appropriate models were incorporated instead. The team also decided to implement strategies to balance covariates accordingly.

The research team decided to use PS weighting rather than matching methods (e.g., Stuart 2010) because matching is most suitable with large pools of potential sites. However, this approach is challenging in the case of small pools, as was the case for the databases in this research because unfeasible locations were filtered out. Therefore, the research team subsequently decided to adopt the framework of PSW. The target population was set to be the overlap between the treated and control populations as proposed by Li, Morgan, and Zaslavsky (2018). Under this scheme, the target population is the set of all sites that have comparable chances to be either in the treatment group or in the comparison group. This approach effectively curbs the undue influence of two subsets of sites when the average treatment effect of the countermeasure is estimated:

- Comparison sites whose characteristics make the sites unlikely to be candidates for the treatment.

- Treated sites with unusual characteristics for which no feasible comparison sites are represented in the data.

An additional advantage of this choice of target population is a desirable small-sample, exact-balance property, as demonstrated by Li, Morgan, and Zaslavsky (2018). Additionally, the corresponding weights are known to minimize the asymptotic variance of the weighted average treatment effect within their class of weights (Li, Morgan, and Zaslavsky 2018).

DATA ANALYSIS METHODS

Team members conducted the data analyses using the statistical methods appropriate to the characteristics of the assembled datasets. The research team used appropriate generalized linear model (GLM) specifications (e.g., negative binomial, Poisson-lognormal mixture, logistic-log normal mixture) as needed by each dataset. PSW was implemented by using the PS obtained from the final datasets.

Generalized Linear Regression Analysis with PSM or PSW

The predictive methods described in the *Highway Safety Manual* are based on cross-sectional statistical models named safety performance functions (SPFs) (AASHTO 2010). These models estimate the long-term expected crash frequency using statistical models derived from multiple sites with similar characteristics. In principle, the effect of a countermeasure can be estimated simply by comparing the counterfactual crash frequencies between treated sites and sites without the treatment, but the risk of that comparison is that the comparison group—implied by the SPF predictions—may not necessarily be representative of sites that have the treatment under study. One way to reduce that risk is to develop the SPF based on a probability sample of the types of sites of interest. Another possibility is to develop the SPF from a complete population of sites (e.g., all sites in a State database inventory), whenever feasible. However, such alternatives are not possible or practical in every case. By using PS-based methods (PSM or PSW), the effect of a treatment can be studied by employing sites with treatment and matching untreated sites in a resulting dataset whose characteristics mimic those expected from a randomized sample (Rosenbaum and Rubin 1984). Essentially, the PS methods ensure that the treated and untreated subsets of data are roughly orthogonal in their covariates, which should result in a nearly unbiased, not confounded estimate of the effect of interest. The effects of selection bias that can be otherwise present in developing the cross-sectional dataset are, thus, mitigated.

Mixed-Effects Models

Within the frame of GLM methods, a distinction can be made between models with:

- Fixed effects.
- Random effects.
- Mixed effects.

Commonly, the coefficients obtained from GLMs can be thought of as fixed effects. The variables corresponding to fixed effects are implied to have time-invariant effects (e.g., roadway design elements). The model coefficients are estimated and interpreted as metrics of underlying parameters from a latent data-generating process.

In contrast, random-effects models estimate the effects of factors that are deemed the observed realizations of a random variable. Therefore, quantifying how the response variable shifts with the observed realizations in the dataset is typically not of interest, but rather accounting for the impact of such variation in the model is. The simplest analogy of random effects in a GLM is the use of blocking in analysis of variance designs. Typically, the effect of each block is not the focus of the analysis. However, accounting for the variability explained by the blocking to quantify the variability explained by the independent variable of interest is important.

Mixed-effects models include both fixed and random effects (Pinheiro and Bates 2000). Generalized linear mixed models (GLMMs) approach the analysis of repeated-measures cross-sectional data by including a random effect per every unit of data aggregation (i.e., the blocking units in the data, such as individual study locations with more than one datum in the analysis). Orthogonal to the random effects, the model estimates fixed effects for the treatment and any additional fixed-effects covariates. As in GLM methods, an appropriate link function can be specified to permit the modeling of count data distributions that are applicable to crash data, such as Poisson and negative binomial.

As described in the preceding section, Generalized Linear Regression Analysis with PSM or PSW, the use of PSM in the data collection stage can produce a more robust comparison, and the resulting PS can also be incorporated through PSW in the analysis stage, including the use of mixed-effects models.

The general functional form of the models is such that for a site i and year j, the model estimates the expected frequency for target crashes as in figure 11.

$$N_{ij} \sim Poisson(\mu_{ij})$$

Figure 11. Equation. Site-level Poisson distribution of yearly crashes.

Where:

N_{ij} = the number of target crashes at site i in year j.
μ_{ij} = the average yearly number of crashes at site i in year j.

The yearly expectation of crashes is further parameterized as in figure 12.

$$\mu_{ij} = RE_i \cdot AADTmaj_{ij}^{a_1} \cdot AADTmin_{ij}^{a_2} \cdot AABTmin_{ij}^{a_3} \cdot exp(X_i^{'} \cdot \beta)$$

Figure 12. Equation. Parameterized yearly expectation of crashes.

Where:

RE_i = the baseline crash expectation at site i (estimated as a random effect).

$AADT\_maj_{ij}$ = the major average annual daily traffic (AADT) at site i and year j.

$AADT\_min_{ij}$ = the minor AADT at site i and year j.

$ADBT_{ij}$ = the average daily bicycle traffic (ADBT) at site i and year j, respectively.

X_i = the set of p independent variables (including BL) at site i.

α_1, α_2, α_3, β = the set of model coefficients (estimated as fixed effects across the complete dataset).

Other variables are as previously defined.

The set of RE_i is modeled to follow the lognormal distribution, with population-level parameters μ_0 and σ_0. Both these parameters are also subject to estimation by the model. The σ_0 parameter is estimated as the standard deviation from the estimated RE_i values in the model link scale. This parameter is a measure of unaccounted variability between sites in excess of the variability attributable to the fixed effects and can be used to estimate the amount of Poisson overdispersion present in the data.

All model variables other than AADT and ADBT were included in the model in the exponential form, per the formulation. For clarity, the last term in figure 12 is implicit of multiple variables and can be expanded as in figure 13.

$$X' \cdot \beta \; = X_1 \cdot \beta_1 + X_2 \cdot \beta_2 + \cdots + X_p \cdot \beta_p$$

Figure 13. Equation. Parameterization of explanatory variables in regression model.

Where:

X = an independent variable in the model, other than major and minor AADT and ADBT.

β = the corresponding estimated coefficient.

CMF Estimation

In most cases, the use of regression models to estimate the influence of a dependent variable consists of extracting a single parameter estimate and its standard error from the analysis after accounting for additional variability in the data due to covariates and an appropriately modeled error distribution. However, single-parameter estimation is not possible in every case, particularly when the estimation requires the use of more than one coefficient, as was the case for some treatments of interest in this report. To estimate the uncertainty of a CMF derived from multiple coefficients, the research team implemented the methods outlined in the following subsections. The appeal of these methods is that they leverage the asymptotically multivariate normal distribution expected from multiple variable model estimates obtained from maximum likelihood estimation (Booth and Hobert 1998; Morrell, Pearson, and Brant 1997; Wackerly Mendenhall, and Scheaffer 2008).

CMF Estimates for Interventions with Multiple Effects

In general, the best fit models are not expected to produce a single coefficient estimate that answers the research question at hand: What is the change in safety performance in a facility when a BL is accommodated while modifying lane width and shoulder width? If a model had a parameter for each of the three elements just described (i.e., BL, MV lane, and shoulder widths), the answer would depend on all three values. Additionally, the literature suggests that the construction of a BL tends to attract more bicycle traffic, so it might be of interest to compare the aggregate of safety effectiveness of the intervention for increased bicycle traffic as well (Litman 2020; Manuel, El-Basyouny, and Islam 2014).

Alternatives exist to consider these features explicitly. The ideal situation would be having volumes and dimensions for the periods before and after the construction of BLs for a sufficient number of sites.

Scenario-Based Estimation

Another alternative is the use of the coefficient estimates from each of the best models to develop crash predictions using appropriate linear combinations for select scenarios. Said linear combinations produce predicted crashes for both the before condition (e.g., no BL and baseline ADBT) and the after condition (e.g., BL, reduced lanes, and shoulders, and increased ADBT). A contrast between the predictions then yields the estimated CMF. In general, producing the CMF estimate for the scenario is straightforward. However, producing the corresponding standard error is a more complicated, but feasible, task. For a given scenario with variable vectors X_A and X_B representing the after and before conditions, respectively, of the safety influential variables in the model, and maximum likelihood model-inversed-information matrix, $\sum$, figure 14 gives the standard error for the contrast (i.e., CMF estimate) (Wackerly, Mendenhall, and Scheaffer 2008; Johnson and Wichern 2007).

$$SE(\log CMF) = \sqrt{(X'_A - X'_B) \times \Sigma \times (X_A - X_B)}$$

Figure 14. Equation. Standard error for contrast in log scale.

However, the potential problem with this approach is that it requires the analyst to exercise some judgment when determining the levels for all covariates in each scenario, as a specific combination of variable or covariate values possibly may not be present in the dataset, and therefore, such estimates carry an increased (but undetermined) uncertainty.

CHAPTER SUMMARY

This chapter describes the statistical methodology, analyses methods, and tools that the research team used in performing the work in this project. The rationale for a cross-sectional study design is presented, along with the use of PS methods to reduce the risk of biased estimates in cross-sectional designs. Finally, this chapter outlines statistical analysis methods to develop statistical models of crashes to be used in developing the CMFs of interest. GLMMs and their ability to manage Poisson overdispersion are discussed. The chapter ends with a discussion of how situations where the safety effectiveness estimate is not captured by a single coefficient in the crash models can be managed with additional procedures based on mathematical statistics that can be applied to develop the required CMF estimates. The next chapter outlines the data collection effort for Virginia and Texas in more detail.

CHAPTER 3. DATA COLLECTION AND INTEGRATION

The data elements needed to develop CMFs can be arranged into three major groups:

1. Crash-related elements.
2. Roadway inventory elements.
3. Traffic and bicycle volumes elements.

This chapter details the selection of data sources and locations for the study to build a database with these types of data for evaluation. To develop the database, the research team collected the following types of data elements:

- Intersection characteristics.
- Intersection leg characteristics.
- Bicycle and traffic counts.
- Bicycle facility type (e.g., BL, buffered BL, SBL).
- Multiple roadway design elements (e.g., functional class, number of lanes, and lane and shoulder widths).
- Posted speed limit.
- Crash data (e.g., location, year, type, and severity).

BIKEWAY FACILITY TYPE AND ROADWAY DATA

To better characterize the bicycle treatments applied at each intersection and its legs, the research team developed and refined a data collection protocol. The database consisted of two Excel® spreadsheets: one for intersection characteristics, and the other for features of each intersection leg. The intersection-level Excel table contains 14 variables to describe the geolocation, control type (signed or signalized), and bike treatment presented over each intersection, whereas the leg-level Excel table contains 35 variables to describe the roadway design characteristics and BL-related features of road segments connected with each intersection.

The collected data can be broadly classified into three categories (table 1), including:

- Intersection characteristics category contains variables to describe the geolocation, control type (signed or signalized), and bike treatment presented for each intersection. Given the amount of sites with enough representation in this study's datasets, the research team focused the analysis on three types of bicycle treatments at the intersection box: presence of chevron pavement markings in the BL across the intersection (figure 4), crossing markings across the intersection (figure 5), and two-stage left-turn pavement markings (figure 6).

- Roadway design characteristics category contains road-related variables to characterize the road segments connected with each intersection. In this study, major legs/streets refer to the road segments with relatively higher annual AADT values, and minor legs/streets refer to the road segments with relatively lower AADT values.

- BL characteristics category contains BL-related variables to describe each intersection's connecting BLs, such as the number of BLs and the existence of six types of BLs that include through BLs (figure 8), buffered BLs (figure 2), colored BLs (figure 4, figure 6, figure 7, and figure 8), and separated BLs (figure 3). The evaluation focused on through lanes and bike boxes versus no BLs at the intersection, given the amount of data available for that evaluation.

Table 1 lists the variables collected at each study location and their definitions. Samples of the intersection characteristics can be found in figure 4 through figure 9. Figure 4 shows intersection chevron pavement markings as well as white crossing markings indicating the BL path through the intersection. Figure 5 shows an example of the same crossing markings with added green colored markings for visibility. The third treatment evaluated was pavement markings for two-phase left turns, as shown in figure 6. These markings indicate the location for a left-turning bicyclist to wait on the far side of the intersection before proceeding with the left turn. The fourth treatment evaluated was bike boxes, which are placed near the stop bar at signalized intersections to mark the location where bicyclists may safely congregate to get a head start when the signal turns green. Figure 7 shows an example of a bike box using colored pavement. The fifth treatment selected was through lanes, indicated by extension of pavement marking delineating the BL through the intersection to the left of a dedicated RTL, as shown in figure 8.

Table 1. List of variables collected for each intersection.

Variable Categories	Variable Name	Variable Description
Intersection characteristics (14 variables)	ID	Unique intersection number.
	Y	Latitude.
	X	Longitude.
	Inter_CTL	Intersection control types, including signalized, one-way stop, two-way stop, and four-way stop.
	Treatment	Whether any treatment at the intersection against the BL is present (binary: Y (yes) or N (no)). Treatments can be of four types: chevrons, crossing markings, two-stage turn queue box, and bike box.
	Chevrons	Whether any chevrons are present over the intersection (binary: Y or N).
	Chev_color	Whether chevrons present are colored (binary: Y or N).
	Cros_markings	Whether crossing markings are present over the intersection (binary: Y or N).
	2_Stage_TQBox	Whether a two-stage turn queue box is present over the intersection (binary: Y or N).
	Bike_box	Whether the bike box is present over the intersection (binary: Y or N).

Variable Categories	Variable Name	Variable Description
	Inter_Length1 (ft)	The edge length of the intersection longer edge—from one leg to its opposite leg (using the ruler tool in Google® Earth™ to measure the length with the unit in feet).
	Inter_Length2 (ft)	The edge length of the intersection longer edge—from one leg to its opposite leg (using the ruler tool in Google Earth to measure the length with the unit in feet).
	Heading (degrees)	The heading (angle) of driving on the leg based on compass directions. Value is in the range of 0–360 degrees.
	Speed_Limit	Driving speed limit (using street view and moving along the increasing milepost direction).
Roadway design characteristics (21 variables)	NumLegs	Number of legs.
	NumLegs_MJ	Number of major legs.
	NumLanes_MJ	Average number of lanes for intersection's major legs.
	NumLanes_T_MJ	Average number of through lanes for intersection's major legs.
	NumeLanes_LT_MJ	Average number of LTLs for intersection's major legs.
	NumeLanes_RT_MJ	Average number of RTLs for intersection's major legs.
	NumeLanes_TL_MJ	Average number of shared through lanes and LTLs for intersection's major legs.
	NumeLanes_TR_MJ	Average number of shared through lanes and RTLs for intersection's major legs.
	NumeLanes_LR_MJ	Average number of shared LTLs and RTLs for intersection's major legs.
	NumeLanes_TLR_MJ	Average number of shared through lanes, LTLs, and RTLs for intersection's major legs.
	NumLegs_MI	Number of minor legs.
	NumLanes_MI	Average number of lanes for intersection's minor legs.
	NumLanes_T_MI	Average number of through lanes for intersection's minor legs.
	NumeLanes_LT_MI	Average number of LTLs for intersection's minor legs.
	NumeLanes_RT_MI	Average number of RTLs for intersection's minor legs.
	NumeLanes_TL_MI	Average number of shared through lanes and LTLs for intersection's minor legs.

Variable Categories	Variable Name	Variable Description
	NumeLanes_TR_MI	Average number of shared through lanes and RTLs for intersection’s minor legs.
	NumeLanes_LR_MI	Average number of shared LTLs and RTLs for intersection’s minor legs
	NumeLanes_TLR_MI	Average number of shared through lanes, LTLs, and RTLs for intersection’s minor legs.
	Lane_width (ft)	Average lane width. This width is determined by first measuring the surface width (i.e., excluding shoulders), and then this width is divided by the number of lanes (at each leg).
	SideW_Wid (ft)	Sidewalk width (at each leg).
BL characteristics (11 variables)	Bike_Lanes	Whether both major and minor legs have BLs, including MJ (major only), MI (minor only), or both.
	NumBikeL_MJ	Average number of BLs for intersection’s major legs.
	NumBikeL_MI	Average number of BLs for intersection’s minor legs.
	Through_BikeL	Number of legs with through BLs.
	Parking_Nby	Number of legs with any parking space adjacent to the BLs.
	Buffered_BikeL	Number of legs with buffered BLs.
	Color_Pave	Number of legs with colored BLs.
	2_Way_Cyc	Number of legs with two-way cycle tracks.
	Ctra_Flow_BikeL	Number of legs with contraflow BLs.
	Protected_BikeL	Number of legs with protected BLs.
	Bike_L_Wid (ft)	Average BL width (at each leg).

Obtaining enough bicycle volume data was a challenging task. Since bicyclist traffic does not necessarily follow the same travel patterns as passenger car traffic, estimating the bicycle volumes from a few hours of data has an inherent risk of producing biased estimates, and so actual large counts were preferred instead of estimates from limited data.

After the team reviewed potential datasets from multiple States (Texas, Washington, Oregon, Florida, and Virginia), the limited availability of locations with actual bicycle counts or a potential for estimation (e.g., through other variables) drove the decision to narrow the evaluation down to the two States with the most promise to develop the dataset for analysis. The research team used data from Virginia and Texas because of the number of potential locations with bicycle exposure estimates or direct measurements that could be obtained.

SUPPLEMENTAL DATA ON INTERSECTION APPROACHES

The researchers collected additional data on the features of each intersection approach to allow a more nuanced analysis on the different ways to handle BLs. The following codes and descriptions were defined, and the sites under study were coded accordingly:

- Treat_1A: Approaches with an auxiliary RT lane where the BL is dropped in advance of the intersection.
- Treat_1B: Same configuration as treatment 1A but includes sharrow (shared lane) markings on the RTL, and a plaque saying “EXCEPT BIKES” posted under the Right-Lane-Must-Turn-Right sign.
- Treat_2A: Approaches with an auxiliary RT lane that maintains the BL to the intersection (with a keyway or pocket for the BL between the through lanes and the RT lane). Extension lines are shown in the weave area.
- Treat_2B: Similar to treatment 2A but does not include extension lines in the weave area.
- Treat_3: Approaches where the right lane can go through or make a right turn, and the BL is dashed in the mixing area on the approach to the intersection. Drivers are often supposed to pull close to the curb when making a right-turn, according to local laws, resulting in a mixing zone for motorists and bicyclists.
- Treat_4: Approaches where the right lane becomes a drop lane. A pocket or keyway may be present.
- Treat_5A: Similar to treatment 4 but the right lane drops at the intersection. In this case, the BL ends before the intersection. Sharrows are added in the RTL, and a plaque saying “EXCEPT BIKES” is installed under the Right-Lane-Must-Turn-Right sign.
- Treat_5B: Same as treatment 5A, except there are no sharrows/sign for through bikes sharing the RTL.

VIRGINIA

Bicycle Count Data

The researchers obtained the bicycle count data from the online repository (Eco-Counter 2022) supported by the Virginia Department of Transportation (VDOT), as recommended in communications with VDOT officials. A third-party company maintains and displays an online portal with bicycle and pedestrian usage data from counters across the State. The data are collected from both permanent and temporary sites with the help of counters and managed by personnel in the corresponding cities. The data are collected from several cities. The cities included in this data collection effort are as follows:

- Alexandria, VA.
- Arlington, VA.
- Blacksburg, VA.
- Charlottesville, VA.
- Richmond, VA.
- Roanoke, VA.

After eliminating locations at dedicated bicycle paths and other locations out of the scope of this evaluation, as well as locations with a limited amount of data, the research team examined a dataset of historical counts from intersections at 59 locations with some level of bicycle treatments represented and enough data to estimate daily bicycle volumes.

To estimate the overall ADBT, the research team used the total counts throughout the day. The research team first collected bike counters' data using open data sources as identified for 2015 through 2019. Then counters nearest to the intersections were linked to the study sites.

Table 2 shows the descriptive statistics of the resulting database after leg-specific variables at the intersection level were aggregated. The average daily bicycle volume at the intersections ranged from roughly 7 to 485 bicycles per day, with an average of 89.

Table 2. Virginia intersections descriptive statistics (*n*=59 sites).

Variable	Mean	Std Dev	Median	Min	Max
MajADT	12,921.95	4,684.51	12,921.95	5,200	28,000
MinADT	10,458.54	5,077.33	10,458.54	1,900	28,000
ADBT	89.38	81.89	63	6.98	484.72
NumLegs	3.29	0.74	3	3	5
NumLanes (major)	2.32	1.12	2	1	6
Nlanes (minor)	1.42	0.7	1	1	4
Lane_width (ft)	10.39	1.03	10	9	14
Inter_Length (major) (ft)	76.32	31.69	74.02	27.37	212.92
Inter_Length (minor) (ft)	57.58	22.97	53.99	22.63	127.66
Signalized	0.59	0.50	1.0	0	1
Chevrons	0.03	0.18	0	0	1
Cross_Markings	0.39	0.49	0	0	1
NumBikeL	0.53	0.3	0.5	0	1
Bike_L_Wid	2.33	1.85	2	0	10.5
Buffered_BikeL	0.04	0.14	0	0	0.67
Bike_Box	0.02	0.09	0	0	0.5
Two_Way_Cyc	0.06	0.16	0	0	0.5
Through_BikeL	0.31	0.32	0.33	0	1

Std Dev = standard deviation; Min = minimum; Max = maximum; MajADT = major annual daily traffic; MinADT = minor annual daily traffic; Num and N = number; Inter = intersection; L = lane; Wid = width; Cyc = bicycle.

Table 3 shows the proportions of intersection control types represented in the Virginia dataset.

Table 3. Virginia traffic control at intersections descriptive statistics (*n*=59 sites).

Intersection Type	Percentage in Dataset
One-way stop	25
Two-way stop	10
Three-way stop	0
Four-way stop	2
Signalized	59
Others	4

Note: Fifty-six percent of the testing intersections have four legs, 42 percent are T-type (three-leg) intersections, and 2 percent have five legs.

Table 3 shows that the majority of intersections are signalized.

Crash Data

The research team obtained crash data from Virginia's online repository (VDOT 2021) to then integrate it with the geometry data described in the first section of this chapter, Bikeway Facility Type and Roadway Data. Specifically, team members identified and linked all the crashes within the vicinity of 200 ft of the intersections included in the database. To match the same period of geometry data and bicycle counts collected, the research team filtered crashes to represent only the period from 2015 to 2019 (i.e., the same period represented in the bicycle volumes and geometry collected). After the intersection- and driveway-related crashes were removed, 471 crashes remained for merging and analysis. Crash summary statistics are shown in table 4.

Table 4. 2015–2019 Virginia crashes descriptive statistics (*n*=59 sites).

Crash Type	Mean	Std Dev	Median	Min	Max	Total
Total	7.98	10.79	5	0	53	471
FI	2.66	4.14	1	0	23	157
Bike	0.41	1.05	0	0	7	24
AdvWeather	1.36	2.34	0	0	12	80
NonAdvWeather	6.63	8.73	4	0	42	391

FI = fatal and injury; Adv = adverse; NonAdv = nonadverse.

Nearly 40 percent of all crashes shown in table 4 were fatal and injury (FI). This table also shows that the proportion of crashes that occurred under adverse weather conditions is relatively small.

TEXAS

For the final Texas database, the research team measured the intersection size and width of vehicle lanes, BLs, and sidewalks for each intersection's connected legs, similar to the case of Virginia. The average lane width in the Texas study sites is 12.05 ft. The average sidewalk width is 6.78 ft. The average daily bicycle volume at the intersections ranged from roughly 17 to 660 with an average of 109 (table 5).

Table 5. Texas descriptive statistics of intersections (*n*=126 sites).

Variable	Mean	Std Dev	Median	Min	Max
AADT.mj	16,132	13,109	12,517.75	2,678	46,640
AADT.mn	4,568	6,299	2,205.5	23.02	32,497
Maj.ADBT	105	139	37	19	826
Min.ADBT	70	96	29.25	17	569
NumLegs	3.63	0.5	4	2	4
Nlanes.mj	2.83	1.12	3	1	6
Nlanes.mn	1.73	0.83	2	1	4
Lane_width	12.07	2.36	11.38	9.18	20.19
Signalized	0.58	0.5	1	0	1
Inter_Length1	74.97	30.78	67.75	22.1	204.8
Inter_Length2	53.61	22.5	46.95	23.3	143.6
NumBikeL	0.88	0.58	1	0	2
Bike_L_Wid	3.56	1.95	4	0	11.23
Buffered_BikeL	0.16	0.35	0	0	1.5
Through_BikeL	0.02	0.18	0	0	2
Treat_1B	0.05	0.31	0	0	2
Treat_2A	0.48	0.95	0	0	4
Treat_3	0.02	0.18	0	0	2
Treat_4	0	0	0	0	0
Chevrons	0.21	0.41	0	0	1
Cros_marki	0.23	0.42	0	0	1

mj = major; mn = minor; Treat = treatment; Cros = cross; marki = markings.

In the Texas database, 60 percent of the collected intersections were signalized, 36 percent had stop signs installed, and 4 percent were neither signalized nor stop signed, as shown in table 6.

Table 6. Texas descriptive statistics of traffic control at intersections (*n*=126 sites).

Intersection Type	Percentage in Dataset
One-way stop	25
Two-way stop	10
Three-way stop	1
Four-way stop	2
Signalized	58
Others	4

Note: Sixty percent of the testing intersections contain four legs, and 40 percent are T-type (three-leg) intersections.

Bicycle Exposure Data

For the Texas sites, the research team used estimated bicycle count data from the crowdsourced database Strava to produce ADBT estimates (Strava 2018). The research team initially intended to apply direct demand models developed in Texas Department of Transportation Project 0-6927 to estimate the bicycle counts from the crowdsourced database (Turner et al. 2019).

This work collected count data from 124 roadway segments in 11 cities. The data can be visualized and queried from the Texas Bicycle and Pedestrian Count Locations Database (Texas DOT 2022). These data were collected during different periods from 2016 to 2017. Turner et al. (2019) integrated the site counts with the Strava sample and developed direct demand models to estimate the average annual daily bicycle counts. The ADBT model from that work was constructed using the three most important variables determined to be significantly associated with bicycle use:

- Strava sample counts.
- Type of roadway functional class (based on OpenStreetMap® definitions).
- Density of high-income households in the given census block group (collected via the American Community Survey (U.S. Census Bureau 2022)).

The research team decided to develop additional models from this data source that included more explanatory variables that better represented the types of facilities under study. The data from 155 stations across Texas were examined and filtered for this effort. Ultimately, only 69 locations were found to represent the types of sites under study in this research. The research team considered 47 variables in the modeling process, including Strava counts, weather conditions, housing, and demographic information obtained from the American Community Survey. Through model selection and cross-validation methods, the research team developed negative binomial models for ADBT as a response variable. Figure 15 shows the functional form of the selected model used in this research. All terms were found statistically significant at the 5-percent level or higher.

$$ADBT = \exp\,(3.44 + 5.1e^{-4} \times CountA + 1.7e^{-4} \times CountC - 2.65e^{-4} \times Edge\_km \\ + 1.71e^{-2} \times College\% - 5.75e^{-2} \times White\%)$$

Figure 15. Equation. ADBT estimation equation developed from crowdsource data.

As figure 15 shows, the most parsimonious model was found to include two count types from the Strava layer (total tips and commuting trips), the length of the Strava segment (*Edge_km*), and the percentages of college students and white population in the corresponding census tract.

Crash Data

The research team identified crashes that had occurred on selected intersections. Because the bicycle counts were estimated for a period between July 2016 and June 2017, the research team selected 2016–2019 crash data for analysis. This range of dates implies the assumption that the bicycle intersection treatments were present at the selected locations 1 yr before the data collection. The research team used a geolocation buffer of 200 ft to initially identify the intersection crashes, per recommendations by Avelar, Dixon, and Escobar (2015). Team members then applied filters to remove crashes from adjacent locations. After identifying crashes corresponding to the facilities under study, filters were applied to remove non-intersection-related crashes before the analysis (e.g., driveway related and non-intersection related). Table 7 shows the crash descriptive statistics in the Texas dataset.

Table 7. Texas 2016-2019 crash descriptive statistics (*n*=138 sites).

Crash type	Mean	Std Dev	Median	Min	Max	Total
Total (crashes)	33.79	45.83	17	0	296	4,663
FI (crashes)	16.36	23.11	7.5	0	127	2,258
Bike (crashes)	0.22	0.59	0	0	3	30
Adv_Wth (crashes)	2.72	4.21	1	0	19	375
NonAdv_Wth (crashes)	31.07	42.55	14.5	0	277	4,288

Wth = weather.

Table 7 indicates more crashes in general and more crashes per intersection in Texas, compared with the Virginia numbers in table 4. Notably, the number of bicycle crashes are about the same in Texas as in Virginia, despite the larger sample size in Texas. Similar to Virginia, the vast majority of crashes are under no adverse weather conditions.

CHAPTER SUMMARY

This chapter documents the process of selecting the States for evaluation, data elements, and data collection in general for the safety evaluation of BLs. Summary statistics are presented for the two databases developed: one for Virginia and one for Texas sites. Comparing the tables shows that more locations were available in Texas, with more crashes per intersection. Additionally, the tables show a similar number of bicycle crashes in Virginia and in Texas, despite the larger sample size for Texas. The chapter describes the data sources and data merging procedures followed to assemble the two State databases. The next chapter describes the statistical evaluations of these datasets that yielded CMF estimates for different safety treatments at intersections.

CHAPTER 4. SAFETY EFFECTIVENESS EVALUATION

This chapter presents the results of the safety effectiveness evaluation and estimated CMFs.

MODELING PROCESS

In general, the research team used entropy metrics (statistics that quantify the quality of information in the data, such as the Akaike information criterion and the Bayesian information criterion) to guide model development. In each case, the research team found the best fitting model for the response variable of interest, namely crash frequency by severity and type, as shown in table 8.

Table 8. Response variable and model specifications.

Response Variable	Model Specifications Considered
Total crash frequency	GLM and GLMM
FI crash frequency	GLM and GLMM
Bicycle crash frequency	GLM and GLMM

The research team decided to perform the analysis separately by State, given the differences observed in the descriptive statistics, especially on the average occurrence of bicycle crashes, which suggests potential underreporting for both States. Additionally, the dataset from Virginia offered ADBT estimates directly from actual counts for multiple years at each location under study, whereas bicycle volumes were estimated for the Texas dataset. By separately performing the analysis, the research team could then identify potentially diverging trends and levels of accuracy between the two analyses.

Virginia

Initially, the research team explored the balance between treated and comparison locations in the Virginia dataset. The team developed a PS model for the presence of any treatment under evaluation (e.g., BL, bicycle box, chevrons, crossing markings, or buffered BL). This analysis showed unbalances indicating overrepresentation on the treated sites for the following covariates: larger ADBTs, more lanes, and number of intersections where through and right-turning movements are combined into one lane. Conversely, comparison locations tended to have overrepresentations in the following variables: number of intersection legs, signal traffic control, and intersection length. Accordingly, the research team then developed overlap weights from the PS results as proposed by Li, Morgan, and Zaslavsky (2018). These weights are defined such that they represent the population of sites in the overlap of the two subsets. The plots in figure 16 and figure 17 demonstrate the impact of the weights on a key variable in the evaluation. Figure 16 shows the initial unbalance in this variable.

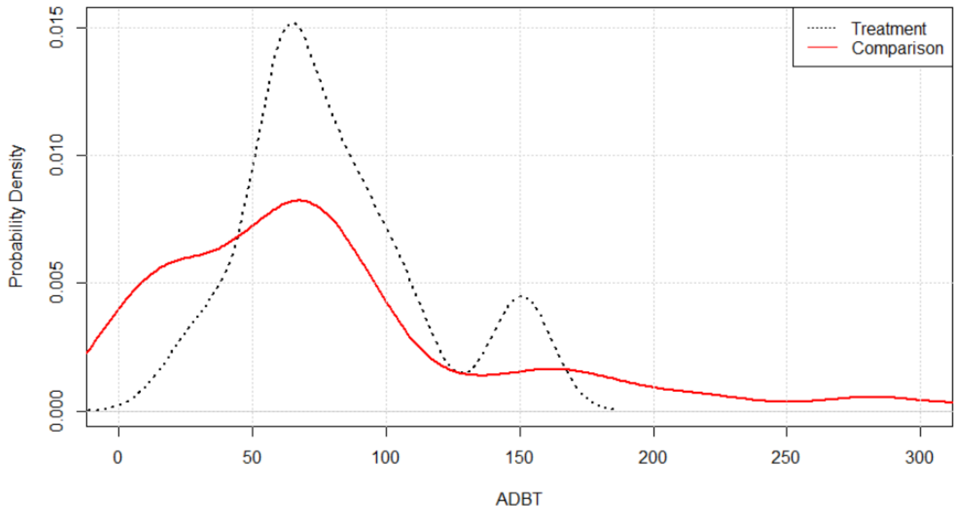

Figure 16. Graph. Bicycle volume distributions by presence of intersection treatments in Virginia.

In contrast, figure 17 shows the corresponding weighted distributions and the overlap distribution for bicycle volumes.

Probability density (from 0.000 to 0.020 in increments of 0.005) of average daily bicycle traffic (ADBT) (from 0 to 300 in increments of 50). There are three lines on the graph for treated, comparison, and overlap. The comparison line increases from the y-axis to its maximum probability density value of approximately 0.012 over an ADBT value of approximately 70, decreases sharply to a point with probability density value of approximately 0.001 over an ADBT value of approximately 120, and then remains relatively flat until it reaches an ADBT value of 300. The treated line increases sharply from the origin to its maximum probability density value of approximately 0.013 above an ADBT value of approximately 70, tracking the comparison line closely. The treated line decreases to a probability density value of approximately 0.002 over an ADBT value of approximately 120, increases to a slightly higher probability density value of approximately 0.0055 above an ADBT value of 150, and then decreases to touch the x-axis at an ADBT value of approximately 180. The overlap line closely follows the treated line's trend, being slightly higher at ADBT 70 with probability density value of approximately 0.014, and slightly lower than the treatment line at ADBT 150, with probability density value of approximately 0.003.

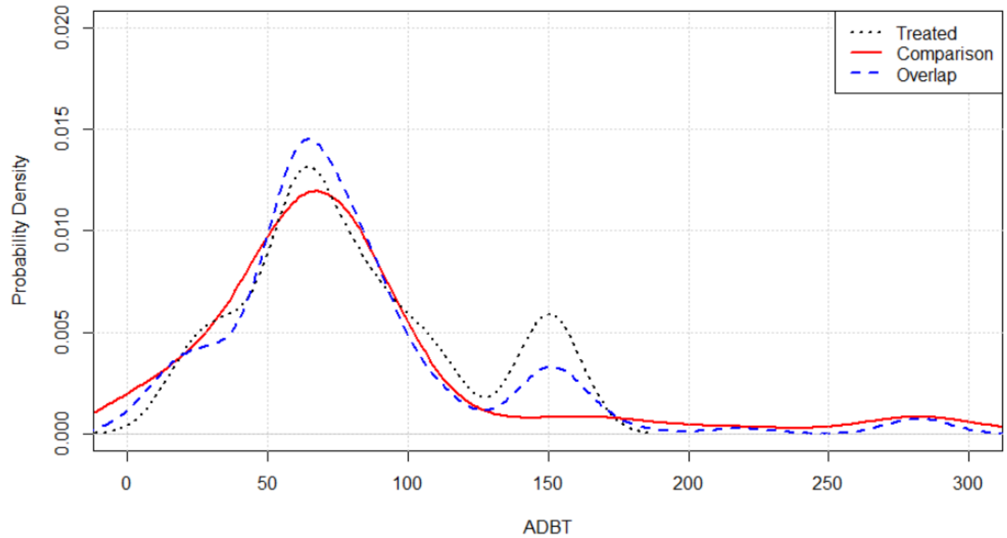

Figure 17. Graph. Weighted bicycle volume distributions by presence of treatments in Virginia.

Figure 17 shows that the application of PS weights balances the distributions, resulting in a more comparable contrast between the two data subgroups. The dashed line represents the overlap population, which is the distribution of sites with characteristics that make them nearly equally likely to be in either the treated group or the comparison group. This distribution of bicycle volumes is applicable for inference when the PS weights are applied.

Because the Virginia dataset was small (59 sites), the research team analyzed the data disaggregated at the yearly level, allowing for yearly fluctuations to be captured by yearly random effects.

Data Analysis Results—Virginia

Table 9 presents the estimates derived from the best fitting model to bicycle crashes in Virginia. As described in chapter 3, statistical models were fit for four crash responses defined in this dataset. The models for these analyses were GLMM with Poisson-lognormal mixture. This approach models site-to-site variability as a lognormal distribution, whereas the crashes within a site are modeled as a Poisson variable. Therefore, any Poisson overdispersion present in the data is captured in the variability of the random effects. An estimate of Poisson overdispersion can then be constructed and reported, analogous to the dispersion parameter in the negative binomial distribution.

Table 9. Coefficient estimates for bicycle crash prediction model in Virginia (n=236 intersection periods).

Parameter	Variable Estimate	Std Error	z Value	Pr (>|z|)	Significance
(Intercept)	−50.49	22.99	−2.196	0.0281	*
Signalized_Control	2.736	1.078	2.537	0.0112	*
log(MajADT)	4.334	1.691	2.562	0.0104	*
log(MinADT)	0.4791	1.409	0.34	0.7339	—
MinADT	−0.0001	0.0002	−0.951	0.3415	—
log(ADBT+0.5)	1.146	0.588	1.949	0.0513	~
NumLanes	−0.5603	0.3551	−1.578	0.1146	—
NumBikeL	−4.549	2.096	−2.17	0.03	*
Bike_L_Wid	0.5425	0.2539	2.137	0.0326	*
Cros_markings	1.653	0.7516	2.2	0.0278	*
Through_BikeL	−0.5141	1.309	−0.393	0.6945	—
Buffered_BikeL	0.2443	2.687	0.091	0.9276	—

~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
—Not statistically significant.

Bicycle Crashes—Virginia

The first analysis the research team developed for Virginia was on bicycle crashes. Table 9 shows the model estimates for this model.

The model results shown in table 9 indicate a consistent safety performance link to major and minor AADT and major ADBT. Additionally, statistically significant safety associations were found for signalized intersections and the width of any BLs in the approaches (within 200 ft from the intersection center). However, regarding the effects of the treatments, the implications are not straightforward, as multiple coefficients are involved in the estimation. Namely, the treatments are contingent on the presence and dimensions of BLs in the main approaches.

The research team developed CMFs for the treatments by defining appropriate contrasts as explained in chapter 3. The results of this exercise are shown in table 10.

Table 10. Bicycle crash CMF estimates for bicycle treatments at intersections in Virginia.

Treatment	CMF	Estimate	Std Error	p Value	Significance
BL Present[a]	0.2740	−1.2947	1.3910	0.3520	—
Cross_Markings[a]	1.4314	0.3586	1.5722	0.8196	—
Through_BikeL[a]	0.1639	−1.8088	1.2563	0.1499	—
Buffered BikeLane[a]	0.3498	−1.0503	2.7098	0.6983	—

—Not statistically significant.
[a]Base condition is no BL within 200 ft of the intersection on the main approaches.

All bicycle crash CMFs developed for bicycle crashes yielded statistically insignificant results. The implication of this outcome is that not enough evidence exists in the dataset to support a difference in safety due to the presence of these treatments at Virginia intersections.

Total Crashes—Virginia

Next, the research team fitted a mixed-effects model for total crashes. The model and uncertainty estimates for this model are shown in table 11.

Table 11. Coefficient estimates for total crashes prediction model in Virginia (n=236 intersection periods).

Parameter	Variable Estimate	Std Error	z Value	Pr (>|z|)	Significance
(Intercept)	14.93	7.788	1.917	0.05526	~
log(MajADT+MinADT)	−0.0185	0.0091	−2.03	0.04232	*
log(MinADT)	−1.453	0.6627	−2.193	0.02831	*
MinADT	−0.2864	0.1716	−1.668	0.09523	~
NumLanes.min	0.2607	0.8469	0.308	0.75821	—
Lane_width	0.4407	0.2384	1.848	0.06458	~
NumeLanes_TL	0.0001	0.0001	2.136	0.0327	*
NumBikeL	−1.453	0.6627	−2.193	0.02831	*
Bike_L_Wid	−0.2119	0.1392	−1.522	0.1279	—
Buffered_BikeL	0.2345	0.1538	1.525	0.12723	—
Through_BikeL	−0.2119	0.1392	−1.522	0.1279	—
Cros_markiY	0.2345	0.1538	1.525	0.12723	—
Inter_Leng	−1.92	1.062	−1.808	0.07059	~
Inter_Leng:Inter_Le_1	−1.92	1.062	−1.808	0.07059	~

~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
—Not statistically significant.
TL = turn lane; Y = yes; L, Leng, and Le = length.

The CMFs corresponding to the bicycle treatments are shown in table 12. The table shows that none of the estimates was found to be statistically significant.

Table 12. Total crash CMF estimates for bicycle treatments at intersections in Virginia.

Treatment	CMF	Estimate	Std Error	p Value	Significance
BL Present[a]	0.9548	−0.0462	0.6902	0.9466	—
Cross_Markings[a]	1.0278	0.0275	0.7831	0.9720	—
Through_BikeL[a]	1.1828	0.1679	0.4601	0.7151	—
Buffered BikeLane[a]	0.2654	−1.3266	0.8416	0.1150	—

—Not statistically significant.
[a]Base condition is no BL on the main approaches.

The results indicate statistically insignificant changes in crash frequency associated with the presence of bicycle treatments at intersections (i.e., the CMF is statistically equivalent to 1.0). This result is not surprising, given that the response variable in this analysis includes non-bicycle-related crashes, which are the majority of all crashes.

FI Crashes—Virginia

As in the prior analyses, the research team estimated the safety effectiveness for the intersection treatments with FI crashes as the response. Results are summarized in table 13.

Table 13. Coefficient estimates for FI crashes prediction model in Virginia (*n*=236 intersection periods).

Parameter	Estimate	Std Error	*z* Value	Pr (>|*z*|)	Significance
(Intercept)	−1.6903	3.654	−0.463	0.64365	—
Signalized	0.8247	0.3678	2.242	0.02495	*
log(MajADT+MinADT)	0.1195	0.2984	0.401	0.68877	—
log(ADBT)	0.4694	0.2013	2.332	0.01972	*
Inter_Leng	−0.0128	0.0076	−1.688	0.09141	~
Inter_Le_1	0.0173	0.0106	1.627	0.10366	—
NumeLanes_RT	0.2009	0.1754	1.145	0.25211	—
NumBikeL	−2.0071	0.7148	−2.808	0.00499	**
Lane_width	−0.1618	0.1473	−1.098	0.272	—
Bike_L_Wid	0.1522	0.1339	1.137	0.25548	—
Through_BikeL	0.9786	0.554	1.767	0.0773	~
Cros_markiY	0.204	0.2685	0.76	0.44743	—
NumLanes	0.1622	0.212	0.765	0.44419	—
Buffered_BikeL	0.5545	1.1116	0.499	0.61789	—

~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
—Not statistically significant.

The CMFs corresponding to the bicycle treatments are shown in table 14. No result in this table showed statistical significance. However, it should be noted that the best fitting model in table 13 from which these CMFs are derived did include bicycle volume as exposure, a feature that suggests representation of bicycle involvement in the count of FI crashes.

Table 14. FI crash CMF estimates for bicycle treatments at intersections in Virginia.

Treatment	CMF	Estimate	Std Error	*p* Value	Significance
BL Present[a]	0.3350	−1.0937	0.6807	0.1081	—
Cross_Markings[a]	0.4108	−0.8897	0.7781	0.2529	—
Through_BikeL[a]	0.8913	−0.1151	0.4181	0.7832	—
Buffered BikeLane[a]	0.5833	−0.5391	1.0772	0.6167	—

—Not statistically significant.
[a]Base condition is no BL on the main approaches.

Although all CMFs shown in table 14 are statistically insignificant, the CMF for BL presence is nearly statistically significant at the 90-percent confidence level (*p* value 0.1081). The magnitudes and directions of all other CMFs in this table are consistent with the hypothesis of a safety benefit of the bicycle treatments under evaluation, which in turn suggests that underreported bicycle crashes might be counted among the crashes analyzed.

Discussion of Virginia Results

The research team estimated CMFs for bicycle intersection treatments with enough representation in the Virginia dataset. These calculations were assessed for three crash types: bicycle, total, and FI. Most CMF estimates were smaller than 1 but with corresponding standard errors, such that all CMFs produced using the data from Virginia were not statistically different from 1.0. In other words, these analyses could not establish statistical evidence supporting the expectation that adding bicycle treatments at intersections influences safety performance of these intersections. Besides the real possibility that there is no safety impact, the research team proposes two likely causes for these results: small sample size regarding both the number of locations and the number of bicycle crashes recorded at those locations. The second potential explanation is linked to the first. The number of bicycle crashes could be underreported, and as such, some bicycle crashes could be absent from the bicycle crash analysis or from all the analyses altogether. Finding bicycle volume as a statistically significant variable in the FI crash analysis is consistent with this potential issue.

Texas

As with the Virginia dataset, the analysis of Texas data began with an examination to understand underlying relationships and to ensure proper representation of key variables. The team developed PS weights similar to those for Virginia to even out any remaining imbalances in the data before the analyses.

The overlap PS developed were based on a model on the presence of bicycle treatments at intersections. The overlap weights were developed as proposed by Li, Morgan, and Zaslavsky (2018). Results indicated a higher likelihood of treatment presence was linked to the following variables: major and minor AADT, number of lanes in the minor approach, crossing distance on the major legs, presence of number of RTL and LTLs, and sidewalk width. Figure 18 shows the distributions of major AADT by presence of bicycle treatments at the Texas intersections under evaluation to demonstrate the balancing effect of the developed PS weights.

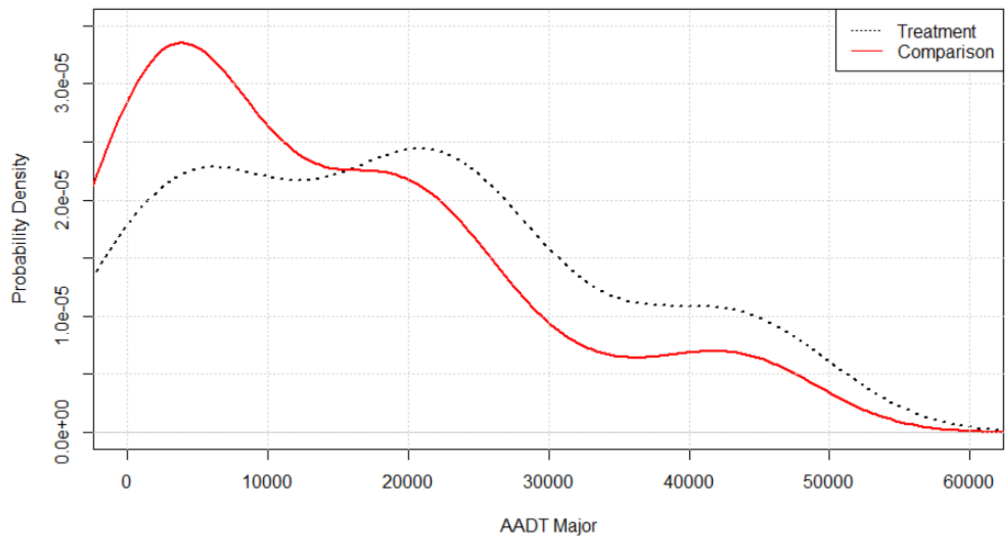

Figure 18. Graph. Major AADT width distributions by bicycle intersection treatments in Texas.

Figure 18 shows a mild imbalance. Among the sites with bicycle treatments, the distribution is flatter and broader, compared with the comparison sites that have a larger mode at low volumes. After PS weights were applied, the comparison by the presence of a bicycle treatment becomes more balanced for this covariate, as depicted in figure 19. The distribution of the overlap population is also shown in this figure as a dashed line.

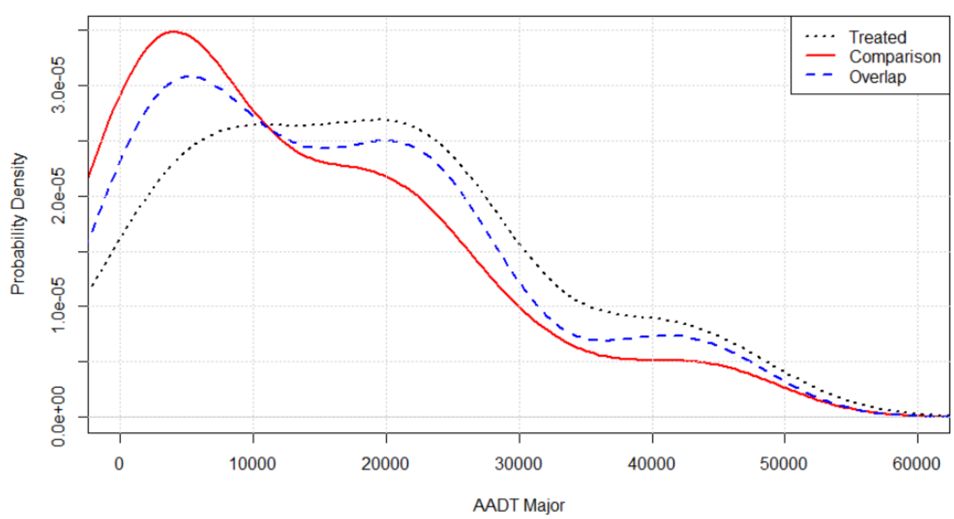

Figure 19. Graph. Major AADT weighted distributions in Texas.

The main changes in AADT distributions are additional weights for treated sites with major AADTs from 10,000 to 25,000 vehicles per day (vpd) and lower weights at comparison sites for AADTs larger than 35,000 vpd.

Data Analysis Results—Texas

In contrast with Virginia analyses, the models used for Texas were negative binomial GLMs. These types of models were preferred in this case due to their increased efficiency and availability of straightforward diagnostic tools, coupled with a sufficiently large pool of intersections for analysis.

For the CMF development, the research team followed a similar approach to the one used in the Virginia analyses. Safety performance models accounted for documented safety performance influential variables, such as major and minor AADTs and estimated bicycle volumes, while producing marginal accounts for the presence of bicycle treatments at intersections.

Total Crashes—Texas

Next, the research team fitted a GLM for three crash types at the Texas sites. The coefficients and uncertainty estimates for this model are shown in table 15.

Table 15. Coefficient estimates for total crashes prediction model in Texas (*n*=126 intersections).

Parameter	Estimate	Std Error	*z* Value	Pr (>|*z*|)	Significance
(Intercept)	−0.098	1.224	−0.080	0.936	—
Inter_CTL="Signalized"	1.016	0.251	4.048	<0.001	***
log(AADT.min)	0.112	0.076	1.480	0.139	—
log(AADT.maj)	−0.040	0.135	−0.297	0.766	—
log(Maj.ADBT+ Min.ADBT)	0.141	0.095	1.492	0.136	—
Nlanes	0.512	0.126	4.074	<0.001	***
TreatmentY	−0.564	0.356	−1.586	0.113	—
Treat_3	0.169	0.142	1.185	0.236	—
Treat_2A	0.084	0.250	0.336	0.737	—
Separated_BikeL	−0.030	0.107	−0.276	0.782	—

***Statistically significant at the 0.001 level.
—Not statistically significant.

The statistically significant coefficients in table 15 indicate associations of type of control and geometry to safety as anticipated. The CMFs corresponding to the bicycle treatments that remained in the most parsimonious model are shown in table 16.

Table 16. Total crash CMF estimates for bicycle treatments at intersections in Texas.

Treatment	CMF	Estimate	Std Error	*p* Value	Significance
Separated BL[a]	0.552	−0.593	0.345	0.086	~
BL mixed with through and RT lane[a]	0.674	−0.395	0.251	0.116	—
Through_BikeL_with_keyway[a]	0.619	−0.480	0.367	0.191	—

~Statistically significant at the 0.1 level.
—Not statistically significant.
[a]Base condition is no BL on the main approaches.

Only for SBL did the results indicate an associated statistically significant safety improvement. The number of total crashes at intersections with SBL was estimated as 44.8 percent smaller than at intersections without BLs, after accounting for exposure, type of traffic control, and number of lanes.

Fatal and Injury Crashes—Texas

The research team estimated the safety effectiveness of intersection treatments as measured by FI crashes next. Table 17 shows this result.

Table 17. Coefficient estimates for FI crash prediction model in Texas (*n*=126 intersections).

Parameter	Estimate	Std Error	*z* Value	Pr (>|*z*|)	Significance
(Intercept)	0.9206	1.845	0.499	0.61778	—
I(Inter_CTL="Signalized") TRUE	0.9227	0.2635	3.502	0.000462	***
log(AADT.mj+AADT.mn)	0.0238	0.1514	0.157	0.875062	—
log(Maj.ADBT+Min.ADBT)	0.1216	0.1025	1.186	0.235446	—
AADT.mn	5.00E-05	2.00E-05	2.602	0.009273	**
Nlanes.mx	0.3486	0.1369	2.547	0.010865	*
TreatmentY	–0.7921	0.3956	–2.002	0.045271	*
Treat_3	0.2324	0.1677	1.386	0.165888	—
Treat_4	0.3861	0.3528	1.094	0.273772	—
Lane_width	–0.0968	0.0687	–1.41	0.158581	—

*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.
—Not statistically significant.

The FI crash CMFs corresponding to the relevant bicycle treatments in the model are shown in table 18. Out of the two treatments, only BL next to RT lane showed statistical significance at the 95-percent confidence level.

Table 18. FI crash CMF estimates for bicycle treatments at intersections in Texas.

Treatment	CMF	Estimate	Std Error	*p* Value	Significance
BL mixed with Through and RT lane[a]	0.571	–0.560	0.264	0.034	*
Through_BikeL_with_keyway[a]	0.666	–0.406	0.373	0.277	—

—Not statistically significant.
*Statistically significant at the 0.05 level.
[a]Base condition is no BL on the main approaches.

Non-Weather-Related Crashes—Texas

The research team next estimated the safety effectiveness of intersection treatments as measured by nonadverse crashes since, logically, bicyclists would avoid riding in adverse weather conditions. The premise is that this subset of crashes should have a larger proportion of crashes involving bicyclists, thus showing sensitivity to the treatments intended for bicyclists. Table 19 shows this result.

Table 19. Coefficient estimates for non-weather-related crash prediction model in Texas (*n*=126 intersections).

Parameter	Estimate	Std Error	*z* Value	Pr (>|*z*|)	Significance
(Intercept)	0.3192	1.8108	0.176	0.860063	—
Inter_CTL="Signalized"	1.0259	0.2497	4.108	0.0000399	***
log(AADT.mj+AADT.mn)	0.0461	0.1372	0.336	0.736533	—
log(Maj.ADBT+Min.ADBT)	0.4285	0.1807	2.371	0.017747	*
Min.ADBT	–0.003	0.0017	–1.793	0.072958	~
Nlanes	0.4264	0.1228	3.474	0.000514	***
Lane_width	–0.115	0.0629	–1.83	0.067302	~
TreatmentY	–0.5614	0.2234	–2.513	0.011977	*
Treat_4	0.0599	0.2986	0.2	0.841094	—
Chev_ColorY	0.7132	0.3102	2.299	0.021505	*
Separated_BikeLRA	–0.2241	0.1256	–1.784	0.074363	~

~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
***Statistically significant at the 0.001 level.
—Not statistically significant.
Chev = chevron.

The non-weather-related CMFs corresponding to the bicycle treatments are shown in table 20. Similar to the total crash analysis, only the treatment of SBL showed statistical significance at the 99-percent level.

Table 20. Non-weather-related crash CMF estimates for bicycle treatments at intersections in Texas.

Treatment	CMF	Estimate	Std Error	*p* Value	Significance
Separated BL[a]	0.456	–0.786	0.253	0.002	**
BL mixed with Through and RT lane[a]	0.606	–0.502	0.316	0.112	—
Through_BikeL_with_keyway and colored chevrons with extension lines[a]	1.236	0.212	0.422	0.616	—

[a]Base condition is no BL on the main approaches.
**Statistically significant at the 0.01 level.
—Not statistically significant.

Table 20 shows one statistically significant CMF for the presence of buffered BLs (figure 3). The analysis indicates that this treatment is associated with a reduction of 54.4 percent in non-weather-related crashes, after controlling for vehicle exposure, bicycle exposure, and other intersection related factors.

Discussion of Results

The research team estimated CMFs for bicycle intersection treatments with enough representation in the Texas dataset, similar to the Virginia dataset. These calculations were assessed for three crash types: total, FI, and non-weather-related crashes. The later crash type was analyzed under the premise that a larger proportion of these crashes could be bicycle-related but not coded as such. The corresponding standard errors suggest that three CMFs produced using the Texas datasets were statistically different from 1.0. The analysis found that the use of SBLs at intersection is linked to total and non-weather crash reductions of 44.8 and 55.4 percent, respectively. The other statistically significant result was found for configuring the approaching BL to the right of a combined through and right-turn MV lane, as shown in figure 9. However, the small number of crashes explicitly flagged as bicycle related suggests an important number of underreported or uncoded bicycle crashes for the State of Texas. Interestingly, ADBT variables were found to be important in explaining the variability of the three types of crashes analyzed. This feature of the analyses supports the hypothesis of an important part of the crashes analyzed being potentially bicycle related.

CHAPTER SUMMARY

This chapter documents the statistical evaluations and steps taken to develop CMFs using the databases from Virginia and Texas, the two States represented in this study. Separate analyses were implemented for each dataset to develop statistical models for three crash types: bicycle, total, and FI for Virginia, and total, FI, and non-weather-related for Texas. Using the model estimates, the research team computed CMFs corresponding to the safety countermeasures under evaluation (i.e., bicycle treatments at intersections). Only three statistically significant results in Texas were found in these analyses: estimated crash reductions in total and non-weather-related crashes for SBL at intersections and for mixing zones (figure 9), for accommodating BLs at intersections. Chapter 5 outlines the benefit–cost (B/C) evaluation of these safety improvement.

CHAPTER 5. ECONOMIC ANALYSIS

The research team conducted an economic analysis to estimate B/C ratios for implementing the bicycle treatments that showed statistically significant results. The Texas CMF results yielded three estimates that were statistically significant for total, FI, and non-weather-related crashes in Texas. Although other estimates from Virginia and Texas were found to be statistically insignificant, many of the treatments generally indicated a trend for reducing crashes. For the economic evaluation, the research team focused on the two treatments that yielded statistically significant results.

To perform a B/C analysis, the research team followed the procedures recommended in the Federal Highway Administration's (FHWA) technical document entitled *Highway Safety Benefit–Cost Analysis Guide* (Lawrence et al. 2018). Also, the value of a statistical life (VSL) was obtained from the most recent memorandum on the U.S. Department of Transportation website (Putnam and Coes 2021). The recommended range for VSL was $10.9 million in 2019, the most recent year included in the evaluations of this study.

According to the Pedestrian and Bicycle Information Center (FHWA 2015), the cost of adding BLs varies depending on the project details. This source argues that reducing the width of MV lanes by adding BLs cost at least $5,000 per mile. However, this cost varies widely based on the pavement condition, which involves the intersection treatment in this assessment. Past research has reported the costs for individual elements included in bicycle treatments at intersections (Weigand, McNeil, and Dill 2013). The authors reported $200 for each pedestrian and bicycle crossing sign, $5,000 per bike box, up to $6.35 per foot of BL, up to $9.33 per foot of buffered BL, up to $340 for a chevron marking, and $0.62 for each foot of pavement line removal. The value reported by Weigand, McNeil, and Dill (2013) for adding a BL by reducing MV lane widths is given in 2013 dollars and must be converted to 2019 dollars before it can be used in the economic analysis. Based on publicly available consumer price index data, the research team estimates a cumulative inflation rate of 9.7 percent between 2013 and 2019. Regarding duration, FHWA reports that methyl methacrylate acryline markings tend to last up to 8 yr, whereas thermoplastic or paint requires more frequent maintenance (FHWA 2015). Wilson (2020) estimated the cost of SBLs could vary from $133,170 to $536,680 per mile in 2020, depending on construction materials and specific design needs. For the purposes of this analysis, a value of $150,000 per mile was assumed for 2019.

Additionally, the base condition of the CMFs of interest is no BL arriving at the intersection. Although acquisition of the right of way (ROW) and construction of additional lanes might not be necessary to convert such an intersection, the research team carried calculations considering and not considering acquisition of the ROW. A 2022 report from Hillsboro, OR, shows cost estimates for various intersection improvement projects approved in that city (David Evans and Assocciates Inc. 2022). A similar intersection project that adds turn lanes and reconfigures the existing lanes is reported to have a cost of $1.4 million in 2022. Considering the cumulative inflation between 2019 and 2022 of 12.5 percent, the estimated cost of such a project in 2019 is $1.24 million. These improvement projects typically have a useful life of 20 yr. Therefore, the economic analysis will be based on a 20-yr horizon.

COST OF CRASHES AND B/C RATIO

To estimate the benefit of SBL, the team calculated the average cost of a non-weather-related crash in Texas as $106,972 in 2019. Considering a period of analysis of 20 yr and a reduction of 94.76 non-weather-related crashes in that period (per a 0.456 CMF (table 20) applied to a total of 7.77 crashes per year times 20 yr), the benefit of implementing SBLs on the main road was estimated as $9,040,250 in 2019 dollars (84.51 prevented crashes times $106,972 per crash).

To estimate B/C ratios, the research team calculated the cost of installing SBLs for a period of 20 yr. With a construction cost of $150,000 in 2019, the cost of restriping for 200 ft of the two opposite main approaches is estimated as $7,302.5 from the work of Weigand, McNeil, and Dill (2013). Assuming restriping and replacing of vertical element separators is needed every 5 yr (thus occurring four times in the life of the project), the cost of maintenance is estimated as $42,918=10,729×20/5. Thus, the total project cost of the improvement is estimated as $292,918 if no additional ROW purchase is necessary. If ROW should be acquired, the total project cost escalates to $15,537,362. Finally, the B/C ratio of adding SBLs is 30.9 if no additional ROW is acquired, whereas the B/C ratio drops to 5.9 in the scenario where ROW is added to accommodate the treatment.

The other treatment that was found beneficial according to the evidence in the dataset was the configuration that creates a mixing zone between the through and RT movement for the MVs and the BLs (figure 9). In this case, the estimate in table 18 indicates a reduction of 42.9 percent in FI crashes. The research team estimated that an FI crash costs $105,676 on average in the corresponding dataset. Given an average of 4.06 FI crashes per year, the benefit is then estimated as $3,708,397 in 20 yr. Assuming that the treatment will not require acquiring additional ROW, the combined cost of initial construction and maintenance over the period of analysis was estimated as $32,707. Therefore, the B/C ratio of this strategy was estimated as 113.3.

CHAPTER SUMMARY

This chapter describes the economic analysis performed to estimate the economic effectiveness of implementing bicycle through lanes at intersections. The benefit calculation was derived from the nonadverse weather crash CMF for SBL in Texas, as well as the FI CMF for mixing the BL with through and right turns at intersection approaches. These CMFs were found statistically significant in the analyses of chapter 4, which outlines the resources and assumptions involved in developing the B/C ratio. With a total benefit of $9.05 million and a total cost of $1.6 million, the economic evaluation yielded a B/C ratio of 5.9 for this intersection treatment when assuming acquisition of additional ROW. If no additional ROW is necessary, the B/C ratio increases to 30.9. In the case of providing a mixing zone between the BL, the through, and the right-turning MV movements, the benefit value in terms of a reduction of nonadverse weather crashes was estimated as $3.7 million. The cost of reconfiguring the approaches was estimated as $32,707, which yielded a B/C ratio of 113.3.

All three B/C results indicate larger benefits than costs expected from the assessed types of implementations. Chapter 6 presents the summary and conclusions for this safety evaluation.

CHAPTER 6. SUMMARY AND CONCLUSIONS

The objective of this study was to perform a rigorous safety effectiveness evaluation of adding bicycle treatments at urban intersections that are candidates for the treatment. To accomplish the goals of this study, the research team compiled safety data from Virginia and Texas. The evaluation included total, FI, and nonadverse weather crashes.

Safety data collection was guided by the availability and location of available bicycle traffic data, which is an influential variable identified in past research on the safety effectiveness of the treatment of interest. Similar to how AADT is used to account for MV exposure, bicycle traffic should reflect exposure for those vulnerable users. In the case of Virginia, the research team developed estimates of ADBT using actual bicycle counts. For Texas, direct demand models were developed and used to estimate bicycle volume.

Statistically significant CMFs were found from Texas for SBL construction with regard to total and non-weather-related crashes, as well as for providing a mixing zone configuration for bicyclists and MVs at the approach with regard to FI crashes. The research team surmises that sample size for both States with enough treated sites and enough crash data might have been a contributing factor for all other evaluations that yielded statistically insignificant results.

In the case of the statistically significant CMFs for SBLs at intersections, this research found a 54-percent crash reduction in non-weather-related crashes in Texas (0.456 CMF, 0.002 *p* value) linked to this treatment. This CMF was used to calculate the benefits of bicycle through lane treatments at intersections in the B/C ratio evaluations. The costs of construction and maintenance were found to be notably smaller than the benefit. The B/C ratio was estimated as 5.9 when the cost of additional ROW is assumed, and 30.9 without that assumption.

In the case of the mixing zone at the approach, the estimated CMF was a reduction of 42.9 percent in FI crashes (0.571 CMF, 0.034 *p* value). The research team estimated the B/C ratio in this case as 113.3 when assuming no additional ROW is required to construct and maintain this treatment.

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