Developing Crash Modification Factors for Wrong-Way-Driving Countermeasures

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FOREWORD

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

This report documents the evaluated safety effectiveness of wrong-way-driving (WWD) crash countermeasures at freeway ramps and frontage roads. This study focused on the safety effectiveness of geometric features, access management strategies, and traffic control devices (TCDs) from various sites in Texas and in Florida. The analysis found statistically significant CMFs for each countermeasure type. The economic evaluation of the countermeasures determined moderate B/C ratios with values greater than 1.0. These study results may be of interest to roadway safety professionals, State and local engineers, and planners responsible for the design, operation, and maintenance of facilities that may have crash risks for WWD.

Brian P. Cronin, P.E.
Director, Office of Safety and Operations
Research and Development

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<tr><td colspan="4">16. Abstract
This study evaluated wrong-way-driving (WWD) crash countermeasures at freeway ramps and frontage roads. Specifically, the study focused on the safety effectiveness of geometric features, access management strategies, and traffic control devices (TCDs) that are potential WWD crash countermeasures. The research team compiled safety data representing 2,722 locations for evaluation in Texas and 697 in Florida. Due to the limited number of WWD crashes identified for the most recent 3-yr periods in each State (375 in Texas and 110 in Florida), the evaluations were carried out only differentiating between daytime and nighttime crashes. A two-phase analysis methodology was developed to combine information from a subset of crashes with known points of WWD maneuvers and data collected in a larger area, including crashes where only potential points of entry were available. Statistically significant crash modification factors (CMFs) were found for three types of countermeasures: geometric features, access management strategies, and TCDs. These analyses found statistically significant CMFs, indicating increased crash risk at locations with more ramps or ramp lanes and at frontage road locations with a higher number of access points. Statistically significant CMFs were also found that indicated reduced crash risks were associated with longer ramps and with longer distances from freeway exits at frontage roads and crossing roads. These analyses also produced statistically significant CMFs, indicating reduced crash risks were associated with adding vertical signage to access points at frontage roads. Similarly, this project found statistically significant CMFs that indicated reduced crash risk at signalized locations, locations displaying more WRONG WAY (WW) signs and DO NOT ENTER (DNE) signs, and locations where pavement markings for the paths of turning lanes were present. The economic evaluation of deploying WW and DNE signs found moderate benefit–cost ratios with values greater than 1.0, indicating that because these countermeasures are expected to produce more safety benefits than costs, their installation is justified.</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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

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LIST OF ABBREVIATIONS AND ACRONYMS

AADT	annual average daily traffic
AASHTO	American Association of State Highway and Transportation Officials
B/C	benefit–cost
CL	confidence level
CMF	crash modification factor
CRIS	Crash Records Information System
D	distance
DCMF	Development of Crash Modification Factors
DNE	DO NOT ENTER
DOT	department of transportation
ELCSI-PFS	Evaluation of Low-Cost Safety Improvements Pooled Fund Study
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GIS	geographic information system
GLM	generalized linear model
GLMM	generalized linear mixed model
LED	light-emitting diode
NCHRP	National Cooperative Highway Research Program
OW	ONE WAY
PFS	Pooled Fund Study
ph-1 risk	WWD crash risk as a function of POE geometry, time of day, and position of the POE relative to the WWD crash location
POE	point of entry
PS	propensity score
PSW	propensity score weighting
RFB	rectangular flashing beacon
RRFBs	rectangular rapid flashing beacons
RHiNo	Roadway-Highway Inventory
ROC	receiver operating characteristic
SPF	safety performance function
TCD	traffic control device
USDOT	U.S. Department of Transportation
VIF	variance inflation factor
WW	WRONG WAY
WWD	wrong-way driving

EXECUTIVE SUMMARY

The Federal Highway Administration's (FHWA) Development of Crash Modification Factors (DCMF) program was established in 2012 (FHWA 2022a). The program was designed to address highway-safety research needs and evaluate new and innovative safety strategies (improvements). To meet these goals, the program works to develop reliable, quantitative estimates of the effectiveness of these strategies in reducing crashes.

The ultimate goal of the FHWA DCMF program "is to save lives by identifying new safety strategies that effectively reduce crashes and promote strategies for nationwide installation by providing measures of their safety effectiveness" (FHWA 2022a). These measures include the following features:

- **Crash modification factors (CMFs):** Multiplicative factors used to compute the expected number of crashes after an improvement has been installed at a location.
- **Benefit–cost (B/C) ratios:** The relationship between the benefits and cost of a proposed improvement.

State departments of transportation (DOTs) and other transportation agencies need to have CMFs to evaluate the safety effectiveness of new strategies and B/C ratios before investing in these new strategies for statewide safety improvements.

The DCMF program gathers technical feedback from 41 State DOTs on safety improvements. These DOTs also implement new safety improvements that facilitate evaluations. These States are members of the Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS) (FHWA 2022b), which functions under the DCMF program.

The ELCSI-PFS Technical Advisory Committee selected evaluating the effects of wrong-way-driving (WWD) countermeasures as one of the ELCSI-PFS priorities. This report documents the evaluation of the safety effects of these strategies to prevent WWD, including the following concepts:

- **Geometric features:** The presence of an off-ramp, frontage road, U-turn lane, etc.
- **Access management strategies:** Processes and technologies used to control access to major roadways.
- **Traffic control devices (TCDs):** Markings, signs, and signal devices that inform, guide, and control traffic.

CMFs and B/C ratios were developed for the safety improvement strategies of interest. Practitioners can use these CMFs and B/C ratios during project development and safety planning to make decisions about which of these strategies would be beneficial.

The CMF study results are as follows:

- **Geometric features:** This study found statistically significant CMFs in Texas and Florida. The results indicated nighttime crash reductions for each ramp or ramp lane that was removed from intersections with off-ramps intersecting cross streets in Florida (0.489 CMF). This CMF indicates that removing ramp lanes or reconfiguring ramps so that fewer ramp lanes are at a given intersection with surface roads could have safety benefits. Similarly, this study produced a CMF of 0.972 for each additional 100 ft of off-ramp length. This CMF indicates that longer lengths should be given preference when constructing or relocating ramps.

- **Access management:** An analysis of the Texas sites with points of entry at frontage roads produced CMFs of 0.873 and 0.925 (daytime and nighttime, respectively) for each removed driveway in a frontage road between off-ramps and crossing roads. This result means that WWD crash reductions of 12.7 percent during the daytime (CMF = 0.873) and 7.5 percent during the nighttime (CMF = 0.925) are expected for each such driveway removed.

- **TCDs:** This study found CMFs indicating WWD crash reductions associated with adding WRONG WAY (WW) signs (CMF = 0.509 for frontage roads intersecting divided cross streets, and CMF = 0.153 at frontage roads intersecting undivided roads) and DO NOT ENTER (DNE) signs (CMF = 0.321 during the daytime and 0.640 during the nighttime at intersections, including off-ramps in Texas, and 0.729 for daytime in Florida). The study also found significant benefits for pavement markings for turning lane paths and for stop bars present on frontage road approaches when intersecting crossing roads (CMFs ranging from 0.129 up to 0.416 in Texas).

The economic evaluation of deploying additional WW and DNE signs found large B/C ratios (29.08 and 55.7, respectively). This result indicates that these countermeasures are expected to produce more safety benefits than costs. Therefore, their installation is justified.

CHAPTER 1. INTRODUCTION TO SAFETY EVALUATION OF WRONG-WAY-DRIVING (WWD) CRASHES AT FREEWAYS

WWD crashes represent a small portion of the total crashes on freeways and highways, but because most of these crashes are higher-speed, head-on collisions, they result in more fatalities than do other crash types.

Multiple past efforts have documented implementation and testing of various strategies and devices to reduce wrong-way movements. Researchers have studied four main types of countermeasures:

- Geometric design elements, such as channelization and access management strategies.
- Conventional traffic control devices (TCDs), such as signs, pavement markings, and signals.
- Enhanced TCDs, such as oversized signs, additional signs, low-placed signs, and retroreflective strips on signposts.
- Intelligent transportation system strategies, including detection, active warning, and driver notification components.

This study focused on evaluating the effectiveness of TCDs, enhanced TCDs, access management, and geometric design elements.

REVIEW OF LITERATURE

WWD crashes occur as a result of one or more vehicles traveling in the opposite direction of the legal traffic flow. The act of driving in the opposite direction might be intentional or unintentional, but the definition of WWD crashes excludes crashes resulting from median crossover encroachment (FHWA 2019).

In the United States, WWD crash studies were conducted as early as the 1960s in States such as California (Tamburri and Theobald 1965). However, in the early 2000s, WWD crash studies gained attention from researchers in the United States and internationally. To date, several States, including Texas, California, Virginia, Michigan, North Carolina, Florida, Alabama, Indiana, Kansas, and Arizona, have conducted research related to WWD crashes (Zhang, Pour-Rouholamin, and Zhou 2016; Copelan 1989; Vaswani 1973; Cooner, Cothron, and Ranft 2004; Finley et al. 2014; Scifres and Loutzenheiser 1975; Fitzsimmons et al. 2019). Studies of WWD crashes from other countries include Japan, France, and the Netherlands (Xing 2013; Kemel 2015; Stichting Wetenschappelijk Onderzoek Verkeersveiligheid (Institute for Road Safety Research) 2007).

In general, past studies show that WWD crashes normally represent a small percentage of all crashes. The special investigation performed by the National Transportation Safety Board (NTSB) (2012) reported that WWD crashes normally make up less than 3 percent of all crashes. Likewise, studies from several States, including Texas, California, and Virginia, have revealed that WWD crashes account for less than 1 percent of all crashes (Cooner, Cothron, and Ranft 2004; Copelan 1989; Vaswani 1973). These crashes, however, tend to be more severe due to the collisions often being head-on (Vaswani 1973, 1977; Cooner, Cothron, and Ranft 2004; Finley et al. 2014; Tamburri and Theobald 1965).

WWD Crash Severity

Statistics show that WWD crashes are more likely to be fatal because most are head-on and involve higher speeds. On average, WWD crashes result in 300–400 fatalities in the United States annually (FHWA 2019). Tamburri and Theobald (1965) reviewed 4 yr of crash data (1961–1964), totaling about 1,200 wrong-way events in California, and found that WWD crashes are as much as 6 times more likely to result in fatalities. Two other studies from Virginia reported even higher chances for fatalities associated with WWD crashes (Vaswani 1973, 1977). The initial 2-yr (1970–1971) study revealed WWD crashes tend to result in fatalities about 30 times more often than general crashes (Vaswani 1973). The second, longer-term study (19701976) examined 114 WWD crashes and found a slightly higher fatality ratio of 31 times more than general crashes (Vaswani 1977).

Since the 1970s, several countermeasures have been developed and installed to deter WWD crashes, but the increased likelihood for crash fatalities has remained mostly unchanged. More recent studies in Texas, Arizona, Alabama, Michigan, and Kansas have revealed relatively similar ratios of fatalities as previous studies (Zhang 2017; Finley et al. 2014; Morena and Leix 2012; Fitzsimmons et al. 2019). A study in Michigan reviewed 110 WWD crashes that occurred between 2005 and 2009 and found that the percentage of fatalities was as high as 32 percent in WWD crashes in comparison to 2 percent in general crashes (Morena and Leix 2012). A 10-yr (2004–2014) study in Arizona revealed that although only 1 percent of total crashes was fatal, about 25 percent of all WWD crashes were fatal (Simpson and Bruggeman 2015). Similarly, in an Alabama study, the chance of a fatal crash was estimated to be about 21 times greater for WWD crashes than for general crashes (Zhang 2017). The study in Alabama also found that for a 5-yr period (2009–2013), the proportion of fatal crashes was 0.6 percent for all crashes and 12.5 percent for WWD crashes. Furthermore, a Kansas-based study estimated the ratio of combined fatal and serious injury crashes was nearly 2.5 times greater for WWD crashes than for general crashes (Fitzsimmons et al. 2019).

These findings are not limited to data from the United States. One study in France found that WWD crashes are six times more likely to be fatal than other crash types (Kemel 2015).

Crash-Prone Locations

The locations and characteristics of WWD crashes are crucial elements for evaluating the strategies to position potential countermeasures. A literature review revealed the following categories for crash locations:

- Land use setting (rural versus urban).
- Facility type (freeway versus arterial).
- Location within the facility (ramp, intersection, midblock, or main lanes).
- Location with respect to the travel lane (turning lane, through lane, left lane, etc.).

Land Use Setting

Studies show that WWD crashes are more likely to occur in urban areas. According to one nationwide study, 57 percent of WWD crashes occurred in urban areas (Baratian-Ghorghi, Zhou, and Shaw 2014). In one statewide study for Arizona, the results were slightly lower than at the national level, with approximately 53 percent of WWD crashes occurring in urban areas (Simpson and Bruggeman 2015). However, the study also revealed that the WWD crashes per mile was 0.667 for urban freeways compared to 0.214 for rural freeways. In contrast, one statewide study for Illinois reported a higher result than at the national level, with approximately 80 percent of all WWD crashes occurring in urban areas (Zhou et al. 2012).

Facility Type

In an early study in California, approximately 64 percent (763 out of 1,200 crashes) and approximately 28 percent (354 out of 1264 crashes) occurred on freeways and expressways, respectively (Tamburri and Theobald 1965). Without expressing the exact percentages, Copelan (1989) found that the urban setting had a greater proportion of WWD crashes from 1983 to 1987. The North Carolina Department of Transportation (NCDOT) found a relatively lower percentage of WWD crashes on freeways in North Carolina: The study revealed that for a 6-yr period (2000–2005), the average prevalence of WWD crashes on freeways was approximately 72 percent (NCDOT 2006).

In contrast, a Virginia study reported only approximately 41 percent of WWD crashes on freeways (Vaswani 1977). Similarly, two recent studies in Florida concluded that more WWD crashes were observed on nonlimited facilities (arterial roadways) (Ponnaluri 2016, 2017). The studies used 8 yr (2003–2010) of Florida crash data, which revealed that approximately 88 percent of WWD crashes occurred on arterial roadways, with approximately 65 percent of these crashes observed on divided roadways (Ponnaluri 2016).

Location Within the Facility

Several studies have explained the difficulty in determining the origin of the WWD vehicle (Morena and Leix 2012; Lathrop, Dick, and Nolte 2010; Zhou et al. 2012). In general, relying solely on the crash data, which often lack important details not typically collected during crash investigation, is a major barrier to determining the origin of a WWD vehicle (Lathrop, Dick, and Nolte 2010; Morena and Leix 2012). For instance, studies that relied on crash reports were able to track only approximately 24 percent (12 out of 49) and approximately 28 percent (31 out of 110) of WWD crashes to their point of entry (POE) (Lathrop, Dick, and Nolte 2010; Morena and Leix 2012). However, recent technological improvements have led to better results for identifying POEs, such as an Iowa study that used high-definition radar and video analysis to correctly identify the origin of approximately 68 percent of 51 WWD events (Athey Creek Consultants 2016).

Studies that identified the origin of WWD crashes on freeways have revealed that the following sites are the main locations where wrong-way traveling vehicles originate (Lathrop, Dick, and Nolte, 2010; Morena and Leix 2012; Zhou et al. 2012; Kayes et al. 2019a):

- Entrance and exit ramps.
- U-turns.
- Partial cloverleafs.
- Diamond interchanges.
- Incomplete or partial interchanges.
- Compressed diamond interchanges.

Exit ramps accounted for 5 out of 10 WWD crashes in New Mexico and 31 out of 110 in Michigan (Lathrop, Dick, and Nolte 2010; Morena and Leix 2012). Two recent studies added several characteristics of exit ramps that are associated with WWD vehicle entry (Kayes et al. 2019a; Atiquzzaman and Zhou 2018):

- Exit ramps with obtuse or right angles.
- Exit ramps with channelized islands between lanes.
- Exit ramps that have multiple lanes.

One of these two studies, Kayes et al. (2019a) also found that entrance ramps with tollbooths accounted for only 12.6 percent of all WWD in the study, but the statistical analysis found this proportion statistically significant among WWD entries.

Partial cloverleaf interchanges represented approximately 61 percent of 31 crashes in Michigan and approximately 11 percent of 47 crashes in Illinois (Morena and Leix 2012; Zhou et al. 2012). In addition, the presence of a U-turn accounted for approximately 33 percent (4 out of 12) and approximately 30 percent of crashes in New Mexico and Michigan, respectively (Lathrop, Dick, and Nolte 2010; Morena and Leix 2012).

On four-lane divided highways, the following are the main locations of origin for WWD vehicles (Tamburri and Theobald 1965; Vaswani 1977; Athey Creek Consultants 2016):

- Intersections with and without median openings.
- Intersections with crossover/ramps connecting freeways.
- Medians.
- U-turns.

Among these locations, one study showed that intersections with median openings represent the largest percentage (approximately 50 percent), followed by locations with medians (approximately 19 percent) and U-turns (approximately 10 percent) (Tamburri and Theobald 1965). However, a later study found U-turn locations only represented approximately 20 percent of crashes, whereas intersections with cross streets or ramps connecting to freeways represented approximately 40 percent of crashes (Vaswani 1977). Driveways from business establishments accounted for approximately 25 percent of crashes (Vaswani 1977).

Location with Respect to the Travel Lane

Studies also show that a large proportion of crashes on freeways occur in the travel lanes, specifically in the left lane of the correct direction of travel (Cooner, Cothron, and Ranft 2004; Morena and Leix 2012; NTSB 2012; Xing 2013). One study showed that approximately 51 percent of crashes occurred in the left-most lane (close to the median), approximately 20 percent in the right lane, approximately 16 percent in the middle lane, and approximately 8 percent on the shoulder (Zhou et al. 2012). Similar trends were observed on arterial divided highways (Athey Creek Consultants 2016; Finley et al. 2018).

Demographics in WWD Crashes

Age

Regarding the age of the drivers, the literature suggests that older drivers are overrepresented in WWD crashes compared with their share in all-freeway crashes, but younger drivers represent a larger overall share of all WWD crashes (Lew 1971; Pour-Rouholamin et al. 2016; Zhang, Pour-Rouholamin, and Zhou 2016; Baratian-Ghorghi, Zhou, and Shaw 2014; NTSB 2012; Kittelson & Associates, Inc. 2015). A few studies reported that young drivers could also be overrepresented, similarly to older drivers (Lew 1971; Institute for Traffic Accident Research and Data Analysis 2002).

Gender

The reviewed literature—regardless of the country/State of origin, geographical coverage, or study sample size—consistently showed that male drivers are more likely to be involved in WWD crashes than female drivers (Tamburri and Theobald 1965; Pour-Rouholamin et al. 2016; Baratian-Ghorghi, Zhou, and Shaw 2014; Kemel 2015). The gender representation in WWD crashes has remained unchanged over the decades, as both older and more recent works indicate (Tamburri and Theobald 1965; Pour-Rouholamin et al. 2016). Other countries also show a similar composition of males in WWD crashes. For example, a study in France reported 75 percent of WWD drivers were male (Kemel 2015).

Occupants of WWD and Right-Way Vehicles

Lathrop, Dick, and Nolte (2010) provided a detailed analysis of the characteristics of WWD crashes' vehicle occupants. According to their study, between 1990 and 2004, 26 passengers (approximately 33 percent of all people involved in crashes) died in WWD crashes in New Mexico. Among the fatalities, 11 were in the WWD vehicle, while 15 were in the right-way vehicle.

Time

The literature shows that WWD crashes are more likely to occur on weekends and at nighttime. A nationwide study revealed that approximately 57 percent of WWD crashes occur on weekends, whereas 78 percent of all crashes occur at nighttime (NTSB 2012). Two studies concluded that the odds of WWD crashes during nighttime are five times more likely than WWDs during daytime (Cooner, Cothron, and Ranft 2004; Finley et al. 2014). However, studies differ in the distribution of nighttime crashes. One study revealed that most crashes happen between 6:00 p.m. and midnight, whereas other studies reported the range for most crashes as between midnight and 6:00 a.m. (Zhang, Pour-Rouholamin, and Zhou 2016; Cooner, Cothron, and Ranft 2004; Finley et al. 2014). Finley et al. (2014) and Copelan (1989) both reported that the nighttime peak for WWD crashes was at 2:00 a.m. According to Copelan (1989), the daytime peak was observed at 11:00 a.m. Furthermore, the same study presented statistics showing that daytime crashes involved more older drivers than younger drivers; the opposite was true for nighttime crashes.

The time elapsed between the moment the WWD vehicle was reported and/or the WWD crash occurred and the response time to the WWD event has recently been researched by using 911 calls and citations for WWD vehicles, which were incorporated into WWD crash investigations (Finley et al. 2018; Sandt, Al-Deek, and Roger 2017; Kayes et al. 2019a, b). A study in Florida found that the median durations for 911 calls, citations, and crashes were 20 min, 54 min, and 122 min, respectively (Sandt, Al-Deek, and Roger 2017). Likewise, studies in San Antonio, TX, and South Florida had relatively similar durations of 911 calls (Finley et al. 2018). In this study, most calls lasted for less than 15 min, peaking at less than 1 min. However, the frequency of 911 calls that lasted for more than 15 min was higher for South Florida (26 percent) than for San Antonio, TX (5 percent).

Distance

Finley et al. (2018) also evaluated the distance covered by the WWD vehicle before crash occurrence and estimated the distance based on multiple 911 calls of the same WWD event at different times for the data collected from San Antonio, TX, and South Florida. The study found that the longest distances for San Antonio, TX, and South Florida were 14 mi and more than 15 mi, respectively. The trend for other distances was relatively similar except that the peak distance was less than 1 mi for San Antonio, TX, and 2 mi for South Florida.

Other Characteristics of WWD Crashes

This section presents additional relevant characteristics of WWD crashes.

Driver Impairment

The association between driver impairment and WWD crashes is well documented in the literature. Many studies have focused on driving under the influence of alcohol, whereas a few other studies have focused on drug impairment. All the reviewed literature supports that driver impairment likely plays a significant role in WWD involvement and resulting crashes. Studies reported varying rates of impaired drivers in WWD crashes. Rates include:

- Approximately 30 percent in Washington State (Tamburri and Theobald 1965).
- Approximately 45 percent in Florida (Kittelson & Associates, Inc. 2015).
- Approximately 48 percent in North Carolina (NCDOT 2006).
- Approximately 50 percent in Alabama and Illinois (Pour-Rouholamin et al. 2016; Zhou et al. 2012).
- Approximately 53 percent in Virginia (Vaswani 1977).
- Approximately 55 percent in Indiana (Scifres and Loutzenheiser 1975).
- Approximately 60 percent in Michigan and California (Morena and Leix 2012; Copelan 1989).
- Approximately 61 percent in Texas (Cooner, Cothron, and Ranft 2004).
- Approximately 63 percent in New Mexico (Lathrop, Dick, and Nolte 2010).
- Approximately 65 percent in Arizona (Simpson and Bruggeman 2015).
- Approximately 90 percent in Texas (Finley et al. 2014).

Estimates from nationwide studies show approximately 58 percent and approximately 60 percent of WWD crashes involved impaired drivers (Baratian-Ghorghi, Zhou, and Shaw 2014; NTSB 2012). However, one study in the Netherlands reported relatively lower rates (Stichting Wetenschappelijk Onderzoek Verkeersveiligheid (Institute for Road Safety Research) 2007).

Multivehicle Crashes

Among the reviewed research, only one study found that a majority of WWD crashes (approximately 87 percent) are multivehicle crashes (Morena and Leix 2012). This finding implies that most WWD crashes involve a vehicle colliding with another vehicle traveling in the correct direction.

TCDs

A recent study on divided highways found that four strategies appear to deter WWD movements (Finley et al. 2018).

- DO NOT ENTER (DNE) and WRONG WAY (WW) signs on the outside of a wrong-way turn.
- Wrong-way arrow markings for the through lanes on the divided highway.
- The presence of a centerline in the median opening.
- Stop or yield lines when interior right-of-way treatments are provided.

These strategies could also be effective at preventing WWD events at high-speed divided highways and freeways.

Other countermeasures of the interest to researchers are flashing-based countermeasures, which include light-emitting diode (LED) signs and red rectangular flashing beacon (RFB) signs. Ozkul and Lin (2017) reviewed public opinion surveys and video data collected from six I–275 off-ramps in Tampa, FL, and found that the red rectangular rapid flashing beacons (RRFBs) are effective countermeasures to WWD incidents. According to their 6-mo video data, between 60 and 85 percent of the WWD vehicles performed corrective maneuvers when the red RRFBs were activated. Kayes, Al-Deek, and Sandt (2020) found the percentage of self-corrected drivers was higher for RFB signs (69.4 percent) than for LED signs (48.1 percent) compared to ramps with non-flashing WWD countermeasures. Another study, which compared the performance of two countermeasures for WWD—LED signs and RFB signs on I–70 in Florida—found that more than 77 percent of the WWD incidents at the sites with RFB self-corrected, whereas only approximately 14 percent of the incidents self-corrected at sites with LED (Kayes et al. 2018).

Lin et al. (2018) evaluated the effectiveness of a range of countermeasures by using incident data, a public opinion survey, and a simulation analysis. Among the evaluated countermeasures, the RRFBs were the most effective, followed by wigwag flashing beacons, detection-triggered blank-out signs, and detection-triggered LED lights around WW signs. In contrast, red flush-mount internally illuminated raised pavement markers were only significant as an additional countermeasure.

CHALLENGES IN ASSESSING THE SAFETY EFFECTS OF WWD COUNTERMEASURES

The focus of this evaluation is on WWD countermeasures commonly used in the United States. The main challenge for developing crash modification factors (CMFs) for WWD countermeasures is relatively small and often incomplete datasets for WWD crashes. Given current reporting and investigation practices, crash data are collected at the location of the crash, but in the case of WWD crashes, that location could be miles away from the location where countermeasures could be applied.

A recently finished National Cooperative Highway Research Program (NCRHP) study (NCHRP Project 03-117 as summarized in NCRHP Report 881) concluded that no one TCD can reduce wrong-way movements across all roadway types (e.g., high-speed rural divided highways, high-speed urban divided highways, and freeways) (Finley et al. 2018).

In addition to these relevant WWD countermeasures, this study considered other promising countermeasures (e.g., changing median width and median openings and using stop and yield signs and appropriate pavement markings) that can be identified at locations with sufficient WWD crash data available for evaluation. Many agencies struggle to accurately quantify the WWD problem and identify locations more prone to wrong-way movements due to the limited number of crashes and lack of information about where the wrong-way movements originate. In addition, determining the effectiveness of wrong-way countermeasures is challenging because of the random nature of wrong-way crashes, lack of data before the countermeasures were implemented, inconsistency in countermeasure deployment, simultaneous installation of multiple countermeasures, and lack of agency resources in general.

SAFETY EFFECTIVENESS ASSESSMENT OF WWD COUNTERMEASURES

Early in this project, the focus of the effort was narrowed to potentially evaluating countermeasures in two facility types: freeways and multilane divided highways. The research team determined that identifying the POEs for WWD maneuvers that resulted in crashes would be key.

Finley et al. (2018) developed a database for multilane highways to collect and store detailed POE information as needed for this research. This dataset represented three States (Texas, California, and Florida) but only had 358 segments with a known history of WWD crashes with their corresponding POEs. For these three States combined, a total of 409 WWD crashes for a 3-yr period were available for analysis. The most common types of POE for WWD crashes at multilane divided highways were three- and four-legged intersections with median openings, in both rural and urban environments.

In the feasibility stage of the project, the Federal Highway Administration (FHWA) requested the focus of the evaluation be placed on freeway facilities. Typically, this facility type carries significantly more traffic than highways, with higher expectation of WWD crash frequencies at higher speeds as well. Therefore, the study would address a larger portion of the WWD problem, in both crash frequency and severity. In addition, these facilities would potentially yield more data for the evaluation.

The data elements and data collection protocol required for this evaluation would be similar to the model used for the past evaluation of divided highways and would now include the following ramp-specific characteristics and applicable countermeasures:

- Geometric design elements.
- Access management around freeway on-ramps and intersections between ramps and cross streets.
- Conventional static TCDs (signs and pavement markings).
    - DNE signs.
    - WW Signs.
    - Stop lines at exit ramps that connect directly to surface streets.
    - Left-turn pavement marking guides at intersections.
    - Painted islands between exit and entrance ramps.
    - Delineators along exit ramps.
    - Green straight arrow signal indications.

This dataset was expected to support an evaluation of geometric design alternatives, access management strategies, and conventional TCDs for the most part. The evaluation of enhanced TCDs was not discarded in the initial stages, but the research team later determined that the portion of locations having these countermeasures was insufficient for a robust statistical evaluation.

CHAPTER 2. STUDY DESIGN AND METHODOLOGY

The study design needed to account for multiple features and overcome the particular challenges anticipated from a safety evaluation of WWD crashes as described in the previous chapter. A proper study design can significantly maximize the chances of obtaining meaningful, quality results. Generally speaking, safety studies rely on observational data because randomization is not possible, and true experiments, such as randomized control group experiments in which injury or death is a potential outcome, are not feasible or ethical. This study is no exception. However, a good observational study should be consistent with key elements of control group experiments to the extent possible. Building a dataset that represents both treated and nontreated sites is one such element, as is an account of key confounding variables.

This study initially investigated the feasibility of a quasi-experimental design, such as the use of a nonequivalent comparison group or a control series design (e.g.,Campbell and Stanley 1966; Campbell and Ross 1968). However, in the case of evaluating the safety potential of WWD countermeasures, obtaining a large before–after dataset representing multiple jurisdictions was deemed infeasible after reviewing potential data sources. Therefore, a cross-sectional analysis was proposed for this evaluation. The selection of jurisdictions was driven mostly by the potential to produce a dataset large enough for a robust safety analysis. The following sections provide details on the study design and the data elements collected for this evaluation.

STUDY DESIGN

Cross-Sectional Versus Longitudinal Evaluation

Longitudinal study designs (e.g., before–after) are preferred when developing CMFs because of their ability to effectively account for site-to-site variability, biases due to omitted variables, and regression to the mean if a large reference group (or a representative safety performance function (SPF)) is available. However, during the revision of potential crash data sources, two significant challenges were identified that would prevent a longitudinal design:

- WWD crashes are extremely rare.
- Availability of SPFs or other crash-driven information is limited, mostly due to the rareness of these types of crashes.

Therefore, the research team recommended a cross-sectional evaluation so that a large database could be developed. Another key aspect of the study design is the use of a retrospective approach to structure the database, as opposed to a more traditional prospective structure, to ensure that enough instances of rare WWD crashes are included in the database. In a retrospective analysis, the data are collected on the basis of the response variable—in this case, at sites with WWD crash history (case sites) and locations with no WWD instances recorded (noncase sites). A retrospective analysis has important implications for the data collection and analysis stages as follows:

- Because the data are collected at locations with and without a history of WWD crashes, the countermeasures that can be evaluated are determined after the data collection, when a contrast of the prevalence of potential countermeasures between case and noncase sites is possible.

- The retrospective distribution of variables (including the outcome variable) depends on the ratio of case to noncase locations and is different from the unconditional distributions that would be obtained from a prospective design. Therefore, statistical methods that characterize the outcome variable distribution (i.e., count models, such as Poisson, negative binomial, or other Poisson mixture models) should not be applied because the assumption of a Poisson process is highly specific to the way the data were collected (i.e., in this case, specific to the particular retrospective distribution of the outcome). However, statistical methods used in risk analysis are appropriate to analyze retrospective designs because they produce odds ratios known to be independent of the design.

Accordingly, groups of countermeasures of interest with sufficient representation for a statistical comparison were identified once partial databases were available. The team planned to use propensity score weighting (PSW) to correct imbalances among covariates of two groups for contrasting the incidences of countermeasures of interest. These contrast groups would be determined when selecting the countermeasures of interest.

Unit of Analysis

For the retrospective cross-sectional design selected, there are two potential units of analysis:

- Corridors of freeway constructed around the location of identified WWD crashes.
- POEs for the wrong-way maneuver that resulted in a WWD crash in the database.

While the first option seems a natural choice because all data collection would be at locations identified at each corridor, this option implies that different types of POEs associated with a given corridor would need to be summarized for analysis. The second alternative is more desirable because the countermeasures under evaluation would be identified at the crash POEs. However, the challenge with this approach is that it requires a positive identification of the true POE for each WWD crash, a situation expected to greatly reduce the size of the database.

Nevertheless, the research team decided to use the POE as the unit of analysis. As explained in the next section, this decision required additional analytical efforts in sequence because the collected data included cases in which uncertainty exists about the true POE associated with each crash corridor.

DATABASE DESIGN AND MANAGEMENT

One of the biggest challenges in this evaluation is the lack of detailed information about the conditions that are conducive to WWD crashes. In other types of crashes, the occurrence of the crash coincides with safety factors (e.g., traffic volumes, signage, and geometry) that could have been influential to the origination of the crash. In contrast, research has shown that the location of WWD crashes and the location where the WWD maneuver took place can be miles apart

(Finley et al. 2018). As a result, the researchers anticipated that identifying the POE for each WWD crash would be a significant challenge. Moreover, based on past experience, the researchers expected that such a match would only be possible for a subset of the WWD crashes for analysis.

Data Management Extraction and Integration

The data management stage of the process involved collecting and revising data, supplementing the data where appropriate, concatenating variables across multiple sources, and preparing the data for statistical analyses. In response to actual data availability, the research team refined the final datasets through a data integration process explained in this section. The research team used geographic information system (GIS) tools to prepare, filter, and combine data from multiple sources and geolocations (typically in shapefile format) (Esri 2019). GIS tools allow the manipulation, combination, and display of data for different types of attributes, including crashes, road infrastructure, traffic volume, census tract, land use, and other types.

Data Balancing

The research team collected the data on the basis of the WWD crash history of sites so that the feasibility of evaluating specific countermeasures of interest could be determined once partial data were available. However, from the study conception, the researchers determined that most emphasis would be placed on countermeasures that fall within the categories of signage and geometry enhancements.

Data-matching and data-balancing methods are used to assist causal inference, which quantifies the impact of a treatment variable on a given response variable. Data matching is essentially a way to achieve data balancing through the process of matching each treated site with at least one nontreated site. Common practice is to use all identified sites in one of the contrast groups (typically the treatment group) and then find suitable sites for contrasts using sampling techniques applied to a wider sampling frame of candidate sites in the nontreatment group. The match determination is done based on a quantity known as the treatment propensity score (PS), which quantifies the probability of a site being in the treatment group, compared to the reference group.

Alternatively, appropriate weights based on the PS can be used to achieve a balanced comparison. This method is known as PSW. The choice between matching and weighting very often comes down to the amount of data available for the study. In either case, the result is a comparison of the mean response between the group of treatment sites and the group of comparison sites while the covariates are balanced.

PS can be implemented in the data collection stage to minimize the chances for producing imbalanced datasets. The PSs of the treatment sites and their corresponding reference sites are estimated and compared. The PS can be estimated using parametric or nonparametric tools, such as logistic regression or random forest analysis (Gross and Jovanis 2007; Sasidharan and Donnell 2013; Guo and Fraser 2015). In the case of using binary logistic regression as a basis for PS estimation, figure 1 shows the definition of the conditional probability of a site receiving a specified treatment (T_i=1), given a set of covariates $\boldsymbol{X_i}$ (bold type indicates a vector or a matrix).

$$P(T_i = 1|\boldsymbol{X_i}) = \frac{e^{\alpha_i \cdot X_i'}}{1 + e^{\alpha_i \cdot X_i'}}$$

Figure 1. Equation. Conditional probability of a site receiving treatment ($\boldsymbol{T} = 1$).

Where:

$P(T_i = 1|\boldsymbol{X_i})$ = PS denoting the probability of the site (i) receiving the treatment (i.e., $T_i = 1$).
T_i = treatment status, which takes binary values {0 if no treatment, 1 if treatment} of site i.
$\boldsymbol{X_i}$ = vector of covariates that vary with T.
$\boldsymbol{\alpha_i}$ = vector of coefficients through the binary logistic regression.

In a balanced sample, the PS distribution is expected to be similar for treated sites ($P(T_i = 1|\boldsymbol{X_i})$) and comparison sites ($P(T_i = 0|\boldsymbol{X_i})$). An examination of these differences at various stages of data collection can be used to direct data collection at additional reference sites to improve the balance in the dataset.

In PSW, the PS is used to balance two or more partitions of the data by the variable of interest (i.e., treatment or reference). In contrast with PS matching, balance is achieved by defining appropriate weights for each unit of analysis so that they are representative of an underlying target population of sites with comparable chances for having the treatment under evaluation. The data are weighted based on the probabilities of being in either the reference or the treatment group, and the selection of the weights defines the target population (Olmos and Govindasamy 2015). If all weights are equal, then the database is implied to be a simple random sample from the larger pool of sites from which the data were collected. However, by using appropriate weights, more flexible definitions of the target population can be assigned, as described in the statistical literature (Olmos and Govindasamy 2015). The definition of the weights also determines quantities that can be estimated, including the average treatment effect, average treatment effect among the treated cases, average treatment effect among the control cases, and average treatment effect among the evenly matched cases.

DATA ELEMENTS AND SOURCES

The following three common data categories are required for crash-based evaluations:

- Crash data (including WWD flags and variables).
- Roadway inventory data.
- Traffic data.

Table 1 shows a list of data elements collected for each dataset in this study. Initially, the research team examined a variety of data sources and potential study locations that could yield enough data for the evaluation. The team intended to select candidate locations that would permit at least a few hundred WWD crashes for analysis, to be consistent with the selected retrospective cross-sectional study design.

Table 1. Data elements of WWD countermeasure evaluation.

Data Type	Elements
Crash data	• State, county, city, and milepost (measure). • Latitude and longitude. • Date (day, month, and year). • Time (nighttime and daytime). • Crash contributing factor (fixed object, speed, and wrong way). • Crash type (single vehicle and multivehicle). • Crash severity (fatal and severe injury). • Driver impairment and distraction. • Vehicle type (passenger and truck).
Road inventory data	• Signs and signals. • Lane width. • Shoulder width. • Number of lanes per approach. • Left-turn lanes. • Left-turn pockets. • Shoulders. • Median type and characteristics.
Traffic data	• Traffic volume for major and minor roads. • Speed limit.

The research team identified a list of potential data sources from at least 11 States. The States with potentially usable data included Texas, Florida, California, Minnesota, Connecticut, Kentucky, Oklahoma, Ohio, Maryland, Nevada, and Iowa. From previous studies, the research team knew that Texas, Florida, and California tend to have large amounts of WWD crash data. Maryland, Nevada, and Iowa were of potential interest because of their open data-sharing policy, which could expedite data collection efforts. In addition, past correspondence with personnel in the other five States—Minnesota, Connecticut, Kentucky, Oklahoma, and Ohio—indicated potential availability of crash data for this study.

After consideration of the amount of crash data, the anticipated amount of effort to collect and integrate safety databases, and the availability of integrated traffic and roadway information, the research team determined this evaluation could include two or three States.

Target Number of Sites

To plan for data collection, the research team estimated a minimum number of sites with the potential to produce reliable CMFs. Determining the sample size required is not a straightforward task and depends on the specific details of the study. However, using examples from similar previous works, when available, the research team can quickly estimate the sample size required, which depends on the size of the effect under evaluation (i.e., the CMF value) and the amount of uncertainty in the estimated CMF.

Anticipated Sample Size and Effect Size

The research team used the safety estimates from a recently published study (NCHRP Report 881), based on three large States (Texas, California, and Florida) (Finley et al. 2018). This three-State database contained 358 WWD crashes, but different evaluations used different subsets of those data. The size of the safety effect of countermeasures evaluated in NCHRP Report 881 ranges from 0.102 to 2.293, including some statistically insignificant results. That evaluation also had a retrospective cross-sectional design, with crash as the unit of analysis, similar to the plans for the current study.

The CMFs obtained for two signs (the R5-1 DNE and the R5-1a WW) prescribed by the *Manual on Uniform Traffic Control Devices* were very similar—0.495 and 0.487—and both were statistically significant (FHWA 2012). Table 2 provides the corresponding calculations of the target number of sites. For each CMF, the following two scenarios are considered:

- With the partial multiple correlation between the treatment and its covariates remaining constant in a second hypothetical study (i.e., variance inflation factor (VIF) ratio = 1).
- VIF ratio = 2.

Table 2. Calculations for the target number of crashes (Finley et al. 2018).

Study Design	No. of Sites (*n1*)	CMF	Standard Error	Target Number of Sites (*n2*)	
				VIF Ratio = 1	VIF Ratio = 2
Cross-sectional	210	0.49	0.19	121	242
Cross-sectional	210	0.49	0.16	78	156

Table 2 indicates that approximately 200 sites should be sufficient for the evaluation of two signs, given the past study design and effect sizes. To initially assess the availability of WWD crash data at limited-access facilities in each State, the research team identified freeway WWD crashes from preliminarily available data sources in each State. Table 3 shows Texas and Florida as the most promising States for this evaluation. Because of their potential to achieve the target number of sites in table 2, these two States were selected for data collection and evaluation in this study.

Table 3. Potential for WWD crashes data at limited-access facilities for select States.

State	Period	No. of Freeway Crashes
Texas	2010–2019	1,123
Florida	2009–2016	221
Maryland	2015–2019	113
Iowa	2008–2018	69

Table 4 shows the data sources that were pursued from the two States with the most potential to yield enough data for a safety evaluation, as shown in table 3. While the data sources in Florida are unrestricted, access to Texas crash data is not available to the general public. However, the Texas Department of Transportation (TxDOT) allowed the research team access to these data sources.

Table 4. Available data sources at Texas and Florida.

State	Crash Data	Traffic Data	Roadway Data
Texas	CRIS database, 2000–2019 (TxDOT 2022a)	CRIS database, 2000–2019 (TxDOT 2022a) RHiNo database, 2014–2019 (TxDOT 2022b)	RHiNo database, 2000–2019 (TxDOT 2022b)
Florida	FDOT Open Data Hub, 2013–2016	FDOT Open Data Hub (2019)	FDOT Open Data Hub (2019)

CRIS = Crash Records Information System; FDOT = Florida DOT; RHiNo = Roadway-Highway Inventory.

Data Collection, Reduction, and Integration

For data manipulation and integration, the research team worked with GIS software, spreadsheets, text files, and relational database software where appropriate. Crash and countermeasure geolocations were the keys to data collection, reduction, and integration (Esri 2019). However, any data without geolocation were integrated using Microsoft® Access® as the database software and sequel query language queries (Microsoft 2018). Finally, the data collection task included a quality assurance step by each team member and a final quality control step before the data analysis was conducted.

After data collection and once potential countermeasures were identified, the research team planned to adopt the framework of PSW in the analysis because balance of covariates was not expected for a retrospective study. The team planned to set balancing weights so that the target population represented by the contrasts consists of the overlap population between sites with the treatment or with a higher number of deployed treatments, and sites without the treatment or with a lower number of deployed treatments, as in the framework proposed by Li, Morgan, and Zaslavsky (2018). This framework establishes a target population of all sites that have comparable chances to be in either the treatment group or the reference group. This approach is expected to curb the undue influence of the following two subsets of sites when the average treatment effect of the countermeasures are estimated:

- Reference sites with characteristics that make them unlikely candidates for the treatment.
- Treated sites with characteristics for which no comparable reference sites are represented in the data.

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

Definition of Crash Corridors

Because a limited number of WWD crashes matched to their corresponding POE was anticipated since the beginning of the study, the research team defined the following three stages of data collection for the study:

- In stage 1, case corridors were defined for each WWD crash, starting from the location of the crash, and continuing down in the wrong-way direction of travel until reaching a distance, *D*. Detailed data were then collected for all POEs within each WWD crash corridor.

- In stage 2, data were collected to determine whether the WWD crash in a corridor could have originated from one of the corridor's POEs. This determination required reviewing individual crash narratives in search of clues about the POE for each particular crash.

- In stage 3, the research team removed WWD crash corridors from the roadway network layer for a given facility of interest. Then, the research team selected random points of the remaining facilities of interest and considered the starting points of non-WWD corridors to be included in the analysis. Data for all POEs within each non-WWD corridor were then collected in the same manner as in stage 2.

The definition of the distance, *D*, was based on reported traveled distances on freeways according to NCHRP Report 881 (Finley et al. 2018). The research team determined that $D = 6$ mi represents roughly the 85th percentile traveled distance between the POE and crash locations.

DATA ANALYSIS METHODOLOGY

The empirical analyses in this study were conducted using the statistical methods appropriate to the characteristics of the assembled datasets. The research team used generalized linear mixed model (GLMM) variants (binomial mixed) to obtain the safety effectiveness estimates of interest, given the retrospective cross-sectional design. Due to the generally scarce number of crashes in the analyses, the safety evaluations were carried over two types of WWD crashes only: daytime and nighttime crashes.

Generalized Linear Regression Analysis with PSW

The predictive methods described in the American Association of State Highway and Transportation Officials' (AASHTO) *Highway Safety Manual* provide crash frequency estimates for a site through the use of an SPF based on the site's key characteristics (AASHTO 2010). SPFs are crash prediction models commonly estimated from regression analyses. Because of the characteristics of crashes—the response variable in such models—most SPFs currently in use are derived from generalized linear models (GLMs) that relate the mean of the response (crashes in this case) to the levels of predictor (i.e., independent) variables linearly through some link function. The model includes an error term that describes the variability between the mean response and the observations. The most common error distribution in current SPFs is the negative binomial. Alternatively, other suitable Poisson mixture distributions can be specified to better account for specific data characteristics.

In the context of predictive methods, the safety effect of a countermeasure is estimated by comparing the expected crash frequency at treated sites to the expected crash frequency when the treatment is absent. However, this comparison could be fraught with a potential issue: The measured difference in crash frequency may be attributable to other safety-influential covariates. For example, if sites with the countermeasure carry more traffic than those without the countermeasure, then the sites with the countermeasure would tend to experience more crashes merely because of their increased exposure to crash risk, despite the presence of the countermeasure. Such potential differences in key covariates must be accounted for while developing CMFs.

In the case of before–after designs (e.g., the empirical Bayes method), an SPF or a reference group is used to adjust crash expectations to the different levels of key covariates before the CMF is estimated. In the case of cross-sectional designs, controlling for the effects of other covariates is achieved by including those key covariates among the explanatory variables so that their safety associations are estimated simultaneously with that of the variable of interest (i.e., the variable linked to the CMF being estimated). However, the estimated CMF could still exhibit bias if a balanced comparison between the treated and reference sites is not supported in the database. Such bias is absent in an ideal case in which all key safety-influential covariates are equally represented among the treated and reference groups of sites, at all levels of the variable of interest. In such circumstances, any difference in safety between the treated and reference groups should be indicative to treatment of interest's effect. Achieving such an ideal case is difficult, however, and uneven distributions of key covariates are commonly observed at different levels of the variable of interest.

One way to reduce the risk for bias is to select study sites in a way that achieves balance in the covariates during database development, for example by using PS-based methods during data collection. However, using such methods during data collection (i.e., controlling for the covariates on both the treated and reference groups) requires a prospective rather than a retrospective design. As in this study, in the case of retrospective designs, PSW can be used after data collection (i.e., at the point that performing PSW is possible). This method allows for adjusting the influence of each data point, by either increasing or decreasing it, to ensure each datapoint is representative of a balanced distribution of covariates, as long as the overlap between the two groups of sites is sufficient (Li, Morgan, and Zaslavsky 2018). Under the PSW framework, weights were developed, based on a PS analysis of the data before the main analysis was conducted, to support the statistical contrasts quantifying the safety of countermeasures being studied.

GLMs for Safety Evaluations

Various types of GLMs are currently used to perform safety statistical evaluations. This section discusses the types used in this research.

Types of GLMs

Within the frame of GLM methods, a distinction can be made between models with fixed effects, random effects, and mixed effects. Commonly, the coefficients obtained from GLMs can be thought of as fixed effects. The variables corresponding to fixed effects are implied to have time-invariant safety associations (e.g., roadway design elements). The model coefficients are measured and interpreted as estimates of underlying parameters in a latent data-generating process.

In contrast, random-effects models estimate the effects of factors that are observed realizations of a random variable. Therefore, quantifying how the response variable shifts with the observed realizations in the dataset is typically not of interest; rather, accounting for the impact of such variation in the model is necessary. The simplest analogy for random effects in a GLM is the use of blocking in analyses of variance: The effect of the blocks is not typically the focus of the analysis but accounts for the blocking variability before the variability explained by the independent variable of interest is quantified.

Mixed-effects models are models that include both fixed and random effects (Pinheiro and Bates 2000). GLMMs approach the analysis of repeated-measures cross-sectional data by including a random effect for every unit of data aggregation (i.e., the blocking units in the data, such as individual study locations with more than one datum in the analysis). Orthogonal to the random effects, the model estimates fixed effects for the variable of interest and any additional fixed-effects covariates. Similar to GLMs, an appropriate link function can be specified to model response distributions that represent probability or odds, such as the binomial distribution applicable to this evaluation.

Binomial Mixed Models for Estimating Crash Risk Retrospectively

The research team used binomial mixed models on data with two levels of aggregation (i.e., crash corridor and POE) to assess the change in safety linked to the presence of the countermeasures of interest. In this instance, the distribution of a response variable Y, indicating the number of success observations from a binomial set of trials, can be modeled conditional to a vector of independent variables $\boldsymbol{X}$ and appropriate adjustments for the two crossed grouping levels. This distribution is modeled to correspond with a binomial variable (figure 2).

$$P(Y = y|\boldsymbol{X}, POE, Corridor) = \binom{n}{y} \cdot p \cdot (1 - p)^{n-y} \cdot k(POE, Corridor)$$

Figure 2. Equation. Conditional probability of *y* value, given explanatory variables and site characteristics.

Where:

- P = probability of Y taking value y, given a vector of explanatory variables $\boldsymbol{X}$ and random effects *POE* and *Corridor*.
- Y = count of observed successes.
- y = a particular value in the domain of random count variable Y.
- $\boldsymbol{X}$ = vector of independent variables (including key variables in evaluation and other safety-influential covariates).
- *POE* = random effect for a particular *POE* in the dataset.
- *Corridor* = random effect for a particular corridor in the dataset.
- n = reference number of trials for which Y is observed.
- p = probability of a crash.
- k = multiplicative random function of *POE* and *Corridor* capturing binomial overdispersion in the data through crossed-random-effects variability.

For a crash in the ith *POE* and jth *Corridor*, the logit of p can be expressed as in figure 3.

$$g(p) = ln\left(\frac{p}{1-p}\right) = \boldsymbol{\beta}' \cdot \boldsymbol{X} + POE + Corridor$$

Figure 3. Equation. Binomial-lognormal mixed-model parameterization.

Where:

- g(p) = logit function of p.
- p = probability of crash.
- $\boldsymbol{X}$ = vector of independent variables (including key variables in evaluation and other safety-influential covariates).
- $\boldsymbol{\beta}$ = vector of regression coefficients.

The mixed-effects model approach allows an explicit account for possible correlations between multiple realizations of the outcome variable at a common POE or from a common WWD crash corridor. From each model, the research team estimated rate parameters, which were used to estimate odds ratios (when combined with the different levels of the independent variables). An odds ratio is a direct estimate of a CMF and is expressed as the expected increase or decrease in crash risk due to the change in a WWD countermeasure. An odds ratio greater than 1.0 indicates that the change in that condition increases risk, and an odds ratio less than 1.0 indicates a decrease in risk.

Crash Risk Definition for Analysis

For the purposes of this section, corridors for crashes successfully matched with their POE in stage 2 (i.e., corridors with complete certainty about each POE being either the origin of the WWD maneuver or not) and all corridors in stage 3 (corridors with no WWD crash involvement) are referred to as type I corridors. Corridors collected in stage 1 but not successfully matched in stage 2 are referred to as type II corridors.

In an ideal dataset, all WWD crashes have a unique POE to identify where the WWD maneuver originated. The analysis then defines a binary Y variable as the response given the type of corridor: $Y = 1$ for WWD crash cases, and $Y = 0$ for noncases. To achieve this dataset, NCHRP Project 03-117 identified as many POEs for WWD crashes from the crash narratives as possible and then used experience and engineering judgment to make the assignment when crash narratives were unclear about the actual POE (Finley et al. 2018). For the current study, the team built on that approach by developing an extended methodology that maximizes dataset size but also minimizes the number of assumptions necessary to assign POEs when narratives lack the necessary details.

As described earlier, the research team constructed a subset of data consisting of ground-truth matches between WWD corridors and POEs (i.e., type I corridors). This subset was limited in size and only available for sites in Texas. In addition, the research team constructed a second, larger multi-State dataset comprising WWD corridors and all potential POEs within 6 mi of each crash. The research team then developed a two-phase methodology to be able to use all the collected data as explained next.

Type I corridors were analyzed in the phase 1 analysis. This dataset met the conditions of the ideal case dataset. Although phase 1 analysis has the potential to yield CMFs directly, the limited dataset size significantly limits the statistical power when relatively small safety effects are estimated. In addition, the range of POE characteristics is also limited in this case. Therefore, the research team used the results from phase 1 to produce crash risk estimates for phase 2, whereby the whole dataset would be analyzed to represent a significantly larger range of POE geometries and signage conditions. The research team directed the analysis in phase 1 to produce estimates of WWD crash risk as a function of POE geometry, time of day, and position of the POE relative to the WWD crash location (this crash risk is referred to as ph-1 risk from this point forward). Therefore, ph-1 risk explicitly avoided including parameters that represent the influence of signage in WWD crash risk. In addition, the research team reasoned that any statistically significant parameter estimates for signage would steer ph-1 risk toward (or away from) sites with that corresponding signage, a situation that could bias the analysis in phase 2 intended to assess the safety effectiveness of this kind of countermeasure.

In phase 2 analysis, the research team estimated the risk for WWD crash for each POE represented in type II corridors, given the results from the phase 1 analysis. Having a data-driven estimate of WWD crash risk allowed an analysis of available POEs, including type II corridors where the actual POE of each crash could not be positively identified, to be included in the analysis. However, the research team recognized that the data from type I corridors should be considered of higher quality than data from type II corridors, given the definition of these two corridor types. The team then implemented some considerations in defining the response variable to ensure the analysis would lean on the data from type I corridors to a greater extent. These considerations, the team reasoned, should allow the statistical analysis to reflect the amount of evidence linking each POE to a particular WWD crash event.

Because all potential POEs within 6 mi of each WWD crash location are available and linked to those corridors, the team recognized the following two alternative ways to define the response variable:

1. Identify an appropriate threshold for ph-1 risk, and then use that definition to assign either $Y = 1$ to a POE whose ph-1 risk is above the threshold or $Y = 0$ otherwise. This alternative is similar to the method used by NCHRP Project 03-117 researchers to assign the most likely POEs to crashes without known POEs (Finley et al. 2018). However, the alternative is considered a slight improvement over the method from NCHRP Project 03-117 because the assignment would be based on a data-driven analysis, as opposed to relying on engineering judgment and experience. This alternative, if implemented, would rely on an analysis of the receiver operating characteristic (ROC) curve for the ph-1 risk model to optimize the tradeoff between false positives and false negatives to avoid subjectivity in the selection of the threshold. However, defining a threshold could significantly affect the assigned response value for each POE and the subsequent analysis results.

2. Avoid defining a threshold altogether and instead recode the ph-1 risk as the response variable for the cases of unknown POEs. That subset combined with the subset from phase 1 analysis would allow the researchers to analyze both WWD crashes with positive POE matches and those WWD crashes with unknown POEs together.

The research team selected the second alternative for the main analysis of the study. Ph-1 risk can be expressed as odds or as probability (i.e., a probability of 0.25 corresponds to 1:3 odds or 0.25/(1−0.25)). Expressing the WWD risk as odds offers the advantage that probability values different from 0.0 or 1.0 can be expressed as ratios of expected successes to the expected count of fails and can then be analyzed using a binomial GLM or GLMM approach. Therefore, the research team used the following definitions to recode the response variable in the final datasets, given the results from the phase 1 analysis:

- For WWD corridors identified in type I corridors (i.e., with known POEs), the WWD odds were defined as 100:0, indicating a probability of 1.0 for the matched POE being the origin of the maneuver that resulted in the WWD crash. Accordingly, the odds were defined as 0:100 or a probability of 0.0 for all other POEs in the corridor.

- For POEs from the stage 3 data collection (i.e., non-WWD corridors), the WWD odds were defined as 0:100, indicating a probability of 0.0 that those POEs were the origin of the maneuver that resulted in a WWD crash, given that POEs in these corridors are not linked to any WWD crash occurrence.

- For all other POEs (i.e., in type II corridors), the only certainties are that they are included in the study because they are within 6 mi of the location of a WWD crash, and 6 mi represents approximately the 85th percentile WWD travel distance between the POE and the WWD crash location. In addition, an estimate of WWD crash risk is available from the phase 1 analysis, whereby the estimate is sensitive to the distance between the WWD crash and the POE as well as other factors, such as the time of the day the crash occurred and the geometric characteristics of the POE. Given this information, the odds of originating a WWD crash were defined for these POEs as follows:

- Ph-1 risk was calculated for all remaining POEs.

- Given that a WWD crash has occurred for each WWD corridor, jointly, all the POEs associated with that corridor must have a 0.85 chance of being the POE for the known WWD crash in that corridor. In addition, because ph-1 risk values represent conditional probabilities—given geometry, time of day, and relative location—these values do not necessarily add up to a combined probability of 0.85 for each corridor. Therefore, all ph-1 risk values in a given corridor were marginalized to 0.85. In other words, for a corridor with k potential POEs, a constant C was defined such that when multiplied to all ph-1 risk values in the corridor, the summation of these values results in the known marginal probability of 0.85 for a WWD crash, as known for each corridor (i.e., 0.85).

- Because the marginal ph-1 probabilities add up to 0.85 for a given corridor, the team was interested in reflecting that reduced evidence of crash involvement in the definition of the odds. To ensure the defined odds are self-weighted in the analysis, the research team established that the combined odds of all POEs in a type II corridor were expressed with a different reference value of n_r such that in a corridor with k POEs, the sum of all $n_r = 85$.

- The WWD odds were then coded using the marginal ph-1 risk values as (n·C·ph.1.risk):(n·1-C·ph.1.risk)).

- An example of the procedure is as follows: for a corridor with two associated POEs and corresponding ph-1 risk probability values of 0.7 and 0.4, C is defined as $C = 0.85/(0.7+0.4) = 0.7727$. The value of n for the first POE in this example is then defined as $n_1 = C$·(ph-1 risk)·100 = (0.7727·0.7·100) = 54. The WWD odds for the first POE are then (54·0.7727·0.7):(54·(1−0.7727·0.7)) or 29:25 after rounding.

- This definition of the odds for type II corridors reflects the amount of evidence supporting that each POE was the POE for the corridor's crash. This feature implies that these odds correspond to marginal probabilities that add up to 0.85 for all POEs in that corridor. The definition is also self-weighted for the odds because the n_i values are directly proportional to the marginal WWD crash probabilities and are such that the sum of all $n_r = 85$.

In summary, by using this alternative coded version of WWD crash risk, a response variable for each POE is computed in the dataset, including those POEs from corridors where a single POE could not be positively identified. In those cases, the odds reflect a reduced amount of evidence supporting that a given POE was actually the origin of the WWD maneuver compared to type I corridors because the definition of WWD crash odds is on the basis of $n \leq 85$ for these POEs and such that $n_r = 85$ for all POEs in the given type II corridor. In contrast, the research team made the deliberate choice of expressing the odds for type I POEs (i.e., with certainty about the origin of a WWD crash) on a basis of $n = 100$ as the reference number of trials in figure 2.

For the analysis, the team used R statistical language functions *glm* and *glmer (*The R Development Core Team*, 2021)*. For each datum in the design matrix, n_i is expected to be as small as 1 and as large as 85 for type II corridors, whereas n_i is always 100 for type I corridors. These values imply previous weights in the estimation of p as explained for figure 2. However, a significant difference exists in how these two functions treat the weights: Whereas *glm* explicitly takes coded odds as an aggregation of the data under analysis, and therefore implies larger datasets in its results, *glmer* uses odds as the basis to calculate prior weights without assuming each row in the design matrix represents multiple trials. To ensure that the estimation procedures do not misrepresent standard errors that imply different sample sizes than those available, the research team passed a uniform scaling factor of 1/100 as prior weights when performing the analyses.

CMF Estimation

In most cases, the process of using regression models to characterize the relationship of a single independent variable and dependent variables comprises extracting a single parameter estimate and its standard error from the model output. This single parameter estimate quantifies the relationship of interest, after accounting for additional variability in the data due to independent covariates and under an appropriately modeled error distribution. However, some research questions may require combining multiple parameter estimates and their standard errors. For instance, the questions of interest in this report—the safety effectiveness of WWD treatments—involve multiple safety elements and their characteristics, with each needing to be accounted for through coding different independent variables in the model. Estimating the CMFs of interest then involves multiple model parameter estimates. The uncertainty of the compound CMF is then a function of the uncertainties of the constituent coefficients.

The methods outlined in the following subsections were used to estimate the required CMF uncertainty. These methods leverage the asymptotically multivariate normal distribution of multiple regression model estimates from maximum likelihood estimation (Morrell, Pearson, and Brant 1997; Booth and Hobert 1998; Wackerly, Mendenhall III, and Scheaffer 2008).

CMF Estimates for Conditions Implying Changes in Multiple Independent Variables

In general, a combination of multiple coefficient estimates is needed to answer the research questions at hand. The answer to the research questions (i.e., the safety implications of installing signals, signs, and markings or modifying access management or geometric features) is a function of the values of the independent variables coding the characteristics under study.

CMF Estimates from Linear Combinations of Regression Estimates

Appropriate linear combinations of coefficient estimates can be developed to estimate the combined safety shifts from changes in multiple predictor variables from a fitted model. These linear combinations can be used, for example, to produce estimates of the crash risk for a treatment condition (e.g., WW sign presence) and a select base condition (e.g., no WW sign). In the link scale, the contrast is carried over the arithmetic contrast of risk, which is equivalent to a ratio of risk estimates in the response scale. Such contrast, therefore, yields an odds ratio for the treatment condition with respect to the base condition. To produce the corresponding standard error, the contrast coefficients must be combined with the model's inverse information matrix. If variable vectors $\boldsymbol{X_B}$ and $\boldsymbol{X_T}$ represent the base and treatment conditions and $\boldsymbol{\Sigma}$ the maximum likelihood model inverse information matrix (bold and italic type represent vector or a matrix), the standard error (*SE*) for the contrast in the link scale (i.e., the logarithm CMF estimate) is given in figure 4.

$$\text{SE}(\ln CMF) = \sqrt{(\boldsymbol{X}_{\boldsymbol{T}}' - \boldsymbol{X}_{\boldsymbol{B}}') \cdot \boldsymbol{\Sigma} \cdot (\boldsymbol{X_T} - \boldsymbol{X_B})}$$

Figure 4. Equation. SE of natural logarithm of *CMF* (scenario based).

Where:

$\boldsymbol{X'_T}$ = transpose vector of treatment conditions.
$\boldsymbol{X'_B}$ = transpose vector of base conditions.

In the contrasts just defined, the levels of safety-influential covariates (e.g., annual average daily traffic (AADT), lane width, and speed limit) are fixed equally at the dataset average for both contrasting subsets.

This approach can be generalized and applied over ranges of values in the dataset for the multiple variables of interest so the contrasts can be calculated to reflect comparisons of physically observed conditions, as represented in the dataset. Under this approach, a model-based estimate for the safety effectiveness is constructed for each unit of analysis and then averaged within each subgroup (i.e., either treated sites or base condition sites). The CMF (odds ratio) is then estimated as the contrast between the two group averages while explicitly accounting for the correlation of multiple estimates from a common model.

The approach described herein compares the average safety expectations of two groups, normalizing other covariates at that average and correcting for covariate imbalances via PSW. As a result, the contrast should reflect only a shift in crash risk (either an increase or a decrease) due to the treatment. For a treatment design matrix ($\boldsymbol{A}$), comparison group design matrix ($\boldsymbol{B}$), maximum likelihood model inverse information matrix ($\boldsymbol{\Sigma}$), and vector of PS weights ($\boldsymbol{w}$), the standard error of the average effect of the treatment condition (i.e., the standard error of the CMF estimate) in the link scale is given in figure 5.

$$\text{SE}(\ln CMF) = \sqrt{\boldsymbol{w}' \cdot \{(\boldsymbol{A} - \boldsymbol{B}) \cdot \boldsymbol{\Sigma} \cdot (\boldsymbol{A}' - \boldsymbol{B}') \cdot \boldsymbol{w}\}}$$

Figure 5. Equation. SE of natural logarithm of *CMF* (PSW).

Where:

$\boldsymbol{w'}$ = transpose vector of PS weights.
$\boldsymbol{A'}$ = transpose of treatment design matrix.
$\boldsymbol{B'}$ = transpose of comparison group design matrix.

The weights in figure 5 are defined as the overlap weights from the PS analysis. The statistical literature provides more details on these formulations (Johnson and Wichern 2007; Wackerly, Mendenhall III, and Scheaffer 2008).

CHAPTER SUMMARY

This chapter describes the study design, database structure, statistical methodologies, analysis methods, and tools that the research team used in performing the safety evaluations in this study. The chapter presents the challenges associated with the evaluation and the critical steps to develop a database suitable for statistical analysis. The rationale for a cross-sectional retrospective study design is presented, as is a detailed discussion about why and how the analysis used PS methods and the odds-based definition of WWD crash risk. Finally, this chapter outlines statistical analysis methods to develop statistical models of WWD crash risk (binomial mixed-effects regression models, as specified in figure 2 and figure 3) to support developing the CMFs of interest. The chapter ends with a discussion of additional techniques based on mathematical statistics that can be applied to the model results to provide average CMF estimates for the treatments of interest. The next chapter outlines the data collection effort for Texas and Florida, the selected States for this evaluation, in more detail.

CHAPTER 3. DATA COLLECTION AND INTEGRATION

The research team identified several data needs for the formulation of the database for WWD crashes for the effective evaluation of different countermeasures. The data needs include the WWD crash data, traffic data, roadway characteristics data, and other related information. The research team initially identified seven States (Texas, Florida, Maryland, Nevada, Illinois, North Carolina, and Connecticut) as potential study sites, and the research team selected the two States with the most potential to yield enough data for a safety evaluation (Texas and Florida). The research team proceeded to collect crash, traffic, and roadway characteristics data from these two States.

CRASH AND TRAFFIC VOLUME DATA COLLECTION

Texas has crash data stored in the Crash Records Information System (CRIS) database (TxDOT 2022a). Currently, the database has all crashes that occurred between 2009 and 2019. The research team has access to the CRIS database. The team only used crash data from 2010 to 2019 because the 2009 data have a different data structure, which would require more effort to merge with the data for other years. In addition to the crash information, the database has roadway features linked to crashes and annual traffic estimates.

The research team collected data for Florida from open-access FDOT websites. The crash data came from FDOT's Unified Basemap Repository, and roadway data and traffic data came from FDOT's GIS (FDOT n.d., 2022). The crash data, which range from 2009 to 2016, have three different recording styles for 2009–2010, 2011–2014, and 2015–2016. The collected roadway characteristics datasets include roadway access management, interchange locations, intersection locations, signalized locations, speed limit, AADT, number of lanes, and other related variables.

WWD Crash Data Reduction

The research team obtained data about all types of crashes. However, the focus of this study is WWD crashes that occurred on limited-access divided freeways. To obtain these WWD crashes, the research team screened the crashes using appropriate variables indicating WWD involvement. Similarly, the team identified WWD crashes that occurred on two-way divided roadways coded to have limited access. For Florida, access management is coded from class 01 to class 07. Class 01 covers limited-access freeways whose ingress and egress are only through interchanges. Class 02 is similar to class 01 but also has either frontage roads or another system of interconnections, and class 02 also has infrequent driveways and median openings. Classes 03 through 06 have fewer restrictions for ingress and egress. Therefore, this study focuses on class 01 only.

Texas has a more detailed database to enable screening of WWD crashes. First, WWD crashes are identified using the contributing factor variable. According to this variable, a crash is considered a WWD crash if the crash is described as involving a vehicle traveling on the wrong side of the road (e.g., approaching an intersection on the wrong side), not passing or traveling the wrong way on a one-way road. Furthermore, Texas flags all crashes that result in either death, injuries, or at least $1,000 in damage. In the dataset, the research team considered only these types of crashes. Since this project involves only limited-access freeways, the roadway functional system classification was used to screen for rural interstate, urban arterials, and urban principal arterials. Only crashes that occurred on divided freeways were retained after an additional round of screening (interstate highway or another freeway, as coded in the corresponding database field). Lastly, the team used the number of lanes and median types to perform a quality control check.

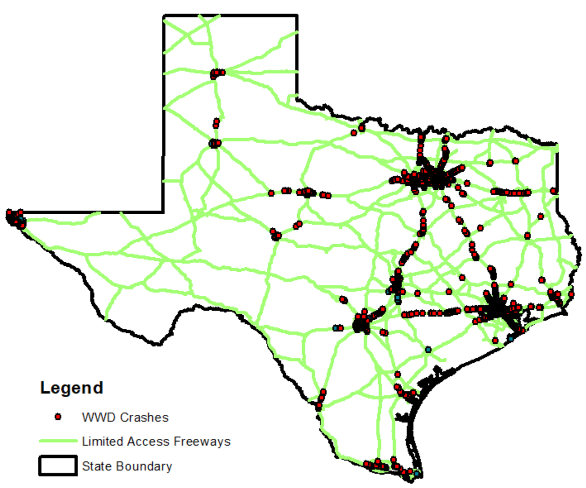
For Florida, apart from indicating the WWD crash, data codes were available that showed the action of each driver involved in the crash. The research team used this variable to ensure only WWD crashes remained for analysis.

Table 5, which displays the number of WWD crashes per State, shows a significantly larger amount of data available in Texas than in Florida.

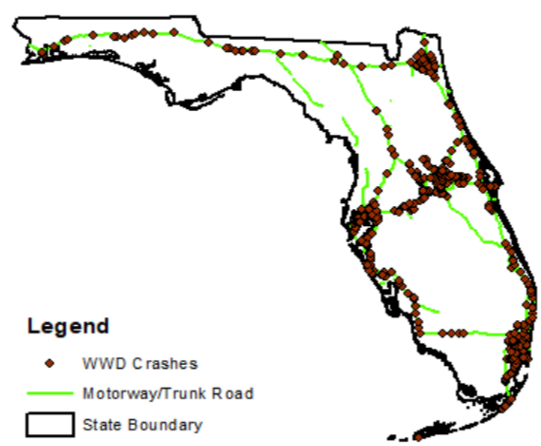
Table 5. Number of WWD crashes per State (unfiltered data).

State	Years	Number of Crashes	Average Number per Year
Texas	2010–2019	1,691	169.1
Florida	2009–2016	323	40.4

Figure 6, which displays the distribution of WWD crashes along the limited-access freeways across Texas and Florida, shows that Freeway WWD occurrences tend to be clustered in urban areas.



A. Texas.



B. Florida.

Figure 6. Maps. Location of WWD crashes in Texas and Florida.

WWD Crash Characteristics

This section presents the characteristics of WWD crashes from the two States in this evaluation. The characteristics include the quantity of crashes per route class, location of the crashes, collision type, crash severities, demographic characteristics of the WWD driver, levels of intoxication, and other characteristics.

The crash trends are presented separately because the two States have different ranges of years represented and different coverage of limited access freeways.

Table 6 shows WWD crash trends in Texas and in Florida. Texas had approximately 1,700 WWD crashes over the 10-yr period initially obtained. The maximum number of crashes (210) was observed in 2015, whereas the minimum (113) was observed in 2017.

Table 6. Trend of WWD crashes on limited-access freeways in Texas (unfiltered data).

Route Class	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avg	Total
All freeways in Texas (number)	—	148	132	173	156	173	210	192	113	187	207	169.1	1,691
All freeways in Florida (number)	43	47	27	40	37	43	48	38	—	—	—	40.4	323

—No data.
Avg = average.

Table 6 also shows the corresponding WWD crash trend in Florida. On average, approximately 40 WWD crashes occur on Florida freeways each year, which is approximately one-fourth of the yearly Texas WWD crash rate.

Crash Locations

For interstate-related crashes, table 7 show that about 64 percent (1,085/1,691) in Texas and more than 85 percent (276/323) in Florida occurred at nonintersection locations. Both intersection and intersection-related crashes accounted for smaller portions of the total WWD crash on limited-access U.S. highways and State routes for both States.

Table 7. Location of freeway WWD crashes (unfiltered data).

Crash Location	Texas		Florida	
	Number	Percent	Number	Percent
Entrance/exit ramp	94	5.6	8	2.5
Intersection	310	18.3	19	5.9
Intersection related	202	11.9	3	0.9
Nonintersection	1,085	64.2	276	85.4
Others	0	0.0	17	5.3
Total	1,691	100.0	323	100.0

Apart from the significantly greater number of crashes in Texas, the proportional breakdown of intersection and intersection-related crashes seems to be heavier in Texas than in Florida, which is likely attributable to the prevalence of frontage roads in Texas.

Manner of WWD Crash Collision

The research team categorized the manner of WWD crash collision into the following five major groups:

- Head-on.
- Angle.
- Sideswipe.
- Rear-end.
- Others.

Table 8 shows that head-on crashes account for the largest percentage of all WWD crashes for all route classes and for both States. Sideswipe, angle, rear-end, and other crash types account for similar proportions in both States.

Table 8. Distribution of WWD crashes by manner of collision.

State	Head-On	Angle	Sideswipe	Rear-End	Others	Unknown	Total
Texas (*n*)	732	394	115	96	354	0	1,691
Texas (percent)	43.3	23.3	6.8	5.7	20.9	0.0	100.0
Florida (*n*)	139	42	39	22	69	12	323
Florida (percent)	43.0	13.0	12.1	6.8	21.4	3.7	100.0

WWD crashes are more likely to result in higher severity levels than other crashes. The results in table 9 show, in general, a large proportion of fatalities and injuries from WWD crashes.

Table 9. Distribution of WWD crashes by crash severity.

State	Fatal	Incapacitating Injury	Nonincapacitating Injury	Possible Injury	No Injury	Total
Texas (*n*)	172	150	307	334	698	1,661
Texas (percent)	10.4	9.0	18.5	20.1	42.0	100.0
Florida (*n*)	62	46	77	41	97	323
Florida (percent)	19.2	14.2	23.8	12.7	30.0	100.0

The data showed that Florida WWD crashes tend to yield more severe outcomes than in Texas. Florida WWD crashes tended to result in approximately twice the number of fatalities and incapacitating injuries than in Texas. The proportion of no-injury crashes was approximately 40 percent higher in Texas than in Florida.

Day and Time of WWD Crash

The research team used the crash date to extract the day of the week for crashes in the two States. The research team explored the general crash time trend and the locational trend. In general, weekends have a relatively higher percentage of WWD crashes than weekdays (figure 7).

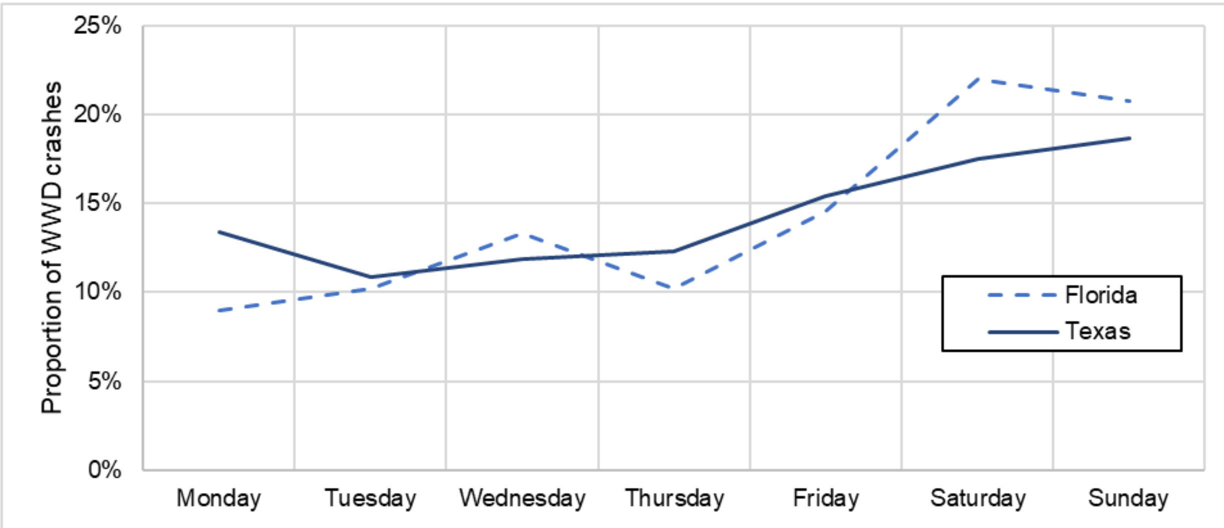


Figure 7. Graph. Distribution of WWD crashes by day of the week.

Figure 8 shows that most of the WWD crashes occurred during nighttime, especially between 8:00 p.m. and 5:00 a.m. Notably, both distributions peak around the time bars typically close.

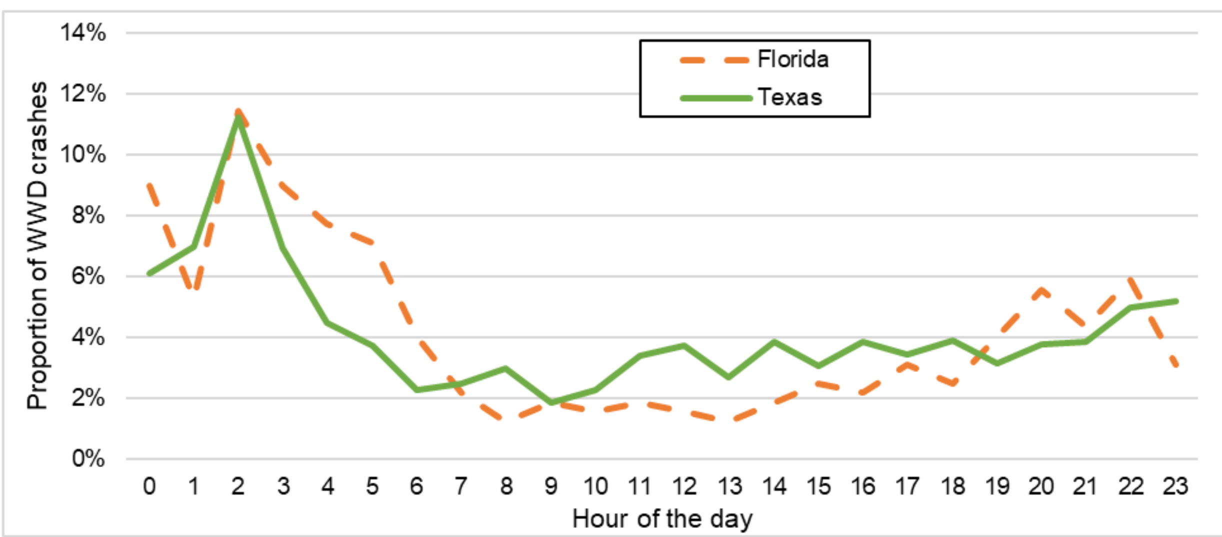


Figure 8. Graph. Distribution of WWD crashes by hour of the day.

Identification of Possible Wrong-Way Entry Locations

Correctly identifying the location where the WWD maneuver happened is key for this study, as discussed in the previous chapter. The research team used the following two approaches to data collection of possible POEs for the wrong-way vehicle to the traffic stream:

- Define corridors where the possible POE could be located within 6 mi (stage 1 data collection).
- Review crash narratives that could indicate the actual POE for a given crash (stage 2 data collection).

Due to resource constraints and the workload anticipated for data collection stages 1 and 3, the research team narrowed the data collection to the three most recent years of crash data available for each State: 2017–2019 for Texas and 2014–2016 for Florida.

The review of crash narratives was performed using only Texas data because the research team did not have access to the Florida crash narratives.

WWD Crash Narrative Approach

In an effort to determine the POE of the WWD vehicle (stage 2 data collection), the research team reviewed crash narratives and supplemented crash diagrams of more than 1,300 crashes that occurred in Texas between 2011 and 2020. Notably, the 3-yr window discussed in the previous section was widened for this effort to maximize the anticipated small sample of identified crashes with known POEs. The team acquired these narratives from the crash analytics unit at the Texas A&M Transportation Institute. The research team then used various text-mining techniques to identify the points of wrong-way maneuvers from the text data.

The research team screened crash narratives by using a set of keywords that indicate the point of the wrong-way maneuvers. The set of keywords used included *entered, exit ramp, entrance ramp, ramp, exited, intersection, turn, took, toward, U-turn, start, one way,* and *call*. For instance, the following crash narratives clearly show the point of WWD vehicle entry:

- "Driver of unit 1 was driving against traffic, traveling northbound on the Clinton *entrance ramp* and struck the driver of unit 2."
- "Unit number 1 was traveling south on-ramp S when made an illegal *U-turn* and began traveling the wrong way on one way colliding with Unit number 2."

The keywords *entrance ramp* and *U-turn* were the main indicators of the points of wrong-way maneuvers, facilitating the identification of both the point that the WWD vehicle entered the freeway and the point of wrong-way maneuver. Using this approach, the research team obtained data on 172 crashes that were eligible for a more thorough narrative review.

Parallel to screening narratives by using keywords, the team also used crash diagrams, where available. Several crashes did not have clear narratives of either the point of a wrong-way maneuver or the POE to the freeway. Therefore, the research team scanned through the crash diagram files to identify the point of the wrong-way maneuver and POE of the WWD vehicle. Figure 9 shows a typical WWD crash diagram that clearly indicates the POE of the WWD vehicle. Using this approach, the research team selected an additional data on 69 crashes for further review, making 241 crashes available for further screening.

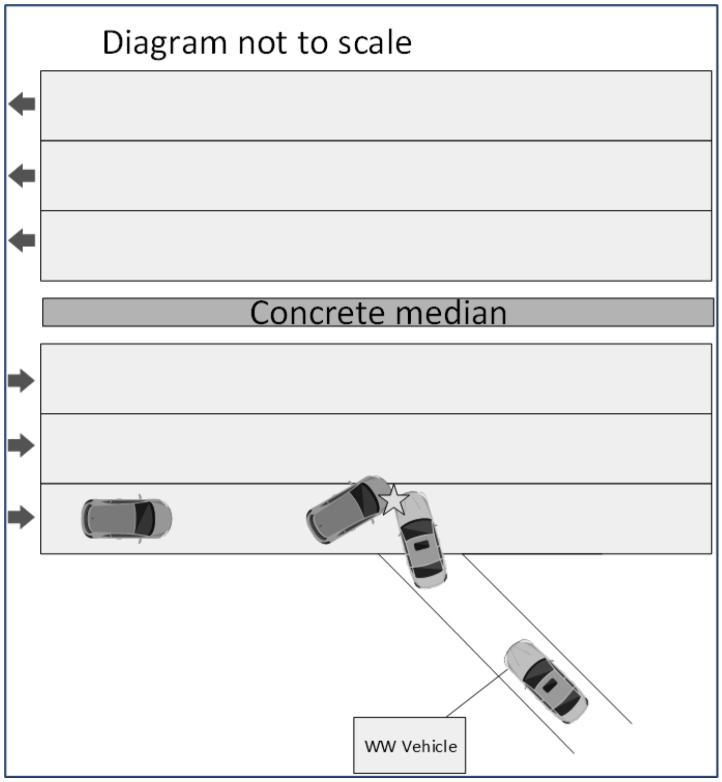


Figure 9. Illustration. Typical WWD crash.

The screened narratives were merged with the crash data using crash identification numbers. The crash data contain information that can facilitate the identification of the point of wrong-way maneuvers. Such information includes crash coordinates, interstates, and cross streets. Using a combination of crash narratives and crash coordinates, further screening of the crashes was possible. The team used narratives, such as the following narrative, to identify some crashes with that mentioned entry ramps used by the exiting WWD vehicle:

> Unit 2 was traveling south on S Clack St. in the inside lane and was going to enter the on ramp for loop 322/Winters freeway. Unit 1 was driving the wrong way on this one-way road and struck unit 2. Unit 1 started to brake just before the collision and lost control of the vehicle. …was 200 ft north of the north curbline of Edgemont Dr and 11 ft west of the east curbline of S Clack St.

With such information, identifying the point of a wrong-way maneuver can be difficult. Other crashes that did not occur on a freeway and were not linked to a freeway, were either the result of sliding vehicles from the other travel direction or the result of a driver reversing. Therefore, 49 crashes were screened out of the data, bringing the number of remaining crashes for further analysis to 192, which includes 85 crashes on interstates, 22 on U.S. freeways, and 53 on other freeway types (State highway, State highway spur, or State highway loop).

Distance Traveled by WWD Vehicles

The distance traveled by the WWD vehicle before crashing with a vehicle traveling in the right direction is very important in the evaluation of WWD countermeasures. The research team determined the distance from the identified point of wrong-way maneuver to the point of the crash using Google® Earth™ tools (Google 2019).

Table 10 summarizes travel time distances by facility type. On average, the travel distance for 192 crashes varied between 0.0 and 5.21 mi.

Table 10. WWD crash traveled distances.

Number of WWD Crashes	Average (mi)	Minimum (mi)	Maximum (mi)	Std. Dev. (mi)
192	0.7	0.0	5.21	0.97

Std. Dev. = standard deviation.

Although the statistics in table 10 provide an indication of the characteristics of the traveled distances, the distribution of the traveled distances reveals more useful information. Figure 10 shows the distribution of the distances traveled by the WWD vehicles. There are significant variations in the distance traveled before the WWD crash across facility types. Overall, the 85th percentile of the distance traveled before a crash has occurred is about 8,300 ft (about 1.6 mi). However, the 85th percentile distance varies according to facility type, with shorter distance (3,700 ft or 0.7 mi) for U.S. freeways and longer distances (7,600 ft or 1.4 mi) for State freeways. These distances were significantly lower than the numbers reported in NCHRP Project 03-117 (about 6 mi) for wrong driving events at freeway facilities determined from 911 calls (Finley et al. 2018). The research team ascertained the notable difference might indicate one of the following scenarios:

- The distance that can be derived from 911 events tends to be longer because they are reported under conditions less conducive to WWD crashes (e.g., lower volumes, more cross-sectional space to avoid a collision) and thus distances derived from crash narratives tend to yield shorter distances; or
- Crash-narrative-derived distances are significantly lower because identifying the POE of a WWD crash is most likely when the crash location happens to be relatively close to the POE.

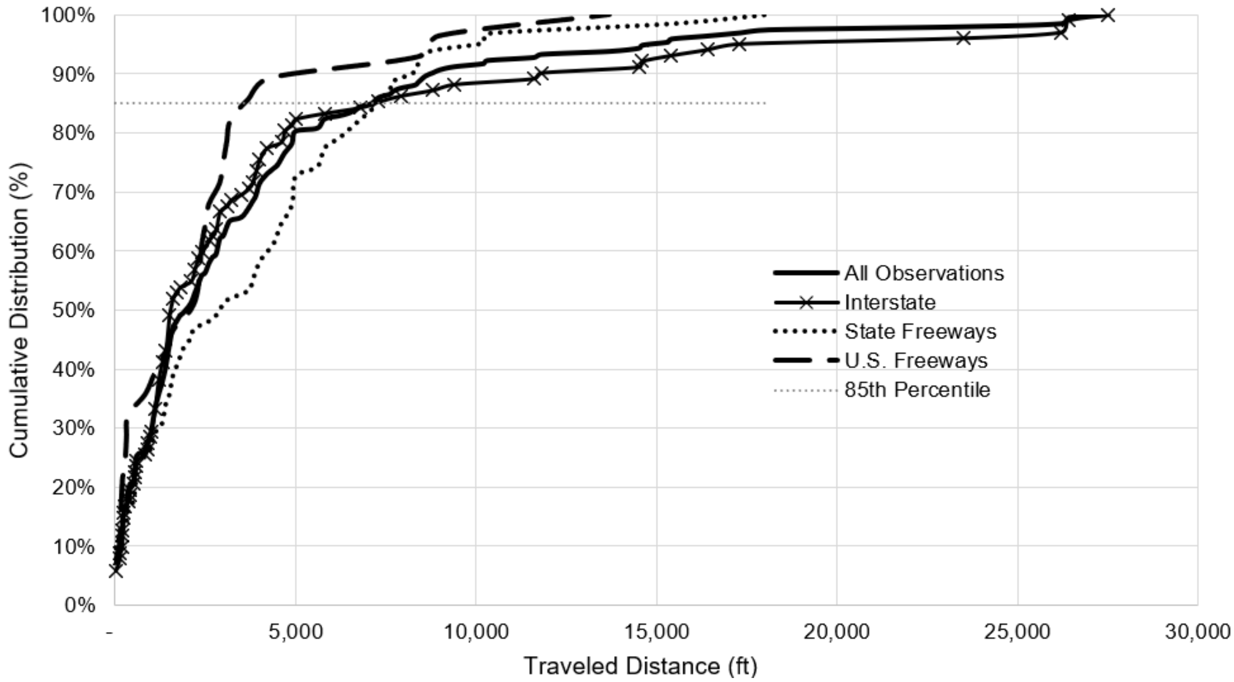


Figure 10. Graph. Distance traveled from the point of wrong-way maneuver to the crash point by facility type.

In reality, a combination of both potential reasons could explain the discrepancy. However, the research team decided to make a conservative assumption moving forward: The reason for the discrepancy is primarily explained in the second scenario, and therefore used a 6-mi threshold, which should capture the actual POE with 85 percent probability, as assumed, or virtually all POEs in case the real reason for the discrepancy is attributable to the first scenario.

In addition, the research team investigated the key attributes associated with the distance traveled before a crash. Figure 11 clearly shows longer traveled distances at nighttime and in rural areas. The next subsection describes the data collection efforts regarding the definition of WWD crash corridors and their corresponding POEs.

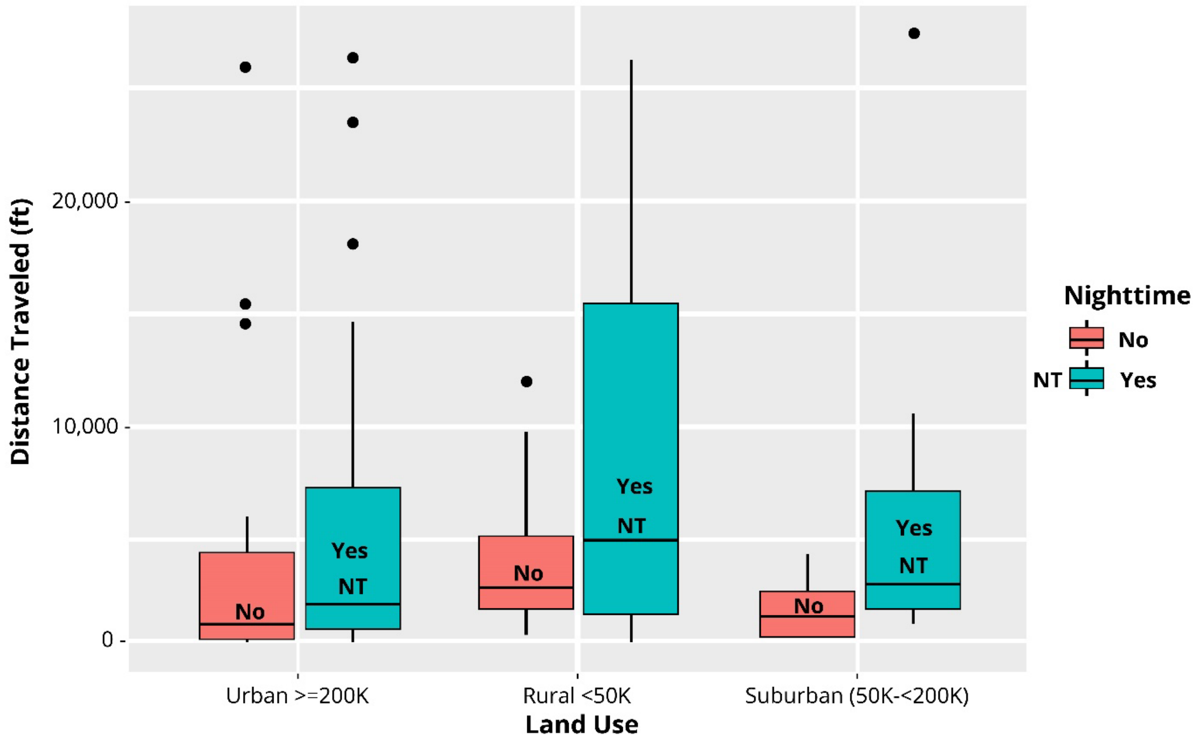


Figure 11. Graph. Distance traveled by WWD vehicles by land use and time of the day.

WWD Crash Corridor Approach

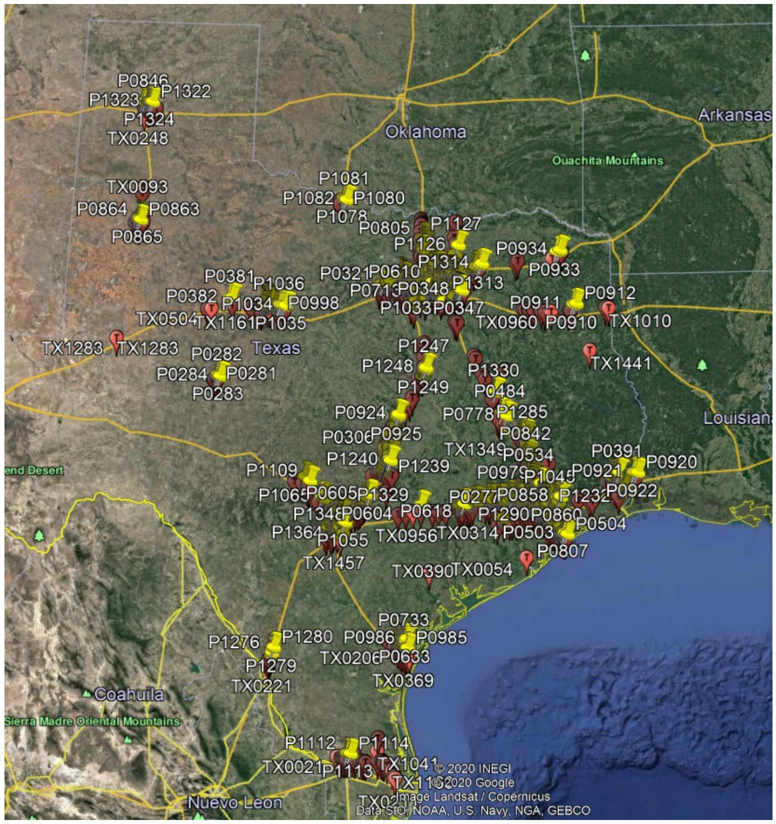
NCHRP Project 03-117 used the 911 call information related to WWD movements and found that about 85 percent of the WWD crashes occur within 6 mi from the point of the first 911 call (Finley et al. 2018). Therefore, the research team defined a 6-mi corridor (i.e., D = 6 mi) for each crash in the process of determining the possible POE of the WWD vehicle as described in chapter 2. The reason to assume the more conservative 6-mi threshold rather than the 2-mi threshold found from crash narratives, is as explained at the end of the previous section. Defining corridors involved the following steps:

1. The research team created Google Earth files (.kmz) for the WWD crashes previously cleaned. All crashes that had either missing coordinates or were not located on the limited-access freeways were screened out.

2. Using the Google Earth files, the research team drew 6-mi corridors, starting from each crash and going in the wrong direction of travel. At locations with multiple crashes, multiple corridors overlapped.

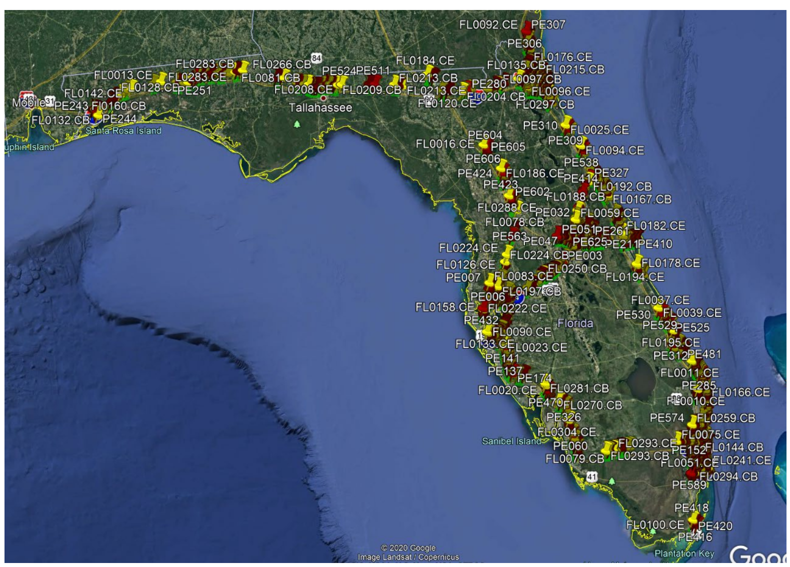
3. The research team identified all possible points of WWD entry within each 6-mi corridor.

Figure 12 and figure 13 show all identified ramps located within 6 mi of the crash location.



Original map © 2022 Google® Earth™. Modified by FHWA (see Acknowledgements).

Figure 12. Map. Marked ramps within 6 mi of the WWD crash location in Texas (Google 2019).



Original map © 2022 Google® Earth™. Modified by FHWA (see Acknowledgements).

Figure 13. Map. Marked ramps within 6 mi of the WWD crash location in Florida (Google 2019).

These figures show that the majority of corridors tend to be located around urban areas in both States, occasionally in suburban environments, and rarely on rural areas. As table 11 shows, with 463 crashes, a total of 1,460 exit ramps are within 6 mi of the WWD crash location in Texas. In Florida, with 256 WWD crashes, a total of 644 ramps fall within 6 mi upstream of the WWD crash location.

Table 11. Number of exit ramps within 6 mi upstream of the WWD crash location.

State	Number of Crashes	Number of Ramps
Texas	463	1,460
Florida	256	644

Each crash and the associated possible POEs were entered into a spreadsheet. Statistics developed from corridors in Texas (table 12) revealed a large number of possible POEs in a corridor as well as crashes per POE. On average, each possible POE is associated with approximately 2 crashes, with a maximum of 15 crashes and a minimum of 1 crash. Furthermore, each 6-mi corridor has, on average, 6 possible POEs, with a minimum of 1 and a maximum of 20 possible POEs.

Table 12. Corridor summary for Texas.

Corridor Feature	Minimum	Maximum	Average	Std. Dev.	Median
Crashes per POE	1	15	1.9	1.6	1
Points of entry in a corridor	1	20	6	6	3.2

The research team found also found, on average, each corridor was associated with 4 possible POEs, with a maximum of 12 and a minimum of 1 possible POE for Florida WWD crash data (table 13). Furthermore, each possible POE is associated with an average of 1.7 crashes and a maximum of seven crashes.

Table 13. Corridor summary for Florida.

Corridor Feature	Minimum	Maximum	Average	Std. Dev.	Median
Crashes per POE	1	7	1.7	1.2	1
Points of entry in a corridor	1	12	4.0	2.3	4

Notably, an interchange might have more than one off-ramp for a particular direction of travel; therefore, the number of POEs per corridor should not be taken to represent the number of interchanges in that corridor.

Identification of Non-WWD Corridors for Stage 3 Data Collection

When selecting non-WWD crash corridors, the research team intended to obtain locations with properties similar to the WWD crash corridors when possible. The research team performed the following steps in this process:

- The research team identified all ramps within 6 mi of the WWD crash location using GIS tools (Esri 2019). In this step, all geocoded WWD crashes were plotted. All ramps within the 6 mi of a WWD crash were also identified and plotted.

- After removing the ramps in proximity of WWD crashes, what remained were all freeway miles and ramps located within 6 mi or more from the WWD crash locations. The research team randomly selected non-WWD crash corridors from this pool of potential locations to supplement the database for analysis.

RAMP GEOMETRY, ACCESS MANAGEMENT, MARKINGS, AND SIGNS

The research team then collected several WWD-related elements for all POEs identified. The collected data elements included the signage, such as the number of DNE, WW, and one-way (OW) signs, and other signage, such as the presence of stop signs, yield signs, no U-turn signs, and no right-turn signs. Furthermore, the team identified the presence several types of pavement markings along the POEs, such as wrong-way arrows and lane use arrows, as well as at the interface between the ramp and cross street, such as lane path and stop bars. Others POE characteristics collected included the type of ramp (single exit, partial cloverleaf, diamond, single-point interchange), ramp length, median type, and lighting. The research team used both Google® Maps™ and Google Earth tools to extract WWD-related elements for the POEs.

The image date information collected was for the three consecutive years before the crash year. In some cases, the image date and crash date differed by a few months from the period of interest.

Ramp Types

Different types of ramps were observed at the study sites. Commonly recorded ramp types included single exit, partial cloverleaf, diamond, and single-point interchange.

Ramp Length

The determination of ramp length involved measuring distances (in feet) from the point of departure from the freeway to the point that the ramp intersects the cross streets. The research team used the measurement tools available in both Google Maps and Google Earth for this task.

Lighting Condition

The research team used Google® Street View™ to observe the presence of lights at the intersecting point of the ramps and cross streets. Lighting along the ramps was also considered. Most of the ramps, regardless of the type, were illuminated.

Median Type

Regarding median type, the research team first observed the presence of divided medians on the cross street and then the type of materials used to separate the traffic flow directions. For undivided cross streets, the research team also recorded the presence of double, solid yellow lines to separate the two directions of traffic flow.

After collecting initial datasets for the evaluations, the research team reviewed the representations and variability of various elements that could have potential for CMF development (table 14).

Table 14. Elements with potential for CMF development in databases.

Type of Feature	Potential Feature for CMF Development
Geometric	• Number and types of ramps. • Length of ramps. • Lengths between freeway exit ramps and crossing roads. • Type of crossing roads. • Median presence and characteristics at crossing roads.
Access management	• Number of ramps or access points at frontage roads. • Signage and pavement markings at access points at ramps or frontage roads.
TCDs	• Number and types of WWD-related signs. • Number and types of WWD-related pavement markings. • Type of traffic control at crossing roads.

The research team kept these elements for potential CMF development in mind during the analysis phases, but, ultimately, CMFs were only developed for those elements with enough data and amount of variation represented after final subsets of data were prepared for analysis.

CHAPTER SUMMARY

This chapter documents the data collection process for this study. Various summary statistics are presented for the two databases that were developed: one database for Texas sites and one for Florida sites. The next chapter describes the statistical evaluations of these datasets and the obtained CMF estimates for WWD countermeasures.

CHAPTER 4. SAFETY EFFECTIVENESS EVALUATIONS

This chapter describes the statistical analysis and presents the results of the safety effectiveness evaluations of WWD countermeasures, including estimated CMFs of interest.

As described in chapter 3, the research team assembled a two-State database for this two-phase statistical evaluation. In the first phase, the research team analyzed the dataset comprising type I corridors. The objective of this initial analysis was to produce a model characterizing the risk for a POE being the originating point for a WWD crash as a function of the relative position between POE and WWD crash, time of day, and POE geometric features. The results from this first phase were later used for a second phase of analysis whereby type I and type II corridors were analyzed together to produce WWD crash CMFs for select countermeasures.

MODELING PROCESS

Model entropy metrics (Akaike information criterion and Bayesian information criterion) were used to guide model development in general. In each analysis, the research team found the best-fitting model for each of the two response variables of interest: daytime and nighttime WWD crashes.

Although the phase 1 analysis focused on a relatively small subset of corridors, no previous weights were passed to the statistical estimation functions except for the constant scaling factor described in chapter 2. The phase 1 modeling process also allowed the inclusion of up to third-order interactions, which the research team considered especially important for a heterogeneous dataset for which multiple risk factors might have different effects at different levels of other covariates.

In contrast, the phase 2 analysis focused on developing CMFs for countermeasures by using larger subsets of data. PSWs were developed for the analyses in this phase to alleviate imbalances present between covariates of the countermeasures of interest.

PHASE 1 ANALYSIS

A subset of WWD crash type I corridors from Texas (those identified in stage 2 data collection) were used to develop a WWD crash risk function intended to be used in phase 2 analysis with the rest of the data. The research team selected a binomial GLM for this analysis because the data structure for this subset implies a one-to-one correspondence between a WWD crash and a POE—and by extension, the noncorrespondence of crashes and additional POEs in each corridor.

Initially, the research team intended to perform the analysis on subsets of data defined by geometric features, given that some distinct geometric characteristics of the POEs make this a heterogeneous dataset. However, that analysis was not feasible, given the small size of the dataset of type I WWD crash corridors. In total, the final filtered version of this dataset contained just 68 WWD crashes and 237 POEs. That is, 68 POEs were confirmed for each WWD crash, and an additional 169 POEs in the vicinity of the WWD crashes were therefore known to not have been the originating point of the WWD crashes. Of the 237 POEs, 110 were at locations where the cross street was a divided road, only 72 were at ramps that connected directly to the surface street network, and the remaining 165 POEs were at frontage road locations. Regarding the representation of traffic control at the intersections, 163 out of the 237 POEs were signalized, whereas only 15 did not have any traffic control. The remaining 74 POEs had either all-way or two-way stop traffic controls.

Key to this phase analysis, the research team explicitly excluded signage variables because they were intended for evaluation in phase 2. The following key groups of variables were considered in the model development for phase 1:

- Distance between each WWD crash and its confirmed POE.
- AADT.
- Multiple variables coding the time of day for each WWD crash.
- Type of traffic control at each POE.
- Variables coding geometric features of POEs; for example, if the POE is at a divided or undivided cross street, if the POE corresponds to a frontage road or if the POE is an off-ramp directly into surface streets, and the distance between the beginning of a freeway off-ramp and the point of connection to the surface street network.

The following implications can be gathered from the direction of the estimates in table 15 and their statistical significance:

- The time of day of WWD crashes influences the impacts of other risk factors, given that this risk factor has significant interactions with the following three risk factors:
    - The WWD crash/POE distance.
    - The number of driveways and T intersections not signalized at frontage roads.
    - The distinction between POEs connected to divided cross streets.

- As expected, the WWD crash/POE distance is inversely proportional to the risk of WWD crashes. In other words, the closer the POE is to the WWD crash location, the more likely the WWD maneuver originated from that POE. However, the interaction terms of this risk factor imply the following shifts in that trend:
    - Because the two-way interaction estimate with time of day is also negative, the results indicate that the inverse relationship between WWD crash risk and WWD crash/POE distance is strengthened during the daytime. In other words, the model supports that shorter WWD crash/POE distances tend to be more likely during daytime than nighttime. This trend makes sense because drivers are less likely to drive longer distances during the daytime when visual cues about WWD are more conspicuous and the traffic on freeways is higher.

    - Because the three-way interaction between WWD crash/POE distance, time of day, and number of driveways and unsignalized T intersections is positive, the daytime risk of WWD crashes decreases with distance at a slower rate when additional driveways or unsignalized T intersections are present in POEs at frontage roads. This finding is intuitive because additional driveways or intersections represent increased chances of WWD maneuvers.

- The negative and statistically significant estimate for the variable indicating a frontage road configuration suggests that this configuration is less prone to WWD crashes. However, other variables in the model that are specific to frontage roads with estimates in different directions make this conclusion less straightforward. Notably, the number of access points not signed on the frontage road is linked to an increase in the risk of WWD crashes, while the number of signed access points is linked to a reduction in WWD crash risk. Additionally, the model implies that longer distances between the cross street and the beginning of a freeway off-ramp is linked to a reduction in WWD crash risk (i.e., variable Length.ft. in table 15). These trends are intuitive as well because signage at access points along the frontage road is expected to reduce the risk of WWD maneuvers, whereas longer distances between the freeway off-ramp and the POE cross street should provide drivers with a longer distance and period of time to turn around before entering a freeway the wrong way.

- Finally, regarding the facility type of the cross street, the insignificant coefficient for the variable *Divided* indicates no difference in crash risk between divided and undivided cross streets, but the significant and negative interaction with daytime implies that the risk of a WWD crash is significantly lower at divided facilities during the daytime than at undivided facilities.

Table 15. Coefficient estimates for urban and suburban WWD crash risk model phase 1 analysis (*N* = 237).

Parameter/Variable	Estimate	Std. Error	*z* Value	*p* Value	Signif.
(Intercept)	−1.19E+00	7.12E−01	−1.674	0.09408	~
Daytime WWD crash (between 5:30 a.m. and 6:00 p.m.)	7.95E−01	6.52E−01	1.219	0.2228	—
Distance to WWD crash (miles) (scaled)	−1.53E+00	3.53E−01	−4.324	1.53E−05	***
Frontage POE	−1.22E+00	4.44E−01	−2.759	0.0058	**
Number of signed T intersections in Frontage POE	−5.69E−01	2.47E−01	−2.309	0.02096	*
Number of T intersections not signed plus number of driveways in frontage POE	1.78E−01	5.98E−02	2.982	0.00286	**
Length.ft.	−1.81E−04	1.01E−04	−1.796	0.07242	~
Divided	3.93E−01	4.80E−01	0.82	0.4123	—
POE Control_Type = stop on exit	−1.65E+01	1.31E+03	−0.013	0.98994	—
Light	1.02E+00	6.59E−01	1.541	0.1234	—
(Divided)×(daytime WWD crash)	−1.92E+00	8.46E−01	−2.27	0.02319	*
(Distance to WWD)×(Daytime WWD Crash)	−5.81E−01	6.19E−01	−0.939	0.34772	—
(Distance to WWD)×(Daytime WWD crash)×(N Int. not signalized and driveways)	9.97E−02	4.95E−02	2.013	0.0441	*

—Not applicable.
~Significant at the 90.0 percent confidence level (CL).
*Significant at the 95.0 percent CL.
**Significant at the 99.0 percent CL.
***Significant at the 99.9 percent CL.
Std. = standard; Signif. = significance.

Because the results from phase 1 are intended to provide WWD crash risk estimates for phase 2, the research team assessed the quality of the estimates from the model in table 15. This assessment was based on the ROC curve shown in figure 14.

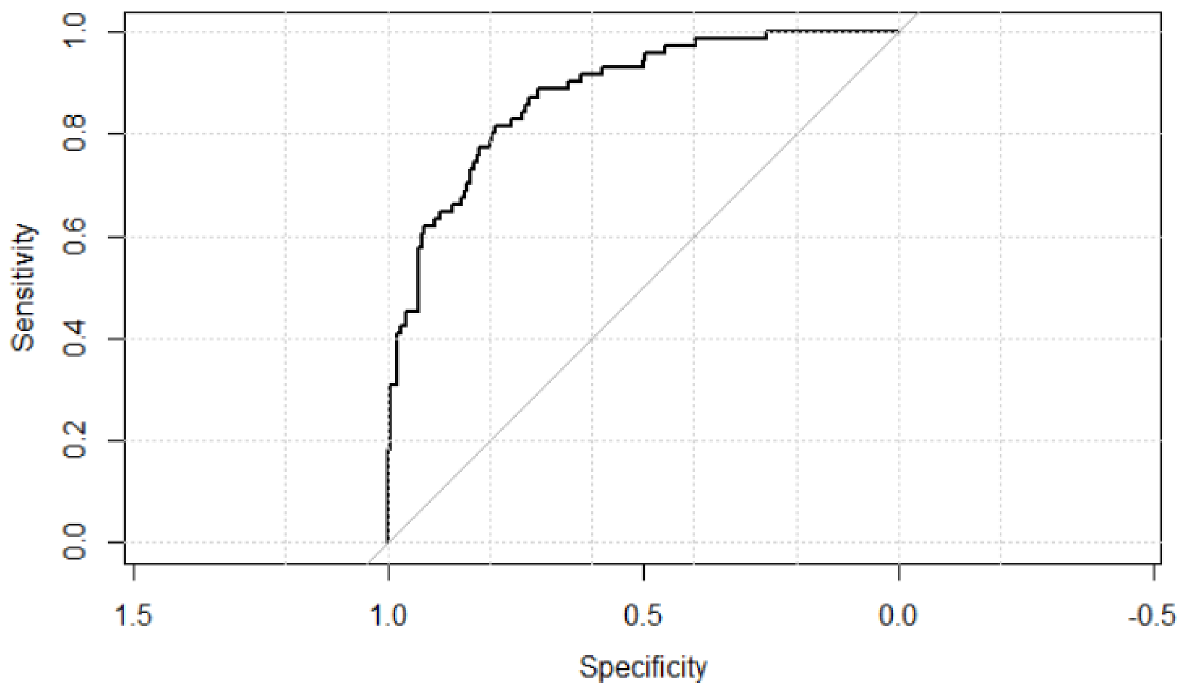


Figure 14. Graph. ROC curve for the ph-1 risk model.

The area under the ROC curve is a measure of the ability of the model to correctly classify the POEs linked to WWD crashes and those not linked. A value of 0.5 is equivalent to chance (i.e., 50 percent chance), whereas a value of 1.0 implies the ability to classify the POEs without misclassifications. In the case of the model provided in table 15, the area under the curve is 0.878, which is notably better than chance. The research team deemed this expected performance appropriate to estimate crash risk at type II corridors for phase 2 analysis, as documented in the following section.

PHASE 2 ANALYSIS

Based on the results in phase 1, the research team incorporated POEs from type II corridors for the phase 2 analysis. As detailed in chapter 2, the relative risks were marginalized at each individual corridor to jointly represent a marginal risk of 0.85 because this risk level is the anticipated risk expectation for a corridor of 6 mi.

The following subsections present the results obtained from the analyses that ensued in the two State databases that were available for this study.

WWD Safety Evaluation in Texas

The complete dataset for urban and suburban environments in Texas consists of 827 corridors, including 452 non-WWD corridors added during the stage 3 data collection. These 827 corridors contain 375 WWD crashes from 2017 to 2019, after the exclusion of partially complete cases. Jointly, this dataset contains 2,722 POEs among type I and type II corridors. Because the corridor length was defined to roughly capture 85 percent of the chances of including the true POEs for all WWD crashes in the dataset, the implication is that all corridors jointly should have a crash expectation of $68\times1.0+(375-68)\times0.85=328.95$ WWD crashes. The research team confirmed this crash expectation by adding the marginal crash risks for all POEs in the dataset. The summation from that exercise yields exactly 328.95 as the result. Therefore, the research team continued to use this statistic (i.e., the total cumulative of the marginal crash risks) as a metric to indicate the WWD crash level of representation of various data subsets to be used in the phase 2 analysis. In contrast with the limited size of the dataset used in phase 1, the datasets in phase 2 were sufficiently large enough to allow breaking them down into more homogeneous subsets for analysis, as shown in table 16.

Table 16 shows that the number of WWD crashes represented remains a limiting factor, even for subsets as large as 910 POEs. However, the research team considered that the estimated number of WWD crashes represented in each data subset is sufficient for applying the statistical methods described in chapter 2. Table 16 also shows the statistics of WWD crashes per POE for each subset. These statistics clearly indicate an increased WWD risk for POEs at frontage roads in general, especially during nighttime. Otherwise, the relative risks appear comparable during the daytime for the last three subsets and during the nighttime for the last two subsets.

Notably, these estimates should not be considered as metrics representative of any POE in the jurisdictions of analysis, given the retrospective nature of the datasets. The results from formal statistical analyses, however, are expected to provide insights applicable to POE crash risk in a prospective manner as indicated.

Table 16. Size of Texas data subsets for analyses in phase 2.

Subset	No. of Corridors	No. of POEs	Daytime WWD Crashes Represented in Subset	Nighttime WWD Crashes Represented in Subset	Daytime WWD Crashes per POE	Nighttime WWD Crashes per POE
POEs at frontage roads intersecting divided cross streets	321	747	45.16	94.43	0.060	0.126
POEs at frontage roads intersecting undivided cross streets	208	325	11.88	34.51	0.037	0.106
POEs at ramps intersecting divided cross streets	467	910	31.34	52.34	0.034	0.058
POEs at ramps intersecting undivided cross streets	432	740	26.52	32.76	0.036	0.044

Note: The total number of WWD crashes represented in the Texas database is 375, with the estimates for each subset obtained as the sum of crash risk for each POE, marginal at the corridor level to jointly represent the known total corridor risk of 1.0 for type I corridors and 0.85 for type II corridors (see chapter 2). This table shows the split of the corresponding total cumulative WWD crash risk of 328.95 WWD crashes (calculated as $328.95=68\times1.0+(375-68)\times0.85$). All ramps are in urban or suburban environments.

PSW Balancing for Signage Comparisons in Texas

Upon revision of the available datasets, the research team confirmed the variability among the signage variables collected to support CMF development for these kinds of countermeasures was sufficient. However, exploratory analyses indicated there would be imbalances in covariates if statistical contrasts were needed for different levels of signage. Therefore, the research team developed overlap PS weights for each dataset to ensure the analysis results were indicative of the overlap population between the POEs under the lower quartile of signage and the three upper quartiles. To define the signage quartiles, the research team used statistics from the marginal distributions for three signage variables: WW_Signs, OW_Sign, and DNE_Sign,

Binomial Models of WWD Crash Risk in Texas

Given the limited representation of crashes shown in table 16, the team developed binomial models to characterize the risk for two WWD crash types only: daytime and nighttime. The research team filtered each dataset for partially complete cases and carried out a stepwise model selection. Similar to the phase 1 analysis, the research team considered up to three-way interactions between variables to allow the model selection some flexibility in uncovering more complex relationships than single-parameter monotonic marginal effects. In contrast with the phase 1 analysis, this analysis used binomial GLMMs with crossed random effects because in these datasets, the correspondence between POE and WWD crashes is not one to one. Indeed, type II corridors have the crash risk represented at more than one potential POE and are therefore linked to multiple potential POEs. Each POE may appear in different corridors and therefore have different relative crash risks for different WWD crashes. This data structure is known as a many-to-many correspondence, whereby the two grouping variables partially overlap without one being a subset of the other.

All models in the evaluation explicitly considered AADT, vertical signage, horizontal signage, and other geometric elements, despite their statistical significance, because past research has documented these elements to be safety influential. Therefore, the linked safety associations must be discounted before producing CMFs that are expected to be free of the influence of these potential confounding factors. However, different accounts for these elements were under consideration in the modeling process and, ultimately, the research team selected the most parsimonious of such accounts for the final models. The research team considered the limitations in statistical power resulting from different dataset sizes and the estimated number of represented WWD crashes, as indicated in table 16.

Table 17 shows the results from phase 2 modeling in Texas. Each column represents the coefficients estimates from the mixed binomial models fitted to the four data subsets shown in table 16.

When a direct comparison is possible for the same estimate across models, a consistent trend is apparent in most cases. For example, the coefficient for AADT is consistently positive (except in one case that is negative but statistically insignificant). However, only in three instances was this coefficient positive and statistically significant. Jointly, this trend suggests that, although useful in some instances, AADT at the POE is not necessarily a good predictor of WWD crashes. Due to a combination of factors—such as the sample sizes, number of WWD crashes represented, and limited variability or availability of some signage elements in some of the estimations—the research team decided to estimate some coefficients for aggregate measures of signage instead of coefficients for individual elements in three of the models shown in table 17. The next section presents CMF estimates supported by the results presented in table 17.

Table 17. Phase 2 analysis results (estimate (standard error)) in Texas (urban and suburban).

Feature	Frontage Road at Divided Street, Day	Frontage Road at Divided Street, Night	Frontage Road at Undivided Street, Day	Frontage Road at Undivided Street, Night	Off-Ramp at Divided Street, Day	Off-Ramp at Divided Street, Night	Off-Ramp at Undivided Street, Day	Off-Ramp at Undivided Street, Night
(Intercept)	−3.0398 (3.5301)	3.8039~ (2.2035)	−7.6099** (2.4865)	−7.2856** (2.2497)	−12.05* (4.897)	−10.1522* (4.0357)	−3.629~ (1.984)	−5.3124** (1.8076)
log(AADT)	0.1499 (0.2492)	−0.1773 (0.1671)	0.4029~ (0.2328)	0.507* (0.2075)	0.7072 (0.4591)	0.6182~ (0.3537)	0.0997 (0.1646)	0.159 (0.1547)
Length.ft.	—	−2.82E−4* (1.42E-4)	—	—	—	—	−0.0004 (0.0004)	—
Two directional Frontage Road	—	—	—	−1.9625 (1.2101)	—	—	—	—
Number of driveways	0.1362*** (0.0314)	0.0781~ (0.04342)	—	—	—	—	—	—
Number of Signed T Intersections	−0.4538* (0.1848)	—	—	—	−1.2158 (1.4541)	—	—	—
Signalized POE	0.9222 (2.2300)	−0.4336 (1.1752)	1.1332 (0.9213)	1.0434~ (0.5616)	5.6786* (2.7268)	5.8592** (2.2415)	—	2.0323~ (1.0532)
TWSC POE	—	—	—	1.1524 (0.739)	—	—	—	3.3357** (1.0254)
No Traffic Control at POE	—	—	—	—	—	—	1.5132~ (0.8426)	2.6808* (1.1611)
No. of Lanes	—	−0.2436 (0.2292)	—	−0.2871 (0.1883)	—	—	0.5033 (0.3341)	—
STOP_Sign	—	—	0.7213 (0.7993)	—	—	—	—	—
DNE_Sign	—	—	—	—	—	—	−1.1353** (0.3509)	−0.4463* (0.2103)
Presence of at least one WW_Sign	—	—	—	−2.2707* (0.9995)	—	—	—	—

Feature	Frontage Road at Divided Street, Day	Frontage Road at Divided Street, Night	Frontage Road at Undivided Street, Day	Frontage Road at Undivided Street, Night	Off-Ramp at Divided Street, Day	Off-Ramp at Divided Street, Night	Off-Ramp at Undivided Street, Day	Off-Ramp at Undivided Street, Night
WW_Signs	−0.6747** (0.2220)	—	—	0.3936~ (0.2061)	—	—	—	−0.2654 (0.4488)
Count of Vertical Signage[a]	—	—	—	—	−0.371 (0.2932)	−0.4739* (0.2235)	—	—
Count of Vertical Signage[b]	—	—	—	—	—	—	0.4198 (0.4016)	—
Count of Horizontal Signage[c]	—	—	—	—	−1.6649~ (0.9829)	−1.4827~ (0.7634)	—	—
LANEUSE_Arrow	—	−1.2697~ (0.7305)	—	—	—	—	—	—
STOP_Bar	—	−2.0441* (0.8246)	−1.2529 (0.7684)	—	—	—	—	—
LANE_Path	—	−0.8775* (0.3709)	—	—	—	—	—	—
LANEUSE_Arrow (2 Lanes or more)	—	−1.2697~ (0.7305)	—	—	—	—	—	—
LANEUSE_Arrow × Number of Lanes	—	0.3911* (0.1808)	—	—	—	—	—	—

—Not applicable.
~Significant at the 90.0 percent CL.
*Significant at the 95.0 percent CL.
**Significant at the 99.0 percent CL.
***Significant at the 99.9 percent CL.
[a]The signage counted in this variable includes DNE_Sign, WW_Signs, and OW_Sign.
[b]The signage counted in this variable includes WW_Signs and OW_Sign.
[c]The signage counted in this variable includes STOP_Bar, LANEUSE_Arrow, and WW_Arrow.
TWSC = two-way stop controlled.
Note: Standard errors are shown in parenthesis.

CMFs from Texas

While developing the models, the research team kept in mind the following three categories of countermeasures at the originating locations of WWD maneuvers:

- Geometric features.
- Access management strategies.
- TCDs.

The following subsections present CMF estimates under each of these categories.

CMFs for Geometric Features

For the POEs at frontage road locations, the datasets support the safety evaluation of just two potential geometric design features that may affect WWD crashes occurrence:

- The length of road between the beginning of an off-ramp and the connecting point at the crossroad, as shown in table 18.
- Reducing the number frontage road lanes at the intersection

Table 18. WWD crash CMFs for geometric features at frontage roads in Texas.

Geometric Feature	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
Additional 100 ft of frontage or off-ramp[a]	Night	0.972	0.946	0.990	0.950	0.995	*
Remove ramp lane[a]	Night	0.863	0.641	1.161	0.672	1.108	—

—Not applicable.
*Significant at the 95.0 percent CL.
[a]Base condition: Frontage road intersecting divided cross street (urban and suburban).

Only the CMF for additional ramp length was statistically significant, meaning the evaluation found statistical evidence of a reduction in nighttime WWD crash risk associated with longer distances between the intersection and the beginning of the off-ramp. Results indicate that at intersections of frontage roads with divided cross streets, the chances for WWD daytime crashes drop by 2.8 percent (0.028=1−0.972) for each additional 100 ft of off-ramp length or segment of frontage road between the off-ramp and the intersection. The research team interprets this result as an indication that during daytime conditions, longer off-ramps could allow wrong-way drivers more opportunities to realize they performed a wrong-way maneuver, therefore making them more likely to turn around and avoid entering the freeway the wrong way. Table 19 shows CMFs for countermeasures at locations where an off-ramp directly connects to a cross street.

Table 19. WWD crash CMFs for geometry modifications at off-ramps on surface streets in Texas.

Geometric Feature	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
Ramp lane removal[a]	Day	0.605	0.314	1.164	0.348	1.049	—
Additional 100 ft of off-ramp[a]	Day	0.960	0.891	1.034	0.902	1.022	—

—Not applicable.
[a]Base condition: Off-ramp intersecting undivided cross street (urban and suburban).

The direction of the CMFs in table 19 is as expected and consistent with the estimates in table 18. However, these estimates are statistically insignificant.

CMFs for Access Management Strategies

For the POEs at frontage road locations, the analyses and amount of data support the development of CMFs for two elements related to access management only:

- The number of driveways on frontage roads.
- The number of T intersections on frontage roads displaying signage.

Table 20 shows the results for these evaluations.

Table 20. WWD crash CMFs for access management strategies at frontage roads in Texas.

Strategy	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
Driveway on frontage road removal[a]	Day	0.873	0.821	0.928	0.829	0.919	**
Driveway on frontage road removal[a]	Night	0.925	0.849	1.007	0.861	0.994	~
Add signage to T intersection on frontage road[a]	Day	0.635	0.442	0.912	0.468	0.862	*

~Significant at the 90.0 percent CL.
*Significant at the 95.0 percent CL.
**Significant at the 99.9 percent CL.
[a]Base condition: Frontage road intersecting divided cross street (urban and suburban).

Table 20 shows that access management at frontage roads is expected to affect the chances for WWD crashes. The analysis indicated that closing access points at frontage roads should result in reduced chances for WWD crashes. For example, for each driveway that was closed between an off-ramp to a frontage road and an intersecting cross street, the chances for daytime WWD crashes were reduced by 12.7 percent (1−0.873=0.127) and by 7.5 percent (1−0.925=0.075) for nighttime WWD crashes.

CMFs for TCDs

The last category of countermeasures in this evaluation focuses on TCDs. Not all TCDs that could be evaluated had enough representation in each dataset to produce robust results. Table 21 shows the results of the evaluations deemed feasible.

Table 21. WWD crash CMFs for TCDs at frontage roads in Texas.

TCD	WWW Crash Type	CMF	Lower Limit 95 Percent CL	Upper Limit 95 Percent CL	Lower Limit 90 Percent CL	Upper Limit 90 Percent CL	Signif.
Additional WW sign[a]	Day	0.509	0.330	0.787	0.353	0.735	**
Lane path[a]	Night	0.416	0.201	0.860	0.225	0.767	*
Stop Bar[a]	Night	0.129	0.026	0.652	0.033	0.505	*
One additional WW sign[b]	Night	0.153	0.028	0.637	0.037	0.833	*
Two additional WW signs[b]	Night	0.227	0.051	0.797	0.065	1.009	~

~Significant at the 90.0 percent CL.
*Significant at the 95.0 percent CL.
**Significant at the 99.0 percent CL.
[a]Base condition: Frontage road intersecting divided cross street (urban and suburban).
[b]Base condition: Frontage road intersecting undivided cross street (urban and suburban).

Table 21 lists several statistically significant CMFs: A decrease in daytime WWD crashes was associated with adding WW signs (0.509 CMF statistically significant at 99 percent confidence level (CL); and large decreases in nighttime WWD crash risks were associated with the following treatments:

- Adding lane path pavement markings for turning lanes (0.416 CMF statistically significant at 95 percent CL).
- Adding stop bar pavement marking (0.129 CMF statistically significant at 95 percent CL), and either adding one WW sign (0.153 CMF statistically significant at 95 percent CL) or adding two WW signs (0.227 CMF statistically significant at 90 percent CL).

Table 22 shows the TCD CMF estimates corresponding to off-ramps at cross-street locations.

Table 22. WWD crash CMFs for TCDs at off-ramps in Texas.

TCD	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
DNE, WW, OW, or STOP additional sign[a]	Day	0.690	0.388	1.226	0.425	1.119	—
DNE, WW, or OW additional sign[a]	Night	0.623	0.402	0.965	0.431	0.900	*
STOP_Bar, WW Arrow, or Lane use Arrow[a]	Day	0.189	0.028	1.299	0.037	0.958	~
Presence of STOP_Bar, WW Arrow, or Lane Use Arrow[a]	Night	0.227	0.051	1.014	0.064	0.800	~
Additional DNE sign[b]	Day	0.321	0.162	0.639	0.180	0.573	**
Additional DNE sign[b]	Night	0.640	0.424	0.905	0.452	0.966	*
Additional WW sign[b]	Night	0.767	0.318	1.608	0.366	1.848	—
WW or OW additional sign[b]	Day	1.522	0.693	3.343	0.784	2.952	—

—Not applicable.
~Significant at the 90.0 percent CL.
*Significant at the 95.0 percent CL.
**Significant at the 99.0 percent CL.
[a]Base condition: Off-ramp intersecting divided cross street (urban and suburban).
[b]Base condition: Off-ramp intersecting undivided cross street (urban and suburban).

Table 22 shows that only five CMFs were statistically significant for off-ramps connecting directly to the surface street network. Large and statistically significant WWD crash reductions were associated with the following pavement markings at intersections with divided cross streets: stop bar, WW arrows, and lane use arrows, both in terms of day WWD crashes (0.189 CMF for day WWD crashes, and 0.227 CMF for night WWD crashes, both statistically significant at the 90 percent CL).

For off-ramps intersecting divided highways, the addition of DNE, WW, or OW signs was linked with a statistically significant reduction in nighttime WWD crashes (0.623 CMF statistically significant at the 95 percent CL). Similarly, comparable reductions in WWD crashes were found to be linked with the presence of DNE signs at off-ramps intersecting undivided cross streets. This estimated impact was larger for daytime than nighttime WWD crashes (0.321 CMF for daytime and 0.640 for nighttime).

Discussion of Results

This section provides CMF estimates for WWD countermeasures using the following four types of POE configurations identified in the Texas datasets:

- Off-ramp onto frontage roads intersecting divided cross streets.
- Off-ramp onto frontage roads intersecting undivided cross streets.
- Off-ramps intersecting divided cross streets.
- Off-ramps intersecting undivided cross streets.

Overall, the statistically significant CMFs had directions with intuitive interpretations and, in most cases, with reasonable magnitudes. Some statistically significant CMF magnitudes were surprisingly large (e.g., stop bar, additional WW signs, and DNE signs), but consistent with the expectation that such TCDs contribute to reducing the likelihood for WWD crashes, during both daytime and nighttime.

An interesting trend in the results is the effectiveness of two types of countermeasures that appeared to be most effective by facility type. In the case of frontage POEs, geometric features and access management countermeasures showed convincing evidence of having good potential to reduce WWD crashes. The corresponding CMFs support the hypothesis that WWD crash risk can be effectively curbed by increasing the distance between the beginning of the off-ramp and the crossroad intersection, reducing the number of frontage road driveways, or applying appropriate signage at T intersections between off-ramps and cross streets (table 20). In contrast, for POEs with off-ramps directly feeding to the surface street network, neither geometric features nor access management produce statistically significant CMFs indicating a reduction of WWD crash risk. (table 19).

Regarding TCDs, the results were consistent, intuitive, and generally showed comparable magnitudes for all types of facilities under evaluation. WWD crash reductions were found to be linked to WW signs, turning lane path markings, and stop bar markings at frontage roads (table 21), whereas DNE signs and various kinds of pavement markings were effective at off-ramps to cross-street locations (table 22). The large magnitude of these estimates was surprising, though the research team reasons that these large reduction estimates may be realistic given the extreme rarity of WWD crashes. If a deployed countermeasure is indeed effective and leads to the prevention of even a moderate number of WWD crashes, such crash reduction should correspond to a very large proportion of the total WWD crashes when expressed as a percentage.

WWD Safety Evaluation in Florida

The complete dataset for Florida consisted of only 172 distinct corridors, or about 20 percent of the size of the Texas dataset. Out of the total 172 corridors in Florida, 110 are type II corridors, and only 62 are type I non-WWD corridors added in the stage 3 data collection. Therefore, 110 crashes are represented among the 172 corridors (2014–2016). Jointly, this dataset contains 708 POEs among type I and type II corridors. The corridor length was defined to have an approximately 85 percent chance of capturing the true POEs for all WWD crashes in the dataset, which implies that all corridors in this dataset should jointly have a crash expectation of

110 × 0.85 = 93.5 WWD crashes. Initially, the research team intended to create subsets for analysis for Florida similar to those in the Texas evaluation, but due to the smaller dataset size and the reduced number of WWD crashes represented, creating the same subsets was deemed unfeasible. In addition, the number of frontage locations in Florida was minimal (only 11 out of 708 POEs in the dataset). The research team then decided to remove the 11 frontage locations and divide the remaining 697 locations by type of intersection, as shown in table 23 (i.e., with either a divided or an undivided crossing road). After removing frontage locations, the total for the marginal crash risks for all POEs was confirmed to be 92.47. Table 23 shows the statistics for the larger subsets of data in Florida.

Table 23. Florida corridors for analyses in phase 2 (urban and suburban).

Subset[a]	No. of Corridors[b]	No. of POEs	Daytime WWD Crashes in Subset[c]	Nighttime WWD Crashes in Subset[c]	Daytime WWD Crashes per POE	Nighttime WWD Crashes per POE
POEs at ramps intersecting divided cross streets	109	382	4.15	24.9	0.038	0.228
POEs at ramps intersecting undivided cross streets	92	315	15.45	47.97	0.168	0.521

[a]These subsets are shown for informational purposes. The complete Florida database consists of 110 WWD crashes and was analyzed altogether. The subsets are shown for informational purposes only. This table shows the split of a total cumulative risk of 92.47 WWD crashes =110 WWD crashes×0.85−1.03 (chances of actual POE represented in the database), after removing frontage locations.
[b]Since there are 172 distinct corridors, 29 corridors have at least 1 POE of each type in this table.
[c]The number of WWD crashes represented was estimated as the sum of crash risk, marginal at the corridor level to jointly represent the known total corridor risk of 1.0 for type I corridors and 0.85 for type II corridors (see chapter 2).

However, since that partition results in small subsets for analysis (e.g., only 4.15 daytime WWD crashes represented in 382 POEs at divided crossing roads), the research team decided to analyze the Florida database without making subsets as they did for Texas, after removing the 11 POEs at frontage locations.

Table 23 clearly indicates an increased WWD risk during nighttime compared to daytime at both types of crossing roads (divided and undivided), which is consistent with the same trend observed in the Texas dataset.

PSW Balancing for Signage Comparisons in Florida

Similar to the Texas analyses, exploratory analyses indicated imbalances in covariates if statistical contrasts are required for different levels of signage. Accordingly, the research team developed overlap PS weights for each dataset to ensure the analysis results are indicative of the overlap population between the POEs under the lower half of signage and the upper half. To define the signage quartiles, the research team used statistics from the marginal distributions for three signage variables: WW_Signs, OW_Sign, and DNE_Sign.

Binomial Models of WWD Crash Risk in Florida

Consistent with the approach followed for Texas, the team developed statistical models to characterize the risk for two WWD crash types only: daytime and nighttime. The research team carried out stepwise model selection by considering up to two-way interactions between variables. Similar to the Texas analyses, the team used binomial GLMMs with crossed random effects because of the many-to-many correspondence between POE and WWD crashes in these datasets.

All models in the evaluation explicitly considered AADT and other relevant geometric elements, regardless of their statistical significance, because past research has documented these elements to be safety influential. Therefore, the linked safety associations of these elements are deemed to be accounted for when producing CMFs that are expected free of the influence of these potential confounding factors. However, different accounts for vertical and horizontal signage and other elements were possible, considering limitations in statistical power resulting from different dataset sizes and estimated number of represented WWD crashes, as indicated in table 23. Table 24 shows the results from daytime WWD crash modeling in Florida, whereas table 25 shows nighttime results.

Similar to some analyses in Texas, the research team estimated coefficients for aggregate measures of signage in some instances due to a combination of factors, such as the sample sizes, number of WWD crashes represented, and limited variability or availability of some signage elements.

Both table 24 and table 25 include a coefficient for vertical signage. However, only the estimate for daytime WWD crashes is statistically significant at the 90 percent CL. Coefficients in table 25 indicate that differences in traffic control and geometry are more important than the presence of TCDs at nighttime.

Table 24. Daytime WWD crash analysis results for nonfrontage ramps in Florida (urban and suburban).

Parameter	Estimate	Std. Error	*z* Value	*p* Value	Signif.
(Intercept)	−2.9851	2.4958	−1.196	0.2317	—
log(AADT)	0.0095	0.2383	0.04	0.9683	—
Count of vertical signage[a]	−0.3164	0.1706	−1.855	0.0636	~

—Not applicable.
~Significant at the 90.0 percent CL.
[a]The signage counted in this variable includes DNE_Sign and WW_Signs.

Table 25. Nighttime WWD crash analysis results for nonfrontage ramps in Florida (urban and suburban).

Parameter	Estimate	Std. Error	*z* Value	*p* Value	Signif.
(Intercept)	−3.6176	1.5519	−2.331	0.019747	*
log(AADT)	0.0424	0.1495	0.284	0.776754	—
No. of ramp lanes	0.7159	0.2099	3.411	0.000647	**
Signalized traffic control	−2.2551	0.6843	−3.296	0.000982	**
TWSC traffic control	−3.5197	1.5062	−2.337	0.019446	*
No Traffic Control	0.1845	0.6308	0.292	0.769916	—
Count of Vertical Signage[a]	0.1875	0.1335	1.405	0.160083	—

—Not applicable.
~Significant at the 90.0 percent CL.
*Significant at the 95.0 percent CL.
**Significant at the 99.9 percent CL.
[a]The signage counted in this variable includes WW_Signs and DNE_Sign.

The next section presents CMF estimates supported by the results presented in table 17.

CMFs from Florida

Similar to Texas, the teams considered the following two categories of countermeasures at the originating locations of WWD maneuvers:

- Geometric features.
- TCDs.

In contrast with Texas, not enough data were available to develop access management countermeasures for Florida. The following subsections present CMF estimates under each of the two feasible categories of countermeasures.

CMF for Geometric Features

Although the researchers considered the ramp length in the initial statistical models, they dropped that feature due to considerations of parsimony. The final models only support assessing the potential outcome of having additional ramps or ramp lanes at an intersection in the road network. Table 26 shows the single result for this evaluation.

Table 26. WWD crash CMFs for geometric features at nonfrontage roads in Florida.

Geometric Feature	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
Remove ramp lane[a]	Night	0.489	0.324	0.737	0.346	0.691	*

—Not applicable.
*Significant at the 99.9 percent CL.
[a]Base condition: Urban or suburban cross street (divided or undivided).

The single CMF was statistically significant, meaning the evaluation found convincing statistical evidence of a reduction in WWD crash expectation associated with each additional ramp or ramp lane removed from a POE intersection (0.489 statistically significant CMF at the 99.9 percent CL). The direction of this CMF is consistent with the corresponding CMF from Texas (CMF 0.605 for day crashes, see table 19), although this Texas CMF was statistically insignificant.

CMFs for TCDs

The second category of countermeasures in this evaluation focused on TCDs at ramp locations. Again, due to limited sample sizes, not all TCDs had enough representation in the Florida dataset, and therefore the analysis developed reduced models that only included the most salient signals in the data about TCD safety. Table 27 shows the CMF results corresponding to those models.

Only one of the two CMFs in table 27 is statistically significant. The 1.206 CMF for night WWD crashes was statistically insignificant, whereas the 0.729 CMF for day WWD crashes was statistically significant at the 90 percent CL. This result indicates suggestive evidence that adding WW or DNE signs at these points of entry is associated with a reduction in day WWD crash risk.

Table 27. WWD crash CMFs for TCDs at off-ramp locations in Florida.

TCD	WWW Crash Type	CMF	Lower Limit (95% CL)	Upper Limit (95% CL)	Lower Limit (90% CL)	Upper Limit (90% CL)	Signif.
Additional DNE or WW sign	Day	0.729	0.522	1.018	0.550	0.966	~
Additional DNE or WW sign	Night	1.206	0.929	1.567	0.968	1.504	—

—Not applicable.
~Significant at the 90.0 percent CL.

SUMMARY OF FINDINGS

This chapter documents the statistical evaluations and steps taken to develop CMFs from the two-State database available for this study. The analysis developed statistical models for WWD crash risk at the study sites by using WWD countermeasures and other influential covariates as explanatory variables. The research team used the model coefficients to compute multiple CMFs. The research team found statistically significant results in the analyses of the larger dataset from

Texas and two statistically significant CMFs in the Florida dataset. Overall, the CMFs that were statistically significant had directions with intuitive interpretations and, in most cases, included reasonable magnitudes. However, the magnitudes for off-ramp locations for the statistically significant CMFs were surprisingly large but consistent with the expectation that such TCDs should contribute to reducing the likelihood of WWD crashes, both during daytime and nighttime.

An interesting trend in the results was the effectiveness of two types of countermeasures that appeared most effective by facility type. In the case of frontage road POEs, relative geometry of the off-ramp, frontage road, and crossroad and access management countermeasures showed convincing evidence of having good potential to reduce WWD crashes. The results suggest that WWD crash risk can be effectively curbed by reducing the number of frontage roads' access points (Stop, OW, no-left-turn signs, or a combination of these points), applying appropriate signage at T intersections between off-ramps and cross streets, or providing longer distances between the beginning of off-ramps and the intersection between the frontage road and cross street (table 18 and table 20). In contrast, for POEs with off-ramps directly feeding to the network of surface roads, evidence of geometry interventions on WWD crash risk was only provided by a single CMF in Florida (CMF 0.489 for ramp lane removal at urban intersections), and no evidence was found to support the effectiveness of access management strategies from either of the two State databases.

Regarding the effectiveness of TCDs, the results across the two States were consistent and intuitive, and the results showed comparable magnitudes for all the types of facilities at evaluations that yielded statistically significant results. WWD crash reductions were found to be linked to WW signs and turning lane path markings at frontage roads (table 21), whereas DNE signs WW signs, OW signs, and various kinds of pavement markings (stop bars, WW arrows, and lane use arrows) were found effective at off-ramps to cross-street locations (table 22 and table 27). The research team reasoned these large reduction estimates may be realistic, given the extreme rarity of WWD crashes. If a deployed countermeasure is indeed effective and leads to the prevention of even a moderate number of WWD crashes, such crash reduction should correspond to a very large reduction in the percentage of total WWD crashes.

CHAPTER 5. ECONOMIC ANALYSIS

The research team conducted an economic analysis to estimate B/C ratios for the evaluated WWD countermeasures on freeways and associated crossroads by using the CMFs developed from the Texas database. The estimates of the B/C ratios were performed on the WWD signs and markings that showed statistical significance regarding the reduction of WWD crashes. The research team adopted the procedures recommended in FHWA's technical document entitled *Highway Safety Benefit-Cost Analysis Guide* (Lawrence et al. 2018).

BENEFITS AND COSTS ESTIMATES

Many possible scenarios could be evaluated for a B/C analysis based on the CMF results from the previous chapter. The team selected WW signs and DNE signs for this estimation because these signs were considered when balancing the data for TCD comparisons. In addition, the team reasoned that vertical signage types of TCDs are among the most versatile and applicable at multiple types of locations and situations.

The research team computed the costs of installation of signs based on the estimates from the 2015 to 2019 construction projects in Arizona reported by Moeur (2021) because those data were considered most current. Those data showed that a 48-inch by 48-inch R5-1 DNE sign mounted on a 6-ft post with a cantilever foundation costs about $10,700, and a 48-inch by 48-inch R5-1a WW sign mounted on a 6-ft post with a cantilever foundation costs about $10,446. However, the costs are estimated in 2019 dollars. When the amounts were converted to 2021 dollars, the estimated installation cost per sign reaches $10,766 for the DNE sign and $11,028 for the WW sign.

The most recent estimate of the value of statistical life is $11.6 million, as reported by the U.S. DOT (Putnam and Coes 2021). This number tracks comparably with the $12.2 million that can be estimated from FHWA's *Crash Costs for Highway Safety Analysis*, considering the national estimates provided in that report for 2010 and given an overall cumulative inflation between 2010 and 2021 (i.e., 20.6 percent) (Harmon, Bahar, and Gross 2018; Macrotrends 2022). The larger value estimated from the FHWA report probably indicates an average of fatalities per fatal crashes slightly larger than one.

The research team proceeded as recommended in the *Crash Costs for Highway Safety Analysis*, to produce average costs values for all levels of the KABCO severity scale (Harmon, Bahar, and Gross 2018). However, because the safety results in the previous chapter did not explicitly account for crash severity, the research team calculated the average cost of a WWD crash, given the updated KABCO cost and the proportions of crashes of each severity present in the combined datasets for Texas and Florida (table 9). The resulting estimation for crash cost average was $1,580,741 in 2021 dollars.

Economic Effectiveness of WW Sign for Daytime Crashes

The research team used the estimated safety changes from the analysis of daytime WWD crashes at frontage roads intersecting divided crossroads to estimate the B/C ratio of WW sign installations. The team rationalized that this process would produce the most robust and conservative estimations of the effectiveness of WW signs from the analyses performed. The researchers were unable to obtain a CMF estimate for nighttime crashes at intersections with frontage roads and divided crossroads. Although these signs were found to be effective for nighttime WWD crashes at intersections with undivided roads, both in Texas and Florida, these CMFs tended to indicate a very large effect, which is often estimated from significantly smaller data subsets. Therefore, the team deemed the daytime estimate from Texas to be the most reliable number from the study.

The team estimated that the benefit of applying WW signs was derived from the 49-percent reduction in WWD crash risk (table 21) during daytime for facilities with frontage roads intersecting divided cross streets. For the calculation, the research team considered that for a 6-mi corridor of this facility type, the average number of POEs is 2.33, meaning that to cover POEs in both directions, WW signs would be required on an average of five POEs (as each corridor was defined directionally). In addition, the average number of daytime WWD crashes at a corridor of this facility type was 0.491 WWD daytime crashes during the 3-yr analysis. The equivalent benefit under these assumptions was $396,194 in terms of prevented WWD daytime crashes. The installation cost of each sign was $1,945, assuming a foundation is required for a breakaway post. The cost of replacing a sign with a breakaway post was $446. Assuming that each sign and post, on average, would be replaced every 2 yr, the estimated B/C ratio is 29.08 for this treatment. The treatment was found to be beneficial, even when adding redundant signs. Repeating the calculations for the installation of two additional WW signs instead of one resulted in a B/C ratio of 21.96, or a B/C ratio of 13.83 when installing four such signs.

Economic Effectiveness of Additional DNE Sign for Daytime and Nighttime Crashes

For the next evaluation, the research team used the estimated safety changes linked to DNE sign installations at off-ramps at divided cross streets because these estimates were considered the most robust and conservative.

The benefit of applying DNE signs was derived from the 68-percent reduction in WWD daytime and 36-percent reduction in nighttime crash risk (table 22) at off-ramps intersecting divided cross streets directly in Texas. For the calculation, the research team considered that for a 6-mi corridor of this facility type, the average number of POEs is 1.71, meaning that to cover POEs in both directions, additional DNE signs would be required on an average of four POEs (as each corridor was defined directionally). In addition, the average crash WWD frequency at night in a corridor with this type of facility was 0.714 WWD crashes during the 3-yr analysis. The equivalent benefit under these assumptions was $724,019.5 in terms of prevented WWD crashes (both daytime and nighttime). The installation cost of each sign was $2,200, assuming a foundation is required for a breakaway post. The cost of replacing a sign with a breakaway post was $700. Assuming that each sign and post, on average, would be replaced every 2 yr, the estimated B/C ratio is 55.7 for this treatment. The treatment was found to be beneficial, even when adding redundant signs. When the research team repeated the exercise for the installation of two additional DNE signs instead of one, the resulting B/C ratio was 37.4, or a B/C ratio of 21.1 when installing four such signs.

CHAPTER SUMMARY

This chapter describes the analysis performed to estimate the economic effectiveness of implementing some of the most common WWD crash TCD countermeasures. The chapter outlines the resources and assumptions involved in developing B/C ratios for the evaluations. All B/C ratios were greater than 1.0, indicating larger benefits than costs for these implementations. The following chapter provides a summary and the conclusions of the project.

CHAPTER 6. SUMMARY AND CONCLUSIONS

The objective of this study was to perform rigorous safety effectiveness evaluations of WWD crash countermeasures at freeways. Specifically, the study focused on the safety effectiveness of geometric features, access management strategies, and TCDs as potential countermeasures for WWD crashes. The study had a retrospective cross-sectional design, and the analysis was performed by using generalized linear mixed binomial models. The research team compiled safety data from 1,460 POEs in Texas and 644 POEs in Florida, representing 463 and 256 WWD crashes, respectively, for 3-yr periods in each State. The team supplemented the datasets with non-WWD crash locations at each State, yielding 2,722 POEs in Texas and 697 POEs in Florida for evaluation, with 375 and 110 WWD crashes, respectively, after filtering and cleaning. Due to the limited number of crashes, the evaluations were performed by only differentiating between daytime and nighttime conditions. In addition to the crash data, the research team collected geometry information and traffic volumes at study locations. The team could only identify the true POE for a small fraction of the data in Texas by reviewing crash narratives, leaving the rest of the datasets with unknown origin of the WWD maneuver that led to the corresponding WWD crash.

The team developed a two-phase methodology to leverage the subset with known POE–WWD crashes correspondence in the analysis of the larger database. In phase 1, the team analyzed the small subset to produce relative crash risk estimates for each POE. With the ability to produce estimates of WWD crash risk of all POEs, the team then estimated the relative risks of all POEs in the larger database to be analyzed in phase 2. This process was deemed to be a sounder approach than assuming equal risks for each potential POE or applying engineering judgment as the sole criterion to identify the most likely POE for each crash. PS weights were applied in the estimation of the models to achieve a balance regarding TCD presence. This complementary method was expected to contribute to the robustness of the study when the intent is to estimate causal effects (Imai and Ratkovic 2015; Vermeulen and Vansteelandt 2015).

All statistically significant CMFs were found in the analyses for the larger database in Texas, and two statistically significant CMFs were found in the Florida data. For geometric features, significant findings corresponded to both frontage roads and off-ramps to surface roads in Texas and off-ramps to surface roads in Florida. These analyses found that the chances for WWD crashes tend to be more likely at locations with more ramps or ramp lanes and less likely at locations with longer ramps. Regarding CMFs for access management, the analysis of Texas sites with POEs at frontage roads produced CMFs indicating that adding vertical signage to frontage T intersections is linked to a statistically significant reduction of daytime WWD crashes. The same analyses found that WWD crash incidence tends to be lower with each removed driveway at frontage roads (between off-ramps and crossing roads), in terms of both daytime and nighttime WWD crashes. Finally, regarding TCDs, the Texas analyses found WWD crash reductions associated with adding WW signs, DNE signs, STOP signs, OW signs, and pavement markings for turning lane paths as well as at locations where stop bars are present on frontage road approaches when intersecting crossing roads. Similarly for Florida, statistically significant CMFs were found for removing ramps or ramp lanes at intersections with off-ramps and for additional WW and DNE signs at these locations.

The economic evaluation of deploying WW and DNE signs found large B/C ratios, with values greater than 1.0 indicating these countermeasures are expected to produce more safety benefits than costs and therefore their installation is justified.

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The original maps in figure 12 and figure 13 are the copyrighted property of Google® Earth™ and can be accessed from https://earth.google.com/web/ (Google 2019). They were edited to show the locations of the crashes and the locations of the POEs identified by the research team.

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