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Examining the Impact of Centerline Rumble-Strip Installation in Prevention of Head-On and Opposite Sideswipe Collisions in Maine

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EXAMINING THE IMPACT OF CENTERLINE RUMBLE-STRIP INSTALLATION IN PREVENTION OF HEAD-ON AND OPPOSITE SIDESIWPE COLLISIONS IN MAINE

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Among all traffic collisions, lane departure crashes are the leading type of serious traffic crashes in Maine, comprising 72% of state-wide traffic fatalities. To reduce these crashes, Maine Department of Transportation (MaineDOT) installed shoulder and centerline rumble strips on roadways to prevent lane departure crashes in Maine. With a total installed length of 1503 miles of rumble strips, specifically 511 miles of centerline rumble strips in bidirectional and undivided rural two-lane roadways, there is a need to understand the impact of rumble strips in reducing lane departure crashes. In this thesis, observational before-after studies with two methods: comparison group, and empirical Bayes (EB) comparison group were used to explore the effectiveness of centerline rumble strips in reducing head-on and opposite sideswipe crashes for rural two-lane roadways and compute crash modification factors (CMFs) in Maine. The evaluation investigated the impact of centerline rumble strips on reducing the total and fatal and injury head-on and sideswipe collisions on rural-two lane roadways. The economic benefits of using rumble strips are also explored by using a benefit-cost analysis. This study finds that the installations of centerline rumble strips are associated with reductions between 28% and 48% of head on and opposite sideswipe collisions on rural two-lane roads. In addition, the rumble strips are a cost-effective countermeasure with the benefits being at least 14 times the costs for the same road facility type.

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CHAPTER 1

INTRODUCTION

According to the definition provided by the Federal Highway Administration (FHWA), a lane-departure crash is a crash that occurs when a vehicle leaves the traveled path, for example, crossing the edge or center line of the road[1]. Lane-departure crashes include head-on, sideswipe (opposite and same direction), went-off-road, and rollover crashes. From these, head-on crashes are the most dangerous type of crash, accounting for 14% of all traffic fatalities and 27% of lane-departure crash fatalities in the U.S. during the period of 2016 to 2018 (Federal Highway Administration - FHWA, 2018).

Maine experiences the highest crash fatality rate among New England states (Bouchard et al., 2020). The majority of these crash fatalities result from lane-departure crashes. In fact, according to crash records from 2010 to 2022, lane departure crashes result in approximately twice (or more) fatalities as other types of crashes each year. Additionally, Maine's lane-departure crashes accounted for approximately 73% of the fatalities, even though only 30% of the total number of crashes in the state were lane departure crashes. Among the lane departure crashes, head-on and opposite sideswipe collisions represented approximately 20% of the total lane departure crashes in the state. Furthermore, according to 2020 crash data, 48% of the crash fatalities in the U.S. occurred in rural areas. In fact, the fatality rate per 100 million vehicles miles travel was 1.7 times higher in rural areas than in urban areas (National Highway Traffic Safety Administration - NHTSA, 2022), and Maine is mainly a rural state where approximately 80% of its roadways are in rural areas (Sawtelle et al., 2023).

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[1] https://highways.dot.gov/safety/RwD

Maine is unique in many ways. Its location, extreme weather, aging infrastructure, older population, land use, and terrain provide unique features (Islam et al., 2023; Rubin et al., 2022; Sawtelle et al., 2022, 2023). The overall Maine infrastructure received a classification of C (mediocre: requires attention) by the ASCE 2020 Infrastructure Report Card (Bouchard et al., 2020), keeping the same classification since 2008. Specifically, the roadway infrastructure in Maine was classified as D (poor: at risk) in the same report, which has been the same since 2008. In addition, Maine has the oldest population in the United States according to the 2020 US Census, with the largest share (21.8%) of people aged 65 or above, and the second largest share (2.4%) of people aged 85 or above (Caplan & Rabe, 2023). The median age in Maine, in 2020, was 6.8 years higher than the national median of US (Sawtelle et al., 2023). This aging trend in Maine has been evident since the 1990 census (Sawtelle et al., 2023).

Rumble strips are a common and relatively low-cost countermeasure used to prevent lane departure crashes (Himes & McGee, 2016; Smadi & Hawkins, 2016). In fact, the results of a survey sent to the U.S. Department of Transportation (U.S. DOT) of 50 states and 42 of them showed that 98% of the states used rumble strips on the roadway's centerline and 100% used rumble strips on the shoulders (McGee, 2018). However, the installation and design of rumble strips across states are not uniform (Smadi & Hawkins, 2016). Rumble strips alert drivers about the lane departure through noise and vibration (Himes et al., 2017; Russell & Rys, 2005). Although, centerline and edge rumble strips target different lane-departure crashes. The centerline rumble strips are commonly used in undivided roadways to prevent head-on and opposite-direction sideswipe crashes (Russell & Rys, 2005). On the other hand, edge rumble strips help prevent and reduce run-off-road crashes that may cause rollover or hit fixed objects.

The Maine Department of Transportation (MaineDOT) has installed 1,503 miles of rumble strips across the state roadways as a countermeasure to prevent lane departure crashes. This corresponds to 6%, according to Bouchard et al. (2020), of 23,000 total miles of roadways in the state. It also corresponds to the 17% of the roadway's mile managed by MaineDOT, which according to Bouchard et al. (2020) are the 37% (8,510 miles) of the total state roadways. The rumble strips were placed either at the centerline (685 miles) or the edge (818 miles) of the roadways. Specifically, the MaineDOT installed 511 miles of centerline rumble strips in bidirectional and undivided rural two-lane roadways. In addition, two types of rumble strips were installed: standard and sinusoidal strips. Sinusoidal rumble strips produced less noise than the standard.

1.1 Problem Statement

The aim of this study is to assess the effectiveness of centerline rumble strips installed in Maine on preventing total and fatal and injury (KABC) head-on and opposite sideswipe collisions on rural two-lane roadways. In this study, the terms fatal and injury crashes and KABC crashes are used interchangeably and refers to the following crash severities defined by the Highway Safety Manual (HSM) (AASHTO, 2010). K: fatal injury, A: incapacitation injury, B: no incapacitating evident injury, and C: possible injury. The effectiveness of the centerline rumble strips is assessed using before-and-after studies with two methods: comparison group, and empirical Bayes (EB) comparison group, to compute crash modification factors (CMFs) and the percentage of change in crash frequency. The results corresponded with the before-and-after study using the EB method is also documented in Appendix B. As part of the before-and-after studies, safety performance functions (SPFs) are estimated for the rural two-lane roadways. In addition, economic analysis is performed to determine the economic benefits of centerline rumble strip installations on the same roadway type.

1.2 Thesis Outline

The outline of this thesis is as follows. Chapter 2 provides a systematic review of the literature on the effectiveness of rumble strips in reducing lane-departure crashes. Chapter 3 presents the data used in this study and a preliminary analysis of the effectiveness of Maine's rumble strips in reducing lane-departure crashes. Chapter 4 documents the before-and-after study using a comparison group evaluation for centerline rumble strips on rural two-lanes. Chapter 5 documents the before-and-after study using the EB comparison group evaluation for the same facility type. Chapter 6 presents an economic analysis of centerline rumble strip installation considering the benefit-cost ratio. Chapter 7 presents the summary of the findings and recommendations.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the studies related to the effectiveness of rumble strips in preventing roadway crashes. As discussed, lane-departure crashes are a concern for Maine. Rumble strips use noise and vibration to make drivers aware of lane departure and are a typical countermeasure for mitigating crashes. A high percentage of lane-departure crashes are caused by distracted driving, operating under the influence, or driving fatigued, and vibration and noise help these drivers become aware of departure. Typically, centerline rumble strips are used to help avoid head-on crashes, whereas the edge or shoulder rumble strips are implemented to reduce run-off-road crashes that may result in rollover or hitting fixed objects. Both centerline rumble strips and shoulder rumble strips are useful countermeasures to mitigate lane-departure crashes because of their relatively low cost and the typically high benefit of reducing crashes.

This chapter is organized as follows. First, the effectiveness of centerline rumble strips in reducing crash frequency and severity is discussed. Second, the effectiveness of shoulder rumble strips in decreasing crash frequency and mitigating crash severity was discussed. Third, the effectiveness of the combination of centerline rumble strips and shoulder rumble strips in reducing crash frequency and crash severity is outlined. Finally, the conclusions of the reviewed studies are documented.

2.1 Effectiveness of Centerline Rumble Strips

Persaud et al., (2004) studied the effectiveness of centerline rumble strips installed on rural two-lane undivided roads on different crash types. This study used data from California, Colorado, Delaware, Maryland, Minnesota, Oregon, and Washington, USA. An EB before-and-after study was developed using 98 treatment sites. Overall, a 12% reduction in the crash frequency was observed on the treated roadways. Frontal and opposing-direction crashes were found to be the most critically affected by the rumble-strip installation and were reduced by 25% during the after period. Overall, a 14% reduction in injury crashes was found on treated roadways. Frontal and opposing crashes had the highest crash severity, although after centerline rumble strip installation, there was a reduction in injury crashes of over 25%.

Sayed et al. (2010) considered both rural two-lane undivided arterials and divided four-lane freeways to analyze the effectiveness of centerline and shoulder rumble strips on crashes in British Columbia, Canada. An EB before-and-after study was conducted to determine the effectiveness of rumble-strip installation. Three years before the treatment and one -to-three years after the treatment crash data were collected for each of the 47 treatment sites. To correct for time-trend effects, 225 comparison segments were considered. These groups have similar attributes and are close to the treated segments. Only arterials received centerline rumble strips treatment. The crash types considered when analyzing centerline rumble strips include head-on or off-road-left crashes. The results indicate a 29.3% reduction in head-on or off-road left crashes on the treated segments. The overall reduction in severe crashes at all the sites was 18%.

Michigan Department of Transportation (Michigan DOT) implemented a rumble-strip installation program from 2008 to 2010. The program installed centerline rumble strips on over 4,000 miles of rural, non-freeway, high-speed roads. The program also installed shoulder rumble strips on some roadways. The program's goal was to mitigate lane-departure crashes. Kay et al. (2015) studied the effectiveness of the rumble-strip installation program performing an EB before-and-after study using crash data from three years before and after treatment. A total of 865 segments treated with centerline rumble strips were analyzed. Overall, a 27.3% reduction in lane-departure crashes was found on roadways treated with centerline rumble strips. The analysis also included the effectiveness of rumble strips on weather-affected pavement. Wet-pavement crashes were reduced by 53.6% and wintery pavement crashes were reduced by 1.4% on centerline rumble strips-treated roads. Operating-under-the-influence crashes were reduced by 28.9%, and passing-related crashes were reduced by 42.8%. Regarding crash-severity reductions, there was a decrease of 44.2%, 31.3%, 39.8%, and 27.9% for fatal, A-injury, B-injury, and C-injury crashes, respectively.

Dissanayake & Galgamuwa (2017) developed before-and-after studies on lane departure countermeasures, including the centerline rumble strips and shoulder rumble strips, along with other methods. Both two-lane undivided and four-lane divided rural road segments in Kansas are considered. In total, 22,060 tangent and 6,442 curved two-lane undivided rural roadway segments, and 12,065 tangent and 4,095 curved four-lane divided rural roadway segments were considered. Two methods were considered: cross-sectional and case-control. Similar to Kay et al. (2015) centerline rumble strips only for two-lane segments were considered. The cross-sectional and case-control methods determined reductions in lane-departure crashes: There was a 4% and 9% crash reduction in tangent segments and a 6% and 13% reduction in curved segments. The cross-sectional and case-control methods show reductions of 4% and 11% in tangent segments and a 5% and 12% reduction in curved segments, respectively.

Guin et al. (2018) evaluated the effectiveness of centerline rumble strips in reducing lane-departure crashes on two-lane highways in Georgia. Using two years of data before and after the initial installation of the centerline rumble strips for each site and 126 miles of treated roadway, an EB before and after method was used. The overall CMF value for all crashes was 0.58, indicating a 48% reduction in lane-departure crashes after centerline rumble strips installation. The study also considered the effects of injury or fatal crashes to estimate the impact of severe crashes, although these outcomes proved insignificant due to the small sample size. Noyce & Elango (2004) studied the effectiveness of the centerline rumble strips in Massachusetts. The results found no significant change in the frequency of lane-departure crashes related to the installation of the centerline rumble strips.

2.2 Effectiveness of Shoulder Rumble Strips

Patel et al. (2007) evaluated the effectiveness of shoulder rumble strips on single-vehicle run-off-road crashes in Minnesota. The analysis considered 183 miles of treated rural two-lane roadways. An EB before-and-after method was performed using three to nine years before treatment and three to seven years after treatment crash data. The study period spanned 13 years and the before-and-after periods depended on when the installation was completed for each segment. The results of the analysis showed a 13% reduction in single-vehicle run-off-road crashes and an 18% reduction in single-vehicle run-off-road injury crashes after installing shoulder rumble strips.

Sayed et al. (2010) considered both rural, two-lane, undivided arterials and divided, four-lane freeways to analyze the effectiveness of centerline and shoulder rumble strips on crashes in British Columbia, Canada. A before-and-after study was performed, and the results indicated that shoulder rumble strips reduced run-off-road crashes by 18.4% on freeways and 26.1% on arterials where shoulder rumble strips were installed. The average outcome of severe crashes was reduced by 18%. Cheng et al. (2001) evaluated the effectiveness of shoulder rumble strips on run-off-road crashes on highways in Utah. A total of 186 treated roadways were considered, and the crash rate comparison method was used for analysis. The study found that total crashes were reduced by 33.4% and run-off-road crashes were reduced by 26.9% after installing shoulder rumble strips.

Khan et al. (2015) analyzed the run-off-road crash reduction benefits of shoulder rumble strips on rural two-lane roads. This study used an EB before-and-after analysis method. In total, 178 miles of treated roads in Idaho were considered. Data from three- to-six years before and two- to five- years after treatment crash were collected. This study analyzed the impact of volume and segment geometry on the effectiveness of treated segments. The results of the study included a 14% reduction in run-off-road crashes on treated roadways. The effects of geometric features with shoulder rumble strips were also considered. Roadways with moderate curvature were the most effective on roads that also had shoulder rumble strips installed. Shoulder widths of three feet or more were also shown to be more effective when shoulder rumble strips were installed compared to smaller treated-shoulder widths. The annual average daily traffic (AADT) results were not statistically significant in this study.

Park et al. (2014) investigated the effectiveness of crash-reducing countermeasures on rural multi-lane roads in Florida. Countermeasures included shoulder rumble strips, widening shoulder widths, and a combination of the two. The effects of several shoulder widths were considered, and the effects of crash severity, crash frequency, and crash type were analyzed. A total of 60 road segments with shoulder rumble strips and 122 road segments with shoulder rumble strips and shoulder widening were considered. Using an EB before-and-after method, CMFs were developed to compare countermeasures. All the countermeasures showed a decrease in crash frequency, with the combined countermeasure being the most effective. When considering all single-vehicle, run-off road crashes, the combined countermeasure proved to be the most effective for safety. However, when considering injury crashes, widening of the shoulders proved to affect crashes the most. Regarding shoulder width, when considering before-and-after shoulder widening installation combined with shoulder rumble strips, when the original shoulders were between four- and six-feet wide, the countermeasures had the greatest impact on safety.

Marvin & Clark (2003) evaluated the effectiveness of shoulder rumble strips for single-vehicle lane-departure crashes on Interstates and highways in Montana. The analysis considered three years of crash data before and after shoulder rumble strips installation, and a total of 606 treated miles of roadways. The results of the study include a 14.0% decrease in the crash rate and a 23.5% reduction in the severity rate after the installation of shoulder rumble strips. Other factors were considered, including time of day, visibility, and driver age. Most factors proved to be insignificant in the study, especially for roads other than Interstates. The sample size and reliable data proved to be limitations of this analysis.

Using Kansa data, Dissanayake & Galgamuwa (2017) considered shoulder rumble strips for two- and four-lane road segments. The cross-sectional and case-control method reductions in lane-departure crashes on two-lane segments are: There is a 6% and 15% reduction in tangent segments. There was a 5% reduction using the cross-sectional method for curved segments and a 25% increase using the case-control method for curved segments. The cross-sectional and case-control method reductions in fatal and injury lane-departure crashes on two-lane road segments are: There is a 5% and 10% reduction in the tangent segments, and a 6% and 19% reduction in curved segments. The cross-sectional and case-control method reductions in lane-departure crashes on four-lane segments with paved shoulders more than two feet wide are: there is a 9% and 20% reduction in the tangent segments, and a 16% and 26% reduction in curved segments. The cross-sectional and case-control method reductions in fatal and injury lane-departure crashes on four-lane road segments with paved shoulders more than two feet wide are: There is a 50% and 68% reduction in the tangent segments, and a 69% and 70% reduction in curved segments.

Griffith (1999) evaluated the reduction in single-vehicle, run-off road crashes in Illinois and California after the installation of the shoulder rumble strips. Rural and urban roadways were considered together, and rural roads were considered separately. The results of the before-and-after study showed an 18.3% reduction in all the crashes analyzed. The results also indicate a 13% reduction in injury-related crashes. When considering only the rural segments, there was a 21% reduction in crashes. Wu et al. (2014) evaluated the effectiveness of shoulder rumble strips on single-vehicle, run-off-road crashes. Using two years of before- and after-treatment crash data, a Panel Fixed Effect Analysis approach was considered, and 310 Pennsylvania-treated roadway segments were used. Single-vehicle, run-off-road crashes were reduced by 7% after shoulder rumble strips were installed. The analysis found no impact on crash severity.

Smith & Ivan (2005) studied the effectiveness of shoulder rumble strips installed in Connecticut. The analysis determined whether there was a reduction in single-vehicle, fixed-object crashes and whether any individual roadway factor impacted run-off-road crashes on segments with the installation of shoulder rumble strips. The study used a General Log-linear modeling approach to determine after-effects. Three years before and after treatment, crash data were used. The results indicated a 33% reduction in single-vehicle, fixed-object crashes. The analysis also considered the effects of individual factors. Run-off-road crashes were found to decrease by 48.5% around interchange areas, and run-off-road crashes were found to decrease by 12.8% on roads with speed limits less than 65 mph.

Gårder & Davies (2006) studied the effectiveness of shoulder rumble strips in mitigating runoff-road crashes on Maine rural, interstate highways. This study considered a before-and-after approach that resulted in a 27% reduction in all run-off-road crashes. The study also considered pavement conditions with respect to weather and found that, with dry pavement surfaces, there was a 43% reduction in run-off-road crashes. The study also found that there was a 58% reduction in sleep-related crashes after the installation of the shoulder rumble strips.

2.3 Effectiveness of combined Centerline and Shoulder Rumble Strips

As discussed, Sayed et al. (2010) considered both rural two-lane undivided arterials and divided four-lane freeways to analyze the effectiveness of centerline rumble strips and shoulder rumble strips on crashes in British Columbia, Canada. When the combination of centerline rumble strips and shoulder rumble strips was analyzed on two-lane undivided arterials, the results of the left run-off road, right run-off road, and head-on crashes indicated a 21.4% reduction in combined crashes. The average outcome of severe crashes decreased by 18%.

Kay et al. (2015) analyzed the safety performance of the rumble-strip installation program set by the Michigan DOT from 2008 to 2010. The majority of roadways only had centerline rumble strips installed; however, shoulder rumble strips were also installed on segments that had over six feet of paved existing shoulders. In total, 384 segments received both treatments, and the results of the combined effect are discussed as follows. Overall, a 32.8% reduction in lane-departure crashes was observed. Wet pavement crashes were reduced by 55.5%, and wintery pavement crashes were reduced by 4.6%. Driving under the influence of crashes decreased by 39.3% and passing-related crashes decreased by 36.5%. Regarding crash-severity reductions, there were decreased by 51.4%, 37.4%, 38.5%, and 35.2% for fatal, A-injury, B-injury, and C-injury crashes, respectively.

Dissanayake & Galgamuwa (2017) studied a combination of centerline rumble strips and shoulder rumble strips for two-lane road segments. The cross-sectional and case-control methods resulted in reductions in lane-departure crashes: There was a 14% and 32% reduction in tangent segments and an 11% and 25% reduction in curved segments. The cross-sectional and case-control methods resulted in reductions in fatal and injury lane-departure crashes: There was a 6% and 27% reduction in tangent segments, and a 13% and 49% reduction in curved segments.

Lyon et al. (2015) and Persaud et al. (2016) evaluated the effectiveness of centerline rumble strips and shoulder rumble strips installation on roadway crashes in Kentucky, Missouri, and Pennsylvania. Only two-lane, undivided rural roads were considered in this study. An EB before and after method was developed. Different crash types and injury- severity crash outcomes were considered in this analysis. Other factors, including the posted speed limit, lane width, and shoulder width, were also considered. All locations showed crash reductions. The CMF values for each crash type evaluated were 0.632, 0.742, and 0.767 for head-on, runoff-road, and sideswipe-opposite-direction crashes, respectively. The overall reduction in lane departure-crashes was 0.733. For all types of crashes, the CMF value was 0.80, and all fatal and injury crashes resulted in a value of 0.771. All CMF values were less than one indicating crash reduction after rumble-strip installation.

2.4 Summary and Conclusions

From the literature reviewed, it is apparent that many states are implementing programs to install various countermeasures to reduce lane-departure crashes. Rumble strips have become a popular countermeasure for reducing these crashes, and many studies have shown a reduction in crashes using before-and-after analyses.

The effectiveness of centerline rumble strips varies, and the reduction in lane-departure crashes ranges from 4% to 48% (Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019; Guin et al., 2018). Various crash types were evaluated, with reductions of 25% in frontal and opposing directions and 29.3% in head-on collisions (Persaud et al., 2004; Sayed et al., 2010). Kay et al. (2015) found that wet-pavement crashes decreased by 53.6%, wintery pavement crashes decreased by 28.9%, operating under the influence crashes decreased by 28.9% and crashes involving passing drivers reduced by 42.8% after the installation of centerline rumble strips. Severe crashes were decreased by 4–44.2% (Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019; Kay et al., 2015).

The effectiveness of shoulder rumble strips also varies; the reduction in total crashes ranges from 6% to 33.4% (Cheng et al., 2001; Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019). The reduction in single-vehicle, run-off-road crashes ranged from 7% to 26.1% (Sayed et al., 2010; Wu et al., 2014). Injury-related, lane-departure crashes had reductions ranging from 13% to 18% (Griffith, 1999; Patel et al., 2007; Sayed et al., 2010). However, Dissanayake & Galgamuwa (2017) found reductions in injury crashes on four-lane curved roads of as much as 70%. The findings also include a 33% reduction in single-vehicle, fixed-object crashes, a 48.5% reduction in single-vehicle, run-off-road crashes at interchanges, and a reduction of 12.8% on roads with posted speeds of less than 65 mph (Smith & Ivan, 2005). Dry pavements were found to decrease run-off-road crashes by 43%, and sleep-related crashes were found to reduce crashes by 58% (Gårder & Davies, 2006). The effectiveness of the combination of both the centerline rumble strips and shoulder rumble strips also varied across studies. The reduction in lane-departure crashes ranged from 11% to 32.8% (Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019; Kay et al., 2015). Lyon et al. (2015) found a reduction of head-on, run-off-road, and sideswipe opposite-direction crashes to be 36.8%, 25.8% and 23.3%, respectively. Kay et al. (2015) found wet-pavement crashes reduced by 55.5%, wintery pavement crashes reduced by 4.6%, operating-under-the-influence crashes decreased by 39.3% and crashes occurring due to passing drivers reduced by 36.5%. Severe crashes were reduced by 6–51.4% (Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019; Kay et al., 2015). Overall, the studies that evaluated centerline rumble strips or shoulder rumble strips and the combination of the two showed that the combination was a more effective countermeasure and had higher reduction values and lower CMF values (Dissanayake & Galgamuwa, 2017; Galgamuwa & Dissanayake, 2019; Kay et al., 2015).

Although many studies have found that centerline rumble strips and shoulder rumble strips reduce crash frequency and severity, many studies have discussed that a limitation of their research was the sample size. For example, Guin et al. (2018) and Khan et al. (2015) discussed that finding a reduction in injury crashes was not possible with their current sample, as it was too small. Noyce & Elango (2004) found insignificant effects from installing of a centerline rumble strips. Dissanayake & Galgamuwa (2017) also discussed sample size as an issue when considering the effectiveness of rumble strips and combined variables.

Finally, a summary of all studies discussed in this chapter (and the main findings) is shown in Table 1.

Table 1. Summary of literature review.

Author	Location	Crash Type	Facility	Rumble-Strip Type	Modeling Approach	Key Results
Persaud et al., (2004)	California, Colorado, Delaware, Maryland, Minnesota, Oregon, Washington	Frontal and opposing direction crashes, Lane-departure crashes	Rural two-lane undivided roads	CLRS	EB before-and-after study	12% reduction in crash frequency
Sayed et al., (2010)	BC, Canada	Head-on, run-off-road	Rural two-lane undivided arterial, divided four-lane freeways	CLRS, shoulder rumble strips, and combination	EB before-and-after study	29.3% reduction in head-on or off-road-left crashes on CLRS segments. 18.4% reduction in run-off-road crashes on shoulder rumble strips segments. 21.4% reduction in all crashes and18% reduction in severe crashes on roads with both CLRS and shoulder rumble strips.
Kay et al., (2015)	Michigan	Lane departure	Rural, non-freeway high-speed roads	CLRS, shoulder rumble strips and combination	EB before-and-after study	27% reduction in all crashes, wet pavement crashes reduced by 53.6%, wintery pavements reduced by 1.4%, OUI crashes reduced by 28.9%, passing related crashes reduced by 43.8% on CLRS segments. 23.8% reduction in all crashes, wet pavement crashes reduced by 55.5%, winter pavement crashes reduced by 4.6%, OUI crashes reduced by 39.3% and passing crashes reduced by 36.5% on roads with both CLRS and shoulder rumble strips.
Dissanayake and Galgamuwa (2017); Galgamua and Dissanayake (2019)	Kansas	Lane departure	Rural two-lane undivided and four-lane divided roads	CLRS, shoulder rumble strips and combination	Cross-sectional and case-control method	4-11% reduction in crashes on tangent CLRS sections, 5-12% reduction on curved CLRS sections, 6-15% reduction on tangent shoulder rumble strips segments, 14-32% reduction on tangent CLRS and shoulder rumble strips segments,11-25% on curved CLRS and shoulder rumble strips segments.

Table 1 Continued.

Author	Location	Crash Type	Facility	Rumble-Strip Type	Modeling Approach	Key Results
Guin et al., (2019)	Georgia	Lane departure	Two-lane highways	CLRS	EB before-and-after study	48% reduction to overall collisions. No significant change to injury-related crashes.
Noyce and Elango 2004	Massachusetts	Lane departure	Two-lane undivided roads	CLRS	Before-and-after study	No significant change.
Patel et al., (2007)	Minnesota	Single-vehicle run-off-road crashes	Rural two-lane roads	shoulder rumble strips	EB before-and-after method	13% reduction in total crashes, 18% reduction in injury crashes.
Cheng et al., (2001)	Utah	Run-off-road	Highways	shoulder rumble strips	Accident rate comparison method	33.4% reduction in total crashes, 26.9% reduction in run-off-road crashes.
Khan et al., (2015)	Idaho	Run-off-road	Rural two-lane roads	shoulder rumble strips	EB before-and-after method	14% reduction in crashes.
Park et al., (2014)	Florida	Single-vehicle run-off-road crashes	Rural multi-lane roads	shoulder rumble strips	EB before-and-after method	When original shoulders were paved and between four and six feet, adding shoulder rumble strips proved most significant.
Marvin and Clark (2003)	Montana	Single-vehicle lane-departure crashes	Interstates	shoulder rumble strips	Before-and-after study.	14% reduction in crash rate, 23.5% reduction in severity rate.
Griffith (1999)	Illinois, California	Single-vehicle run-off-road crashes.	Rural and urban freeways.	shoulder rumble strips	Before-and-after study.	18.3% reduction in all crashes, 13% reduction in injury crashes, 21% reduction in total rural crashes.
Wu et al., (2014)	Pennsylvania	Single-vehicle run-off-road crashes.	Highways, arterials, collectors, local roads	shoulder rumble strips	Panel fixed-effect analysis	7% reduction in crashes. No impact to crash severity.
Smith and Ivan (2005)	Connecticut	Single-vehicle fixed object, Run-off-road	Freeways	shoulder rumble strips	General log-linear approach	33% reduction in single-vehicle fixed-object crashes, run-off road crashes reduced by48.5% around interchanges, 12.8% reduction in run-off-road crashes on roads with speed limits less than 65 mph.
Garder and Davies (2006)	Maine	Run-off-road	Rural Interstates	shoulder rumble strips	Before-and-after	27% reduction in crashes, dry pavement crashes reduced by 58%.
Lyon et al., (2015); Persaud et al., (2016)	Kentucky, Missouri, Pennsylvania	Head-on, run-off-road, sideswipe-opposite direction.	Two-lane undivided rural roads	Combination of shoulder rumble strips and CLRS	EB before-and-after analysis	Head-on crashes CMF value of 0.632, run-off-road CMF value of 0.742 and sideswipe-opposite direction crashes CMF value of 0.767.

CHAPTER 3

DATA DESCRIPTION AND PRELIMINARY ANALISYS

This chapter documents the description of collected data, as well as a preliminary analysis of the safety effectiveness of rumble strips. This chapter is divided into five sections. Section 3.1 provides an overview of the study area and the data sources used for analysis. Section 3.2 explores lane-departure crashes in Maine. Section 3.3 describes the rumble strips installed in Maine. Section 3.4 presents a naïve before-and-after analysis to evaluate the safety effectiveness of the rumble strips. Finally, Section 3.5 presents the summary and conclusions of the chapter.

3.1 Study Area and Data Collection

This study focuses on rural two-lane roadways in Maine. Data were obtained from two sources: the MaineDOT internal information and the MaineDOT Public Map Viewer[2]. Crash records from January 2010 to November 2022, the geometric characteristics of roadways, roadway sections with rumble strips, and roadway curve information were provided by a MaineDOT representative. The crash records for December 2022 were collected from the MaineDOT Public Map Viewer.

All the collected information is geolocated[3]. It also contains milepost and route code. This information allowed for merging different datasets. Crashes were matched to roadway segments by comparing the route code and mileposts. The Curve segments, rumble strips, and roadway geometry datasets combined using GIS. For this purpose, new segments were created whenever needed to match the data. This was done because the curve dataset has a different route reference system than roadway geometry and rumble strips.

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[2] https://www.maine.gov/mdot/mapviewer/
[3] An ESRI file geodatabase was provided by MaineDOT, and shapefile was downloaded from the public map viewer.

In addition to geometric characteristics, the collected roadway dataset also contains information about traffic volume, specifically AADT. However, further computations were needed to obtain the AADT for each year of analysis during the study period of 2010 to 2022. In Maine, only the Interstate highways have a new estimated AADT by traffic counts each year, while for the other facility types of roadways, only certain zones of the state have traffic counts, and the rest use expansion factors. MaineDOT divides the state into three zones, and each year, traffic counts are collected in one zone, while the AADT of the other two zones is estimated using expansion factors by county. To obtain the AADT of each roadway segment for all years of analysis, the expansion factors provided by MaineDOT were used when there were no traffic counts.

3.2 Lane-Departure Crashes in Maine

The total number of reported vehicle crashes in Maine (including all crash types) from January 2010 to December 2022 was 413,817. The most common crash type was rear-ended and sideswipe (32.9%), run off-road (26.4%), intersection movement (16.6%), and deer (14.5%). Regarding lane-departure crashes, the run off-road (26.4%), head-on and opposite sideswipe (2.6%), and rollover (0.6%) collisions constitute approximately 30% of the total crashes in Maine. This is illustrated in Figure 1.

While lane-departure crashes make up around 30% of the total crash count, their severity exceeds that of other crash types. As illustrated in Figure 2, the lane-departure crashes account for around 72.7% of the total vehicle crash-related fatalities between 2010 and 2022. This statistic highlights that, although lane-departure crashes may not be the most frequent type of collisions when compared to other categories, they are the leading cause of fatal collisions in Maine.

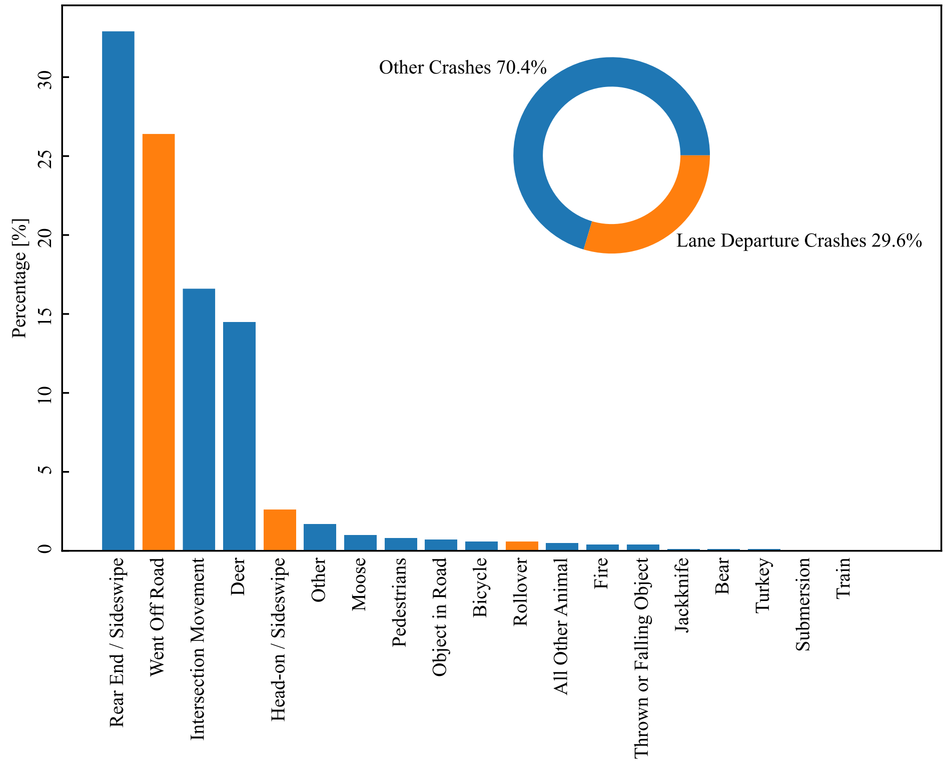

Figure 1. The proportion of total crashes by crash type in Maine.

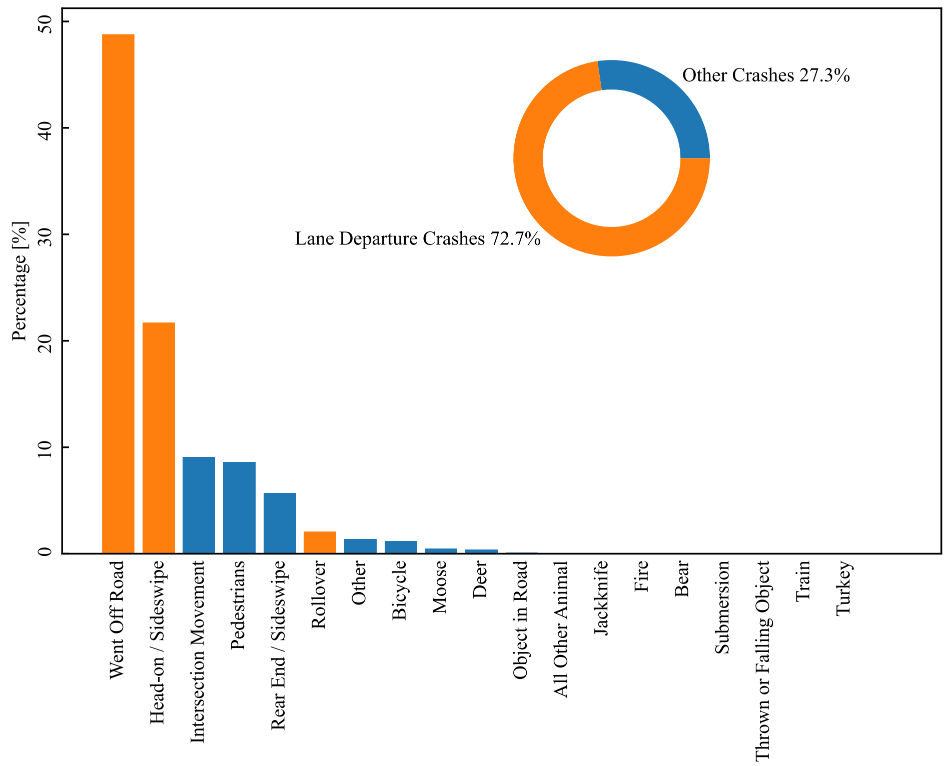

Figure 2. The proportion of fatalities according to the type of crash in Maine.

Examining the aggregated proportion of lane-departure crashes during the entire period of crash records, most of them are run off-road collisions. In fact, looking at the amount of each type of lane-departure crash by year, the recorded run-off road collisions are significantly higher than head-on and opposite sideswipe collisions, and rollovers. Each year, approximately 8,000 run off-road crashes are recorded, whereas the recorded head-on and opposite sideswipe, and rollovers are less than 1,000 crashes. This is illustrated in Figure 3.

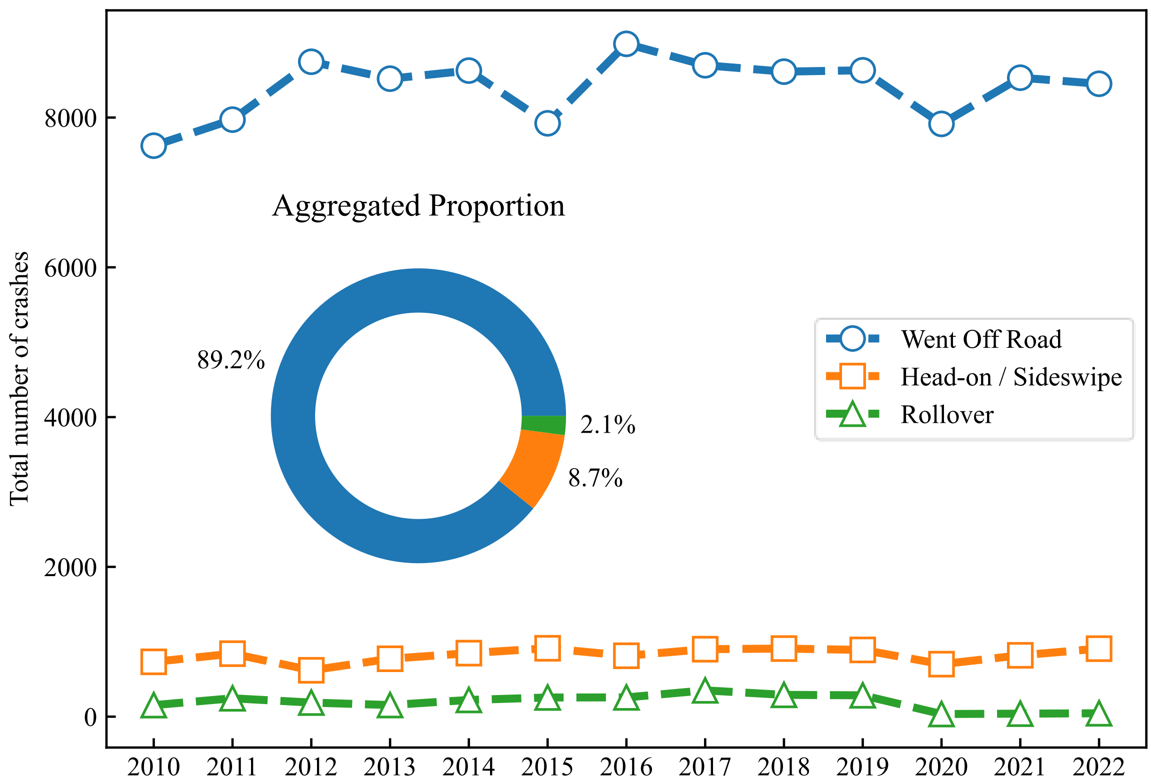

Figure 3. Lane-departure crashes in Maine.

3.3 Rumble Strips in Maine

As mentioned before, rumble strips can be installed both in the centerline separator of the lanes to deter vehicles from crossing into oncoming traffic and at the edge of the road to prevent vehicles from veering off the road. Moreover, in Maine, two variations of rumble strips - standard and sinusoidal - are deployed, positioned either at the centerline or along the edge of the roadway. Figure 4 shows a map indicating the locations of the rumble strips. Rumble strips were installed on different facility types, such as Interstates, major collectors, minor arterials, and other principal arterials. It is worth noting that the majority of the edge rumble strips are installed on Interstate highways including I-95. In fact, edge rumble strips were implemented along almost the entire length of the Interstate highway system in Maine.

The installed lengths of the edge rumble strips on the rural two-lanes roadways are presented in Table 2. As noted earlier, the majority of edge rumble strips were installed on Interstates, predominantly of the standard type. Although the year of installation was not recorded for Interstate rumble-strip installations, our anecdotal information suggests that these rumble strips (487 miles) were installed well before 2010. As a result, the Interstate rumble strips are not considered in our analysis. The length of installed edge rumble strips on rural two-lanes on major collectors and minor arterials is less than 1 mile, and on other principal arterials around 12 miles (all installed in 2019). Due to the limited extent of these installations, the evaluation of edge rumble-strip installations is not taken into consideration in the subsequent chapters.

Table 2. Length of edge rumble-strips installations on rural two-lane roads.

	Type of Rumble Strip	
Facility Type	**Standard**	**Sinusoidal**
Major Collector		
2020	0	0.7
Minor Arterial		
2020	0	0.2
Other Principal Arterial		
2017	0.7	0
2019	0	11.2

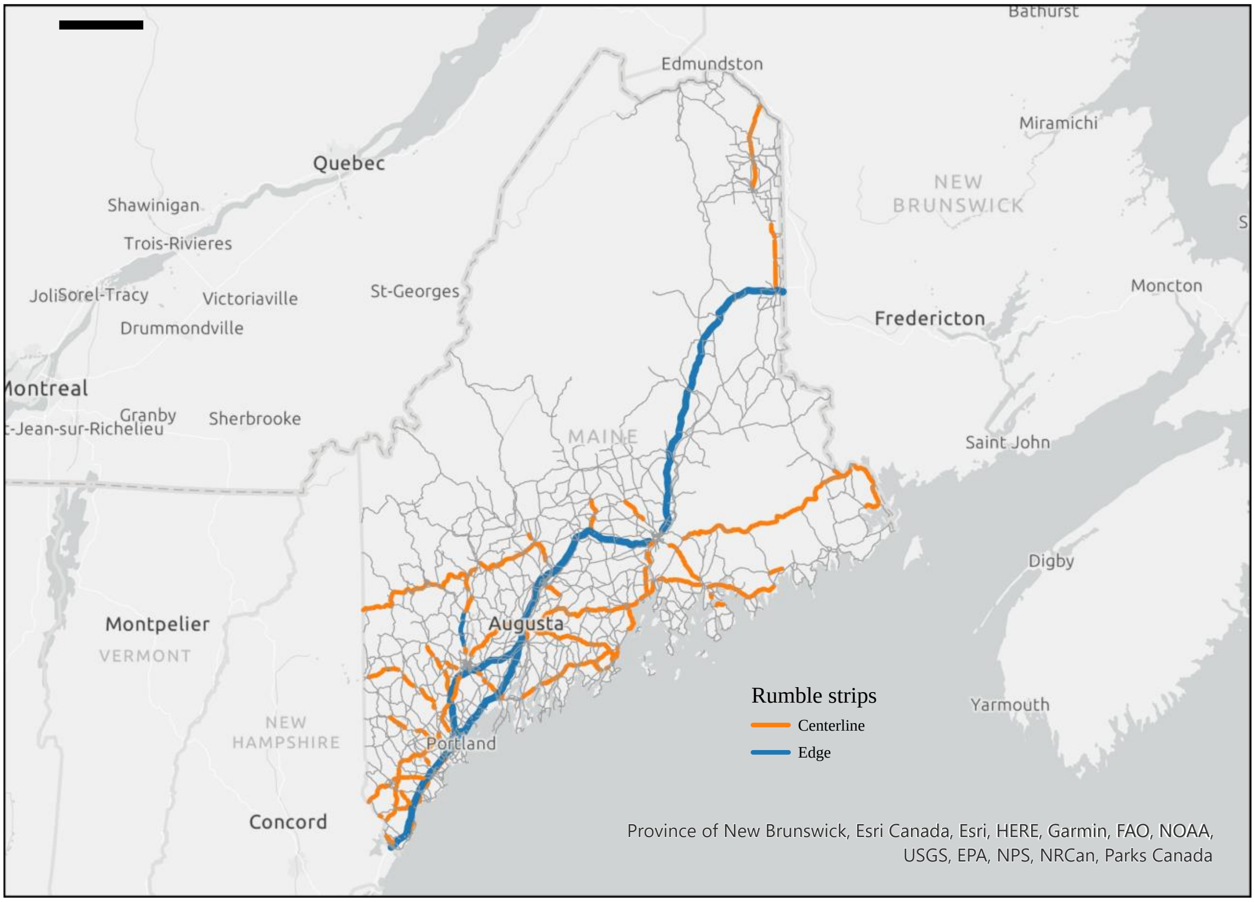

Figure 4. Location of rumble strips installed in Maine.

Centerline rumble strips have been installed on rural two-lanes major collectors, minor arterials, and other principal arterials. Table 3 presents an overview of the installed lengths categorized by facility type for bidirectional and undivided rural two-lane roadways. Notably, the facility type with the highest number of installations is the ‘other principal arterials’, followed by ‘minor arterials’ and ‘major collectors.

Table 3. Length of the centerline rumble-strip installations on rural two-lane roads

Facility Type	Type of Rumble Strip Standard	 Sinusoidal	 Both
Major Collector			
2016	1.3	2.9	4.2
2020	0.0	4.6	4.6
2021	0.0	7.3	7.3
Minor Arterial			
2011	1.3	0.0	1.3
2013	6.9	0.0	6.9
2014	0.0	0.6	0.6
2015	26.9	0.0	26.9
2016	10.4	6.3	16.7
2017	32.7	9.6	42.3
2018	0.0	29.4	29.4
2019	0.0	2.2	2.2
2020	0.0	16.0	16.0
2021	0.0	20.4	20.4
Other Principal Arterial			
2013	10.6	8.6	19.2
2015	25.8	10.0	35.8
2016	72.9	24.7	97.6
2017	28.0	21.5	49.5
2018	0.0	38.5	38.5
2019	0.0	8.6	8.6
2020	0.0	11.2	11.2
2021	0.0	72.1	72.1

3.4 Naïve Before-and-after Study

An initial assessment of the safety effectiveness of the rumble strips is conducted by comparing the total observed crashes in the three-year period prior to installation with the three years following installation. This approach aligns with a basic before-and-after study design known as ‘native before-and-after analysis.’ To ensure a consistent three-year interval both before and after installation, and considering the limitations posed by the COVID-19 stay-at-home restrictions by changes on traffic volumes and driver behavior (Marshall et al., 2023; Marshall et al., 2023; Shahlaee et al., 2022), only rumble strips installed between 2013 and 2016 are considered for analysis.

For centerline rumble strips installed on rural two-lane bidirectional and undivided roadways, our analysis focuses exclusively on head-on and opposite sideswipe collisions. A naive before-and-after analysis is performed for each individual year of installation and facility type, and the results are presented in Table 4. Overall, centerline rumble strips seem effective in reducing the total number of crashes and fatal and injury crashes, showing a crash reduction of at least 20% in most cases. However, there are still cases where there is no change or an increase in crash frequency. Major collector roads with sinusoidal centerline rumble strips installed in 2016 exhibited a 20% increase in total crashes. Minor arterials with sinusoidal rumble strips installed in 2016 showed an increase of 50% in total crashes and 200% in fatal and injury crashes. However, these results are due to limited installed miles of rumble strips (less than three miles); therefore, the sample size produced biased results (see the installed lengths of the rumble strips are listed in Table 3.)

Additionally, preforming the similar analysis considering only the facility and rumble-strip types (Table 5) and the rumble strips type and installation year (Table 6), a reduction in crash frequency is still present. However, in Table 5, sinusoidal rumble strips on the major collectors and minor arterials show an increase in the crash frequency. In addition, in Table 6, the sinusoidal rumble strips show an increase in the crash frequency; however, as noted regarding the results in Table 3, this is the case when the installed length of the rumble strips is small (less than 3 miles).

Table 4. Naïve before-and-after analysis of centerline rumble strips for rural two-lane roadways by facility and rumble-strip types, and installation year.

Type of Rumble Strip	Total Crashes: Before	Total Crashes: After	Total Crashes: Crash Frequency Change[1]	Fatal/ and Injury (KABC) Crashes: Before	Fatal/ and Injury (KABC) Crashes: After	Fatal/ and Injury (KABC) Crashes: Crash Frequency Change[1]
Major Collector						
Standard						
2016	2	1	-50%	1	1	0%
Sinusoidal						
2016	5	6	20%	3	3	0%
Both						
2016	7	7	0%	4	4	0%
Minor Arterial						
Standard						
2013	3	1	-67%	2	0	-100%
2015	28	11	-61%	22	6	-73%
2016	5	2	-60%	4	1	-75%
Sinusoidal						
2016	2	3	50%	1	3	200%
Both						
2016	7	5	-29%	5	4	-20%
Other Principal Arterial						
Standard						
2013	7	5	-29%	7	5	-29%
2015	16	16	0%	16	16	0%
2016	47	27	-43%	47	27	-43%
Sinusoidal						
2013	14	10	-29%	14	10	-29%
2015	12	7	-42%	12	7	-42%
2016	16	14	-13%	16	14	-13%
Both						
2013	21	15	-29%	21	15	-29%
2015	28	23	-18%	28	23	-18%
2016	63	41	-35%	63	41	-35%
Arterials						
Standard						
2013	10	6	-40%	8	4	-50%
2015	44	27	-39%	29	17	-41%
2016	52	29	-44%	34	16	-53%
Sinusoidal						
2013	14	10	-29%	9	9	0%
2015	12	7	-42%	9	6	-33%
2016	18	17	-6%	8	1	-88%
Both						
2013	24	16	-33%	17	13	-24%
2015	56	34	-39%	38	23	-39%
2016	70	46	-34%	42	17	-60%

[1]A negative change in the crash frequency means a reduction in crashes. Hence a positive effectiveness of the rumble strips.

Table 5. Naïve before-and-after study of centerline rumble strips on rural two-lane roadways by facility and rumble strips.

Type of Rumble Strip	Total Crashes			Fatal and Injury (KABC) Crashes		
	Before	After	Crash Frequency Change[1]	Before	After	Crash Frequency Change[1]
Major Collector						
Standard	2	1	-50%	1	1	0%
Sinusoidal	5	6	20%	3	3	0%
Both	7	7	0%	4	4	0%
Minor Arterial						
Standard	36	14	-61%	28	7	-75%
Sinusoidal	2	3	50%	1	3	200%
Both	38	17	-55%	29	10	-66%
Other Principal Arterial						
Standard	70	48	-31%	43	30	-30%
Sinusoidal	42	31	-26%	25	23	-8%
Both	112	79	-29%	68	53	-22%
Arterials						
Standard	106	62	-42%	71	37	-48%
Sinusoidal	44	34	-23%	26	26	0%
Both	150	96	-36%	97	63	-35%

[1]A negative change in the crash frequency means a reduction in crashes. Hence a positive effectiveness of the rumble strips.

Table 6. Naive before-and-after analysis of centerline rumble strips on Maine rural two-lane roadways by rumble-strip type and installation year.

Type of Rumble Strip	Total Crashes			Fatal and Injury (KABC) Crashes		
	Before	After	Crash Frequency Change[1]	Before	After	Crash Frequency Change[1]
Standard						
2013	10	6	-40%	8	4	-50%
2015	44	27	-39%	29	17	-41%
2016	54	30	-44%	35	17	-51%
Sinusoidal						
2013	14	10	-29%	9	9	0%
2015	12	7	-42%	9	6	-33%
2016	23	23	0%	11	14	27%
Both						
2013	24	16	-33%	17	13	-24%
2015	56	34	-39%	38	23	-39%
2016	77	53	-31%	46	31	-33%

[1]A negative change in the crash frequency means a reduction in crashes. Hence a positive effectiveness of the rumble strips.

It is important to note that this preliminary study is merely an exploratory approach and serves as an initial indicator of expected outcomes. Nevertheless, these results do not provide definitive conclusions regarding the safety effectiveness of rumble strips to prevent lane-departure crashes in Maine. To draw more robust and conclusive insights, a meticulously structured and comprehensive study is required. Therefore, in this study, more robust before-and-after studies conducted to evaluate the safety effectiveness of rumble strips. The results of these studies are documented in the subsequent chapters.

3.5 Summary and Conclusions

This chapter described the collected crash data spanning from January 2010 to December 2022 as well as the geometric characteristics and traffic-related information. To facilitate the analysis, these data were meticulously processed through Geographic Information Systems (GIS) for integration and mapping. Additionally, the AADT values for roadways were obtained using traffic counts and expansion factors by county. Edge rumble strips are predominantly installed in Interstates, but there are no records for the year of installation for these rumble strips, precluding the possibility of conducting a before-and-after study to measure their effectiveness. Furthermore, the installed lengths of edge rumble strips in other facility types are insufficient for meaningful analysis. In contrast, centerline rumble strips exhibit more substantial installation lengths. Therefore, the future chapters are focused solely on centerline rumble strips. As an initial step, a preliminary analysis was conducted, suggesting that rumble strips appear to be effective in reducing total and fatal and injury-related lane-departure crashes. However, it is essential to acknowledge that the naïve before-and-after study does not account for the phenomenon of regression to the mean, necessitating more robust methodologies and further in-depth investigation.

CHAPTER 4

BEFORE-AND-AFTER STUDY USING COMPARISON GROUP

This chapter documents the findings of the comparison group before-and-after study. This chapter is divided into four sections. Section 4.1 provides a comprehensive overview of the methodology in two parts. Section 4.1.1 documents the procedure used to select an appropriate comparison group. Section 4.1.2 outlines the steps taken to compute the CMFs. Section 4.2 describes the characteristics of the selected treatment and comparison group. Section 4.3 presents the computed CMFs. Finally, Section 4.4 provides a summary and recommendations.

4.1 Methodology

The before-and-after study with comparison group analysis involves comparing the observed crash frequency of treatment sites with those at untreated sites that share similar characteristics, referred to as the comparison group (Gross et al., 2010). The simple comparison group method is an alternative to more complex methods, such as EB, when a suitable comparison group is available, and the regression-to-the-mean bias is not an issue. Although the latter assumption may not entirely hold in our context, we resort to this method because of data limitations in Maine. That said, Gross et al., (2010) noted that the comparison group approach may account for the regression-to-the-mean bias when the comparison group is selected based on the trends in the observed crash frequency during the before period. We took this into consideration in this study to minimize the adverse effects of the regression-to-the-mean bias.

4.1.1 Comparison Group Selection

The comparison group accounts for changes in causal factors over time (e.g., traffic volume) unrelated to the treatment (Gross et al., 2010; Hauer, 1997). Therefore, the comparison group is a set of sites that have not received treatment but have similar geometric and operational characteristics to the treated sites. In addition, the comparison group should be selected considering the observed crash frequency during the before period to ensure that the regression-to-the-mean is accounted for. It is important to note that the before-and-after periods for the treatment and comparison group should usually be the same (Gross et al., 2010). Choosing an ideal comparison group is complex. Therefore, Hauer (1997) proposed a method referred to as "test of comparability" or "comparability test" to aid in selecting a suitable comparison group among various alternatives. The comparability test revolves around the fundamental concept that the comparison group is appropriate for analysis if the annual trend of the observed crash frequency is similar in both the treatment and comparison groups during the before period. To conduct this test, a series of sample tests (STs) are computed for each successive pair of years in the before period using Eq. (1).

$$\text{Sample ST}_{\text{i}} = \frac{\dfrac{\text{N}_{\text{T,i}} \cdot \text{N}_{\text{C,i+1}}}{\text{N}_{\text{T,i+1}} \cdot \text{N}_{\text{C,i}}}}{1 + \dfrac{1}{\text{N}_{\text{T,i+1}}} + \dfrac{1}{\text{N}_{\text{C,i}}}} \tag{1}$$

where,

i-th index: year in the before period. If there are n years, then i varies from 1 to $n-1$.

$N_{T,i}$: total observed crashes in the treatment group in the i-th year of the before period.

$N_{C,i}$: total observed crashes in the comparison group in the i-th year of the before period.

From the computed sample tests, the mean, variance, and confidence interval of the sample tests are estimated. If the mean of the computed STs is close to 1 and the confidence interval of the sample STs contains the value 1, the selected sites are suitable to be considered as a comparison group.

4.1.2 Computing the CMF

The comparison group method employs the crash frequency observed in the periods before and after treatment in both the treatment and comparison groups to estimate CMFs. Table 7 summarizes the data required to compute the CMF using this method. The mentioned data refer to the aggregated crashes over the entire duration of the before-or-after period.

Table 7. Data needed for the comparison-group before-and-after study.

Period	Treatment Group	Comparison Group
Before	$N_{observed,T,B}$: observed crashes during the before period at the treatment sites.	$N_{observed,C,B}$: observed crashes during the before period at the comparison sites.
After	$N_{observed,T,A}$: observed crashes during the after period at the treatment sites.	$N_{observed,C,A}$: observed crashes during the before period at the comparison sites.

The expected number of crashes at the treatment sites during the after period is computed using Eq. (2), under the assumption that the treatment has not been implemented.

$$N_{expected,T,A} = N_{observed,T,B} \cdot \frac{N_{observed,C,A}}{N_{observed,C,B}} \tag{2}$$

The variance $N_{expected,T,A}$ is derived using Eq. (3).

$$Var(N_{expected,T,A}) = {N_{expected,T,A}}^2 \left(\frac{1}{N_{observed,T,B}} + \frac{1}{N_{observed,C,B}} + \frac{1}{N_{observed,C,A}}\right) \tag{3}$$

Then, the CMF is estimated using Eq. (4).

$$CMF = \frac{\frac{N_{observed,T,A}}{N_{expected,T,A}}}{1 + \frac{Var(N_{expected,T,A})}{{N_{expected,T,A}}^2}} \tag{4}$$

The variance of the CMF is computed using Eq. (5).

$$Var(CMF) = \frac{CMF^2 \left(\frac{1}{N_{observed,T,A}} + \frac{Var(N_{expected,T,A})}{{N_{expected,T,A}}^2}\right)}{\left(1 + \frac{Var(N_{expected,T,A})}{{N_{expected,T,A}}^2}\right)^2} \tag{5}$$

Eqs. (4) and (5) operate under the assumption that an ideal comparison group is accessible and is employed for the analysis. However, as mentioned previously, selecting an ideal comparison group is often challenging. Consequently, we often rely on a comparability test to select a comparison group.

Consequently, the estimated CMF and its associated variance approximate the true values (Gross et al., 2010).

Finally, the statistical significance of the estimated CMF is assessed by comparing the value z computed using Eq. (6).

$$z = \left| \frac{1 - \mathrm{CMF}}{\sqrt{\mathrm{Var(CMF)}}} \right| \tag{6}$$

If z is less than 1.7, there is insufficient evidence to consider the treatment effect as significant at the 90% confidence level. However, if z is greater than or equal to 1.7, the treatment effect is considered significant at the 90% confidence level. Moreover, if z is greater than or equal to 1.96, the treatment effect is considered significant at the 95% confidence level.

4.2 Treatment and Comparison Group Sites

The effectiveness of the centerline rumble strips is evaluated for two rural two-lane roadway facility types: minor arterial, and other principal arterial. It is also evaluated for all rural two-lane arterials together. The results for major collectors are excluded given the small sample size. Evaluating centerline rumble strips targeted head-on and opposite sideswipe crashes. Head-on and opposite sideswipe crashes occur when vehicles depart from one lane to the lane in the other direction. Centerline rumble strips may prevent these types of collisions. Head-on or opposite side-swipe collisions can be classified based on the severity of the crashes. Therefore, the CMFs are estimated for both total (including all severities) and fatal and injury collisions (KABC). The effectiveness of the centerline rumble strips is quantified using the CMFs. With the CMF, it is possible to compute the expected change in crash frequency. The safety evaluation is performed using a before-and-after study with the comparison group method described in Section 4.1.

Because head-on and opposite sideswipe are not common crashes, the lack of crashes is a challenge to compute CMFs. To address this issue, four approaches are used to compute the CMFs: 1) using a single installation year and three years in the before-and-after periods, 2) using a single installation year and five years in the before-and-after periods, 3) using multiple installation years and three years in the before-and-after periods, and 4) using multiple installation years and five years in the before-and-after periods. Subsequently, the significant CMFs with the best comparison group for each analysis were selected.

4.2.1 Treatment Sites

Selecting the treatment sites is based on several factors, including the geometric and roadway characteristics, year of rumble-strip installation, frequency and severity of crashes, and segment length. Considering the geometric and roadway characteristics, the selected sites included rural, two-lane, bidirectional, and undivided segments with centerline rumble strips. For simplicity, only segments with a length greater or equal to 0.01 miles are considered for analysis.

It is common to use a duration of three to five years for the before-and-after period (which corresponds to the four approaches mentioned before.) Collected crash records included collisions between 2010 and 2022. Therefore, to ensure a duration of three years for the before-and-after periods, only rumble strips installed between 2013 and 2019 are used for the analysis, and for five years, only installations between 2015 and 2017 are used. It is important to note that the crashes that occurred in the year of installation are not considered in the analysis; for example, if the rumble strips are installed in 2015, the before period is 2010-2014 and the after period is 2016-2020.

To further refine the analysis, the year with the most installed length of rumble strips and most crashes is selected for the analysis to ensure an adequate sample size. Table 8 shows the length of the centerline rumble-strip installations during 2013-2019 for each individual facility type and the arterials aggregated case (i.e., minor arterials and other principal arterials rural two-lane segments.) Additionally, when considering the two types of rumble strips together in the analysis, it is also considered to have a balance between the two types. For example, considering both rumble strips in other principal arterials the year with more installed length 2016. However, in 2016, the standard rumble strips are 75% of the total installed length in that year, whereas the sinusoidal type is 25%. But, in 2016, the proportions of the installed rumble strips are: 56% for standard and 44% for sinusoidal. Then, in this case, the year 2016 is preferred for the analysis since the installed length of the two rumble strips is more balanced than in 2017. Although, if the balanced scenario does not show conclusive results, then the unbalanced is also used. It is also noteworthy that, as shown in Table 8, the installed length of the major collector is not sufficient to estimate the CMFs for this facility type. Therefore, a CMF development is not considered for this facility type.

Table 8. Length (in miles) of treatment sites for two-lane rural segments based on facility type.

	Rumble-strip Type		
Rumble Strips Year of Installation	**Standard**	**Sinusoidal**	**Both**
Major Collector			
2016	1.3	2.9	4.2
Minor Arterial			
2013	6.9	0.0	6.9
2014	0.0	0.6	0.6
2015	26.9	0.0	26.9
2016	10.4	6.3	16.7
2017	32.7	9.6	42.3
2018	0.0	29.4	29.4
2019	0.0	2.2	2.2
Other Principal Arterial			
2013	10.6	8.6	19.2
2015	25.8	10.0	35.8
2016	72.9	24.7	97.6
2017	28.0	21.5	49.5
2018	0.0	38.5	38.5
2019	0.0	8.6	8.6
Arterials			
2013	17.5	8.6	26.1
2014	0.0	0.6	0.6
2015	52.7	10.0	62.7
2016	83.3	31.0	114.3
2017	60.7	31.2	91.9
2018	0.0	67.9	67.9
2019	0.0	10.8	10.8

4.2.2 Comparison Group Sites

The comparison group sites are selected by identifying segments with the same geometric characteristics as the treatment sites but without rumble-strip installation. The collected sites are then filtered based on the AADT to ensure that the AADT values of the comparison sites closely matched those of the treatment sites. Specifically, whenever possible, similar sites with an AADT within 5% of treatment sites are selected for analysis; whenever the 5% threshold does not produce an adequate sample, the threshold is changed until suitable samples are found. Finally, the comparability test described in Section 4.1.1 is used to select a suitable comparison group. Table 9 presents the results of comparability tests considering 5 years trend in the before period.

Table 9. Comparability test results[1,2].

Rumble Strips Type	Total Crashes Mean	SE	Lower 95% CL	Upper 95% CL	Slack	Fatal and Injury Crashes (KABC) Mean	SE	Lower 95% CL	Upper 95% CL	Slack
Minor Arterial										
Standard	**1.03**	**0.99**	**-0.91**	**2.98**	**25%**	0.60	0.38	-0.13	1.34	5%
Sinusoidal	0.80	0.07	0.65	0.94	25%	0.87	0.09	0.70	1.05	40%
Both	**1.05**	**0.98**	**-0.86**	**3.00**	**35%**	**1.05**	**1.11**	**-1.12**	**3.21**	**40%**
Other Principal Arterial										
Standard	**0.98**	**0.23**	**0.53**	**1.44**	**1%**	**0.96**	**0.34**	**0.30**	**1.62**	**1%**
Sinusoidal	0.77	0.45	-0.11	1.66	5%	0.74	0.57	-0.38	1.87	1%
Both	**0.93**	**0.22**	**0.50**	**1.35**	**1%**	**0.97**	**0.42**	**0.14**	**1.80**	**1%**
Arterials										
Standard	**1.02**	**0.61**	**0.18**	**2.22**	**5%**	**0.90**	**0.22**	**0.48**	**1.32**	**5%**
Sinusoidal	0.87	0.35	0.19	0.35	35%	**0.95**	**0.69**	**-0.40**	**2.31**	**1%**
Both	**1.00**	**0.51**	**0.00**	**2.00**	**5%**	**1.04**	**0.56**	**-0.06**	**2.13**	**1%**

[1]CMF estimates that are subjectively close to 1 (within 0.9 and 1.1) and showed evidence to be statistically significant at the 5% level are stated in bold.
[2]A duration of 5 years in the before period was considered for evaluating the crash trend in the comparability test.

It is important to note that to compute the comparability test, the observed crash frequency for each year of the before period is necessary, and if it is zero, then the sample test cannot be computed. However, the CMF can still be estimated if the crash frequency aggregated over the before period is not zero. In addition, as shown in Table 8, the installed length of the major collector is not sufficient to estimate the CMFs for this facility type.

4.3 CMF Development

The layout of the study data is assembled after the selection of the treatment and comparison groups, and presented in Tables Table **10** and Table **11**. Table 10 presents the selected years of installation and duration of the before and after periods of the study for each facility and rumble strips type, whereas Table 11 presents the descriptive statistics of the data used for the safety evaluation using the comparison group method.

When determining the study layout, certain guidelines are considered, including (1) a preference for analyzing with a single installation year as opposed to multiple, and (2) a preference for a shorter time span in the before-and-after periods. Considering these guidelines, the analysis was proceeded in following sequence: (1) using a single installation year with three years of data in the before-and-after periods, (2) using a single installation year with five years of data in the before-and-after periods, (3) using multiple installation years with three years of data in the before-and-after periods, and (4) using multiple installation years and five years of data in the before-and-after periods. Case (1) does not provide conclusive results (see Appendix A), but case (2) does in some analyses. Then, case (3) and (4) are used in the specific cases where case (2) do not provide conclusive results. However, cases of (3) and (4) do not provide conclusive results for these scenarios either. Then, as shown in Table 10, the reported results correspond to single installation year with 5 years of data in the before-and-after periods.

Table 10. Years of installation and duration of before and after periods used to compute CMFs.

	Total Crashes		Fatal and Injury Crashes (KABC)	
Rumble Strips Type	**Installation Year**	**Years in Before-and-After Periods**	**Installation Year**	**Years in Before-and-After Periods**
Minor Arterial				
Standard	2017	5	2017	5
Sinusoidal	2016	5	2016	5
Both	2016	5	2016	5
Other Principal Arterial				
Standard	2016	5	2016	5
Sinusoidal	2016	5	2016	5
Both	2016	5	2016	5
Arterials				
Standard	2017	5	2017	5
Sinusoidal	2016	5	2016	5
Both	2017	5	2017	5

Table 11. Statistics of the treatment and comparison groups.

Rumble Strips Type	Group Type	Sites[1]	Miles[1]	Total Crashes		KABC Crashes	
				Before	After	Before	After
Minor Arterial							
Standard	Treatment	35	22.8	26	17	17	10
	Comparison	442/319	254.7/166.7	253	296	106	126
Sinusoidal	Treatment	4	4.7	5	4	4	3
	Comparison	180/289	78.5/149.8	123	115	101	106
Both	Treatment	13	10.8	14	11	12	8
	Comparison	329/375	154.9/195.8	204	213	136	147
Other Principal Arterial							
Standard	Treatment	77	50.7	75	38	48	19
	Comparison	125/125	47.4	83	72	49	35
Sinusoidal	Treatment	23	16.9	24	22	11	13
	Comparison	159/62	56.0/22.6	101	86	21	16
Both	Treatment	100	67.6	99	60	59	32
	Comparison	156	59.2	104	90	62	42
Arterials							
Standard	Treatment	65	43.1	53	36	36	20
	Comparison	599/599	303.8	339	388	193	224
Sinusoidal	Treatment	27	21.7	29	26	15	16
	Comparison	639/170	312.5/64.5	396	398	66	59
Both	Treatment	81	60.8	59	51	39	29
	Comparison	686/378	375.5/201.8	383	447	116	128

[1]Total/KABC crashes

As expected, the installation of centerline rumble strips overall shows evidence of a reduction in the crash frequency of head-on and opposite sideswipe collisions. Table 12 presents the estimated CMFs and changes in the number of total and fatal and injury crashes by implementing centerline rumble strips on rural two-lane roadway segments in Maine. Only CMFs that are computed with a suitable comparison group and show evidence to be statistically significant at (minimum) 10% levels are considered reliable, and their use is recommended. Those CMFs are noted with a bold font in Table 12. As noted previously, the CMFs of the major collectors could not be estimated. For minor arterials, reliable CMFs are found for standard rumble strips considering total crashes, and for both types of rumble strips considering fatal and injury crashes. CMFs for other principal arterials are reliable for total crashes with standard and both rumble strips, and for fatal and injury crashes with standard rumble strips. The combined arterials show reliable CMFs for standard and both rumble strips (total, and fatal and injury crashes.) While computed CMFs for standard rumble strips considering fatal and injury crashes in minor arterials exhibit significance, their utilization is not recommended due to the absence of a suitable comparison group.

Table 12. Safety effectiveness of centerline rumble strips.

Rumble Strips Type	Total Crashes				Fatal and Injury Crashes (KABC)			
	CMF[1]	SE	Crash Frequency Change[2]	Z-Test	CMF[1]	SE	Crash Frequency Change[2]	Z-Test
Minor Arterial								
Standard	**0.53**	**0.17**	**-47%**	2.82	0.46	0.38	-54%	3.01*
Sinusoidal	0.70	0.39	-30%	0.75	0.56	0.34	-44%	1.27
Both	0.70	0.27	-30%	1.14	**0.56**	**0.24**	**-44%**	**1.81**
Other Principal Arterial								
Standard	**0.56**	**0.14**	**-44%**	**3.16**	**0.52**	**0.17**	**-48%**	**2.84**
Sinusoidal	1.01	0.31	1%	0.04	1.29	0.57	29%	0.51
Both	**0.68**	**0.14**	**-32%**	**2.23**	0.76	0.21	-24%	1.14
Arterials								
Standard	**0.58**	**0.13**	**-42%**	**3.26**	**0.46**	**0.13**	**-54%**	**4.10**
Sinusoidal	0.86	0.23	-14%	0.62	1.09	0.40	9%	0.22
Both	**0.72**	**0.14**	**-28%**	**1.91**	**0.65**	**0.17**	**-35%**	**2.06**

[1]CMF estimates that were computed using a suitable comparison group and showed evidence of being statistically significant at least at the 10% level are stated in bold.
[2]A negative change (-) shows a reduction. A positive change (+) shows an increase.
*Although it is significant, the comparison group was considered not suitable.

4.4 Summary and Recommendations

This chapter examined the effectiveness of rumble-strip installation in preventing lane-departure crashes for rural two-lane roadways in Maine using a comparison group before-and-after study. The methodology involved selecting an appropriate comparison group based on the observed crash frequency during the before period. Comparability tests for the comparison groups were performed to find suitable comparison groups and address the issue of the regression to the mean to some degree. The results show evidence in some combinations of facilities and rumble strips that the installation of centerline rumble strips is effective in reducing lane-departure crashes. However, not all the estimated CMFs show evidence of statistical significance; therefore, only some are recommended for use:

- Minor arterial roadways with standard rumble strips for total crashes (47% reduction).
- Minor arterial roadways with both types of rumble strips for fatal and injury (KABC) crashes (44% reduction).
- Other principal arterial roadways with standard rumble strips for total and fatal and injury (KABC) crashes (44% reduction).
- Other principal arterial roadways with both types of rumble strips for total crashes (32% reduction).
- Arterials roadways with standard rumble strips for total crashes (42% reduction).
- Arterials roadways with standard rumble strips for fatal and injury (KABC) crashes (28% reduction).
- Arterials roadways with both types of rumble strips for total and fatal and injury crashes (54% reduction).
- Arterials roadways with both types of rumble strips for fatal and injury (KABC) crashes (35% reduction).

CHAPTER 5

BEFORE-AND-AFTER STUDY USING EMPIRICAL BAYES COMPARISON GROUP

This chapter documents the findings of the EB comparison group before-and-after study. This chapter is divided into five sections. Section 5.1 provides a comprehensive overview of the methodology in three parts. Section 5.1.1 documents the procedure used to select treatment and comparison groups. Section 5.1.2 outlines the steps taken to compute the CMFs. Section 5.1.3 documents the procedure used to fit SPFs. Section 5.2 describes the characteristics of the selected treatment and the comparison groups. Section 5.3 presents the computed SPFs. Section 5.4 presents the computed CMFs. Finally, Section 5.5 provides the chapter summary and recommendations.

5.1 Methodology

The before-and-after study with EB comparison group is a mix between the EB method (see Appendix B regarding the EB method) and the comparison group. The EB comparison group method addresses the challenge of regression to the mean by using SPFs to predict crashes in the post-treatment period for both the treatment and comparison groups. As explained by Hauer (1997), before-and-after studies are based on a comparison between what would have been the safety of an entity in the period after the countermeasure if no countermeasures had been installed, and the safety after the countermeasure installation. Therefore, timeframe plays a vital role in before-and-after studies. Two crucial periods must be defined: the time prior to the installation of the countermeasure, called the before period, and the time after the installation of the countermeasure, called the after period. A before-and-after study compares the following: $N_{observed,A}$: observed crash frequency in the after period at sites with the countermeasure, and $N_{expected,A}$: expected crash frequency in the after period at the sites with the countermeasure if the countermeasure has not been installed. The subsequent subsections delineate the procedures entailed in before-and-after studies using the EB comparison group methodology.

5.1.1 Treatment and Comparison Group Selection

According to the recommendations of the HSM (AASHTO, 2010), at least 10–20 sites are required in the treatment and comparison groups. In addition, the comparison group should have a minimum of 650 aggregated crashes. Furthermore, it is a usual practice to use before and after periods of three to five years. However, the periods before and after installation do not need to have the same duration. It is important to note that this method may underestimate the safety effectiveness of treatments. This is because the method is unable to use sites with an observed crash frequency of zero (0) in the before or after period. For example, a site that experiences zero crashes in the defined period after treatment implementation is not considered in this method. Likewise, if a site has experienced zero crashes in the before period, it again is not considered for the safety evaluation.

5.1.2 Computing the CMF

The EB comparison group method employs the crash frequency observed and predicted in the periods before and after treatment in both the treatment and comparison groups to estimate CMFs. Table 7 summarizes the crash data required to compute the CMF using this method. The mentioned data refer to the aggregated crashes over the entire duration of the before- or after-period. It is noteworthy that the predicted average crash frequency is presented as an input. However, to compute the prediction, it is necessary to use SPFs. The section 5.3 describes the procedure for fitting the SPFs.

Table 13. Crash data needed for the EB comparison-group before-and-after study.

Group	Before Period	After Period
Treatment	$N^{i}_{observed,T,B}$: observed crashes during the before period at the i-th treatment site. $N^{i}_{predicted,T,B}$: predicted crashes during the before period at the i-th treatment site.	$N^{i}_{observed,T,A}$: observed crashes during the after period at the i-th treatment site. $N^{i}_{predicted,T,A}$: predicted crashes during the after period at the i-th treatment site.
Comparison	$N^{j}_{observed,T,B}$: observed crashes during the before period at the j-th comparison site. $N^{j}_{predicted,C,B}$: predicted crashes during the before period at the j-th comparison site.	$N^{j}_{observed,C,A}$: observed crashes during the after period at the j-th comparison site. $N^{j}_{predicted,C,A}$: predicted crashes during the after period at the j-th comparison site.

Additionally, the duration of the before and after periods for the treatment and comparison groups is required.

$Y_{T,B}$: duration of the before period for the treatment group.

$Y_{T,A}$: duration of the after period for the treatment group.

$Y_{C,B}$: duration of the before period for the comparison group.

$Y_{C,A}$: duration of the after period for the comparison group.

To account for changes in traffic volumes and durations of the before period, the adjustment factor for each combination of treatment and comparison sites, $Adj^{i,j}_{B}$, is computed using Eq. (7), and for the after period, the adjustment factor, $Adj^{i,j}_{A}$, is computed using Eq. (8).

$$Adj^{i,j}_{B} = \frac{N^{i}_{predicted\ T,B}}{N^{j}_{predicted,C,B}} \cdot \frac{Y_{T,B}}{Y_{C,B}} \tag{7}$$

$$Adj^{i,j}_{A} = \frac{N^{i}_{predicted\ T,A}}{N^{j}_{predicted,C,A}} \cdot \frac{Y_{T,A}}{Y_{C,A}} \tag{8}$$

Then, the expected average crash frequency for each comparison site in the before period is computed using Eq. (9), and for the after period with Eq. (10)

$$N^{j}_{expected\ C,B} = \sum_{j} \left(N^{i}_{predicted,C,B} \cdot Adj^{i,j}_{B} \right) \tag{9}$$

$$N^{j}_{\text{expected C,A}} = \sum_{j} \left(N^{i}_{\text{predicted,C,A}} \cdot Adj^{i,j}_{A} \right) \tag{10}$$

The total expected average crash frequency of the comparison group for each treatment site in the before period is computed using Eq. (11) and for the after period using Eq. (12).

$$N^{i}_{\text{total expected C,B}} = \sum_{j} \left(N^{j}_{\text{expected C,B}} \right) \tag{11}$$

$$N^{i}_{\text{total expected C,A}} = \sum_{j} \left(N^{j}_{\text{expected C,A}} \right) \tag{12}$$

For each treatment site the comparison ratio $r_{i,C}$ is computed using Eq.(13).

$$r_{i,C} = \frac{N^{i}_{\text{total expected C,A}}}{N^{i}_{\text{total expected C,B}}} \tag{13}$$

The expected crash frequency for each treatment site in the after period, if no treatment has been installed, $N^{i}_{\text{expected,T,A}}$, is computed as shown in Eq. (14).

$$N^{i}_{\text{expected,T,A}} = N^{i}_{\text{observed,T,B}} \cdot r_{i,C} \tag{14}$$

Subsequently, by comparing the observed and expected crashes, the CMF for each treatment site is computed using Eq. (15). The natural logarithm of the CMF is then calculated using Eq. (16).

$$CMF^{i} = \frac{N^{i}_{\text{expected,T,A}}}{N^{i}_{\text{observed,T,A}}} \tag{15}$$

$$R^{i} = \ln\left(CMF^{i}\right) \tag{16}$$

The weight of each treatment site is computed using Eq. (17).

$$w^{i} = \frac{1}{(R^{i}_{se})^{2}} \tag{17}$$

Where,

$$\left(R^{i}_{se}\right)^{2} = \frac{1}{N^{i}_{\text{observed,T,B}}} + \frac{1}{N^{i}_{\text{observed,T,A}}} + \frac{1}{N^{i}_{\text{total expected C,B}}} + \frac{1}{N^{i}_{\text{total expected C,A}}} \tag{18}$$

The weighted average natural logarithm of CMF is computed using Eq. (19), and exponentiated to obtain the actual CMF as Eq. (20). The standard error of CMF is given by Eq. (21).

$$R = \frac{\sum_i (w^i \cdot R^i)}{\sum_i w^i} \tag{19}$$

$$CMF = \exp(R) \tag{20}$$

$$SE = \frac{CMF}{\sqrt{\sum_i w^i}} \tag{21}$$

Once the CMF is known, it is possible to find the safety effectiveness (in percentage) of the treatment using Eq. (22).

$$\text{Safety effectiveness}(\%) = (1 - CMF) \cdot 100 \tag{22}$$

Finally, to assess the statistical significance of CMF, the test statistic z shown in Eq. (23) must be computed. If z is less than 1.7, there is insufficient evidence to consider the treatment effect as significant at the 90% confidence level. However, if z is greater than or equal to 1.7, the treatment effect is considered significant at the 90% confidence level. Moreover, if z is greater than or equal to 1.96, the treatment effect is considered significant at the 95% confidence level.

$$z = \left| \frac{1 - CMF}{SE} \right| \tag{23}$$

5.1.3 Developing Safety Performance Functions

Over-dispersed crash data is a common issue that can be addressed using a NB model. The NB model can be described as a combination of independent Bernoulli trials (Hilbe, 2011). The probability density function (PDF) of the NB distribution is given in Eq (24).

$$NB(p_i, \phi) \equiv P(y_i \mid p_i, \phi) = \frac{\Gamma(y_i + \phi)}{\Gamma(y_i + 1) \times \Gamma(\phi)} (p_i)^y (1 - p_i)^\phi \, ; \quad \phi, p > 0 \tag{24}$$

Where,

y_i: observed number crashes at the i-th site.

p_i: event probability at the i-th site.

Φ: inverse over-dispersion parameter $(1/\theta)$.

The parameter p_i can be defined by the following equation as a function of the long-term mean response value at the i-th site (μ_i) and the inverse over-dispersion parameter (ϕ).

$$p_i = \frac{\mu_i}{\mu_i + \phi} \tag{25}$$

Therefore, Eq. (25) n be rewritten as:

$$NB\ (\mu_i, \phi) \equiv P(y_i \mid \mu_i, \phi) = \frac{\Gamma(y_i + \phi)}{\Gamma(y_i + 1) \times \Gamma(\phi)} \left(\frac{\mu_i}{\mu_i + \phi}\right)^y \left(\frac{\phi}{\mu_i + \phi}\right)^\phi ; \phi, \mu > 0 \tag{26}$$

Where,

y_i: observed number crashes at the i-th site.

μ: long-term mean of crashes at the i-th site.

ϕ: inverse over-dispersion parameter.

Then, a regression analysis using the NB model is used to predict the number of crashes based on a set of variables, such as AADT, segment length, shoulder width, etc. A log-linear function was assumed to develop the SPFs, as shown in Eq (27):

$$\ln(\mu_i) = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} \tag{27}$$

Where:

μ_i: long-term mean of crashes at the i-th site.

β_{ij}: regression coefficient for the j-th variable.

x_{ij}: value of the j-th variable for the i-th site.

m: number of independent variables.

Once the NB model is fitted, parameter ϕ, known as the inverse dispersion parameter, is recorded, and used in the CMF development.

5.2 Treatment and Comparison Group

The effectiveness of the centerline rumble strips is evaluated for two rural two-lane roadway facility types: minor arterial, and other principal arterial. It is also evaluated for all two-lane arterials together. As noted earlier, the major collectors are not included in analysis due to small sample size. Evaluation of centerline rumble strips targeted head-on and opposite sideswipe crashes. Head-on and opposite sideswipe crashes occur when vehicles depart from one lane to the lane in the other direction. Centerline rumble strips may prevent these types of collisions. Head-on or side-swipe collisions can be classified based on the severity of the crashes. Therefore, the CMFs are estimated for both total (including all severities) and fatal and injury collisions (KABC). The effectiveness of the centerline rumble strips is quantified using the CMFs. Knowing the CMF, it is possible to compute the expected change in crash frequency. Note that the safety evaluation performed in chapter 4 used before-and-after studies with the simple comparison group method. This section uses the EB and comparison group to estimate the CMFs.

5.2.1 Selecting the Treatment and Comparison Groups

The selection of the treatment sites is based on several factors, including the geometric and roadway characteristics, year of rumble-strip installation, frequency and severity of crashes, and segment length. Considering the geometric and roadway characteristics, the selected sites included rural, two-lane, bidirectional, and undivided segments with centerline rumble strips. For simplicity, only segments with a length greater or equal to 0.1 miles are considered for analysis. The standard practice is to use a timeframe of three to five years for the before-and-after period. The collected data include crash records from 2010 to 2022. Consequently, the analysis only considers rumble strips installed between 2015 and 2019, for a duration of five years prior to the installation and three years after the installation. In this case, three years in the after period are selected to be able to consider installed rumble strips in 2018, since this is the year with most installations of sinusoidal rumble strips. The crashes that occurred in the year of installation are not included in the analysis; for example, if the rumble strips are installed in 2015, the before period is 2010-2014 and the after period is 2016-2019.

Trying to overcome the limitation of the method, which does not allow the consideration of sites with zero observed crashes, different years of rumble-strip installation are considered. This allowed us to increase the number of sites. For example, if a facility type has rumble-strip installations in 2016 and 2017, the sites with installed treatment in those years are considered together in the treatment group. Table 8 shows the length of the centerline rumble-strip installations for each individual facility type and the arterials aggregated case (i.e., minor arterials and other principal arterials rural two-lane segments.)

The comparison group sites are selected by identifying segments with the same geometric characteristics as the treatment sites but without rumble-strip installation. The collected sites are then filtered based on the AADT to ensure that the AADT values of the comparison sites closely matched those of the treatment sites. Whenever possible, sites similar to an AADT within 5% of the treatment sites are selected for analysis. The layout of the study is presented in Table 14, Table 15, and Table 16. Table 14 shows the years of treatment installation, the AADT slack used to select the comparison group, and the duration of the before and after periods. Table 15 and Table 16 present the number of sites in the treatment and comparison groups as well as the observed crash frequency and predicted crash frequency in the before and after periods. Table 15 focuses on total crashes and Table 16 focuses on fatal and injury crashes.

Table 14. Installation and duration of the before and after periods used to compute CMFs.

Rumble Strips Type	Total Crashes: Installation Year	Total Crashes: AADT Slack	Total Crashes: Number of Years Before Period	Total Crashes: Number of Years After Period	Fatal and Injury (KABC) Crashes: Installation Year	Fatal and Injury (KABC) Crashes: AADT Slack	Fatal and Injury (KABC) Crashes: Number of Years Before Period	Fatal and Injury (KABC) Crashes: Number of Years After Period
Minor Arterial								
Standard	2015, 2016, 2017	45%	5	3	2015, 2016, 2017	35%	5	3
Sinusoidal	2016, 2017, 2018	45%	5	3	2016, 2017, 2018	15%	5	3
Both	2016, 2017, 2018	45%	5	3	2016, 2017, 2018	30%	5	3
Other Principal Arterial								
Standard	2015, 2016, 2017	10%	5	3	2015, 2016, 2017	5%	5	3
Sinusoidal	2016, 2017, 2018	45%	5	3	2016, 2017, 2018	20%	5	3
Both	2016, 2017, 2018	10%	5	3	2016, 2017, 2018	5%	5	3
Arterials								
Standard	2015, 2016, 2017	30%	5	3	2015, 2016, 2017	30%	5	3
Sinusoidal	2016, 2017	45%	5	3	2016, 2017	30%	5	3
Both	2016, 2017	25%	5	3	2016, 2017	30%	5	3

Table 15. Summary of treatment and comparison sites used for the study of total crashes.

Rumble Strips Type	Treatment group: Sites	Treatment group: Observed Crashes Before	Treatment group: Observed Crashes After	Treatment group: Predicted Crashes Before	Treatment group: Predicted Crashes After	Comparison Group[1]: Sites	Comparison Group[1]: Observed Crashes Before	Comparison Group[1]: Observed Crashes After	Comparison Group[1]: Predicted Crashes Before	Comparison Group[1]: Predicted Crashes After
Minor Arterial										
Standard	10	16	12	8.0	5.0	121	207	150	106.4	66.2
Sinusoidal	5	9	6	3.7	2.3	119	187	147	95.2	59.2
Both	9	15	10	7.2	4.5	128	201	157	205.4	65.5
Other Principal Arterial										
Standard	25	49	29	28.4	17.8	61	95	72	32.4	20.2
Sinusoidal	6	8	10	6.9	4.3	66	91	80	34.3	21.3
Both	27	49	34	30.9	19.3	55	77	66	28.5	17.8
Arterials										
Standard	35	65	41	36.5	22.9	201	330	244	147.9	92.1
Sinusoidal	11	17	16	10.6	6.5	214	324	263	150.6	93.7
Both	31	56	39	35.1	21.9	141	225	172	103.2	64.4

[1]Note: as shown in the layout of the study, the before period is 5 years, and the after period 3 years.

Table 16. Summary of treatment and comparison sites used for study of fatal and injury crashes.

Rumble Strips Type	Treatment group					Comparison Group[1]				
		Observed Crashes		Predicted Crashes			Observed Crashes		Predicted Crashes	
	Sites	Before	After	Before	After	Sites	Before	After	Before	After
Minor Arterial										
Standard	4	6	5	2.3	1.4	58	89	68	34.9	21.7
Sinusoidal	2	5	3	1.6	1.0	36	51	43	19.9	12.4
Both	4	7	5	2.8	1.7	62	85	72	34.1	21.2
Other Principal Arterial										
Standard	11	21	13	7.4	4.6	17	20	18	5.9	3.7
Sinusoidal	5	5	6	3.1	1.9	11	14	11	4.7	2.9
Both	16	26	19	10.5	6.5	17	20	18	5.9	3.7
Arterials										
Standard	15	27	18	9.7	6.0	93	134	105	49.6	30.8
Sinusoidal	2	4	3	1.7	1.0	59	83	65	31.6	19.6
Both	14	24	16	9.4	5.9	66	92	73	34.8	21.6

[1]Note: as shown in the layout of the study, the before period is 5 years, and the after period 3 years.

5.3 Safety Performance Functions

SPFs are developed for all arterials (minor arterials and other principal arterials) and rural two-lane roadways (major collectors, minor arterials, and other principal arterials), considering total and fatal and injury crashes. The SPFs are developed using the NB2 regression model. In all SPFs, the length of the roadway section, in miles, and the number of years (i.e., ten years) are included as an offset. Different variables related to the geometric characteristics and traffic of roadways are tested. These variables include but not limited to,

- Average annual daily traffic (AADT)
- Speed limit
- Left shoulder width (in feet)
- Right shoulder width (in feet)
- Average shoulder width (in feet)
- Lane width (in feet)

- Total width (in feet)
- Curve presence (1: yes, 0:no)
- Left turn lane count.

The shoulder widths (left and right) are correlated. Therefore, each of them is included in a different model. The average shoulder width is calculated and tested as a variable to account for both variables. The SPF models are presented in Table 17. In that table, the regression coefficients, standard errors, and p-values are provided. The table also includes an estimation of the inverse dispersion parameter for the NB model. All SPF models predict the number of head-on and opposite sideswipe collisions per year per mile of targeted cash.

It is worth mentioning that the first objective was to obtain the SPFs for each facility type. However, the number of crashes is insufficient, resulting in an estimated inverse dispersion parameter that showed no statistical significance. This makes the SPFs unreliable. Subsequently, to improve the SPFs, different rural-two-lane facility types are aggregated. This increases the amount of data used in the estimation and improves the SPFs. So, Table 17 present to cases: SPF fitted considering arterial rural two-lane roadways (minor arterial and other principal arterial), and SPF fitted considering rural two-lane roadways (major collector, minor arterial and other principal arterial). In both cases SPFs for total and fatal and injury crashes are fitted.

Table 17. SPFs fitted with 10 years of cross-sectional data.

Variable	Total Crashes		Fatal and Injury (KABC) Crashes	
	Arterials	Aggregated	Arterials	Aggregated
Constant	-12.312^{***}	-11.479^{***}	-12.566^{***}	-12.186^{***}
	(0.525)	(0.254)	(0.664)	(0.332)
Ln(AADT)	1.165^{***}	1.082^{***}	1.128^{***}	1.091^{***}
	(0.061)	(0.031)	(0.077)	(0.041)
Curve presence				
No	Base	Base	Base	Base
Yes	0.397^{***}	0.345^{***}	0.371***	0.327^{***}
	(0.075)	(0.048)	(0.095)	(0.063)
Road segments	1,838	6,538	1,838	6,538
Crashes	815	2,092	457	1,181
AIC	2,747.1	8,030.1	1916.6	5300.0
BIC	2,769.2	8,057.2	1938.6	5327.2
Log likelihood	-1,369.5	-4,011.0	−954.3	−2646.0
Inverse dispersion Parameter	7.622^{***}	3.763^{***}	42.173	6.233^{**}
	(3.485)	(0.713)	(148.987)	(2.994)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.4 CMF Development

Considering the SPFs in Table 17 and the EB comparison group study mentioned previously, the CMFs for different types of rumble strips (standard and sinusoidal) were calculated. When considering total crashes, the SPF fitted for arterial two-lane roadways was used. However, when considering fatal and injury (KABC) crashes the SPF fitted for rural two-lanes aggregated in was used since the one fitted for arterials was not reliable. Table 18 displays the computed CMFs and their safety effectiveness in head-on and opposite sideswipe crashes resulting from the implementation of centerline rumble strips. This table provides results for both total and fatal and injury crashes. However, since the total length of the major collectors with installed centerline rumble strips between 2015 and 2016 was approximately 4 miles, it was not possible to compute the CMFs. Nevertheless, only CMF computed for standard rumble strips in other principal arterials considering total crashes, showed evidence to be statistically significant. The results are presented in Table 18.

Table 18. Safety effectiveness of centerline rumble strips on head-on and sideswipe crashes in rural two-lanes roadways with multiple years of installation and five years period.

Rumble Strips Type	Total Crashes CMF[1]	Total Crashes SE	Total Crashes Crash Frequency Change[21]	Total Crashes Z-Test	Fatal and Injury Crashes (KABC) CMF[1]	Fatal and Injury Crashes (KABC) SE	Fatal and Injury Crashes (KABC) Crash Frequency Change[2]	Fatal and Injury Crashes (KABC) Z-Test
Minor Arterial								
Standard	0.96	0.38	-4%	0.11	0.94	0.58	-6%	0.10
Sinusoidal	0.78	0.42	-22%	0.52	0.58	0.43	-42%	0.98
Both	0.79	0.33	-21%	0.64	0.74	0.44	-26%	0.59
Other Principal Arterial								
Standard	**0.67**	**0.16**	**-33%**	**2.06**	0.63	0.23	-37%	1.61
Sinusoidal	1.30	0.64	30%	0.47	1.34	0.84	34%	0.40
Both	0.73	0.17	-27%	1.59	0.75	0.23	-25%	1.09
Arterials								
Standard	0.76	0.16	-24%	1.50	0.73	0.23	-27%	1.17
Sinusoidal	1.04	0.38	4%	0.11	0.82	0.63	-37%	0.29
Both	0.81	0.18	-19%	1.06	0.73	0.24	-27%	1.13

[1] CMF estimates that were computed using a suitable comparison group and showed evidence of being statistically significant at least at the 10% level are stated in bold.
[2]A negative change (-) shows a reduction. A positive change (+) shows an increase.

5.5 Summary and Recommendations

This chapter examined the effectiveness of rumble-strip installation in preventing lane-departure crashes in Maine's rural two-lane roadways using an EB comparison group before-and-after study. The methodology involved comparing the observed and predicted crash frequency of a group of sites where the treatment has been installed and a group of comparison sites with similar characteristics but without the treatment. This method requires considerably more data than the comparison group and EB before-and-after studies for which the use of this method resulted in only one CMF with evidence of statistical significance, and it is recommended for use:

- Other principal arterial roadways with standard rumble strips for total crashes (33% reduction).

CHAPTER 6

ECONOMIC ANALISYS

This chapter documents the findings of an economic analysis for installation of rumble strips. This chapter is divided into three sections. Section 6.1 provides an overview of the proposed method. Section 6.2 presents the results of the study. Section 6.3 presents the summary and conclusions.

6.1 Methodology

The economic analysis is performed by computing the benefit-cost ratio considering the roadway sections without the installation of rumble strips and the CMFs computed in Chapter 4. Chapter 4 presents significant CMFs for standard centerline rumble strips on rural, bidirectional, undivided, two-lane roadways targeting head-on and opposite sideswipe collisions. It is noteworthy that significant CMFs ae found for the facility types: minor arterial segments, other principal arterial segments, and all arterial segments together. Thus, the economic analysis focusses on these scenarios.

The benefits are assumed to be savings on the crash cost if rumble strips are installed. To estimate the savings, the total crash cost should first be computed and then converted to savings multiplying by (1-CMF). However, to use the same units, the savings are converted to USD per mile per year, dividing by the number of miles and years considered in the crash counts. The cost is considered as the rumble-strip installation cost per mile divided by the number of years of service life. With this, the benefit-cost ratio (BC) is computed using Eq. (28).

$$\mathrm{BC} = \frac{(\text{Crash cost per mile per year}) \cdot (1 - \text{CMF})}{(\text{Cost of installation per mile per year})} \qquad (28)$$

6.2 Benefit-Cost Ratio

The total crash cost is estimated using the value of unit crash cost per severity for the state of Maine. This information was provided by the Federal Highway Administration (Harmon et al., 2018). The total crash cost by severity is computed by multiplying the cost of a crash by the number of crashes.

Then, the total cost by severity is computed by summing over all costs. The total cost of head-on and opposite sideswipe collisions on rural two-lane roadways is listed in Table 19. Knowing the total crash cost, the number of years (10 years, from 2010 to 2019), the length of the roadway sections used in the estimation, and the CMF, the cost is converted to savings per mile per year. The number of miles and the countermeasure effectiveness (1-CMFs) are shown in Table 20.

Table 19. Estimation of total crash cost of head-on and sideswipe collisions for rural two-lane roadways in Maine

Crash Severity	Unit Crash Cost	Number of Crashes	Total Cost
Minor Arterial			
A	$304,400	62	$18,872,800
B	$111,200	114	$12,676,800
C	$62,700	206	$12,916,200
K	$5,740,100	29	$166,462,900
PDO	$10,100	853	$8,615,300
Total	**-**	**-**	**$219,544,000**
Other Principal Arterial			
A	$304,400	39	$11,871,600
B	$111,200	59	$6,560,800
C	$62,700	111	$6,959,700
K	$5,740,100	4	$22,960,400
PDO	$10,100	469	$4,736,900
Total	**-**	**-**	**$53,089,400**
Arterials			
A	$304,400	101	$30,744,400
B	$111,200	173	$19,237,600
C	$62,700	317	$19,875,900
K	$5,740,100	33	$189,423,300
PDO	$10,100	1322	$13,352,200
Total	**-**	**-**	**$272,633,400**

Table 20. Number of miles and (1-CMFs) used in the savings estimation.

Facility Type	Roadway Miles	(1-CMF)
Minor Arterial	720.52	0.47
Other Principal Arterial	324.75	0.44
Arterials	1045.27	0.42

The cost of rumble-strip installation per mile, as provided by the Maine Department of Transportation (MaineDOT), is $3,500 per mile. A study on the safety effectiveness of centerline plus rumble strips on two-lane rural roads by Persaud et al. (2016) reported that the service life of rumble strips in Missouri and Kentucky is 7–10 years and 12–15 years, respectively. To ensure a conservative estimate, we considered the 7-year service life as the lowest service life applicable to rumble strips in Maine. The results of the analysis, accounting for this assumption, are shown in Table 21. Even under the assumption of the shortest service life, the minimum benefit-cost ratio remains at 14.4 (for other principal arterials), confirming the cost-effectiveness of the treatment. Furthermore, the analysis is extended by considering a rumble-strip service life of 10 years, which is assumed to be the highest service life of rumble strips in Maine. The results of the analysis, taking this assumption into account as presented in Table 22. Both scenarios suggest that treatment is cost-effective for all facility types. Under the assumption of a higher service life, the minimum benefit-cost ratio remains at 20.6 (for other principal arterials), confirming the cost-effectiveness of the treatment.

Table 21. Benefit-cost ratio estimation considering a rumble strips service life of 7 years.

Total Crash Cost	Crash Cost per Mile	Crash Cost per Mile per Year	Benefit	Rumble-Strip Cost per Mile per Year	Benefit-Cost Ratio
Minor Arterial					
$219,544,000	$304,702	$30,470	$14,321	$500	28.6
Other Principal Arterial					
$53,089,400	$163,476	$16,348	$7,193	$500	14.4
Arterials					
$272,633,400	$260,825	$26,082	$10,950	$500	21.9

Table 22. Benefit-cost ratio estimation considering a rumble-strip service life of 10 years.

Total Crash Cost	Crash Cost per Mile	Crash Cost per Mile per Year	Benefit	Rumble-Strip Cost per Mile per Year	Benefit-Cost Ratio
Minor Arterial					
$219,544,000	$304,702	$30,470	$14,321	$350	40.9
Other Principal Arterial					
$53,089,400	$163,476	$16,348	$7,193	$350	20.6
Arterials					
$27,263,3400	$260,825	$26,082	$10,950	$350	31.3

6.3 Summary and Conclusions

In this chapter, a comprehensive analysis conducted to determine the benefit-cost ratio of implementing rumble strips as a safety measure to mitigate head-on and opposite sideswipe collisions on rural two-lane roadways. The economic benefits were evaluated by quantifying the potential savings in crash-related expenses that would result from the installation of rumble strips and compared these benefits to the associated installation costs. The findings indicated that the installation of rumble strips is a highly cost-effective approach for analyzed facilities. Even when factoring in the most conservative estimates for service life and cost, the benefits outweigh the costs by a significant margin, with a ratio of nearly 14 to 1.

CHAPTER 7

SUMMARY AND RECOMMENDATIONS

The aim of this study was to assess the impact of sinusoidal and standard centerline rumble strips on the frequency of head-on and opposite sideswipe crashes in Maine's rural two-lane roadways using a before-and-after studies. Two methods were used: comparison group (Chapter 4), and EB comparison group (Chapter 5). The results of the EB before-and-after study was also documented in Appendix B. The study analyzed 12 years of crash records and roadway segment information provided by the MaineDOT considering total and fatal and injury (KABC) crashes.

The comparison group method considers the aggregated crashes of all treatment/comparison sites during the entire duration of the before and after periods; the duration of the before and periods must be the same. However, this method does not necessarily address the regression to the mean phenomena. To overcome this limitation, a suitable comparison group was selected. The selection of a suitable comparison group is based on selection of sites with similar geometric and traffic characteristics and yearly crash trend in the period prior to the installation of the countermeasure, in this case, rumble strips. The selection of similar geometric and traffic characteristics is easier than that of a similar crash trend. A comparability test was performed for this purpose. It is worth mentioning again that for this method to address the regression to the mean (to some degree), a suitable comparison group must be used. However, this method requires less data than EB and EB comparison group.

The EB method addresses the regression to the mean; it is not restricted to having the same duration in the before and after periods, and it is considered one of the most robust before-and-after studies. It addresses the regression to the mean predicting the number crash frequency if no countermeasure is installed using the SPF. It also considers the dispersion of the data using the dispersion parameter obtained from the SPF. However, this requires more data because the analysis is not performed with aggregated crashes but with crashes per section per year. In addition, SPFs are necessary; if SPFs are not available, data for fitting them are also necessary. This increases the data requirements, because fitting reliable SPFs requires much more data than 5 years of crashes.

The EB comparison group method is a combination of the comparison group and EB methods. It is also a method that requires additional data. It can also underestimate the effect of the countermeasure of analysis, in this case the rumble strips, since it cannot consider sites that experienced zero crashes either in the before or after period. This method also addresses the regression to mean and requires SPFs. However, this method does not explicitly require the dispersion parameter. The comparison group did not require a comparability test because the crash trends are considered in the SPF. However, the comparison group must have geometric and traffic characteristics that are similar to those of the treatment group. This method is not restricted to before and after periods to have the same duration.

Estimating the effects of centerline rumble strips was challenging due to the type of crash that it impacts. Despite being one of the most serious types of crash, it is one of the less frequent types of lane-departure collisions. This created the challenge of lack of data. In addition, the stay-at-home restrictions of 2020 also restricted the data available for the study because they disrupted the normal traffic characteristics, and this effect was not possible to capture in the SPFs with the available data. One way to overcome this is to use comparison group-based methods, because both the treatment and comparison groups are affected in the same way.

This study found the percentage change in the crash frequency for a specific combination of roadway facilities and types of rumble strips. Most of the effects were estimated using the comparison group method; however, there are also results from the EB comparison group method. All the reliable CMFs are presented in Table 23.

Table 23. Safety effectiveness of centerline rumble strips for rural two-lane roadways.

Rumble Strip Type	Crash Severity	Method	CMF	SE	Crash Frequency Change[1]	Z-Test
Minor Arterial						
Standard	All Crashes	Comparison group	0.53	0.17	-47%	2.82
Both	Fatal and injury	Comparison group	0.56	0.24	-44%	1.81
Other Principal Arterials						
Standard	All Crashes	Comparison group	0.56	0.14	-44%	3.16
Standard	All Crashes	EB comparison group	0.67	0.16	-33%	2.06
Standard	Fatal and injury	Comparison group	0.52	0.17	-48%	2.84
Both	All Crashes	Comparison group	0.68	0.14	-32%	2.23
Arterials						
Standard	All Crashes	Comparison group	0.58	0.13	-42%	3.26
Standard	Fatal and injury	Comparison group	0.46	0.13	-54%	4.10
Both	All Crashes	Comparison group	0.72	0.14	-28%	1.91
Both	Fatal and injury	Comparison group	0.65	0.17	-35%	2.06

[1]A negative change (-) shows a reduction. A positive change (+) shows an increase.

The specific changes in the crash frequency due to rumble strip installation computed with the comparison group method are listed below.

- Standard centerline rumble strips installed in minor arterials reduced the total crash frequency of head-on and opposite sideswipe collisions by 47%.
- Standard and sinusoidal centerline rumble strips in minor arterials reduced the fatal and injury crash frequency of head-on and opposite sideswipe collisions by 44%.
- Standard centerline rumble strips installed in other principal arterials reduced the total crash frequency of head-on and opposite sideswipe collisions by 44%.
- Standard centerline rumble strips installed in other principal arterials reduced the fatal and injury crash frequency of head-on and opposite sideswipe collisions by 48%.
- Standard and sinusoidal centerline rumble strips in other principal arterials reduced the total crash frequency of head-on and opposite sideswipe collisions by 32%.
- Standard centerline rumble strips installed in arterial roadways reduced the total crash frequency of head-on and opposite sideswipe collisions by 42%.

- Standard centerline rumble strips installed in arterial roadways reduced the fatal and injury crash frequency of head-on and opposite sideswipe collisions by 54%.
- Standard and sinusoidal centerline rumble strips installed in arterial roadways reduced the total crash frequency of head-on and opposite sideswipe collisions by 28%.
- Standard and sinusoidal centerline rumble strips installed in arterial roadways reduced the fatal and injury crash frequency of head-on and opposite sideswipe collisions by 35%.

The specific changes in the crash frequency due to rumble strip installation computed with the EB comparison group method are listed below.

- Standard centerline rumble strips installed in other principal arterials reduced the total crash frequency of head-on and opposite sideswipe collisions by 33%.

Likewise, the economic benefits in installation of centerline rumble strips on rural two-lanes was assessed by computing the potential savings in expenses associated with and compared that with the cost of installation. The research suggests that the installation of rumble strips is a highly cost-effective solution for the analyzed facilities. Even when considering the most conservative estimates for service life and cost, the benefits exceed the costs by a considerable margin, with a ratio of nearly 14 to 1.

Finally, it is worth posting out that an additional effective countermeasure for reducing head-on crashes is the consideration of cable barriers. Qawasmeh & Eustace (2021) conducted a systematic review of the cable barriers effectiveness in preventing cross median crashes. Examining data from 12 states, they found a reduction range of 50% to 96% in total crashes, and 42% to 93% considering fatal and serious injuries. However, it is important to note that the cable barrier reduces the lane departure collisions, but the cars still impact the barrier, however, as shown by Zou et al. (2014) hitting a barrier is associated with a lower risk of injury, specifically for cable barriers the odds of injury reduced between 78% and 85%.

BIBLIOGRAPHY

AASHTO. (2010). *Highway Safety Manual* (1st ed.). https://www.highwaysafetymanual.org/Pages/default.aspx

Bouchard, D., Bizier, E. K., Kuchinski, J., Hayes, H. N., Merfeld, P. S., Frazier, L. B., & Northgraves, J. (2020). *Report Card for Maine's Infrastructure*. American Society of Civil Engineers - ASCE. https://infrastructurereportcard.org/state-item/maine/

Caplan, Z., & Rabe, M. (2023). The Older Population: 2020. In *2020 Census Briefs* (Issue May). United States Census Bureau. https://www.census.gov/library/publications/2023/decennial/c2020br-07.html

Cheng, E. Y.-C., Gonzalez, E., & Christensen, M. O. (2001). *Application and Evaluation of Rumble Strips on Highways*. https://rosap.ntl.bts.gov/view/dot/35761

Dissanayake, S., & Galgamuwa, U. (2017). *Estimating crash modification factors for lane-departure countermeasures in Kansas*. Kansas Department of Transportation.

Federal Highway Administration - FHWA. (2018). *Head-On Crashes Brochure*. Federal Highway Administration - FHWA. https://highways.dot.gov/safety/RwD

Galgamuwa, U., & Dissanayake, S. (2019). Evaluation of the safety effectiveness of lane-departure countermeasures on two-lane undivided roadways using crash modification factors. *Journal of Transportation Safety & Security*, *11*(4), 377–397. https://doi.org/10.1080/19439962.2017.1419523

Gårder, P., & Davies, M. (2006). Safety Effect of Continuous Shoulder Rumble Strips on Rural Interstates in Maine. *Transportation Research Record: Journal of the Transportation Research Board*, *1953*(1), 156–162. https://doi.org/10.1177/0361198106195300118

Griffith, M. S. (1999). Safety Evaluation of Rolled-In Continuous Shoulder Rumble Strips Installed on Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *1665*(1), 28–34. https://doi.org/10.3141/1665-05

Gross, F., Persaud, B., & Lyon, C. A. (2010). *A Guide to Developing Quality Crash Modification Factors* (FHWA-SA-10-032). http://www.cmfclearinghouse.org/collateral/cmf_guide.pdf

Guin, A., Rodgers, M. O., Hunter, M. P., Pena, M., Sin, J., & Lee, D. (2018). *Centerline Rumble Strips Safety Impact Evaluation— Phase 2* (FHWA-GA-18-1428 2.).

Harmon, T., Bahar, G., & Gross, F. (2018). *Crash Costs for Highway Safety Analysis* (FHWA-SA-17-071 2.). Federal Highway Administration - FHWA. https://safety.fhwa.dot.gov/hsip/docs/fhwasa17071.pdf

Hauer, E. (1997). *Observational Before-After Studies in Road Safety: Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety* (1st ed.). Pergamon.

Hilbe, J. M. (2011). *Negative Binomial Regression*. Cambridge University Press. https://doi.org/10.1017/CBO9780511973420

Himes, S., & McGee, H. (2016). *Decision Support Guide for the Installation of Shoulder and Center Line Rumble Strips on Non-Freeways* (FHWA-SA-16-115). Federal Highway Administration - FHWA. https://highways.dot.gov/safety/rwd/keep-vehicles-road/rumble-strips/decision-support-guide-installation-shoulder-and-center

Himes, S., McGee, H., Levin, S., & Zhou, Y. (2017). *State of the Practice for Shoulder and Center Line Rumble Strip Implementation on Non-Freeway Facilities* (FHWA-HRT-17-026; Issue March). https://www.fhwa.dot.gov/publications/research/safety/17026/index.cfm

Islam, A. S. M. M., Shirazi, M., & Lord, D. (2023). Grouped Random Parameters Negative Binomial-Lindley for accounting unobserved heterogeneity in crash data with preponderant zero observations. *Analytic Methods in Accident Research*, *37*, 100255. https://doi.org/10.1016/j.amar.2022.100255

Kay, J., Savolainen, P. T., Gates, T. J., Datta, T. K., Finkelman, J., & Hamadeh, B. (2015). Safety Impacts of a Statewide Centerline Rumble Strip Installation Program. *Transportation Research Record: Journal of the Transportation Research Board*, *2515*(1), 34–40. https://doi.org/10.3141/2515-05

Khan, M., Abdel-Rahim, A., & Williams, C. J. (2015). Potential crash reduction benefits of shoulder rumble strips in two-lane rural highways. *Accident Analysis & Prevention*, *75*, 35–42. https://doi.org/10.1016/j.aap.2014.11.007

Lyon, C. A., Persaud, B., & Eccles, K. (2015). Safety Evaluation of Centerline Plus Shoulder Rumble Strips. In *Federal Highway Administration, Report FHWA-HRT-15-048* (FHWA-HRT-15-048). Federal Highway Administration. https://www.fhwa.dot.gov/publications/research/safety/15048/15048.pdf

Marshall, E., Shirazi, M., & Ivan, J. N. (2023). COVID-19 and transport safety. *Transport Reviews*, 1–26. https://doi.org/10.1080/01441647.2023.2251684

Marshall, E., Shirazi, M., Shahlaee, A., & Ivan, J. N. (2023). Leveraging probe data to model speeding on urban limited access highway segments: Examining the impact of operational performance, roadway characteristics, and COVID-19 pandemic. *Accident Analysis & Prevention*, *187*(April), 107038. https://doi.org/10.1016/j.aap.2023.107038

Marvin, R. R., & Clark, D. J. (2003). *AN EVALUATION OF SHOULDER RUMBLE STRIPS IN MONTANA.* (FHWA/MT-03-008/8157; Issue March). https://doi.org/10.21949/1518187

McGee, H. W. (2018). Practices for Preventing Roadway Departures. In *National Cooperative Highway Research Program (NCHRP) Synthesis 515*. National Academies Press. https://doi.org/10.17226/25165

National Highway Traffic Safety Administration - NHTSA. (2022). *Rural/Urban Comparison of Motor Vehicle Traffic Fatalities For* (DOT HS 813 336; Issue July). U.S. Department of Transportation. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813375

Noyce, D. A., & Elango, V. V. (2004). Safety evaluation of centerline rumble strips crash and driver behavior analysis. *Transportation Research Record*, *1862*, 44–53. https://doi.org/10.3141/1862-06

Park, J., Abdel-Aty, M., & Lee, C. (2014). Exploration and comparison of crash modification factors for multiple treatments on rural multilane roadways. *Accident Analysis & Prevention*, *70*, 167–177. https://doi.org/10.1016/j.aap.2014.03.016

Patel, R. B., Council, F. M., & Griffith, M. S. (2007). Estimating Safety Benefits of Shoulder Rumble Strips on Two-Lane Rural Highways in Minnesota. *Transportation Research Record: Journal of the Transportation Research Board*, *2019*(1), 205–211. https://doi.org/10.3141/2019-24

Persaud, B., Lyon, C. A., Eccles, K., & Soika, J. (2016). Safety Effectiveness of Centerline Plus Shoulder Rumble Strips on Two-Lane Rural Roads. *Journal of Transportation Engineering*, *142*(5), 04016012. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000821

Persaud, B., Retting, R. A., & Lyon, C. A. (2004). Crash reduction following installation of centerline rumble strips on rural two-lane roads. *Accident Analysis & Prevention*, *36*(6), 1073–1079. https://doi.org/10.1016/j.aap.2004.03.002

Qawasmeh, B., & Eustace, D. (2021). Effectiveness of Cable Median Barriers in Preventing Cross Median Crashes and Related Casualties in the United States - A Systematic Review. In *Advances in Road Infrastructure and Mobility. Proceedings of the 18th International Road Federation World Meeting & Exhibition, Dubai 2021* (pp. 589–601). Springer. https://doi.org/10.1007/978-3-030-79801-7_42

Rubin, J., Jain, S., Shirazi, M., Sawtelle, A., Parauli, D., McKee, P., & Bailey, M. (2022). *Road Salt in Maine: An Assessment of Practices , Impacts and Safety*. https://digitalcommons.library.umaine.edu/mcspc_transport/11

Russell, E. R., & Rys, M. J. (2005). Centerline Rumble Strips. In National Cooperative Highway Research Program - NCHRP (Ed.), *National Cooperative Highway Research Program (NCHRP) Synthesis339* (20-5 FY 2002 (Topic 34-01)). The National Academies Press. https://doi.org/10.17226/23327

Sawtelle, A., Shirazi, M., Garder, P. E., & Rubin, J. (2022). Exploring the impact of seasonal weather factors on frequency of lane-departure crashes in Maine. *Journal of Transportation Safety and Security*, *0*(0), 1–22. https://doi.org/10.1080/19439962.2022.2086952

Sawtelle, A., Shirazi, M., Garder, P. E., & Rubin, J. (2023). Driver, roadway, and weather factors on severity of lane departure crashes in Maine. *Journal of Safety Research*, *84*, 306–315. https://doi.org/10.1016/j.jsr.2022.11.006

Sayed, T., Deleur, P., & Pump, J. (2010). Impact of rumble strips on collision reduction on highways in British Columbia, Canada: Comprehensive before-and-after safety study. *Transportation Research Record*, *2148*, 9–15. https://doi.org/10.3141/2148-02

Shahlaee, A., Shirazi, M., Marshall, E., & Ivan, J. N. (2022). Modeling the impact of the COVID-19 pandemic on speeding at rural roadway facilities in Maine using short-term speed and traffic count data. *Accident Analysis & Prevention*, *177*(September), 106828. https://doi.org/10.1016/j.aap.2022.106828

Smadi, O., & Hawkins, N. (2016). Practice of Rumble Strips and Rumble Stripes. In *National Cooperative Highway Research Program (NCHRP) Synthesis 490*. Transportation Research Board. https://doi.org/10.17226/23522

Smith, E., & Ivan, J. N. (2005). Evaluation of Safety Benefits and Potential Crash Migration Due to Shoulder Rumble Strip Installation on Connecticut Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *1908*(1908), 104–113. https://doi.org/10.3141/1908-13

Wu, K.-F., Donnell, E. T., & Aguero-Valverde, J. (2014). Relating crash frequency and severity: Evaluating the effectiveness of shoulder rumble strips on reducing fatal and major injury crashes. *Accident Analysis & Prevention*, *67*, 86–95. https://doi.org/10.1016/j.aap.2014.02.004

Zou, Y., Tarko, A. P., Chen, E., & Romero, M. A. (2014). Effectiveness of cable barriers, guardrails, and concrete barrier walls in reducing the risk of injury. *Accident Analysis & Prevention*, *72*, 55–65. https://doi.org/10.1016/j.aap.2014.06.013

APPENDICES

APPENDIX A: COMPUTED CMFs WITH A SINGLE INSTALLATION YEAR AND 3 YEARS OF BEFORE-AND-AFTER PERIODS

This section presents the results of the comparability test and CMFs computed with the comparison group method using a 3-year duration for the before and after periods.

Table A-1. Comparability test results.

	Total Crashes						Fatal and Injury Crashes (KABC)					
Rumble Strips Type	**Year**	**CMF**	**SE**	**Lower 95% CL**	**Upper 95% CL**	**Slack**	**Year**	**CMF**	**SE**	**Lower 95% CL**	**Upper 95% CL**	**Slack**
Minor Arterial												
Standard	2017	0.77	0.54	-0.3	1.83	35%	2017	0.84	0.52	-0.17	1.85	25%
Sinusoidal	2018	0.47	0.36	-0.23	1.18	5%	2018	0.50	0.05	0.40	0.60	45%
Both	2017	0.77	0.54	-0.28	1.82	35%	2017	0.87	0.48	-0.08	1.81	15%
Other Principal Arterial												
Standard	2016	0.87	0.34	0.21	1.535	1%	2016	0.86	0.50	-0.12	1.84	1%
Sinusoidal	2018	0.76	0.43	-0.07	1.60	1%	2018	0.34	0.13	0.09	0.60	10%
Both	2017	0.97	0.44	0.10	1.83	5%	2017	1.12	0.78	-0.41	2.64	35%
Arterials												
Standard	2017	0.80	0.23	0.35	1.25	35%	2017	0.91	0.02	0.86	0.95	35%
Sinusoidal	2018	0.62	0.25	0.13	1.10	25%	2018	0.58	0.18	0.22	0.93	40%
Both	2017	0.86	0.15	0.57	1.16	35%	2017	0.96	-	-	-	10%

Note: CMF estimates that are subjectively close to 1 (within 0.9 and 1.1) and showed evidence to be statistically significant at the 5% level are stated in bold.

Table A-2. Safety effectiveness of centerline rumble strips.

Rumble Strips Type	Total Crashes					Fatal and Injury Crashes (KABC)				
	Year	CMF[1]	SE	Change[1]	Z-Test	Year	CMF_1	SE	Change[1]	Z-Test
Minor Arterial										
Standard	2017	0.31	0.13	-69%	5.53	2017	0.84	0.52	-16%	13.38
Sinusoidal	2018	0.55	0.22	-45%	2.02	2018	0.41	0.20	-59%	2.90
Both	2017	0.33	0.14	-67%	4.95	2017	0.10	0.07	-90%	13.28
Other Principal Arterial										
Standard	2016	0.69	0.20	-31%	1.53	2016	0.74	0.28	-26%	0.92
Sinusoidal	2018	0.31	0.16	-69%	4.21	2018	0.35	0.21	-65%	3.03
Both	2017	0.99	0.35	-1%	0.04	2017	1.00	0.44	0%	0.01
Arterials										
Standard	2017	0.52	0.15	-48%	3.18	2017	0.31	0.12	-69%	5.56
Sinusoidal	2018	0.44	0.15	-56%	3.84	2018	0.48	0.20	-52%	2.63
Both	2017	0.60	0.16	-40%	2.52	2017	0.42	0.15	-58%	3.85

[1] CMF estimates that were computed using a suitable comparison group and showed evidence of being statistically significant at least at the 10% level are stated in bold.
[2]A negative change (-) shows a reduction. A positive change (+) shows an increase.

APPENDIX B: BEFORE-AND-AFTER STUDY WITH EMPIRICAL BAYES

This appendix documents the findings of the EB before-and-after study. This chapter is divided into five sections. Section B.1 provides a comprehensive overview of the methodology in three parts. Section B.1.1 documents the general scope of the EB before-after studies. Section B.1.2 outlines the steps taken to compute the CMFs. Section B.1.3 documents how to estimate the SPF. Section B.2 describes the selection of the treatment sites used in the study. Sections B.3 and B.4 present the estimated and computed CMFs, respectively. Finally, Section B.5 provides a summary of the study and recommendations.

B.1 Methodology

The EB method for before-and-after studies accounts for the issue of regression to the mean and stands as one of the most reliable methods for estimating CMFs and quantifying the safety effectiveness of countermeasures. The subsequent subsections delineate the procedures entailed in before-and-after studies using the EB methodology.

B.1.1 Before-After Studies with EB

This method uses SPFs to account for the regression to the mean issue by weighting the observed crash frequency with the average crash frequency predicted using the SPF (AASHTO, 2010). The HSM (AASHTO, 2010). also states that safety evaluation using the EB method requires at least 10 to 20 treatment sites and three to five years of crash records in the before and after periods. However, the safety evaluation can still be performed with fewer sites or years, but the results are less likely to show evidence of statistical significance.

B.1.2 Computing CMFs

In the context of the EB before-and-after study, the CMF and the percentage of safety improvement are derived by applying Eq. (29), and Eq. (30).

$$\mathrm{CMF} = \frac{\sum_i N_{observed,A} / \sum_i N^i_{expected,A}}{1 + \frac{Var\left[\sum_i N^i_{expected,A}\right]}{\left(\sum_i N^i_{expected,A}\right)^2}} \tag{29}$$

$$\Delta safety = (1 - \mathrm{CMF}) \times 100 \tag{30}$$

Furthermore, the variance of CMF is computed using Eq. (31).

$$Var(\mathrm{CMF}) = \frac{\mathrm{CMF}^2 \times \left(\frac{1}{N_{observed,A}} + \frac{Var\left(\sum_i N^i_{expected,A}\right)}{\left(\sum_i N^i_{expected,A}\right)^2}\right)}{1 + \frac{Var\left[\sum_i N^i_{expected,A}\right]}{\left(\sum_i N^i_{expected,A}\right)^2}} \tag{31}$$

The variable $N^i_{expected,A}$ is found using Eq. (32).

$$N^i_{expected,A} = N^i_{expected,B} \times \frac{N^i_{predicted,A}}{N^i_{predicted,B}} \tag{32}$$

Where,

$N^i_{expected,B}$: the expected number of crashes in the before period at the i-th site with treatment.

$N^i_{predicted,B}$: the predicted number of crashes in the before period at the i-th site with treatment.

$N^i_{predicted,A}$: the predicted number of crashes in the after period at the i-th site with treatment.

The predictions of $N^i_{predicted,B}$ and $N^i_{predicted,A}$ are computed using SPFs. In this study, SPFs were developed using the data collected in Maine. To estimate the number of crashes expected in the before period at the sites with the countermeasure ($N^i_{expected,B}$), the EB method is applied using Eq. (33) and Eq. (34).

$$N^i_{expected,B} = w_{i,B} \times N^i_{predicted,B} + (1 - w_{i,B}) \times N^i_{observed,B} \tag{33}$$

$$w_{i,B} = \frac{1}{1 + \frac{Var[N^i_{predicted,B}]}{E[N^i_{predicted,B}]}} \tag{34}$$

Where,

$N^i_{observed,B}$: the number of crashes observed in the before period at the i-th treated site.

$N^{i}_{predicted,B}$: the number of crashes predicted in the before period at the i-th treated site.

$w_{i,B}$: the weight for the i-th site.

The expected value ($E[N^{i}_{predicted,B}]$) and variance ($Var[N^{i}_{predicted,B}]$) of the predicted number of crashes in the before period depend on the model used to develop the SPFs. In this case, a negative binomial (NB) model was chosen. Subsequently, the weight presented in Eq. (34) is equivalent to Eq. (35).

$$w_{i,B} = \frac{1}{1 + (\theta \times \sum_{i} N^{i}_{predicted,B})} \tag{35}$$

Where,

θ : the dispersion parameter of the NB model.

To estimate the expected number of crashes in the after period ($N^{i}_{expected,A}$), changes in different factors, such as the traffic volume, from the before to the after period must be considered. Accounting for these changes is accomplished with the ratio of SPF prediction in the after and before periods as shown in Eq. (36).

$$N^{i}_{expected,A} = N^{i}_{expected,B} \times \frac{N^{i}_{predicted,A}}{N^{i}_{predicted,B}} \tag{36}$$

Where,

$N^{i}_{expected,B}$: number of expected crashes in the before period at the i-th treated site.

$N_{predicted,A}$: number of predicted crashes in the after period at the i-th treated site.

$N_{predicted,B}$: number of predicted crashes in the before period at the i-th treated site.

B.2 Treatment Sites

This study focuses on the rural two-lane roadways in Maine. The data include information on roadway elements (including rumble-strip information) and crash records. The rumble-strip data include variables such as length, unique element identification, type of rumble-strip (standard or sinusoidal), rumble-strip location (centerline, left edge, or right edge), and year of installation. Crash records have data from January 2010 to December 2022, containing information such as the type of crash, unique crash identification, type of crash, date, hour, injuries, and location. Information on the crash data was combined with rumble-strip data to create a final database for the study. This contains information about the crash and rumble strips of the element where the crash occurred. Because head-on crashes are uncommon, different years of installation were considered for each combination facility and rumble-strip type to increase the number of sites and crashes. The treatment sites were then selected considering the geometric and roadway characteristics, year of rumble-strip installation, and segment length. Considering the geometric and roadway characteristics, the selected sites included rural, two-lane, bidirectional, and undivided segments with centerline rumble strips. Only the segments with lengths greater than or equal to 0.1 miles were considered for analysis.

Typically, before-and-after studies employ durations ranging from three to five years for analysis. The duration of the before and after period does not necessarily have to match. In this study, the choice of the 'before' and 'after' period durations is guided by the availability of crash records spanning from 2010 to 2022. Additionally, it is imperative to acknowledge the unique impact of stay-at-home order restrictions resulting from the COVID-19 pandemic in 2020 on traffic volumes and driver behavior (Marshall, Shirazi, & Ivan, 2023; Marshall, Shirazi, Shahlaee, et al., 2023; Shahlaee et al., 2022). Consequently, crash records from 2020 onwards are excluded from analysis. This limitation led to considering the year 2016 as the most recent installation year that three years ‘after’ data is readily available. Furthermore, to increase the robustness of analysis, a five-year duration is also chosen for the 'before' period. Thus, only rumble-strip installations occurring in 2015 and 2016 are considered for analysis, with a 'before' period of five years and an 'after' period of three years. The layout of the study is presented in Tables B-1, B-2, and B-3. Table B-1 lists the selected years of installation and the durations of the before and after periods. In some cases, for example, with minor arterials, standard rumble strips were installed in 2015 and 2016; therefore, both years are considered, but sinusoidal rumble strips were installed only in 2016. When evaluating both types of rumble strips together, only 2016 is used because the installation of both types occurred in that year. Tables B-2 and B-3 and summarizes the number of sites, miles, and crashes used for each case for total and fatal and injury (KABC) crashes, respectively.

Table B-1. Installation years and duration of the before and after periods used to compute CMFs.

Rumble Strips Type	Total Crashes			Fatal and Injury Crashes (KABC)		
	Installation Year	Years in Before Period	Years in After Period	Installation Year	Years in Before Period	Years in After Period
Minor Arterial						
Standard	2015, 2016	5	3	2015, 2016	5	3
Sinusoidal	2016	5	3	2016	5	3
Both	2016	5	3	2016	5	3
Other Principal Arterial						
Standard	2015, 2016	5	3	2015, 2016	5	3
Sinusoidal	2015, 2016	5	3	2015, 2016	5	3
Both	2015, 2016	5	3	2015, 2016	5	3
Arterials						
Standard	2015, 2016	5	3	2015, 2016	5	3
Sinusoidal	2016	5	3	2016	5	3
Both	2016	5	3	2016	5	3

Table B-2. Summary of treatment sites used for the safety effectiveness of centerline rumble strips considering total crashes.

Rumble Strips Type	Sites	Miles	Observed Crashes Before	Observed Crashes After	Predicted Crashes Before	Predicted Crashes After
Minor Arterial						
Standard	40	25.2	49	13	23.7	15.0
Sinusoidal	4	4.7	5	3	2.9	1.8
Both	13	10.8	14	5	8.16	5.1
Other Principal Arterial						
Standard	117	66.4	105	43	41.9	43.2
Sinusoidal	35	23.4	42	21	25.5	15.9
Both	152	89.8	147	64	94.9	59.2
Arterials						
Standard	157	91.5	154	56	93.1	58.3
Sinusoidal	27	21.7	29	17	19.3	12.0
Both	196	119.7	201	80	121.6	76.0

Table B-3. Summary of treatment sites used for the safety effectiveness of centerline rumble strips considering fatal and injury (KABC) crashes.

Rumble Strips Type	Sites	Miles	Observed Crashes Before	Observed Crashes After	Predicted Crashes Before	Predicted Crashes After
Minor Arterial						
Standard	40	25.2	38	7	13.4	8.4
Sinusoidal	4	4.7	4	3	1.7	1.0
Both	13	10.8	12	4	4.7	2.9
Other Principal Arterial						
Standard	117	66.4	63	26	38.6	24.0
Sinusoidal	35	23.4	24	14	14.2	8.8
Both	152	89.8	87	40	52.8	32.8
Arterials						
Standard	157	91.5	101	33	51.2	32.5
Sinusoidal	27	21.7	15	11	10.9	6.7
Both	196	119.7	129	50	67.9	42.3

B.3 CMF Development

The implementation of a countermeasure, such as rumble strips, is anticipated to influence the trend in crash occurrences. CMFs serve as a metric for assessing the effectiveness of safety treatments, illustrating the extent to which the countermeasure, like rumble strips, alters the frequency of crashes. In other words, when the CMF is known, it facilitates the determination of the countermeasure's safety effectiveness in terms of crash reduction. Using the SPFs presented in chapter 5.3 and the EB before-and-after study noted earlier, the CMFs for different rumble-strip types (standard and sinusoidal) are computed. Table B-4 presents the CMFs and safety effectiveness of centerline rumble strips in reduction of head-on and opposite sideswipe crashes. The total length of the major collectors with installed centerline rumble strips between 2015 and 2016 is too small (~4 miles) to compute the CMFs. Therefore, no results are presented. However, reliable CMFs were obtained for standard and both types of rumble strips considering total and fatal and injury (KABC) crashes on arterials. Also, for standard rumble strips considering fatal and injury (KABC) crashes on minor arterials. Table B-4 presents the results.

Table B-4. Safety effectiveness of centerline rumble strips on head-on and sideswipe crashes in rural two-lane roadways with multiple years of installation and a five-year period.

Rumble Strips Type	Total Crashes				Fatal and Injury Crashes (KABC)			
	CMF	SE	Crash Frequency Change[1]	Z-Test	CMF	SE	Crash Frequency Change[1]	Z-Test
Minor Arterial								
Standard	0.80	0.23	-20%	0.86	0.75	0.29	-25%	0.88
Sinusoidal	1.47	0.93	47%	0.93	2.27	1.46	127%	0.87
Both	0.93	0.43	-7%	0.16	1.22	0.63	22%	0.35
Other Principal Arterial								
Standard	0.94	0.15	-6%	0.42	1.08	0.22	8%	0.37
Sinusoidal	1.27	0.29	27%	0.94	1.52	0.42	52%	1.23
Both	1.07	0.14	7%	0.48	1.20	0.20	20%	1.04
Arterials								
Standard	0.94	0.13	-6%	0.47	0.99	0.18	-1%	0.07
Sinusoidal	1.38	0.35	38%	1.07	1.57	0.50	57%	1.14
Both	1.03	0.12	3%	0.21	1.14	0.17	14%	0.85

[1]CMF estimates that showed evidence of being statistically significant at least at the 10% level are stated in bold.
[2]A negative change (-) shows a reduction. A positive change (+) shows an increase.

B.4 Summary and Conclusions

This appendix documented the CMFs and the percentage of change in safety upon installation of centerline rumble strips on rural two-lanes in Maine using the EB before-and-after study. SPFs were fitted, and CMFs were computed for total and fatal and injury head-on and opposite sideswipe collisions considering multiple years of rumble-strip installation. The study found inconclusive results since none of the CMFs showed evidence of statistical significance. The use of the CMFs presented in this chapter is not recommended.

APPENDIX C: CODE FOR COMPARISON GROUP BEFORE-AND-AFTER STUDY

The section presents a sample Python code of the developed functions for the comparison group before-and-after evaluation. In each case, only the core part of the code is shown, that is, excluding data entry and manipulation.

Function to prepare the treatment group data.

```
def prepare_treatment_data(
    df_data,
    treatment_query,
    crash_count
    ):
    """Prepares treatment data for analysis.
    Parameters:
    -----------
    - df_data (pd.DataFrame): The input DataFrame containing the raw data.
    - treatment_query (str): The query string to filter the data for the
        treatment group.
    - crash_count (str): The column name representing crash counts.

    Returns:
    --------
    - df_treatment (pd.DataFrame): The DataFrame containing the filtered
        treatment data.
    - obs_treat_before (int): The sum of crash counts for the treatment group
        before the treatment.
    - obs_treat_after (int): The sum of crash counts for the treatment group
        after the treatment.
    """

    # Study data
    df_treatment = (
        df_data
        .query(treatment_query)
        .reset_index(drop=True)
        )

    # Aggregate crash counts
    obs_treat_before = (
        df_treatment
        .query("BEFORE_AFTER_5Y == 'Before'")[crash_count].sum()
        )

    obs_treat_after = (
        df_treatment
        .query("BEFORE_AFTER_5Y == 'After'")[crash_count].sum()
        )
    return(df_treatment, obs_treat_before, obs_treat_after)
```

Function to prepare the comparison group data.

```
def prepare_comparison_data(
    df_data,
    df_treatment,
    slack,
    comparison_query,
    crash_count,
    years_before,
    years_after
    ):
    """Prepares the comparison group data for analysis.

    Parameters:
    -----------
    - df_data (pd.DataFrame): The input DataFrame containing the raw data.
    - df_treatment (pd.DataFrame): The DataFrame containing the filtered
        treatment data.
    - slack (float): The slack value for AADT range comparison.
    - comparison_query (str): The query string to filter the data for the
        comparison group.
    - crash_count (str): The column name representing crash counts.
    - years_before (list): The list of years for the period before treatment.
    - years_after (list): The list of years for the period after treatment.

    Returns:
    --------
    - df_comparison (pd.DataFrame): The DataFrame containing the filtered
        comparison data.
    - obs_comp_before (int): The sum of crash counts for the comparison group
        before the treatment.
    - obs_comp_after (int): The sum of crash counts for the comparison group
        after the treatment.
    """

    # Comparison roads data
    df_comparison_roads = (
        df_data
        .query(comparison_query)
        .drop_duplicates(subset=['ID_NS'])
        .reset_index(drop=True)
        )

    # Subset unique AADT values in the treatment group
    df_treatment_aadt = (
        df_treatment
        .drop_duplicates(subset=['AADT_EF_2016'])
        .reset_index(drop=True)
        )

    # Initialize an empty list to store the rows of df2 that meet the condition
    selected_rows = []

    # Iterate through each row in df2
    for index, row_comparison in df_comparison_roads.iterrows():
        aadt_comparison = row_comparison['AADT_EF_2016']

        # Check if aadt_df2 is within any range in df1
        for _, row_treatment in df_treatment_aadt.iterrows():
            min_range = (1-slack) * row_treatment['AADT_EF_2016']
            max_range = (1+slack) * row_treatment['AADT_EF_2016']
```

```
        if min_range <= aadt_comparison <= max_range:
            selected_rows.append(row_comparison)
            break

# Create a DataFrame from the selected rows
subset_comparison = pd.DataFrame(selected_rows)

# Filter unique road id
subset_comparison_id = subset_comparison['ID_NS'].unique()

# Subset the comparison groupd data
df_comparison = (
    df_data
    .query(comparison_query)
    .query("ID_NS in @subset_comparison_id")
    .reset_index(drop=True)
    )

# Aggregate crash counts
obs_comp_before = (
    df_comparison
    .query("CRASH_YEAR in @years_before")[crash_count].sum()
    )

obs_comp_after = (
    df_comparison
    .query("CRASH_YEAR in @years_after")[crash_count].sum()
    )

return(df_comparison, obs_comp_before, obs_comp_after)
```

Function to prepare the data for the comparability test.

```
def prepare_comparability_test_data(
    df_treatment,
    df_comparison,
    years,
    crash_count_col
    ):
    """Prepares data for the comparability test.

    Parameters:
    -----------
    - df_treatment (pd.DataFrame): The DataFrame containing the filtered
        treatment data.
    - df_comparison (pd.DataFrame): The DataFrame containing the filtered
        comparison data.
    - years (list): The list of years for the analysis.
    - crash_count_col (str): The column name representing crash counts.

    Returns:
    --------
    - df_crash_data (pd.DataFrame): The DataFrame containing crash data for the
        comparability test.
    """

    # Subset crash data in study population
```

```
    crash_data_study = (
        df_treatment
        # Filter for before crashes
        .query('BEFORE_AFTER_5Y == "Before"')
        # Summarize the crashes by year
        .groupby(['CRASH_YEAR'], as_index=False)[[crash_count_col]].sum()
        )

    # Subset crash data in comparsion group
    crash_data_compa = (
        df_comparison
        # Summarize the crashes by year
        .groupby(['CRASH_YEAR'], as_index=False)[[crash_count_col]].sum()
        )

    # Create the dataframe for the comparability test
    df_crash_data = pd.DataFrame(years, columns=['YEAR'])

    # Add the crashes in the study population to the dataframe
    df_crash_data['TREATMENT'] = (
        df_crash_data['YEAR']
        .map(crash_data_study.set_index('CRASH_YEAR')[crash_count_col])
        )

    # Add the crashes in the reference population to the dataframe
    df_crash_data['COMPARSION'] = (
        df_crash_data['YEAR']
        .map(crash_data_compa.set_index('CRASH_YEAR')[crash_count_col])
        )

    return df_crash_data
```

Function to compute the comparability test.

```
def comparability_test(df_crash_trend):
    """Conducts the comparability test of the treatment and comparisong groups.

    Parameters:
    - df_crash_trend (pd.DataFrame): The DataFrame containing crash trends for
        the comparability test. It is the ouput of the function
        `prepare_comparability_test_data`.

    Returns:
    - mean (float): The mean of the sample CMF.
    - se (float): The standard error of the sample CMF.
    - lower_limit (float): The lower limit of the confidence interval for the
        sample CMF.
    - upper_limit (float): The upper limit of the confidence interval for the
        sample CMF.
    """

    df_crash_trend['SAMPLE_CMF'] = np.NAN
```

```
    for i in range(len(df_crash_trend) - 1):

        df_crash_trend.loc[i,'SAMPLE_CMF'] = (
            (
                (
                    df_crash_trend.loc[i,'TREATMENT'] *
                    df_crash_trend.loc[i+1,'COMPARSION']
                    ) /
                (
                    df_crash_trend.loc[i+1,'TREATMENT'] *
                    df_crash_trend.loc[i,'COMPARSION']
                    )
                ) /
            (
                1 +
                (1/df_crash_trend.loc[i+1,'TREATMENT']) +
                (1/df_crash_trend.loc[i,'COMPARSION'])
                )
            )

    mean = df_crash_trend['SAMPLE_CMF'].mean()
    se = df_crash_trend['SAMPLE_CMF'].std()

    lower_limit = mean - 1.96*se
    upper_limit = mean + 1.96*se

    return(mean, se, lower_limit, upper_limit)
```

Function to compute the CMF.

```
def cmf_comp_group2(
    obs_treat_before,
    obs_treat_after,
    obs_comp_before,
    obs_comp_after
    ):
    """Computes the Crash Modification Factor (CMF) and its standard error
    for the comparison group.

    Parameters:
    -----------
    - obs_treat_before (int): The sum of crash counts for the treatment group
        before the treatment.
    - obs_treat_after (int): The sum of crash counts for the treatment group
        after the treatment.
    - obs_comp_before (int): The sum of crash counts for the comparison group
        before the treatment.
    - obs_comp_after (int): The sum of crash counts for the comparison group
        after the treatment.

    Returns:
    --------
    - cmf (float): The Crash Modification Factor for the comparison group.
```

```
    - se_cmf (float): The standard error of the CMF.
    """

    # Expected crash counts in the treatment group after the treatment
    expect_treat_after = obs_treat_before * (obs_comp_after/obs_comp_before)

    # Variance of the expected crash counts in the treatment group after
    # the treatment
    var_expect_treat_after = (
        expect_treat_after**2
        * ((1/obs_treat_before) + (1/obs_comp_before) + (1/obs_comp_after))
        )

    # Crash modification factor - CMF
    cmf = (
        (obs_treat_after/expect_treat_after) /
        (1 + (var_expect_treat_after/expect_treat_after**2))
        )

    # CMF variance
    var_cmf = (
        (
            (cmf**2) *
            (
                (1/obs_treat_after) +
                (var_expect_treat_after/expect_treat_after**2)
                )
            ) /
        (1 + (var_expect_treat_after/expect_treat_after**2))**2
        )

    # CMF standard error
    se_cmf = np.sqrt(var_cmf)

    return (cmf,se_cmf)
```

APPENDIX D: CODE FOR EMPIRICAL BAYES BEFORE-AND-AFTER STUDY

The section presents a sample Python code of the developed functions for the EB before-and-after evaluation. In each case, only the core part of the code is shown, that is, excluding data entry and manipulation.

Function to prepare the data.

```
def prepare_data_eb(
    df: pd.DataFrame,
    crash_count: str,
    spf,
    dispersion_param: float,
    n_years_before: int,
    n_years_after: int,
    ):
    """Prepare data for input in function `compute_eb_cmf()`.

    This function takes a (tidy) data frame with road segments and crashes and
    then manipulates it to create a data frame in the format required by the
    function that computes the CMFs with the empirical bayes method
    (`compute_eb_cmf()`

    Parameters
    ----------
    df : pd.DataFrame
        Data frame with road segments and crashes. Each row corresponds to a
        roadsegment and crashes. Different crashes are in the same roadd segment
        are in different rows.
    crash_count : str
        Name of the column with the crash counts.
    spf : function
        Safety performance function to predict crashes.
    dispersion_param : float
        Dispersion parameter associated to the SPF.
    n_years_before : int
        Number of years to study before the treatment.
    n_years_after : int
        Number of years to study after the treatment.

    Returns
    -------
    df_eb : pd.DataFrame
        Data frame with road segments and crashes in the format required by the
        function `compute_eb_cmf()`.
    """

    # 1.0 Unique road segments
    # ---------------------------------------------------------------------------
    df_eb = (
        df
```

```
    # Drop duplicated segments
    .drop_duplicates(subset=['ID_NS'])
    # Keep only the columns of interest
    .loc[:,'ID_NS']
    # Copy in a new data frame
    .copy()
    )

# 2.0 Aggregate observed crashes
# --------------------------------------------------------------------------

##  2.1 Subset before crashes
df_before = df.query('BEFORE_AFTER_5Y in ["Before", "No Crash"]').copy()

## 2.2 Aggregate crashes in the before period
df_temp_before = (
    df_before
    # Group roads by segmente id
    .groupby(['ID_NS'], as_index=False)
    # Aggregate crashes counts (total and kabc) by road segment
    [[crash_count]].sum()
    # Rename columns
    .rename(columns={crash_count: "OBSERVED_BEFORE"})
    )

## 2.3 Merge unique roads and aggregated crashes
df_eb = pd.merge(
    df_eb,
    df_temp_before,
    how='left',
    on='ID_NS'
    )

del(df_temp_before)

## 2.4 Fill missing values with 0 in crash count columns
df_eb.loc[:, 'OBSERVED_BEFORE'] = (
    df_eb.loc[:, 'OBSERVED_BEFORE']
    .fillna(value=0)
    )

## 2.5 Subset after crashes
df_after = df.query('BEFORE_AFTER_3Y in ["After", "No Crash"]').copy()

## 2.6 Aggregate crashes in the after period
df_temp_after = (
    df_after
    # Group roads by segmente id
    .groupby(['ID_NS'], as_index=False)
    # Aggregate crashes counts (total and kabc) by road segment
    [[crash_count]].sum()
    # Rename columns
```

```
    .rename(columns={crash_count: "OBSERVED_AFTER"})
    )

## 2.7 Merge unique roads and aggregated crashes
df_eb = pd.merge(
    df_eb,
    df_temp_after,
    how='left',
    on='ID_NS'
    )

del(df_temp_after)

## 2.8 Fill missing values with 0 in crash count columns
df_eb.loc[:, 'OBSERVED_AFTER'] = (
    df_eb.loc[:, 'OBSERVED_AFTER']
    .fillna(value=0)
    )


# 3.0 Predict crashes in the before period
# -----------------------------------------------------------------------------

## 3.1 Years in the before period
years_before = np.arange(
    start = np.min(df_before["RS_YEAR_INSTALL"].astype(int))-n_years_before,
    stop = np.max(df_before["RS_YEAR_INSTALL"].astype(int)),
    step = 1
)

## 3.2 Subset unique roads
df_temp_before = df.drop_duplicates(subset=['ID_NS']).copy()

## 3.3 Predict crashes in the before period
for year in years_before:
    df_temp_before[year] = spf(
        df_temp_before,
        year
        )

## 3.4 Aggregate predicted crashes in the before period
df_temp_before['PREDICTED_BEFORE'] = (
    df_temp_before.loc[:, years_before]
    .sum(axis=1)
    )

## 3.5 Merge unique roads and aggregated crashes
df_eb = pd.merge(
    df_eb,
    df_temp_before[['ID_NS', 'PREDICTED_BEFORE']],
    how='left',
    on='ID_NS'
    )
```

```
    del(df_temp_before)


    # 4.0 Predict crashes in the after period
    # ---------------------------------------------------------------------------

    ## 4.1 Years in the after period
    years_after = np.arange(
        start = np.min(df_after["RS_YEAR_INSTALL"].astype(int))+1,
        stop = np.max(df_after["RS_YEAR_INSTALL"].astype(int))+1+n_years_after,
        step =1
    )

    ## 4.2 Subset unique roads
    df_temp_after = df.drop_duplicates(subset=['ID_NS']).copy()

    ## 4.3 Predict crashes in the after period
    for year in years_after:
        df_temp_after[year] = spf(
            df_temp_after,
            year
            )

    ## 4.4 Aggregate predicted crashes in the before period
    df_temp_after['PREDICTED_AFTER'] = (
        df_temp_after.loc[:, years_after]
        .sum(axis=1)
        )

    ## 4.5 Merge unique roads and aggregated crashes
    df_eb = pd.merge(
        df_eb,
        df_temp_after[['ID_NS', 'PREDICTED_AFTER']],
        how='left',
        on='ID_NS'
        )

    # 5.0 Add dispersion parameter
    # ---------------------------------------------------------------------------

    df_eb['DISPERSION'] = dispersion_param

    return df_eb
```

Function to compute the CMF.

```
def compute_eb_cmf(
    df: pd.DataFrame,
    ) -> tuple[pd.DataFrame, float, float, float]:

    """ Compute crash modification factor (CMF) using the empirical Bayes
```

```
This function computes the CMF using the empirical Bayes method. It follows
the procedure of the Highway Safety Manual 2010 presented in appendix 9A.

Parameters
----------
df : pandas.DataFrame
    Dataframe with the site id and the aggregated crash frequency in the
    before and after periods. The colomns must be named: "OBSERVED_BEFORE",
    "OBSERVED_AFTER", "PREDICTED_BEFORE", "PREDICTED_AFTER", and
    "DISPERSION".

Returns
-------
df : pandas.DataFrame
    Dataframe with the results of the calculation steps.
cmf : float
    Unbiased overall CMF
safety_effectiveness : float
    Unbiased overall safety effectiveness as decimal (not percentage)
std_error_cmf : float
    Standar error of the unbiased overall CMF (and safety effectiveness)

Notes
-----
The stesps 1 and 3 are not included in this function. The results of these
steps correspond to the columns "PREDICTED_BEFORE" and "PREDICTED_AFTER"
that are input of this function.

"""
# Step 2 - Compute the expected crash frequency in the before period
# for each site
# ---------------------------------------------------------------------------

## 2.1 Compute the weigth for each site
df["WEIGHT"] = (
    1 / (1 + df['DISPERSION'] * df["PREDICTED_BEFORE"])
    )

## 2.2 Compute the crash frequency for each site
df['EXPECTED_BEFORE'] = (
    df["WEIGHT"] * df["PREDICTED_BEFORE"]
    + (1-df["WEIGHT"]) * df["OBSERVED_BEFORE"]
    )

# Step 4 - Compute the adjustment factor for each site
# ---------------------------------------------------------------------------

df["ADJUST_FACTOR"] = (
    df["PREDICTED_AFTER"] / df["PREDICTED_BEFORE"]
    )

# Step 5 - Compute expected crash frequqency in the after period
# for each site
```

```
# ---------------------------------------------------------------------------

df["EXPECTED_AFTER"] = (
    df["ADJUST_FACTOR"] * df["EXPECTED_BEFORE"]
    )

# Step 6 - Compute an estimated CMF (odds ratio) for each site
# ---------------------------------------------------------------------------

df["CMF"] = (
    df['OBSERVED_AFTER'] / df["EXPECTED_AFTER"]
    )

# Step 7 - Compute the safety effectiveness for each site
# ---------------------------------------------------------------------------

df["SAFETY_EFFECTIVENESS"] = (
    1 - df["CMF"]
    )

# Step 8 - Compute the overall CMF
# ---------------------------------------------------------------------------

cmf_biased = (
    np.sum(df['OBSERVED_AFTER']) / np.sum(df["EXPECTED_AFTER"])
    )

# Step 9 - Compute the overall unibiased CMF
# ---------------------------------------------------------------------------

## 9.1 Copmute tha variance of expected crashes in the after period
var_expected_after = np.sum(
    (df["ADJUST_FACTOR"]**2)
    * df["EXPECTED_BEFORE"]
    * (1 - df["WEIGHT"])
    )

## 9.2 Copmute the average unbiased CMF
cmf = (
    cmf_biased
    /
    (1 + (var_expected_after / df["EXPECTED_AFTER"].sum()**2))
    )

# Step 10 - Compute the overall unbiased safety effectiveness
# ---------------------------------------------------------------------------

safety_effectiveness = 1-cmf

# Step 11 - Compute the variance of the unibiased CMF
# ---------------------------------------------------------------------------
```

```
    variance_cmf = (
        (cmf_biased**2
        * (
            (1/df['OBSERVED_AFTER'].sum())
            + (var_expected_after / np.sum(df["EXPECTED_AFTER"])**2)
            )
        )
        /
        (1 + (var_expected_after / np.sum(df["EXPECTED_AFTER"])**2))
        )

    # Step 12 - Compute the standard error of the CMF
    # --------------------------------------------------------------------------

    std_error_cmf = np.sqrt(variance_cmf)

    # Step 13 - Compute the standard error of the safety effectiveness
    # --------------------------------------------------------------------------

    # std_error_safety_effectiveness = std_error_cmf

    return df, cmf, safety_effectiveness, std_error_cmf
```

APPENDIX E: CODE FOR EMPIRICAL BAYES COMPARISON GROUP BEFORE-AND-AFTER STUDY

The section presents a sample Python code of the developed functions for the comparison group EB before-and-after evaluation. In each case, only the core part of the code is shown, that is, excluding data entry and manipulation.

Function to predict the crashes in the before period for the treatment group.

```
def predict_before(df_before, spf, n_years):

    """Predict crashes in the before period.
    This function predicts crashes in the before period using a specified SPF.

    Parameters
    ----------
    df_before : pandas.DataFrame
        DataFrame containing information for the before period.
        It must have columns "RS_YEAR_INSTALL", "ID_NS".
    spf : function
        A function that takes two arguments: df (DataFrame) and year (int),
        and returns a DataFrame with crash predictions for the specified year.
    n_years : int
        Number of years in the before period.

    Returns
    -------
    pandas.DataFrame
        DataFrame with predicted crashes in the before period.
        It includes columns: "ID_NS", "RS_YEAR_INSTALL", <years_before>,
"CRASH_SUM".
        <years_before> represent individual years in the before period.

    """

    # Years in the before period
    years_before = np.arange(
        start = np.min(df_before.query("RS_YEAR_INSTALL !=0
")["RS_YEAR_INSTALL"].astype(int))-n_years,
        stop = np.max(df_before["RS_YEAR_INSTALL"].astype(int)),
        step = 1
    )

    # Empty dataframe to store the predicted crashes in the before period
    df_pred_before = pd.DataFrame(
        # number of rows
        index = range(
            len(df_before.index)
```

```
        ),
        # columns
        columns = [year for year in years_before],
    )

    # Add id to the predicted crashes data frame
    df_pred_before['ID_NS'] = df_before['ID_NS']

    # Predict the crashes in the before period
    for i, val in enumerate(years_before):
        # Iterate over each year in the before period

        # Predict the crashes in each site in each period
        df_pred_before.loc[:,val] = spf(df_before, val)

    # Add year of installation to the predicted crashes data frame
    df_pred_before["RS_YEAR_INSTALL"] = df_before["RS_YEAR_INSTALL"]

    # Tidy the predicted crashes data frame
    df_pred_before= pd.melt(
        df_pred_before,
        id_vars=['ID_NS', 'RS_YEAR_INSTALL'],
        var_name='CRASH_YEAR',
        value_name='CRASH_PRED'
    )

    # Fill in zeros for the years outside the period of analysis
    df_pred_before['CRASH_PRED'] = np.where(
        # Condition fro zero values
        df_pred_before['CRASH_YEAR'] <
(df_pred_before["RS_YEAR_INSTALL"].astype(int)-n_years),
        # Value if true
        0,
        # Value if false
        df_pred_before['CRASH_PRED']
    )

    df_pred_before['CRASH_PRED'] = np.where(
        # Condition fro zero values
        df_pred_before['CRASH_YEAR'] >=
df_pred_before["RS_YEAR_INSTALL"].astype(int),
        # Value if true
        0,
        # Value if false
        df_pred_before['CRASH_PRED']
    )

    # Un-tidy the predicted crashes data frame
    df_pred_before = df_pred_before.pivot(
        index='ID_NS',
        columns='CRASH_YEAR',
        values='CRASH_PRED'
    ).reset_index(drop=False)
```

```
    # Sum predicted crashes in the before period
    df_pred_before["CRASH_SUM"] = (
        df_pred_before[years_before]
        .sum(axis=1)
    )

    return(df_pred_before)
```

Function to predict crashes in the after period for the treatment group.

```
def predict_after(df_after, spf, n_years):

    """Predict crashes in the after period.
    This function predicts crashes in the after period using a specified SPF.

    Parameters
    ----------
    df_after : pandas.DataFrame
        DataFrame containing information for the after period.
        It must have columns "RS_YEAR_INSTALL", "ID_NS".
    spf : function
        A function that takes two arguments: df (DataFrame) and year (int),
        and returns a DataFrame with crash predictions for the specified year.
    n_years : int
        Number of years in the after period.

    Returns
    -------
    pandas.DataFrame
        DataFrame with predicted crashes in the after period.
        It includes columns: "ID_NS", "RS_YEAR_INSTALL", <years_after>,
"CRASH_SUM".
        <years_after> represent individual years in the after period.
    """

    # Years in the after period
    years_after = np.arange(
        start = np.min(df_after.query("RS_YEAR_INSTALL !=0
")["RS_YEAR_INSTALL"].astype(int))+1,
        stop = np.max(df_after["RS_YEAR_INSTALL"].astype(int))+n_years+1,
        step =1
    )

    # Empty dataframe to store the predicted crashes in the after period
    df_pred_after = pd.DataFrame(
        # number of rows
        index=range(
            len(df_after.index)
            ),
        # columns
        columns = [year for year in years_after],
```

```
    )

    # Add id to the predicted crashes data frame
    df_pred_after['ID_NS'] = df_after['ID_NS']

    # Predict the crashes in the after period
    for i, val in enumerate(years_after):
        # Iterate over each year in the after period

        # Predict the crashes in each site in each period
        df_pred_after.loc[:, val] = spf(df_after, val)

    # Add year of installation to the predicted crashes data frame
    df_pred_after["RS_YEAR_INSTALL"] = df_after["RS_YEAR_INSTALL"]

    # Tidy the predicted crashes data frame
    df_pred_after = pd.melt(
        df_pred_after,
        id_vars=['ID_NS', 'RS_YEAR_INSTALL'],
        var_name='CRASH_YEAR',
        value_name='CRASH_PRED'
        )

    # Fill in zeros for the years outside the period of analysis
    df_pred_after['CRASH_PRED'] = np.where(
        # Condition fro zero values
        df_pred_after['CRASH_YEAR'] >
(df_pred_after["RS_YEAR_INSTALL"].astype(int)+n_years),
        # Value if true
        0,
        # Value if false
        df_pred_after['CRASH_PRED']
        )

    df_pred_after['CRASH_PRED'] = np.where(
        # Condition fro zero values
        df_pred_after['CRASH_YEAR'] <=
df_pred_after["RS_YEAR_INSTALL"].astype(int),
        # Value if true
        0,
        # Value if false
        df_pred_after['CRASH_PRED']
        )

    # Un-tidy the predicted crashes data frame
    df_pred_after = df_pred_after.pivot(
        index='ID_NS',
        columns='CRASH_YEAR',
        values='CRASH_PRED'
        ).reset_index(drop=False)

    # Sum predicted crashes in the before period
    df_pred_after["CRASH_SUM"] = (
```

```
        df_pred_after[years_after]
        .sum(axis=1)
    )

    return(df_pred_after)
```

Function to predict crashes in the comparison group.

```
def predict_comp(df, spf, years):

    """Predict crashes in the comparison group for a specified period.
    This function predicts crashes for a specified period using a specified SPF.

    Parameters
    ----------
    df : pandas.DataFrame
        DataFrame containing information for the specified period.
        It must have the column "ID_NS" as the unique id of the road segment.
    spf : function
        A function that takes two arguments: df (DataFrame) and year (int),
        and returns a DataFrame with crash predictions for the specified year.
    years : list of int
        List of years to predict crashes for.

    Returns
    -------
    pandas.DataFrame
        DataFrame with predicted crashes for the specified years.
        It includes columns: "ID_NS", <years>, "CRASH_SUM".
        <years> represent individual years in the specified period.

    """

    # Empty dataframe to store the predicted crashes in the after period
    df_pred = pd.DataFrame(
        # number of rows
        index=range(
            len(df.index)
            ),
        # columns
        columns = [year for year in years],
    )

    # Add the ID
    df_pred['ID_NS'] = df['ID_NS']

    # Predict the crashes in the after period
    for i, val in enumerate(years):
        # Iterate over each year in the after period

        # Predict the crashes in each site in each period
        df_pred.loc[:, val] = spf(df, val)
```

```
    # Sum predicted crashes in the before period
    df_pred["CRASH_SUM"] = (
        df_pred[years]
        .sum(axis=1)
    )

    return(df_pred)
```

Function to prepare the data for the treatment group.

```
def agregate_crashes_treatment(df, crash_count, spf, n_years_before,
n_years_after):

    # Create data frame to store the results
    df_data = pd.DataFrame()
    df_data['ID_NS'] = df['ID_NS'].unique()

    # Observed crashes
    # ----------------

    # Count observed crashes in the before period
    df_temp = (
        df
        .query('BEFORE_AFTER_5Y == "Before"')
        .groupby(['ID_NS'], as_index=False)[crash_count].sum()
        )

    # Populate observed crashes at treatment sites in the before period
    df_data['OBS_BEFORE'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')[crash_count])
        )

    # Count observed crashes in the after period
    df_temp = (
        df
        .query('BEFORE_AFTER_3Y == "After"')
        .groupby(['ID_NS'], as_index=False)[crash_count].sum()
        )

    # Populate observed crashes at treatment sites in the before period
    df_data['OBS_AFTER'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')[crash_count])
        )

    # Predicted crashes
    # -----------------

    # Predict crashes in the before period
    df_temp = predict_before(
        # data frame filtered with only the unique road segments
        df_before = (
```

```
            df
            .drop_duplicates(subset=['ID_NS'])
            .reset_index(drop=True)
            ),
        # safety performance functions
        spf = spf,
        # number of years in the before period
        n_years=n_years_before
        )

    # Populate predicted crashes at treatment sites in the before period
    df_data['PRED_BEFORE'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')['CRASH_SUM'])
        )

    # Predict crashes in the after period
    df_temp = predict_after(
        # data frame filtered with only the unique road segments
        df_after = (
            df
            .drop_duplicates(subset=['ID_NS'])
            .reset_index(drop=True)
            ),
        # safety performance function
        spf = spf,
        # number of years in after period
        n_years=n_years_after
        )

    # Populate predicted crashes at treatment sites in the before period
    df_data['PRED_AFTER'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')['CRASH_SUM'])
        )

    return(df_data)
```

Function to prepare the data for the comparison group.

```
def agregate_crashes_comparison(
    df,
    aadt_list,
    year,
    slack,
    crash_count,
    years_before,
    years_after,
    spf
    ):

    """Aggregate crash data for treatment sites.
```

```
    Parameters
    ----------
    df : pandas.DataFrame
        DataFrame containing crash data.
    aadt_list : list of int
        List of AADT values to filter the comparison group.
    slack : float
        Percentage of slack to apply to the AADT values.
    crash_count : str
        Name of the column containing crash counts.
    years_before : list of int
        List of years in the before period.
    years_after : list of int
        List of years in the after period.
    spf : function
        A function that takes two arguments: df (DataFrame) and year (int),
        and returns a DataFrame with crash predictions for the specified year.

    Returns
    -------
    pandas.DataFrame
        DataFrame with aggregated crash data for treatment sites.
        It includes columns: "ID_NS", "OBS_BEFORE", "OBS_AFTER", "PRED_BEFORE",
"PRED_AFTER".

    Notes
    -----
    This function aggregates crash data for treatment sites, including observed
and predicted crashes.

    Examples
    --------
    >>> df = ...
    >>> crash_count = 'CRASH_COUNT'
    >>> query_treatment = 'TREATMENT == "Yes"'
    >>> def spf(df, year):
    ...     # Define spf function logic
    ...     return df_predictions
    >>> aggregate_crashes_treatment(df, crash_count, query_treatment, spf)
    """

    # Initialize an empty list to store the rows of df2 that meet the condition
    selected_rows = []

    # Iterate through each row in df2
    for index, row in df.iterrows():
        aadt_comparison = row[f'AADT_EF_{year}']

        # Check if aadt_df2 is within any range in df1
        for aadt in aadt_list:
            min_range = (1-slack) * aadt
            max_range = (1+slack) * aadt
```

```
        if min_range <= aadt_comparison <= max_range:
            selected_rows.append(row)

            break

# Create a DataFrame from the selected rows
df = pd.DataFrame(selected_rows)

# Create data frame to store the results
df_data = pd.DataFrame()
df_data['ID_NS'] = df['ID_NS'].unique()

# Observed crashes
# ----------------

# Count observed crashes in the before period
df_temp = (
    df
    .query('CRASH_YEAR in @years_before')
    .groupby(['ID_NS'], as_index=False)[crash_count]
    .sum()
    )

# Populate observed crashes at treatment sites in the before period
df_data['OBS_BEFORE'] = (
    df_data['ID_NS']
    .map(df_temp.set_index('ID_NS')[crash_count])
    )

# Count observed crashes in the after period
df_temp = (
    df
    .query('CRASH_YEAR in @years_after')
    .groupby(['ID_NS'], as_index=False)[crash_count]
    .sum()
    )

# Populate observed crashes at treatment sites in the before period
df_data['OBS_AFTER'] = (
    df_data['ID_NS']
    .map(df_temp.set_index('ID_NS')[crash_count])
    )

# Predicted crashes
# -----------------

# Predict crashes in the before period
df_temp = predict_comp(
    # data frame filtered with only the unique road segments
    df = (
        df
        .drop_duplicates(subset=['ID_NS'])
```

```
            .reset_index(drop=True)
            ),
        # safety performance functions
        spf = spf,
        # years in the before period
        years = years_before
        )

    # Populate predicted crashes at treatment sites in the before period
    df_data['PRED_BEFORE'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')['CRASH_SUM'])
        )

    # Predict crashes in the after period
    df_temp = predict_comp(
        # data frame filtered with only the unique road segments
        df = (
            df
            .drop_duplicates(subset=['ID_NS'])
            .reset_index(drop=True)
            ),
        # safety performance function
        spf = spf,
        # years in after period
        years = years_after
        )

    # Populate predicted crashes at treatment sites in the before period
    df_data['PRED_AFTER'] = (
        df_data['ID_NS']
        .map(df_temp.set_index('ID_NS')['CRASH_SUM'])
        )

    return df_data
```

Function to compute the CMF.

```
def compute_cmf_comparison_group_eb(
        df_treatment,
        df_comparsion,
        n_treatment_before,
        n_treatment_after,
        n_comparsion_before,
        n_comparsion_after
        ):

    """ Compute CMF with empirical Bayes comparison group method.

    This functions computes the Crash Modification Factor (CMF) and its Standard
    Error (SE) using the empirical Bayes comparison group method.

    Parameters:
        df_treatment (DataFrame): Data for treatment sites.
```

```
    df_comparison (DataFrame): Data for comparison sites.
    n_treatment_before (int): Number of years before in the treatment sites.
    n_treatment_after (int): Number of years after in the treatment site.
    n_comparison_before (int): Number of years before in the comparison sites.
    n_comparison_after (int): Number of years after in the comparison sites.

Returns:
    tuple: A tuple containing:
        - CMF (float): The Crash Modification Factor.
        - SE_CMF (float): The Standard Error of the CMF.
"""

# Step 3a - before adjustment factor comparsion sites
adj_factor_before = np.matmul(
    df_comparsion[['PRED_BEFORE']].to_numpy()**-1,
    np.transpose(df_treatment[['PRED_BEFORE']].to_numpy())
    )* (n_treatment_before/n_comparsion_before)

# Step 3b - after adjustment factor comparsion sites
adj_factor_after = np.matmul(
    df_comparsion[['PRED_AFTER']].to_numpy()**-1,
    np.transpose(df_treatment[['PRED_AFTER']].to_numpy())
    )* (n_treatment_after/n_comparsion_after)

# Step 4a - before expected average crash frequency for copmarsion sites
expected_before = np.multiply(
    df_comparsion[['OBS_BEFORE']].to_numpy(),
    adj_factor_before
    )

# Step 4b - after expected average crash frequenc for comparsion sites
expected_after = np.multiply(
    df_comparsion[['OBS_AFTER']].to_numpy(),
    adj_factor_after
    )

# Step 5 - total expected comparsion-group crash frequency before
# total_expected_before = expected_before.sum(axis=0)
total_expected_before = np.nansum(expected_before, axis=0)

# Step 6 - total expected comparsion-group crash frequency after
# total_expected_after = expected_after.sum(axis=0)
total_expected_after = np.nansum(expected_after, axis=0)

# Step 7 - comparsion ratio (r) for each treatment site
r = total_expected_after/total_expected_before

# Step 8 - expected average crash frequency for treatment sites
# in the after period, had no treatment been implemented
expected_treatment_after = df_treatment['OBS_BEFORE'].to_numpy() * r

# Step 9 - cmf for each site
```

```python
    cmfs = np.where(
        # Condition: denomitar diferent than 0
        expected_treatment_after != 0,
        # If true: compute the cmf
        df_treatment['OBS_AFTER'] / expected_treatment_after,
        # If false: fill with nan
        np.nan
        )

    # Convert CMF = 0 to nan to avoid indeterminations in Ln(cmf)
    cmfs[cmfs==0] = np.nan

    # Step 10 - ln(cmfs)
    ln_cmfs = np.log(cmfs)

    # Handle inf values
    # ln_cmfs[np.isinf(ln_cmfs)] = np.nan

    # Step 11 - weigth for each site
    sqr_se_ln_cmfs = (
        np.where(df_treatment['OBS_BEFORE'] != 0, 1/df_treatment['OBS_BEFORE'],
np.nan) +
        np.where(df_treatment['OBS_AFTER'] != 0, 1/df_treatment['OBS_AFTER'],
np.nan) +
        np.where(total_expected_before != 0, 1/total_expected_before, np.nan) +
        np.where(total_expected_after != 0, 1/total_expected_after, np.nan)
    )

    w = 1/sqr_se_ln_cmfs

    # Step 12 - Ln(CMF) - weigthed average ln cmf for treatment sites
    ln_CMF = np.nansum(w*ln_cmfs)/np.nansum(w)

    # Step 13 - CMF
    CMF = np.exp(ln_CMF)

    # Step 14 - safety effectivenes

    # Step 15 - SE
    SE_CMF = CMF/np.sqrt(np.nansum(w))
    return(CMF, SE_CMF)
```

BIOGRAPHY OF THE AUTHOR

Jhan Kevin Gil Marin was born and raised in Medellin, Colombia on November 5, 1996. He graduated from High School at I.E. INEM Jose Felix de Restrepo in 2013. He attended the Universidad Nacional de Colombia and graduated in 2021 with a bachelor’s degree in civil engineering. Then he began his Master of Science in Civil Engineering at the University of Maine in the Spring 2022 session. After receiving his degree, Jhan plans to do a PhD. Jhan is a candidate for the Master of Science degree in Civil Engineering from the University of Maine in December 2023.