Developing Crash Modification Factors for Adaptive Signal Control Technologies

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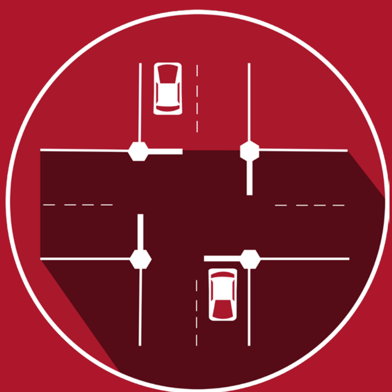

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Federal Highway Administration

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FOREWORD

The research documented in this report was conducted as part of the Federal Highway Administration's (FHWA's) Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS). FHWA established this PFS in 2005 to conduct research on the effectiveness of the safety improvements identified by the National Cooperative Highway Research Program's Report 500 Series as part of the implementation of the American Association of State Highway and Transportation Officials Strategic Highway Safety Plan (NCHRP 2003–2009, AASHTO 2005). The ELCSI-PFS evaluations provide a crash modification factor and economic benefit–cost (B/C) analyses for each of the targeted safety strategies identified as priorities by PFS member States.

This study evaluated the safety effectiveness of adaptive signal control technologies (ASCTs) at urban corridors. The research team compiled safety data relevant to the evaluation from Florida, Texas, and Virginia. Results from Florida and Texas did not offer statistical evidence of a change in safety derived from implementing ASCTs, except for a statistically large and significant reduction in rear-end crashes. The results from Virginia produced evidence of significant reductions in total crashes, fatal and severe crashes, and angle crashes. The economic evaluation considered two scenarios: one in which the safety benefit estimated from the Virginia analysis is realized and one in which operational benefits are realized after ASCT installation. This report will benefit safety and traffic engineers and safety planners by providing greater insight into how ASCTs impact intersection safety.

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16. Abstract
The objective of this study was to perform rigorous safety effectiveness evaluations of adaptive signal control technologies (ASCTs) used on urban corridors. To accomplish the goal of this study, the research team compiled safety data from Florida, Texas, and Virginia. Results from Florida and Texas did not offer statistical evidence of a change in safety derived from implementing ASCTs, except for a statistically large and significant reduction in rear end crashes (0.560 crash modification factor (CMF)). Conversely, the results from Virginia produced evidence of significant reductions in total crashes (a 13.3-percent reduction, or 0.867 CMF, at the 10-percent significance level), fatal and severe crashes (a 35.8-percent reduction, or 0.642 CMF, at the 5-percent significance level), and angle crashes (39.6-percent reduction, or 0.604 CMF, at the 5-percent significance level). The research team also conducted an economic evaluation that considered two scenarios: one in which the safety benefit estimated from the Virginia analysis is realized and one in which no measurable safety effect is realized (the worst-case outcome observed in this study), but operational benefits accrue after ASCT installation. When assuming a 13.3-percent reduction in total crashes, the benefit–cost (B/C) ratio was estimated as 65.56. When assuming no safety benefit derived from ASCT installations, the B/C ratio estimate reduced to 25.46. Data were analyzed using multiple estimation methods, including empirical Bayes, full Bayes, and interrupted time series with generalized estimating equations.

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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 ACRONYMS OR ABBREVIATIONS

AADT	annual average daily traffic
ACS Lite	Adaptive Control Software Lite
ADT	average daily traffic
ASCT	adaptive signal control technology
B/C	benefit–cost
CMF	crash modification factor
DCMF	Development of Crash Modification Factors
DOT	department of transportation
EB	empirical Bayes
ELCSI-PFS	Evaluation of Low-Cost Safety Improvements Pooled Fund Study
FB	full Bayes
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GEE	generalized estimating equation
GLSR	generalized linear segmented regression
ITS	interrupted time series design
ITS-CG	interrupted time series design with comparison group
KABCO	injury severity scale in which K is fatal injury, A is incapacitating injury, B is nonincapacitating injury, C is possible injury, and O is property damage only
MCMC	Markov Chain Monte Carlo
NCHRP	National Cooperative Highway Research Program
OPAC	optimized policies for adaptive control
PDO	property damage only
RHODES	Real Time Hierarchical Optimized Distributed Effective System
SCATS™	Sydney Coordinated Adaptive Traffic System
SCOOT™	Split Cycle Offset Optimization Technique
SPF	safety performance function
TEV	total entering vehicles
TWLTL	two-way left-turn lane
TxDOT	Texas Department of Transportation
VDOT	Virginia Department of Transportation
vpd	vehicles per day

EXECUTIVE SUMMARY

The Federal Highway Administration (FHWA) established the Development of Crash Modification Factors (DCMF) Program in 2012 to address highway safety researchers' need to evaluate new and innovative safety improvement strategies using reliable, quantitative estimates of the effectiveness of these approaches 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 to promote these approaches for nationwide installation by providing measures of their safety effectiveness and benefit–cost (B/C) ratios established through research. State departments of transportation (DOTs) and other transportation agencies need to have objective measures for safety effectiveness and B/C ratios before investing in new strategies for statewide safety improvements.

Forty-one State DOTs provide technical feedback on safety improvements to the DCMF Program and implement new safety improvements to facilitate evaluations. These States are members of the Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS), which is conducted under and supported by the DCMF Program.

The research summarized in this report evaluates adaptive signal control technologies (ASCTs) as a safety improvement strategy (safety intervention). ASCTs adjust when green lights start and end to accommodate changes in traffic demand, smoothing flow and easing congestion. The ELCSI-PFS Technical Advisory Committee determined that such an evaluation was among its high-priority evaluations.

Using total, fatal, injury, and property-damage-only crash frequencies, this evaluation assessed the potential to reduce crashes—expressed as crash modification factors (CMFs)—at locations where ASCTs have been implemented. An additional product of this research was an economic analysis that resulted in the development of B/C ratios for this safety improvement. Practitioners can use these CMFs and B/C ratios for decisionmaking during the project-development and safety-planning processes.

This research focused on multilane arterials in urban corridors, where these technologies are often implemented. The research team obtained geometric, traffic, and crash data at treated and control locations in Florida, Texas, and Virginia. The study design was an interrupted time series with a comparison group. Due to differences in the databases, the estimation was performed using either empirical Bayes (EB) or full Bayesian (FB) methods.

The results from Florida produced one statistically significant CMF, indicating a crash increase using the EB method, but the same CMF was statistically insignificant when using the more robust FB method. Considering both results, researchers concluded that no statistical evidence of any changes in safety was supported by the Florida data for the implementation of ASCTs. Results from Texas indicated a large, statistically significant reduction in rear-end crashes (44 percent), although researchers detected no other safety changes in this dataset. The results from Virginia indicated that statistically significant crash reductions are associated with ASCT installations (a 13.3-percent reduction in total crashes and a 35.8-percent reduction in fatal and severe crashes).

The economic analysis indicated a B/C ratio of 65.56 if ASCT installations indeed yield a 13.3-percent reduction in total crashes, as was found for Virginia. If for any reason new ASCT installations do not yield a safety benefit of such magnitude (e.g., in the case of Florida), researchers still found the congestion-reduction benefits to out-weigh the costs of installation and maintenance of the ASCTs. In this case, the B/C ratio was estimated as 25.46.

CHAPTER 1. INTRODUCTION

The Federal Highway Administration (FHWA) established the Development of Crash Modification Factors (DCMF) Program in 2012 to identify new safety strategies that effectively reduce crashes. The program promotes these strategies for nationwide installation by providing reliable, quantitative estimates of their effectiveness in reducing crashes. State departments of transportation (DOTs) and other transportation agencies use these objective measures of safety effectiveness and benefit–cost (B/C) ratios resulting from economic analyses to support decisionmaking when selecting and investing in new strategies for statewide safety improvements.

Forty-one States are members of the Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS), which provides technical feedback on priority safety improvement evaluations to the DCMF program and implements new safety treatments to facilitate these assessments. The ELCSI-PFS Technical Advisory Committee determined that evaluating adaptive signal control technologies (ASCTs) as a safety improvement strategy was among its high-priority activities.

This evaluation assessed the potential of the ASCT safety-improvement strategy to reduce crashes in terms of total, fatal, injury, and two intersection-specific crash types. The intent of the research team was to develop crash-modification factors (CMFs) and B/C ratios that would quantitatively describe safety improvements resulting from ASCT installation. Practitioners can use these CMFs and B/C ratios for decisionmaking in project-development and safety-planning processes.

ADAPTIVE SIGNAL CONTROL TECHNOLOGIES

ASCTs continuously monitor arterial traffic conditions and queuing at intersections, dynamically adjusting signal timing plan parameters to optimize one or more operational objectives (e.g., minimize overall delays, balance queue growth, or prevent queue spillback, among others) based on measured travel conditions in the corridor (FHWA 2014). Adaptive signal control is effective where daily variability in traffic demand results in unpredictable travel patterns. Adaptive signal controls rely on both traffic sensor systems to measure changes in normal travel patterns and algorithms to alter traffic signal timing parameters (i.e., cycles, splits, and/or offsets) in response to measured or predicted conditions.

Many traffic industry vendors have developed and deployed an array of ASCT products during the last 30 yr. Examples of these systems are the Split Cycle Offset Optimization Technique (SCOOT™), Sydney Coordinated Adaptive Traffic System (SCATS™), Real Time Hierarchical Optimized Distributed Effective System (RHODES), optimized policies for adaptive control (OPAC) (or virtual fixed cycle), Adaptive Control Software Lite (ACS Lite), and InSync.

The principal benefits of ASCTs compared to conventional fixed-time signal systems derive from a better distribution of signal green time, which improves corridor progression and reduces delay and congestion. Improving traffic flow and reducing stops may also improve traffic safety. This evaluation summarizes the findings from the research team's efforts to quantify potential safety improvements and economic benefits through the development of B/C ratios.

CHAPTER SUMMARY

This chapter introduced the project background and outlined the characteristics of ASCTs.

CHAPTER 2. LITERATURE REVIEW ON ASCT

The research team began by conducting a review of the available literature on previous studies to determine the safety effectiveness and economic benefits of ASCT. The team found relevant studies assessing the safety effectiveness of ASCTs to compare with the results found in this research, while studies on the economic benefit provided inputs for the economic analysis described later in this report.

SAFETY EFFECTIVENESS STUDIES

Anzek et al. (2005) studied the safety benefits of incorporating an ASCT at an intersection in the city of Zagreb in Croatia. City transportation officials upgraded the signal operations from pretimed phasing to simple adaptive traffic control. The research team observed a 35-percent reduction in crashes based on an analysis that used before–after data from a single year (Anzek et al. 2005).

Dutta et al. (2010) analyzed the safety performance of SCATS based on crash and volume data from the ASCT test bed in Oakland County, MI. The researchers compared a 9-intersection corridor equipped with SCATS to a similar corridor containing 14 intersections with pretimed signals. Using the KABCO injury severity scale,[1] they estimated SCATS reduced total crashes per mile per year by 16.8 percent, crashes of severity type A by 31 percent, crashes of severity type B by 43 percent, crashes of severity type C by 10 percent, and crashes of type O by 16 percent. Researchers did observe a shift in type A and B crashes to type C crashes, but crash reductions were not significant at the 95-percent confidence level (Dutta et al. 2010).

Stevanovic (2010) conducted a comprehensive literature review and survey to address the major problems with ASCT implementations worldwide (with emphasis on the United States) and published the findings in National Cooperative Highway Research Program (NCHRP) Synthesis 403. The researcher reported that ASCT deployments indirectly improved the safety of traffic operations by reducing efficiency-related performance measures, which are highly correlated with some safety metrics. Stevanovic reported that the ASCT implementations reduced the number of stops, intersection delays, and queue lengths in 37, 37, and 23 percent of the cases, respectively, and increased average speeds in 35 percent of cases (Stevanovic 2010).

Stevanovic et al. (2011) developed a microsimulation model that connected to SCATS to generate vehicle trajectories. The researchers then fed these simulated trajectories into a surrogate safety assessment model to estimate crash occurrence. The study used real-world data from two State Routes in Utah and included crash data from both before and after ASCT installation. The ASCT produced fewer total and rear-end conflicts than traditional traffic signal control. However, crossing and lane-changing conflicts increased (Stevanovic et al. 2011).

Lodes and Benekohal (2013) evaluated the costs and safety benefits associated with implementing ASCTs. This evaluation used an online survey to query 62 agencies that had implemented an adaptive control system in the United States. The researchers evaluated crash

[1]KABCO is an injury severity scale in which K is fatal injury, A is incapacitating injury, B is nonincapacitating injury, C is possible injury, and O is property damage only.

data for 1 yr before and 1 yr after the installation at three sites and observed a reduction in crashes. However, the sample size was too small to perform statistically rigorous tests (Lodes and Benekohal 2013).

Sabra et al. (2010, 2013) conducted a two-phase simulation study to balance safety and capacity in an adaptive signal system. The first phase identified the signal timing parameters that had the most impact on conflicts. Cycle length was the dominant factor affecting the number of conflicts. However, offsets, splits, left-turn phasing (protective/permissive), and phase sequence were also reported to be associated significantly with safety performance. For the second phase of this study, Sabra et al. developed safety performance functions (SPFs) using neural networks based on data from intersections equipped with both ASCTs and uncoordinated signals. The researchers trained the network with approximately 150 signal timing scenarios. The results showed reductions in conflicts along with improved travel time and reduced delays for various scenarios that optimized signal timing, including a surrogate safety measure that used an algorithm sensitive to conflicts (Sabra et al. 2010, 2013).

Despite their promise in evaluating safety, simulation-based safety evaluations of ASCTs are limited due to incomplete models of adaptive signal operations and performance. To overcome this issue, Ma et al. (2016) used the empirical Bayes (EB) method to analyze 47 urban and suburban intersections in Virginia where ASCTs were deployed. Analysis of 235 site-yr of before data and 66 site-yr of after data produced crash modification factor (CMF) values of 0.83 and 0.92, with a standard error of 0.05 for total intersection crashes and 0.08 for KABC crashes, respectively. The primary safety benefit of ASCT deployment was the reduction in PDO crashes, even though the safety benefits varied among corridors and different traffic volumes (Ma et al. 2015). This research observed reductions in total, fatal, and injury crashes at highway intersections where ASCTs were installed. Additional safety and mobility analyses were recommended before future installations.

Fink et al. (2016) collected data from SCATS-controlled intersections in Oakland, MI. For comparison purposes, Fink et al. collected a wide variety of geometric, traffic, and crash characteristic data for similar intersections in metropolitan areas elsewhere in Michigan. The researchers used negative binomial models to estimate three dependent crash variables. They used multinomial logit models to develop an injury severity model. A total of 498 signalized intersections were evaluated. This research estimated that SCATS controllers produced a CMF value of 0.807 for angle crashes. Severity results showed a statistically significant increase in nonserious injuries but no significant reduction in incapacitating injuries or fatal crashes (Fink et al. 2016).

Computer vision techniques can automate the extraction of traffic conflict details from video data. Tageldin et al. (2014) adopted this technique to conduct a before–after safety study of ASCTs. The evaluation focused on two intersections in Surrey, British Columbia, Canada. The analysis reported an increase in vehicle travel time after the ASCT installation coupled with a considerable increase in the frequency and severity of conflicts. The frequency of conflicts increased by 15.6 to 69.3 percent, and the severity index, defined by the authors as the exponential of minus half the squared ratio of time to collision to perception-reaction time, increased by 14.6 to 61.0 percent, depending on the type of road (major or minor) (Tageldin et al. 2014).

Khattak (2016) explored the potential safety benefits of ASCTs deployed in Pennsylvania. The first stage of this study focused on a 23-intersection corridor with adaptive signals. The second stage of the study selected 41 urban and suburban intersections equipped with SURTRAC and InSync ASCT systems. The author performed an EB before–after analysis, reporting a reduction in total crashes by 34 percent (a CMF value of 0.66) and fatal and injury crashes by 45 percent (a CMF value of 0.55) (Khattak 2016).

BENEFIT–COST RATIO STUDIES

Lodes and Benekohal (2013) argued that limited knowledge about operational and safety benefits and costs associated with ASCTs are deterrents for widespread adoption of these systems. The related literature indicates that the clearer benefits that ASCT deployments can yield are reductions in delays, number of stops, and other negative measures of traffic performance (Stevanovic 2010). The degree of operational benefit derived from installing ASCTs depends on several factors, such as the previous type of traffic control, the quality of previous signal timing, and the predictability or stability of traffic demand (Lodes and Benekohal 2013). ASCT deployments are most effective at locations where demand conditions are variable and unpredictable (FHWA 2012).

In addition to operational benefits, other potential nonsafety benefits of ASCTs noted in the literature include the following:

- Reduced fuel consumption.
- Decreased emissions and air pollution.
- Improvements in signal timing:
  - Decreased effort to develop signal timing plans; in some cases, it can reduce retiming intervals from years to minutes (FHWA 2012).
  - Lowered cost of periodic operational data collection and retiming.
  - Reduced cycle length, which results in better pedestrian response.
- Establishment of public transport and emergency vehicle priority.
- Better accommodation of roadwork and special events (compared with traditional systems).

Hutton et al. (2010) evaluated travel time, delay, number of stops, fuel consumption, and emissions to analyze the operational benefits of ASCT deployment on a 12-signal, 2.5-mi arterial in Lee’s Summit, MO. The period of analysis included 1 mo before and 5 mo after system installation. Depending on the time of day and direction of travel, analysis indicated that ASCTs decreased travel time through the corridor by 0 to 39 percent compared with closed-loop intersection control. All times of day in both directions of travel saw a decrease in the average number of stops, except for the AM peak period in the northbound direction. The research found reductions in the average number of stops through the corridor, fuel consumption, and emissions for every period where travel times decreased (Hutton et al. 2010). Given the results, no statistically significant increase in travel time was found during any time. The authors recommended a safety analysis be conducted, arguing that the reduced delays and stops along the corridor attributable to ASCT installations may relieve driver frustration and potentially result in fewer crashes related to aggressive driving.

A simple before–after safety evaluation at select locations equipped with InSync systems showed crash reductions ranging from 15 to 30 percent (Clark 2013). Although this preliminary safety evaluation suggests this type of signal control may result in crash reductions, it is unknown how strong the evidence supporting this finding is because the analysis did not explicitly quantify uncertainty (i.e., standard errors).

Consistent with the vendor's claim, a study of 17 corridors with InSync deployments in Virginia reported a 17-percent reduction in crashes and an annual B/C ratio of 8.17 (Ma et al. 2016). A monetary evaluation of the benefits emphasized the need for deploying ASCTs.

Tian et al. (2011) documented the benefits of SCATS at a major signalized arterial in Las Vegas, NV, with 10 intersections. The researchers performed extensive before–after travel-time runs at selected routes within the study network. They observed no significant improvement in terms of arterial progression under normal traffic conditions when compared with optimized time-of-day coordinated-plan operations. Tian et al. (2011) speculated that ASCTs might work better when traffic flow is highly variable and therefore can serve demand for a longer period without involving major retiming efforts.

Kergaye et al. (2009) evaluated a SCATS deployment in Park City, UT. The researchers inferred that various performance metrics were measurably greater with SCATS turned on than with SCATS turned off, including travel time, number of stops, and stopped delay.

ASCT systems vary widely in their detection configurations, communications, system architecture, type of installation, and other characteristics. Costs and benefits vary greatly among the alternatives (USDOT 2011). For example, some systems have significantly lower costs than others because they integrate well with existing controllers (FHWA 2012). Even though ASCTs have been found to provide benefits in most cases, it is difficult to provide a detailed overview of the benefits (Stevanovic 2010). ASCT costs include the capital, operational, and maintenance costs of the system. In the literature, costs are often shown as the cost of system installation per intersection. However, NCHRP Synthesis 403 provides the following information regarding the costs of ASCT systems (Stevanovic 2010):

- Licensing costs to run a system contribute an additional 10 to 15 percent to the overall installation costs and are usually not one-time costs.
- Reported costs often include more than just the installation of the adaptive component of the system. Replacements of the local intersection hardware and software (sometimes even installation of new communication infrastructure) often occur in conjunction with installation of the adaptive algorithms.
- In addition to the costs of operating both the hardware and software of the system, infrastructure maintenance may be costlier because of the higher needs required by an ATCS operation (e.g., more detectors or newer communications).
- Consulting costs and the costs of maintaining ATCS hardware and software should also be considered.

Based on a survey of 62 jurisdictions in 2012, Lodes and Benekohal (2013) discussed a range of ASCT costs for different systems as well as detection types used with the system. The average cost per intersection was estimated at $38,332 when cost data from all agencies were included and at $28,725 when agencies with the lowest and highest figures were excluded (to avoid undue influence of extreme values in the average). The authors report average costs per intersection by ASCT systems as well: $26,250 for ACS Lite, $30,739 for InSync, and $61,161 for SCATS. When breaking down the cost per intersection by detection technology, values ranged from $15,000 with magnetometer detection to $50,552 with video detection.

An FHWA report provides estimates of the monetary benefit of reducing emissions, fuel consumption, and vehicle delays resulting from crash reductions (Lawrence et al. 2018).

CHAPTER SUMMARY

The chapter presented a brief literature review that covered past research on the topic and similar efforts to evaluate the safety effectiveness of the treatment. It also addressed prior efforts to develop B/C ratios for ASCTs. The next chapter outlines the study design and analytical methods implemented for the safety effectiveness evaluation in this project.

CHAPTER 3. STUDY DESIGN AND STATISTICAL METHODOLOGY

The research team considered multiple factors in designing this study. The study design had to account for the features of the available data and the ultimate purpose of the analysis. The research team initially identified potential data sources with one key element that would allow a before–after evaluation: known date of the installation of ASCTs. For a strong before–after study design, however, it is important to select a comparison group of untreated sites that have characteristics similar to those with installations.

In the case of ASCT, establishing a comparison group was a challenge. The literature review indicates that the effectiveness of the treatment depends on several factors, such as the previous type of traffic control, the phasing and general quality of previous signal timing, and the predictability or stability of traffic demand. According to FHWA, ASCT deployments are most effective at locations where demand conditions are variable and unpredictable (FHWA 2012). Selecting control sites that met these criteria required reviewing variations in detailed hourly traffic data, signal timing, and signal phasing, but limited data were available at this level of detail. The team decided to look at sites that had previously been evaluated by transportation agencies and determined to be good candidates for ASCTs. This approach served as a proxy indicator of operational conditions that may warrant ASCT installation, making these sites ideal for a comparison group evaluation. Because this approach has the potential to produce a small number of sites in the comparison group (given the limited availability of said operational evaluations), the research team procured crash and traffic data for any years available at the treated corridors. In cases where there were no or not enough sites to serve as a comparison group, the team employed the interrupted time series approach, in which time plays the role of a comparison group, accounting for changes in stable baseline conditions.

Initially, the research team focused on two to five ASCT-type alternatives, including the most commonly used in the United States (SCOOT, SCATS, RHODES, OPAC, and InSync). The team requested data from multiple agencies and received various positive responses from several (Oregon, Florida, South Dakota, Virginia, and Texas). The research team assessed the potential of each dataset received based on its format and completeness. The research team ultimately decided to pursue additional data collection and assembly for only three States: Florida, Texas, and Virginia. The limited number of sites and reduced availability of key variables (e.g., dates of installation or average annual daily traffic (AADT) for minor roads at intersections) were the main reasons for narrowing the scope of additional data collection.

Safety studies are often limited to evaluations of observational data since randomization is not possible and true experiments, such as randomized comparison group trials, are not feasible. This study initially planned a quasi-experimental design to the extent possible, such as the nonequivalent comparison group (or comparison group) design or a control series design (Campbell and Stanley 1966; Campbell and Ross 1968). Unfortunately, a robust comparison group could only be developed for one of the three evaluations.

STUDY DESIGN

The research team identified available sources that would support a before–after design to evaluate the safety of ASCTs. The number of ASCT sites in the United States that have been maintained in continuous operation for several years and can be aligned with a time series of crash data is limited in most of the cases the research team reviewed. This significantly influenced the study design.

As mentioned previously, the research team added comparison groups to strengthen the design whenever possible. As described by Stuart (2010), the study team used matching methods, such as propensity score matching, when assigning control locations for use in comparing treatment sites that have similar covariate distributions. "Matching" is a statistical technique pairing treated and similar nontreated sites in an observational study or quasi-experiment (i.e., when the treatment is not randomly assigned). Given the multiple locations and different installation years available in the final dataset, the research team implemented an interrupted time-series (ITS) design for Virginia and Texas data (because no comparison groups were available) and an interrupted time series design with comparison group (ITS-CG) for Florida data (Campbell and Ross 1968; Gillings et al. 1981; Wagner et al. 2002; Friedman et al. 2009; Grundy et al. 2009).

The research team implemented an ITS-CG to accommodate the small number of treatment sites and the lack of a large reference group. ITS-CG is a quasi-experimental method used to determine the impact of an intervention, such as a deployment of ASCTs (Campbell and Stanley 1966; Campbell and Ross 1968). The study design requires crashes to be aggregated monthly or yearly at each site.

According to Campbell and Ross (1968), for ITS, the variable of interest (i.e., the "causal" variable) is treated in the analysis as an indicator of a change or event at a single point in time that is determined a priori and independently of the data. Here the causal variable (intervention) is a deployment of ASCTs. ITS-CG has previously been applied to before–after data to evaluate the impact of the intervention treatments on crash frequency (Wagenaar and Maybee 1986; Wagenaar 1986). In an ITS-CG, an intervention group is also evaluated against a comparison group that had not undergone the treatment. In an ITS-CG, the comparison group is selected to be as similar as possible to the intervention group to better estimate the true implications of the intervention treatment more accurately.

DATA ANALYSIS METHODS

The researchers selected statistical methods that are appropriate to the study design and characteristics of the datasets to conduct the empirical analyses. Analysis methods used in this evaluation included variants of EB and full Bayesian (FB) estimation methods as well as generalized linear models with generalized estimating equations (GEEs). The following sections provide more details about some of these methods.

Empirical Bayes

In recent years, EB methods have been widely used as safety evaluation tools in before–after analyses. What is referred to as the EB method in the transportation safety community is actually a combination of a specific study design (i.e., a before–after design with a reference group) and

EB estimation methods. It is based on the concept of weighting predicted crashes from an SPF developed from reference sites and the observed crash data at evaluation sites. Transportation professionals use this approach to obtain estimates of expected crash counts at the treated sites, where the weighting factors depend on the overdispersion parameter and predicted frequencies estimated from the SPF (AASHTO 2010). This approach assumes that as the overdispersion parameter grows, the reliability of the SPF diminishes, and thus more weight is given to the observed data. This approach enables EB methods to correct for regression-to-the-mean bias. Although an EB before–after evaluation has been a preferred method for developing CMFs during the last two decades, employing this method may not be feasible in every case because an EB evaluation requires the user to develop and calibrate a reliable SPF, which in turn must be based on a relatively large reference group. Such a group was not always available for the ASCT improvements evaluated in this project (comparable reference sites were only available for one State), as discussed previously in this chapter.

The research team considered using an EB analysis when it was possible to obtain a reasonably large number of reference sites that are similar to the treatment sites. In that case, the team also used matching methods in selecting relevant reference sites.

Full Bayes

The research team applied FB methods for the before–after analysis with the ITS-CG design. Although the EB method has been widely used as a safety evaluation tool in observational before–after studies for more than two decades, the EB method has known limitations, such as requiring reliable SPFs based on a large reference group. Additionally, uncertainty in the estimated SPFs is not reflected in the final safety effectiveness estimate of the EB method. Even though inherent uncertainties are associated with the estimated SPF coefficients, EB methods do not allow those uncertainties to be incorporated into the estimated index of effectiveness or percentage by which crashes are reduced.

FB methods have been introduced as an alternative to EB methods because they can compensate for the aforementioned issues associated with the EB approach. An important point is that FB methods refer to estimation methods that can, in principle, be applied to any study design, including cross-sectional and before–after designs. FB methods are becoming more popular in safety effectiveness evaluations because of their ability to overcome the previously identified limitations associated with EB methods. As a result, they have been successfully applied in many observational before–after studies over the last decade (Pawlovich et al. 2006; Li et al. 2008; Park et al. 2010, 2019). Several authors have also performed comparative studies that explore the differences between EB and FB approaches and have found that, even with a smaller sample size, the FB method can perform as well as the EB method (Park et al. 2010 2019; Miaou and Lord 2003; Persaud et al. 2010; Yanmaz-Tuzel and Ozbay 2010). However, while some early (and recent) applications of FB have been confined within the framework of the popular EB method (i.e., a design-analysis combination, as understood in the transportation safety community), they are considered a hybrid of the EB and FB methods as understood in this document (Lan et al. 2009; Persaud et al. 2010). Those early applications of FB adopted a framework that is very close to the EB approach in that they compared the predicted crashes in the after period without treatment to the observed crashes in the after period, not to the long-term expected crashes in the after period with the treatment.

Park et al. (2010, 2019) presented an FB multivariate approach tailored to before–after studies using a comparison group along with a clear step-by-step implementation procedure within the formal Bayesian modeling framework (rather than as a hybrid of EB and FB approaches). Under this approach, the counterfactual crash frequency in the after period is predicted for the treatment group based on the before period and the observed change in the comparison group. This prediction is defined as the *expected* crash frequency in the before period for the treatment group adjusted by the ratio of the expected crash frequencies for the before and after periods in the comparison group. In this framework, this estimate of predicted crashes is compared to the long-term *expected* crash frequencies in the after period for the treatment group as opposed to the *observed* crash frequencies in the after period, as is the case in the popular EB method. The FB evaluation of ASCT in this study builds on the basic modeling framework from previous research (Park et al. 2010, 2019).

Modeling Framework for FB Analysis of Before–After Designs with Comparison Groups

An ITS-CG was adapted as a study design for the FB analysis to assess the safety effectiveness of ASCT. In this study, researchers employed Poisson–gamma mixture models. Poisson–gamma mixture models are equivalent to negative binomial distributions for observed crash frequencies. This section presents the modeling framework of Poisson–gamma mixture models for an FB before–after evaluation with comparison groups.

Let y_{it} denote an observation at site i where ($i = 1, \ldots, I$) during time (year) t where ($t = 1, \ldots, T$). That is, y_{it} is the number of crashes that occurred in year t at site i. Let K be the number of covariates, and let $\mathbf{X}_{it} = (1, X_{1it}, \ldots, X_{Kit})$ be a (K+1)-dimensional vector of covariates.

Let $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_K)'$ denote the (K+1)-dimensional column vector of the regression coefficients for the crash count. Let υ_{it} denote a vector of yearly random effects corresponding to site i and year t, explaining extra-Poisson variability. Suppose that, conditional on υ_{it} and $\boldsymbol{\beta} \in R^{K+1}$, y_{it} follows a Poisson distribution with mean μ_{it}, as in figure 1.

$$y_{it} \,\middle|\, \upsilon_{it}, \boldsymbol{\beta} \sim Poisson(\mu_{it})$$

Figure 1. Equation. Poisson conditional distribution of yearly crashes at site *i*.

Figure 2 gives the value of μ_{it}.

$$\mu_{it} = \upsilon_{it} \exp(\mathbf{X_{it}} \cdot \boldsymbol{\beta})$$

Figure 2. Equation. Poisson mean parameterization.

The y_{it} are independent given the μ_{it}, as in figure 3.

$$\upsilon_{it} \sim Gamma(\eta, \quad 1/\eta)$$

Figure 3. Equation. Gamma distribution for mixture parameter.

Under the model, the marginal distribution of y_i is given as a negative binomial distribution with mean λ_i and variance λ_i $[1 + \lambda_i | \eta]$, where λ_i = exp($\mathbf{X}_i\boldsymbol{\beta}$).

Let the elements of the covariate vector $X_{it} = (1, X_{1it}, \ldots, X_{Kit})$ be those in figure 4.

$$\begin{aligned}
X_{1it} &= Trt_i, \\
X_{2it} &= time, \\
X_{3it} &= Trt_i \times time, \\
X_{4it} &= \mathbf{I}[t > t_{0i}], \\
X_{5it} &= Trt_i \times \mathbf{I}[t > t_{0i}], \\
X_{6it}, \ldots, X_{Kit}&: \text{intersection characteristic variables}
\end{aligned}$$

Figure 4. Equations. Definition of model covariates.

Where:

Trt_i = 1 if the ith site is a treatment site, otherwise it is zero.
$time$ = the tth year in the study period (t = 1, 2, …, T).
t_{0i} = the year in which the countermeasure was installed at site i (for a site in the comparison group, it is defined to be the same year as that for the corresponding treatment group).
$\mathbf{I}[t > t_{0i}]$ = the intervention variable, which takes a value of 1 if t belongs to the after period, otherwise it is zero.

Then, figure 2 can be rewritten as figure 5.

$$\begin{aligned}
\mu_{it} = \upsilon_{it} \exp\Big(\beta_0 &+ \beta_1 Trt_i + \beta_2 time + \beta_3 Trt_i \times time + \beta_4 \mathbf{I}\left[t > t_{0i}\right] \\
&+ \beta_5 Trt_i \times \mathbf{I}\left[t > t_{0i}\right] + \beta_6 X_{6it} + \cdots + \beta_K X_{Kit}\Big)
\end{aligned}$$

Figure 5. Equation. Reexpression of model parameterization for intervention coding variables.

This model can be viewed as a change-point model, which assumes that at the time of implementation there is a possible change in the response variable with respect to time at treatment sites that might be attributable to the implementation of the countermeasure. Specifically, the coefficient for $X_{5it} = Trt_i \times \mathbf{I}\ [t > t_{0i}]$ represents a possible increase or decrease in crashes at the treatment site resulting from countermeasure implementation. As previously noted, the comparison group also has the same imaginary before and after periods defined as those for the matching treatment group, although no treatment is applied to sites in the comparison group. The term corresponding to the change in the slope before and after the countermeasure implementation was not included in figure 5 due to the limited number of years for which there were crash data (e.g., there was only 1 yr of crash data for the after period at 25 sites with ASCT implemented in 2015 and 2 yr of crash data for the after period at 20 sites with ASCT implemented in 2014). For each group (comparison (*Comp*) and treatment (*Trt*)) and period (before (*B*) and after (*A*)), figure 5 can be rewritten in terms of *mean crash count* versus *time* as in figure 6.

$$(\mu_{it})_{Comp,B} = \upsilon_{it} \exp\left(\beta_0 + \beta_2 time + \beta_6 X_{6it} + \cdots + \beta_K X_{Kit}\right),$$

$$(\mu_{it})_{Comp,A} = \upsilon_{it} \exp\left(\beta_0 + \beta_4 + \beta_2 time + \beta_6 X_{6it} + \cdots + \beta_K X_{Kit}\right),$$

$$(\mu_{it})_{Trt,B} = \upsilon_{it} \exp\left\{\beta_0 + \beta_1 + (\beta_2 + \beta_3) time + \beta_6 X_{6it} + \cdots + \beta_K X_{Kit}\right\},$$

$$(\mu_{it})_{Trt,A} = \upsilon_{it} \exp\left\{\beta_0 + \beta_1 + \beta_4 + \beta_5 + (\beta_2 + \beta_3) time + \beta_6 X_{6it} + \cdots + \beta_K X_{Kit}\right\}$$

Figure 6. Equations. Mean crash predictions for evaluation subgroups.

An FB analysis of the model given in figure 1, figure 2, figure 3, and figure 5 requires (second-level) prior distributions for the parameters, $\beta_0, \beta_1, \beta_2, \ldots, \beta_K$ as well as η to be chosen. Implementation of such a model calls for simulation-based methods, such as a Markov chain Monte Carlo (MCMC) method. This method is one of the most frequently used techniques for computing posterior distributions. It consists of a sampling technique that enables simulation of posterior samples from the complex distributions of interest (Gelfand and Smith 1990; Liu 2001; Gilks et al. 1996).

Steps for Implementing FB Before–After Evaluations with Multiple (G) Comparison Groups

Once the posterior samples for model parameters and the true average crash frequencies (μ_{it}) per period for the treatment and comparison groups have been obtained, the following steps can be used to estimate the index (θ) of safety effectiveness (CMF) of the ASCT:

1. Specify the hyperparameter values (c_0, C_0, r_0, R_0) for prior distribution of model parameters.

2. Obtain the draws of model parameters and the expected annual crash frequency for each site i and year t by MCMC.

3. Obtain posterior distributions of crash frequencies during the before period for the treatment group (μ_{TB}), during the after period for the treatment group (μ_{TA}), during the before period for the comparison group (μ_{CB}), and during the after period for the comparison group (μ_{CA}) by taking an average of the expected crash frequencies over the appropriate years and sites.

4. Obtain a posterior distribution of the ratios of the expected crash frequency before and after periods for the comparison group (comparison ratio) for the gth comparison group using figure 7.

$$R_{C(g)} = \frac{\mu_{CA(g)}}{\mu_{CB(g)}}, \qquad g = 1, \cdots, G$$

Figure 7. Equation. Ratio of expected crash frequencies.

5. Obtain a posterior distribution of the predicted frequencies that would have occurred without treatment in the after period for the gth treatment group using figure 8.

$$\pi_{(g)} = \mu_{TB(g)} R_{C(g)}$$

Figure 8. Equation. After period counterfactual crash frequency estimate for treatment group.

6. Obtain a posterior distribution of the index of effectiveness (of the countermeasure) for the crashes using figure 9.

$$\theta = \frac{\sum_{g=1}^{G} \mu_{TA(g)}}{\sum_{g=1}^{G} \pi_{(g)}} = \frac{\sum_{g=1}^{G} \mu_{TA(g)}}{\sum_{g=1}^{G} \left\{ \mu_{TB(g)} R_{C(g)} \right\}}$$

Figure 9. Equation. Index of effectiveness estimate.

7. Obtain the point estimates for β_k and θ as the sample means of corresponding posterior distributions.

8. Obtain the uncertainty estimates for β_k and θ as the sample standard deviations of corresponding posterior distributions.

9. Construct the 95-percent (or 90-percent) credible intervals of β_k and θ using the 2.5th (or 5th) percentiles and the 97.5th (or 95th) percentiles of the corresponding posterior distributions. If the credible interval contains the value 1, then no significant effect has been observed. A credible interval of less than 1 (i.e., the upper limit of the interval is less than 1) implies that the countermeasure has a significant positive effect on safety (i.e., a reduction in crashes). A credible interval greater than 1 (i.e., the lower limit of the interval is greater than 1) implies that the countermeasure has a significant negative effect on safety (i.e., an increase in crashes).

The FB approach addresses the regression-to-the-mean problem by focusing on estimating the *expected* number of crashes for both before and after periods without directly using the *observed* crash count in the comparison. This feature implies that the observed yearly crash count is a noisy measurement of the true long-run mean crash frequency. As mentioned previously, to account for regression-to-the-mean bias, some of the previous FB applications compared the predicted crash count (based on both reference sites and the before period of treated sites) to the *observed* crash count for the after period (Lan et al. 2009; Persaud et al. 2010). This feature is rather like the EB approach. Although the observed after period crash count is an unbiased estimate of the expected after period crash count, it is still subject to uncertainty (and thus it is not the ideal estimate of the true crash count). In the FB approach, this uncertainty, as well as the uncertainty in other model parameters, is incorporated into the final CMF estimate.

CHAPTER SUMMARY

This chapter described the statistical methodology, analysis methods, and tools that the research team used in performing the work in this project. This chapter presented and discussed the challenges associated with the evaluation and the critical steps for developing a database with a large enough comparison group, and how including longer interrupted time series can help mitigate the risk of regression-to-the-mean bias. Then, the rationale for a before–after study design was presented. Finally, this chapter outlined statistical analysis methods to develop statistical models of crashes to be used in estimating the CMFs of interest. The next chapter outlines the subsequent data collection effort in detail.

CHAPTER 4. DATA COLLECTION AND INTEGRATION

Although ASCT systems have been in use for 30 yr (roughly 20 yr in the United States), many of them were implemented for demonstration or experimental purposes. Additionally, in most of the cases the research team reviewed, only a limited number of ASCT sites have been in continuous operation over multiple years, which enables them to be aligned with a time series of crash data. Further, the United States has various detection layouts and strategies to adjust network traffic control of ASCT deployments. As noted in chapter 3, the research team focused on two to five ASCT-type alternatives (SCOOT, SCATS, RHODES, OPAC, and InSync), the most commonly used in the United States. Ultimately, datasets from three States were prepared for evaluation due to the limited number of sites with sufficient implementation history and complete data for before and after periods.

As noted in chapter 3, after requesting data and locations for evaluation from several agencies, the research team received positive responses from multiple States (Oregon, Florida, South Dakota, Virginia, and Texas). The research team assessed the potential of each State's dataset to be included in the study based on its format and completeness. Ultimately, datasets representing two ASCT types (ASC Lite and InSync) from three States (Florida, Texas, and Virginia) were prepared for evaluation due to the limited number of sites with sufficient implementation history and complete data for before and after periods.

Overall, the datasets from these three States represented 191 different intersections with ASCT installed or sites with comparable characteristics. Ten different counties were represented, as shown in table 1.

Table 1. List of counties represented in ASCT datasets.

States (Number of ASCT Sites/Intersections)	County (Number of ASCT Sites/Intersections)
Florida (98)	• Orange (78) • Pinellas County (20)
Texas (25)	• Tyler (25)
Virginia (68)	• Salem (5) • Charlottesville (7) • Stephen's City (7) • Warrenton (6) • Winchester (22) • York County (17) • Staunton (4)

For all three datasets, the research team selected 46 variables to characterize each ASCT installation site. This variable information can be broadly classified into four categories:

- Traffic control device (TCD) (ASCT-related variables)—contains 13 variables to describe when and where the ASCT was installed or scheduled to be installed but does not include the after period (in which case the site was part of a comparison group in the analysis).
- Roadway design (RD) elements—contains 25 road-related variables to characterize the road segments connected with each study site (intersection). In this study, "major legs" refers to the road segments constituting a corridor and typically having higher AADT values; conversely, "minor legs" refers to the road segments intersecting the main corridor and typically showing lower AADT values.
- Traffic volume—contains two variables to show the AADT for the major and minor legs connected with a specific study site in a given year.
- Crash data—contains six variables to show the intersection crash counts for each study site, including crash counts based on their injury severity (e.g., KABCO). To select intersection-related crashes, the research team limited its selections to crashes occurring within a 250-ft buffer around each intersection.

Table 2 lists the variables collected for the study sites.

Table 2. List of variables collected for each study site.

Variable Category	Variable Name	Variable Description
TCD	ID	Unique intersection number
TCD	InstDate	Installation year
TCD	Year	Data collection year
TCD	Period	Indicating data collected before (B), during (D), or after (A) the installation year
TCD	State	State
TCD	County	County
TCD	CorrName	Corridor name
TCD	MJ_Name	Major street name
TCD	MN_Name	Minor street name
TCD	Project	ASCT installation project name
TCD	Y	Latitude
TCD	X	Longitude
TCD	TrafCont	Traffic control (ASCT) type
RD	NumLegs	Number of legs
RD	NumLegs_MJ	Number of major legs
RD	NumLanes_MJ	Number of through lanes for intersection's major legs
RD	NumeLanes_LT_MJ	Number of left-turn lanes for intersection's major legs
RD	NumeLanes_RT_MJ	Number of right-turn lanes for intersection's major legs
RD	TWLTL_MJ	TWLTL for major legs (binary)
RD	RT_Chan_MJ	Right-turn channelization for major legs (binary)
RD	BLane_MJ	Number of bike lanes for intersection's major legs
RD	LaneWid_MJ	Lane width for intersection's major legs
RD	BLaneWid_MJ	Bike lane width for intersection's major legs
RD	ShldWid_MJ	Shoulder width for intersection's major legs
RD	MedWid_MJ	Median width for intersection's major legs

Variable Category	Variable Name	Variable Description
RD	NumLegs_MN	Number of minor legs
RD	NumLanes_MN	Number of through lanes for intersection's minor legs
RD	NumeLanes_LT_MN	Number of left-turn lanes for intersection's minor legs
RD	NumeLanes_RT_MN	Number of right-turn lanes for intersection's minor legs
RD	TWLTL_MN	TWLTL for minor legs (binary)
RD	RT_Chan_MN	Right-turn channelization for minor legs (binary)
RD	BLane_MN	Number of bike lanes for intersection's minor legs
RD	LaneWid_MN	Lane width for intersection's minor legs
RD	BLaneWid_MN	Bike lane width for intersection's minor legs
RD	ShldWid_MN	Shoulder width for intersection's minor legs
RD	MedWid_MN	Median width for intersection's minor legs
RD	Med_Type_MJ	Median type for major legs: raised (R), flush (F), depressed (D), and no median (N)
RD	Med_Type_MN	Median type for minor legs: raised (R), flush (F), depressed (D), and no median (N)
Traffic volume	AADT_MJ	Average AADT for major legs
Traffic volume	AADT_MN	Average AADT for minor legs
Crash data	Crash	Total number of crashes
Crash data	K	Fatal crashes
Crash data	A	Major injury
Crash data	B	Minor injury
Crash data	C	Possible injury
Crash data	O	PDO
Crash data	Angle	Angled motor vehicle crash
Crash data	Rear End	Rear-end motor vehicle crash

TWLTL = two-way left-turn lane.

The following sections discuss the data collection and integration steps for the databases representing these States in greater detail.

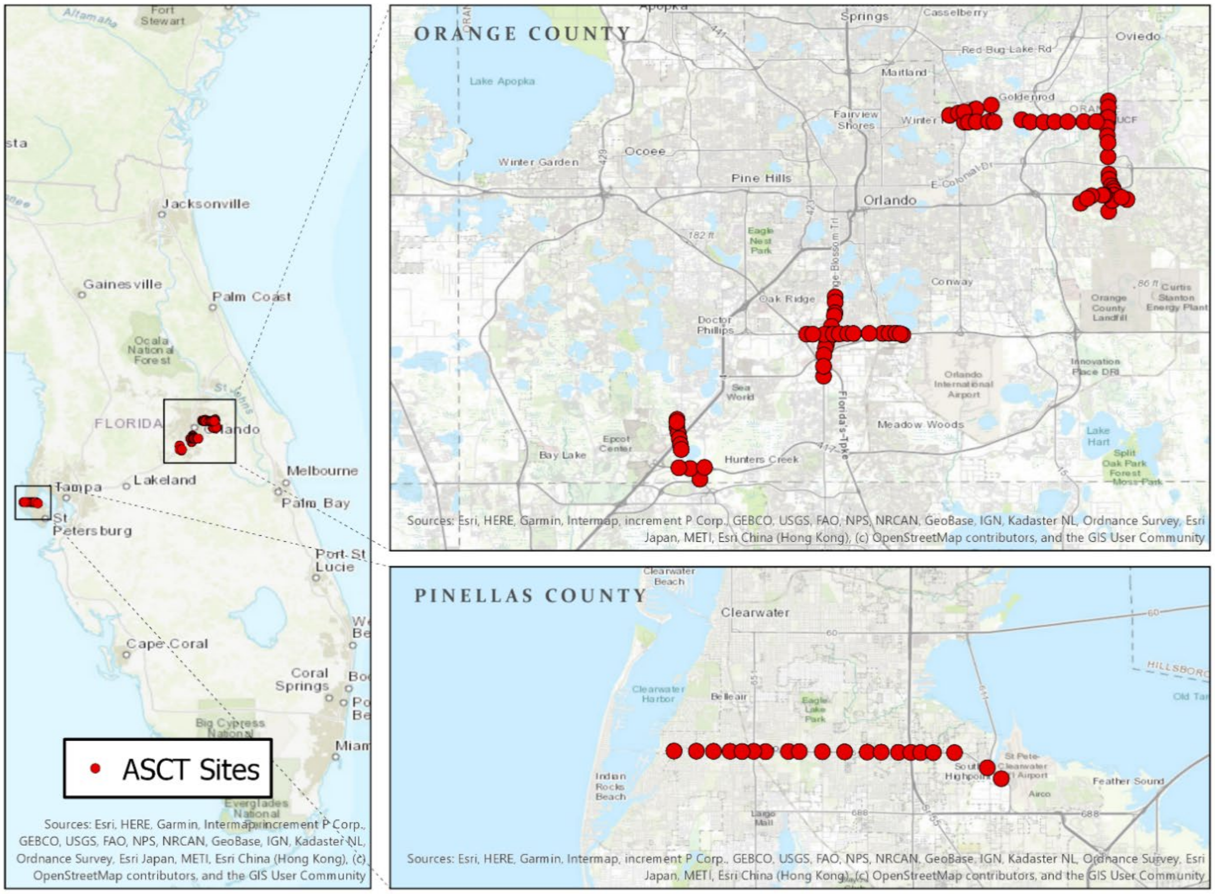
FLORIDA

ASCT and Roadway Design Data

The research team collected data from 98 intersections from two counties in Florida, including 78 from Orange County and 20 from Pinellas County (figure 10). These ASCT signals were distributed through six areas (or corridors):

- Walt Disney World in Orange County.
- Florida Mall in Orange County.
- University Boulevard in Orange County.
- East Bay Drive in Pinellas County.
- West Bay Drive in Pinellas County.
- Florida State Road 686 in Pinellas County.

All 20 ASCT signals in Pinellas County were equipped with InSync systems in 2014. The InSync ASCT signals in Orange County were installed in three different years: 2015 (25 intersections), 2016 (11 intersections), and 2017 (42 intersections). Because after period crash data were not available for the intersections treated in 2017, the research team used these sites as comparison corridors. The roadway design characteristics for major and minor legs were manually measured and collected from Google Earth™ satellite imagery (Google Inc. 2019).



Screen capture by Texas A&M Transportation Institute using ArcGIS software. © 2019 Esri and its licensors. All rights reserved. Service Layer Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), © OpenStreetMap contributors, and the GIS User Community.

Figure 10. Map. Study sites map. ACST sites in Florida.

Crash Data

The research team collected 7 yr of crash data (2010 through 2016) for each intersection from the Florida Department of Transportation (FDOT) State Safety Office (FDOT 2019). The research team created a 250-ft buffer around each intersection to identify intersection-related crashes, resulting in data for a total of 10,385 crashes being collected at the study sites.

AADT Data

The research team collected 7 yr of AADT data (2010 through 2016) for the major and minor legs. AADT data came from three data sources:

- Historical Annual Average Daily Traffic Shapefile, which was obtained from the FDOT Transportation Data and Analytics Office website. This shapefile contains 5 yr of AADT data (2014 through 2018) for road segments in Florida (FDOT 2019).
- Orange County traffic counts accessed through the Orange County Government website. This web-based platform provides up to 20 yr (1999 through 2018) of traffic volume data for each traffic count location (Orange County Government Florida 2019).
- Pinellas County traffic count maps obtained from the county's website. These maps represented 8 yr of traffic averages (2011 through 2018) (Pinellas County Florida 2019).

For the road segments with missing AADT values, the research team used the traffic volume of the nearest roadway segment with the same functional class to estimate the missing value. These data are labeled as imputed AADT in the database. Table 3 gives the descriptive statistics of the study sites features.

Table 3. Descriptive statistics of ASCT sites in Florida.

Variable Description	Minimum	Maximum	Mean	Standard Deviation
Number of legs for each study site	3.00	4.00	3.82	0.39
Number of major legs	2.00	2.00	2.00	0.00
Number of through lanes for major legs	2.00	9.00	545	1.04
Number of left-turn lanes for major legs	0.00	3.00	1.40	0.57
Number of right-turn lanes for major legs	0.00	2.00	0.63	0.54
Lane width for major legs	10.25	13.09	11.63	0.68
Shoulder width for major legs	0.00	16.54	1.34	2.94
Median width for major legs	0.00	178.98	16.22	18.97
Number of minor legs	1.00	2.00	1.82	0.39
Number of through lanes for minor legs	0.00	6.00	2.80	1.22
Number of left-turn lanes for minor legs	0.00	2.00	1.42	0.55
Number of right-turn lanes for minor legs	0.00	2.00	0.92	0.57
Lane width for minor legs	9.73	22.79	12.85	1.85
Shoulder width for minor legs	0.00	13.22	1.14	2.94
Median width for minor legs	0.00	49.09	10.46	10.69
AADT for major legs	14,223.00	207,000.00	47,731.36	17,797.57
AADT for minor legs	1,669.00	64,500.00	14,828.67	12,036.16
Total crashes	0.00	65.00	15.14	11.83
Fatal crashes (K)	0.00	2.00	0.05	0.23
Major injury (A)	0.00	9.00	0.96	1.36
Minor injury (B)	0.00	15.00	2.02	1.92
Possible injury (C)	0.00	21.00	3.64	3.18
Property damage only (O)	0.00	48.00	8.39	7.54
Angle	0.00	20.00	3.14	3.39
Rear end	0.00	37.00	8.54	7.02

In addition to the variables in table 3, indicator (binary) variables were collected to determine the presence of two-way left-turn lanes (TWLTL) and right-turn channelization at both major and minor legs.

TEXAS

ASCT and Roadway Design Data

The research team collected data from 25 intersections in Tyler, TX (figure 11). These locations were on three corridors:

- Loop 323 from US 69N south, east, and north to Commerce Street.
- US 69 (Broadway) from Amherst Drive to Cumberland Road.
- Beckham Avenue from Frontage Road (SH 31) south to Loop 323.

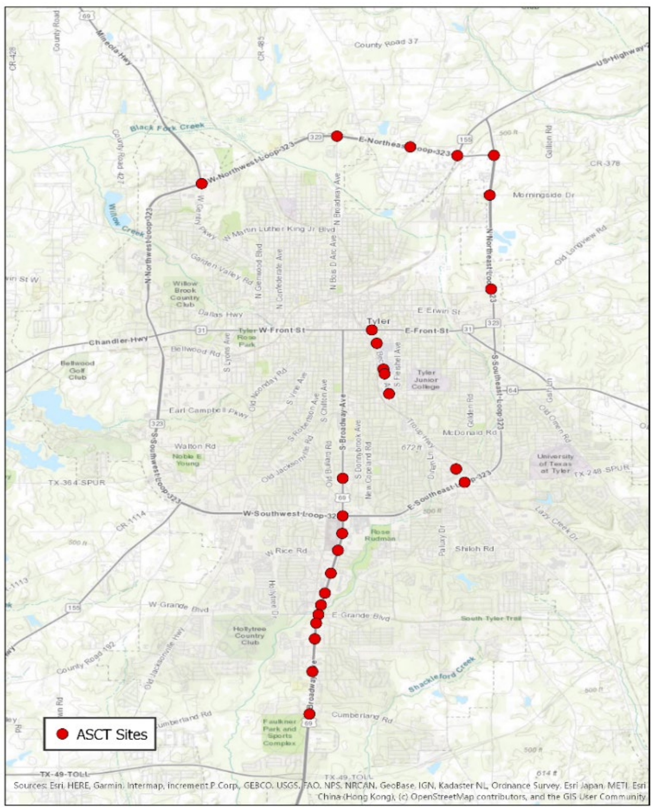


Figure 11. Map. ASCT sites in Tyler, TX.

These ASCTs were installed in 2012 using ASC Lite equipment. The roadway design elements for major and minor legs were manually measured and collected from Google Earth satellite imagery (Google Inc. 2019).

Crash Data

The research team collected 8 yr of crash data (2010 through 2017) for each study site. The Texas Department of Transportation (TxDOT) Crash Records Information System supplied the crash data (TxDOT 2019a). As for the Florida sites, the research team created a 250-ft buffer around each intersection to select intersection-related crashes. The period of analysis was expanded to 8 yr to obtain a stable baseline of comparison for the after period. The team identified a total of 4,067 intersection-related crashes during the 2010–2017 period.

AADT Data

The TxDOT Roadway Inventory Data table supplied the AADT data for the major and minor legs of each intersection (TxDOT 2019b). The research team collected 8 yr of AADT data corresponding to the years of crash data (2010 through 2017) for both major and minor legs. Table 4 gives the descriptive statistics of the resulting Texas database.

Table 4. Descriptive statistics of ASCT sites in Texas.

Variable Description	Minimum	Maximum	Mean	Standard Deviation
Number of legs for each study site	3.00	4.00	3.88	0.32
Number of major legs	2.00	2.00	2.00	0.00
Number of through lanes for major legs	4.00	6.00	5.00	0.94
Number of left-turn lanes for major legs	0.00	2.00	1.24	0.51
Number of right-turn lanes for major legs	0.00	1.00	0.60	0.49
Lane width for major legs	11.06	15.54	12.12	0.97
Shoulder width for major legs	0.00	11.94	3.01	4.50
Median width for major legs	0.00	34.12	7.79	10.27
Number of minor legs	1.00	2.00	1.88	0.32
Number of through lanes for minor legs	2.00	6.00	3.00	1.30
Number of left-turn lanes for minor legs	0.00	2.00	1.32	0.68
Number of right-turn lanes for minor legs	0.00	1.00	0.80	0.40
Lane width for minor legs	11.07	18.35	13.16	1.33
Shoulder width for minor legs	0.00	11.56	2.00	3.81
Median width for minor legs	0.00	29.17	3.24	6.69
AADT for major legs	13,366.00	43,589.00	28,767.70	9,174.28
AADT for minor legs	73.00	37,134.00	8,725.05	961.07
Total crashes	0.00	99.00	20.38	17.26
Fatal crashes (K)	0.00	1.00	0.05	0.22
Major injury (A)	0.00	2.00	0.31	0.57
Minor injury (B)	0.00	9.00	1.66	1.52
Possible injury (C)	0.00	19.00	3.97	3.73
Property damage only (O)	0.00	71.00	14.35	13.00
Angle	0.00	13.00	3.11	2.74
Rear end	0.00	15.00	2.39	2.58

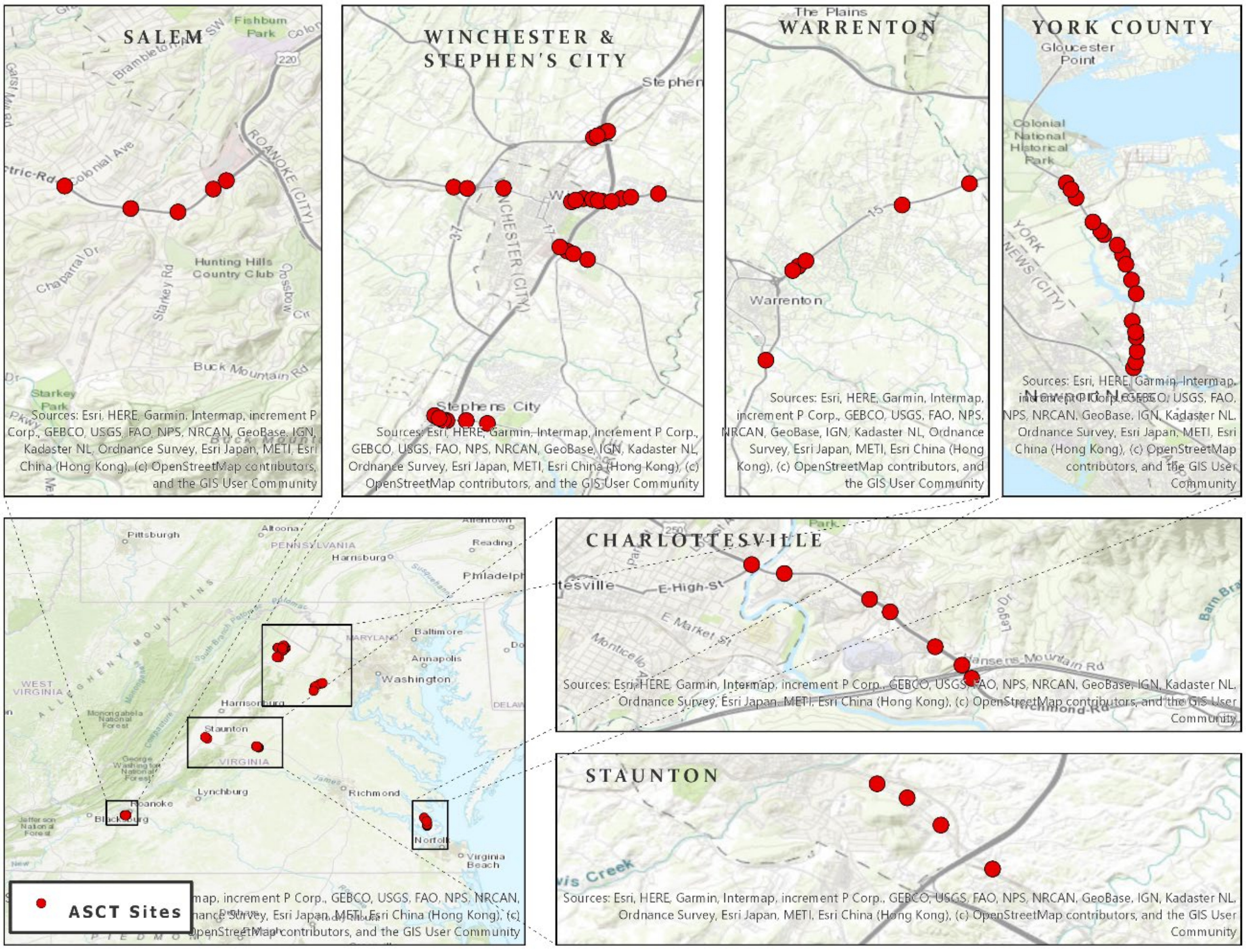
As with the Florida dataset, indicator (binary) variables were also collected to determine the presence of TWLTLs and right-turn channelization at both major and minor roads.

VIRGINIA

ASCT and Roadway Design Data

The research team collected data from 68 intersections with the ASCT systems from 7 counties in Virginia (figure 12). These ASCTs were installed along 10 different corridors:

- Virginia State Route 277 in Stephen’s City.
- Virginia State Route 419 (Electric Road) in Salem.
- Virginia State Route 7 in Winchester.
- US 11 in Winchester.
- US 17/50/522 in Winchester.
- US 50 (Northwestern Pike) in Winchester.
- US 17 York City Route in York City.
- US 250 Pantops Mountain Road in Charlottesville.
- US 250 Staunton Route in Staunton.
- US 29 in Warrenton.



Screen capture by Texas A&M Transportation Institute using ArcGIS software. © 2019 Esri and its licensors. All rights reserved. Service Layer Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), © OpenStreetMap contributors, and the GIS User Community.

Figure 12. Map. ASCT sites in Virginia.

In 2011, 18 InSync ASCT systems were installed at study sites, while 2012 saw 50 installations. The research team manually measured the roadway design characteristics of major and minor legs using Google Earth satellite imagery (Google Inc. 2019).

Crash Data

The Virginia Department of Transportation (VDOT) provided crash data for 8 yr (2006 through 2013) (VDOT 2018). The research team collected a total of 3,547 intersection-related crashes at these study sites from 2006 through 2013.[2]

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[2]The study team obtained this crash data via email from the Safety, Operations, and Traffic Engineering Team at VDOT in February 2018.

AADT Data

VDOT also provided 8 yr of AADT data (2006 through 2013) (VDOT 2018). Table 5 lists the descriptive statistics for the features of study sites in Virginia.

Table 5. Descriptive statistics of ASCT sites in Virginia.

Variable Description	Minimum	Maximum	Mean	Standard Deviation
Number of legs for each study site	3	4.00	3.75	0.43
Number of major legs	2	2.00	2.00	0.00
Number of through lanes for major legs	2	7.00	4.09	0.97
Number of left-turn lanes for major legs	0	2.00	1.22	0.48
Number of right-turn lanes for major legs	0	2.00	1.22	0.51
Lane width for major legs	10	16.06.00	12.13	1.05
Shoulder width for major legs	0	22.59.00	7.47	4.97
Median width for major legs	0	126.39.00	20.17	19.09
Number of minor legs	1	2.00	1.74	0.44
Number of through lanes for minor legs	0	5.00	2.19	0.86
Number of left-turn lanes for minor legs	0	4.00	1.25	0.75
Number of right-turn lanes for minor legs	0	2.00	1.15	0.62
Lane width for minor legs	6	22.50	13.09	2.34
Shoulder width for minor legs	0	16.02	2.40	3.78
Median width for minor legs	0	32.75	3.90	6.90
AADT for major legs	6,140	52,723.00	29,300.22	11,754.22
AADT for minor legs	329	39,755.00	6,228.08	6,047.88
Total crashes	0	39.00	6.52	5.69
Fatal crashes (K)	0	1.00	0.01	0.11
Major injury (ABC)	0	14.00	2.23	2.31
Property damage only (O)	0	29.00	4.24	4.09
Angle	0	18.00	1.88	2.29
Rear end	0	34.00	3.54	3.95

In addition to the variables in table 5, and similar to the data collection approach for the Florida and Texas sites, the team also gathered indicator (binary) variables to identify TWLTLs and right-turn channelization at both major and minor roads.

CHAPTER SUMMARY

This chapter documented the data collection and integration activities for a multistate ASCT safety evaluation. Since ASCT systems have been in use for roughly 20 yr in the United States, the research team developed time series safety datasets from three States: Florida, Texas, and Virginia. For each of these States, this chapter described the collection and assembly of the datasets, which comprised data reflecting ASCT and roadway design, crash, and AADT variables. The next chapter details the statistical analyses performed on these datasets and the corresponding results of the safety effectiveness evaluation of ASCTs.

CHAPTER 5. SAFETY EFFECTIVENESS EVALUATION

This chapter documents the statistical evaluations and analyses performed to develop CMFs from the databases for Florida, Texas, and Virginia developed in this study. Researchers assessed the safety benefits of ASCT on the following crash types: total, fatal and injury (obtained as the sum of K, A, B, and C crashes), and PDO (O) crashes. Due to nonnegligible differences in intersection characteristics across the three States, the research team performed a separate crash analysis for each State.

FLORIDA CRASH ANALYSIS

The research team conducted the safety evaluation of ASCT in Florida by employing two different evaluation approaches: EB before–after analysis and FB before–after analysis with comparison groups. ASCTs were installed at 98 intersections in Florida. As described in chapter 4, the team obtained yearly crash data for each of the 98 intersections for 2010 through 2016. The ASCT implementation year for each intersection varies between 2014 and 2017. Because the period for the Florida crash data is from 2010 through 2016, the team used the intersections with ASCT implementation in 2017 as the reference sites for the EB analysis and the comparison sites for the FB analysis. The 11 intersections treated in 2016 were excluded from both EB and FB before–after analyses because there were no after data. Table 6 gives the number of intersections for each implementation year.

Table 6. Number of Florida intersections for each implementation year.

Implementation Year	Number of Intersections	Site Type
2014	20	Treatment sites
2015	25	Treatment sites
2016	11	Removed
2017	42	Comparison sites
Total	**98**	**All**

EB Before–After Analysis

In the EB method, the research team used SPFs based on the data from the reference sites to estimate the expected crash frequencies at the treated sites had treatments not been applied. Negative binomial regression models are often used to derive the SPFs. In this evaluation, SPFs are calibrated for each year of the before and after periods rather than just for each period (Hauer 1997; Park et al. 2010, 2019).

The research team developed the negative binomial regression models with indicator variables by year (2010 through 2016) to control for general trends along with safety-sensitive variables, as shown in table 7, following the general functional form shown in figure 13.

$$\log \mu_{it} = \beta_{yr} + \beta_1 \times \log TEV + \cdots + \beta_k \times X_k$$

Figure 13. Equation. Link between average crashes and covariates.

The term β_{yr} denotes a different intercept per year, which indicates the baseline level of the log mean annual crash frequency for that year, while X_k indicates any additional covariate utilized in the analysis and logTEV is defined as the natural logarithm of the total entering vehicles as a measure of exposure. The underlying assumption for the above model is that the relationship between the log mean annual crash frequency and other covariates is linear for a given year.

Table 7. Estimates of coefficients for Florida SPFs developed based on a reference group consisting of crashes at 42 intersections.

Coefficient	Variable	Total	Fatal and Injury	PDO	Angle	Rear End
$\beta_{yr\,=\,2010}$	Indicates year = 2010	−14.604	−16.944	−18.906	−6.9698	−15.3787
$\beta_{yr\,=\,2011}$	Indicates year = 2011	−14.58	−16.92	−18.912	−6.8989	−15.3784
$\beta_{yr\,=\,2012}$	Indicates year = 2012	−14.461	−16.699	−18.908	−6.9573	−15.2317
$\beta_{yr\,=\,2013}$	Indicates year = 2013	−14.341	−16.732	−18.61	−7.0334	−15.0794
$\beta_{yr\,=\,2014}$	Indicates year = 2014	−14.309	−16.729	−18.561	−6.9879	−15.0815
$\beta_{yr\,=\,2015}$	Indicates year = 2015	−14.189	−16.622	−18.421	−6.8844	−14.9591
$\beta_{yr\,=\,2016}$	Indicates year = 2016	−14.25	−16.624	−18.516	−6.6899	−15.0585
β_1	LogTEV	0.9501	1.071	1.2729	0.5711	0.9123
β_2	NumLegs_MN	0.4233	0.2071	0.4298	—	0.3385
β_3	NumLanes_MJ	0.2372	0.2417	0.2954	0.1925	0.2925
β_4	NumLanes_MN	0.1488	—	—	0.0902	0.1747
β_5	RT_Chan_MJ	−0.6926	−0.5338	−0.8981	−0.9369	−0.7176
β_6	RT_Chan_MN	—	—	—	0.3028	—
β_7	NumLanes_LT_MJ	—	0.2543	—	0.1359	—
β_8	NumLanes_RT_MJ	—	—	0.1784	0.1037	0.1217
β_9	MedWid_MJ	0.0205	—	—	—	0.0261
β_{10}	MedWid_MN	—	—	—	0.003	—
β_{11}	Med_Type_MJ_R	0.5521	0.4525	0.6499	0.7283	0.4699
β_{12}	LaneWid_MJ	0.3538	0.3747	0.389	—	0.3734
β_{13}	LaneWid_MN	−0.0634	—	−0.0761	−0.051	−0.0540
β_{14}	BLaneWid_MJ	—	—	0.0543	—	0.0239
K	Dispersion	0.1302	0.1053	0.1294	0.1772	0.1474
χ^2:d.f	Pearson chi-square:DF	1.2181	1.1454	1.1449	1.0899	1.3364

—Variable not included in model.
LogTEV = log(AADT_MJ+AADT_MN).

The research team employed independent variables to develop SPFs based on the reference group, which consisted of 42 intersections treated in 2017. Table 7 presents the estimated coefficients for SPFs for total, fatal and injury, and PDO crashes.

Table 8 presents the results of an EB before–after evaluation for crashes. For each type of crash in table 8, the research team used the SPFs estimated from the reference sites to predict the expected number of crashes had ASCTs not been installed. The results of table 8 are not statistically significant for total, fatal and injury, PDO, and rear-end crashes. The results were statistically significant, however, for angle crashes.

Table 8. Results of EB before–after evaluations based on crashes obtained from 45 treated and 42 control intersections in Florida.

Crash Type	Crashes in the After Period: Observed	Crashes in the After Period: EB Estimate ($\hat{\pi}$)	CMF ($\hat{\theta}$) (SE)	95-Percent CI for CMF	90-Percent CI for CMF
Total	1,093	1,046.0	1.045 (0.038)	(0.970, 1.119)	(0.983, 1.106)
Fatal and injury	484	465.6	1.039 (0.055)	(0.931, 1.147)	(0.949, 1.129)
PDO	607	595.2	1.022 (0.049)	(0.926, 1.119)	(0.942, 1.103)
Angle	245	202.6	1.207 (0.089)*	(1.033, 1.382)	(1.061, 1.353)
Rear end	558	556.1	1.003 (0.050)	(0.905, 1.101)	(0.921, 1.085)

*EB estimates were statistically significant either at the 90- or 95-percent confidence level.
EB estimate ($\hat{\pi}$) = the predicted number of crashes in the after period had ASCT not been deployed; $\hat{\theta}$ = the estimated index of effectiveness; CI = confidence interval; SE = standard error.
Note: Numbers in parenthesis represent standard errors.

As shown in table 8, the analyses estimated the CMFs close to 1.0 in value. However, none of these estimates was statistically significant.

FB Before–After Analysis with Comparison Groups

The research team also analyzed crashes by employing an FB before–after evaluation method described in chapter 3. The 42 sites treated in 2017 that do not have after data were used as a reference group in the EB analysis and as comparison sites in the FB analysis. In the safety effectiveness estimate, the EB analysis cannot account for the uncertainty characteristic of the SPF estimates. In contrast, the FB analysis can incorporate uncertainty into the model parameters for the final safety effectiveness estimate.

The treatment group consists of crashes from intersections where ASCTs were installed during 2014 and 2015. As in the case of EB analysis, the 11 intersections implemented in 2016 (table 6) were excluded from the treatment group because before data were not available. Therefore, the FB analysis is also based on crashes from 87 intersections consisting of 45 treatment sites where ASCTs were installed in 2014 and 2015 and 42 comparison sites where ASCTs were installed in 2017.

The research team fitted the Poisson–gamma mixture model with a change point, shown in figure 5, to total, fatal and injury, PDO, angle, and rear-end crashes. This model included appropriate indicator functions for site type (specifying whether a segment is a treatment site or a comparison site) and period (specifying whether it belongs to the before or the after period) as well as time trend for each site type and other covariates. Exposure was accounted for by the total entering vehicles (TEV) variable, obtained by adding both major and minor leg AADTs. Additionally, the following variables (defined in table 2) were included as model covariates:

- NumLegs_MN.
- NumLanes_MJ.
- NumLanes_MN.
- RT_Chan_MJ.
- NumLanes_RT_MJ.

- NumLanes_LT_MJ.
- MedWid_MJ.
- Med_Type_MJ_R.
- LaneWid_MJ.
- LaneWid_MN.
- BLaneWid_MJ.

The research team followed the steps for implementing FB before–after evaluations with two comparison groups (corresponding to implementation years 2014 and 2015 with $G = 2$) presented in chapter 2. For the prior distributions of the model parameters, proper but diffuse priors were used to reflect the lack of precise a priori knowledge of the parameters. The inferences on the parameters of interest were based on the samples from the posterior distribution obtained by the MCMC algorithm coded in MATLAB. The functional form of this model was initially presented and discussed in chapter 3 (figure 5).

As noted in chapter 3, the coefficient for $X_{5it} = Trt_i \times \mathbf{I}[t > t_{0i}]$ represents a possible increase or decrease in crashes at the treatment site resulting from countermeasure implementation. For each group and period, figure 5 can be rewritten in terms of *mean crash count* versus *time,* as illustrated in figure 6.

Also as noted in chapter 3, an FB analysis of the model given in figure 1, figure 2, figure 3, and figure 5 requires the (second level) prior distributions for the parameters $\beta_0, \beta_1, \beta_2, \ldots, \beta_K$, as well as η, to be chosen.

Table 9 summarizes the results from the FB analysis based on 5,000 posterior samples collected over 250,000 iterations by subsampling every 50th sample after discarding the first 50,000 draws.

Table 9. Results for FB evaluation of total, fatal and injury, PDO, angle, and rear-end crashes in Florida at 87 intersections.

Coefficient	Variable	Total	Fatal and Injury	PDO Crashes	Angle	Rear End
β_0	*Intercept*	−20.0280	−11.0490	−22.4837	−4.8859	−12.7079
β_1	*Trt*	0.0934	−0.0897	0.5825	0.3594	−0.9146
β_2	*time*	0.0896	0.0630	0.0977	0.0758	0.0947
β_3	*Trt* × *time*	0.0018	−0.0130	0.0475	0.0582	0.0254
β_4	$\mathbf{I}[t > t_0]$	−0.1002	−0.0533	−0.0755	−0.1633	−0.1281
β_5	*Trt* × $\mathbf{I}[t > t_0]$	0.0326	0.0789	−0.1577	0.0387	−0.0978
β_6	NumLegs_MN	—	0.0655	0.5707	−4.8859	—
β_7	NumLanes_MJ	—	0.02448	−0.5586	—	0.0987
β_8	NumLanes_MN	0.4497	—	—	0.1298	0.5701
β_9	RT_Chan_MJ	0.1735	−0.0475	−0.0468	0.4063	−1.3440
β_{10}	RT_Chan_MN	0.4235	—	—	−0.3219	3.0909
β_{11}	NumLanes_LT_MJ	—	0.1154	—	−0.0989	—
β_{12}	NumLanes_RT_MJ	1.9914	—	2.3759	−0.5380	1.7768
β_{13}	MedWid_MJ	−0.0421	—	—	0.4250	−0.0401
β_{14}	MedWid_MN	0.0373	—	—	—	0.0203
β_{15}	Med_Type_MJ_R	1.8991	0.3874	1.9617	0.0081	1.9188
β_{16}	LaneWid_MJ	—	0.2987	−1.1083	0.5794	—
β_{17}	LaneWid_MN	—	—	0.2682	—	0.3120
β_{18}	BLaneWid_MJ	—	—	−0.1058	−0.0065	—
β_{19}	LogTEV	1.8004	0.6583	3.0843	0.3218	0.6817

—Variable not included in model.
LogTEV = log(AADT_MJ+AADT_MN).

Table 10 presents the CMFs estimates obtained from the FB model detailed in table 9.

Table 10. Results of EB before–after evaluations based on crashes obtained from 45 treated and 42 control intersections in Florida.

Index of Effectiveness	Total	Fatal and Injury	PDO Crashes	Angle	Rear End
CMF ($\hat{\theta}$)	1.0421	1.0326	1.0274	1.2396	0.9398
Std. dev. CMF	0.0628	0.0958	0.0840	0.1612	0.0781
95-percent credible interval	(0.9223, 1.1713)	(0.8539, 1.2354)	(0.8706, 1.2036)	(0.9528, 1.6092)	(0.7963, 1.1044)
90-percent credible interval	(0.9415, 1.1486)	(0.8847, 1.1979)	(0.8939, 1.1720)	(0.9980, 1.5266)	(0.8190, 1.0766)

$\hat{\theta}$ = estimated index of effectiveness.
Notes: Std. dev. represents the posterior standard deviation for θ. Numbers in parenthesis indicate standard errors.

The research team obtained the estimated index of effectiveness (CMF, or $\hat{\theta}$) by accounting for the changes in unmeasured factors between the before and after periods using the comparison ratio (following steps 4 through 6) described in chapter 3. The uncertainty estimates for the CMF, the posterior standard deviation, and the 90- or 95-percent credible interval play the same role as the standard error and the 90- or 95-percent confidence interval in nonBayesian or EB approaches. The team determined slight but not statistically significant increases (i.e., negative crash reductions) in total, fatal and injury, and PDO crashes have occurred.

Table 11 summarizes the results from the EB and FB analyses. The results from both analyses appear to be consistent in general, except that the increase in angle crashes is statistically significant based on the EB estimates, while it is not statistically significant based on the FB estimates. Because the FB analysis method better accounts for uncertainty in the data used than the EB method, FB uncertainty estimates can be larger and quantify true uncertainty more accurately than those resulting from the EB approach. As a result, EB analysis results often underestimate true uncertainty and may less accurately indicate statistical significance.

Table 11. Comparison of safety effectiveness estimates for ASCT obtained by EB and FB before–after evaluation approaches for Florida sites.

Approach	Total	Fatal and Injury	PDO Crashes	Angle Crashes	Rear-End Crashes
EB	1.045 (0.038)	1.039 (0.055)	1.022 (0.049)	1.207** (0.089)**	1.003 (0.050)
FB	1.0421 (0.0628)	1.0326 (0.0958)	1.0274 (0.0840)	1.2396 (0.1612)	0.9398 (0.0781)

**Statistically significant results at the 95-percent confidence level.

Notes: The uncertainty estimate is the standard error for EB and the posterior standard deviation for FB. Numbers in parenthesis indicate standard errors.

TEXAS CRASH ANALYSIS

The Texas crash data contain 25 intersections with ASCTs installed in 2012. The yearly crash data were obtained at each of those intersections for years 2010 through 2017. Because comparison sites (or reference sites) were not available in the Texas data, the research team conducted the safety evaluation of ASCTs in Texas by employing a generalized linear segmented regression (GLSR) analysis.

Specifically, team members applied a negative binomial regression model that introduces *time* as a variable to control for overall trend and *Intervention* (installation of ASCT) as a variable to estimate the effect of the ASCT. For *time*, the years prior to the installation of ASCT were coded as negative integers starting at −1 and descending in magnitude, while the years after the installation of ASCT were coded as positive integers starting at 1 and ascending in magnitude. For *Intervention*, the years corresponding to the after period were coded 1, and the years in the before period were coded 0. Then, at intersection *i,* the log of the expected number of annual crashes in year *t* can be expressed, as shown in figure 14.

$$\log \mu_{it} = \beta_0 + \beta_1 \times time_t + \beta_2 \times Intervention + \beta_3 X_{i,3t} + \cdots + \beta_k X_{i,kt}$$

Figure 14. Equation. Model parameterization for intervention coding variables.

In this equation, μ_{it} is the expected number of annual crashes in year *t* at intersection *i*, and *X* comprises variables representing intersection characteristic. For the variable *time*, the years prior to the installation of ASCT were coded as negative integers starting at −1 in descending order, and the years after the installation of ASCT were coded as positive integers starting at 1 in ascending order. For the variable *Intervention*, the years corresponding to the after period were coded 1, and the years in the before period were coded as 0. In addition to *time* and *Intervention*, the following variables (defined in table 2) were included in the analysis:

- NumLegs_MJ.
- NumLegs_MN.
- NumLanes_MJ.
- NumLanes_LT_MJ.
- NumLanes_RT_MJ.
- RT_Chan_MJ.
- LaneWid_MJ.
- MedWid_MJ.
- NumLanes_MN.
- NumLanes_LT_MN.
- NumLanes_RT_MN.
- RT_Chan_MN.
- MedWid_MN.
- Med_Type_MJ_R.
- Med_Type_MN_R.
- LogTEV.

The GEE was employed as an estimation method to account for correlation in crash counts obtained for multiple years from the same intersection.

Table 12 contains the estimated coefficients for negative binomial regression models considered and the corresponding estimates for percentage by which crashes will be reduced. It shows slight crash reductions in total and PDO crashes, a modest increase in fatal and injury crashes, and a slight increase in angle crashes. None of the changes were statistically significant. On the other hand, the team observed a statistically (and practically) significant crash reduction of 44 percent for rear-end crashes.

Table 12. Results of GLSR analysis of intersection crashes in Texas.

Coefficient	Variable	Estimate by Crash Type				
		Total	Fatal and Injury	PDO	Angle	Rear End
β_0	*Intercept*	−14.143**	−16.576**	−13.516**	−5.2938	−20.6933**
β_1	*time*	0.0174	−0.0209	0.0352	0.0108	0.1486**
β_2	*Intervention*	−0.0005	0.0996	−0.0486	0.0276	−0.5794**
β_3	NumLegs_MJ	−0.3847**	−0.2461**	−0.5009**	0.6508**	−0.5935**
β_4	NumLegs_MN	0.0511	0.6356**	−0.1742**	0.6309**	0.8163**
β_5	NumLanes_MJ	2.525**	1.9969**	2.7139**	1.4583**	2.6729**
β_6	NumLanes_LT_MJ	−1.0888**	−0.508**	−1.243**	−0.9945	0.3090
β_7	NumLanes_RT_MJ	−1.8851**	−1.4174**	−2.0594**	−1.2115**	−2.2929**
β_8	TWLTL_MJ	0.2626**	0.3569**	0.3414**	−0.2849	0.3225
β_9	RT_Chan_MJ	0.5365**	—	0.728**	0.7933**	−0.3363
β_{10}	LaneWid_MJ	0.2043**	0.2999**	0.1537**	−0.1038	0.4729**
β_{11}	ShldWid_MJ	0.0809**	0.0686**	0.0945**	0.0587**	0.0312
β_{12}	NumLanes_MN	0.4255**	0.2035**	0.4798**	0.8173**	−0.2951
β_{13}	NumLanes_LT_MN	0.61**	0.1818**	0.7739**	0.4976**	−0.0065
β_{14}	NumLanes_RT_MN	—	0.2393**	—	−1.2216**	0.9491**
β_{15}	RT_Chan_MN	2.0342**	1.5874**	2.2288**	0.2653	2.8650**
β_{16}	BLane_MN	0.2446**	—	0.3753**	0.5129**	−0.4552**
β_{17}	LaneWid_MN	−0.1538**	−0.166**	−0.1505**	−0.2293**	−0.3107**
β_{18}	ShldWid_MN	0.0802**	0.0863**	0.0709**	0.0098	0.1339**
β_{19}	MedWid_MN	0.1151**	0.0745**	0.1336**	0.0157	0.0719**
β_{20}	Med_Type_MJ_R	−4.7645**	−3.684**	−5.0937**	−2.3655**	−5.2907**
β_{21}	Med_Type_MN_R	−1.3699**	−0.5109**	−1.6537**	−1.9653**	−0.1041
β_{22}	LogTEV	0.5691**	0.6917**	0.4931**	0.1326	0.8172**
CMF		1.000	1.105	0.953	1.028	0.560**

**Statistically significant results at the 95-percent confidence level.
—The variable was not included in the model.
Notes: The GEE approach was used as an estimation method. Estimates of the percentage by which crashes are reduced are obtained by $\{1 - \exp(\beta_I)\}\times 100$, where β_I represents the estimated coefficient of the intervention variable.

VIRGINIA CRASH ANALYSIS

Virginia transportation agencies installed 68 intersections with ASCTs. As described in chapter 4, the yearly crash data were obtained at each of those 68 intersections for years 2006 through 2013. ASCTs were installed at 18 intersections in 2011 and 50 intersections in 2012. Because comparison sites (or reference sites) were not available for the Virginia data, the research team conducted the safety evaluation of ASCTs in Virginia by employing a GLSR analysis. The functional form of the model was the same as that used in the Texas analysis and illustrated in figure 14.

The underlying assumption for this model is that the relationship between the log mean annual crash frequency and time is linear within each period (i.e., for the time period before the intervention and independently for the time period after the intervention). The intercept β_0 represents the baseline level of the log mean annual crash frequency, and β_1 represents the baseline trend that corresponds to the change in the log mean annual crash frequency that occurs each year before the intervention. The coefficient β_2 represents a possible increase or decrease in crashes at the treatment site resulting from countermeasure implementation. The term corresponding to the change in slope before and after countermeasure implementation was not included due to the limited number of crash years (e.g., there was only 1 yr of after crash data at the 50 sites treated in 2012 and 2 yr of after crash data at 18 sites treated in 2011).

Table 13 contains the estimated coefficients for negative binomial regression models considered and the corresponding estimated percentage by which crashes are reduced.

Table 13. Results of GLSR analysis of intersection crashes in Virginia.

Regression Coefficient	Variable	Estimates by Crash Type				
		Total	Fatal and Injury	PDO	Angle	Rear End
β_0	Intercept	−9.2664**	−9.1251**	−8.8667**	−0.5665	−15.5373**
β_1	Time	−0.0132	0.0186	−0.0328	0.0034	−0.0221
β_2	Intervention	−0.1432*	−0.4437**	0.0191	−0.5045**	0.0195
β_3	NumLegs_MN	0.3198	0.2829	0.2602	0.1295	0.3218
β_4	NumLanes_MJ	−0.0102	—	−0.0269	—	−0.1073
β_5	NumLanes_LT_MJ	0.2530	−0.1759	0.3925**	0.4271**	—
β_6	NumLanes_RT_MJ	−0.3726**	−0.2510	−0.4597**	−0.4989**	−0.2907
β_7	RT_Chan_MJ	−0.4560**	−0.2766*	−0.4649**	−0.3853	−0.4759
β_8	LaneWid_MJ	0.1461**	—	0.1528**	—	0.1372
β_9	MedWid_MJ	−0.0080**	—	−0.0111**	−0.0053	−0.0083
β_{10}	NumLanes_MN	0.0101	0.1795	—	—	0.0990
β_{11}	NumLanes_LT_MN	−0.1496	−0.1170	−0.1554	−0.2442	—
β_{12}	NumLanes_RT_MN	0.3204**	0.2385*	0.3617**	0.5515**	0.1931
β_{13}	RT_Chan_MN	0.3530**	0.2891*	0.3244**	0.2835	0.3371**
β_{14}	MedWid_MN	−0.0121*	—	−0.0214**	—	−0.0175**
β_{15}	Med_Type_MJ_R	−0.1392	−0.1896	−0.1247	−0.2733	−0.1410
β_{16}	Med_Type_MN_R	−0.0452	−0.0895	—	−0.2886	—
β_{17}	LogTEV	0.8769**	0.9305**	0.7983**	0.1199	1.4551**
CMF		0.867*	0.642**	1.019	0.604**	1.020

*Statistically significant results at the 90-percent confidence level.
**Statistically significant results at the 95-percent confidence level.
—Variable not included in model.
Note: The GEE approach was used as an estimation method.

In addition to *time* and *Intervention*, several variables were included as predictors in the negative binomial regression model for the Virginia crash data. These predictors included the following:

- NumLegs_MN.
- NumLanes_MJ.
- NumLanes_LT_MJ.
- NumLanes_RT_MJ.
- RT_Chan_MJ.
- LaneWid_MJ.
- MedWid_MJ.
- NumLanes_MN.

- NumLanes_LT_MN.
- NumLanes_RT_MN.
- RT_Chan_MN.
- MedWid_MN.
- Med_Type_MJ_R.
- Med_Type_MN_R.
- LogTEV.

The research team applied the GEE approach as an estimation method to account for correlation in crash counts obtained for multiple years from the same intersection. Table 13 contains the estimated coefficients for the negative binomial regression models considered and the corresponding estimates of percentage by which crashes are reduced. Table 13 shows that, for total as well as fatal and injury crashes, the research team found that statistically significant (at the 90-percent confidence level and 95-percent confidence level, respectively) crash reductions occurred, although there was a slight, statistically insignificant, increase in PDO crashes.

CHAPTER SUMMARY

This chapter documents the statistical evaluations of the three databases developed in this study to estimate CMFs for ASCT. Separate analyses were implemented for each dataset attending to the differences in data structure. Table 14 summarizes the results from these analyses.

Table 14. Comparison of CMFs for ASCT obtained by State and analysis approach.

State	Approach	Total	Fatal and Injury	PDO	Angle	Rear End
FL	EB	1.045	1.039	1.022	1.207**	1.003
FL	FB	1.042	1.033	1.027	1.239	0.940
TX	GLSR	1.000	1.105	0.953	1.028	0.560**
VA	GLSR	0.867*	0.642**	1.019	0.604**	1.020

*Statistically significant results at 90-percent confidence level.
**Statistically significant results at 95-percent confidence level.

For Florida, the study design was an ITS-CG. For this evaluation, the research team conducted both EB and FB methods. The database included 87 intersections: 45 treated with InSync ASCT systems and 42 comparison sites. The results of both analyses indicated no statistically significant changes in total, fatal and injury, PDO, or rear-end crashes. The increase in angle crashes for the Florida sites, however, was statistically significant based on the EB analysis, although it was not statistically significant for the FB analysis. This was expected because, as explained in chapter 3, the FB analysis accounts for parameter uncertainty ignored in the EB procedure. Thus, the uncertainty estimates from the FB approach are expected to be closer to true uncertainty than those from the EB approach.

The analysis of the three Texas corridors was based on a negative binomial GLSR analysis using GEEs for estimation. The research team obtained data from 25 intersections in Tyler, TX, that were treated with ASC Lite installations. Eight years of crash data were collected to implement an interrupted time series analysis. The research team estimated a CMF of 1.000 (0-percent reduction) for total crashes (statistically insignificant). It also showed a 10.5-percent increase in fatal and injury crashes (statistically insignificant), a 4.7-percent decrease in PDO crashes (statistically insignificant), a 2.8-percent increase in angle crashes (statistically insignificant), and a 44-percent reduction in rear-end crashes (statistically significant).

For Virginia, the team obtained data from 50 intersections treated with InSync ASCT at different points in time to conduct safety evaluations. Seven years of safety data were collected to implement an interrupted time series analysis. The research team estimated the CMF of 0.867 for total crashes based on a negative binomial GLSR analysis using GEEs for estimation. The analysis indicated a 13.3-percent reduction in total crashes (statistically significant at the 10-percent significance level), a 35.8-percent reduction in fatal and injury crashes (statistically significant at the 5-percent significance level), a 1.9-percent increase in PDO crashes (statistically insignificant), a 39.6-percent reduction in angle crashes (statistically significant at the 5-percent significance level), and a 2.0-percent increase in rear-end crashes (statistically insignificant).

CHAPTER 6. ECONOMIC ANALYSIS

As part of this effort, the research team conducted an economic analysis to estimate B/C ratios for installing ASCT on urban arterials. Except for the case of Virginia (where the results indicated safety improvements associated with ASCT installations), the safety evaluations indicated small and insignificant changes in safety due to the ASCT treatments. In general, these results suggest that ASCT may provide safety benefits under certain conditions (e.g., for the sites in Virginia), but no evidence of a safety detriment was identified for locations where the conditions were not met (e.g., for the Florida and Texas sites). The research team performed the B/C analysis documented in this chapter based on the two potential safety outcomes that the analyses revealed (either a safety benefit or no change in safety performance).

To perform a B/C analysis, the research team followed the procedures recommended in the FHWA document entitled *Highway Safety Benefit–Cost Analysis Guide* (Lawrence et al. 2018). The team obtained the value of a statistical life from the most recent memorandum posted on the U.S. Department of Transportation website (Trottenberg and Rivkin 2016). The recommended range for the value of a statistical life is from \$5.2 million to \$12.9 million in 2012 dollars. Knowing the range for 2001 dollars allows the computation of the underlying geometric rate of inflation. Therefore, the range for 2019 was determined to be between \$5.7 million and \$14.9 million. A nominal midrange value of \$10.08 million was adopted for this evaluation.

COSTS AND BENEFITS OF ASCT INSTALLATIONS

The research team compiled cost information from various sources to incorporate this information into the cost–benefit analysis. Lodes and Benekohal (2013) reported in 2013 an average cost per intersection of \$28,725 for a pool of 62 jurisdictions surveyed in 2012. Specific to the systems evaluated in this study, the average cost was \$26,250 for ASC Lite and \$30,739 for InSync. Considering economic data in the last decade (Bureau of Labor Statistics 2019), the cumulative inflation rate between 2012 and 2019 in the United States is 11.8 percent. Therefore, the corresponding cost figures for 2019 are estimated at \$32,114 for the average, with the estimated value of ASC Lite and InSync being \$29,348 and \$30,739, respectively. For the analysis, the team used the average cost of installation for 2019: \$32,114. Lodes and Benekohal (2013) also report yearly maintenance costs ranging from \$5,000 to \$25,000, depending on the number of intersections. The research team interpolated between these values for a corridor of 20 intersections used in the calculations and obtained an average yearly cost of \$15,900. To calculate the cost of maintenance, the team used a 10-yr service life.

In addition, because NCHRP Synthesis 403 outlines additional recommended elements to include in cost estimations, the research team incorporated an additional cost of 10 to 15 percent per intersection to account for licensing to run the system (Stevanovic 2010).

A quantifiable benefit of installing ASCT is in reduced congestion. Shelby et al. (2008) reported a 35-percent reduction in delay per intersection from an evaluation of ASC Lite in Houston, TX. For this economic analysis, the research team assumed this reported average benefit. To translate this benefit to dollars, the research team revised the cost of congestion in the most recent INRIX traffic score card (INRIX 2019), which reports that the yearly cost of congestion per person is

97 hr, which translates to $1,348 in 2018. Considering consumer price index information between 2018 and 2019, the corresponding future-to-present factor was determined to be 1.023, which translates to $1,379 per person, or $14.22 per hour in 2019.

To determine the scale of this cost at an intersection, the research team examined the survey results from a study by Lodes and Benekohal (2013) in which the authors reported average daily traffic (ADT) for intersections with ASCT installations. These researchers reported the average ADT on major roads was 32,667 vehicles per day (vpd), while the average ADT on minor roads was 14,133 vpd. Because these numbers are from 2012, they translate respectively to 36,521 vpd and 15,801 vpd in 2019. In comparison, the overall major and minor road ADT averages for the three States in this study were 35,266 and 9,927 vpd, respectively. Broken out by State, the averages for major and minor roads, respectively, were 47,731 and 14,828 vpd for Florida; 28,768 and 8,725 vpd for Texas; and 29,300 and 6,228 vpd for Virginia. The research team decided to adopt the average from the three States in this study in conjunction with two additional assumptions:

- An average level of service D (i.e., approaching unstable flow) per intersection, with 45 s of delay per vehicle is reduced to an average level of service C (i.e., stable but with occasional backups) with 28 s of delay per vehicle.
- An average of 1.2 passengers per vehicle.

Using these assumptions, the research team estimated the benefit of ASCTs due to congestion reduction as 86,602 passenger-hours saved per user per year per intersection, or $1.23 million per year per intersection. This cost represents the cumulative value of lost time and productivity by roadway users over a year at an intersection due to congestion.

The average cost of a crash was computed using all severities, the guidance from U.S. Department of Transportation (Trottenberg and Rivkin 2016), and the average distribution of severe crashes at intersections. The proportion of KABC (i.e., fatal and injury) crashes found in the literature ranges from a low of 12 percent to a high of 38 percent (Anzek et al. 2005; Schroeder et al. 2012; Dutta et al. 2010; Ma et al. 2016). In the assembled databases, the KABC proportion was found to be consistent with that range: 44.6 percent for Florida, 29.6 percent for Texas, and 35.0 percent for Virginia. The research team selected the average of the three States (36.4 percent) for the economic analysis. Considering the average fatality rate as well (0.3 percent), the research team estimated the average cost of a crash at sites with ASCT installations as being $470,139.

Considering this, the research team calculated the B/C ratio to be 65.56 in the case where the ASCT installation achieves the 13.3-percent reduction in total crashes, as was found for the Virginia dataset. The B/C ratio remains large (25.46) in the case where no crash reduction is achieved by the ASCT installation and only operational benefits are observed due to reduced congestion, as reported in the literature.

CHAPTER SUMMARY

This chapter describes the economic analysis performed to estimate the economic effectiveness of ASCTs. The chapter begins outlining the resources and assumptions involved in developing

B/C ratios for the three States in the evaluation. The economic analysis yielded B/C ratios larger than 1.0, a fact that indicates larger benefits than costs resulting from these types of implementation. The following chapter presents a summary and conclusions for the project.

CHAPTER 7. SUMMARY AND CONCLUSIONS

The objective of this study was to perform a rigorous safety effectiveness evaluation of ASCT at urban corridors. To accomplish the goals of this study, the research team compiled safety data from Florida, Texas, and Virginia. The evaluation included total, fatal and injury, and PDO crashes.

The project encompassed various corridors from multiple States. Results from Florida and Texas did not offer statistical evidence of a change in safety frequency derived from implementing ASCTs. For the analysis in Florida, the research team used an ITS-CG design, given the availability of a suitable set of control locations and implemented two estimation methods (EB and FB methods) that yielded similar, statistically insignificant estimates of effectiveness for four out of the five crash types evaluated. However, the EB analysis indicated a large and statistically significant increase (20.7 percent) in angle crashes after the installation of ASCTs. The more robust FB method found a similar estimate (a 23.9-percent increase) not to not statistically significant. The result from the FB method is considered the most plausible (i.e., no evidence of a change in angle-crash frequency) given that this method accounts for uncertainties that the EB method ignores.

The results from Virginia, which are based on an ITS design, indicated significant reductions in total crashes (13.3-percent reduction, or a CMF of 0.867, significant at the 10-percent significance level), fatal and severe crashes (35.8-percent reduction, or a CMF of 0.642, significant at the 5-percent significance level), and angle crashes (39.6-percent reduction, or a CMF of 0.604, significant at the 5-percent significance level). Safety improvements have been suggested by other authors as the result of reductions in delay, queue lengths, and travel time, as reported by Stevanovic et al. (2011). Other operational studies have shown reduced conflicts that could potentially yield fewer crashes (Sabra et al. 2010, 2013). Regarding crash-based evaluations, Ma et al. (2016) estimated a CMF of 0.83 for fatal and injury crashes and 0.92 for total crashes. The most optimistic results were reported by Khattak (2016) with reductions of 34 percent in total crashes and 45 percent in fatal and injury crashes.

Results from Texas, also based on an ITS design, showed mostly insignificant changes in safety associated with ASCT installations. The notable exception was a statistically significant reduction in rear-end crashes (44-percent reduction, or 0.560 CMF, significant at the 95-percent confidence level). The magnitude of this estimate is surprising, but the implication of a safety benefit is consistent with the ample trends in the literature.

Because of the mixed results (no statistically significant change in safety in Florida and significant crash reductions in Virginia and Texas), the research team conducted an economic evaluation using two scenarios: one in which the safety benefit estimated from the Virginia dataset is realized and one in which no measurable safety effect is realized (the worst-case outcome observed in this study). When assuming a safety improvement of a 13.3-percent reduction in total crashes (as indicated by the analysis results in Virginia), the research team estimated a B/C ratio of 65.56. When assuming no safety benefit derived from ASCT installations (as the results from Florida suggested), the B/C ratio estimate decreased to 25.46.

In both cases, a B/C ratio larger than 1.0 indicated that the benefits obtained from implementing ASCT outweigh the costs.

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