Adaptive Signal System Safety Impacts

Final Report

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16. Abstract

The research team conducted a literature review and a nation-wide survey at the beginning of the research. The literature review revealed that Adaptive Signal Control System (ASCS) was effective in reducing crashes in some studies, while in other studies, the crash reduction due to ASCS was not statistically significant. Twenty-eight states participated in the nation-wide survey and helped the research team identify corridor characteristics, such as the design speed and Annual Average Daily Traffic (AADT) of an ASCS corridor, which would allow for the best operational and safety outcomes. Then, to determine the safety effects of ASCS, the research team evaluated the safety effectiveness of ASCS in terms of reducing the crash frequency at 11 ASCS corridors with a total of 109 signalized intersections located throughout South Carolina. This analysis showed that ASCS reduced the number of crashes for most ASCS corridors and intersections. ASCS also reduced the severity level of crashes. Additionally, it was found that ASCS deployed on a corridor parallel to a freeway reduced the likelihood of secondary crashes on the freeway by 47%. To determine the operational effectiveness of ASCS in travel time reduction and travel time reliability improvement, the research team evaluated 11 ASCS corridors with a total of 102 signalized intersections. The results indicated that when ASCS was operational, it reduced the travel time by 6.4% on average and improved the travel time reliability by 31.4% on average compared to the case when the ASCS was not operational.

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EXECUTIVE SUMMARY

Adaptive Signal Control System (ASCS) is typically deployed at intersections and corridors to improve operational performance, such as travel time and traffic delay. Compared to the conventional signal control systems (i.e., pre-timed signal control, semi-actuated and fully-actuated signal control) with predefined timing parameters (ideally re-adjusted every two to three years), ASCS can change the signal timings (i.e., phase splits, phase sequence, offsets, and cycle length) in real-time to accommodate fluctuating traffic demand at intersections. Also, ASCS can adjust offsets to coordinate several intersections along a corridor, thus leading to fewer traffic stops. By handling conflicting traffic movements and establishing dynamic coordination between intersections along a corridor in real-time, ASCS can potentially improve traffic operations. The question the South Carolina Department of Transportation (SCDOT) had, and one that is addressed in this research, is: What are the safety benefits of ASCS, and which corridors would benefit most from ASCS in terms of safety and operation? To answer this question, the research team focused on the following objectives:

1. Determine the effect of ASCS on the crash frequency.
2. Investigate the effect of ASCS on the crash severity.
3. Determine the effect of ASCS on the likelihood of secondary crashes on those freeway sections that have alternate corridors with ASCS.
4. Determine the operational effectiveness of ASCS in the travel time and travel time reliability.
5. Recommend the type of corridors that are best suited for ASCS implementation for traffic safety and operational improvement.

Based on the literature review, it was found that ASCS was effective in reducing crashes in some studies, while in others, ASCS was not effective in significantly reducing crashes. Evaluation of the effects of ASCS on crash severity was predominantly absent from the literature.

A national survey was conducted of State Departments of Transportation in the U.S. The survey results showed that most states considered or studied ASCS, though many have not implemented ASCS. The survey also identified corridor characteristics, such as the design speed and Annual Average Daily Traffic (AADT) of an ASCS corridor, which would allow for the best operational and safety outcomes.

To determine the safety effects of ASCS on the crash frequency, the research team developed a Fully Bayesian (FB) framework for the before-and-after study. The research team evaluated the safety effectiveness of ASCS at 11 ASCS corridors with a total of 109 signalized intersections located throughout South Carolina. ASCS showed crash reductions for most ASCS corridors and intersections. The safety effectiveness of ASCS varied across the intersections, depending on their characteristics (e.g., AADT at a major street and the speed limit at a major street).

To determine the effect of ASCS on crash severity, the research team developed random-parameter ordered regression models using crash data from 11 ASCS corridors with a total of 109 signalized intersections. The analyses revealed that the presence of ASCS was associated with lower crash severity.

The crash severity study revealed practical implications: 1) when the speed limit difference (the maximum and minimum value of the speed limit in the study intersections is 55 mph and 20 mph, respectively) between a major street and a minor street at an ASCS intersection is equal to or greater than 10 mph, and the average signal distance on an ASCS corridor is less than the threshold of 0.49 miles, ASCS was more likely associated with lower crash severity, and 2) when speed limit difference between a major street and a minor street at an ASCS intersection is less than 10 mph, and the average signal distance on an ASCS corridor is less than the threshold of 0.69 miles, ASCS was more likely associated with lower crash severity.

To assess whether ASCS deployed on an arterial parallel to the freeway reduced secondary crashes on the freeway, the research team developed a binary logistic regression model using 52 months of crash data on I-26 (Eastbound). On the study segment of I-26, it has a route with ASCS deployed, which motorists often used when there is an incident on I-26. The analysis showed a 47% reduction in the likelihood of freeway secondary crashes when ASCS is deployed on the alternate route to a freeway. The benefit of ASCS deployment on an alternate route towards freeway secondary crash reduction was found to be dependent on the location of the primary crash. The location of the primary crash determines how much of the upstream traffic will elect to or be able to take the exit ramp to the ASCS deployed alternate route.

To evaluate whether ASCS is effective in terms of travel time reduction and travel time reliability improvement, the research team evaluated 11 ASCS corridors, with a total of 102 intersections. This study revealed that when ASCS was operational, it reduced travel time by 6.4% on average and improved the travel time reliability by 31.4% on average for all the study corridors, compared to when the ASCS was not operational (i.e., when the signal control system on the same study corridor uses a predefined signal timing strategy, which could either be a pre-timed or an actuated signal timing plan based on the particular intersection on the corridor). The effectiveness of ASCS in reducing travel time was found to be consistent in both directions on an hourly basis for eight ASCS corridors out of 11, whereas the effectiveness of ASCS in improving travel time reliability was consistent in both directions on an hourly basis for only five ASCS corridors out of 11. This study also found that ASCS produced higher operational benefits if the average speed of an ASCS corridor is equal to or lower than 35 mph, and the number of signals on an ASCS corridor is more than 10.

Figure 1 highlights the safety and operational impacts of ASCS at the study corridors as found in this study.

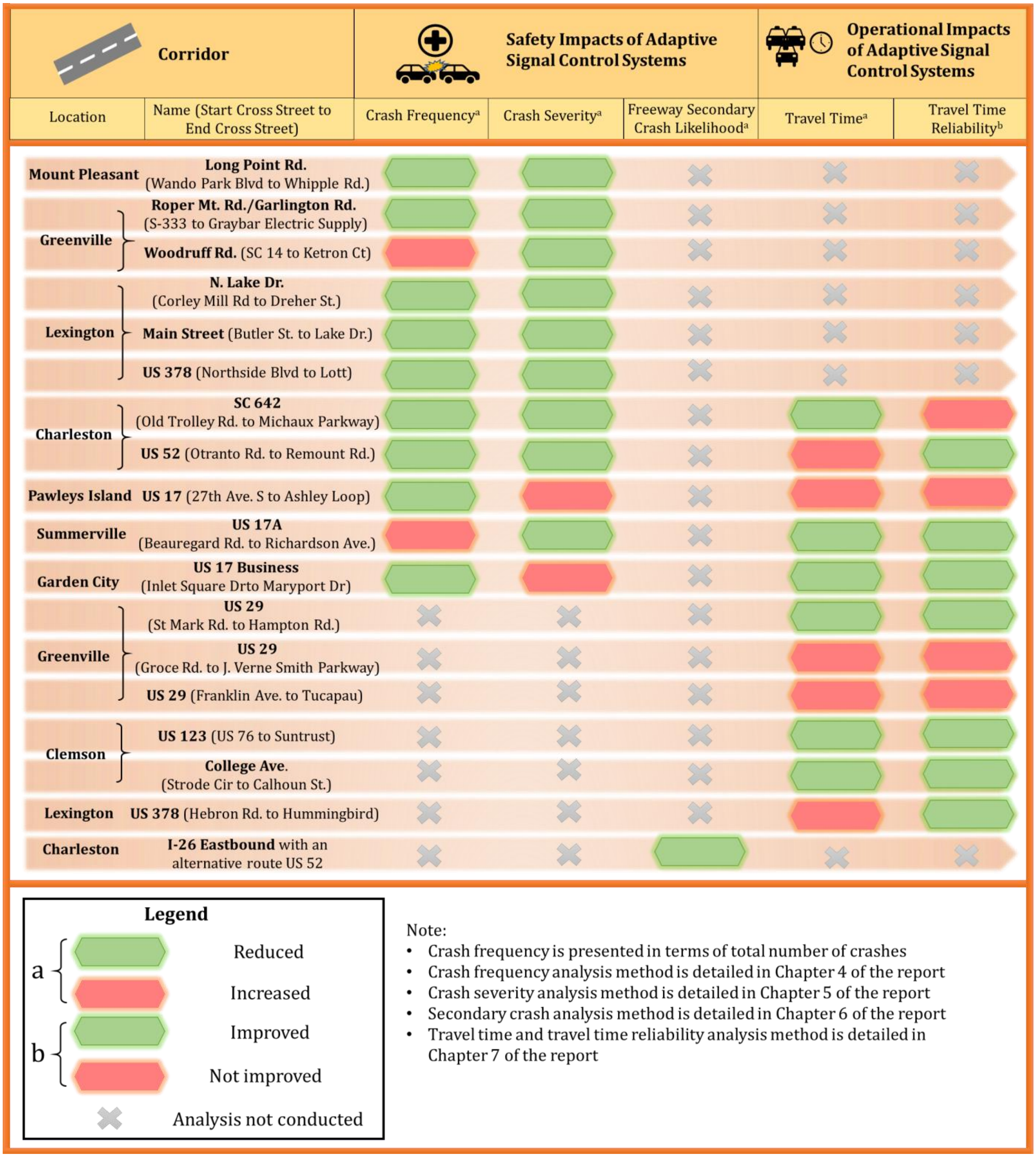

Figure 1 Safety and operational impacts of adaptive signal control systems at study corridors

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LIST OF ABBREVIATIONS

AADT	Average Annual Daily Traffic
ASCS	Adaptive Signal Control System
ANOVA	Analysis of Variance
BCI	Bayesian Credible Intervals
C	Possible injury
DIC	Deviance Information Criterion
DOT	Department of Transportation
EB	Empirical Bayes
FB	Fully Bayesian
F+I	Fatal and Injury
FYA	Flashing Yellow Arrow
KAB	Fatal, incapacitating injury, and non-incapacitating injury combined
MC	Multicollinearity
MCMC	Markov Chain Monte Carlo
MLE	Maximum Likelihood Estimation
O	No injury
OR	Odds Ratio
RMSE	Root Mean Square Error
ROP	Random-parameter ordered probit model with observed heterogeneity
ROL	Random-parameter ordered logit model with observed heterogeneity
RP	Random-parameter ordered probit model
RL	Random-parameter ordered logit model
SCDOT	South Carolina Department of Transportation
SPF	Safety Performance Function
VIF	Variance Inflation Factor

CHAPTER 1 INTRODUCTION

From 2008 to 2012, 25% of the total crashes in South Carolina were intersection-related crashes (SCDOT, 2015). During this five-year period, about 166 people were killed and about 1,520 people annually were severely injured in intersection-related crashes in South Carolina. According to the state's Strategic Highway Safety Plan, reducing crash frequency and severity at intersections by traffic control has been identified as a primary objective (SCDOT, 2015). Transportation agencies have been seeking new insights and approaches to improve safety at signalized intersections.

The South Carolina Department of Transportation (SCDOT) has installed several Adaptive Signal Control Systems (ASCSs) in the state, with more planned in the near future. Some counties and cities in South Carolina are also planning to install ASCS. In South Carolina, at the time of writing this report, two types of ASCS (SynchroGreen and InSync), are operated at 189 intersections on 19 corridors throughout the state.

ASCS is an advanced signal control system typically deployed at intersections and corridors to improve operational performance, such as travel time and traffic delay. Compared to the conventional signal control systems (i.e., pre-timed signal control and actuated signal control) with predefined signal plans (ideally re-adjusted every two to three years), ASCS can change the signal timings (i.e., phase splits, phase sequence, offsets, and cycle length) in real-time to accommodate fluctuating traffic demand at intersections. Also, ASCS can adjust offsets to coordinate several intersections along a corridor, leading to fewer traffic stops. ASCS is believed to be superior to conventional coordinated signal systems in that they: 1) improve traffic flow and ease congestion, 2) provide a faster response to changing traffic conditions, such as traffic incidents, 3) reduce costs to businesses and consumers by reducing delay and associated wasted fuel and lost productivity, and 4) potentially reduce the number of crashes at intersections.

Operational benefits of ASCS in both corridor and intersection have been documented (Eghtedari, 2005; Elkins & Niehus, 2012; Fontaine et al., 2015; Kergaye et al., 2009; Khattak, 2016; Khattak et al., 2020; So et al., 2014). By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, ASCS can improve operational traffic conditions, which may potentially improve the safety of signalized intersections and corridors (Dutta et al., 2010; Jin et al., 2019; Khattak et al., 2018; Ma et al., 2016).

While the operational benefits of ASCS are well documented (Stevanovic, 2010), the information available regarding the safety impacts of ASCS is scarce. The question the South Carolina Department of Transportation (SCDOT) had and one that is addressed in this research is: What are the safety benefits of ASCS, and which corridors would benefit most from ASCS in terms of safety and operation?

The objectives of this research are to:

1. Determine the effect of ASCS on the crash frequency.
2. Investigate the effect of ASCS on the crash severity.

3. Determine the effect of ASCS on the likelihood of secondary crashes on those freeway sections that have alternate corridors with ASCS.
4. Determine the operational effectiveness of ASCS in the travel time and travel time reliability.
5. Recommend the type of corridors that are best suited for ASCS implementation for traffic safety and operational improvement.

To this end, the research team evaluated the safety effects of ASCS on the crash frequency at 11 ASCS corridors with a total of 109 signalized intersections by developing a Fully Bayesian (FB) paradigm for a before-and-after study. Additionally, the research team investigated the effects of ASCS on the crash severity at 11 ASCS corridors with a total of 109 signalized intersections by developing random-parameter ordered regression models. To assess whether ASCS deployed on an arterial parallel to the freeway could reduce secondary crashes on the freeway, the research team developed a binary logistic regression model using 52 months of crash data on I-26 (Eastbound). To evaluate whether ASCS is effective in terms of travel time reduction and travel time reliability improvement, the research team evaluated 11 ASCS corridors, with a total of 102 intersections.

CHAPTER 2 LITERATURE REVIEW

2.1 Crash Frequency Study

Safety benefits of ASCS were demonstrated in several studies. Fontaine et al. (Fontaine et al., 2015) evaluated the safety effects of InSync, a type of ASCS, for different corridors in Virginia using an Empirical Bayes (EB) before-and-after study. Based on the analysis, the authors found that crashes are reduced by 17% due to ASCS. Dutta et al. (Dutta et al., 2010) studied crash data for one type of ASCS (i.e., SCATS) and fixed-time signal control systems for two corridors in Michigan. The authors (Dutta et al., 2010) evaluated the change in the crash rate before and after the ASCS deployment. The authors found that the total crash rate is reduced by 6% after installing ASCS. The incapacitating injury crashes were reduced by 22% after ASCS deployment. The most significant improvement was found for non-incapacitating injury crashes, which were reduced by 35%. Fink et al. (Fink et al., 2016) studied the safety impacts of SCATS installed at signalized intersections in Oakland County. The authors performed a cross-sectional study using data from 498 signalized intersections and found that a reduction of 19.3% in angle crashes was associated with SCATS. This study found that SCATS did not significantly reduce incapacitating injuries or fatality (Fink et al., 2016). Khattak (Khattak, 2016) evaluated 41 intersections in Pennsylvania where SURTRAC and InSync were installed. The author implemented an EB before-and-after safety study and computed Crash Modification Factors (CMF) for total crashes and fatal and injury crashes. The author found reductions of 34% and 45% in total crashes and fatal and injury crashes, respectively, due to ASCS.

ASCS is not always effective in reducing crashes in a statistically significant manner. Jesus and Benekohal implemented the EB method to determine the safety effectiveness of the ASCS (Jesus & Benekohal, 2019). The authors (Jesus & Benekohal, 2019) found that the CMF of ASCS for fatal and injury crashes was 0.67 (CMF less than 1 indicates that ASCS reduces crashes), which was not statistically significant at a 0.05 significance level. CMFs of property damage only and total crashes were close to one, which indicated no crash reduction due to ASCS. The CMF for fatal, incapacitating injury and non-incapacitating injury combined was 0.68, which was not significant at a 0.05 significance level. The angle, rear-end, incapacitating injury, and reported/not evident injury (i.e., this includes momentary unconsciousness, claims of no evident injuries, limping, complaints of pain, nausea, hysteria) crashes showed insignificant reductions.

2.2 Crash Severity Study

Evaluation of the impact of ASCS deployment on crash severity outcomes is predominantly absent from the literature. Only a few studies related to crash severity effects of ASCS were identified. Dutta et al. (Dutta et al., 2010) used before period (1999 to 2001) and after period (2003 to 2008) crash data from one corridor with SCATS and another with the pre-timed signal. They performed a *t*-test analysis and found that a definite change in severity from incapacitating injury and non-incapacitating injury to possible injury. But the *t*-test failed to prove the superiority of SCATS over the pre-timed signal control system in lowering the crash severity at a 0.05 significance level.

In their analysis, Fink et al. (Fink et al., 2016) used data from 498 signalized intersections in Michigan. They found that a statistically significant reduction in non-incapacitating injuries was associated with SCATS deployment. However, they did not find a statistically significant reduction in fatal and incapacitating injuries associated with SCATS.

Similarly, in the examination of the effects of ASCS on the crash severity, Khattak et al. (Khattak et al., 2019) identified the disparity between two different types of ASCS and between two states- Pennsylvania and Virginia, where ASCS was deployed. They found that both ASCS systems were associated with lower crash severity, and ASCS systems implemented in two states were also associated with lower crash severity.

2.3 Secondary Crash Study

Several studies have investigated the criteria to identify secondary crashes. Table 1 shows a summary of these criteria. Raub (Raub, 1997a, 1997b) assumed that any crashes within the time period of primary crash plus 15 minutes and within a mile from the primary crash in the upstream are accounted for as secondary crashes. Based on these criteria, the author identified secondary crashes and found that 81 primary crashes were followed by 97 secondary events. They concluded that one of every 11 incidents that occurred in Rolling Meadows (between January 9, 1995, and February 5, 1995) was associated with one or more secondary crashes. Karlaftis et al. (Karlaftis et al., 1999) analyzed five years of incident data on Borman Expressway in Illinois to identify the primary crash characteristics that led to the secondary crashes. Latoski et al. (Latoski et al., 1999) analyzed the data from portions of I-80, I-94, and I-65 in North West Indiana. Both Karlaftis et al. (1999) and Latoski et al. (Latoski et al., 1999) considered three miles upstream of the primary crash and the clearance time plus 15 minutes of the primary crash to identify secondary crashes.

Moore et al. (Moore et al., 2004) studied 84,684 crashes in California. The authors considered crashes that occurred within a two-hour period and two miles in both directions of the primary crashes as an identification measure for secondary crashes. Hirunyanitiwattana and Mattingly (Hirunyanitiwattana & Mattingly P, 2006) studied the characteristics of secondary crashes using two years of data from the California highway system from 1999 to 2000. They found that a secondary crash was the one that occurred within an hour and two miles upstream of the primary crash. They also found that the proportion of secondary crashes was higher in urban areas compared to rural areas. Yang et al. (Yang et al., 2013) developed a method based on a binary speed contour plot to account for the dynamic characteristics of spatial-temporal impact range in identifying secondary crashes. This study used sensor data from a 27-mile urban highway section in New Jersey. The authors found that almost 50% of the secondary crashes occurred within a two-mile range in the upstream, and 75% of the secondary crashes occurred within up to two hours of the primary crashes.

Table 1 Review of secondary crash identification criteria

Author(s), year	Secondary crash identification criteria	Road type
Raub, 1997a,b	Clearance time + 15 minutes, 1 mile	Urban arterial
Karlaftis et al., 1999	Clearance time + 15 minutes, 1 mile	Freeway/expressway
Latoski et al., 1999	Clearance time + 15 minutes, 3 miles	Freeway
Moore et al., 2004	2 hours, 2 miles	Freeway
Hirunyanitiwattana and Mattingly, 2006	1 hour, 2 miles	Urban/rural freeway/highway
Yang et al., 2013	2 hours, 2 miles	Urban highway

Karlaftis et al. (Karlaftis et al., 1999) primarily investigated contributing factors that induce a secondary crash. They developed a binary logistic regression model using the attributes of primary crashes to estimate the possibility of a secondary crash. The study concluded that the attributes such as clearance time, season, type of vehicle involved, and lateral location of the primary crash were the most significant factors for the increased likelihood of secondary crashes. Goodall (Goodall, 2017) developed a binary logistic regression model to predict the occurrence of secondary crashes over time. Three contributing factors were considered, namely whether congestion occurred or did not occur by the incident, the incident duration, and the approximate number of vehicles that encountered the incident if no congestion or its queue if congestion was present in the same direction. The results revealed that, for every two to three minutes spent for a congested scenario, the secondary crash occurrence probability approximately increased by 1%. Xu et al. (Xu et al., 2016) used the Bayesian random effect logit model to develop a secondary crash risk prediction model. The model associated the prediction probability of secondary crashes with real-time traffic variables (e.g., average speed, traffic volume, and the standard deviation of detector occupancy), primary crash characteristics (e.g., date and time of the primary crash, primary crash severity, and crash type), weather conditions, and geometric characteristics. The most significant real-time traffic variables were traffic volume, average speed, the standard deviation of detector occupancy, and volume difference between adjacent lanes. The study concluded that secondary crash prediction accuracy could be increased by 16.6% by including traffic flow variables.

2.4 Operational Evaluation Study

The following provides a review of prior studies that evaluated the operational effectiveness of ASCS.

Kergaye et al. evaluated the operational effectiveness of SCATS, a type of ASCS, for two corridors in Utah (Kergaye et al., 2009). They found that SCATS was effective in reducing stopped delay at intersections, the number of stops, and travel time. Another performance evaluation study on SCATS was conducted by Tian et al. based on travel time and traffic stops data collected from a major arterial section in Las Vegas, Nevada (Tian et al., 2011). However, they found that SCATS was not effective in reducing the number of stops and travel time compared to conventional optimized Time of Day (TOD) coordinated signal system. Hunter et al. (2012) evaluated SCATS deployed at 15 intersections in Cobb County in Georgia (Hunter et al., 2012). However, the authors did not find any significant improvement in terms of speed, travel time, and delay caused by SCATS compared to the TOD signal control systems.

Hutton et al. evaluated the operational performance of InSync, another type of ASCS, for one corridor with 12 intersections located in Missouri (Hutton et al., 2010). The authors found up to a 39% decrease in travel time resulted from ASCS implementation, which varied with the direction of travel and time of day. In addition, they observed a reduction in the number of stops, fuel consumption, emission in the after period of ASCS implementation. Elkins and Niehus evaluated the effectiveness of InSync for one corridor located in New York (Elkins & Niehus, 2012). The authors found that InSync reduced travel times by 9%-43% in eastbound and 10%-29% in westbound during peak periods. In a simulation study conducted by Stevanovic and Zlatkovic, InSync deployed on a corridor in Florida was compared with the TOD signal system (Stevanovic & Zlatkovic, 2013). They found improvement in travel time in the AM peak, midday peak, and PM peak, while the most considerable difference between the TOD-based traffic signal and ASCS was observed at the midday peak. Hu et al. evaluated the operational effectiveness of InSync, a type of ASCS, for six corridors in Virginia (Hu et al., 2016). The authors found that InSync reduced the mainline delay by 25% and improved the travel time reliability by 16%.

So et al. evaluated the operational effectiveness of SynchroGreen, another type of ASCS, for one corridor in Florida (So et al., 2014). The authors found that SynchroGreen was able to reduce travel times from 2.4 % to 8.6 %. Benekohal et al. evaluated SynchroGreen on a corridor in Illinois with six intersections (Benekohal et al., 2019). Based on the evaluation of operational performance in terms of traffic volume, intersection delays, and queue length for each lane group, they found that for 41% of the lane groups, SynchroGreen improved the operational performance; for 30% of the lane groups, SynchroGreen did not change the operational performance; and for 29% of the lane groups, SynchroGreen reduced the operational performance .

Shelby et al. evaluated the operational performance of Adaptive Control System Lite (ACS-Lite) through simulation and field tests (Shelby et al., 2008). The field tests were performed at different locations throughout the United States (i.e., Ohio, Texas, Florida, and California). The authors found up to 35% improvement in the number of stops, travel time, delay, and fuel consumption in their field tests compared to non-ASCS intersections. Ban et al. evaluated Adaptive Control System Lite (ACS-Lite) on Wolf Road in Albany, New York, which was a heavily congested urban corridor (Ban et al., 2014). They found that ACS-Lite software was able to improve traffic flow in terms of decreasing travel time slightly within its own system, except for one intersection at the boundary of the ACS-Lite deployed corridor. In another study, Gettman et al. evaluated ACS-Lite through field testing at five intersections in Arizona (Gettman et al., 2013). The authors found that at some intersections, ACS-Lite performed well in terms of improving travel time and reliability, whereas at some intersections, the coordinated TOD-based systems performed better. Smith et al. evaluated the operational performance of Scalable Urban Traffic Control (SURTRAC), another type of ASCS, through pilot deployment at nine intersections in Pittsburg, Pennsylvania (Smith et al., 2013). The authors found that SURTRAC improved traffic flow efficiency in terms of the number of stops, travel time, speed, wait time, and emission by 20-40%.

In a recent study, Khattak et al. evaluated the operational impacts of SURTRAC, another type of ASCS, which was deployed in 23 intersections of Pittsburgh, Pennsylvania (Khattak et al., 2020). They found that SURTRAC was effective in reducing travel time during AM and PM peak periods in the westbound direction on Baum Blvd and Centre Avenue. In Baum Blvd, speed was improved by SURTRAC during midday in the eastbound and during AM and PM peaks in the westbound. In Center Avenue also, speed was improved by SURTRAC in the westbound.

Table 2 presents a summary of the evaluation studies, including our study, which is shaded in grey color. Most of these studies did not compare the performance of ASCS deployed on multiple corridors throughout a state, as shown in Table 2. Additionally, these studies did not evaluate the consistency of the operational effectiveness of ASCS in both directions of a corridor, which has been evaluated in this study. Our study includes both these evaluations for ASCS, which will provide a more comprehensive assessment of the operational impacts of ASCS.

Table 2 Evaluation studies of ASCS

Type of ASCS	Area	Number of corridors	Number of intersections	Evaluation metrics	Authors
SCATS	Utah	2	14	Travel time, number of stops, and intersection stopped delay	Kergaye et al. (Kergaye et al., 2009)
	Nevada	1	10	Travel time, number of stops	Tian et al. (Tian et al., 2011)
	Georgia	3	15	Speed, travel time, and intersection delay	Hunter et al. (Hunter et al., 2012)
InSync	Missouri	1	12	Travel time, number of stops, average speed, delay along a corridor, stopped time, congested time, fuel consumption, and emissions	Hutton et al. (Hutton et al., 2010)
	New York	1	9	Travel time, the number of stops, average speed, delay, fuel consumption, and emissions	Elkins and Niehus (Elkins & Niehus, 2012)
	Florida	1	12	Travel time, number of stops, and intersection delays	Stevanovic and Zlatkovic (Stevanovic & Zlatkovic, 2013)

Type of ASCS	Area	Number of corridors	Number of intersections	Evaluation metrics	Authors
	Virginia	6	62	Main road delay reductions, 95th percentile travel time, and buffer index	Hu et al. (Hu et al., 2016)
SynchroGreen	Florida	1	9	Travel time, spot speed, and vehicle occupancy rate	So et al. (So et al., 2014)
	Illinois	1	6	Traffic volume, intersection delays, and queue length	Benekohal et al. (Benekohal et al., 2019)
	South Carolina	11	102	Mainline travel time and travel time reliability during 24 h of a day and during peak periods, direction-wise consistency of ASCS effectiveness in travel time reduction, and travel time reliability improvement	Chowdhury et al. (this study)
ACS-Lite	Ohio, Texas, Florida, and California	NA*	9 (Ohio), 8 (Texas), 8 (Florida), 10 (California)	Travel time, delay time, number of stops, fuel consumption	Shelby et al. (Shelby et al., 2008)
	Arizona	2	5	Green occupancy ratio (i.e., detector occupancy of the green phase divided by the total available green time in a phase split), percent arrivals on green (i.e., percent of vehicles arriving on the green phase of the total number of vehicles arriving on the red phase), travel time, and travel time reliability	Gettman et al. (Gettman et al., 2013)
	New York	1	9	Intersection delay, queue length, travel time, average speed, the number of stops,	Ban et al. (Ban et al., 2014)

Type of ASCS	Area	Number of corridors	Number of intersections	Evaluation metrics	Authors
				emission, and fuel consumption	
SURTRAC	Pennsylvania	2	9	Travel time, number of stops, speed, wait time, fuel consumption, and emissions	Smith et al. (Smith et al., 2013)
	Pennsylvania	2	23	Main street travel time and speed, the number of stops, side street speed and travel time, travel time reliability, volatility in speed, and acceleration/ deceleration	Kattak et al. (Khattak et al., 2020)

*NA=not available

CHAPTER 3 SURVEY

3.1 Introduction

The online survey distributed to the state Departments of Transportation (DOTs) was divided into two parts to encourage more participation. The overall purpose of the survey was to understand the perspectives of the state and local public agencies, who make decisions regarding the implementation of ASCS, as well as results over time, through operational studies conducted by the public agencies.

Part I of the survey was distributed nationally through SCDOT's network of contacts to each of the 50 states' Departments of Transportation. This top-level survey was intended to gather a brief overview at the state level of ASCS testing and deployment. Twenty-eight states (i.e., 56%) responded to part one of the surveys. The intent of part one was to establish which states had experimented with or installed ASCS. Based on this information, the states were asked to identify the current state of ASCS in their state. The states that responded are highlighted in Figure 2 in green.

The second part of the survey included a follow-up, which was distributed to a list of 28 contacts gathered in part one of the survey to the state DOTs. This survey went into greater detail to examine what each governance had considered when deploying ASCS. The survey was intended to be answered by city and county personnel who work with ASCS daily and in a more hands-on environment. The detailed questions were designed to be answered by someone with plentiful first-hand experience studying, operating, and evaluating ASCS in their jurisdiction. The findings of the survey are summarized in the following subsections (Brunk et al., 2019).

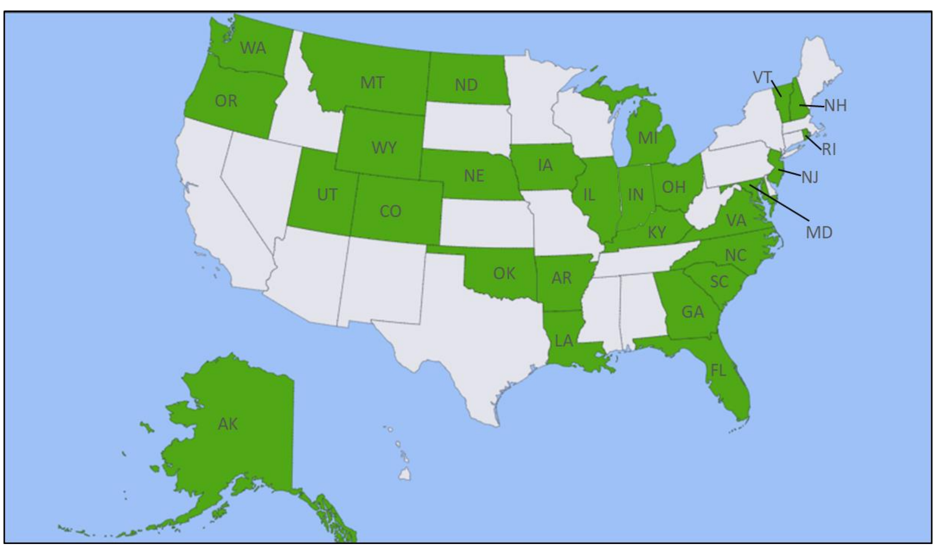


Figure 2 Survey part I responding states

3.2 Current ASCS Deployment

Fourteen states responded that their ASCS system is fully deployed and active. Three states at one point had deployed ASCS and then removed it. Two states indicated they had tested but never deployed ASCS and four states intend to deploy ASCS soon. Five of the respondents indicated that their state has neither tested nor deployed ASCS. The primary reason indicated by the four of the seven states that have not deployed ASCS was "insufficient benefits" based on their testing and study. The second most common reason selected by the two states was "insufficient manpower." ASCS is expensive concerning up-front costs in the form of installation. Therefore, it is logical that many states would feel there were insufficient benefits to justify the cost, especially with a limited annual budget and ambiguity for future funding.

As seen in Figure 3, the majority of states with the current or future deployment of ASCS have or will have 20 or more intersections with ASCS.

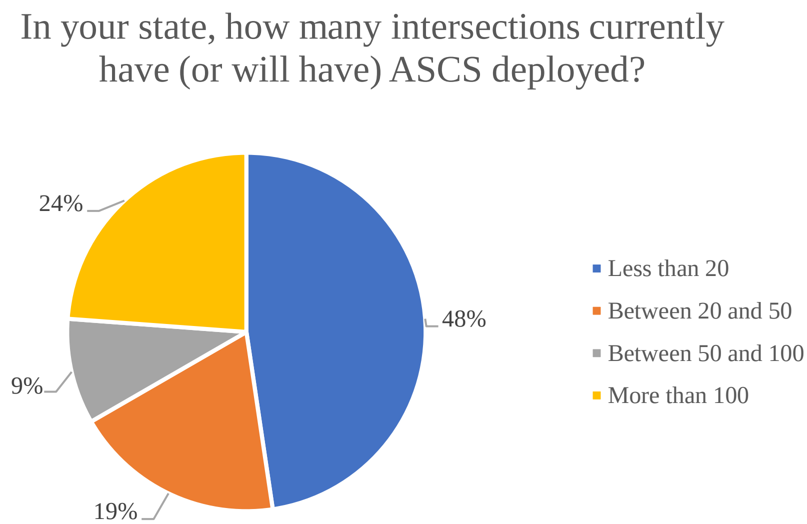


Figure 3 Number of intersections with ASCS

As expected, the primary reason for which the states surveyed in this study chose to install ASCS was the operational benefits. Since the operational benefits of ASCS have been widely studied and published, it makes sense that the primary justification for the cost is improved travel time and decreased the number of stops. Nineteen of 28 states selected this. The second most selected positive aspect was the safety benefits, which are selected by 10 states.

Of the 28 states that responded to the survey, most (i.e., 52.4%) currently run InSync. The second most adopted system is SynchroGreen, selected by eight of the 28 respondents. These were closely followed by SCATS and ACS Lite, each operating in five states. Others mentioned included Intelight (2), SCOOT (2), and MAXAdapt (3), and one each for RHODES, OPAC, Centracs. Some states run more than one system because it is often the case that a city or county will make its own decision on which system to run in their jurisdiction, which can vary within a state. The selection of ASCS largely depends on the cost and customer service availability while maintaining the ASCS.

For those states that indicated they had not deployed ASCS or had removed ASCS, the survey included a question about the challenges preventing the state from deploying ASCS. The primary reason, as indicated by four of the seven states that answered this survey question, stated that they found insufficient benefits when considering ASCS for their state. The second most common answer was insufficient manpower, indicated by two states. One state that responded that they had neither tested nor deployed ASCS and also specified that their current infrastructure needs to be updated, and their exploration of the available technology led them to select advanced traffic signal performance measures to see if this improves their operations. This state also disclosed that they do not yet have the communication network to deploy ASCS.

Another state responded that upon testing ASCS, they decided to use different software that will collect high-resolution data to optimize current signal timing. This state cited prohibitive upfront costs based on the benefits they believed possible for statewide deployment as contributing to this decision.

Seven respondents from three states responded to part two of the follow-up survey. Five respondents represent South Carolina, two engineers responded from Michigan, and one engineer responded from Wyoming. Four of the respondents were from the State DOTs, two from county agencies, and one from a city agency. It is worth noting that one additional state contact responded outside the survey, via email, that a city in their state is in the process of conducting a Before and After Study of both operational and safety benefits. However, as their research project is currently underway and incomplete, they felt uncomfortable completing the survey at this time.

3.3 ASCS Impact Assessment Findings

Each of the survey respondents was asked to identify how many corridors are in their jurisdiction. However, for the survey, they were asked only to answer questions regarding one corridor at a time. Four of the eight respondents indicated that they had not conducted any safety or operational study on their ASCS corridors. As such, the remaining four states responded to the next set of questions, identifying four corridors for study.

These four corridors ranged from six to 19 intersections per corridor. Two of the four corridors run InSync, one runs SynchroGreen, and one runs MaxAdapt and Intelight. Before the installation of ASCS, two of the corridors had a Fixed-Time Coordinated plan, and two had Actuated Coordinated plans. All four of the corridors in this survey are arterial networks.

When evaluating the impacts of ASCS, the results of any operational or safety study could be skewed by other changes made to the corridors during or around the same time that the signal system was changed. To account for this, one survey question asked the respondents to identify what alterations had been made along their route. Along two corridors, a flashing yellow arrow was installed. Two corridors implemented new access management strategies. One corridor’s lanes were widened. While the specific effects of these additional measures have not been accounted for in this survey, the data can be used to follow up in future studies regarding the effect of potential benefits when combining ASCS and additional operational improvements.

None of the four corridors have been studied from a safety perspective. Furthermore, only one respondent indicated a desire to conduct such a study in the future. The other three cited justifications of insufficient manpower, data, funding, or low prioritization as the reasons for not pursuing a safety study. In a similar vein, none of the four corridors were selected for benefit-cost analysis.

3.4 ASCS Corridor Applicability

The final section of the survey gathered the opinions of the four respondents regarding the best fit for ASCS in various corridors. While this data is based purely on experience and opinion, it serves as a direction for future study. While each of the four respondents identifies ASCS as "expensive," the range of price is $40,000/intersection or less and is broken down in Figure 4. The respondents to the corridor-specific study paid less per-intersection in installation costs than the average cost in the NCHRP Report, which had an average of $65,000/intersection.

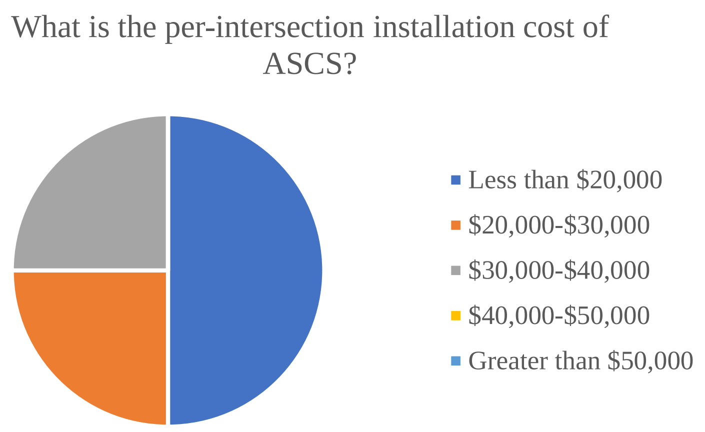


Figure 4 Per-intersection ASCS installation cost

Three of the four respondents indicated that expected performance had been sustained since installation. One respondent does not yet have enough data to evaluate the sustained performance. Of the four respondents, two felt that ASCS works best in an Average Annual Daily Traffic (AADT) volume range of 30,000-50,000 vehicles/day. One believed ASCS works best in a low AADT volume of fewer than 10,000 vehicles/day, and one holds the opinion that somewhere between 10,000 and 30,000 vehicles/day is the best volume for operations of ASCS. The survey also asked the respondents to address the design speed and operational efficiency of ASCS. The results of this question can be seen in Figure 5.

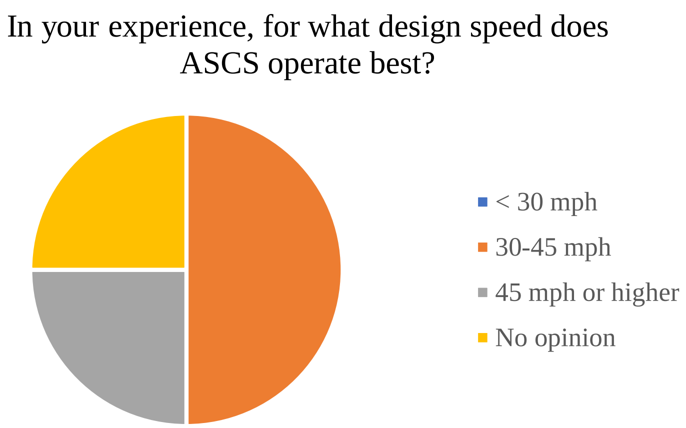


Figure 5 Design speed for ASCS operational efficiency

Most responses indicated that ASCS works best in the morning off-peak period. The afternoon peak and off-peak hold the second rank, receiving an equal number of votes. The breakdown of answers to this survey question can be found in Figure 6.

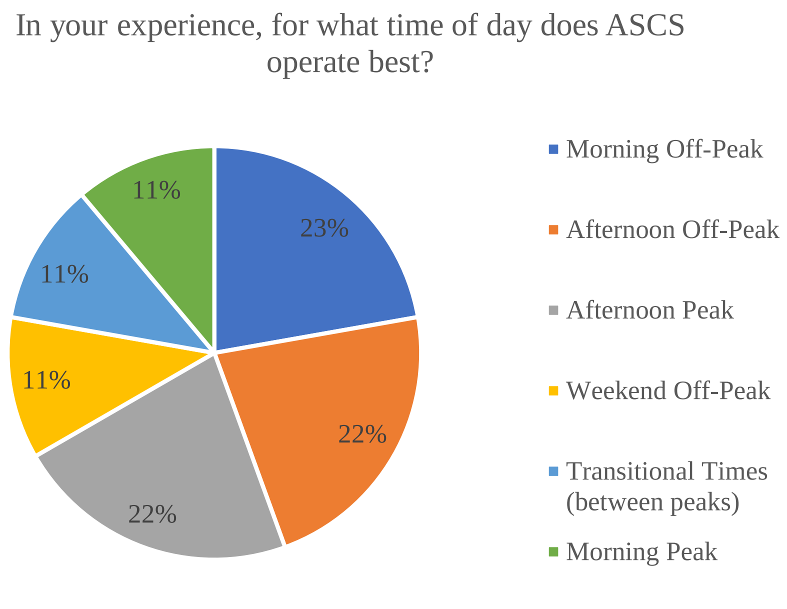


Figure 6 Time of day for ASCS operational efficiency

Due to the limited number of responses to this survey, it is challenging to draw any confident conclusions for the best fit of corridor type for ASCS. The conclusions of most of the respondents, when indicating their opinion, is limited because their experience is limited. However, as previously mentioned, these opinions do provide direction for our future research and serve as a jumping-off point. Though previous studies have found specific times of day to have varying results with ASCS, the sporadic opinions in time of day in which ASCS operates the best prove that further study of this parameter is necessary.

Table 3 summarizes the detailed responses contributed by four of the survey respondents. Each of the cities or counties that indicated that they have planned or will conduct an operational study in the future has chosen to implement ASCS on an arterial corridor. Two of the four previously ran Actuated Coordinated signals, and two had Fixed Time signals. Three of the four have noticed sustained performance in their systems, and one plans to evaluate the performance of ASCS in the future.

Table 3 Summary of corridor specific survey responses

Corridor	Number of intersections	Corridor type	Previous traffic signal system	Date last retimed	ASCS type installed	Operational or safety study conducted	Performance sustained
A	19	Arterial	Actuated Coordinated	1/1/11	SynchroGreen	Operational – Before & After	Yes
B	7	Arterial	Actuated Coordinated	4/1/11	Intelight MaxAdapt	None, but expect to conduct both safety and operational in the future	No data yet
C	6	Arterial	Fixed Time Coordinated	1/1/09	InSync	Operational	Yes
D	7	Arterial	Fixed Time Coordinated	1/1/08	InSync	None	Yes

3.5 Chapter Conclusions

Based on the results of the survey, it is clear that many states and public agencies continue to express interest in implementing or experimenting with ASCS. The initial survey response of 28 out of 50 states indicates an overall familiarity with or interest in the technology and the possibility of implementing ASCS in their states. Almost three-quarters of the state respondents to the survey have experimented with ASCS, and over half have maintained their systems over the years.

For many respondents, the deployment of ASCS was based on the operational benefits and safety benefits of ASCS. However, the lack of resources allocated to their agencies has hindered their ability to evaluate ASCS along corridors in their jurisdictions. Increasing these resources to devote to the study of traffic signal performance is necessary to improve the current state of the practice. The opportunity for improved operational performance is excellent, especially in a future that is sure to contain more connected and data-driven environments. ASCS is a useful application that should continue to be explored and developed to best suit the needs of users of the road.

It is important to note that the respondents to the survey provided different answers to many of the questions. Some of this can be attributed to the multitude of Adaptive Signal Control System options as well as the differences between states/cities/jurisdictions and corridor types where implemented. These differences between corridors as well as cities and counties resulted in a different experience in each. Thus, evaluation on a case by case basis will help to build the knowledge base for all those stakeholders with interest in improving roadways.

CHAPTER 4 CRASH FREQUENCY STUDY

4.1 Introduction

EB method has been used for the safety evaluation previously in before-and-after studies (Hovey et al., 2010; Hovey & Chowdhury, 2005). The research team implement different models into the ASCS safety evaluation and investigate how different crash prediction models impact the estimator of the safety effectiveness of ASCS in the EB and Fully Bayesian (FB) before-and-after studies. A series of EB and FB models are compared and evaluated. An FB model that accounts for traffic volume, roadway geometric features, year factor, and spatial effects is deemed as the best model. The research team evaluated the safety effectiveness of ASCS in terms of reducing the crash frequency at 11 ASCS corridors with a total of 109 signalized intersections located throughout South Carolina. ASCS effect may vary across sites due to specific features of the sites that are deployed with ASCS. To explore the variations in ASCS effect across sites, the research team evaluates the safety effectiveness of ASCS for different corridors and intersections.

4.2 Method

This section firstly discusses model forms in the development of crash prediction models in the EB and FB before-and-after study procedures (Jin et al., 2020). Then, this section provides a validation procedure that uses two criteria to validate possible models: 1) the potential bias and variance of prediction, and 2) the estimation accuracy of safety effectiveness. Lastly, this section discusses an approach to investigate the variation of ASCS safety effects.

4.2.1 Model Development and Evaluation Procedure

This subsection introduces the models that will be incorporated into the EB and FB before-and-after study procedures. Traffic volume, roadway geometric features (e.g., the number of access points at an intersection, and the number of exclusive left-turn lanes, right-turn lanes, and through lanes on major or minor streets), year factor, and spatial effect are used to produce different sets of the models. For each model, four crash types of interest are accounted for: total crash, Fatal and Injury (F+I) crash, rear-end crash, and angle crash. Two primary forms of models, Poisson-Gamma and Poisson-Lognormal, are introduced. A spatial model is also used with a Poisson-Lognormal model in this study to account for the spatial effect existing in the investigated sites. Model 1, Model 2, and Model 3 are implemented within the EB framework. Model 4A, Model 4B, Model 5A, Model 5B, Model 6A, and Model 6B are implemented within the FB framework. EB and FB model development and estimation and EB and FB before-and-after evaluation procedure are detailed in APPENDIX A-2.

EB Model Development

A general Poisson-Gamma model with two tiers is expressed as the following:

$$y_{m,it} \sim Poisson(\lambda_{m,it}) \tag{1}$$

$$\lambda_{m,it} \sim Gamma(\alpha,\phi) \tag{2}$$

where, $y_{m,it}$ is the observed crash frequency at an intersection i (i.e., $i = 1, 2, ..., 109$ for a total of 109 intersections considered in this study) on the corridor m (i.e., $m = 1, 2, ..., 11$ for a total of 11 corridors considered in this study) in a given year t (i.e., $t = 2011, 2012, ..., 2019$); $\lambda_{m,it}$ is the Poisson mean. The expectation of $\lambda_{m,it}$, $E(\lambda_{m,it})$ is the expected yearly number of crashes at an intersection i on the corridor m in the year t for a specified crash type (i.e., total crash, F+I crash, rear-end crash, or angle crash). α is the shape parameter of Gamma distribution, and ϕ is the inverse scale parameter (i.e., rate parameter) of the Gamma distribution.

Three crash prediction models (i.e., Safety Performance Function (SPF) in the EB framework) are specified in terms of different explanatory variables. Model 1 and Model 2 account for the year factor by introducing annual multipliers. The year factor is often introduced into the crash prediction model to account for temporal variation of crash expectation, which accounts for possible unobserved factors such as weather conditions, road conditions, and vehicle technology improvements (Persaud et al., 2010). Model 3 accounts for the year factor by introducing the year variable as one of the explanatory variables in the model. Model 1 includes an annual multiplier, and Annual Average Daily Traffic (AADT) without considering the difference in roadway geometric features. Model 2 includes an annual multiplier, AADT, and roadway geometric features. Model 3 includes AADT, roadway geometric features, and the year factor.

FB Model Development

A general Poisson-Lognormal model is introduced with multiple hierarchical levels in the following:

$$y_{m,it} \sim Poisson(\lambda_{m,it}) \tag{3}$$

$$\log(\lambda_{m,it}) = \sum_{j=0}^{p} \beta_{mj,B} B_{mj,it} + \varepsilon_{m,it} \tag{4}$$

$$\varepsilon_{m,it} \sim Normal(0, \sigma_{\varepsilon}^2) \tag{5}$$

$$\beta_{mj,B} \sim Normal(0, \sigma_{\beta,j}^2) \tag{6}$$

where, $y_{m,it}$ is the observed crash frequency at the intersection i on the corridor m in a given year t; $\lambda_{m,it}$ is the Poisson mean. $B_{mj,it}$ is the explanatory variable in the model. $\beta_{mj,B}$ is the j^{th} coefficient for the explanatory variable in the model. P is the total number of explanatory variables. The distribution of parameters such as $\lambda_{m,it}$, $\beta_{mj,B}$, and $\varepsilon_{m,it}$ in the model is evaluated based on the estimation of the posterior distribution of these parameters using the FB approach. In the FB models, $\lambda_{m,it}$ is the site-specific expected crash frequency, and each $\lambda_{m,it}$ represents a model parameter. $\varepsilon_{m,it}$ is introduced to account for the variation across intersections and years. σ_{ε}^2 is assumed to follow a prior Inverse-Gamma (0.001, 0.001) distribution for all models based on previous studies (Cai et al., 2018; Carriquiry & Pawlovich, 2004;

Sacchi & Sayed, 2014). $\sigma^2_{\beta,j}$ is set to 1000 for all the prior distributions of $\beta_{mj,B}$ for all models resulting in a non-informative prior distribution for $\beta_{mj,B}$ (Persaud et al., 2010). Consequently, estimation of the posterior distribution of $\beta_{mj,B}$ largely depends on observed data.

Three FB non-spatial models are defined in terms of different explanatory variables. Model 4A and Model 5A introduce a random effect to account for variation caused by the various intersections and years, while Model 6A directly treats the year factor as a covariate in the model. Based on the inclusion of the spatial effect into the models, three different FB spatial models-Model 4B, Model 5B, and Model 6B are developed.

4.2.2 Validation of the Before-and-after Evaluation Methods

This subsection provides a validation procedure that uses two criteria to validate EB and FB models: 1) the potential bias and variance of prediction, and 2) the estimation accuracy of safety effectiveness. In this way, EB and FB models are compared using the same criteria adopted in this study.

Evaluation of Potential Bias and Variance of Prediction

Root Mean Square Error (RMSE) is used to compare the potential bias and variance of prediction among different models. RMSE is also used to measure the quality of an estimator and represent the model prediction error and the model goodness of fit. A lower value of RMSE indicates a smaller difference between the estimated value and the actual observed crash frequency for non-ASCS intersections. The equation is shown below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(E_{it} - O_{it}\right)^2}{NT}} \tag{7}$$

where, E_{it} is the expected number of the crashes of non-ASCS intersections in an intersection i in the year t; O_{it} is the observed crashes of non-ASCS intersections in an intersection i in the year t; N is the total number of non-ASCS intersections used for validation; T is the total number of years.

In the EB procedure, the expected number of crashes in the subsequent years for a specific intersection can be estimated by multiplying a correction factor due to the difference between the subsequent years and the predecessor year by the expected number of crashes in the predecessor years. For example, the estimated crash in 2012 for an intersection can be obtained by multiplying the correction factor due to the difference between 2011 and 2012 by the expected number of crashes in 2011. Likewise, the estimated crash frequency in 2013, 2014, 2015, 2016, and 2017 can be predicted in this way. In the FB procedure, the expected number of crashes for a specific intersection each year can be estimated directly by the Markov Chain Monte Carlo (MCMC) simulation.

Estimation of Safety Effectiveness of Non-ASCS Intersections

To evaluate the performance of the candidate models in estimating the safety effectiveness of ASCS, the research team computes and compares the safety effectiveness of ASCS for non-ASCS intersections among different models since no ASCS effect exists for the non-ASCS intersections. Thus, crash reduction percentage for the non-ASCS intersections (i.e., zero) can be deemed as the ground truth. In the EB procedure, the null hypothesis is that the crash reduction percentage is equal to zero, and the alternative hypothesis is that the crash reduction percentage is not equal to zero. In the FB procedure, the significance of the crash reduction percentage is determined if the 95% Bayesian Credible Intervals (BCI) does not contain zero. To calculate the crash reduction percentage for the non-ASCS intersections, the research team assumes that 2011-2014 is the "before period"; 2015-2017 is the "after period" used for creating a case evaluating the safety effects for the non-ASCS intersections for both EB and FB procedure.

4.2.3 Investigation of Variation of ASCS Safety Effects

ASCS safety effects could vary across different intersections with different features. The evaluation results of the safety effectiveness of ASCS are analyzed based on different AADT groups, geometric features, and speed limits of intersections. The evaluation results are aggregated by three groups of AADT at major roads: AADT <= 20,000 vehicles/day, 20,000 vehicles/day <AADT <= 50,000 vehicles/day, and AADT>50,000 vehicles/day. This grouping of AADT is in line with a previous study (Khattak et al., 2019). The evaluation results are aggregated by two groups based on the number of legs at an intersection (i.e., three-legged or four-legged intersections). The evaluation results are aggregated by three groups based on different speed limits at major roads: 30 ~ 35 mph, 40 ~ 45 mph, and 50 ~ 55 mph. A linear regression model is developed to explore the linear relationship between the ASCS safety effects and other variables considered in this study (i.e., AADT at minor roads, speed limits at minor roads, the number of exclusive left-turn lanes/right-turn lanes/through lanes on major or minor roads, or the number of access points at an intersection).

4.3 Data Description

SCDOT initially provided the research team with crash data from 2011 to 2018. Later, SCDOT provided the research team with crash data for 2019 for the following corridors – US 17 Business, US 378, Woodruff Rd, Long Point Rd, and Main Street so that the research team can have at least two-year after period crash data for all the ASCS corridors. The crash data contain attributes including the crash type and AADT on major and minor streets at intersections. The following roadway geometric features are also collected from Google Earth: 1) the number of exclusive left-turn lanes, right-turn lanes, and through lanes on major or minor streets, and 2) the number of access points within the influence area of an intersection. In terms of crash type, crash data are aggregated in four categories: total crashes, F+I crashes, rear-end crashes, and angle crashes. In this study, intersection crashes are investigated for evaluating the ASCS safety effect. According to SCDOT's strategy, intersection crashes are those that happened within 0.05 miles of the center of the intersection.

As shown in Table 4, reference crash data (i.e., no ASCS is installed) are obtained from similar signalized intersections and corridors (e.g., similar roadway geometrics, the location of proximity, and same functional class of corridors) without ASCS at different locations in South Carolina. The sample size of reference crash data is 680 across different years and different signalized intersections. ASCS has not been installed in the 24 signalized intersections on the US 29 corridor in Greenville, and the corridor could be deemed as a non-ASCS corridor. The crash data of the US 29 corridor from 2011 to 2017 during which ASCS is not implemented, are used for validating EB and FB models.

Initially, the research team obtained 13 corridors that have installed ASCS. Original crash data have before period and after period data. Two corridors- SC 19 in Aiken and US 17 in Mount Pleasant installed with Insync were removed because before period crash data, including crash data before 2011, is not accurate for the crash location. The research team only includes 11 corridors that have at least a two-year after period crash data for this study. The location, number of signalized intersections, and installation date of these corridors are detailed in Table 5. Safety effects of ASCS are evaluated for 11 corridors with a total of 109 signalized intersections, installed with SynchroGreen in South Carolina. The study crash data pool for safety evaluation excludes crashes that occurred during the ASCS installation year to minimize evaluation bias caused by installation before activating ASCS and driver's adaption to the new driving environment with ASCS.

Table 4 Crash data usage and resource

Crash data type	**Crash data resource**
Reference Crash Data	Similar signalized corridors without ASCS (i.e., US 78 in Berkeley, the segment of US 17A without ASCS in Berkeley, US 1 in Lexington, SC 6 in Lexington, another segment of US 29 without ASCS in Greenville, S-311 in Greenville, SC 146 in Greenville, US 17 in Charleston, SC 171 in Charleston, SC 61 in Charleston, and US 17 in Horry), and ASCS corridors (i.e., before period crash data of SC 642, US 52, US 17, Roper Mt. Rd./Garlington Rd., N. Lake Drive, and US 17A)
Crash Data for Validation of EB and FB Models	Non-ASCS corridor (i.e., US 29) with 24 intersections
Crash Data for Safety Evaluation for ASCS Corridors	Eleven ASCS corridors with 109 intersections (i.e., crash data of SC 642, US 52, US 17, Roper Mt Rd./Garlington Rd., N. Lake Drive, US 17A, Long Point Rd., US 17 Business, Woodruff Rd., Main Street, and US 378)

Table 5 ASCS corridors used in this study

Location	**Corridor**	**Number of signalized intersections**	**Installation date**
Greenville	Roper Mt Rd./ Garlington Rd.	5	November 2016
Greenville	Woodruff Rd.	17	November 2017
Charleston	SC 642	18	June 2015
	US 52	17	October 2016

Location	Corridor	Number of signalized intersections	Installation date
Pawleys Island	US 17	6	February 2016
Summerville	US 17A	12	June 2015
Garden City/ Surfside	US 17 Business	9	March 2017
Lexington	N. Lake Drive	7	December 2015
	Main Street	5	June 2017
	US 378	7	June 2017
Mount Pleasant	Long Point Rd.	6	November 2017

APPENDIX A-1 Table A-1 shows a summary of descriptive statistics of the geometric features of intersections and speed limits data. The difference in the geometric features of intersections and speed limits between the before and after period is very small.

APPENDIX A-1 Table A-2 shows descriptive statistics of the intersection crash frequency (i.e., number of crashes per year) for the before and after period for the ASCS corridors. The crash frequency statistics show that crashes are over-dispersed (i.e., variance greater than mean) in the total crash, F+I, rear-end, and angle crash for the ASCS corridors.

To properly analyze the crash dataset, the research team collected information from SCDOT regarding whether any other possible safety improvements, in addition to the ASCS, have been made at intersections. Flashing Yellow Arrow (FYA) was installed at some signalized intersections before or after the ASCS was installed. The research team considers FYA as one of the explanatory variables of the model. A categorical variable is considered to distinguish the effects of different numbers of FYA at the intersections on the crash frequency outcomes. It is found that the categorical variable is not significant and adding the categorical variable increases the AIC of the model. Thus, the FYA variable is taken out of the model since it cannot provide useful information. Offset improvements for left-turn lanes, which have the potential to reduce crashes and crash severity at signalized intersections, were made on one intersection after the ASCS was installed. To exclude the effect of such safety improvements, crashes that occurred during the period after offset improvements were made are not included in the analysis. An additional signal phase was added to one signal after the ASCS was installed, so the crashes that occurred during the period after such changes were made are not included in the analysis as well.

4.4 Results

This section presents the corridor-specific and intersection-specific evaluation results.

4.4.1 Corridor-specific Evaluation Results

Based on the comparison results between the FB and EB models shown in APPENDIX A-3, a FB model (Model 6B) that includes AADT, roadway, year factor, and spatial effect, performs best among all models. Eleven ASCS corridors at different locations in South Carolina are evaluated using Model 6B.

Positive signs of values shown in the orange highlighted cells in Table 6 indicate crash increases, while negative signs of values shown in the green highlighted cells indicate crash reductions. The 95% BCI of each model is shown in parentheses in Table 6. The ASCS shows crash reductions for most corridors for different crash types.

As shown in Table 6, 10 out of 11 ASCS corridors show the F+I crash reduction due to ASCS. For US 52, ASCS shows a crash increase in F+I, possibly because US 52 has the highest traffic volume among these corridors, leading to higher crash severity.

Nine out of 11 ASCS corridors show the angle crash reduction due to ASCS. ASCS shows an increase in angle crashes for US 17A and Woodruff Rd. For Woodruff Rd., there was construction in I-385, which intersects Woodruff Rd. For US 17A, there was land development near the Sigma Dr./US 17A intersection.

For rear-end crashes, four corridors (i.e., US 52, N. Lake Drive, Woodruff Rd., and US 17A) show ASCS increases in rear-end crashes, possibly because traffic demands at side streets are relatively high, which may interrupt the major traffic flow. The interruption may lead to more stops, and more stops may lead to more rear-end crashes.

Table 6 Corridor-specific safety effect estimation

Corridor Name	Crash change percentage (95% BCI)			
	Total crash	**F+I**	**Rear-end**	**Angle**
SC 642	-32.2%* (-45.0% ~ -17.4%)	-16.3% (-36.7% ~ 8.5%)	-16.7% (-34.3% ~ 5.1%)	-41.7 %* (-55.8% ~ -24.8%)
Roper Mt. Rd./ Garlington Rd.	-41.1 %* (-64.9% ~ -8.1%)	-73.7%* (-88.7% ~ -52.6%)	-3.4% (-45.5% ~ 54.3%)	-92.0%* (-99.4% ~ -75.3%)
US 17	-49.8%* (-66.8% ~ -27.2%)	-46.7%* (-68.2% ~ -16.3%)	-39.4%* (-61.1% ~ -9.8%)	-57.4%* (-73.3% ~ -35.2%)
US 52	-4.6% (-25.7% ~ 20.8%)	+16.2% (-15.7% ~ 55.9%)	+0.4% (-24.4% ~ 30.5%)	-15.6% (-37.8% ~ 11.8%)
N. Lake Drive	-6.5% (-31.2% ~ 24.4%)	-26.8% (-52.1% ~ 6.4%)	+3.2% (-25.8% ~ 39.5%)	-28.0% (-51.0% ~ 1.8%)
US 17A	+19.7% (-5.7% ~ 19.8%)	-31.8%* (-49.8% ~ -10.0%)	+17.1% (-9.7% ~ 49.4%)	+10.8% (-15.4% ~ 42.8%)
Woodruff Rd.	+2.8% (-8.2% ~ 13.9%)	-19.6%* (-34.2% ~ -3.6%)	+4.6% (-7.9% ~ 17.9%)	+1.7% (-13.1% ~ 17.8%)
Long Point Rd.	-35.9%* (-7.0% ~ -57.5%)	-56.7%* (-31.0% ~ -74.8%)	-31.1% (-57.0% ~ 4.5%)	-27.9% (-57.0% ~ 13.4%)
US 17 Business	-61.4%* (-72.6% ~ -47.4%)	-63.8%* (-77.1% ~ -45.9%)	-59.9%* (-72.4% ~ -43.8%)	-51.3%* (-67.9% ~ -29.2%)
Main Street	-32.2%* (-55.9% ~ -0.1%)	-60.7%* (-77.7% ~ -36.2%)	-16.4% (-47.5% ~ 26.7%)	-54.9%* (-72.9% ~ -29.2%)
US 378	- 27.8% (-50.5% ~ 1.6%)	-63.5%* (-78.7% ~ -42.3%)	-9.1% (-39.0% ~ 30.1%)	-62.5%* (-78.5% ~ -39.9%)

*: statistically significant in terms of 95% BCI

4.4.2 Intersection-specific Evaluation Results

The safety effectiveness of ASCS is also evaluated for different intersections. As shown in Figure 7, a negative value means that ASCS reduces crashes. The figure shows that most of the intersections with ASCS show crash reductions for the total crash, F+I crash, and angle crash. The ASCS decreases rear-end crashes for 55 out of 109 intersections.

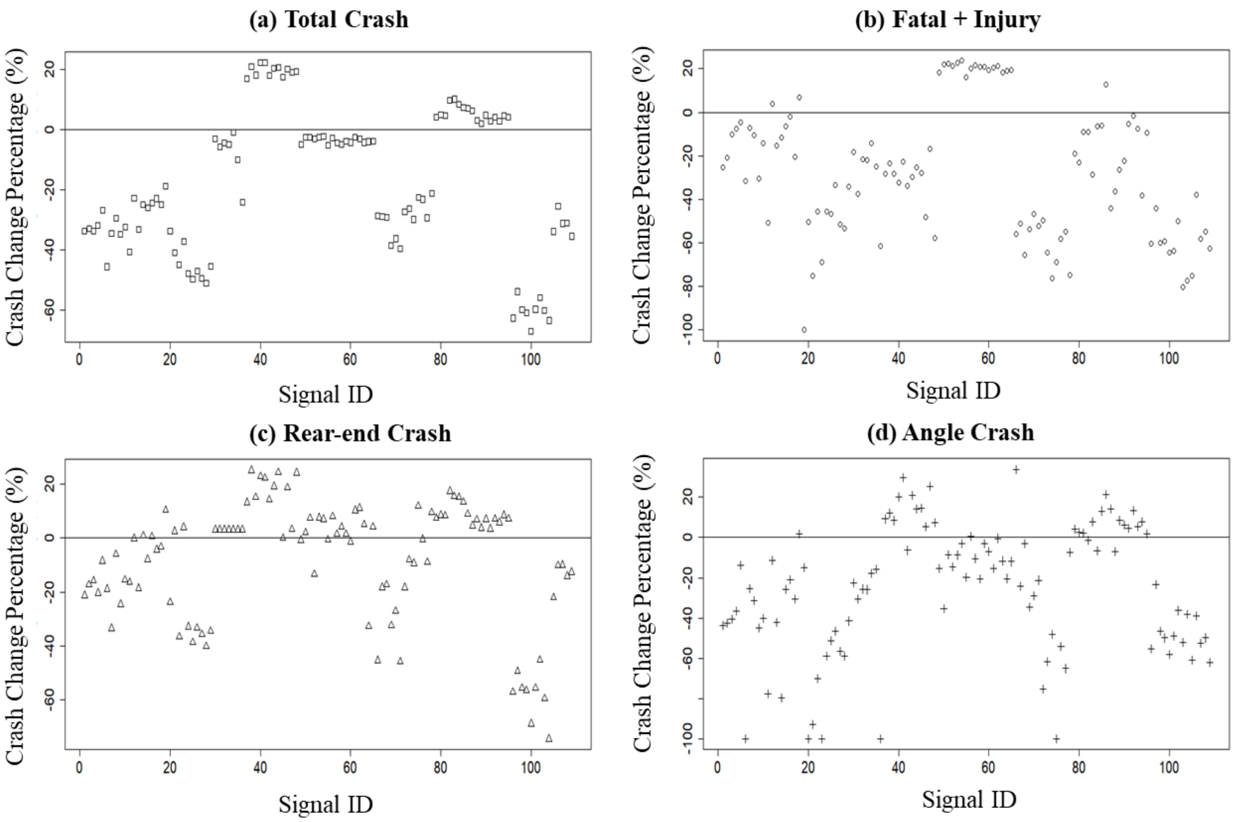


Figure 7 Percent change of crashes due to ASCS at each intersection for different crash types

The evaluation results are aggregated by three groups of AADT at major roads: AADT Group 1 with AADT less than or equal to 20,000 vehicles/day (sample size = 19), AADT Group 2 with AADT between 20,000 vehicles/day and 50,000 vehicles/day (sample size = 87), and AADT Group 3 with AADT greater than 50,000 vehicles/day (sample size = 3). This grouping of AADT is in line with a previous study (Khattak et al., 2019). As shown in Figure 8(a), changes in total crashes due to the ASCS are different between AADT Group 1 and Group 2. The changes are statistically different between AADT Group 1 and Group 2 based on the Analysis of Variance (ANOVA) analysis, suggesting that intersections with AADT between 20,000 vehicles/day and 50,000 vehicles/day at major roads achieve higher safety benefit compared to intersections with AADT less than or equal to 20,000 vehicles/day. Changes in total crashes due to the ASCS are not statistically different between AADT Group 1 and Group 3 and between AADT Group 2 and Group 3.

As shown in Figure 8(b), changes in F+I crashes due to the ASCS are different between AADT Group 1 and Group 3 and between AADT Group 2 and Group 3. The changes are statistically different between AADT Group 1 and Group 3 and between AADT Group 2 and Group 3 based on the ANOVA analysis, suggesting that intersections with AADT less than or equal to 50,000 vehicles/day achieve higher safety benefit compared to intersections with AADT greater than 50,000 vehicles/day. The possible reason could be that higher traffic volume may be associated with more severe crashes. Changes in F+I crashes due to the ASCS are not statistically different between AADT Group 1 and Group 2.

As shown in Figure 8(c), changes in rear-end crashes due to the ASCS are different between AADT Group 1 and Group 2. The changes are statistically different between AADT Group 1 and Group 2 based on the ANOVA analysis, suggesting that intersections with AADT between 20,000 vehicles/day and 50,000 vehicles/day achieve higher safety benefit compared to intersections with AADT less than or equal to 20,000 vehicles/day. Changes in rear-end crashes due to the ASCS are not statistically different between AADT Group 1 and Group 3 and between AADT Group 2 and Group 3.

As shown in Figure 8(d), changes in angle crashes due to the ASCS are similar for AADT Group 1, Group 2, and Group 3. The changes are not statistically different between AADT Group 1, Group 2, and Group 3 based on the ANOVA analysis.

Based on the above analysis, it is concluded that intersections with AADT at a major road between 20,000 and 50,000 vehicles/day achieve higher safety benefits after deploying ASCS.

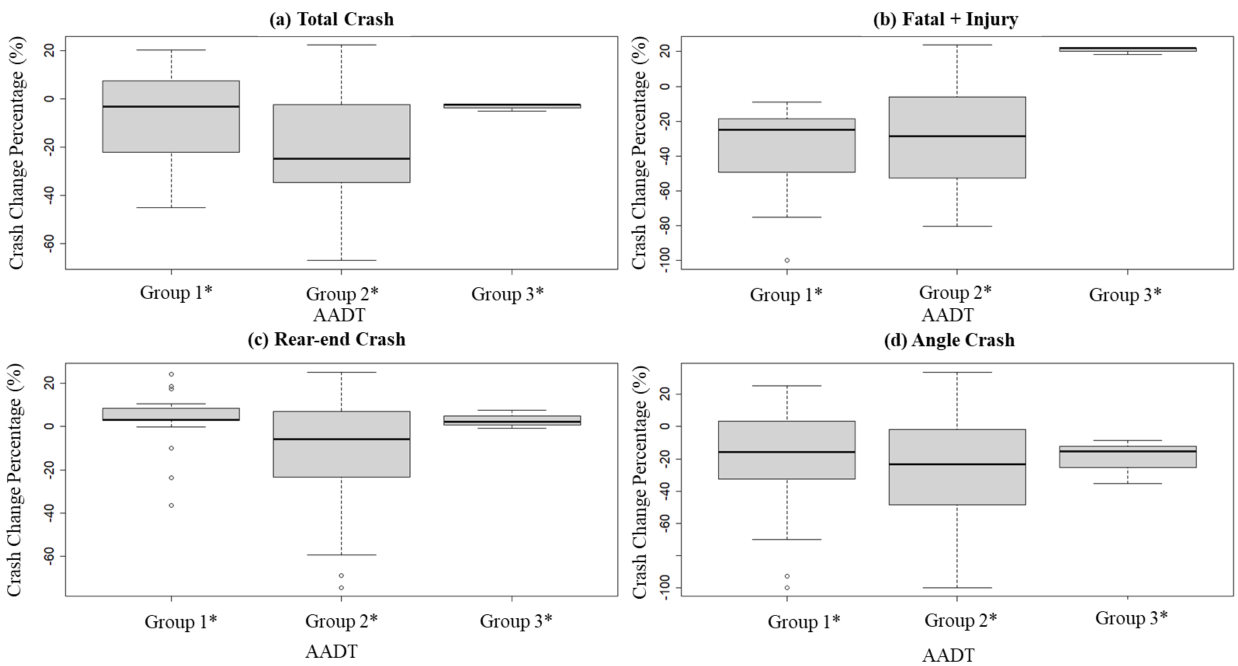


Figure 8 Evaluation results aggregated by AADT of major roads

*AADT Group 1 (sample size = 19): AADT <= 20,000 vehicles/day; AADT Group 2 (sample size = 87): 20,000 vehicles/day <AADT <= 50,000 vehicles/day; AADT Group 3 (sample size =3): AADT>50,000 vehicles/day

The evaluation results are aggregated by two groups based on the number of legs at an intersection, i.e., T-intersections (sample size = 29) and four-legged intersections (sample size = 80). As shown in Figure 9(a), (b), (c), and (d), for the total crash, F+I crash, rear-end crash, and angle crash, crash changes due to the ASCS are similar for both four-legged intersections and T-intersections. The changes are not statistically different between four-legged intersections and T-intersections based on the *t*-test results.

Based on the above analysis, it is concluded that intersections have the same ASCS safety benefit regardless of four-legged intersections or T-intersections.

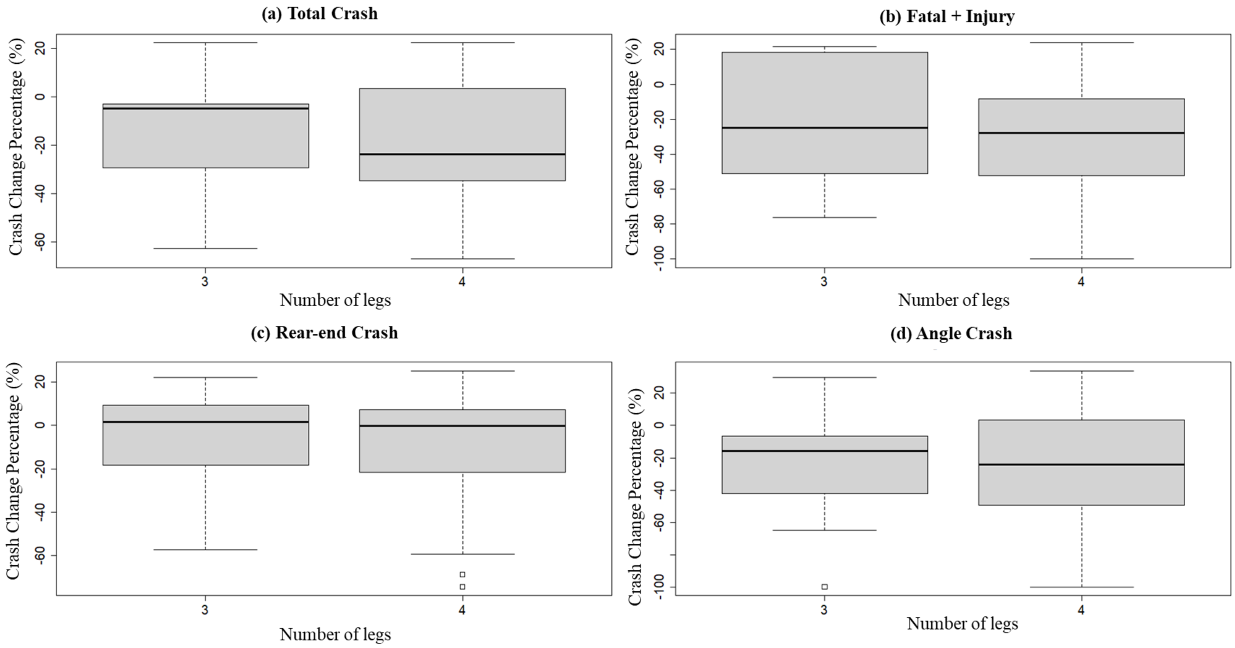


Figure 9 Evaluation results aggregated by number of legs at an intersection

Additionally, the evaluation results are aggregated by three groups based on different speed limits at major roads: Speed Group 1 with 30 ~ 35 mph, Speed Group 2 with 40 ~ 45 mph, Speed Group 3 with 50 ~ 55 mph. As shown in Figure 10(a), changes in total crashes due to the ASCS are different between Speed Group 1 and Group 2 and between Speed Group 1 and Group 3. The changes are statistically different between Speed Group 1 and Group 2 and between Speed Group 1 and Group 3 based on the ANOVA analysis, suggesting that intersections with a speed limit of 40 ~ 45 mph and 50 ~ 55 mph at major roads achieve higher safety benefit compared to intersections with a speed limit of 30 ~ 35 mph at major roads. Changes in total crashes due to the ASCS are not statistically different between Speed Group 2 and Group 3.

As shown in Figure 10(b), changes in F+I crashes due to the ASCS are statistically different between Speed Group 1 and Group 2. The changes are statistically different between Speed Group 1 and Group 2 based on the ANOVA analysis, suggesting that intersections with a speed limit of 30 ~ 35 mph at major roads achieve higher safety benefit compared to intersections with a speed limit of 40 ~ 45 mph at major roads. It is expected that the higher average speed may be associated with higher severe crashes. Changes in F+I crashes due to the ASCS are not statistically different between Speed Group 1 and Group 3 and between Speed Group 2 and Group 3.

As shown in Figure 10(c), changes in rear-end crashes due to the ASCS are different between Speed Group 1 and Group 2 and between Speed Group 1 and Group 3. The changes are statistically different between Speed Group 1 and Group 2 and between Speed Group 1 and Group 3 based on the ANOVA analysis, suggesting that intersections with a speed limit of 40 ~ 45 mph and 50 ~ 55 mph at major roads achieve higher safety benefit compared to intersections with a speed limit of 30 ~ 35 mph at major roads. It is expected that the higher average speed leads to fewer stops, thus reducing the rear-end crashes. Changes in rear-end crashes due to the ASCS are not statistically different between Speed Group 2 and Group 3.

As shown in Figure 10(d), changes in angle crashes due to the ASCS are different between Speed Group 1 and Group 3 and between Speed Group 2 and Group 3. The changes are statistically different between Speed Group 1 and Group 3 and between Speed Group 2 and Group 3 based on the ANOVA analysis, suggesting that intersections with a speed limit of 50 ~ 55 mph at major roads achieve higher safety benefit compared to intersections with a speed limit of 30 ~ 35 mph and 40 ~ 45 mph at major roads. It is expected that the higher average speed leads to fewer stops, thus reducing the angle crashes. Changes in angle crashes due to the ASCS are not statistically different between Speed Group 1 and Group 2.

Based on the above analysis, it is concluded that intersections with a speed limit at a major road between 40 to 55 mph achieve higher safety benefits after deploying ASCS.

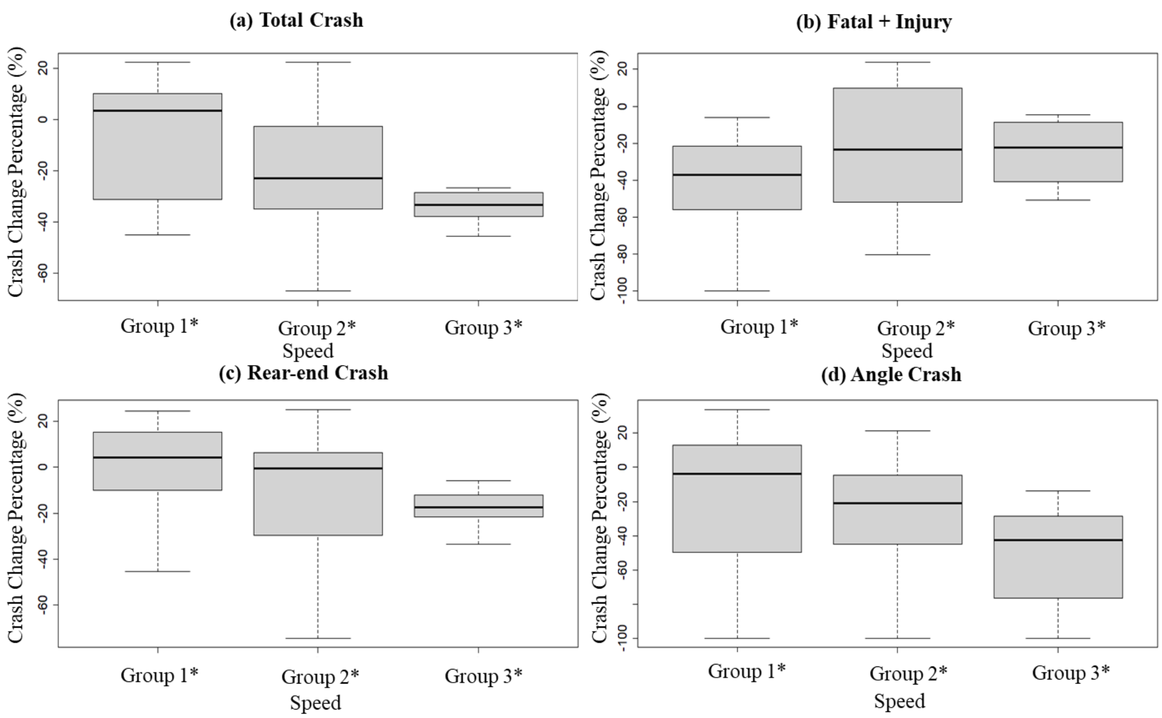


Figure 10 Evaluation results aggregated by speed limits at major streets

*Speed Group 1 (sample size = 30): speed limit = 30 ~ 35 mph; Speed Group 2 (sample size = 71): speed limit=40 ~ 45 mph; Speed Group 3 (sample size =8): speed limit = 50 ~ 55 mph

A linear regression model was developed to explore the linear relationship between the ASCS safety effects and other variables (i.e., the number of exclusive left-turn lanes/right-turn lanes/through lanes on major streets, the number of exclusive left-turn lanes/right-turn lanes/through lanes on minor streets, and the number of access points at an intersection) considered in this study. Based on our analysis, for F+I crashes, as the number of through lanes on a major street increases, the ASCS safety benefit decreases. A higher number of through lanes on a major street are associated with higher traffic volume, so the ASCS safety benefit decreases with the increasing traffic volume. For the total crash, rear-end crash, and the angle crash, there is no linear relationship between the safety effectiveness of the ASCS and the number of through lanes on major streets. For the F+I crashes, as the number of access points on minor streets increases, the ASCS safety benefit increases. The possible reason could be that the average speed of the traffic is lower due to the interruption of traffic from/to the access points, so the severe crashes are reduced. For the total crash, rear-end crash, and the angle crash, there is no linear relationship between the safety effectiveness of the ASCS and the number of access points on minor streets.

For all crash types (i.e., total crash, F+I, rear-end crash, and angle crash) considered in this study, based on the regression analysis, there is no linear relationship between the safety effectiveness of ASCS and AADT of a minor road, the number of the exclusive right-turn lanes on a major street, the number of the exclusive left-turn lanes on a major street, the number of through lanes at a minor street, the number of the exclusive right-turn lanes on a minor street, the number of the exclusive left-turn lanes on a minor street, the number of access points on a major street, and the speed limit at a minor street.

4.5 Chapter Conclusions

This study develops a series of models, including the Poisson-Lognormal models, Poisson-Gamma models, and spatial models that are implemented in the EB and FB before-and-after studies. Different EB and FB models are validated using non-ASCS intersections. It investigates how model variations would affect: 1) potential bias (e.g., bias due to regression-to-the-mean, traffic volume changes, and roadway geometric feature changes) and variance of prediction, and 2) estimation accuracy of safety effectiveness. The findings would provide useful guidance for determining appropriate models for before-and-after safety studies. The FB model that accounts for traffic volume, roadway geometric features, year factor, and spatial effects shows the best performance in reducing potential bias and variance of prediction and improving the accuracy of safety effect estimation.

This study then applies the best FB model to the safety evaluation of ASCS and evaluates the safety effectiveness of ASCS at 11 ASCS corridors with a total of 109 signalized intersections. ASCS shows crash reductions for most of the ASCS corridors and intersections. It is also found that the safety effectiveness of ASCS varies across the intersections with different features, such as AADT at a major street and the speed limit at a major street.

CHAPTER 5 CRASH SEVERITY STUDY

5.1 Introduction

Crash severity (i.e., no injury, possible injury, non-incapacitating injury, incapacitating injury, or fatal) could be associated with a series of variables related to the corridor, intersection, and crash features. A multilevel structure (i.e., hierarchical structure) inherent in the crash data will be overlooked if all the variables are viewed at one level. Hierarchical modeling is used to represent the multilevel-structure of the crash data. In this study, ASCS is usually deployed at several signalized intersections on corridors; thus, the hierarchical structure exists inherently in the crash data. The crash data structure can be viewed as a two-level hierarchy, with Level 1 being an individual crash, and Level 2 being the intersection and corridor (i.e., one individual crash can be associated with one specific intersection and corridor). The ASCS effect on the crash severity that exists in the hierarchical structure can be estimated by implementing hierarchical models. A random-parameter ordered regression model integrating observed heterogeneity (also known as a hierarchical model) allows the ASCS parameter to vary both as a function of explanatory variables related to the intersection and corridor features, and across crashes. This kind of ASCS effect that exists in the hierarchical structure is referred to as "Hierarchical Effects of ASCS on the Crash Severity" in this study.

One of the objectives of this study is to determine the hierarchical effects of ASCS on crash severity. Through accounting for the observed heterogeneity in random-parameter ordered regression models (Jin et al., 2021), the hierarchical effects of ASCS on the crash severity are identified. The identification of the hierarchical effects of ASCS on the crash severity provides several practical implications on ASCS implementations from the standpoint of safety.

5.2 Method

Ordered regression models (i.e., ordered probit and logit models) are implemented to account for the ordinal nature (i.e., ranging from non-injury to possible injury, to non-incapacitating injury, to incapacitating injury, to fatal) of crash severity. The ordered regression models have been widely used to consider the ordinal nature of crash data mainly. However, an underlying assumption of ordered regression models is that the estimated parameters across crash severity levels are constant. This assumption is referred to as "the proportional odds or parallel regression" assumption. In this study, the research team initially fits ordered regression models and test this possible assumption by using the Brant test (Brant, 1990). It is found that the variable associated with the presence of ASCS does not violate the assumption. However, ordered regression models cannot capture unobserved heterogeneity across observations. Thus, the models may result in incorrect estimates (Washington et al., 2020). The random-parameter ordered regression model enables the parameters to vary across observations and has been explored by previous studies (Dabbour et al., 2017; Jalayer et al., 2018; Khattak et al., 2019). However, in previous studies related to crash severity outcome modeling, random-parameter ordered regression models have not been integrated with observed heterogeneity. The research team accounts for the observed heterogeneity in random-parameter ordered regression models (Jin et al., 2021). The observed heterogeneity means changes in the effect of predictors that are known and can be captured by available explanatory variables.

5.2.1 Random-parameter Ordered Regression Model

The random-parameter ordered regression models (Greene, 2003) are implemented in this study. The ordered regression model is used to study the following latent process:

$$y_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_i, \quad i = 1, ..., n \tag{8}$$

$$\boldsymbol{\beta}_i \sim g(\boldsymbol{\beta}_i \,|\, \boldsymbol{\theta}) \tag{9}$$

where y_i^* is a latent variable for the observation (i.e., crash) i; $\mathbf{X}_i$ (we use bold fonts for vectors in the report) is a vector of the explanatory variables; $\boldsymbol{\beta}_i$ is a vector of the coefficients; ε_i is the error term; n is the total number of observations.

In Eq. (8) and (9), $\boldsymbol{\beta}_i$ is allowed to be different for each observation i rather than fixed for all observations. The distribution $g(\boldsymbol{\beta}_i \,|\, \boldsymbol{\theta})$ is specified to enable $\boldsymbol{\beta}_i$ vary across observations, where $\boldsymbol{\theta}$ is a vector of the mean and variance of the random distribution.

$\boldsymbol{\beta}_i$ can be written as $\boldsymbol{\beta}_i = \boldsymbol{\beta} + \mathbf{L}\boldsymbol{\omega}_i$, where $\boldsymbol{\beta}$ is the vector of the mean of the coefficients. Each coefficient β_{ki} can be expressed as $\beta_{ki} = \beta_k + \sigma_k \omega_{ki}$. β_{ki} is the k^{th} element in $\boldsymbol{\beta}_i$. ω_{ki} is the k^{th} element in $\boldsymbol{\omega}_i$. ω_{ki} has a specific random distribution such as normal distribution and uniform distribution. $\mathbf{L}$ is a diagonal matrix of the standard deviations of the coefficients, σ_k. The unobserved heterogeneity is represented by σ_k. β_{ki} has a specific random distribution such as normal distribution and uniform distribution. For example, β_{ki} follows a normal distribution with a mean of β_k and a variance of σ_k^2 when $\omega_i \sim N(0,1)$.

The probability of the crash severity level j for the crash i, can be calculated as:

$$p(y_i = j) = P(\mu_{j-1} < \mathrm{y}_i^* \le \mu_j) = F(\mu_j - \mathbf{X_i}\boldsymbol{\beta}_i) - F(\mu_{j-1} - \mathbf{X_i}\boldsymbol{\beta}_i) \tag{10}$$

where y_i is an ordered categorical variable, μ_j is the j^{th} threshold in the model, and F is the standard normal Cumulative Distribution Function (CDF) for the ordered probit model or logistic CDF for the ordered logit model.

“KABCO” injury scale (K- fatal; A- incapacitating injury; B- non-incapacitating injury; C- possible injury; O- no injury) is usually used for classifying injuries. The crash severity levels provided by the SCDOT crash database include five categories: non-injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal, which correlates to the KABCO injury scale. Since relatively fewer crashes (i.e., 1.08% out of observations) are reported for incapacitating injury (i.e., A) and fatal (i.e., K) categories in this study, the two categories are combined with the non-incapacitating injury (i.e., B) category. The KAB represents a sum of K level, A level, and B level injury crashes, which is typically evaluated in safety studies (National Research Council (US), 2010). The crash severity levels are coded as three categories in this study: 1) non-injury (i.e., O), 2) possible injury (i.e., C), and 3) non-incapacitating injury, incapacitating injury, and fatal combined (i.e., KAB).

The research team uses the following model to express the response variable, y_i which is composed of three crash severity levels. It is expressed as

$$y_i = 0 \text{ if } y_i^* \leq \mu_0 \tag{11}$$

$$y_i = 1 \text{ if } \mu_0 < y_i^* \leq \mu_1 \tag{12}$$

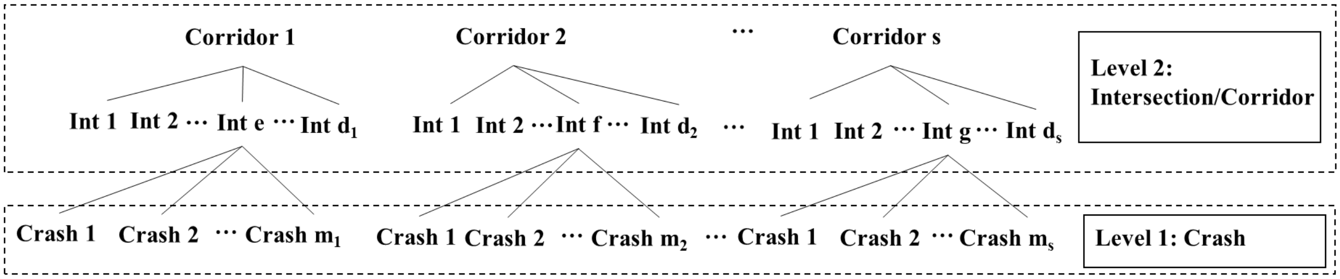
$$y_i = 2 \text{ if } y_i^* > \mu_1 \tag{13}$$

where, $y_i = 0$ indicates that the crash is O (KABCO scale); $y_i = 1$ indicates that the crash is C (KABCO scale); $y_i = 2$ indicates that the crash is K, A, or B (KABCO scale); μ_0 and μ_1 represent different thresholds for three crash severity levels; μ_0 is 0 here for non-injury. Here, only one threshold (i.e., μ_1) needs to be estimated.

5.2.2 Random-parameter Ordered Regression Model with Observed Heterogeneity

The random-parameter ordered regression model with observed heterogeneity can accommodate observed heterogeneity by allowing parameter variation to be captured by available explanatory variables. This model is also referred to as a hierarchical model (Greene & Hensher, 2010; Sarrias, 2016).

The hierarchical model is used to represent the multilevel-structure of the crash data. In this study, ASCS is usually deployed at several signalized intersections along corridors; thus, the hierarchical structure exists inherently in the crash data. As shown in Figure 11, each crash can be associated with one specific intersection that belongs to one specific corridor. The crash data structure can be viewed as a two-level hierarchy, with Level 1 being an individual crash, and Level 2 being the intersection and corridor that include the individual crash. Also, the two-level hierarchy model is considered to avoid excessive complexity of the model development. The ASCS effect on the crash severity that exists in the hierarchical structure can be estimated by implementing the hierarchical model.



Notation:
$\mathbf{m_1}$-the number of crashes associated with Intersection e and Corridor 1
$\mathbf{m_2}$-the number of crashes associated with Intersection f and Corridor 2
$\mathbf{m_s}$-the number of crashes associated with Intersection g and Corridor s
s-the number of corridors
$\mathbf{d_1}$-the number of intersections on Corridor 1
$\mathbf{d_2}$-the number of intersections on Corridor 2
$\mathbf{d_s}$-the number of intersections on Corridor s

Figure 11 Hierarchical structure of crash data

In the crash level (i.e., Level 1 in the hierarchical model), y_i^* is used to study the latent process as shown below:

$$y_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_i, \quad i = 1, \ldots, n \tag{14}$$

where, $\mathbf{X}_i$ is a vector of the crash-level explanatory variables for the i^{th} observation; $\boldsymbol{\beta}_i$ is a vector of the coefficients; ε_i is the error term; n is the total number of observations.

In the intersection/corridor level (i.e., Level 2 in the hierarchical model), $\boldsymbol{\beta}_i$ is specified by Eq. (15). The specification of Eq. (15) allows the coefficients to vary with different intersections and corridors.

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Pi}\mathbf{s}_i + \mathbf{L}\boldsymbol{\omega}_i \tag{15}$$

where, $\boldsymbol{\beta}$ is a vector of the mean of coefficients; $\boldsymbol{\omega}_i$ is a vector of random variables that follow random distributions; $\mathbf{L}$ is a diagonal matrix of the standard deviations of the coefficients; $\mathbf{s}_i$ is a vector of intersection/corridor-level explanatory variables; $\boldsymbol{\Pi}$ is a matrix of coefficients of the intersection and corridor related variables. Then, the expectation of coefficients is $E(\boldsymbol{\beta}_i) = \boldsymbol{\beta} + \boldsymbol{\Pi}\mathbf{s}_i$. The expectation of coefficients is a function of the intersection/corridor-level variables, $\mathbf{s}_i$.

More specifically, in Eq. (15), two components, $\boldsymbol{\Pi}\mathbf{s}_i$ and $\mathbf{L}\boldsymbol{\omega}_i$ are introduced to allow the coefficients to vary with different levels. First, $\boldsymbol{\Pi}\mathbf{s}_i$ is a linear function depending on the intersection/corridor related variables, $\mathbf{s}_i$. The primary purpose of using $\boldsymbol{\Pi}\mathbf{s}_i$ is to capture the observed heterogeneity across different intersections and corridors. It is expected that the varying intersections and corridor features (e.g., number of legs at an intersection, number of through/left/right lanes at an intersection, speed limit difference between major streets and minor streets at an intersection, and signalized intersection distance on a corridor) may lead to different crash severity. Second, $\mathbf{L}\boldsymbol{\omega}_i$ represents random effects, which capture both the intersection/corridor-level and the crash-level variability. The primary purpose of using $\mathbf{L}\boldsymbol{\omega}_i$ is to capture the unobserved heterogeneity in the crash data. These random effects are assumed not only to vary across various intersections/corridors but also to vary for the crashes within the same intersection/corridor.

To evaluate the effect of the explanatory variables on the probability of crash severity, especially on the intermediate level (i.e., possible injury), marginal effects for the three crash severity levels (i.e., O, C, and KAB) are computed. The marginal effect of explanatory variables indicates the change of the probability of crash severity level associated with a one-unit change in the continuous variables or change from ‘‘0” to ‘‘1” in the indicator variables. It should also be noted that marginal effects are estimated at the sample mean of the explanatory variables using the expectation of parameters when computed for random parameters. Marginal effects for the three crash severity levels are computed (Greene, 2003; Washington et al., 2020) as follows:

$$\frac{\partial p(y_i = 0)}{\partial x} = -\varphi(-\mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \tag{16}$$

$$\frac{\partial p(y_i = 1)}{\partial x} = \varphi(-\mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} - \varphi(\mu_1 - \mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \tag{17}$$

$$\frac{\partial p(y_i = 2)}{\partial x} = \varphi(\mu_1 - \mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \tag{18}$$

where, φ is the standard normal Probability Density Function (PDF) for the ordered probit model or logistic PDF for the ordered logit model; x is the explanatory variable.

Model implementation and estimation procedure is detailed in APPENDIX B-2.

5.3 Data Description

Initially, the research team obtained crash data from 13 corridors that have installed ASCS. Original crash data have before period and after period data. The research team only includes corridors that have at least two-year before and after period crash data for this study. As listed in Table 7, there is a total of 11 corridors with a total of 109 intersections where ASCS has been deployed. In total, 13,262 crashes are analyzed in this study.

Table 7 Corridor information

Location	Corridor	Number of signalized intersections	ASCS installation date	Number of crashes at intersections
Greenville	Roper Mt. Rd./ Garlington Rd.	5	November 2016	193
	Woodruff Rd.	17	November 2017	3585
Charleston	SC 642	18	June 2015	931
	US 52	17	October 2016	2387
Pawleys Island	US 17	6	February 2016	552
Summerville	US 17A	12	June 2015	2005
Garden City/ Surfside	US 17 Business	9	March 2017	1198
Lexington	N. Lake Drive	7	December 2015	502
	Main Street	5	June 2017	753
	US 378	7	June 2017	741
Mount Pleasant	Long Point Rd.	6	November 2017	415

According to SCDOT, intersection-related crashes are those that occurred within 0.05 miles of the center of the intersection. Using the threshold of 0.05 miles, the intersection-related crashes are identified. The year of crash data varies from 2011 to 2019. Crash data of six months after the installation of ASCS are removed from the analysis, which eliminates the effect of acclimation to ASCS of drivers. As shown in Table 8, 81.2% of the crashes are no injury, 13.5% of the crashes are possible injury, and a small proportion (i.e., 5.2%) of the crashes is KAB (i.e., fatal, incapacitating injury, and non-incapacitating injury combined).

Table 8 Frequency (and percentage) of crash severity

Crash severity outcome	Frequency (Percentage)
O*	10775 (81.2%)
C*	1792 (13.5%)
KAB*	695 (5.2%)

*KABCO crash severity scale. KAB: fatal, incapacitating injury, and non-incapacitating injury combined, C: possible injury, and O: no injury

In the development of the random-parameter regression models, the research team initially considers FYA as one of the explanatory variables of the model. A categorical variable is considered to distinguish the effects of different numbers of FYA at the intersections on crash severity outcomes. It is found that the categorical variable is not significant, and adding the categorical variable increases the AIC of the model. Thus, the FYA variable is taken out of the model since it cannot provide useful information.

Left-turn lanes were modified at one intersection in one of the study corridors after the ASCS was installed. To exclude the effect of such improvements that may impact safety, the crashes that occurred at this intersection are not included in the analysis. An additional signal phase was added to one signal after the ASCS was installed; thus, the crashes located at this intersection are not included in the analysis.

The following crash attributes are provided by SCDOT: collision time, crash severity, Annual Average Daily Traffic (AADT), light condition, road surface condition, crash type, weather condition, work zone, first harmful event (e.g., motor vehicle, animal, and pedestrian), and probable cause. The purpose of the inclusion of the first harmful event is to determine the involvement of pedestrians. The purpose of the inclusion of probable cause is to identify the distracted or aggressive drivers (i.e., aggressive operation of the vehicle or at excessive speed). The light (i.e., dawn, daylight, dusk, or dark), and weather conditions (rain or not) are accounted for because those attributes may have impacts on crash severity. Peak periods for each corridor analyzed in this study are identified by analyzing hourly average travel time data provided by the Iteris ClearGuide system (Iteris, 2020). The peak periods only exist on weekdays for the study corridors, and we found that the hourly average travel time does not vary much over the 24 hours during weekends on our study corridors. That is why only weekday peak periods are considered in this study, as shown in Table B-1 in APPENDIX B-1. Crash data available for South Carolina and provided by the SCDOT do not map crashes to traffic signal status (i.e., green, yellow, or red) (SCDOT, 2020d). Consequently, each crash cannot be associated with a specific signal phase from the available data. Due to this limitation, signal related parameters, such as signal status (i.e., green, yellow, or red) and green/yellow/red time, could not be introduced into the model.

The attributes from the crash database are converted to the response and explanatory variables. The response variable includes three crash severity levels- O, C, and KAB. The explanatory variables include light condition, ASCS presence, FYA presence, peak period, crash type (i.e., rear-end or angle), weather condition, careless driving, aggressive driving, the presence of pedestrians, and AADT. Also, the research team has collected area type (urban or not) and speed limit data from the SCDOT website (SCDOT, 2020a), and corridor geometric features (i.e., the average distance between signalized intersections) from Google Earth. The descriptive statistics for the response and the significant explanatory variables for both before period and after period are shown in Table B-2 in APPENDIX B-1. A Pearson correlation test between AADT and the peak period is conducted, and it is found that there is no correlation between AADT and the peak period in this study. A high traffic volume may be associated with a higher crash severity. An AADT threshold of 30,000 is used to identify relatively high traffic volume in this study based on a previous study (Fink et al., 2016). A threshold of 10 mph speed difference between a major road and a minor road at an intersection is used to divide the observations into two groups (one group for which the speed limit difference between a major road and a minor road is equal to or greater than 10 mph; another group for which the speed limit difference between a major road and a minor road is less than 10 mph) because, based on our analysis, the median speed limit difference between a major road and a minor road in the sample is about 10 mph. In this study, all explanatory variables are tested in terms of Multicollinearity (MC). It is found that the maximum value of the Variance Inflation Factor (VIF) is 2.37. Thus, the MC issue should not be of concern for the variables considered in this study. The research team initially includes the interaction variables into the model to account for the interaction between ASCS and angle crash and the interaction between ASCS and rear-end crash in the model. However, the interaction variables are not significant, and adding these interaction variables increases the AIC of the model. Therefore, the interaction variables are later excluded from the model.

5.4 Results

5.4.1 ASCS Effects on Crash Severity

The hierarchical effects of ASCS on the crash severity represent the ASCS effect varied by intersection and corridor features, detailed in APPENDIX B-4.

The marginal effects for the three crash severity levels are computed, as shown in Table 9. A positive sign of the value in the marginal effects table indicates an increase in the probability of a severity level for the ASCS variable, meaning that such a level is indeed likely to increase due to ASCS. However, a negative sign of the value in the marginal effects table indicates a decrease in the probability of the severity level for the ASCS variable, meaning that such a level is likely to decrease due to ASCS.

The marginal effects in Table 9 show that ASCS can reduce the probability of C and KAB for the majority of intersections and corridors except for the N. Lake Dr., SC 642, US 17, and US 17 Business with the speed limit difference between a major road and a minor road equal to or greater than 10 mph (orange-colored area in Table 9). The marginal effects of ASCS vary in terms of intersection and corridor features. For example, for US 17A with the speed limit difference between a major road and a minor road less than 10 mph, ASCS can reduce the probability of C and KAB by 4.76% and 2.13%, respectively, while increasing the probability of O level by 6.89%. Although the absolute value of the ASCS effect on the KAB level seems to be small, for the case of the small proportion of KAB (i.e., the average is around 5.2%) in the studied intersections, ASCS is quite effective in reducing the probability of being KAB level for crashes that occurred at intersections. The effectiveness of reducing the KAB (i.e., marginal effect for KAB divided by the proportion of KAB for the corresponding intersections) is computed in the last column in Table 9. For example, the highest benefit is achieved for US 378 with a speed limit difference between a major road and a minor road less than 10 mph by 2.21%/1.80%=122.56%.

Table 9 Marginal effects of ASCS on crash severity levels

Corridor	Intersection feature	Corridor feature	Marginal effect			Proportion of KAB	Effectiveness of reducing KAB
	Speed limit difference equal to or greater than 10 mph?	Average signal distance (miles)	For O	For O	For KAB		
US 17A	No	0.27	6.89%	-4.76%	-2.13%	4.17%	51.12%
	Yes	0.27	3.87%	-2.61%	-1.25%	4.29%	29.11%
Roper Mt. Rd./ Garlington Rd.	No	0.36	5.58%	-3.82%	-1.76%	1.55%	113.23%
N. Lake Dr.	No	0.55	2.38%	-1.59%	-0.79%	5.43%	14.54%
	Yes	0.55	-1.01%	0.66%	0.35%	4.40%	-7.95%
SC 642	No	0.52	3.05%	-2.05%	-1.00%	6.40%	15.62%
	Yes	0.52	-0.45%	0.30%	0.16%	7.13%	-2.24%
US 52	No	0.31	6.31%	-4.35%	-1.97%	5.61%	35.09%
	Yes	0.31	3.22%	-2.16%	-1.05%	6.47%	16.23%
US 17	Yes	0.61	-2.15%	1.39%	0.77%	9.96%	-7.73%
Long Point Rd.	No	0.26	7.28%	-4.98%	-2.30%	13.30%	17.29%
	Yes	0.26	4.05%	-2.73%	-1.31%	9.90%	13.27%
Main Street	No	0.26	7.28%	-4.98%	-2.30%	3.40%	67.62%
	Yes	0.26	4.05%	-2.73%	-1.31%	5.40%	24.33%
US 17 Business	No	0.66	0.63%	-0.42%	-0.21%	7.70%	2.72%
	Yes	0.66	-2.99%	1.97%	1.03%	9.40%	-10.91%
US 378	No	0.28	6.97%	-4.76%	-2.21%	1.80%	122.56%
	Yes	0.28	3.72%	-2.51%	-1.21%	3.80%	31.82%
Woodruff Rd.	No	0.23	7.75%	-5.31%	-2.44%	2.30%	105.96%
	Yes	0.23	4.55%	-3.08%	-1.47%	3.00%	48.98%

5.4.2 Effects of Other Contributing Factors on Crash Severity

As depicted by the marginal effects in Table 10, other contributing factors except for the peak period are associated with higher crash severity levels (i.e., C and KAB) while less likely to be a lower crash severity (i.e., O). Crashes involving pedestrians will lead to higher crash severity levels and increase the probability of KAB by 57.69%. The presence of AADT over 30,000 vehicles/day results in a corresponding increase in the likelihood of C and KAB given the critical role of high traffic volume in overall crashes at the signalized intersections. Not surprisingly, an increase in the posted speed limit is associated with a greater likelihood of C and KAB. The higher speed limit naturally results in a higher vehicle operational speed, with an increase in the severity of crashes. The bad light condition (i.e., dark, dawn, or dusk) of roadways is associated with a higher likelihood of C and KAB. The peak period leads to lower crash severity (i.e., O). During peak periods, the traffic volume is higher compared to off-peak periods, which would contribute to lower average speeds of the vehicles during peak periods, thus resulting in reduced crash severity. The crash, which is either rear-end or angle crash, is associated with more probability of being C and KAB.

Table 10 Marginal effects of other contributing factors

Other contributing factors	**Marginal effect for O**	**Marginal effect for C**	**Marginal effect for KAB**
Pedestrian	-69.83%	12.14%	57.69%
AADT_over_30*k*	-5.92%	4.11%	1.81%
Speed_Limit	-0.24%	0.16%	0.07%
Light	-9.14%	6.01%	3.13%
Peak	2.30%	-1.59%	-0.71%
Rear_end	-3.47%	2.38%	1.09%
Angle	-9.21%	6.09%	3.12%

5.5 Chapter Conclusions

This study investigated the hierarchical effects of ASCS on the crash severity by developing random-parameter ordered regression models with observed heterogeneity, which accounts for both observed and unobserved heterogeneity. Four different random-parameter ordered regression models (two ordered probit models, and two ordered logit models) are established and compared, as shown in APPENDIX B-3. It is found that the random-parameter ordered probit and logit models (ROP and ROL) with observed heterogeneity perform better than the random-parameter ordered probit and logit models (RP and RL) without observed heterogeneity in terms of the AIC and the goodness of fit of the model. The ROP model outperforms the ROL model in terms of classification model performance measures: accuracy, overall precision, and overall recall. This study demonstrates the existence of the hierarchical effects of ASCS on the crash severity. The analyses reveal that the presence of ASCS is associated with lower crash severity. Speed limit difference between major streets and minor streets at an intersection (i.e., intersection feature) and average signal distance on a corridor (i.e., corridor feature) are found to be capable of capturing the hierarchical effects of ASCS on the crash severity. Other variables related to intersection features such as the number of legs at an intersection and number of through/left/right lanes at an intersection and corridor features, such as average AADT on a corridor, are attempted in the modeling, but these variables are not statistically significant. Thus, in this study, these variables are not able to capture the hierarchical effects of ASCS on the crash severity. In the future, variables related to zonal features such as population densities could be accounted for to capture the hierarchical effects of ASCS on the crash severity. Other contributing factors, such as high annual average daily traffic, speed limit, lighting, crash type (i.e., rear-end or angle), pedestrian involvements, are associated with higher crash severity. The peak period leads to lower crash severity. Unobserved heterogeneity of the effect of angle crashes on crash severity is found to exist across the observations while using the uniform distribution to explicitly account for crash-specific variations in the effects of angle crashes.

The findings of this study have several practical implications for establishing ASCS implementation guidelines from the standpoint of safety. Two useful metrics, speed limit difference between a major street and a minor street at an intersection (i.e., intersection feature) and average signal distance on a corridor (i.e., corridor feature), could help transportation agencies to deploy ASCS appropriately. Two practical implications are found: 1) when speed limit difference between major streets and minor streets at an intersection is equal to or greater than 10 mph, and the average signal distance on a corridor is less than the threshold of 0.49 miles, the ASCS is more likely associated with lower crash severity; and 2) when speed limit difference between major streets and minor streets at an intersection is less than 10 mph, and the average signal distance on a corridor is less than the threshold of 0.69 miles, the ASCS is associated with lower crash severity. These findings are related to a particular type of ASCS, SynchroGreen, and future studies may be conducted to include multiple types of ASCS. Identifying the hierarchical effects of ASCS on the crash severity helps transportation agencies achieve higher safety benefits by selecting ASCS deployment sites considering the specific intersection and corridor features.

CHAPTER 6 SECONDARY CRASH STUDY

6.1 Introduction

With real-time traffic signal parameters adjustment capability, ASCS can better accommodate fluctuating traffic demand or extreme traffic conditions caused by traffic incidents or special events. Thus, any alternate route to a freeway segment with ASCS deployed on that alternate route can be used to potentially improve the traffic conditions on a freeway in case any incident happens on that freeway. However, to the best of our knowledge, there exists no such study in the literature that evaluated the possible benefits of having an ASCS deployed alternate route to a freeway segment towards the reduction in the likelihood of freeway secondary crashes.

In this study, the research team develops a method for assessing the likelihood of secondary crashes on freeways with alternate routes where ASCS has been deployed (Salek et al., 2021). The applicability of the method is firstly demonstrated with two freeway segments where ASCS is deployed in several intersections within the alternate route used by diverted freeway traffic when a crash occurs on the freeway segment. The research team developed binary logistic regression models for Charleston I-26 (Eastbound and Westbound) in South Carolina to investigate if the presence of an ASCS deployed alternate route is associated with a reduction in the likelihood of freeway secondary crashes. This study also developed binary logistic regression models for two freeway sections with non-ASCS (i.e. pre-timed, semi-actuated, or fully-actuated) alternate routes to examine if the likelihood of secondary crashes differs between freeways with ASCS deployed on alternate routes and freeways with non-ASCS alternate routes. In addition, the effect of ASCS on the likelihood of secondary crashes on a freeway may vary across observations (i.e., primary crashes). To capture unknown variations in the effect of ASCS across the observations (which the research team refers to as "unobserved heterogeneity"), the research team developed a random-parameter binary logistic regression model to account for observation-specific variations in the effects of ASCS and to provide more accurate inferences.

6.2 Method

The method to assess the likelihood of secondary crashes on freeways with alternate routes includes four steps:

1. Identification of secondary crashes using fixed spatial-temporal criteria and other factors such as manner and probable cause of the collision
2. Verification of alternate routes with SCDOT and travel time data from the alternate routes
3. Modeling the likelihood of secondary crashes for both ASCS deployed alternate routes and non-ASCS alternate routes using a binary logistic regression model
4. Investigation of unobserved heterogeneity of ASCS using a random-parameter binary logistic regression model.

This section explains these four steps of the method in detail (Salek et al., 2021).

6.2.1 Identification of Secondary Crashes

Selecting spatial-temporal criteria for identifying secondary crashes on freeways is a challenging task. Secondary crashes are typically induced by primary crashes that cause adverse effects on traffic flow. These impacts of primary crashes on traffic flow vary depending on many factors such as the number of blocked lanes, clearance time, and crash severity. However, lane blockage and clearance time information are not available for the study corridors. Thus, the individual impact of each primary crash cannot be determined. Therefore, the research team considered a fixed spatio-temporal range as a primary criterion for the identification of secondary crashes. The research team considers a crash to have the possibility of being induced by a primary crash if it occurs within a one-hour period after the primary crash and within a two miles range in the upstream of the primary crash. The research team used a fixed spatio-temporal range for secondary crash identification as there is no available real-time traffic volume data for the freeway segments considered in this study that may be used to develop individual crash-specific spatio-temporal ranges for secondary crash identification. A detailed identification procedure of secondary crashes is documented in APPENDIX C-1.

6.2.2 Verification of Alternate Routes

The research team investigated the parallel arterials of the freeway segments for alternate route verification. Firstly, the research team verified the alternate routes with SCDOT. Then, the research team utilized real-time travel data to investigate the change in traffic conditions of the parallel arterials in the event of crashes on the freeways. Hourly travel time data recorded by ClearGuide (Iteris, 2020) is used to observe how the average travel time of the parallel arterial changes in the one-hour after period when a crash occurs on the freeway segment. For each crash on the freeway, weighted average travel time in one-hour after period is computed from the hourly travel time data. For example, if a crash occurs at 05:25 PM, then the weighted average travel time on the ASCS-deployed alternate route for the one-hour after period (i.e., 05:25 PM to 06:25 PM) is calculated as follows:

$$\text{Weighted average travel time (05:25 PM to 06:25 PM)} = \frac{35}{60} \times \text{(average travel time from 05:00 PM to 06:00 PM)} + \frac{25}{60} \times \text{(average travel time from 06:00 PM to 07:00 PM)}$$

The weighted average travel time is then compared with the historical weighted average of travel time for that segment of the day. Hourly travel time data recorded by ClearGuide (Iteris, 2020) from four consecutive months around the time when the crash occurred is used to compute historical averages of hourly travel time data. The historical weighted average of travel time for 1-hour after period of the crash is then computed from the historical average of hourly travel time data similarly as shown in the last example above. The historical weighted average is computed separately for weekdays and weekends. The weighted average travel time for one-hour after period of a crash occurrence is compared with the 95% confidence interval of the historical weighted average of travel time for that period. If the weighted average exceeds the upper confidence limit of 95% confidence interval of the historical weighted average, then the change in travel time (i.e., through the alternate route) due to crash occurrence on the freeway is considered to be significant.

6.2.3 Binary Logistic Regression Model

The research team developed binary logistic regression models to evaluate the likelihood of secondary crashes, as the secondary crash occurrence is a binary outcome (i.e., occurrence or non-occurrence) that can depend on many factors.

The binary logistic regression (i.e., logit) model used to evaluate the likelihood of a secondary crash occurrence is formulated as follows,

$$\ln\left(\frac{P(y=1\,|\,\mathbf{X})}{1-P(y=1\,|\,\mathbf{X})}\right)=\mathbf{X}\boldsymbol{\beta} \tag{19}$$

where, $P(y=1\,|\,\mathbf{X})$ = the conditional probability of a secondary crash occurrence given a primary crash occurred; $\mathbf{X}$ = the vector of explanatory variables associated with primary crashes; $\boldsymbol{\beta}$ = the vector of coefficients corresponding to the explanatory variables.

Eq. (19) presents a general form of the binary logistic regression model. The research team developed corridor-specific binary logistic regression models from Eq. (19) and identified statistically significant explanatory variables. The response variable, y in Eq. (19) is equal to 1 if a secondary crash occurred or 0 otherwise.

The research team used open-source R software to perform the regression analysis. The generalized linear model, "glm" function in R is used to estimate the coefficients of the logistic regression model. This function uses Iterative Weighted Least Squares (IWLS) to find the Maximum Likelihood Estimation (MLE) of the coefficients in $\boldsymbol{\beta}$. Using the fitted model, the effect of k^{th} explanatory variable on the occurrence of a secondary crash can be evaluated by Odds Ratios (ORs) given by,

$$OR=e^{\beta_k} \tag{20}$$

where β_k is the coefficient of the k^{th} explanatory variable in the fitted model.

The Variance Inflation Factor (VIF) is used to check for potential Multicollinearity (MC). Many researchers used a VIF of 10 as a rule of thumb to indicate excessive or severe MC issues (O'Brien, 2007). Akaike Information Criteria (AIC) was compared among different candidate models and the model with the lowest AIC value is preferred.

6.2.4 Random-parameter Binary Logistic Regression Model

Compared to the fixed-parameter binary logistic regression model, a random-parameter binary regression model can capture unobserved heterogeneity across observations. Eq. (19) can be rewritten as,

$$\ln\left(\frac{P(y_i=1\,|\,\mathbf{X}_i)}{1-P(y_i=1\,|\,\mathbf{X}_i)}\right)=\mathbf{X}_i\boldsymbol{\beta}_i\,;\; i=1,2,3,.....n \tag{21}$$

$$\boldsymbol{\beta}_i \sim g(\boldsymbol{\beta}_i\,|\,\boldsymbol{\theta}) \tag{22}$$

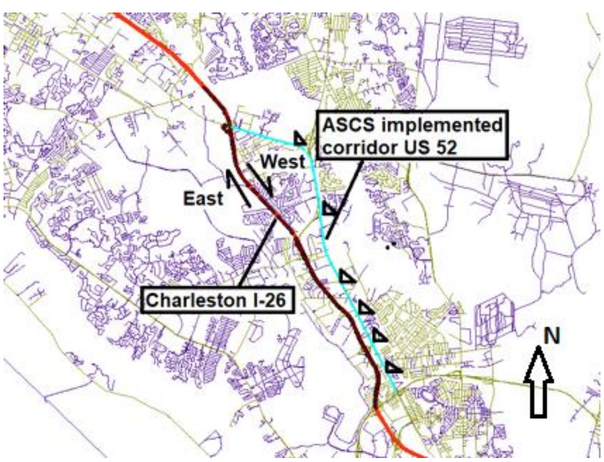
where, $\mathbf{X}_i$ is a vector of the explanatory variables of observation (i.e., primary crash) i, $\boldsymbol{\beta}_i$ is a vector of the coefficients, and $\boldsymbol{\theta}$ is a vector of the mean and variance of the random distribution.

Model estimation and implementation procedures are detailed in APPENDIX C-4.

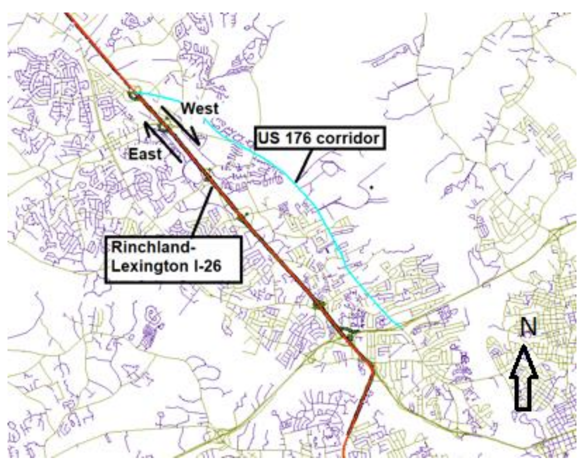
6.3 Data Description

The research team considered two freeway segments with ASCS deployed on alternate routes to investigate the likelihood of secondary crash occurrences (see Figure 12(a)): 1) an 8.92-mile section of Charleston I-26 E, and 2) a 9.6-mile section of Charleston I-26 W. These two corridors are referred as "Freeways with ASCS deployed on alternate routes" in the rest of the study as they have an ASCS deployed parallel arterial (US 52). For the Charleston I-26 freeway sections, ASCS was deployed at 17 intersections of parallel US 52 in October 2016. US 52 is considered an alternate route (verified by SCDOT and with ClearGuide data) for diverting traffic of I-26 Eastbound and Westbound sections in the event of a freeway primary crash. The functional class of US 52 is "principal arterial."

This study also uses freeways with non-ASCS (i.e., pre-timed, semi-actuated or fully-actuated) alternate routes similar to the freeways with ASCS deployed on alternate routes to examine if the effect of the after-period indicator (i.e., based on ASCS deployment) differs between these freeways. The research team selects two freeway sections with non-ASCS alternate routes that have comparable segment lengths, AADT of the freeway sections and the same functional classes as the freeways with ASCS deployed on alternate routes (see Figure 12(b)). The freeways with non-ASCS alternate routes are: 1) a 7.75-mile section of Richland-Lexington I-26 E, and 2) a 7.64-mile section of Richland-Lexington I-26 W. In addition, both the ASCS-deployed sites and the control sites considered for this study are located within the jurisdiction of the SCDOT. Therefore, the research team assumes similar management and maintenance characteristics, such as pavement maintenance, traffic management, and enforcement for the corridors considered in this study. A comparison of characteristics of the freeways with ASCS deployed on alternate routes and freeways with non-ASCS alternate routes are presented in Table 11.



(a)



(b)

Figure 12 (a) Charleston I-26 with ASCS deployed on alternate route US 52, and (b) Richland-Lexington I-26 with non-ASCS alternate route US 176

Table 11 Comparison of freeways with ASCS deployed on alternate routes and non-ASCS alternate routes

Corridor name	Corridor length	Mean AADT	Alternate route	Functional class of the alternate route
Freeways with ASCS deployed on alternate routes				
Charleston I-26 E	8.92 miles	149852	US 52	Principal arterial
Charleston I-26 W	9.6 miles	145875	US 52	Principal arterial
Freeways with non-ASCS alternate routes				
Richland-Lexington I-26 E	7.75 miles	119699	US 176	Principal arterial
Richland-Lexington I-26 E	7.64 miles	115983	US 176	Principal arterial

For the analysis, the research team uses "crash code" as the response variable. Crash code 0 and crash code 1 indicate primary crashes that did not induce any secondary crash and primary crashes that induced one or more secondary crashes, respectively. Table 12 and Table 13 present a summary of the crash data used for analysis based on the crash codes.

Table 12 Summary of response variables of freeways with ASCS deployed on alternate routes

Corridor name	Crash code	Frequency	Percentage
Charleston I-26 E	0	1443	91.04%
	1	142	8.96%
Charleston I-26 W	0	1518	92.17%
	1	129	7.83%

Table 13 Summary of response variables of freeways with non-ASCS alternate routes

Corridor name	Crash code	Frequency	Percentage
Richland-Lexington I-26 E	0	1233	90.73%
	1	126	9.27%
Richland-Lexington I-26 W	0	1368	90.66%
	1	141	9.34%

To evaluate the effect of ASCS deployment on the likelihood of freeway secondary crashes, the research team extracted a total of 52 months of crash data for Charleston I-26 (East and West) corridors. The extracted crash data include26 months spanning from September 2014 to October 2016 for the before period of the ASCS deployment, and 26 months spanning from November 2016 to December 2018 for the after period of the ASCS deployment. The same period of data is extracted for Richland-Lexington I-26 Eastbound and Westbound corridors. A total of 1757 crash data from Charleston I-26 E section were used: 772 crashes occurred in the before-deployment period and 985 crashes occurred in the after-deployment period. A total of 1805 crash data from Charleston I-26 W section were used: 849 crashes occurred in the before-deployment period and 956 crashes occurred in the after-deployment period.

For each freeway section, the crash data does not only include crashes that occurred on the freeway but also includes the crashes that occurred on the entrance ramps to the freeway section. The rationale for including the entrance ramp crashes in the analysis is that when a crash occurs on the freeway, sometimes if it creates major congestion, then traffic can back up to the entrance ramp and can cause secondary crashes on the ramps as well. Therefore, the entrance ramp crashes are used in the dataset only to check if there was any secondary crash on the ramps induced by a primary crash on the freeway. Table 14 lists the number of entrance ramps included in the crash data set for secondary crash detection.

Table 14 Number of entrance ramps included in crash data set

Study corridor name			**Number of entrance ramps**
Freeways with ASCS deployed on alternate routes	Charleston I-26	Eastbound	11
		Westbound	15
Freeways with non-ASCS alternate routes	Richland-Lexington I-26	Eastbound	8
		Westbound	8

SCDOT provided the crash data for the analysis presented in this study. The crash data includes several attributes such as collision time, AADT, light condition, roadway surface condition, manner of the collision, weather condition, first harmful event, and probable cause of the crash. Variables such as light condition (i.e., dawn, daylight, dusk, or dark), roadway surface condition (i.e., dry, icy, wet or snowy), weather condition (i.e., adverse or not adverse condition), manner of collision (e.g., rear-end, angle, head-on, and side-swipe) help to account for various possible attributes that may affect the secondary crash occurrence. The research team does not use real-time traffic volume data since there is a significant amount of missing data in the whole study period. Model variables are detailed in Appendix C-2.

6.4 Results

6.4.1 Verification of Alternate Routes

Table 15 presents the results from the alternate routes verification for all the corridors. Travel time data for the time period between September 1, 2018 to December 31, 2018 were analyzed because ClearGuide travel time data were not available for the period before September 1, 2018 and the study period for this project for the study corridors ends on December 31, 2018. It is observed that for over 40% of the crashes that occurred on the freeway sections from September 1, 2018 to December 31, 2018, travel time increased significantly, over 40% of the times, compared to the historical average travel time in the corresponding parallel alternate routes, indicating that drivers often use these routes when a crash occurs on the freeway.

Table 15 Alternate route verification with travel time information

Study corridor name		Percentage of crashes on the freeway causing average travel time to significantly increase in the parallel alternate route
Freeways with ASCS deployed on alternate routes	Charleston I-26 E	44.76%
	Charleston I-26 W	51.56%
Freeways with non-ASCS alternate routes	Richland-Lexington I-26 E	47.42%
	Richland-Lexington I-26 W	42.02%

6.4.2 Binary Logistic Regression Model Results

Based on the explanatory variables considered here, Eq. (19) can be rewritten as follows,

$$\ln\left(\frac{P(y=1\mid \mathbf{X})}{1-P(y=1\mid \mathbf{X})}\right) = \beta_0 + \beta_1 \times \text{(after-period indicator of ASCS deployment)} + \beta_2 \times \text{(light condition)} + \beta_3 \times \text{(roadway surface condition)} + \beta_4 \times \text{(weather condition)} + \beta_5 \times \text{(rear-end crash)} + \beta_6 \times \text{(angle crash)} + \beta_7 \times \text{(weekday)} + \beta_8 \times \text{(peak period)} + \beta_9 \times \text{(crash severity)} + \beta_{10} \times \text{(temporal trend)} + \beta_{11} \times \log(\text{AADT}) \quad (23)$$

The research team applied the binary logistic regression model, shown in Eq. 23, to the crash datasets for all the study corridors. Table 16 presents the model estimation results of "After-period indicator variable of ASCS deployment" for the freeways with ASCS deployed on alternate routes and freeways with non-ASCS routes (based on corridor-specific binary logistic regression models). For all the corridor-specific models, the research team checks for any existing multicollinearity using the VIF. For all the ASCS and the non-ASCS corridors, the maximum VIF is found to be less than or equal to 3.5. Therefore, it is assumed the multicollinearity does not exist among the explanatory variables as VIF < 10.

The Odds Ratio (OR) is defined as the ratio of the odds of an outcome occurring by exposure of a variable to the odds of the outcome occurring in the absence of that exposure. From the odds ratios, percentage changes in secondary crash occurrence odds are evaluated. In Table 16, the odds ratios and percentage changes in secondary crash occurrence odds are displayed only if the predictor (i.e., after-period indicator of ASCS deployment) is found to be statistically significant at a 0.1 significance level.

As shown in Table 16, for Charleston I-26 E, a 47.32% reduction in the likelihood of secondary crashes is associated with the after period of ASCS deployment. However, for Charleston I-26 W, binary logistic regression models cannot reveal any statistical significance of ASCS deployment for reducing the likelihood of secondary crashes. As the same parallel arterial may not always be convenient as an alternate route for the drivers traveling in opposing directions, the effect of ASCS deployment on the alternate routes can also be different for opposing traffic on the freeway. Opting for an alternate route depends on many factors such as drivers' behavior, freeway crash severity, lane blockage, and the number of vehicles involved in the crash.

As mentioned in the "6.2 Method" section, for freeways with non-ASCS alternate routes, "after period indicator for freeways with alternate non-ASCS corridors" is included in the model as a predictor in order to observe if the temporal division used for ASCS deployment's before and after period signifies anything. In Table 16, it is observed that for none of the freeways with non-ASCS alternate routes is this variable significant. It indicates that this temporal division of the study period signifies nothing for the freeways with non-ASCS alternate routes as there was no ASCS deployment.

Table 17 presents the other statistically significant predictors and their corresponding coefficients estimate from logistic regression model. For both freeways with ASCS deployed on alternate routes and non-ASCS alternate routes, frequently observed statistically significant variables include rear-end crashes, light condition, weekday, and AADT. Note that crash severity and roadway surface condition are not included in Table 17, as neither of these two variables is significant for these corridors.

Table 16 Model estimates & interpretations of after-period indicator of ASCS deployment

Corridor type	**Corridor name**	**Coefficients: Estimate**	**Pr(>|z|)**	**Odds ratio**	**Percentage change in secondary crash occurrence odds**
Freeways with ASCS deployed on alternate routes	Charleston I-26 E	- 0.641	0.059*	0.527	-47.324%
	Charleston I-26 W	0.222	0.5182	-	-
Freeways with non-ASCS alternate routes	Richland-Lexington I-26 E	- 0.065	0.8518	-	-
	Richland-Lexington I-26 W	0.334	0.3030	-	-

'*' statistically significant at a 0.1 significance level

Table 17 Model estimates of other predictors

Predictors	**Coefficients estimate (with Pr(>|z|) in the parentheses)**			
	Freeways with ASCS deployed on alternate routes		**Freeways with non-ASCS alternate routes**	
	Charleston I-26 E	**Charleston I-26 W**	**Richland-Lexington I-26 E**	**Richland-Lexington I-26 W**
Light condition	0.190 (0.533)	0.378 (0.093*)	0.599 (0.028**)	0.355 (0.204)
Weather condition	NS	0.547 (0.015**)	NS	NS
Rear end	0.821 (0.0008**)	1.417 (4.96e-07**)	0.949 (0.0003**)	1.077 (3.72e-05**)
Angle crash	NS	1.397 (0.0006*)	NS	NS
Weekday	NS	NS	0.498 (0.068*)	-0.912 (4.4e-05**)
Peak period	0.929 (7.32e-06**)	NS	NS	NS

Predictors	Coefficients estimate (with Pr(>|z|) in the parentheses)			
	Freeways with ASCS deployed on alternate routes		**Freeways with non-ASCS alternate routes**	
	Charleston I-26 E	**Charleston I-26 W**	**Richland-Lexington I-26 E**	**Richland-Lexington I-26 W**
Temporal trend	0.268 (0.041**)	NS	NS	NS
ln (AADT)	1.916 (0.0001**)	NS	1.876 (0.001**)	NS

'**' statistically significant at a 0.05 significance level

'*' statistically significant at a 0.1 significance level

'NS' not statistically significant

The research team performed additional analysis for Charleston I-26 E with traffic count and speed data collected from SCDOT Traffic Polling and Analysis System (SCDOT, 2020c). Detailed analysis is shown in APPENDIX C-3. The research team performed this analysis exclusively for Charleston I-26 E to prove that the favorable effect of ASCS found for Charleston I-26 E is not a contribution of reduced crash exposure (i.e., lower freeway traffic counts after a crash occurrence) or reduced speed on the freeway due to any primary crash on the freeway.

6.4.3 Random-parameter Logistic Regression Model Results

Fixed-parameter binary logistic regression models help to identify the statistically significant variables in the likelihood of a secondary crash. However, a limitation of the fixed-parameter binary logistic regression model is that it cannot capture unobserved heterogeneity since the model assumes the global effect of each predictor across observations. Therefore, a random parameter logistic regression model is deployed to study the heterogeneous effect of the ASCS deployment for Charleston I-26 E. It is found that 84% of all observations have a negative coefficient associated with the presence of the ASCS corridor, suggesting an association between the presence of the ASCS deployed on the alternate route and the reduction of the likelihood of secondary crashes on the parallel freeway. The detailed model results for Charleston I-26 E are presented in Table C-4 in APPENDIX C-4.

The research team then investigates the locations of individual observations (i.e., primary crashes) for which the presence of the ASCS deployed on the alternate route is associated with an increase in the likelihood of freeway secondary crashes. The motivation behind doing this is to investigate the reasons behind the increased likelihood of secondary crashes. Figure 13 shows the locations of the crashes on I-26 E freeway and the possible exit ramps that freeway drivers can take to exit Charleston I-26 E and to access US 52. As observed from Figure 13, most of the primary crashes for which the coefficients of ASCS are positive occurred closer to the east end of the Charleston I-26 E section and took place past the second possible exit ramp to access US 52. Also, closer to the east end of the Charleston I-26 E section means closer to the Charleston city downtown. When a crash occurs closer to the east end of the Charleston

I-26 E section, it may not always seem to be a convenient choice for the upstream traffic to divert as they may think that they are already very close to their destination and sometimes it may not be a feasible option to divert as they may have already passed the nearest exit ramp. The benefit of ASCS deployed on the alternate route may not be that much since fewer signals are involved when a crash occurs closer to the east end of the Charleston I-26 E section. Therefore, the effect of ASCS deployed on the alternate route in the likelihood of freeway secondary crashes can vary depending on the location of the primary freeway crash as it affects the amount of traffic are able or choose to divert.

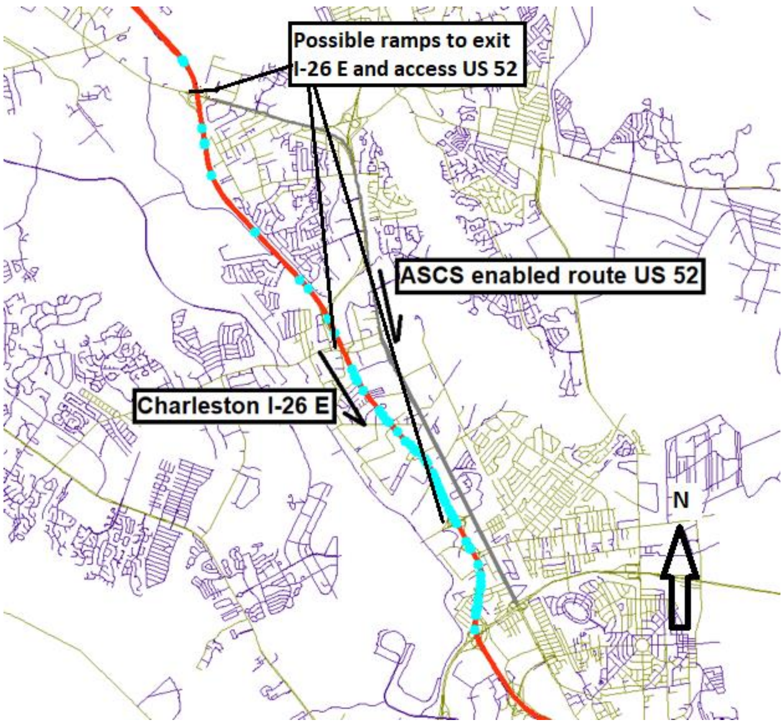


Figure 13 Location of Charleston I-26 E freeway crashes associated with the increase in the likelihood of secondary crashes

6.5 Chapter Conclusions

Reduction in the likelihood of secondary crashes can noticeably decrease emission, delay, vehicle operating cost, and safety issues on the freeways. This research unveils a unique interrelation between ASCS deployed on an alternate route and the likelihood of parallel freeway secondary crashes. The findings from a binary logistic regression model using 52 months of crash data of Charleston I-26 E with ASCS deployed on alternate route US 52 shows a 47% reduction in the likelihood of freeway secondary crashes. The research team further investigated Charleston I-26 E using a random-parameter binary logistic regression model to explore the unobserved heterogeneity and finds that 84% of all observations have negative coefficients associated with the presence of ASCS deployed on the alternate route, suggesting an association between the presence of ASCS deployed on an alternate route and reduction in the likelihood of secondary crashes on the parallel freeway. The benefit of ASCS deployment on an alternate route towards freeway secondary crash reduction is found to be dependent on the location of the primary crash as the location of the primary crash determines whether and how much of the upstream traffic will be able or choose to take the exit ramp to the ASCS deployed alternate route. Therefore, the findings provide new insight on improving safety on a freeway with the implementation of ASCS on arterials that could be used as alternate routes during an incident on the freeway. The results also reveal that other contributing factors, such as rear-end crash, light condition, peak period, weekday and AADT, may increase the likelihood of secondary crashes on a freeway.

Analysis results indicate that there is an association between ASCS deployed on an alternate route and the likelihood of secondary crashes on the parallel freeway. Therefore, it is recommended that the SCDOT considers utilizing ASCS on corridors that are often used as alternate routes when there is an incident on the adjacent parallel freeways. According to the findings of this study, the existence of such an ASCS-deployed alternate route can help reduce the likelihood of secondary crashes and improve freeway safety.

CHAPTER 7 OPERATIONAL EVALUATION STUDY

7.1 Introduction

The objectives of this study are to evaluate the operational performance of ASCS corridors located throughout South Carolina using the following metrics: 1) effectiveness of ASCS in reducing travel time during the day and the peak periods, 2) effectiveness of ASCS in improving travel time reliability during the day and the peak periods, and 3) consistency of effectiveness of ASCS in both directions on an hourly basis on a corridor. This study also identifies the key corridor characteristics that contribute to higher ASCS operational benefits. The operational analysis is conducted using data from 11 corridors located throughout South Carolina that are operated with the SynchroGreen ASCS.

7.2 Method

An OFF and ON study was conducted to evaluate the operational effectiveness of ASCS. "ON" period refers to the time when ASCS is operational in the study corridors and the "OFF" period refers to the time when the signal control systems on the same study corridor use a predefined signal timing strategy, which could either be a pre-timed or an actuated signal timing plan based on the particular intersection on the corridor. This study performs an operational evaluation of ASCS with multiple metrics: 1) effectiveness of ASCS in reducing travel time during the day and during the peak periods, 2) effectiveness of ASCS in improving travel time reliability during the day and the peak periods, and 3) consistency of effectiveness of ASCS in both directions on a corridor. To analyze these metrics, the research team uses different statistical methods such as paired *t*-test, meta-analysis, and tetrachoric correlation analysis (Jin et al., 2021). This study also identifies the key corridor characteristics that can help produce higher ASCS operational benefits by using a multiple linear regression model (Jin et al., 2021).

7.2.1 Paired T-test and Meta-analysis

To test whether the travel time and buffer index for the ON period is statistically different from that for the OFF period over 24 hours of a day, the research team conducted a paired *t*-test for each corridor and obtained a *p*-value for each corridor. Then, the research team combined all p-values by conducting a meta-analysis. Fisher's method is considered in the meta-analysis (Dewey, 2017; Fisher, 1992). Fisher's method relies on the fact that,

$$\chi^2_{2k} \sim \sum_{j=1}^{k} -2\log(p_j) \tag{24}$$

where χ^2_{2k} has a chi-squared distribution with $2k$ degrees of freedom, p_j is the *p*-value for j^{th} paired *t*-test for the corresponding study site, k is the number of paired *t*-tests. In this study, both directions for a corridor are considered as two different study sites. Therefore, there are 22 paired *t*-tests to be conducted for 22 study sites in this study. Eq. (24) is used to determine the *p*-value for the hypothesis test combining the individual *t*-tests.

7.2.2 Tetrachoric Correlation Analysis

To investigate whether the operational effectiveness of ASCS is consistent for both directions on a corridor, the research team uses tetrachoric correlation analysis to explore two binary variables that are outcomes of the operational effectiveness of ASCS for the two directions. The purpose of doing tetrachoric correlation analysis is to present the temporal pattern of the operational effectiveness of ASCS in both directions on an hourly basis for the corridors in this study. For example, there are two possible outcomes (i.e., ASCS is effective or not effective) for each of the two directions (i.e., westbound and eastbound) on a corridor. The research team used the "tetrachoric" function in the "psych" package (Revelle, 2019) in the open-source R software to perform the tetrachoric correlation analysis.

7.2.3 Multiple Regression Analysis

To explore the relationship between the operational benefit of ASCS and corridor characteristics, the research team develops a multiple linear regression model using corridor characteristics as explanatory variables and the number of hours during a day when ASCS is effective in travel time reduction as the response variable. Table 18 summarizes the variables considered in the regression model in this study.

Among the corridor characteristics for each corridor, the research team considers the 2018 AADT, the number of signals on a corridor, signal density (i.e., number of signals divided by the length of the corridor), and the average speed of the vehicles on a corridor. In the multiple linear regression model, the research team uses the information related to these corridor characteristics to create the following four binary explanatory variables: "AADT_2018_over_30*k*", "No_of_signals_over_10", "Signal_density_over_2_69", and "Average_speed_over_35". The thresholds utilized to define these dummy explanatory variables are obtained by determining the median of the corresponding corridor characteristics. For example, "AADT_2018_over_30*k*" is a dummy variable, which is one if the average AADT of a corridor of 2018 is over 30,000 vehicles/day. Here, 30,000 vehicles/day is the median of AADTs of the corridors of 2018 considered in this study. Therefore, the threshold to define the dummy variable "AADT_2018_over_30*k*" is chosen to be 30,000 vehicles/day. Thus, "AADT_2018_over_30*k*" is one for a corridor, if AADT of 2018 for that corridor exceeds 30,000 vehicles/day and "AADT_2018_over_30*k*" is zero for a corridor if AADT of 2018 for that corridor is less than or equal to 30,000 vehicles/day. Similarly, the medians for the number of signals, signal density, and average speed are 10, 2.69 signals/mile, and 35 mph, respectively, which are used as the thresholds to define the corresponding dummy variables "No_of_signals_over_10", "Signal_density_over_2_69", and "Average_speed_over_35", respectively.

Table 18 Summary of the model variables for multiple linear regression modeling

Category	**Variable name**	**Description**
Response variable	Number_of_Hours	Number of hours during a day when travel time for ASCS ON period is less than ASCS OFF period
Explanatory variables	AADT_2018_over_30*k*	1 - AADT of 2018 is over 30,000 vehicles/day 0 - otherwise
	No_of_signals_over_10	1 - No. of signals is over 10 0 - otherwise
	Signal_density_over_2_69	1 - Signal density is over 2.69 signals/mile 0 - otherwise
	Average_speed_over_35	1 - Average speed is over 35 mph 0 - otherwise

A full multiple linear regression model that includes all the explanatory variables listed in Table 18 can be expressed as follows,

$$\begin{aligned} y_i &= \beta_0 + \beta_1 \times (\text{AADT\_2018\_over\_30}k) + \beta_2 \times (\text{No\_of\_signal\_over\_10}) \\ &+ \beta_3 \times (\text{Signal\_density\_over\_2\_69}) + \beta_4 \times (\text{Average\_speed\_over\_35}) + e_i \end{aligned} \tag{25}$$

Where, y_i is the response variable (i.e., Number_of_Hours); i is each observation; β_n is the coefficient of the n^{th} explanatory variable, and e_i is error term of the model.

The research team uses the multiple linear regression model, "lm" function in the open-source R-software package (Dessau & Pipper, 2008) to perform the multiple linear regression. Among different candidate models, a model with the lowest Akaike Information Criterion (AIC) is preferred.

7.2.4 Data Processing

To perform ON and OFF analysis, the research team requested the South Carolina Department of Transportation (SCDOT) to turn off the ASCS on each corridor, so that travel time data for both the ON and OFF periods could be collected. Later, SCDOT provided several corridors where ASCS was recently installed. In this case, the period after ASCS was installed on these corridors is considered as the ON period while the period before ASCS was installed on these corridors is considered as OFF period. Based on the period during which ASCS was not operational, the research team identified the ON period and

OFF period for these corridors. The ON and OFF periods for each study corridor are listed in Table 19. The research team kept the ON and OFF periods as close as possible to make sure that the traffic conditions remained similar. The authors used hourly traffic volume data provided by the Iteris ClearGuide system (Iteris, 2020) and performed a *t*-test to determine if there was a statistical difference in traffic conditions between the ON period and OFF period for the corridors in this study. As shown in the last column in Table 20, the *p*-value is larger than 0.05 for all the corridors in this study. A *p*-value larger than 0.05 indicates that the research team could not reject the null hypothesis in the *t*-test. Therefore, the research team cannot reject the null hypothesis that traffic volumes between the ON period and OFF period are the same for the corridors considered in this study at a 0.05 significance level. The results indicate that there is no difference in traffic conditions between the ON period and OFF period for the corridors in this study at a 0.05 significance level. Thus, the ON period and OFF period are considered similar and therefore comparable for all the study corridors. The research team uses one week for the ON period and one week for the OFF period. Only weekdays are considered, and holidays are avoided. The research team collected the travel time data for each direction of a corridor for both ON and OFF periods from the Iteris ClearGuide system (Iteris, 2020), which provides travel time data for every five minutes for both ON and OFF periods.

Also, evaluating the travel time reliability is crucial because travelers are sensitive to unexpected traffic conditions. Buffer index is a travel time reliability index. The buffer index is calculated using travel time data. Buffer index (Florida Department of Transportation, 2016) is calculated as follows:

$$\text{Buffer Index} = \frac{95^{th}\text{ percentile of travel time} - \text{average travel time}}{\text{free flow travel time}} \tag{26}$$

Hourly average travel time and buffer index are calculated using traffic time data in five-minute granularity for both ON and OFF periods. Lower hourly travel time or lower buffer index for the ON period compared to the OFF period indicates that the ASCS is effective in reducing the travel time or improving the travel time reliability, respectively, on that corridor.

Table 19 ON and OFF periods for ASCS corridors

Location	**Corridor**	**ON period (Start date - End date)**	**OFF period (Start date - End date)**
Greenville	US 29 (St Mark Rd. to Hampton Rd.)	2/3/2020 - 2/7/2020	11/4/2019 - 11/8/2019
	US 29 (Groce Rd. to J. Verne Smith)	2/3/2020 - 2/7/2020	11/4/2019 - 11/8/2019
	US 29 (Franklin Ave. to Tucapau)	2/3/2020 - 2/7/2020	11/4/2019 - 11/8/2019
Clemson	US 123	2/3/2020 - 2/7/2020	10/7/2019 - 10/11/2019
	College Ave.	2/3/2020 - 2/7/2020	10/7/2019 - 10/11/2019

Location	Corridor	ON period (Start date - End date)	OFF period (Start date - End date)
Lexington	US 378 (Hebron Dr. to Hummingbird Dr.)	11/4/2019 - 11/8/2019	10/7/2019 - 10/11/2019
Charleston	SC 642	9/9/2019 - 9/13/2019	9/10/2018 - 9/14/2018
	US 52	9/23/2019 - 9/27/2019	9/30/2019 - 10/4/2019
Summerville	US 17A	9/10/2018 - 9/14/2018	9/9/2019 - 9/13/2019
Pawleys Island	US 17	10/21/2019 - 10/25/2019	10/28/2019 - 11/1/2019
Garden City/Surfside	US 17 Business	10/21/2019 - 10/25/2019	10/28/2019 - 11/1/2019

Table 20 Average hourly traffic volumes for ON period and OFF period and *t*-test result

Location	Corridor	Direction*	ON period average hourly traffic volume (vehicle/h)	OFF period average hourly traffic volume (vehicle/h)	*p*-value of the *t*-test
Greenville	US 29 (St. Mark Rd. to Hampton Rd.)	EB	657	656	0.997
		WB	659	659	0.998
	US 29 (Groce Rd. to J. Verne Smith)	EB	509	509	0.997
		WB	471	471	0.998
	US 29 (Franklin Ave. to Tucapau)	EB	751	751	0.999
		WB	752	751	0.997
Clemson	US 123	EB	613	609	0.928
		WB	612	611	0.986
	College Ave.	NB	240	239	0.952
		SB	240	238	0.942
Lexington	US 378 (Hebron Dr. to Hummingbird Dr.)	EB	577	574	0.948
		WB	579	576	0.955
Charleston	SC 642	EB	841	841	1.000
		WB	841	841	1.000
	US 52	EB	1049	1031	0.843
		WB	805	794	0.853

Location	Corridor	Direction*	ON period average hourly traffic volume (vehicle/h)	OFF period average hourly traffic volume (vehicle/h)	*p*-value of the *t*-test
Summerville	US 17A	EB	836	837	0.997
		WB	829	829	1.000
Pawleys Island	US 17	EB	814	844	0.645
		WB	810	844	0.624
Garden City/Surfside	US 17 Business	EB	577	598	0.651
		WB	568	593	0.617

*Note: EB=Eastbound; WB=Westbound; NB=Northbound; SB=Southbound

7.3 Data Description

In this study, data from 11 ASCS corridors were used to conduct operational analysis. All study corridors are operated by SynchroGreen. As shown in Figure 14, the corridors with SynchroGreen are located throughout South Carolina. As presented in Figure 14, the corridor length is between 0.45 and nine miles. The average AADT of the corridors ranges from 16,000 to 49,000 vehicles/day in 2018. In this study, the speed limit of a corridor is estimated as a weighted average of speed limits of different roadway segments on a corridor. The estimated weighted-average speed limits of the corridors are between 35 and 48.7 mph. The number of signals in each of the corridors is between three and 18. The average signal distance (i.e., the spacing of two successive signalized intersections on a corridor) of a corridor is between 0.20 and 1.07 miles. Thus, some corridors have intersections that are in close proximity to each other, while other corridors have intersections that are far apart. Other corridor characteristics, such as average travel time and average travel speed, are also presented in Table 21.

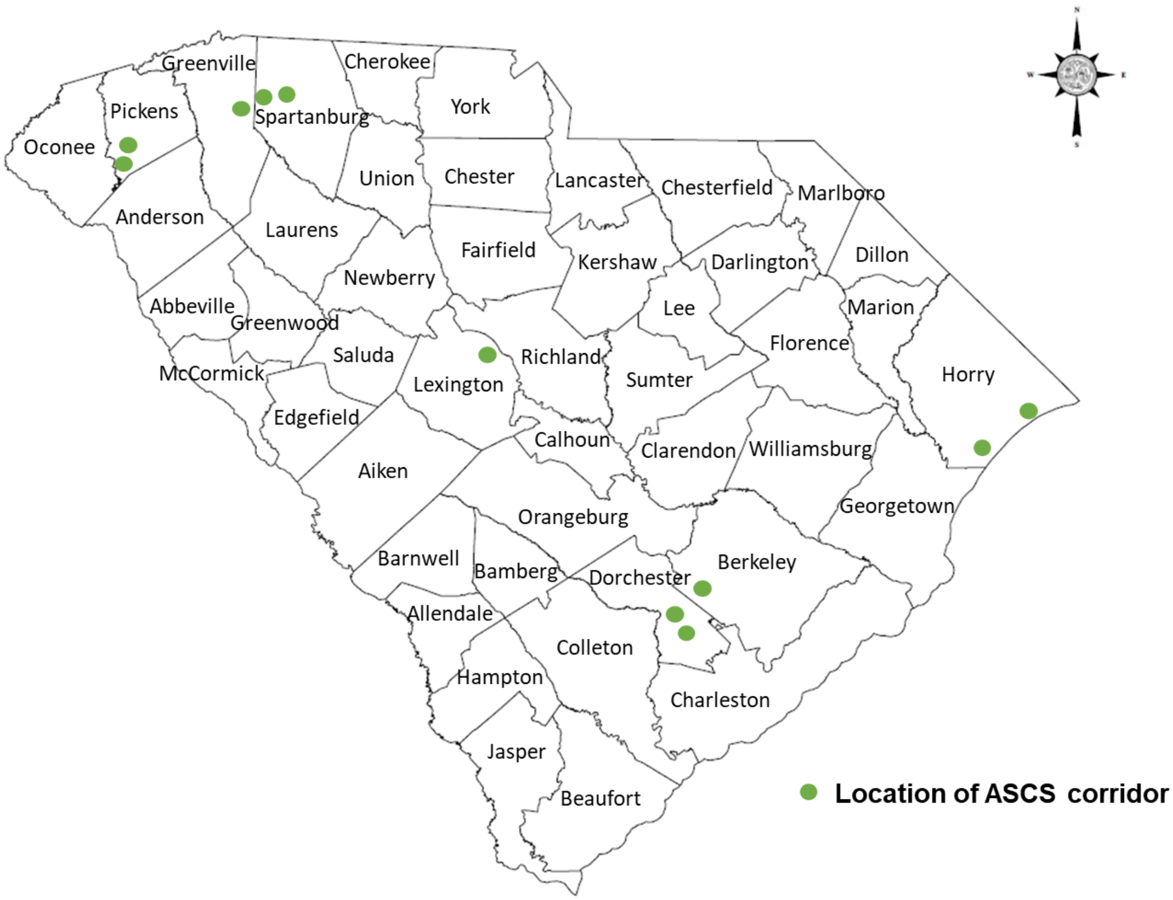


Figure 14 Location of ASCS corridors in South Carolina

Table 21 Corridor characteristics

Corridor name	AADT (vehicles/day)	Length (miles)	# of signals	Average speed limit (mph)	Average signal distance (miles)	Average travel time (min)	Average speed (mph)
US 29 (St. Mark Rd. to Hampton Rd.)	33,333	5.2	14	46.3	0.40	EB: 8.3 WB: 8.4	EB: 37.6 WB: 37.1
US 29 (Groce Rd. to J. Verne Smith)	18,700	3.12	5	47.4	0.78	EB: 4.7 WB: 4.5	EB: 39.8 WB: 41.6
US 29 (Franklin Ave. to Tucapau)	22,100	5.33	6	47.4	1.07	EB: 7.3 WB: 7.2	EB: 43.8 WB: 44.4
US 123	31,300	0.92	3	40	0.46	EB: 1.7 WB: 1.8	EB: 32.7 WB: 30.7
College Ave.	16,750	0.45	3	35	0.23	NB: 1.3 SB: 1.4	NB: 20.3 SB: 19.3
US 378	27,500	1.77	10	40.8	0.20	EB: 3.3 WB: 3.4	EB: 32.0 WB: 31.1
SC 642	38,123	9	18	48.7	0.53	EB: 13.9 WB: 14.9	EB: 38.8 WB: 36.2
US 17A	33,062	3	12	39.1	0.27	EB: 7.3 WB: 8.1	EB: 24.7 WB: 22.2
US 52	48,651	5	17	45	0.31	EB: 9.0 WB: 9.3	EB: 33.3 WB: 32.3
US 17	37,899	3.7	6	41.8	0.74	EB: 5.6 WB: 5.5	EB: 39.6 WB: 40.4
US 17 Business	28,533	5.3	9	45	0.66	EB: 8.9 WB: 9.0	EB: 35.7 WB: 35.3

*Note: EB=Eastbound; WB=Westbound; NB=Northbound; SB=Southbound

7.4 Results

7.4.1 Effectiveness of ASCS in Reducing Travel Time

Figure 15 shows which period ASCS is effective in reducing the travel time over 24 hours. As shown in Figure 15, on average, 61% of the time during a day, ASCS is effective in reducing travel time for the study corridors. Peak periods are identified for each corridor and each direction. It is found that in 77% of the time during the peak periods, ASCS is effective in reducing travel time. Evaluation results of travel time for all corridors are shown in APPENDIX D-1. As indicated by the results marked in red in Figure 15, the percentage of time when ASCS is effective during the peak periods is lower than 50% on US 17 in Pawleys Island and on US 17 Business in Garden City/Surfside, indicating that ASCS is not effective during the peak periods on these two corridors. It is noted that these two corridors are in cities frequented by tourists. The possible reason for finding low percentages of time during the peak periods when ASCS is effective for these two corridors is that traffic conditions during the peak periods vary minimally by the hour.

Reducing travel time	# of	19	10	17	7	10	7	19	16	10	23	8	16	21	19	24	24	13	10	13	7	14	17	Avg.
	%	79%	42%	71%	29%	42%	29%	79%	67%	42%	96%	33%	67%	88%	79%	100%	100%	54%	42%	54%	29%	58%	71%	61%
% during peak periods		100%	75%	100%	67%	67%	67%	100%	100%	83%	100%	67%	100%	100%	100%	100%	100%	75%	60%	33%	33%	67%	0%	77%

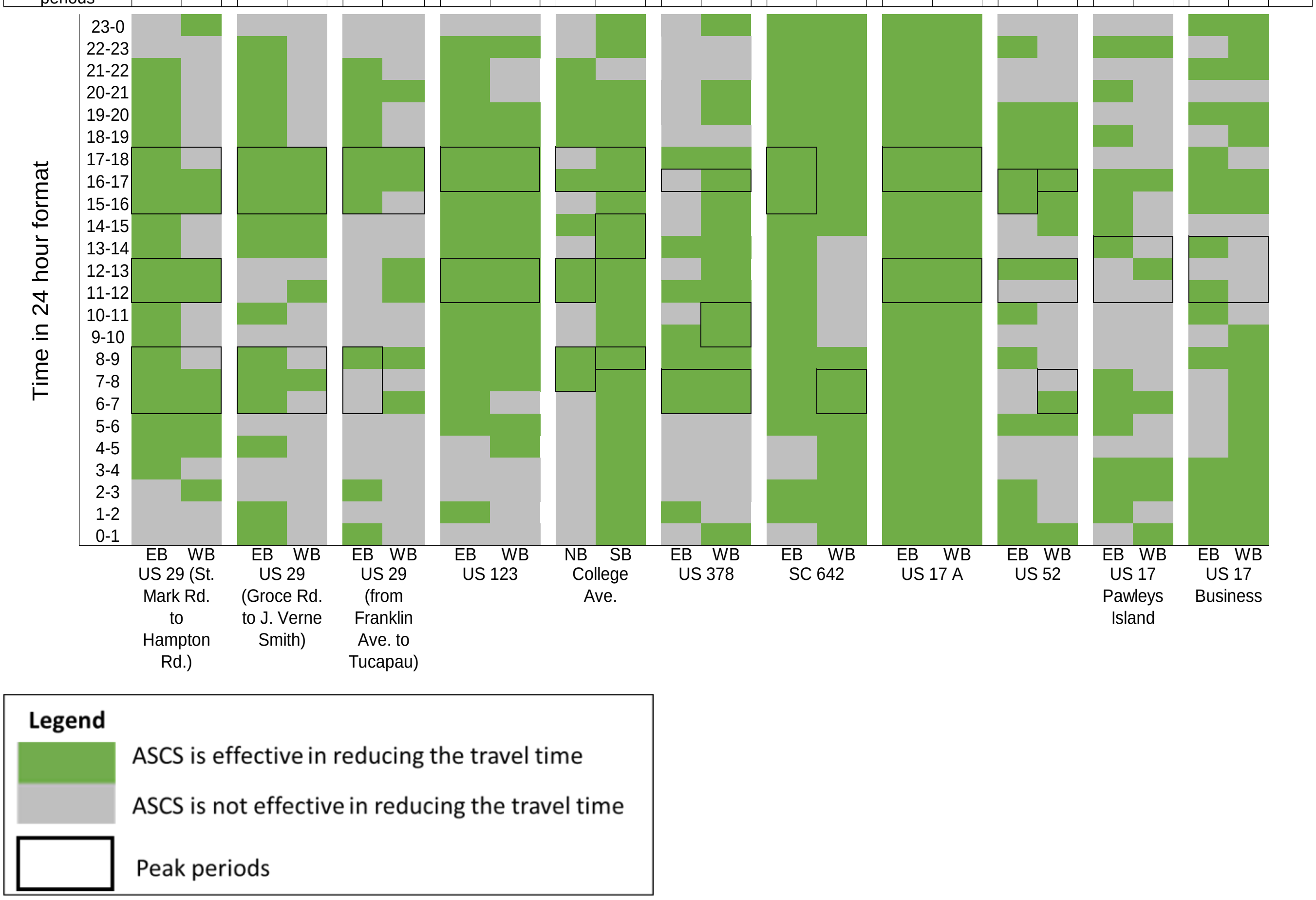


Figure 15 Time periods during 24 hours of a day in which ASCS is effective in reducing the travel time

To test whether the travel time for the ON period is statistically different from that for the OFF period over 24 hours, the research team conducted a paired t-test for each corridor and obtained the *p*-value for each corridor. As an example, Figure 16(a) shows the average travel times for the ON period and OFF period during a day for SC 642 eastbound. The *p*-value obtained by the paired *t*-test for SC 642 eastbound is 2.23 E-02. The research team performed paired *t*-tests for all the study corridors to obtain *p*-values, as shown in Figure 16(b), and combined all p-values using meta-analysis (i.e., Fisher's method) as described in the "7.2 Method" section. The combined *p*-value (i.e., 6.72 E-19) determined by using Eq. (24) is less than 0.05. Therefore, it is concluded that travel time for the ON period is statistically different from travel time for the OFF period at a 0.05 significance level. The average travel time of all the study corridors is 6.39 and 6.83 minutes for ON and OFF periods, respectively, indicating that ASCS is effective in reducing the travel time by 6.4%. Travel time reduction due to ASCS during the peak period is 8.6%, while travel time reduction due to ASCS during the off-peak period is 6.0%. The result indicates that ASCS brings higher operational benefits during the peak period compared to the off-peak period.

Hour	Travel time for ON period	Travel time for OFF period
0	11.99	11.94
1	11.88	12.09
2	11.78	11.99
3	12.12	12.09
4	11.62	12.16
5	11.71	13.01
6	12.87	18.91
7	17.95	42.52
8	15.30	25.50
9	13.92	15.13
10	13.60	14.60
11	13.73	14.88
12	13.72	15.07
13	14.15	15.14
14	13.77	15.52
15	13.24	15.32
16	12.87	15.24
17	13.38	15.75
18	13.08	14.71
19	13.01	14.06
20	12.76	13.81
21	12.62	13.33
22	12.69	13.11
23	12.15	12.18

(a) Travel time for ON period and OFF period on SC 642 Eastbound

Site Name	p-value
US 29 EB (St. Mark Rd. to Hampton Rd.)	3.27E-05
US 29 WB (Hampton Rd. to St. Mark Rd.)	8.96E-01
US 29 EB (Tucapau to Franklin Ave.)	4.66E-01
US 29 WB (Franklin Ave. to Tucapau)	9.63E-03
US 29 EB (J. Verne Smith Parkway to Groce Rd.)	1.58E-02
US 29 WB (Groce Rd. to J. Verne Smith Parkway)	4.89E-01
US 123 EB	4.06E-03
US 123 WB	4.14E-03
SC 642 EB	2.23E-02
SC 642 WB	3.69E-02
US 17A EB	3.24E-08
US 17A WB	6.32E-06
US 378 EB	4.89E-01
US 378 WB	1.20E-03
College Ave. NB	6.75E-01
College Ave. SB	8.25E-04
US 52 EB	4.22E-01
US 52 WB	1.09E-01
US 17 EB	8.69E-01
US 17 WB	8.10E-03
US 17 Business EB	6.67E-01
US 17 Business WB	8.31E-01
Combined *p*-value	6.72 E-19

(b) *p*-value obtained from paired *t*-test on each site

Figure 16 Paired *t*-test results for travel time

7.4.2 Effectiveness of ASCS in Improving Travel Time Reliability

Figure 17 shows periods in which ASCS is effective in reducing the buffer index during a day. As shown in Figure 17, on average, 53% of the time during a day, ASCS is effective in reducing the buffer index for our study corridors. Peak periods are identified separately for each direction for each corridor. In 52% of the time during the peak periods, ASCS is effective in reducing the buffer index. Evaluation results of buffer index for all corridors are shown in APPENDIX D-1. As indicated by the results marked in red in Figure 17, the percentage of reducing the buffer index during the peak period is lower than 50% for both directions on US 29 in Greenville and US 17 in Pawleys Island. The results indicate that ASCS is not effective in terms of improving travel time reliability during peak periods on these two corridors. A possible reason is that the traffic demand during peak periods vary minimally compared to the other hours of the day.

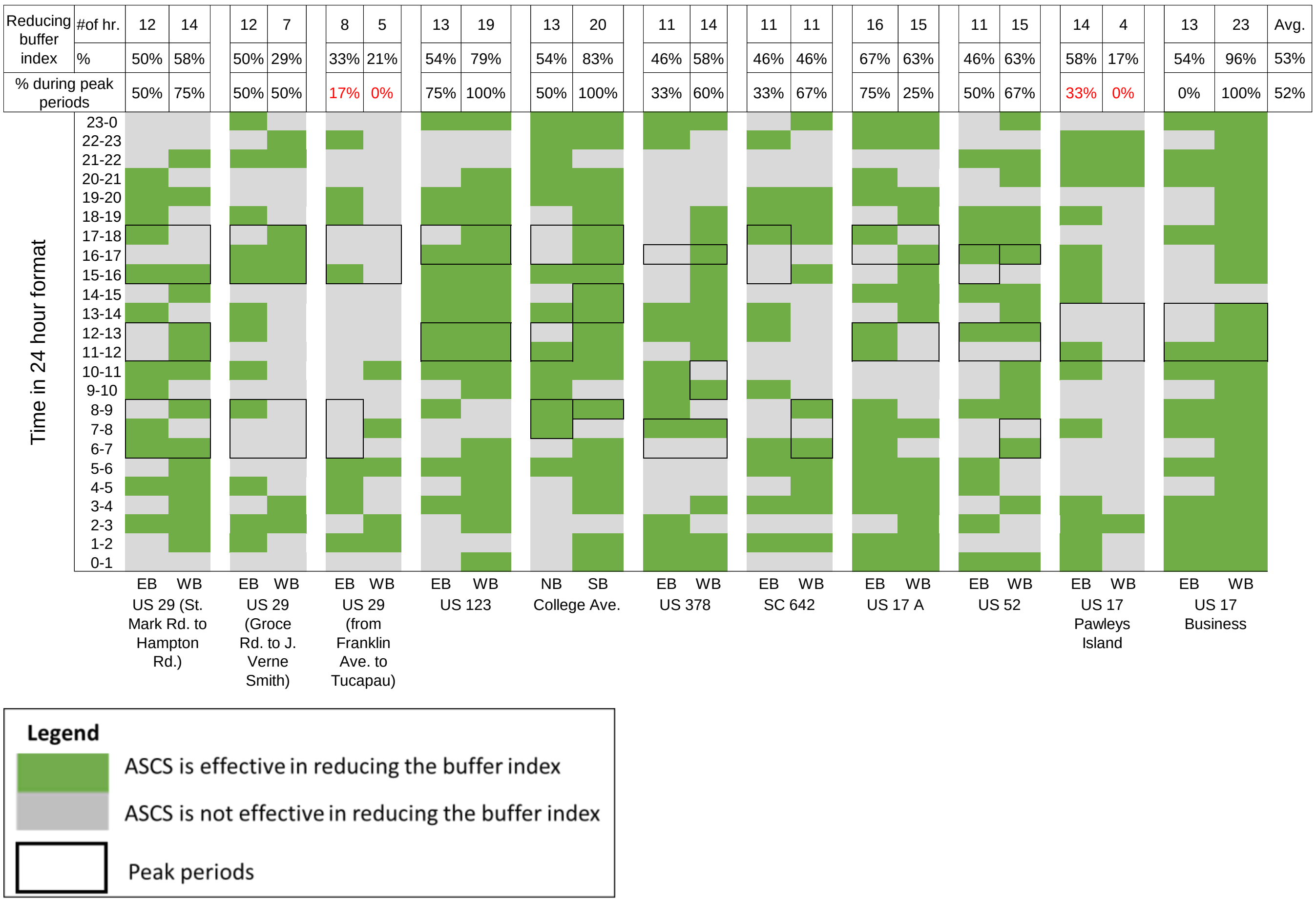


Figure 17 Time periods in 24 hr. in which ASCS is effective in reducing the buffer index

To test whether the travel time reliability for the ON period is statistically different from that for the OFF period over 24 hours, the research team conducted a paired *t*-test for each corridor and obtained the *p*-value for each corridor. As an example, Figure 18(a) shows buffer indexes for the ON period and OFF period over 24 hours for US 29 westbound (Franklin Ave. to Tucapau). The *p*-value that is obtained by the paired *t*-test for US 29 westbound (Franklin Ave. to Tucapau) is 0.002. The research team performed paired *t*-tests for other corridors to obtain the *p*-values, as shown in Figure 18(b), and combined all *p*-values using meta-analysis, as discussed in the "7.2 Method" section. The combined p-value (i.e., 7.51 E-13) determined by Eq. (24) is less than 0.05. Therefore, it is concluded that travel time for the ON period is statistically different from that for the OFF period at a 0.05 significance level. The average buffer index of all corridors is 0.24 and 0.35 for ON and OFF periods, respectively, indicating that ASCS is effective in improving the travel time reliability by 31.4%. The buffer index reduction due to ASCS during the peak period is 35.7%, while the buffer index reduction due to ASCS during the off-peak period is 30.0%. The result indicates that ASCS brings higher operational benefits during the peak period compared to the off-peak period.

Hour	Buffer index for ON period	Buffer index for OFF period
0	0.10	0.03
1	0.06	0.05
2	0.05	0.02
3	0.05	0.05
4	0.01	0.02
5	0.12	0.06
6	0.13	0.10
7	0.14	0.14
8	0.15	0.10
9	0.09	0.11
10	0.27	0.10
11	0.42	0.11
12	0.18	0.19
13	0.21	0.14
14	0.53	0.11
15	0.26	0.13
16	0.17	0.13
17	0.15	0.14
18	0.12	0.11
19	0.13	0.12
20	0.22	0.07
21	0.21	0.08
22	0.15	0.10
23	0.10	0.04

(a) Buffer index for ON period and OFF period on US 29 WB (Franklin Ave. to Tucapau)

Site Name	*p*-value
US 29 EB (St. Mark Rd. to Hampton Rd.)	0.264
US 29 WB (Hampton Rd. to St Mark Rd.)	0.611
US 29 EB (Tucapau to Franklin Ave.)	0.049
US 29 WB (Franklin Ave. to Tucapau)	0.002
US 29 EB (J. Verne Smith Parkway to Groce Rd.)	0.968
US 29 WB (Groce Rd. to J. Verne Smith Parkway)	0.045
US 123 EB	0.000
US 123 WB	0.006
SC 642 EB	0.525
SC 642 WB	0.198
US 17A EB	0.524
US 17A WB	0.244
US 378 EB	0.211
US 378 WB	0.503
College Ave. NB	0.273
College Ave. SB	0.001
US 52 EB	0.135
US 52 WB	0.012
US 17 EB	0.305
US 17 WB	0.035
US 17 Business EB	0.743
US 17 Business WB	0.000
Combined p-value	7.51 E-13

(b) *p*-value obtained from paired *t*-test on each site

Figure 18 Paired *t*-test results for the buffer index

7.4.3 Consistency of Effectiveness of ASCS in terms of Travelling Directions

The research team explored the consistency of effectiveness of ASCS in terms of reducing the travel time for both directions of traffic through the same corridor. In Figure 19, the colored areas present the hours during a day for each corridor when ASCS is found to be effective for travel time reduction. The brown-shaded areas in Figure 19 present the hours during a day when ASCS is effective in travel time reduction for eastbound or northbound corridors, whereas the purple-shaded areas present the hours during a day when ASCS is effective for westbound or southbound corridors. To better understand the association between the effectiveness of ASCS in reducing travel time for the two opposing directions of traffic on a corridor, Figure 19 also presents the tetrachoric correlation coefficients of the eleven corridors analyzed in this study. Out of the eleven corridors, one corridor (i.e., US 17A) shows strong association (i.e., the absolute value of the tetrachoric correlation coefficient is greater than 0.8), seven corridors show moderate associations (i.e., the absolute value of the tetrachoric correlation coefficient is between 0.3 and 0.8), and three corridors show weak association (i.e., the absolute value of the tetrachoric correlation coefficient is less than 0.3) in direction-wise comparison of travel time reduction. As eight of the eleven corridors show moderate to strong associations, the implication is that for more than 80% of the observed cases, the effectiveness of ASCS in terms of travel time reduction is consistent for both directions of a corridor.

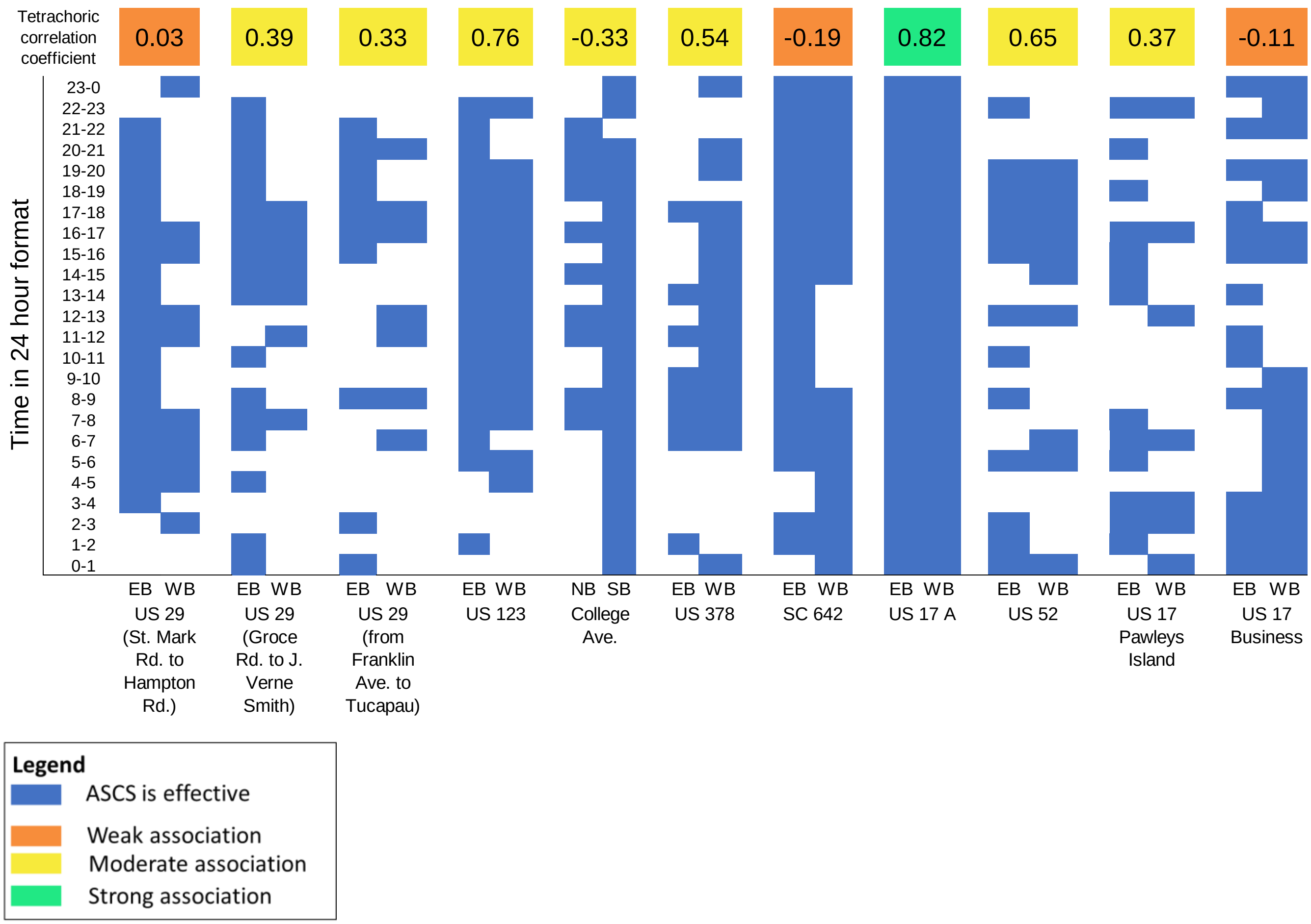


Figure 19 Direction-wise comparison of the effectiveness of ASCS in terms of travel time reduction

The research team also explored the consistency of effectiveness of ASCS in terms of reducing the buffer index for both directions of traffic through the same corridor. In Figure 20, the colored areas present the hours during a day for each corridor when ASCS is found to be effective for buffer index reduction. The brown-shaded areas in Figure 20 present the hours during a day when ASCS is effective in buffer index reduction for eastbound or northbound corridors, whereas the purple-shaded areas present the hours when ASCS is effective for westbound or southbound corridors. Here, the association between the effectiveness of ASCS in reducing the travel time for two opposing directions of traffic is presented in the figure using the tetrachoric correlation coefficient. As observed from Figure 20, based on the tetrachoric correlation coefficients, only five out of the eleven corridors shows moderate associations (i.e., the absolute value of the tetrachoric correlation coefficient is between 0.3 and 0.8), and six corridors show weak associations (i.e., the absolute value of the tetrachoric correlation coefficient is less than 0.3) in direction-wise comparison of buffer index reduction. The implication is that ASCS is not consistently effective for both directions of the traffic of the same corridor in terms of reducing the buffer index.

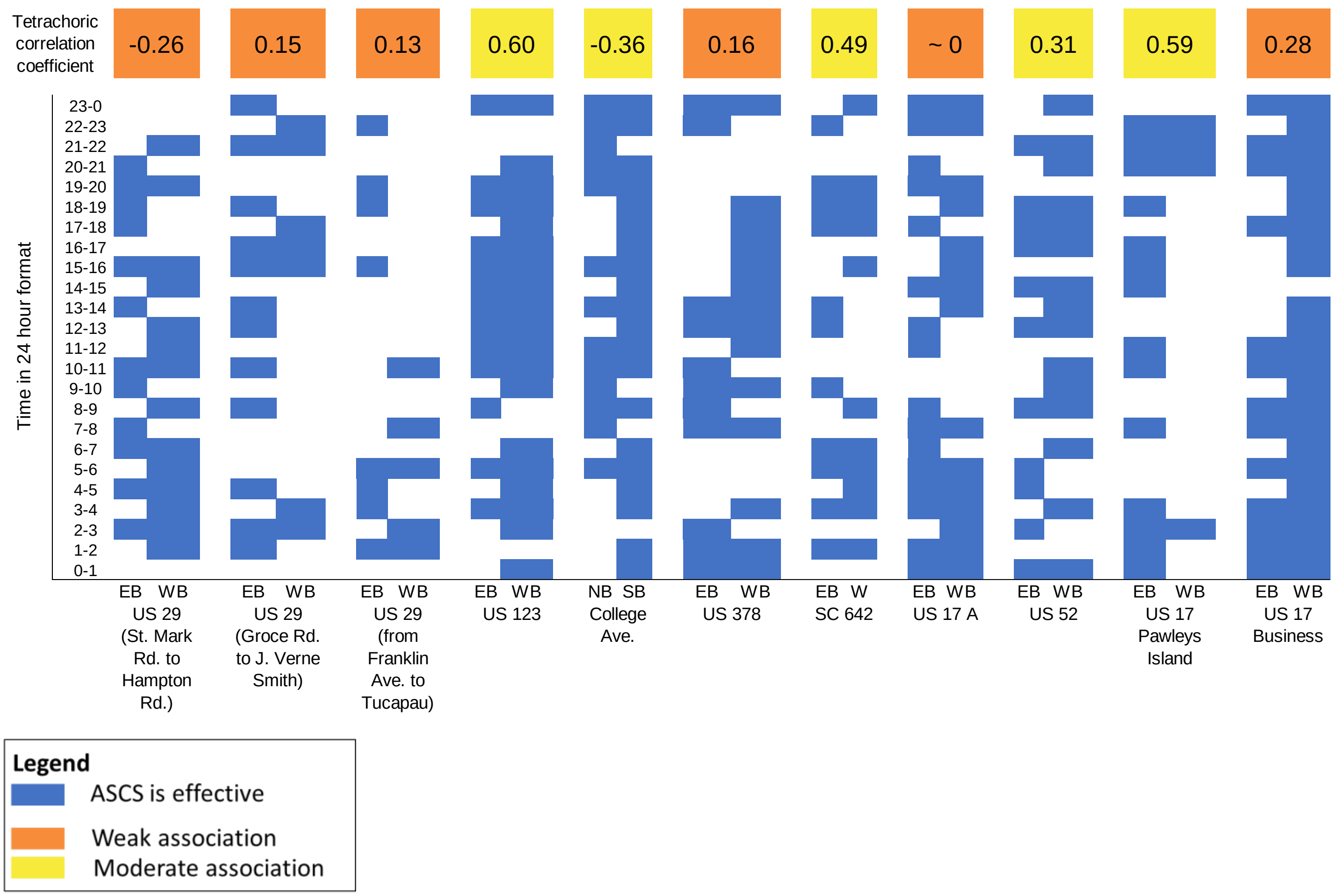


Figure 20 Direction-wise comparison of the effectiveness of ASCS in terms of buffer index reduction

7.4.4 Relationship between Operational Benefits of ASCS and Corridor Characteristics

The research team applied a multiple linear regression model to investigate the relationship between the operational benefit of ASCS (i.e., travel time reduction) and corridor characteristics, as explained by Eq. (25). Two variables- “Average_speed_over_35” and “No_of_signals_over_10” are found to be statistically significant. As the coefficient of “Average_speed_over_35” in the model is negative (i.e., -5.737), it indicates that if the average speed of an ASCS corridor exceeds 35 mph, then ASCS is less effective in reducing the travel time during a day compared to the case when the average speed is equal to or lower than 35 mph. The coefficient of “No_of_signals_over_10” is positive (i.e., 3.697), it indicates that if an ASCS corridor has more than 10 signals, then ASCS is more effective in reducing travel time during a day compared to the case when the number of signals in the ASCS corridor is equal to or less than 10.

7.5 Chapter Conclusions

This study evaluates the operational effectiveness of ASCS corridors located throughout South Carolina. This study evaluates the operational effectiveness of ASCS in terms of travel time reduction and travel time reliability improvement for 11 ASCS corridors, with a total of 102 intersections throughout South Carolina. In addition, the consistency of the operational effectiveness of ASCS in both directions on an hourly basis on a corridor has been evaluated.

Our analyses reveal that when ASCS is operational, it reduces travel time by 6.4% and improves the travel time reliability by 31.4% in a corridor compared to when a non-ASCS traffic signal control system is operational (i.e., when the signal control systems on the same study corridor use a predefined signal timing strategy, which could be either a pre-timed or actuated signal timing plan based on the particular intersection on the corridor). Paired *t*-tests and meta-analysis indicate that the reduction of 6.4% in travel time and improvement of 31.4% in travel time reliability due to ASCS is statistically significant. Based on the operational analysis results, it is concluded that ASCS is effective in reducing travel time, on average, 61% of the time during a day, and 77% of the time during peak periods on a corridor. ASCS is effective in improving travel time reliability, on average, 53% of the time during a day and 52% of the time during peak periods. The effectiveness of ASCS in reducing travel time is consistent in both directions on a corridor for eight ASCS corridors out of 11, whereas the effectiveness of ASCS in improving travel time reliability is consistent in both directions on a corridor for only five ASCS corridors out of 11.

This study also explores the relationship between ASCS operational benefits and different corridor characteristics by using a multiple linear regression model. It is found that ASCS produces higher operational benefits if the average speed of an ASCS corridor is equal to or lower than 35 mph, and the number of signals on an ASCS corridor exceeds 10. Based on the analyses conducted in this study, it is recommended that ASCS be considered to be deployed on a signalized corridor if: 1) the average speed of vehicles on a corridor is equal to or lower than 35 mph, 2) multiple peak periods (i.e., AM, Noon, or PM) exist on a corridor, 3) the traffic conditions are variable or fluctuate by the hour, and 4) the number of traffic signals on a corridor exceeds 10.

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CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

The research team investigated the safety effects of ASCS on crash frequency, crash severity, and the likelihood of secondary crashes on freeways with alternate routes where ASCS has been deployed. The research team also assessed the operational effectiveness of ASCS. The research team recommended the types of corridors that are best suited for ASCS implementation for traffic safety and operational improvement.

The nation-wide survey results showed that most states have considered or studied ASCS, though many have not implemented ASCS. The survey also identified corridor characteristics, such as the design speed and AADT of an ASCS corridor, which would allow for the best operational and safety outcomes.

The research team evaluated the safety effects of ASCS on crash frequency at 11 ASCS corridors that have a total of 109 signalized intersections by developing a Fully Bayesian (FB) framework for the before-and-after study. Based on the evaluation results, ASCS was found to reduce crashes for most of the corridors and intersections. It was also found that the safety effectiveness of ASCS varied across the intersections with different features, such as AADT at a major street and the speed limit at a major street.

The research team investigated the effects of ASCS on the crash severity at 11 ASCS corridors that have a total of 109 signalized intersections by developing random-parameter ordered regression models. The analyses revealed that the presence of ASCS was associated with lower crash severity. Two practical implications were found: 1) when the speed limit difference between major streets and minor streets at an ASCS intersection is equal to or greater than 10 mph, and the average signal distance on an ASCS corridor is less than the threshold of 0.49 miles, ASCS was more likely associated with lower crash severity, and 2) when speed limit difference between major streets and minor streets at an ASCS intersection is less than 10 mph, and the average signal distance on an ASCS corridor is less than the threshold of 0.69 miles, ASCS was associated with lower crash severity.

The research team found a unique interrelation between ASCS deployed on alternate routes and the likelihood of parallel freeway secondary crashes. The analysis showed that a 47% reduction in the likelihood of freeway secondary crashes for I-26 (Eastbound) was associated with an ASCS deployed on alternate route US 52. The benefit of ASCS deployment on an alternate route for freeway secondary crash reduction was found to be dependent on the location of the primary crash as it determines how much of the upstream traffic will be able to or elect to take the exit ramp to the ASCS deployed alternate route.

The research team evaluated the operational effectiveness of ASCS in terms of travel time reduction and travel time reliability improvement for 11 ASCS corridors that have a total of 102 intersections. In addition, the consistency of the operational effectiveness of ASCS in both directions on an hourly basis on a corridor was evaluated. The results indicated that when ASCS was operational, it reduced travel time by 6.4% on average and improved the travel time reliability by 31.4% on average for all the study corridors, compared to when ASCS was not operational (i.e., when the signal control systems on the same study corridor use a predefined signal timing strategy, which could be either a pre-timed or actuated signal timing strategy based on the particular intersection on the corridor). Based on the operational analysis results, it was concluded that ASCS was effective in reducing travel time in a corridor, on average, 61% of the time during a day, and 77% of the time during the peak periods. ASCS was effective in improving travel time reliability, on average, 53% of the time during the day and 52% of the time during the peak periods. The effectiveness of ASCS in reducing travel time was consistent in both directions on an hourly basis for eight ASCS corridors out of 11, whereas the effectiveness of ASCS in improving travel time reliability was consistent in both directions on an hourly basis for only 5 ASCS corridors out of 11. The research team also explored the relationship between ASCS operational benefits and different corridor characteristics. It was found that ASCS produced higher operational benefits if the average speed of an ASCS corridor is equal to or lower than 35 mph, and the number of signals on an ASCS corridor exceeds 10.

Figure 21 highlights the safety and operational impacts of ASCS at the study corridors as revealed in this study.

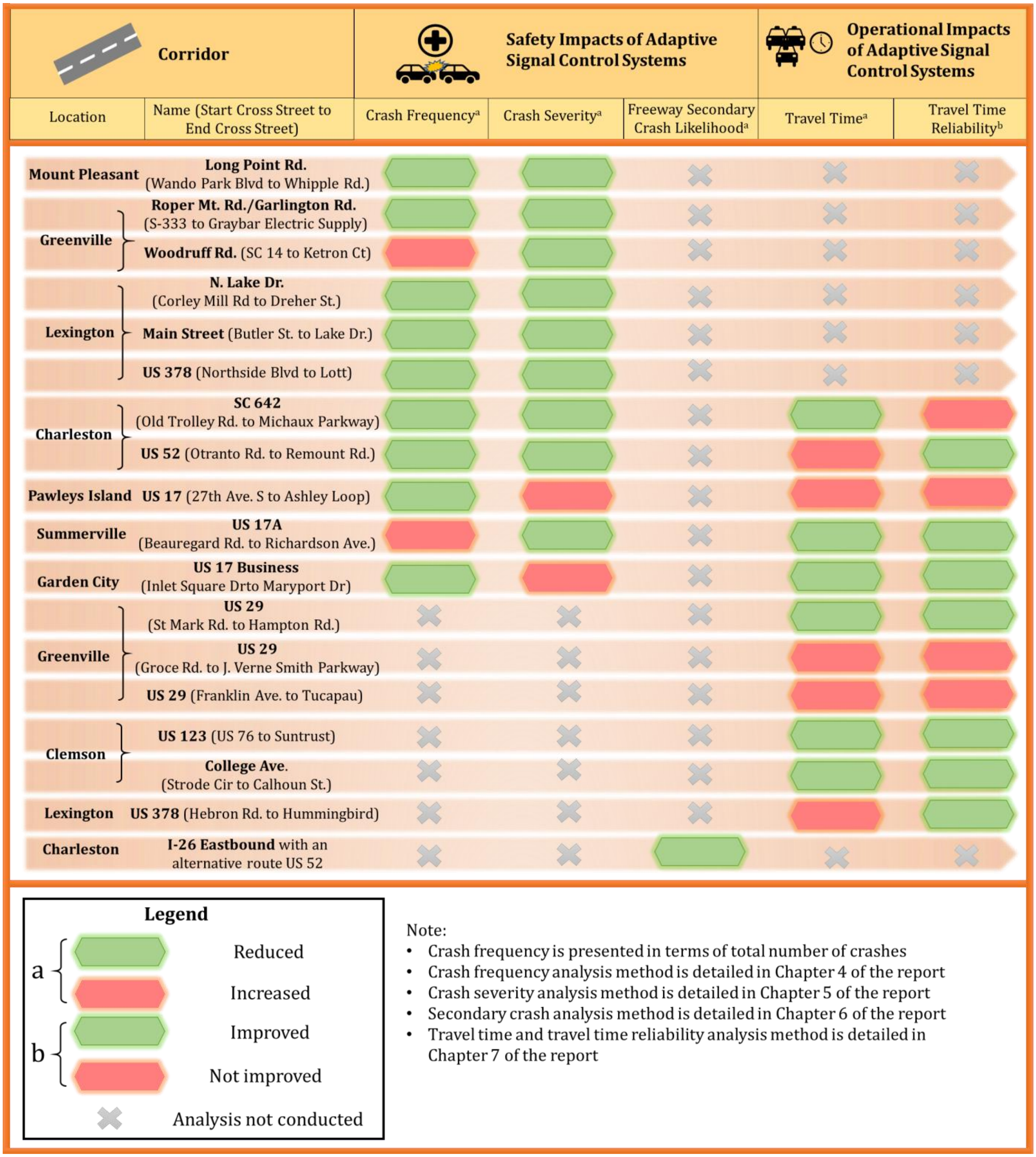

Figure 21 Safety and operational impacts of adaptive signal control systems at study corridors

8.2 Recommendations for Implementation

The research team provides the following recommendations for SCDOT's consideration in implementing ASCS based on findings from the safety analysis, operational analysis, and state DOTs survey.

While Considering Traffic Safety

The research team recommends SCDOT to select future ASCS deployment sites, for improving traffic safety, by considering intersection and corridor features such as AADT at major roads, speed limits at major roads and minor roads, intersection geometry, average signal distance on a corridor, and whether the corridor could be used as a detour route when there is an incident on the freeway.

Based on the findings of the crash frequency study, the research team recommends that ASCS be considered for deployment on a corridor if: 1) AADT on major roads is between 20,000 vehicles/day and 50,000 vehicles/day, and 2) speed limits on major roads are between 40 and 55 mph. Assuming that the above conditions are met, ASCS is effective regardless of intersection geometry (i.e., four-legged or T-intersections).

Based on findings of the crash severity study, the research team recommends that ASCS be considered for deployment on a corridor if the speed limit difference between a major street and a minor street at an intersection is equal to or greater than 10 mph, and the average signal distance on a corridor is less than 0.49 miles. The research team also recommends that ASCS be considered for deployment on a corridor if the speed limit difference between a major street and a minor street at an intersection is less than 10 mph, and the average signal distance on a corridor is less than 0.69 miles.

Based on the findings of the secondary crash study, the research team recommends that ASCS be considered for deployment on an alternate route to a freeway if the corridor is often used by commuters in the event of an incident on the freeway.

While Considering Traffic Operations

The research team recommends SCDOT to select ASCS deployment sites, for operational improvements, by considering corridor features such as the design speed of a corridor, the average speed of vehicles on a corridor, AADT of a corridor, the number of traffic signals on a corridor, presence of multiple peak periods on a corridor, and traffic conditions on a corridor.

Based on the findings of the nation-wide survey, the research team recommends that ASCS be considered for deployment on a corridor if the design speed of the corridor is between 30 and 45 mph and the average AADT of the corridor is between 30,000 and 50,000 vehicles/day.

Based on findings of the operational evaluation study, the research team recommends that ASCS be considered for deployment on a corridor if: 1) the average speed of vehicles on a corridor is equal to or lower than 35 mph, 2) the number of traffic signals on a corridor is more than 10, 3) there are multiple peak periods (AM, Noon, or PM) on the corridor, and 4) the traffic conditions are variable or fluctuate by the hour.

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APPENDIX A

CRASH FREQUENCY STUDY

APPENDIX A-1 DATA DESCRIPTION

Table A-1 Descriptive statistics of intersection geometric features and speed limits data

Variables	Before period				After period			
	Mean	S.D.*	Min	Max	Mean	S.D.*	Min	Max
Number of legs at intersections	3.82	0.38	3	4	3.8	0.4	3	4
Number of through lanes on major streets	5.37	1.44	2	8	5.29	1.28	2	8
Number of the exclusive right-turn lanes on major streets	1.2	0.8	0	2	1.16	0.84	0	2
Number of the exclusive left-turn lanes on major streets	2.28	0.91	0	4	2.22	0.89	0	4
Number of through lanes on minor streets	2.16	1.21	0	5	2.14	1.19	0	5
Number of the exclusive right-turn lanes on minor streets	1.02	0.7	0	2	0.87	0.75	0	2
Number of the exclusive left-turn lanes on minor streets	1.81	0.89	0	4	1.89	0.89	0	4
Number of access points within the influence area of intersection on major streets	3.03	1.75	0	7	3.27	1.8	0	7
Number of access points within the influence area of intersection on minor streets	2.38	1.92	0	7	2.39	1.88	0	7
Speed limit on major streets (mph)	42.64	5	25	55	41.47	5.53	25	55
Speed limit on minor streets (mph)	32.15	4.89	25	50	31.78	4.71	25	50

* S.D.-Standard deviation

Table A-2 Crash frequency (number of crashes per year) statistics for ASCS corridors

Crash Types	Before period				After period			
	Min	Mean	Max	Stdv.	Min	Mean	Max	Stdv.
US 17A	**2011-2014**				**2016-2018**			
Total Crash	5	19.40	52	12.04	7	29.5	86	17.65
F+I	0	4.67	15	3.33	0	5.97	22	4.58
Rear-end	1	9.96	35	8.13	1	14.06	50	10.50
Angle	0	5.88	18	3.76	2	8.06	20	4.16
SC 642	**2011-2014**				**2016-2018**			
Total Crash	0	13.32	51	13.07	0	15.13	68	12.46
F+I	0	5.12	21	5.22	0	6.17	19	5.26

Crash Types	Before period				After period			
	Min	Mean	Max	Stdv.	Min	Mean	Max	Stdv.
Rear-end	0	6.43	24	5.8	0	7.83	30	5.42
Angle	0	4.22	26	5.85	0	4.2	28	5.04
Roper Mt Rd/Garlington Rd	**2011-2015**				**2017-2018**			
Total Crash	0	4.96	23	6.61	0	7.40	28	10.20
F+I	0	0.68	4	1.22	0	0.90	3	1.20
Rear-end	0	3.60	18	4.47	0	5.40	23	7.95
Angle	0	1	8	1.96	0	1.40	7	2.37
US 17	**2011-2015**				**2017-2018**			
Total Crash	2	11.70	51	11.14	4	15.75	36	9.74
F+I	0	4.03	18	4.82	2	5.25	16	4
Rear-end	0	6.17	32	6.89	1	9.75	26	8.15
Angle	0	3	11	2.67	1	3.67	8	1.92
US 52	**2011-2015**				**2017-2018**			
Total Crash	0	16.88	65	16.56	3	29.5	89	22.13
F+I	0	6.67	34	7.92	2	12.15	38	10.13
Rear-end	0	9.09	44	9.25	1	15.94	48	12.05
Angle	0	3.94	23	4.55	1	6.76	21	6.15
N. Lake Drive	**2011-2014**				**2016-2018**			
Total Crash	0	6.71	18	3.99	1	14.76	36	9.07
F+I	0	1.71	6	1.78	0	4.43	17	4.78
Rear-end	0	3.79	11	2.42	1	6.71	23	5.16
Angle	0	1.82	5	1.44	0	4.29	11	3.36
Long Point Rd	**2012-2016**				**2018-2019**			
Total Crash	0	7.83	23	5.66	3	11.42	24	5.98
F+I	0	2.03	6	1.75	0	2.5	7	1.98
Rear-end	0	3.47	10	2.87	1	5.58	18	4.56
Angle	0	2.77	12	3.23	1	3.92	12	2.97
Main Street	**2012-2016**				**2018-2019**			
Total Crash	5	15.48	39	9	7	20.7	38	10.78
F+I	0	4.36	11	3.12	0	4.5	14	4.03

Crash Types	Before period				After period			
	Min	**Mean**	**Max**	**Stdv.**	**Min**	**Mean**	**Max**	**Stdv.**
Rear-end	0	7.64	22	5.11	3	9.4	19	5.3
Angle	1	4.84	13	3.35	1	5.5	13	3.84
US 378	**2012-2016**				**2018-2019**			
Total Crash	1	11.57	40	9.38	2	13.43	29	9.02
F+I	0	3.8	18	4.26	0	2.5	9	2.53
Rear-end	1	6.14	18	4.12	2	7.14	13	3.53
Angle	0	2.91	11	3.22	0	2.64	8	2.95
US 17 Business	**2012-2016**				**2018-2019**			
Total Crash	2	16.56	34	9.32	0	9.89	21	7.13
F+I	0	6.82	22	5.39	0	3.39	15	4.1
Rear-end	1	7.13	17	3.76	0	4.33	12	3.41
Angle	0	6.71	18	5.23	0	3.89	9	2.76
Woodruff Rd	**2012-2016**				**2018-2019**			
Total Crash	2	23.68	52	11.77	8	27.09	53	12.28
F+I	0	4.53	14	3.52	1	5.53	13	3.13
Rear-end	0	13.79	36	8.09	2	14.56	43	8.79
Angle	0	7.02	15	4.03	1	7.85	15	3.86

* S.D.-Standard deviation

APPENDIX A-2 MODEL DEVELOPMENT AND EVALUATION PROCEDURE

EB Model Development

Model 1 (AADT+ Annual multipliers):

$$E(\lambda_{m,it}) = a_{m,t}\exp(\beta_{m,0} + \beta_{m,maj-aadt}\log(\text{majorAADT}_{m,it}) + \beta_{m,\min-aadt}\log(\text{minorAADT}_{m,it})) \tag{A-1}$$

Model 2 (AADT+ Roadway factor+ Annual multipliers):

$$E(\lambda_{m,it}) = a_{m,t}\exp(\beta_{m,0} + \beta_{m,maj-aadt}\log(\text{majorAADT}_{m,it}) + \beta_{m,\min-aadt}\log(\text{minorAADT}_{m,it}) + \sum_{n=1,j=1}^{Q}\beta_{m,j}X_{mn,it}) \tag{A-2}$$

Model 3 (AADT+ Roadway factor+ Year):

$$E(\lambda_{m,it}) = \exp(\beta_{m,0} + \beta_{m,maj-aadt}\log(\text{majorAADT}_{m,it}) + \beta_{m,\min-aadt}\log(\text{minorAADT}_{m,it}) + \sum_{n=1,j=1}^{Q}\beta_{m,j}X_{mn,it} + \beta_{m,T}T_{m,it}) \tag{A-3}$$

where, $\text{majorAADT}_{m,it}$ is AADT of major roads at the intersection i on the corridor m in a given year *t*; $\text{minorAADT}_{m,it}$ is AADT of minor streets at the intersection i on the corridor m in a given year *t*; $X_{mn,it}$ is the n^{th} explanatory variable of roadway geometric features (e.g., the number of exclusive left-turn, right-turn lane(s) and through lane(s) on major or minor streets and the number of access point(s) at an intersection) for the intersection i in a given year *t*; Q is the total number of explanatory variables of roadway geometric features; $T_{m,it}$ is the year factor which is numeric, for example, 0 if year is 2011, 1 if year is 2012, and so on; $\beta_{m,T}$ is the coefficient for the year factor of Model 3; $\beta_{m,maj-aadt}$ is the coefficient for AADT of major roads; $\beta_{m,\min-aadt}$ is the coefficient for AADT of minor streets; $\beta_{m,0}$ is the intercept and $\beta_{m,j}$ is the j^{th} coefficient for roadway geometric features in the model; $a_{m,t}$ is the annual multiplier which is obtained by dividing the sum of predicted number of crashes in a given year t by the sum of observed crashes in a given year t after the EB models are fitted.

EB model estimation is performed in the R environment by calling the R package "MASS". Concerns about multicollinearity (MC) occurs if an explanatory variable is a function of other explanatory variables. Potential MC issues are checked by evaluating the Variance Inflation Factor (VIF) statistic. VIF values greater than 10 are used to check whether MC is of concern (O'Brien, 2007). Using this criterion, the research team finds that no MC issues exist among the explanatory variables used in this study. Akaike's Information Criterion (AIC) is used to select the set of variables used in the regression models (Bumham & Anderson, 2002). The best-fitted model is found with the lowest AIC. For example, roadway geometric features have some variables, including the number of exclusive left-turn lanes, right-turn lanes, and through lanes on major or minor streets and the number of the access points at an intersection. After model selection based on AIC, only a few roadway geometric variables will be kept.

EB Before-and-After Evaluation Procedure

The expected number of crashes in the before period for a site E_b, , is obtained by combining two different information: 1) the observed crash data for a site, O_b, and 2) the sum of the predicted number of crashes during the before period, P_b, estimated by the crash prediction models (i.e., Model 1, Model 2, and Model 3) for the individual site. E_b is obtained by using the following equation (Hauer, 1997; Persaud & Lyon, 2007),

$$E_b = wP_b + (1-w)O_b \tag{A-4}$$

The weight factor w is estimated from P_b and ψ, which are estimated from the SPF development,

$$w = \frac{1}{1 + P_b / \psi} \tag{A-5}$$

where ψ is the value of the dispersion parameter obtained by the NB regression-based SPF.

A correction factor that accounts for the length of the after period, changes in traffic volumes, and changes in roadway geometric characteristics is multiplied with E_b to obtain the E_a. This factor is the ratio of the sum of the after-period SPF predictions, P_a and the sum of the before-period SPF predictions, P_b. Thus, E_a can be obtained below,

$$E_a = E_b \frac{P_a}{P_b} \tag{A-6}$$

The observed number of crashes at a site with treatment during the after period (O_a) is then compared to the expected number of crashes on the same site (E_a) which is the expected number of crashes that would have occurred if the treatment had not been implemented. An estimate of the index of safety effectiveness of treatment, θ, is:

$$\theta = \frac{\sum_{all} O_a / \sum_{all} E_a}{1 + Var\left(\sum_{all} E_a\right) / \left(\sum_{all} E_a\right)^2} \tag{A-7}$$

$$Var\left(\sum_{all} E_a\right) = \sum_{all} [(P_a / P_b)^2 E_b (1-w)] \tag{A-8}$$

where, $\sum_{all} O_a$ is the summation of O_a for all studied sites; $\sum_{all} E_a$ is the summation of E_a for all studied sites.

The estimated percentage of reduction in crashes is $100(1-\theta)$. For example, a value of $\theta = 0.45$ indicates a 55 percent decrease in crashes with treatment. The uncertainty of the index of effectiveness (i.e., standard deviation) is calculated by taking the square root of the variance of θ. The variance of θ is (Hauer, 1997; Persaud & Lyon, 2007):

$$Var(\theta) = \frac{\theta^2 \left(\frac{Var\left(\sum_{all} O_a\right)}{\left(\sum_{all} O_a\right)^2} + \frac{Var\left(\sum_{all} E_a\right)}{\left(\sum_{all} E_a\right)^2} \right)}{\left(1 + \frac{Var\left(\sum_{all} E_a\right)}{\left(\sum_{all} E_a\right)^2} \right)^2} \tag{A-9}$$

In the Eq. (A- 8), the assumption is that the ratio P_a to P_b is a constant variable, not a random variable, which would affect the Eq. (A-7) and Eq. (A-9) containing the term $Var\left(\sum_{all} E_a\right)$.

FB Model Development

A corridor-specific ASCS indicator variable $\mathrm{I}_{m,it}$ that labels the after period during which ASCS is installed on the corridor m is included as shown below (1 is the after period; 0 otherwise). $\beta_{\mathrm{m,I}}$ is the coefficient of the ASCS presence indicator variable of the following models. The research team initially included the interaction variables into the model to account for the possible interaction between ASCS and AADT and the interaction between ASCS and roadway geometric features in the model. But the interaction variables are not significant. Thus, the interaction variables are not used for the following models.

Model 4A (AADT):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\mathrm{majorAADT}_{m,it}) + \beta_{\mathrm{m,min}-aadt} \log(\mathrm{minorAADT}_{m,it}) + \beta_{m,I}\, \mathrm{I}_{m,it} + \varepsilon_{m,it}) \tag{A-10}$$

Model 4B (AADT +Spatial effect):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\mathrm{majorAADT}_{m,it}) + \beta_{\mathrm{m,min}-aadt} \log(\mathrm{minorAADT}_{m,it}) + \beta_{m,I}\, \mathrm{I}_{m,it} + \varepsilon_{m,it} + \mathrm{s}_{m,i}) \tag{A- 11}$$

Model 5A (AADT+ Roadway factor):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\text{majorAADT}_{m,it}) + \beta_{\text{m,min}-aadt} \log(\text{minorAADT}_{m,it}) + \beta_{m,I}\ \text{I}_{m,it} + \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \varepsilon_{m,it})$$

(A-12)

Model 5B (AADT +Roadway factor+ Spatial effect):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\text{majorAADT}_{m,it}) + \beta_{\text{m,min}-aadt} \log(\text{minorAADT}_{m,it}) + \beta_{m,I}\ \text{I}_{m,it} + \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \varepsilon_{m,it} + \text{s}_{m,i})$$

(A-13)

Model 6A (AADT+ Roadway factor+ Year):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\text{majorAADT}_{m,it}) + \beta_{\text{m,min}-aadt} \log(\text{minorAADT}_{m,it}) + \beta_{m,I}\ \text{I}_{m,it} + \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \beta_{m,T} T_{m,it} + \varepsilon_{m,it})$$

(A-14)

Model 6B (AADT+ Roadway factor+ Year+ Spatial effect):

$$\lambda_{m,it} = \exp(\beta_{m,0} + \beta_{m,maj-aadt} \log(\text{majorAADT}_{m,it}) + \beta_{\text{m,min}-aadt} \log(\text{minorAADT}_{m,it}) + \beta_{m,I}\ \text{I}_{m,it} + \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \beta_{m,T} T_{m,it} + \varepsilon_{m,it} + \text{s}_{m,i})$$

(A-15)

where, $s_{m,i}$ could be considered as a latent variable that captures the effect of unknown or unmeasured covariates that are assumed spatially structured. The intrinsic Conditional Autoregressive (CAR) model (Besag et al., 1991) is used for estimating $s_{m,i}$, which is given by:

$$s_{m,i} \mid s_{m,j} \sim Normal\left(\frac{\sum_{j \in \partial_i} w_{ij} s_{m,j}}{\sum_{j \in \partial_i} w_{ij}}, \frac{1}{\tau_s \sum_{j \in \partial_i} w_{ij}}\right), j \neq i \qquad \text{(A-16)}$$

where ∂_i is the set of intersections adjacent to i; w_{ij} is a spatial proximity weight; τ_s is the precision parameter which is the inverse of the variance. τ_s is assumed to follow a prior Gamma (0.001, 0.001) (Cai et al., 2018). w_{ij} is equal to 1 for $i \in \partial_i$; otherwise, w_{ij} is equal to 0.

“OpenBUGS” is open-source software that performs Bayesian inference using the Gibbs sampling algorithm. Bayesian model estimation and MCMC simulation are performed in the R environment by calling the R package “R2OpenBUGS”. For each FB model, two Markov chains are used in MCMC simulations. Each chain has 200,000 iterations and a total of 20,000 iterations are discarded during the burn-in (i.e., warm-up) period. Bayesian estimation provides posterior probability distributions and Bayesian Credible Intervals (BCI) for statistical inference. Before implementing the estimation of the posterior distribution of parameters of interest, convergence must be checked in the MCMC simulation. As a rule of thumb, Rhat statistics (i.e., scale reduction factor) less than 1.2 (Brooks et al., 1998) is used to identify convergence. Also, viewing graphical summaries and the number of effective samplings (i.e., the number of independent samples drawn from the posterior distribution in the MCMC simulation) for the parameters of interest could help to check the convergence. Deviance Information Criterion (DIC) can be used to determine the best set of predictors for each FB model (Spiegelhalter et al., 2002). In general, differences of more than 10 (DIC value) may suggest that the FB model with lower DIC is preferred (Spiegelhalter et al., 2002). Also, the significance of the spatial effect is evaluated to determine if the spatial effect exits in the crash data.

FB Before-and-After Evaluation Procedure

In the FB before-and-after study procedure, Crash Reduction Rate (CRR) is calculated (Lan et al., 2009; Persaud et al., 2010; Yanmaz-Tuzel & Ozbay, 2010), as

$$CRR = 1 - \frac{\sum_{all} O_a}{\sum_{all} \mu_a} \tag{A-17}$$

$\frac{\sum_{all} O_a}{\sum_{all} \mu_a}$ is similar to the index of the safety effectiveness used in the EB method.

The observed number of crashes at a site with treatment during the after period (O_a) is compared with the expected number of crashes on the same site (μ_a) which is the number of crashes that would have occurred if the treatment had not been implemented. μ_a can be obtained through developing crash prediction models (i.e., Model 4A, Model 4B, Model 5A, Model 5B, Model 6A, and Model 6B) in the FB procedure. $\sum_{all} \mu_a$ is the summation of μ_a for all studied intersections on a corridor across studied years for corridor-specific safety effectiveness calculation or the summation of for a specific intersection across studied years for intersection-specific safety effectiveness calculation.

CRR is obtained directly by MCMC simulation. The uncertainty of CRR can be evaluated with a 95% BCI by MCMC simulation. The significance of CRR can be determined if the 95% BCI does not contain zero.

APPENDIX A-3 MODEL COMPARISON RESULTS

Comparison of Potential Bias and Variance of Prediction

As shown in Table A-3, the FB models have lower RMSE values than that of EB models in all scenarios involving different crash types and predictors. Lower RMSE values indicate lower potential bias and variance of prediction.

Table A-3 RMSE for EB and FB models

Model		RMSE			
		Total crash	**F+I**	**Rear-end**	**Angle**
EB Models	Model 1 (AADT + Annual SPF multipliers)	9.91	5.59	7.07	4.49
	Model 2 (AADT + Road + Annual SPF multipliers)	9.83	5.59	6.92	4.44
	Model 3 (AADT + Road + Year)	9.75	5.54	6.67	4.43
FB Non-spatial Models	Model 4A (AADT)	1.23	1.04	1.31	1.09
	Model 5A (AADT + Road)	1.26	1.01	1.34	1.09
	Model 6A (AADT + Road + Year)	1.15	0.97	1.23	1.01
FB Spatial Models	Model 4B (AADT + Spatial effect)	1.24	0.97	1.30	1.03
	Model 5B (AADT + Road + Spatial effect)	1.31	0.98	1.34	1.05
	Model 6B (AADT + Road + Year + Spatial effect)	1.22	0.91	1.24	0.95

Safety Effect Estimation Comparison

As shown in Figure A-1, Model 6A (AADT+ Roadway factor+ Year) and Model 6B (AADT+ Roadway factor+ Year+ Spatial effect) have the best estimation because the mean of the crash reduction percentage is quite close to zero (in the "rectangle" box in Figure A-1). This finding indicates that adding the year factor as a covariate into the FB non-spatial model and FB spatial model could improve the accuracy of estimation of the safety effectiveness of ASCS. So safety researchers and practitioners are encouraged to include the year factor in before-and-after evaluation studies.

The difference in the mean of the crash reduction percentage between FB non-spatial models and FB spatial models is small. However, based on the FB spatial model estimation, the spatial effect is statistically significant, which indicates that the spatial effects exist. In addition, DIC is compared between FB non-spatial models and FB spatial models. The difference between the DIC of spatial and non-spatial models is more than 10 in all types of models, which indicates that FB spatial models are preferred over the FB non-spatial models. Safety researchers and practitioners are encouraged to include the spatial effects in FB before-and-after evaluation studies.

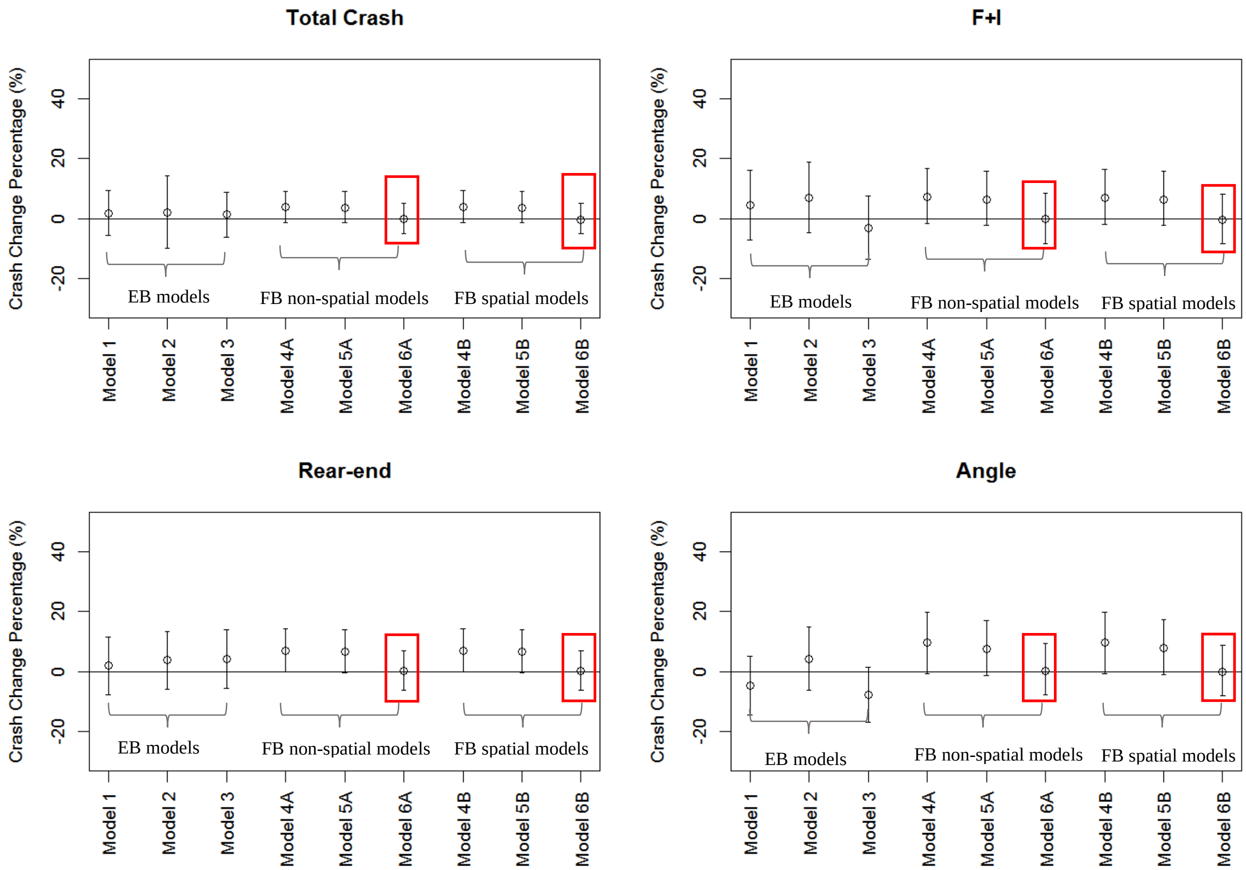


Figure A-1 Crash change percentage with 95% CI among EB models and with 95% BCI among FB models

APPENDIX B

CRASH SEVERITY STUDY

APPENDIX B-1 DATA DESCRIPTION

Table B-1 Peak periods for the study corridors

Location	Corridor name	Peak period
Greenville	Roper Mt Rd./ Garlington Rd.	7:00 - 9:00 16:00 -18:00
Charleston	SC 642	6:00 - 8:00 15:30 - 18:30
Charleston	US 52	7:00 - 9:00 14:00 - 18:00
Lexington	N. Lake Drive	7:00 - 9:00 15:00 - 19:00
Pawleys Island	US 17	11:00 -15:00
Summerville	US 17A	11:00 -13:00 16:00 -18:00
Garden City/Surfside	US 17 Business	11:00 – 13:00
Lexington	Main Street	6:00 – 8:00 11:00 – 13:00 16:00 – 18:00
Lexington	US 378	6:00 – 8:00 12:00 – 14:00 15:00 – 17:00
Mount Pleasant	Long Point Rd.	6:00 – 8:00 11:00 – 13:00 15:00 – 17:00
Greenville	Woodruff Rd.	7:00 – 9:00 11:00 – 13:00 15:00 – 17:00

Table B-2 Summary of descriptive statistics of response variables and significant explanatory variables

Variable	Definition	Level/data type	Before period	After period
			Frequency (Percentage)	**Frequency (Percentage)**
Crash_Severity	Crash Severity Outcome	0 - O	3093 (77.7%)	2089(80.6%)
		1 - C	631 (15.9%)	374 (14.4%)
		2 - KAB	255 (6.4%)	128 (4.9%)
Light	Dark (1 if dark, dawn, or dusk, otherwise 0)	1	912 (22.9%)	579(22.3%)
		0	3067 (77.1%)	2012(77.7%)
ASCS	The presence of ASCS (1 if Yes, otherwise 0)	1	-	2591 (39.4%)
		0	3979 (60.6%)	-
Peak	Peak period (1 if peak period, otherwise 0)	1	1075 (27.0%)	698 (26.9%)
		0	2904 (73.0%)	1893 (73.1%)
Rear_end	Rear-end (1 if rear-end, otherwise 0)	1	2140 (53.8%)	1335(51.5%)
		0	1839 (46.2%)	1256(48.5%)
Angle	Angle (1 if angle, otherwise 0)	1	1073 (27%)	672(25.9%)
		0	2906 (73%)	1919(74.1%)
Pedestrian	The presence of pedestrian (1 if pedestrian-involved, otherwise 0)	1	21 (0.5%)	12 (0.5%)
		0	3958 (99.5%)	2579 (99.5%)
AADT_over_30k	AADT at a road on which a crash occurred (1 if greater than 30k, otherwise 0)	1	3256(81.8%)	2272 (87.7%)
		0	723 (18.2%)	319 (12.3%)
S_Difover10	Speed limit difference between major roads and minor roads at an intersection (1 if equal to or greater than 10 mph, otherwise 0)	1	2894 (72.7%)	1882(70.3%)
		0	1085 (27.3%)	769(29.7%)
			Mean (S.D*)	**Mean (S.D*)**
Speed_Limit	Speed limit (mph)	*Numeric*	*40.71 (6.20)*	39.83 (6.33)
Signal Distance	Average signal distance on a corridor (miles)	*Numeric*	0.38 (0.12)	0.36 (0.12)

* S.D.-Standard deviation

APPENDIX B-2 MODEL IMPLEMENTATION AND ESTIMATION

The random-parameter ordered regression models are estimated through the SML procedure described in (Sarrias, 2016). R software is used to perform SML procedure to obtain model estimation results using the "Rchoice" library (Sarrias, 2016). 300 Halton draws are used in the SML procedure, which is in line with a previous study (Khattak et al., 2019). "Rchoice" library provides some options of distributions for random parameters, such as normal distribution and uniform distribution. Different distributions of random parameters are implemented and tested in the models. Eventually, the uniform distribution is used since it provides a better model fit. The signs of the coefficient of predictors are of particular interest. In the model estimation results in this study, a positive sign of the coefficient of predictors is associated with higher crash severity (i.e., C and KAB levels), whereas a negative sign of the coefficient is associated with lower crash severity (i.e., O level).

The conditional mean of the parameters (Sarrias, 2016), conditional on the specific data of each crash is estimated by Simulated Maximum likelihood (SML) procedure, which is expressed as:

$$\hat{E}(\boldsymbol{\beta}_i \mid data_i) = \sum_{r=1}^{R} \left(\frac{\hat{P}(\mathbf{y}_i \mid \mathbf{X}_i, \boldsymbol{\beta}_{ir})}{\sum_{r=1}^{R} \hat{P}(\mathbf{y}_i \mid \mathbf{X}_i, \boldsymbol{\beta}_{ir})} \right) \hat{\boldsymbol{\beta}}_{ir} \tag{B-1}$$

where, $\hat{\boldsymbol{\beta}}_{ir} = \hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\Pi}}\mathbf{s}_i + \hat{\mathbf{L}}\boldsymbol{\omega}_{ir}$; $\hat{P}(\mathbf{y_i} \mid \mathbf{X_i}, \boldsymbol{\beta}_{ir})$ is the estimated simulated probability for a crash i evaluated at the r^{th} draw of $\boldsymbol{\beta}_i$; $data_i$ represents the explanatory variables; R is the total number of draws in the SML procedure. The random draws are generated by a Halton random number generator with a standard uniform distribution, $U(0,1)$. Detail Halton draws procedure can be found in (Sarrias, 2016).

The Variance Inflation Factor (VIF) is used to check for potential Multi-Collinearity (MC). Commonly a VIF of 10 has been used by many researchers as a rule of thumb to indicate severe MC issues (O'Brien, 2007). The best fit models are selected based on a comparison of the Akaike Information Criteria (AIC) (Burnham & Anderson, 2004), with the model with the lowest AIC value deemed the best fit model. Also, the likelihood ratio test (Washington et al., 2020) is used to select a model with better goodness of fit of the model. Three classification model performance metrics: accuracy, precision, and recall, which are widely used for evaluating a classification model, are used for evaluating the performance of the random-parameter ordered regression model (i.e., ordered probit or logit) with observed heterogeneity. A training dataset with 80% of the sample and a test dataset with 20% of the sample are obtained. The training dataset and test dataset are randomly sampled. During the sampling, both datasets are ensured to have similar percentages of data points by category (i.e., by crash severity outcomes). The sampling procedure is repeated 30 times (Rahman et al., 2019; Xie et al., 2019). For each time, the model is developed using the training dataset, and then the model is evaluated using the test dataset. The accuracy, precision, and recall are computed for the test dataset using Eq. (B-2) to Eq. (B-4) (Sammut Claude and Webb, 2010; Ting, 2010).

$$\text{Accuracy} = CT / N \tag{B-2}$$

$$\text{Precision} = TP_n / (TP_n + FP_n) \tag{B-3}$$

$$\text{Recall} = TP_n / (TP_n + FN_n) \tag{B-4}$$

where, CT is the total number of correctly classified instances for all classes; N is the total number of instances for all classes; n is the class label (i.e., O, C, or KAB); TP_n is true positive for the class label n; FP_n is false positive for the class label n; FN_n is false negative for the class label n.Overall precision and recall are evaluated by computing the micro-average values of precision and recall (Van Asch, 2013), which are derived by Eq. (B-5) and Eq. (B-6).

$$\text{Precision}_{Micro-average} = \sum_{n=1}^{T} TP_n / (\sum_{n=1}^{T} TP_n + \sum_{n=1}^{T} FP_n) \tag{B-5}$$

$$\text{Recall}_{Micro-average} = \sum_{n=1}^{T} TP_n / (\sum_{n=1}^{T} TP_n + \sum_{n=1}^{T} FN_n) \tag{B-6}$$

where, T is the total number of classes, including three classes (i.e., O, C, and KAB) in this study.

APPENDIX B-3 MODEL COMPARISON RESULTS

The following four models are estimated and compared:

- Random-parameter ordered probit model with observed heterogeneity (ROP)
- Random-parameter ordered logit model with observed heterogeneity (ROL)
- Random-parameter ordered probit model (RP)
- Random-parameter ordered logit model (RL)

In the model estimation results in Table B-3, a positive sign of the coefficient of predictors is associated with higher crash severity, while a negative sign of the coefficient is associated with lower crash severity. From the negative sign of the coefficient (i.e., -0.113 for the RP model and -0.205 for the RL model) of ASCS variable in Table B-3, it shows that the presence of ASCS is associated with lower crash severity. Since the standard deviation associated with ASCS is found to be statistically insignificant in the RP, RL, ROP, and ROL models, ASCS is not considered as a random parameter for these models. Instead, ASCS is considered as a fixed parameter for the RP and RL models, and a varying parameter depending on intersection/corridor-level variables (i.e., S_Difover10 and Signal Distance) for the ROP and ROL models. Only the angle variable is considered as a random parameter with the mean (i.e., mean.Angle) and the standard deviation (i.e., S.D. Angle) in these models. Note that, the coefficient of the angle variable is a random parameter that follows a random distribution. As shown in Table B-3, the mean of the coefficient (mean.Angle) associated with angle is found to be positive and statistically significant in the ROP model. Its standard deviation (S.D.Angle) is also found to be statistically significant, implying the existence of unobserved heterogeneity across observations. The coefficient of the angle variable is estimated to follow a uniform distribution with a mean of 0.330 and a standard deviation of 1.030. It is found that all observations have a positive coefficient associated with the angle crashes, suggesting an association between angle crashes and higher crash severity.

Table B-3 Model estimation results

	ROP[a]		ROL[a]		RP[a]		RL[a]	
Coefficients	**Est.**	**p-value**	**Est.**	**p-value**	**Est.**	**p-value**	**Est.**	**p-value**
Threshold, μ_1 [b]	0.858	< 0.001	1.675	< 0.001	0.855	< 0.001	1.671	< 0.001
Constant	-1.554	< 0.001	-2.822	< 0.001	-1.618	< 0.001	-2.947	< 0.001
Pedestrian	2.078	< 0.001	3.711	< 0.001	2.061	< 0.001	3.660	< 0.001
AADT_over_30k	0.235	< 0.001	0.425	< 0.001	0.225	< 0.001	0.405	< 0.001
Speed_Limit	0.009	0.008	0.019	< 0.001	0.011	0.001	0.022	< 0.001
Light	0.324	< 0.001	0.553	< 0.001	0.321	< 0.001	0.543	< 0.001
Rear_end	0.133	0.006	0.319	< 0.001	0.134	0.005	0.318	< 0.001
Peak	-0.090	0.037	-0.178	0.027	-0.093	0.031	-0.183	0.023
ASCS	-	-	-	-	-0.113	0.002	-0.205	0.003
mean.ASCS[c]	-0.443	< 0.001	-0.799	< 0.001	-	-	-	-
mean.Angle[c]	0.330	< 0.001	0.416	0.016	0.331	< 0.001	0.501	< 0.001
S_Difover10[d]	0.127	0.071	0.256	0.055	-	-	-	-
Signal Distance[d]	0.637	0.007	1.081	0.013	-	-	-	-
S.D.Angle[e]	1.030	< 0.001	2.532	< 0.001	1.018	< 0.001	1.369	< 0.001
Log-Likelihood	-4024		-4025		-4030		-4031	
Number of observations	6570		6570		6570		6570	
AIC	8076.28		8078.20		8082.41		8084.15	

a: ROP stands for random-parameter ordered probit model with observed heterogeneity; ROL stands for random-parameter ordered logit model with observed heterogeneity; RP stands for random-parameter ordered probit model; RL stands for random-parameter ordered logit model.

b: estimated threshold in Eq. (12) – (13)

c: mean of the coefficient

d: observed variable used to capture the observed heterogeneity of ASCS

e: standard deviation of the coefficient

As indicated in the previous studies, the AIC difference between two competing models that is greater than 2 (Burnham & Anderson, 2004) or 2.5 (Hilbe, 2011) could be used as a threshold to distinguish different models. Based on the recommendation of these studies, the difference of AIC between two models greater than 2.5 is considered as the threshold to select the preferred models in this study. As indicated in Table B-4, the ROP and ROL models are better than the RP and RL models in terms of AIC. As indicated in Table B-4 (in the last two columns), in terms of AIC, there are no significant differences between the ROP and ROL models, as well as between the RP and RL models.

Table B-4 Model comparison based on AIC difference

	Model comparisons					
	RL VS. ROL*	RP VS. ROP*	RL VS. ROP*	RP VS. ROL*	ROP VS. ROL*	RP VS. RL*
AIC difference	5.95	6.13	7.87	4.21	1.92	1.74
Preferred model (with a lower AIC)	ROL	ROP	ROP	ROL	No significant difference	No significant difference

*: ROP stands for random-parameter ordered probit model with observed heterogeneity; ROL stands for random-parameter ordered logit model with observed heterogeneity; RP stands for random-parameter ordered probit model; RL stands for random-parameter ordered logit model.

In addition to using AIC, a likelihood ratio test (Washington et al., 2020) for comparing nested models (i.e., RL VS. ROL, RP VS. ROP, RL VS. ROP, and RP VS. ROL) is conducted in this study to identify a superior model with better goodness of fit of the model, as shown in Table B-5. The likelihood ratio Chi-squared statistics are statistically significant at a 0.05 significance level, suggesting that the ROP and ROL models are better than the RP and RL models in terms of the goodness of fit of the model. The likelihood ratio tests are not conducted for comparing non-nested models (i.e., ROP VS. ROL and RP VS. RL) as the likelihood ratio test does not apply to compare non-nested models. Based on both AIC (Table B-4) and the likelihood ratio test (Table B-5) findings, the ROP and ROL models are better than the RP and RL models in terms of both the AIC and goodness of fit of the model.

Table B-5 Likelihood ratio test results for nested models

	Model comparisons			
	RL VS. ROL*	RP VS. ROP*	RL VS. ROP*	RP VS. ROL*
Difference of degrees of freedom between two competing models	3	3	3	3
Likelihood ratio Chi-squared statistic	12.28	12.44	14.78	9.94
p-value	0.006**	0.006**	0.002**	0.02 **
Superior model (with better goodness of fit of the model)	ROL	ROP	ROP	ROL

*: ROP stands for random-parameter ordered probit model with observed heterogeneity; ROL stands for random-parameter ordered logit model with observed heterogeneity; RP stands for random-parameter ordered probit model; RL stands for random-parameter ordered logit model.

** statistically significant at a 0.05 significance level.

Since ROL and ROP are compared as non-nested models, the likelihood ratio test does not apply to the comparison of ROL and ROP models. Alternatively, three metrics: precision, recall, and accuracy, which are widely used for evaluating a classification model, are used for evaluating the performance of ROP and ROL models. A training dataset with 80% of the sample and a test dataset with 20% of the sample are obtained. The training dataset and test dataset are randomly sampled. During the sampling, both datasets are ensured to have similar percentages of data points by category (i.e., by crash severity outcomes). The sampling procedure is repeated 30 times (Rahman et al., 2019; Xie et al., 2019). For each time, the model is developed using the training dataset, and then the model is evaluated using the test dataset. The three metrics are evaluated for 30 times, and the results are averaged and presented in Table B-6. The precision and recall are evaluated for each crash severity level (i.e., O, C, or KAB). Also, the overall precision and recall are evaluated by computing the micro-average values of the precision and recall, and the results are shown in Table B-6. A *t*-test is conducted to determine if the means of evaluated metrics for ROP and ROL models are significantly different from each other. In terms of accuracy, overall precision, and overall recall, the ROP model outperforms the ROL model. The results of accuracy, overall precision, and overall recall for ROP and ROL models are significantly different from each other at a 0.05 significance level.

Table B-6 Classification model performance metrics

Model	Accuracy	Precision				Recall			
	Overall	For O Level	For C Level	For KAB Level	Overall (Micro-average)	For O Level	For C Level	For KAB Level	Overall (Micro-average)
ROP#	74.8%**	80.0%	19.1%*	49.5%**	74.8%**	92.5%**	10.5%**	3.9%	74.8%**
ROL#	72.6%**	80.1%	17.8%*	37.5%**	72.6%**	89.1%**	13.5%**	4.3%	72.6%**

#: ROP stands for random-parameter ordered probit model with observed heterogeneity; ROL stands for random-parameter ordered logit model with observed heterogeneity

*: results of ROP and ROL are statistically different at a 0.1 significance level

**: results of ROP and ROL are statistically different at a 0.05 significance level

APPENDIX B-4 MODEL ESTIMATION RESULTS

Since the ROP model is deemed as best based on the discussion in APPENDIX B-3, only ROP model estimation results are discussed here. As shown in Table B-3, the observed heterogeneity of ASCS is estimated by two intersection/corridor-level variables (i.e., S_Difover10 and Signal Distance). Other variables related to intersection features such as the number of legs at an intersection and the number of through/left/right lanes at an intersection are attempted in the model, but these variables are not significant. Other variables related to corridor features such as average AADT on a corridor are tried in the model, but they are not significant.

The coefficient of the ASCS variable is a function of intersection/corridor-level variables (i.e., speed limit difference between a major road and a minor road at an intersection that is equal to or greater than 10 mph or S_Difover10, and average signal distance on a corridor or Signal Distance). Based on the estimation of the coefficient, the coefficient of the ASCS variable in the ROP model can be expressed as,

$$\beta_{ASCS,i} = -0.443 + 0.127(x_{S\_Difover10,i}) + 0.637(x_{Signal\ Distance,i}) \quad \text{(B-7)}$$

where, i is an observation ID (i.e., a specific crash). $x_{S\_Difover10,i}$ is one if the speed limit difference between a major street and a minor street at an intersection is equal to or greater than 10 mph and otherwise is zero. $x_{Signal\ Distance,i}$ is the average signal distance on a corridor.

Figure B-1 to Figure B-3 show observed heterogeneity in terms of coefficient of the ASCS variable estimated by the ROP model, which represents hierarchical effects of ASCS on the crash severity. The hierarchical effects of ASCS on the crash severity represent the ASCS effect varied by intersection and corridor features. Based on Eq. (B-7), two linear functions are plotted in Figure B-1. In Figure B-1, a negative coefficient in the y-axis indicates that the presence of ASCS is associated with lower crash severity, whereas a positive coefficient indicates that the presence of ASCS is associated with higher crash severity. The following observations are derived from Figure B-1:

- In Case 1, where speed limit difference between a major street and a minor street at an intersection (intersection feature) is equal to or greater than 10 mph, the coefficient of ASCS increases as the average signal distance on a corridor increases. When the average signal distance on a corridor (corridor feature) exceeds the threshold of 0.49 miles, the coefficient of ASCS becomes positive, suggesting the presence of ASCS associated with higher crash severity.
- In Case 2, where speed limit difference between a major street and a minor street at an intersection is less than 10 mph, the coefficient of ASCS increases as the average signal distance on a corridor increases. When the average signal distance on a corridor exceeds

the threshold of 0.69 miles, the coefficient of ASCS becomes positive, suggesting the presence of ASCS associated with higher crash severity.

- The threshold of Case 2 is larger than that of Case 1, indicating that when the intersection features are less likely to increase the crash severity level, the larger signal distance on a corridor can be accepted to deploy the ASCS without increasing the probability of higher crash severity.

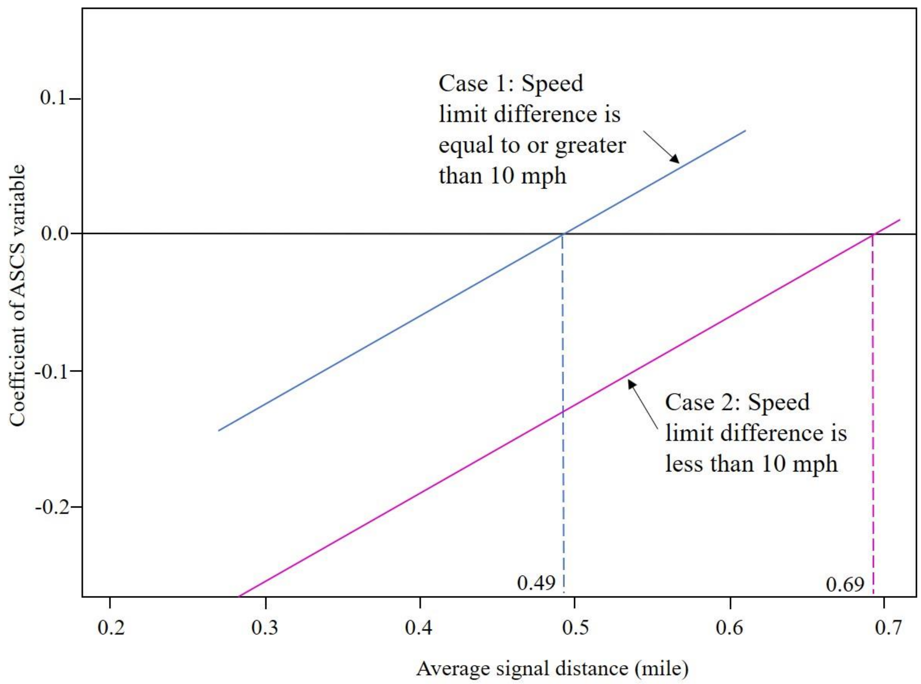


Figure B-1 Coefficient of ASCS VS. average signal distance

Figure B-2 shows the kernel density of conditional means for the coefficient of ASCS. It turns out that the majority (78%) of the conditional means (the unshaded portion in the figure) has negative signs, suggesting the presence of ASCS associated with lower crash severity for most of the observations. It is concluded that the presence of ASCS is associated with lower crash severity.

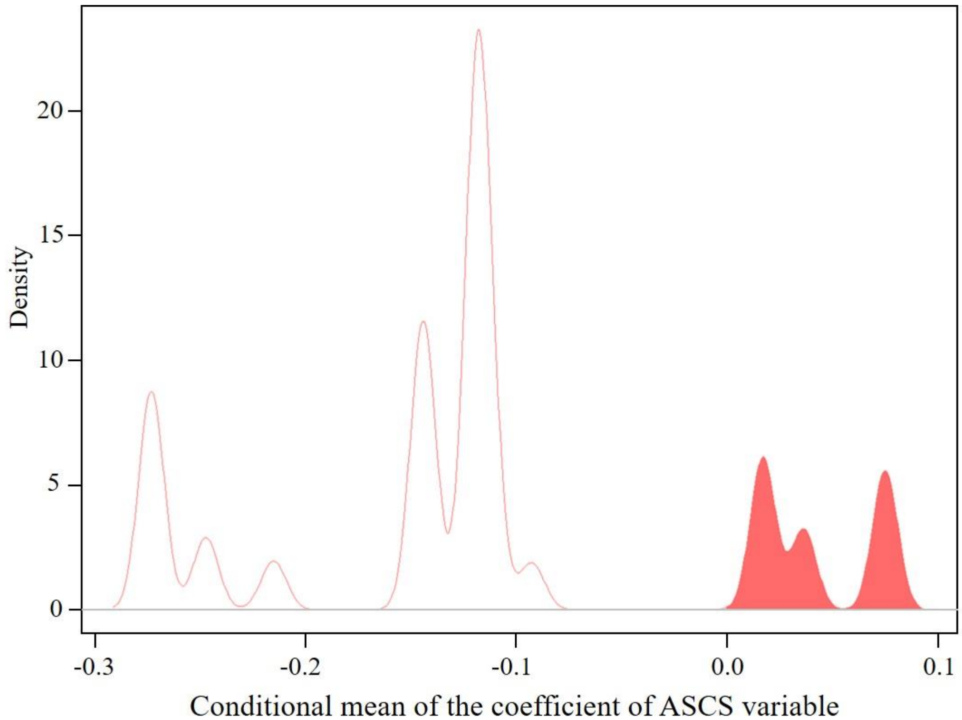


Figure B-2 Kernel density of the conditional means for the coefficient of ASCS variable

Figure B-3 shows 95% confidence intervals for the conditional means of the coefficient of the ASCS variable in the ROP model for observation IDs from 2600 to 2800. The ASCS effect on crash severity varies across different intersections and corridors. In contrast, some crashes have the same ASCS effect since they occurred at a similar intersection (same speed limit difference category) on the same corridor.

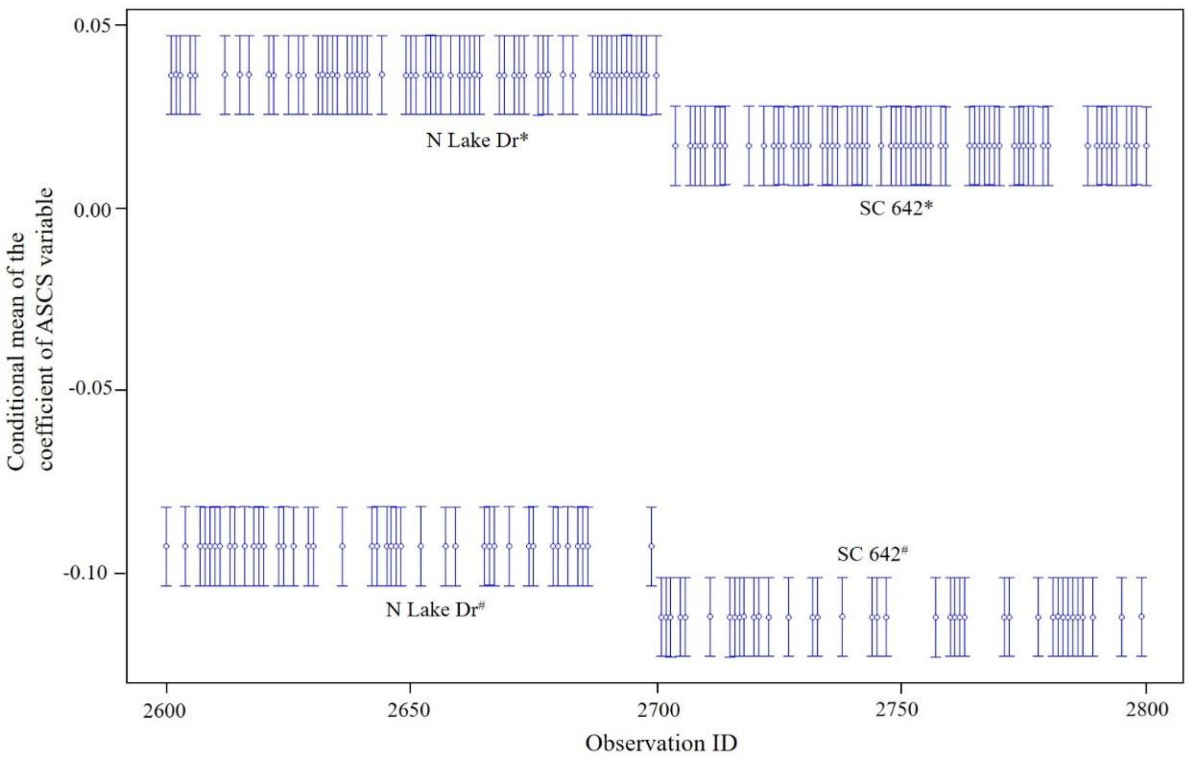


Figure B-3: 95% confidence intervals for the conditional means of the coefficient of the ASCS variable in the ROP model for observation IDs from 2600 to 2800

*: Crashes that occurred at intersections where speed limit difference between major streets and minor streets is equal to or greater than 10 mph

#: Crashes that occurred at intersections where speed limit difference between major streets and minor streets is less than 10 mph

APPENDIX C

SECONDARY CRASH STUDY

APPENDIX C-1 IDENTIFICATION OF SECONDARY CRASHES

The temporal threshold used in this study to identify secondary crashes (i.e., up to 1 hour after a crash occurrence on the freeway) can be justified based on the overall crash detection, response and clearance time in South Carolina. According to Chowdhury et al. (Chowdhury et al., 2007), the incident detection time of Traffic Management Center (TMC) is 1-5 minutes for South Carolina and arrival of the first responder takes 9-10 minutes after that. In addition, according to SCDOT State Highway Emergency Program’s (SCDOT, 2020b) 2019 database (obtained from SCDOT), the average clearance time for Charleston (where the freeways with ASCS deployed on alternate routes are located) is 38.5 minutes and for Richland-Lexington (where the freeways with non-ASCS alternate routes are located) is 38.7 minutes. Therefore, on average we get 48-54 minutes by combining the detection, response and clearance time which is lower than the selected temporal threshold of 1 hour for secondary crash identification. Using this 1-hour temporal threshold, the research team can decide on the spatial threshold for secondary crash identification by observing the relative change in the number of identified secondary crashes as we vary the spatial threshold. Figure C-1 presents the relative change in the number of identified secondary crashes for spatial threshold ranging from 1 mile to 4 miles. As observed from Figure C-1, an increment of the spatial threshold from 2 miles to 2.5 miles causes less than 10% relative change (i.e., less than 10% relative increase) in the number of identified secondary crashes. While increasing the spatial threshold beyond 3 miles can cause this relative change to be lower than 5%, the research team chooses to use a fixed spatial threshold of 2 miles as it makes more sense with SCDOT practitioners as an upper limit for the spatial impact range based on their experience.

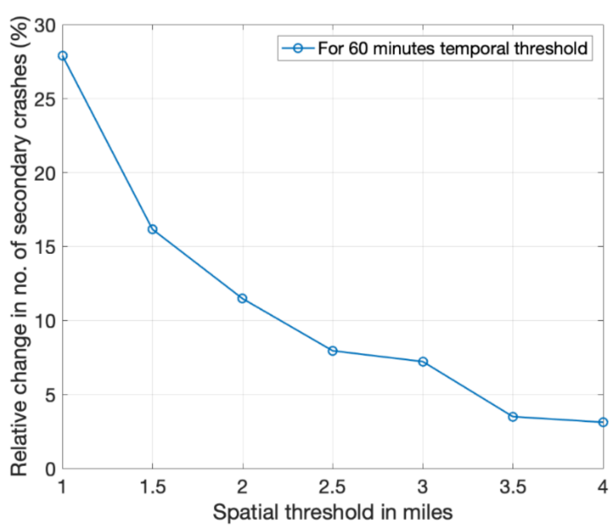


Figure C-1 Relative change in number of secondary crashes with varying spatial threshold

The limitation of using a fixed spatio-temporal criterion is that it may not capture all induced secondary crashes since the impact of some primary crashes on traffic may exceed the predefined spatio-temporal range. Also, this may include some crashes that may have been caused by some other factors. Therefore, the research team utilizes two additional criteria, which are "manner of collision" and "probable cause of collision", after applying spatial and temporal thresholds for filtering the secondary crashes. The rationale behind using these two criteria is to prevent any crashes from being misclassified as secondary crashes that occurred due to some other reasons. To be more specific, if the "manner of collision" for a crash that falls within the spatio-temporal impact range of a primary crash is listed as a "head-on collision", then the research team does not label that crash as a secondary crash. Typically, a head-on collision can occur only between two vehicles traveling in opposing directions. Therefore, crash data related to either one of two vehicles involved in a head-on collision should not be labeled as a secondary crash. Apart from that, the other types of crashes, for example, rear-end, angle, and side-swipe crashes, are not discarded this way because it is not reasonable to assume that these types of crashes cannot be caused by a primary crash's impact. Similarly, if the "probable cause of collision" for a crash that falls within the spatio-temporal impact range of a primary crash is listed as either one of (a) tire/wheel failure, (b) mechanical failure of the vehicle, (c) debris/obstruction or animal on the roadway, and (d) medical related, then the research team deems it reasonable to not label that crash as a secondary crash. Thus, the research team does not label a crash within the spatio-temporal impact range of a primary crash as a secondary crash, only if it is clearly not reasonable to be labeled as a secondary crash. While this information might be subject to police misspecification and reporting practice, the research team could not find any additional means to cross-validate this information. However, the research team observes that after satisfying the spatio-temporal criteria, only a few crashes are not considered as secondary crashes due to their "manner of collision" or "probable cause of collision". For example, for Charleston I-26 E and I-26 W, only 6 out of total 3562 crashes, and for Richland-Lexington I-26, no crashes out of total 3179 crashes are discarded as secondary crashes (after satisfying the spatio-temporal criteria) due to their manner of collision or probable cause of collision. Figure C-2 presents this crash identification procedure with a flow diagram.

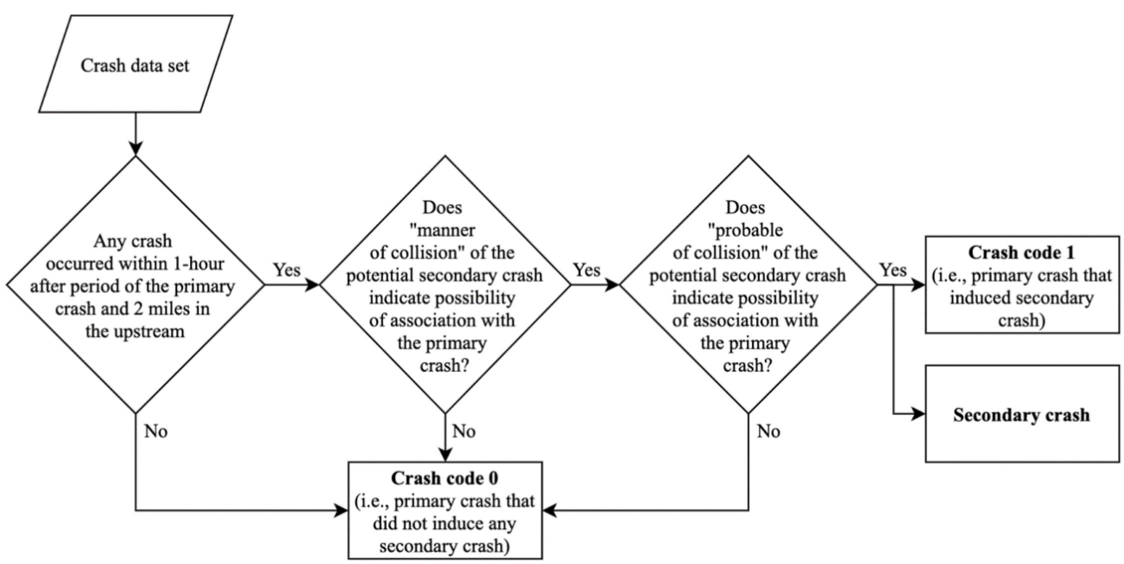


Figure C-2 Crash identification procedure

APPENDIX C-2 MODEL VARIABLES

"Peak period" is used as a predictor for modeling the likelihood of secondary crash occurrences on all the freeway sections. For each freeway section, the research team analyzes the hourly average travel time recorded by ClearGuide (Iteris, 2020) to define corridor-specific peak periods. The research team observes hourly average travel time for weekdays and weekends separately. However, no significant weekend peak periods are detected. Peak periods only exist on weekdays for the freeway sections considered here. Table C-1 presents the corridor-specific weekday peak periods that are considered for logistic regression modeling. Note that, both Charleston I-26 E and Richland-Lexington I-26 E experience AM peak periods as traffic goes in to the center of the cities during this time (Charleston I-26 E goes in to the center of Charleston, and Richland-Lexington I-26 E goes in to the center of Columbia). Similarly, Charleston I-26 W and Richland-Lexington I-26 W experience PM peak periods as traffic comes out of the center of the cities during this time.

Table C-1 Corridor-specific weekday peak periods

Corridor type	**Corridor name**	**Corridor-specific weekday peak period**
Freeways with ASCS deployed on alternate routes	Charleston I-26 E	5:30 AM to 8:30 AM
	Charleston I-26 W	3.00 PM to 6.00 PM
Freeways with non-ASCS alternate routes	Richland-Lexington I-26 E	6.30 AM to 8.30 AM
	Richland-Lexington I-26 W	3.30 PM to 6.30 PM

"After-period indicator for freeways with ASCS deployed on alternate routes" is used as a predictor to investigate the effect of ASCS deployment in the alternate route on the likelihood of freeway secondary crashes. In the models, "after-period indicator for freeways with ASCS deployed on alternate routes" is specified as 1 if a crash occurs in the after period of ASCS deployment, and 0 if a crash occurs in the before period of ASCS deployment. For the freeways with non-ASCS alternate routes, ASCS was not deployed on the alternate routes. The research team still includes a predictor called "after-period indicator for freeways with non-ASCS alternate routes" with same temporal division as the freeways with ASCS deployed on alternate routes in order to examine if the effect of the temporal division (before-after period) differs between the freeways with ASCS deployed on alternate routes and the freeways with non-ASCS alternate routes.

"Temporal trend" variable is included to account for long-term temporal trends in safety due to unobserved factors such as long-term roadway conditions, weather conditions, and improvements in vehicular technologies (Persaud et al., 2010). The "Temporal trend" variable is coded as numerical values. For example, if a crash occurs in 2014, it is specified as 0, if a crash occurs in 2015, it is specified as 1, and so on.

Table C-2 summarizes all the variables that are considered for the analysis of the likelihood of secondary crashes.

Table C-2 Model variables

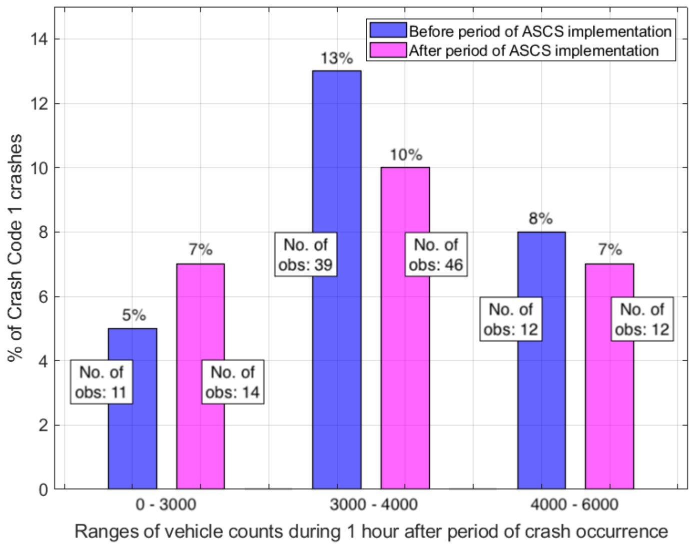
Category	Variable name	Description
Response variable	Crash code	1 – Primary crash that induces secondary crash 0 – Primary crash that does not induce any secondary crash
Explanatory variables	After period indicator	1 – Crash occurs in the after period of ASCS deployment 0 – Crash occurs in the before period of ASCS deployment
	Light condition	1 – Dawn, dusk, dark or limited light 0 – Daylight
	Roadway surface condition	1 – Icy, snowy or wet 0 – Dry
	Weather condition	1 – Adverse weather 0 – otherwise
	Rear end	1 – Primary crash is rear end 0 – otherwise
	Angle crash	1 – Primary crash is angle crash 0 – otherwise
	Weekday	1 – Primary crash occurs on a weekday 0 – otherwise
	Peak period	1 – Primary crash occurs during peak period 0 – otherwise
	Crash severity	Five levels (0, 1, 2, 3, and 4); 0 = no injury, 1 = possible injury, 2 = minor injury, 3 = serious injury, 4 = fatal
	Temporal trend	Numerical values. 0 if a crash occurs in 2014, 1 if a crash occurs in 2015, 2 if a crash occurs in 2016, 3 if a crash occurs in 2017, 4 if a crash occurs in 2018.
	AADT	Numerical values. ln (AADT) is used for scaling down purpose.

APPENDIX C-3 RELATIONSHIP BETWEEN THE LIKELIHOOD OF SECONDARY CRASHS AND TRAFFIC VOLUME AND SPEED

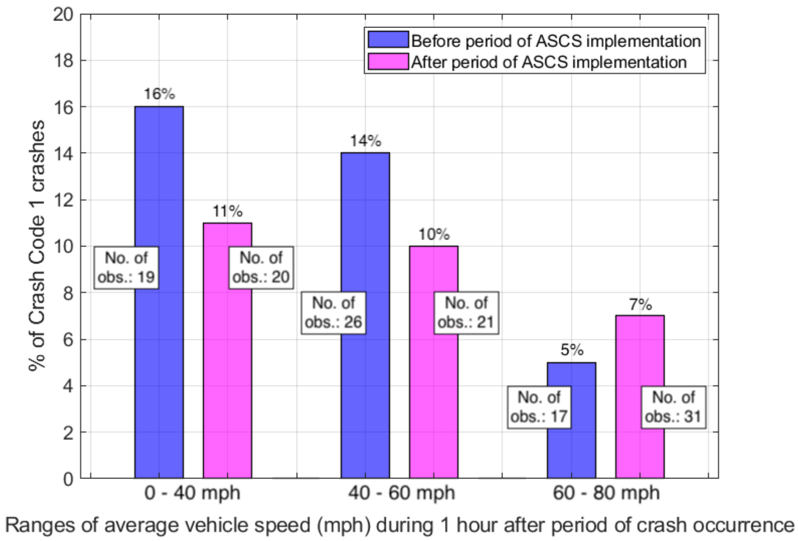
The research team computes the weighted average traffic count and speed on the freeway for the one-hour after period of each crash occurrence based on the hourly traffic count and speed data collected from SCDOT Traffic Polling and Analysis System. The weighted average of traffic count and speed is computed in the same way as the weighted average travel time computation explained in subsection “6.2.2 Verification of Alternate Routes”.

In Figure C-3, the research team presents two bar charts that present the percentages of “Crash code 1” (i.e., crashes that induced secondary crashes) across various ranges of traffic counts and speed on the freeway during the one-hour after period of a freeway crash occurrence. For each range shown in Figure C-3(a) and Figure C-3(b), two separate bars are used to show the percentages of “Crash code 1” during the before period and the after period of ASCS implementation. In Figure C-3(a), the research team combines vehicle counts during the one-hour after period of freeway crash occurrences ranging from 0 to 3000 vehicles/hour into one bar and from 4000-6000 vehicles/hour into another bar because of small number of observations. Therefore, three ranges can be considered for Figure C-3(a); lower range (i.e., 0-3000 vehicles/hour), mid-range (i.e., 3000-4000 vehicles/hour), and upper range (i.e., 4000-6000 vehicles/hour). As observed from Figure C-3(a), first of all, no consistent positive or negative trend is found between the percentages of “Crash code 1” and varying ranges of traffic counts during the one-hour after period of freeway crash occurrences; the maximum percentage of “Crash code 1” is found for the mid-range (i.e., 3000-4000 vehicles/hour). Second, lower percentages of “Crash code 1” during the after period of ASCS implementation compared to the before period of ASCS implementation are found for middle (i.e., 3000-4000 vehicles/hour) and upper ranges (i.e., 4000-6000 vehicles/hour). Therefore, it can be concluded that the favorable effect of ASCS found for Charleston I-26 E is not contributed by reduced exposure or low traffic counts on the freeway (i.e., traffic counts on the freeway can be lower than usual as the freeway drivers start to take the alternate route after a crash occurrence on the freeway).

However, in Figure C-3(b), it is observed that there is a negative or downward trend between the percentages of “Crash code 1” and the ranges of average vehicle speed during the one-hour after period of freeway crash occurrences. While it is pretty much intuitive for primary crashes that increased speed on the freeway could cause higher percentage of primary crashes (Abdel-Aty et al., 2007), the same cannot be stated with confidence for secondary crashes. It is to be noted that, secondary crashes are caused due to sudden congestion/queue on the freeway because of sudden lane blockage or disturbance in the traffic flow caused by a primary crash on the freeway. Thus, higher average speed on the freeway during the one-hour after period of a freeway crash occurrence indicates less impact due to that crash. On the contrary, lower average speed on the freeway during the one-hour after period of a freeway crash occurrence indicates higher disturbance caused by that crash which would increase the risk for a secondary crash.



(a)



(b)

Figure C-3 Bar charts showing percentages of crash code 1 across ranges of (a) traffic counts and (b) average speed on the freeway during the one-hour after period of freeway crash occurrences

To validate this further, the research team also performs a separate logistic regression modeling (as shown in Table C-3) utilizing the traffic counts and average speed information during the one-hour after period of freeway crash occurrences as continuous variables. As the "traffic counts" variable is not found significant at a 0.1 significance level, the research team omits it and other insignificant variables from the model presented in Table C-3 in order to obtain a better fit. It should be mentioned that these two variables were not used in the models presented earlier in this study because the traffic counts and average speed information is not available for all the crashes. The research team found that, the traffic counts and average speed information is available for about 95% of the crash data considered for Charleston I-26 E. However, just for the sake of investigating if there is any relationship between the likelihood of secondary crashes and traffic counts or average speed during the one-hour after period of freeway crash occurrences, the available data can be considered sufficient. As shown in Table C-3, the "Speed" variable (i.e., average speed on the freeway during the one-hour after period of a freeway crash occurrence) is found to be significant at a 0.05 significance and it has a negative coefficient which further validates that as the average speed on the freeway is higher during the one-hour after period of a freeway crash occurrence, the likelihood of secondary crash occurrence is lower (same as concluded based on Table C-3(b)). Therefore, the research team concludes that the favorable effect of ASCS found for Charleston I-26 E in terms of reducing the likelihood of secondary crashes is not a contribution of reduced crash exposure (i.e., lower freeway traffic counts after a crash occurrence) or reduced speed on the freeway.

Table C-3 Estimates of logit model using speed as an explanatory variable (for Charleston I-26 E)

Predictors	Coefficients:	
	Estimate	**Pr(>|z|)**
(Intercept)	-507.5	0.061*
Rear-end	0.911	5.02e-05**
After-period indicator of ASCS deployment	-0.588	0.089*
Temporal trend	0.239	0.075*
Speed	-0.021	2.80e-04**
log(AADT)	1.810	6.56e-04**

'*' statistically significant at a 0.1 significance level

'**' statistically significant at a 0.05 significance level

APPENDIX C-4 RANDOM-PARAMETER LOGISTIC REGRESSION MODEL ESTIMATION AND RESULTS

In the random-parameter binary logit model, $\boldsymbol{\beta}_i$ is allowed to be varying for each observation i rather than fixed for all observations. The distribution, $g(\boldsymbol{\beta}_i \mid \boldsymbol{\theta})$ is specified to enable $\boldsymbol{\beta}_i$ vary across each individual observation, where $\boldsymbol{\theta}$ is a vector of the mean and variance of a random distribution.

$\boldsymbol{\beta}_i$ can be written as $\boldsymbol{\beta}_i = \boldsymbol{\beta} + \mathbf{L}\boldsymbol{\omega}_i$, where $\boldsymbol{\beta}$ is the vector of the mean of coefficients. Note that, each coefficient can be written as $\beta_{ki} = \beta_k + \sigma_k \omega_i$. β_{ki} is k^{th} element in $\boldsymbol{\beta}_i$. $\boldsymbol{\omega}_i$ is a vector of random variables that follow random distributions. $\mathbf{L}$ is a diagonal matrix that contains the standard deviations of the coefficients, σ_k. In this study, β_{ki} is considered to follow a normal distribution, which is specified as $\beta_{ki} \sim N(\beta_k, \sigma_k^2)$. The normal distribution specification for β_{ki} provides a better model fit, compared to other possible distibutions such as log normal distibution based on our analysis.

To explore the unobserved heterogeneity of the parameters (i.e., coefficients in the model) across observations, conditional mean of parameters is estimated. The estimator of the conditional mean of the random parameters (Sarrias, 2016) is obtained by Simulated Maximum likelihood (SML) procedure, which is expressed as:

$$\hat{E}(\boldsymbol{\beta}_i \mid data_i) = \sum_{r=1}^{R} \left(\frac{\hat{P}(y_i \mid \mathbf{X}_i, \boldsymbol{\beta}_{ir})}{\sum_{r=1}^{R} \hat{P}(y_i \mid \mathbf{X}_i, \boldsymbol{\beta}_{ir})} \right) \hat{\boldsymbol{\beta}}_{ir} \tag{C-1}$$

where, $\hat{\boldsymbol{\beta}}_{ir} = \hat{\boldsymbol{\beta}} + \hat{\mathbf{L}}\boldsymbol{\omega}_{ir}$; y_i is the response variable (1 if seconary crash occurred; 0 otherwise). $data_i$ stands for explanatory variables associated with each observation. $\hat{P}(\mathbf{y_i} \mid \mathbf{X_i}, \boldsymbol{\beta}_i)$ is the estimated simulated probablity for the observation i evaluated at the r^{th} random draw of $\boldsymbol{\beta}_i$; R is the total number of random draws in the SML procedure. In the estimation of conditional mean of paramter, a Halton random number generator with a standard uniform distribution, $U(0,1)$ generates the random draws. Detail Halton draws procedure can be found in (Sarrias, 2016).

The SML procedure is conducted to obtain the model estimation results using the "Rchoice" library in the R software. 100 Halton draws are used in the SML procedure for the purpose of model estimation (Sarrias, 2016). Likelihood ratio test is used to compare the performance between random-parameter models and fixed-parameter models (Washington et al., 2020).

The estimations of random-parameter logistic model for Charleston I-26 E is presented in Table C-4. The random-parameter model explains the variability in the effect of ASCS deployment (i.e., ASCS deployment variable) across observations and provides more significant parameters over the fixed-parameter model (e.g., angle crash variable becomes significant in the random-parameter model). Although the weekday variable is not significant in the random-parameter model, it is still kept since keeping the weekday variable reduces the AIC value and improves the overall goodness of fit of the model as observed in our analyses. The likelihood ratio test suggests that the random-parameter model improves the overall goodness of fit of the model compared to the fixed-parameter model, as shown in Table C-5. The standard deviation associated with the presence of ASCS (i.e., S.D. ASCS) is statistically significant at a 0.05 significance level, indicating the presence of unobserved heterogeneity across observations.

As indicated in Table C-4, the random parameter of ASCS follows a normal distribution with a mean of -2.305 and a standard deviation of 2.351. Since the parameter of ASCS follows the normal distribution, it is estimated that 84% of all observations have a negative coefficient associated with the presence of ASCS in a corridor, suggesting an association between the presence of the ASCS deployed on the alternate route and the reduction of the likelihood of secondary crashes on the parallel freeway. For the remaining 16% of all observations, the coefficients associated with the presence of ASCS deployed on the alternate route are positive, suggesting an association between the presence of the ASCS on the alternate route and the increase of the likelihood of freeway secondary crashes.

Table C-4 Results of model estimation for Charleston I-26 E with ASCS deployed on alternate route

Predictors	**Coefficients**			
	Fixed-parameter model		**Random-parameter model**	
	Estimate	**Pr (>|z|)**	**Estimate**	**Pr (>|z|)**
Constant	-26.209	1.73E-05 **	-31.396	6.73e-05 **
Temporal trend	0.265	0.0439 **	0.3230	0.0433 **
Rear end	0.802	0.001 **	1.087	0.002 **
Angle crash	0.679	0.117	0.959	0.082*
Weekday	-0.370	0.302	-0.628	0.168

Predictors	Coefficients			
	Fixed-parameter model		Random-parameter model	
	Estimate	Pr (>|z|)	Estimate	Pr (>|z|)
Peak period	0.916	8.63E-06 **	1.107	3.06E-05 **
log(AADT)	1.916	0.0002 **	2.334	0.0003**
Mean. ASCS	-0.631	0.063*	-2.305	0.06*
S.D. ASCS	NA	NA	2.351	0.0247**

'**' statistically significant at a 0.05 significance level

'*' statistically significant at a 0.1 significance level

'NA' not available for the fixed-parameter model

Table C-5 Likelihood ratio tests results

	Degree of freedom	Log-likelihood	Difference of degrees of freedom	Chisq	Pr(>Chisq)
Fixed-parameter model	8	-450.22			
Random-parameter model	9	-448.53	1	3.3736	0.066*

'*' statistically significant at a 0.1 significance level

Figure C-4 shows the kernel density of the individual's conditional means for the coefficient of ASCS. It turns out that the majority of the individual's conditional means (the unshaded portion in Figure C-4) has negative signs, suggesting the presence of ASCS associated with reductions of the likelihood of the secondary crashes for most of the observations.

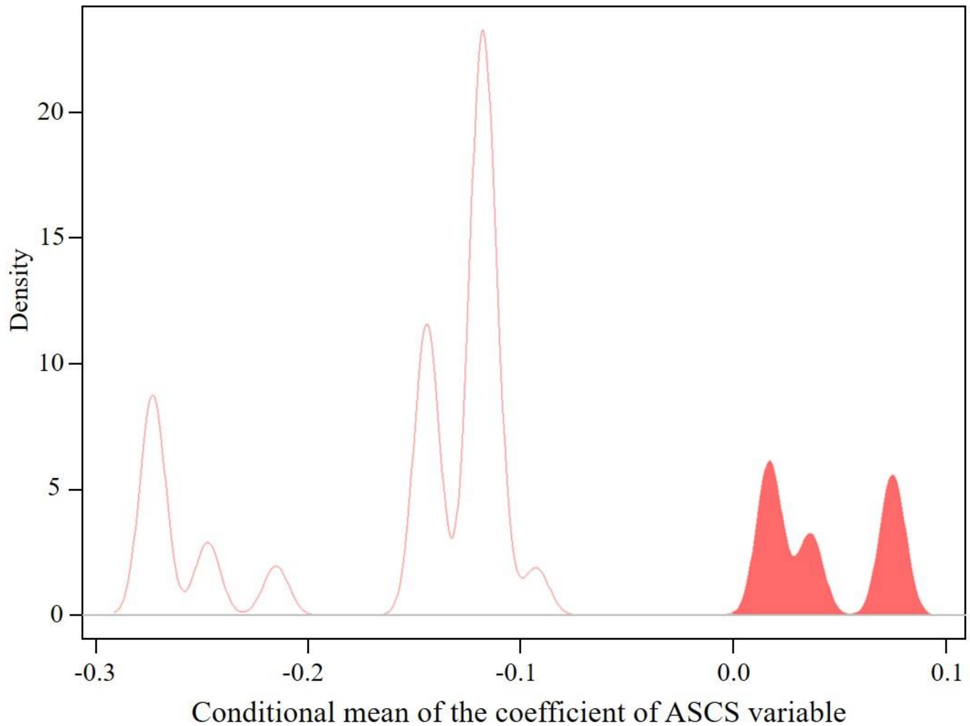


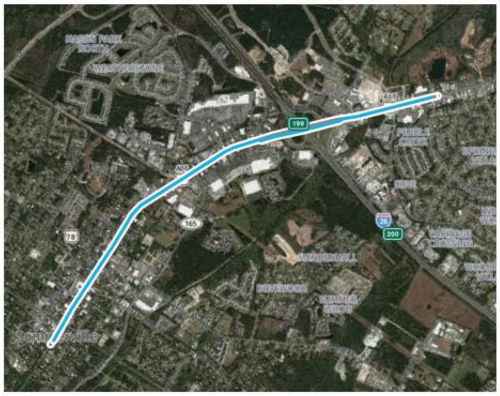
Figure C-4 kernel density of the individual's conditional means for the coefficient of ASCS (Charleston I-26 E with ASCS deployed on alternate route US 52)

APPENDIX D

OPERATIONAL EVALUATION STUDY

APPENDIX D-1 RESULTS FOR EACH ASCS CORRIDOR

- US 17A in Summerville
- 12 signalized intersections
- Average Travel Time = 7.3 mins
- Coordinated with SynchroGreen since June 2015



Results for Eastbound:

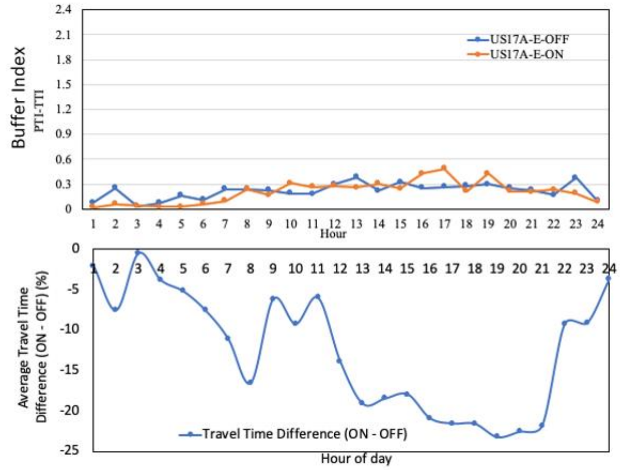
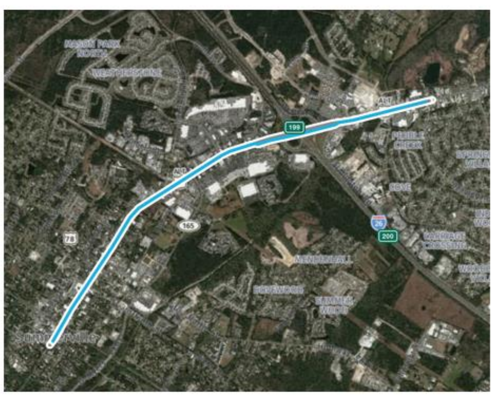


Figure D-1 Operational analysis results for US 17A eastbound

- US 17A in Summerville
- 12 signalized intersections
- Average Travel Time = 8.1 mins
- Coordinated with SynchroGreen since June 2015



Results for Westbound:

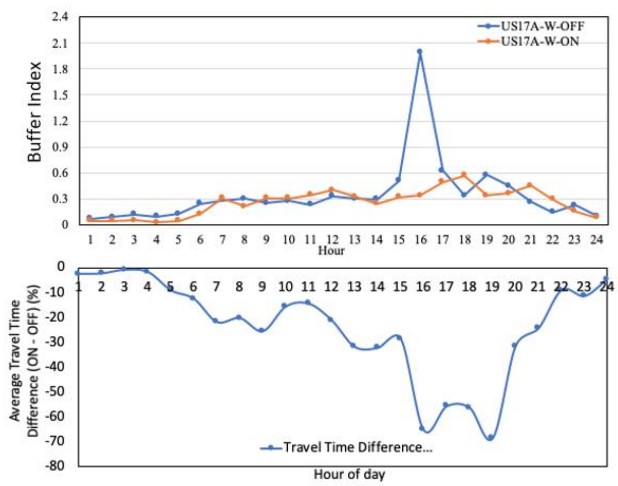
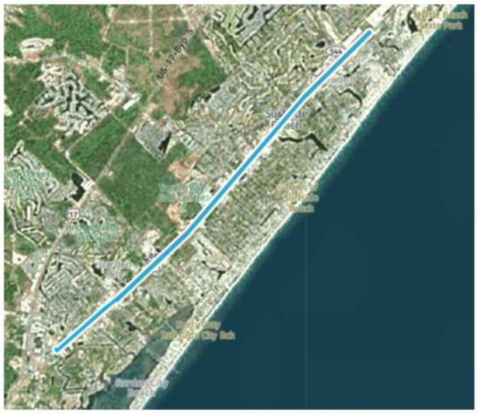


Figure D-2 Operational analysis results for US 17A westbound

- US 17 Business in Garden City/Surfside
- 9 signalized intersections
- Average Travel Time = 8.9 mins
- Coordinated with SynchroGreen since March 2017



Results for Eastbound:

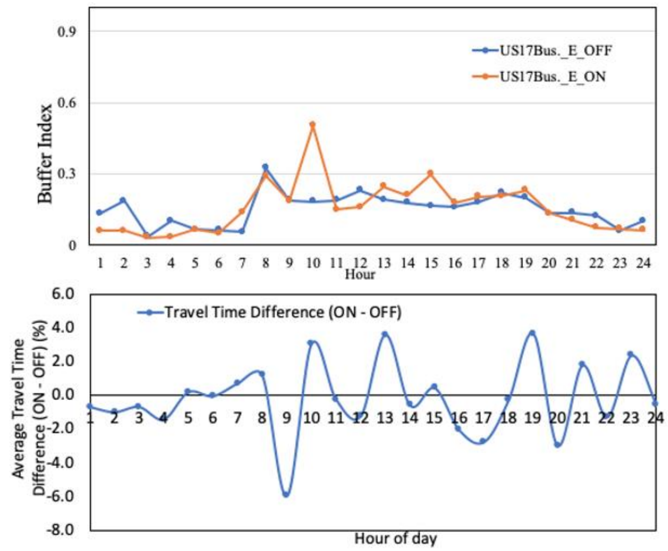
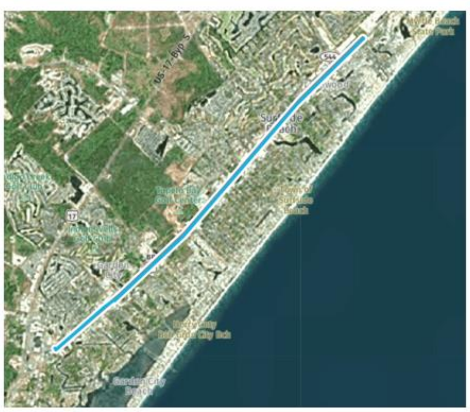


Figure D-3 Operational analysis results for US 17 Business eastbound

- US 17 Business in Garden City/Surfside
- 9 signalized intersections
- Average Travel Time = 9 mins
- Coordinated with SynchroGreen since March 2017



Results for Westbound:

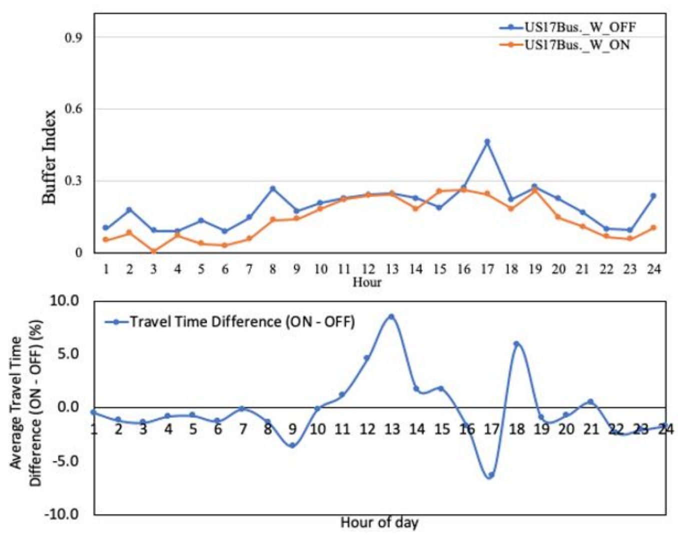


Figure D-4 Operational analysis results for US 17 Business westbound

- US 52 in Charleston
- 17 signalized intersections
- Average Travel Time = 9.0 mins
- Coordinated with SynchroGreen since October 2016

Results for Eastbound:

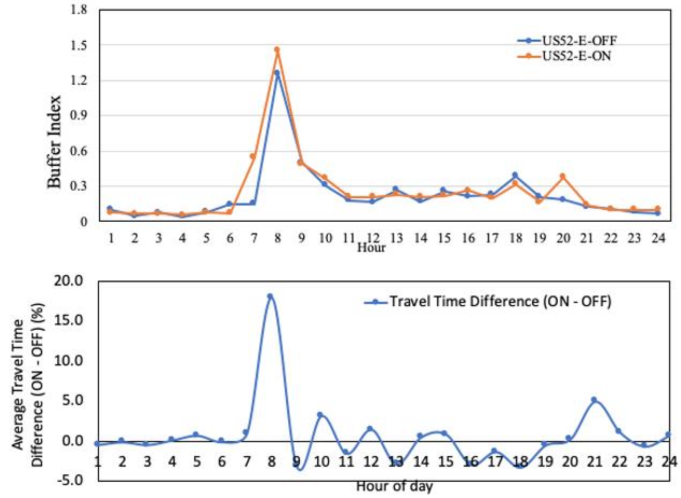


Figure D-5 Operational analysis results for US 52 eastbound

- US 52 in Charleston
- 17 signalized intersections
- Average Travel Time = 9.3 mins
- Coordinated with SynchroGreen since October 2016

Results for Westbound:

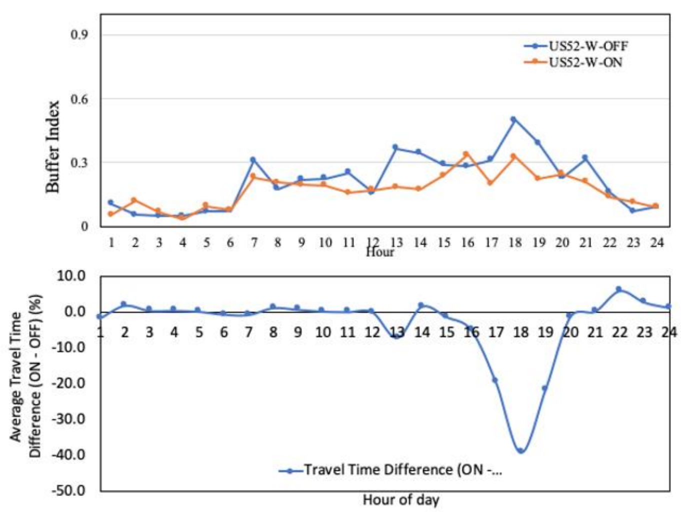


Figure D-6 Operational analysis results for US 52 westbound

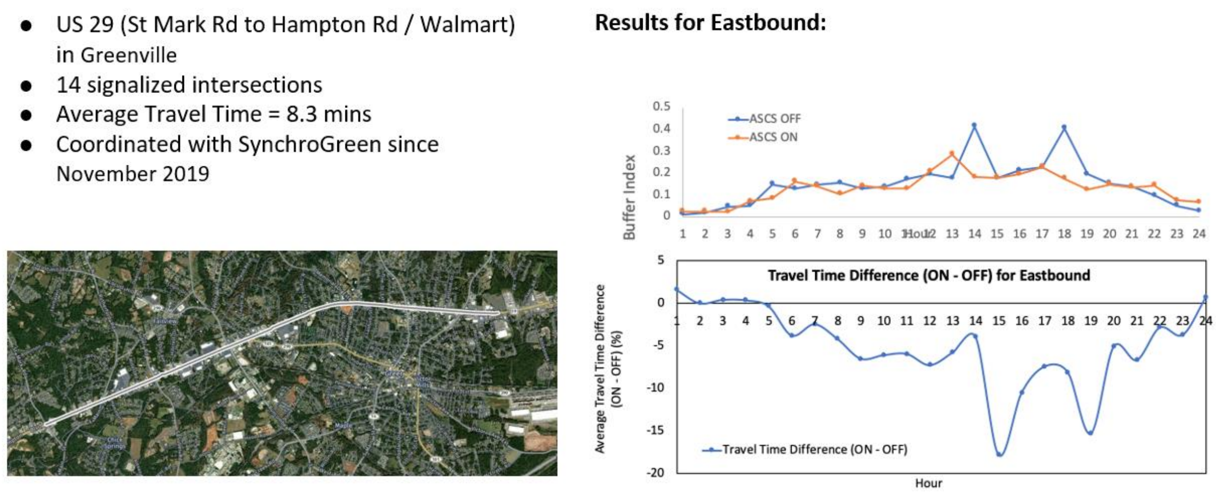


Figure D-7 Operational analysis results for US 29 (St Mark Rd. to Hampton Rd.) eastbound

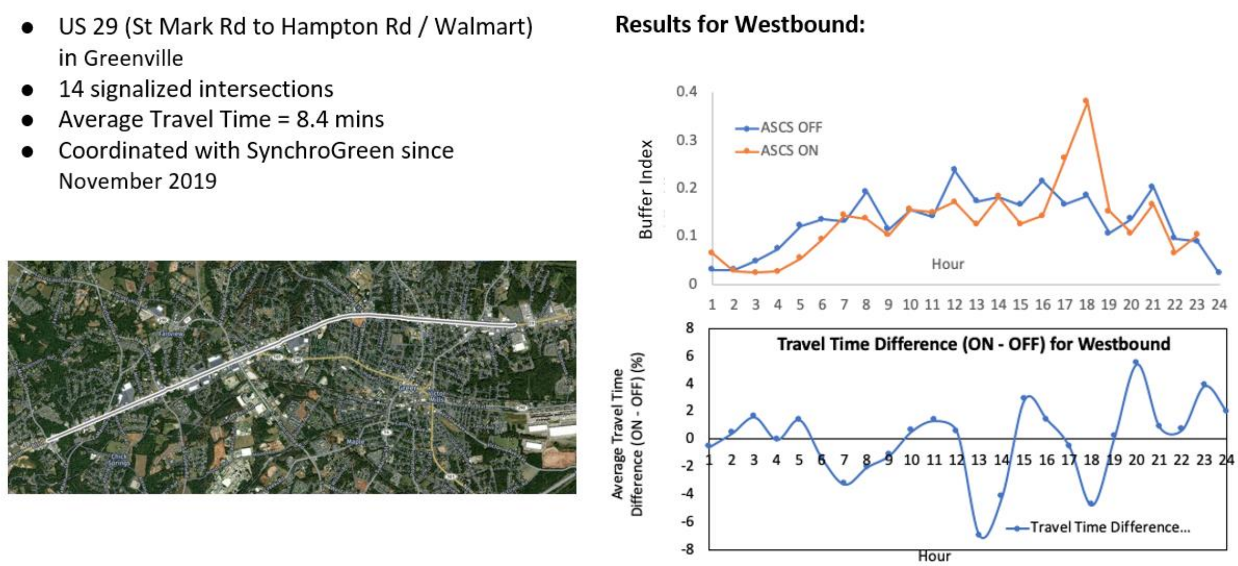


Figure D-8 Operational analysis results for US 29 (St Mark Rd. to Hampton Rd.) westbound

- US 29 (Groce Rd to J Verne Smith Parkway) in Greenville
- 5 signalized intersections
- Average Travel Time = 4.7 mins
- Coordinated with SynchroGreen since December 2019

Results for Eastbound:

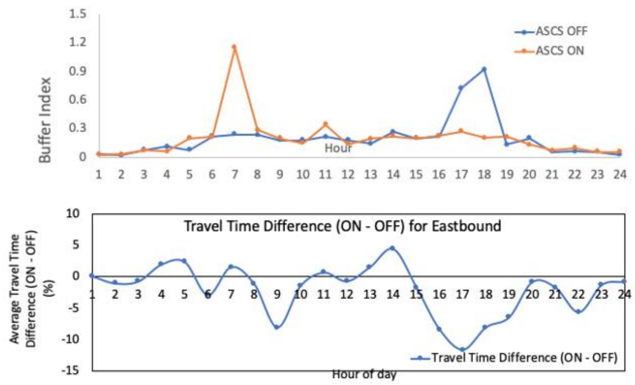


Figure D-9 Operational analysis results for US 29 (Groce Rd. to J. Verne Smith Parkway) eastbound

- US 29 (Groce Rd to J Verne Smith Parkway) in Greenville
- 5 signalized intersections
- Average Travel Time = 4.4 mins
- Coordinated with SynchroGreen since December 2019

Results for Westbound:

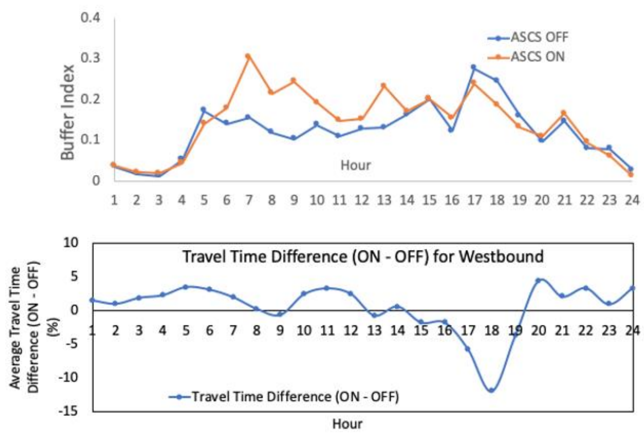
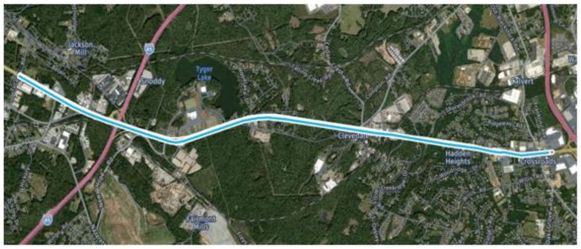


Figure D-10 Operational analysis results for US 29 (Groce Rd. to J. Verne Smith Parkway) westbound

- US 29 (Franklin Ave to Tucapau) in Greenville
- 6 signalized intersections
- Average Travel Time = 7.3 mins
- Coordinated with SynchroGreen since December 2019



Results for Eastbound:

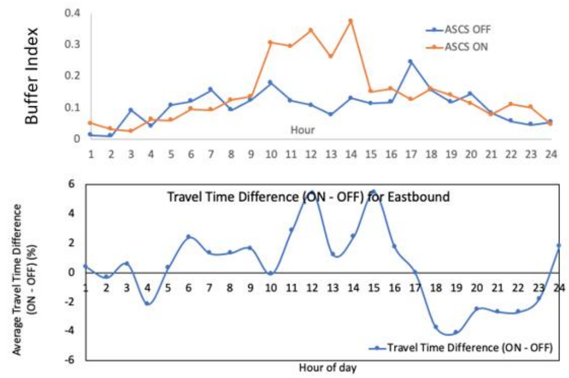
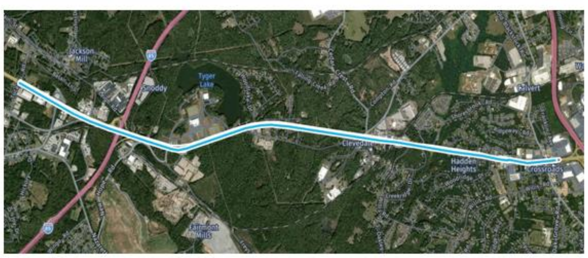


Figure D-11 Operational analysis results for US 29 (Franklin Ave. to Tucapau) eastbound

- US 29 (Franklin Ave to Tucapau) in Greenville
- 6 signalized intersections
- Average Travel Time = 7.2 mins
- Coordinated with SynchroGreen since December 2019



Results for Westbound:

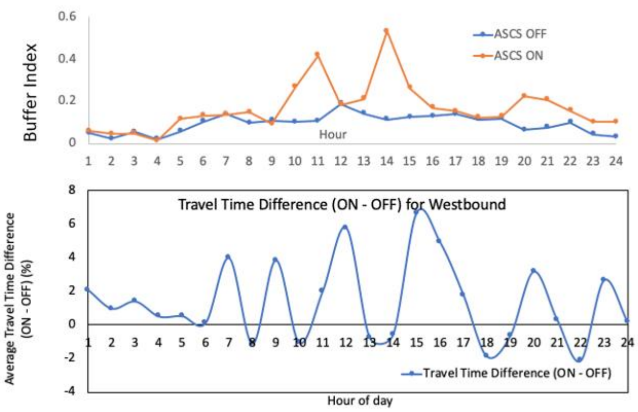


Figure D-12 Operational analysis results for US 29 (Franklin Ave. to Tucapau) westbound

- US 123 in Clemson
- 3 signalized intersections
- Average Travel Time = 2 mins
- Coordinated with SynchroGreen since November 2019

Results for Eastbound:

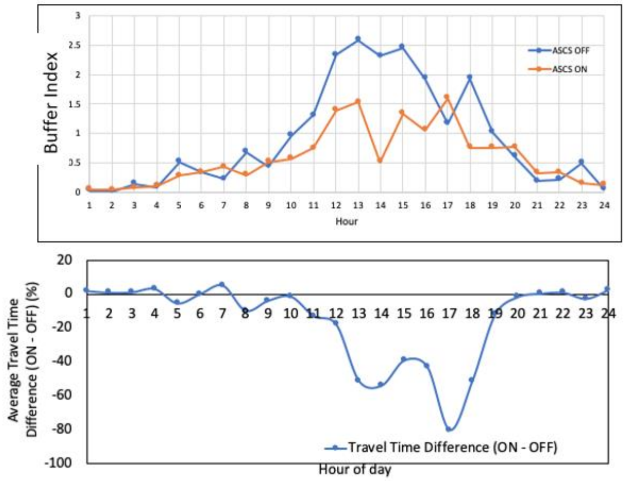


Figure D-13 Operational analysis results for US 123 eastbound

- US 123 in Clemson
- 3 signalized intersections
- Average Travel Time = 2.2 mins
- Coordinated with SynchroGreen since November 2019

Results for Westbound:

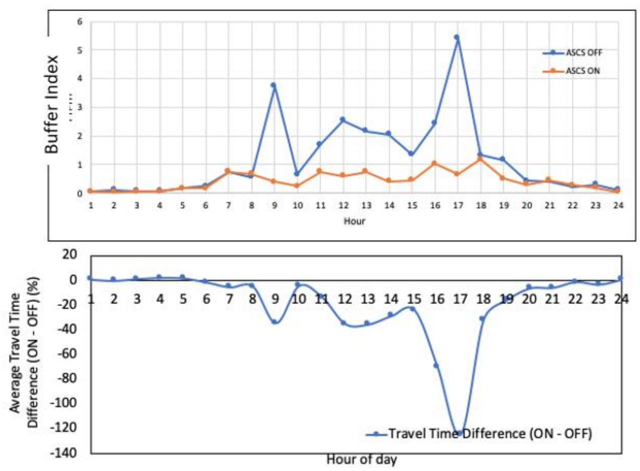


Figure D-14 Operational analysis results for US 123 westbound

- College Ave in Clemson
- 3 signalized intersections
- Average Travel Time = 1.3 mins
- Coordinated with SynchroGreen since November 2019

Results for Northbound:

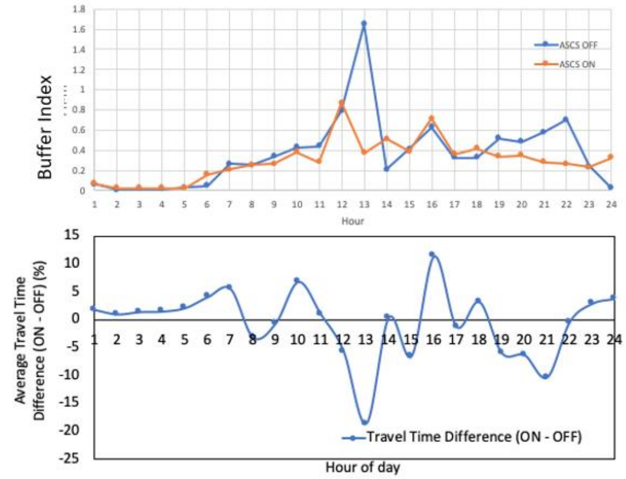


Figure D-15 Operational analysis results for College Ave. northbound

- College Ave in Clemson
- 3 signalized intersections
- Average Travel Time = 2.0 mins
- Coordinated with SynchroGreen since November 2019

Results for Southbound:

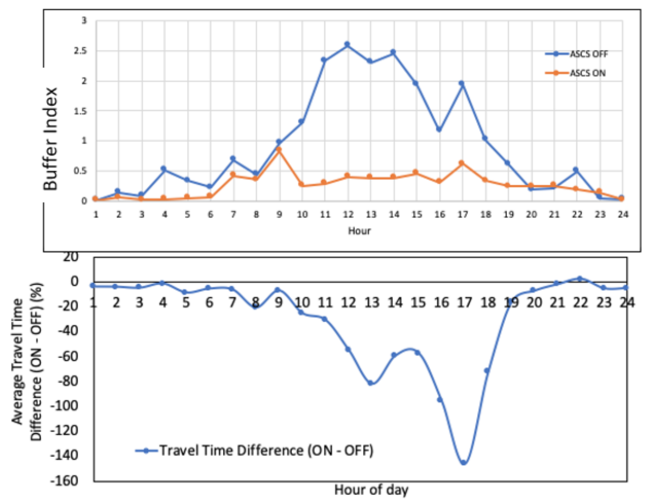


Figure D-16 Operational analysis results for College Ave. southbound

- US 378 in Lexington
- 10 signalized intersections
- Average Travel Time = 3.4 mins
- Coordinated with SynchroGreen since October 2019

Results for Eastbound:

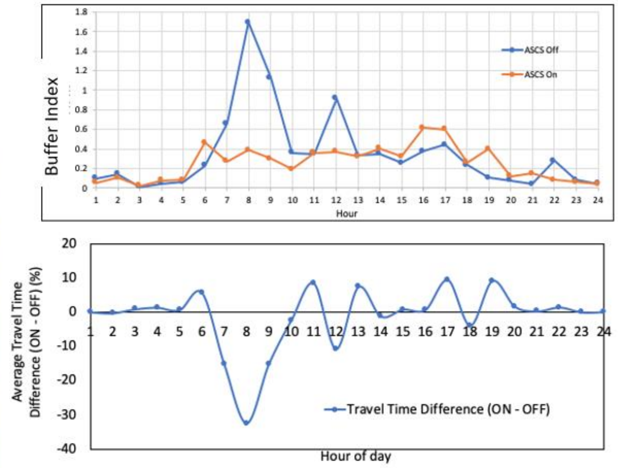


Figure D-17 Operational analysis results for US 378 eastbound

- US 378 in Lexington
- 10 signalized intersections
- Average Travel Time = 3.8 mins
- Coordinated with SynchroGreen since October 2019

Results for Westbound:

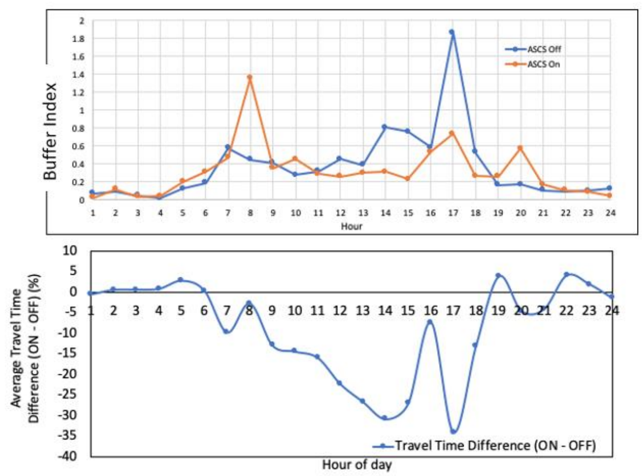


Figure D-18 Operational analysis results for US 378 westbound

- SC 642 in Charleston
- 18 signalized intersections
- Average travel time = 13.9 mins
- Coordinated with SynchroGreen since June 2015

Results for Eastbound:

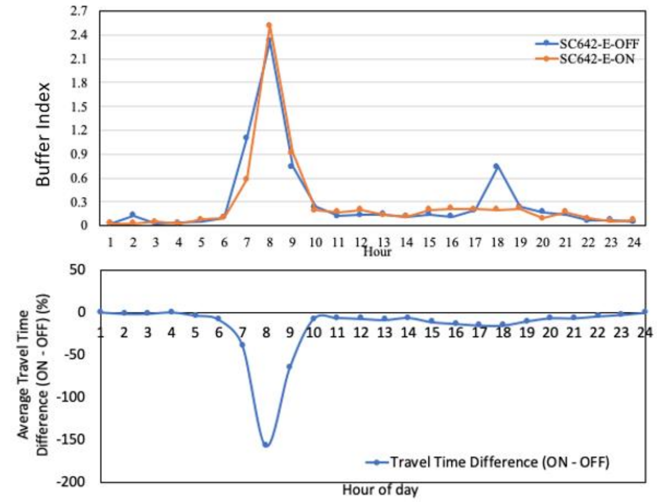


Figure D-19 Operational analysis results for SC 642 eastbound

- SC 642 in Charleston
- 18 signalized intersections
- Average travel time = 14.9 mins
- Coordinated with SynchroGreen since June 2015

Results for Westbound:

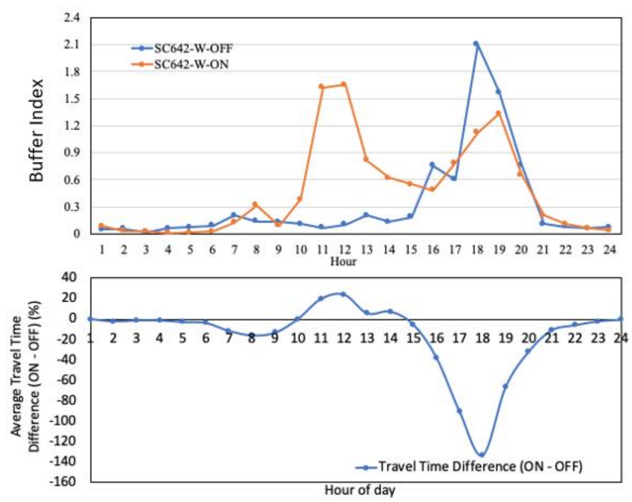


Figure D-20 Operational analysis results for SC 642 westbound

- US 17 in Pawleys Island
- 6 signalized intersections
- Average travel time = 5.5 mins
- Coordinated with SynchroGreen since February 2016

Results for Westbound:

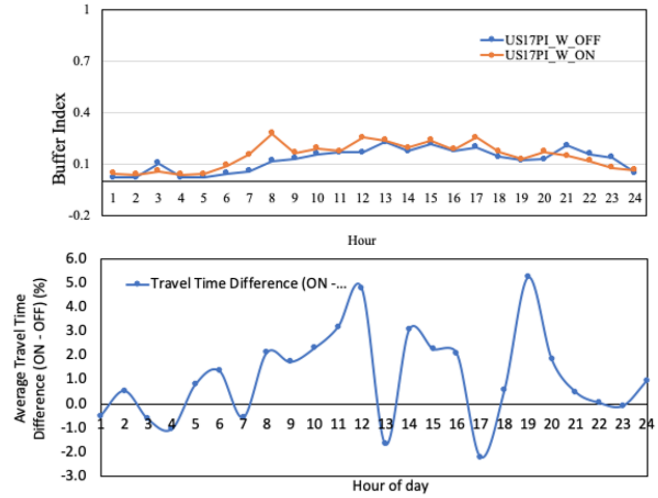


Figure D-21 Operational analysis results for US 17 westbound

- US 17 in Pawleys Island
- 6 signalized intersections
- Average travel time = 5.6 mins
- Coordinated with SynchroGreen since February 2016

Results for Eastbound:

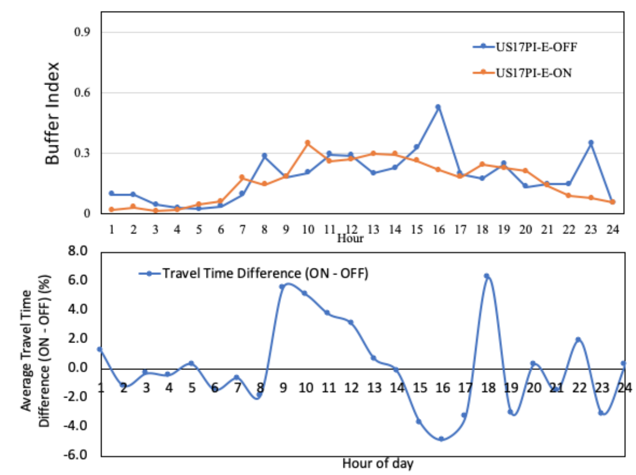


Figure D-22 Operational analysis results for US 17 eastbound