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Estimating safety effects of adaptive signal control technology using the Empirical Bayes method

Zulqarnain H. Khattak, [a,*] Mark J. Magalotti, [b] Michael D. Fontaine [c]

[a] Center for Transportation Studies, Department of Civil and Environmental Engineering, Thornton Hall D101, 351 McCormick Road, University of Virginia, Charlottesville, VA 22904, United States
[b] Center for Sustainable Transportation Infrastructure, Department of Civil and Environmental Engineering, 706 Benedum Hall, University of Pittsburgh, Pittsburgh, PA 15213, United States
[c] Virginia Transportation Research Council, 530 Edgemont Rd., Charlottesville, VA 22903, United States

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ABSTRACT

Introduction: Adaptive signal control technology (ASCT) has long been investigated for its operational benefits, but the safety impacts of this technology are still unclear. The main purpose of this study was to determine the safety effect of ASCT at urban/suburban intersections by assessing two different systems. *Method:* Crash data for 41 intersections from the Pennsylvania Department of Transportation (PennDOT), along with crash frequencies computed through Safety Performance Functions (SPFs), were used to perform the Empirical Bayes (E-B) method to develop crash modification factors (CMF) for ASCT. Moreover, a crash type analysis was conducted to examine the safety impact of ASCT on a regional scale and the variation of safety among type of crashes observed. *Results:* The results from this study indicated the potential of ASCT to reduce crashes since the Crash Modification Factor (CMF) values for both ASCT systems (SURTRAC and InSync) showed significant reductions in crashes. Average CMF values of 0.87 and 0.64 were observed for total and fatal and injury crash categories at a 95% confidence level, and results were consistent between systems. While a reduction in the proportion of rear end crashes was observed, the change was not determined to be statistically significant. The overall distribution of crash types did not change significantly when ASCT was deployed. *Conclusion and practical application:* The results indicate that safety benefits of ASCT were generally consistent across systems, which should aid agencies in making future deployment decisions on ASCT.

1. Introduction

Adaptive Signal Control Technology (ASCT) is an Intelligent Transportation System (ITS) technology developed to optimize cycle lengths, green times, and/or phasing sequences for traffic signals based on changing traffic volumes collected from advanced detectors (Sussman, 2008). Since ASCT optimize signal timing plans in real time, it is expected to reduce traffic congestion and improve traffic safety, particularly when traffic conditions are highly variable. Before the emergence of ASCT, traffic engineers were limited to using Time-of-Day (TOD) timing plans, which are a set of signal-timing plans that run on a specified schedule for multiple hour time periods during specific days of the week. Because these predetermined TOD timing plans cannot accommodate variable and unpredictable traffic demands within those particular time periods, the control delay of traffic signals may increase with the passage of time until those outdated signal timing plans are retimed. ASCT adjusts signal timings and phasing scenarios in real time. This helps to accommodate the changing traffic demand and patterns observed at a particular intersection over time. Past studies have shown that ASCT can improve traffic signal operations by reducing stops and delays (Khattak, Fontaine, & Boateng, 2018), which in turn can improve traffic safety (Stevanovic, 2010).

Traffic safety is one of the major concerns for transportation engineers throughout the world. According to FHWA (2015), an average of one-quarter of traffic fatalities and roughly half of all traffic injuries in the United States are attributed to intersections. While the operational benefits of ASCT have been proven (Tian, Ohene, & Hu, 2011), the safety impacts of ASCT is an area which has not been investigated. Furthermore, since there are many vendors of ASCT systems that optimize signal operations differently, there are questions as to whether different systems may produce differing safety effects. This paper assesses whether ASCT creates safety benefits, and whether those benefits are similar across different systems.

2. Literature review

In recent years, adaptive signal control technology systems have become more widespread, and a significant amount of academic research has been conducted on ASCTs. The safety effects of traffic signal installation are well-established in the literature, but the impact of how the signal is operated has not been thoroughly studied. For example, the safety

* Corresponding author.
E-mail addresses: zk6cq@virginia.edu (Z.H. Khattak), mjm25@pitt.edu (M.J. Magalotti), Michael.Fontaine@VDOT.Virginia.gov (M.D. Fontaine).

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impact of a new traffic signal installation was examined by Sacchi, Sayed, and El-Basyouny (2016), who found that traffic signal installation reduces crashes by 21.8% for severe crashes and 10.2% for non-severe crashes. The study results suggested incorporation of spatial effects to consider variation of safety benefits from one site to another for before and after studies.

Scant literature is available regarding the safety benefits of adaptive traffic control systems. Lodes and Benekohal (2013) evaluated ASCT through an online survey of 62 agencies that had implemented the system in the United States. The researchers conducted a cost benefit analysis using crash data from three intersections and found statistically insignificant crash reductions. Rhythm Engineering (2010) studied the InSync adaptive signal system through a simple observational before and after crash data analysis on different corridors and found reductions in the total number of crashes. For example, Highway 71 in Arkansas showed a 30% reduction in crashes using a one year before and after evaluation from 2009 to 2010.

Similarly, Dutta, Bodke, Dara, and Lynch (2010) analyzed intersection and segment crash data before and after installation of the Sydney Coordinated Adaptive Traffic System (SCATS). They observed a shift in crash severity from A (incapacitating injury) and B (visible injury) to C (possible injury), but statistical tests were not able to identify any significant difference at a 95% confidence level. Fink, Kwigizile, and Oh (2016) studied the safety benefits of the SCATS system in Oakland County, Michigan using a cross sectional analysis. Multinomial logit models of injury severity revealed that SCATS reduced angle crashes by 19.3%, with a statistically significant increase in non-serious injuries and no significant reduction in incapacitating injuries or fatal crashes. Similarly, Ma, Fontaine, Zhou, Hale, and Clements (2015) used an Empirical Bayes (E-B) before and after analysis for 47 urban/suburban ASCT intersections in the state of Virginia to calculate CMFs for ASCT. That study found a reduction in both total and fatal + injury crashes, with CMFs of 0.83 and 0.92 for total and fatal and injury crashes, respectively. That study only examined one type of ASCT system (InSync), and used limited after deployment data. The study was later published as Ma et al. (2016).

A few studies used simulation techniques to assess safety benefits of ASCT. Kergaye and Haigwood (2011) compared real world data from two sites in Utah to relevant safety surrogate measures from microsimulation to find correlations between the two datasets. They concluded that SCATS generated fewer rear end and total conflicts than traditional signalized traffic control and that field crashes increased as a consequence of road construction activities, not the ASCT. Similarly, Shahdah, Saccomanno, and Persaud (2015) used a VISSIM microsimulation to develop a statistical relationship between traffic conflicts (an event involving two or more vehicles approaching each other that may lead to collision) estimated from simulation and observed crashes at signalized intersections to evaluate safety performance. The researchers concluded that countermeasure effects can be estimated reliably from conflicts derived from microsimulation when a suitable number of simulation runs and conflict tolerance thresholds are used to create the crash-conflict relationship. The study was only able to prove the validity of using the relationship to evaluate safety performance and did not estimate the accuracy of crash estimates. Sabra, Gettman, Henry, and Nallamothu (2010) and Sabra, Gettman, Henry, and Nallamothu (2013) also developed a crash prediction method using field data from ASCT and actuated signals, but after training the network with around 150 signal timing scenarios, the crash prediction method produced an average conflict prediction error of 17%. Most other researchers (Chilukuri, Perrin, & Martin, 2004; Kergaye, Stevanovic, & Martin, 2010; Tian et al., 2011) analyzed ASCT only for its operational benefits.

As a result, there is limited literature available on the safety benefits of ASCT. Past studies have suffered from limited data, did not use robust analytical techniques to assess safety, or relied primarily on simulation based estimates of safety. This paper fills this gap in literature through using a rigorous Empirical Bayes before-after evaluation and crash type proportions analysis to assess the safety effect of multiple ASCT systems. Up to five years of post-activation ASCT data were analyzed, and performance of two different types of ASCT (InSync and SURTRAC) was examined in order to determine safety benefits associated with these systems. The findings of this research could help agencies to estimate and realize the reduction in crashes that would occur after deploying these systems at intersections.

3. Objectives and scope

This study was conducted to provide a rigorous evaluation of ASCT safety benefits utilizing a large amount of after deployment data to develop crash modification factors. This study built on the previous literature to help answer the following questions:

1) How did deployment of ASCT affect intersection safety?
2) Do safety benefits vary based on type of ASCT deployed?
3) Does urban or suburban location have any influence on safety benefits of ASCT?
4) Does intersection configuration impact safety effects of ASCT?
5) Does the distribution of crash type change following ASCT installation?

ASCT safety effects were evaluated using national safety performance functions. Crash modification factors (CMFs) were developed using only multivehicle crashes. Single vehicle and pedestrian crashes were excluded since they represented a very small proportion of the total number of crashes. Pedestrian crashes were only 2% of the total crashes in both the before and after period while single vehicle crashes were only 4% and 5% of total crashes in the before and after period. Since crash counts were so much smaller for these crash types, it would have been much more difficult to generate statistically significant CMFs for

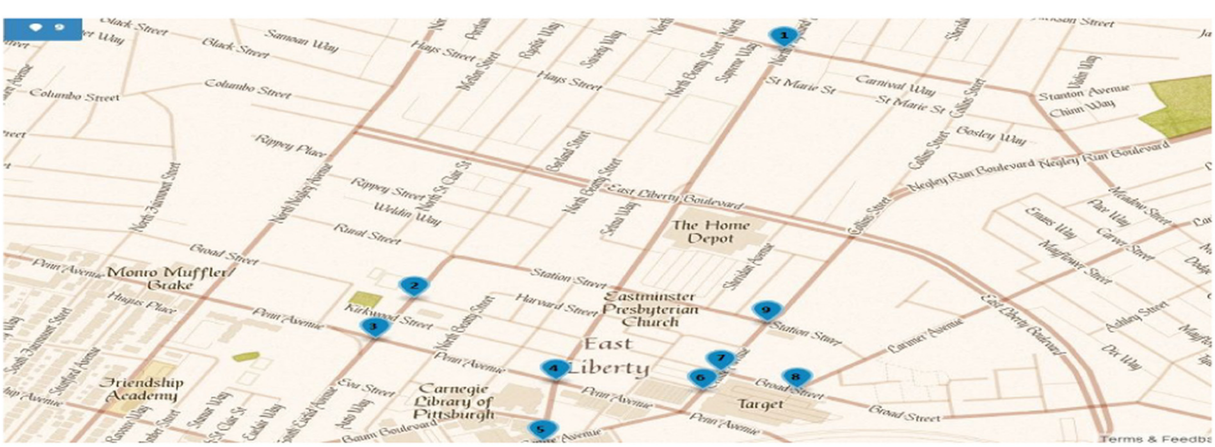

Fig. 1. Allegheny County East Liberty Intersections, City of Pittsburgh Pennsylvania.

Fig. 2. Montgomery County Intersections, Montgomery Township Pennsylvania.

pedestrian and single vehicle crashes. As a result, they were excluded from the analysis. This study analyzed two different types of ASCT systems (SURTRAC and InSync) to assess whether they had similar safety benefits, although both optimize signal timings using different algorithms. SURTRAC uses real time data mainly collected from radar and video cameras along with other vehicle sensors, such as stop bar detectors and advance detectors for traffic far from intersection. These sensors are used to develop a schedule driven approach while looking at each intersection individually to optimize signal timings second by second over an extended horizon. Optimization is based on minimizing waiting time, travel time and environmental pollution (Smith, Barlow, Xie, & Rubinstein, 2013). InSync uses real-time data collected through 4 video detection cameras at each intersection to select signalization parameters such as state, sequence, and amount of green time to best service the prevailing conditions second by second. Optimization is based on minimizing the overall delay and reducing stops (Rhythem Engineering, 2017). While the optimization approach differs, it is unclear whether the different systems produce differing safety impacts. Knowledge on the degree of similarity in safety impact among disparate systems could be beneficial to agencies seeking to invest in ASCT.

4. Data description

The data collection was a critical step for this research. Data requirements for the Empirical Bayes method include crash data, average annual daily traffic (AADT), and geometric and traffic control characteristics of the treated intersections. After reviewing all of the intersections where ASCT was currently installed throughout the state of Pennsylvania, those systems and intersections that had a significant amount of after ASCT deployment crash data available were selected for this study. A minimum of two years of crash data after ASCT deployment was used to select sites. The selected locations included the East Liberty section of Pittsburgh (9 intersections), Montgomery Township (20 intersections), and Upper Merion Township (12 intersections). The 9-intersection system in Pittsburgh (Khattak, Magalotti, Miller, & Fontaine, 2017) was deployed with SURTRAC ASCT, and had two lanes in each direction of travel along with on-street parking at certain places, which limited the through traffic to one lane. The 9-intersection corridor in Pittsburgh had an average AADT of 25,605 and a speed limit of 25 mph. Both the Montgomery Township and Upper Merion Township systems were deployed with InSync ASCT. The Montgomery Township corridor had two lanes of travel in each direction with an average AADT of 26,414 and a speed limit of 45 mph, while the Upper Merion Township corridor had two lanes of travel in each direction, an average AADT of 28,089, and a speed limit of 40 mph. The locations of all the selected intersections are shown in Figs. 1 to 3.

After selecting the study intersections, crash data were then collected from the Pennsylvania Department of Transportation (PennDOT). The nine intersections in the East Liberty Section of Pittsburgh City had two years of before and five years of after crash data. The 20 intersections in Montgomery County, Pennsylvania had four years of before and three years of after crash data, and the 12 intersections in the Upper Merion region had four years of before and three years of after deployment crash data. Crashes within 350 ft. of the intersection were regarded as intersection crashes.

Similarly, another important data requirement for Empirical Bayes safety analysis is the Average Annual Daily Traffic (AADT) of the major and minor road. AADTs were collected from PennDOT's Internet Traffic Management (iTMS) website for the before period, while the AADT data for after deployment period was collected from Highway Performance Monitoring System (HPMS) shapefiles of Pennsylvania, available at the Federal Highway Administration (FHWA) website. A huge challenge was to transform AADT data for before period from one year to another since the iTMS website had AADT data only for specific years. To overcome this, AADT was projected from one period in time to another

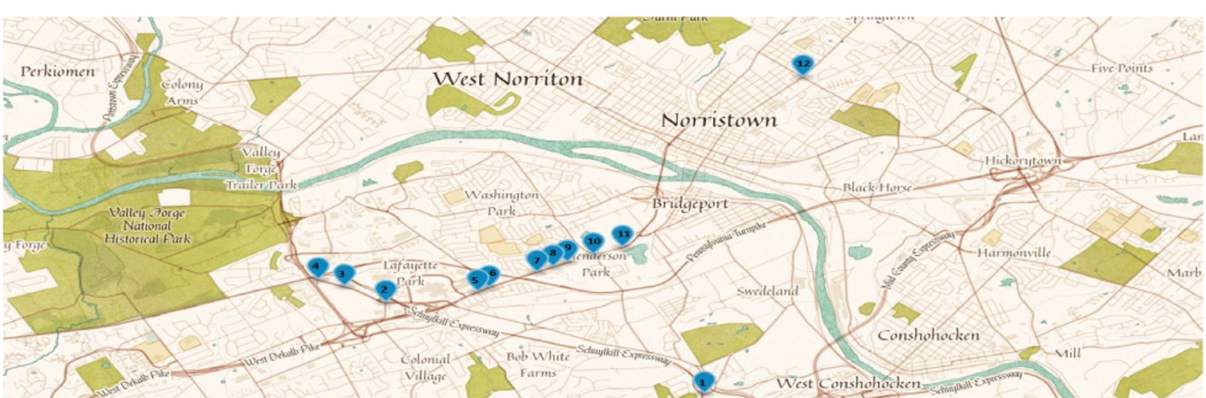

Fig. 3. Montgomery County Upper Merion Intersections, Upper Merion Township Pennsylvania.

Table 1
Average annual characteristics of study sites.

Region	Variable	Before deployment				After deployment			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
East Liberty (SURTRAC) Intersections	Total crashes	9.33	6.85	1	7	2.89	3.33	0	5
	Fatal and injury crashes	3.33	2.34	0	2	1.45	1.50	0	2
	$AADT_{maj}$	18,790	6,670	3,148	29,340	18,988	7,096	3,164	32,947
	$AADT_{min}$	4,755	1,794	1,224	6,690	4,966	1,715	1,230	6,630
Montgomery Township (InSync) Intersections	Total crashes	11.57	10.67	0	18	9.79	8.23	0	11
	Fatal and injury crashes	5.53	5.20	0	8	5.13	4.71	0	8
	$AADT_{maj}$	24,658	12,505	8,239	51,833	24,436	12,393	8,165	61,581
	$AADT_{min}$	7,380	5,412	900	19,849	7,111	5,410	1000	18,472
Upper Merion (InSync) Intersections	Total crashes	7.5	6.09	0	8	4.08	2.84	0	4
	Fatal and injury crashes	5.83	4.63	0	6	3.08	2.23	0	4
	$AADT_{maj}$	31,340	7,421	19,175	38,662	31,059	7,355	19,003	38,315
	$AADT_{min}$	6,313	4,124	1,332	14,076	6,257	4,087	1,320	13,950

using PennDOT growth rates for various classifications of highways and establishing a growth trend from the available HPMS data. This was done by selecting the applicable growth factors maintained by PennDOT and establishing a growth trend based on their comparison to HPMS data. The value for growth rate established for each year was multiplied by the available AADT to estimate future year AADTs. The characteristics of the intersections including number of left turn lanes, left turn signal phasing, intersection right turn lanes, usage of right turn on red, intersection lighting, and presence of red light cameras was collected by visually observing the intersections on Google Earth. The descriptive statistics of the data set for the three deployment regions are provided in Table 1.

5. Methodology

The Empirical Bayes (E-B) predictive method prescribed in Highway Safety Manual (AASHTO, 2010) was used to estimate the crash modification factors for ASCT. The Empirical Bayes method was selected because it is considered be much more reliable and rigorous than other methods since it takes observed crash frequency into account and combines it with long term expected crash frequencies calculated through the use of statistical models (safety performance functions). The E-B method eliminates regression to the mean (RTM) bias associated with traditional crash rate and frequency based safety evaluation methods. A similar Empirical

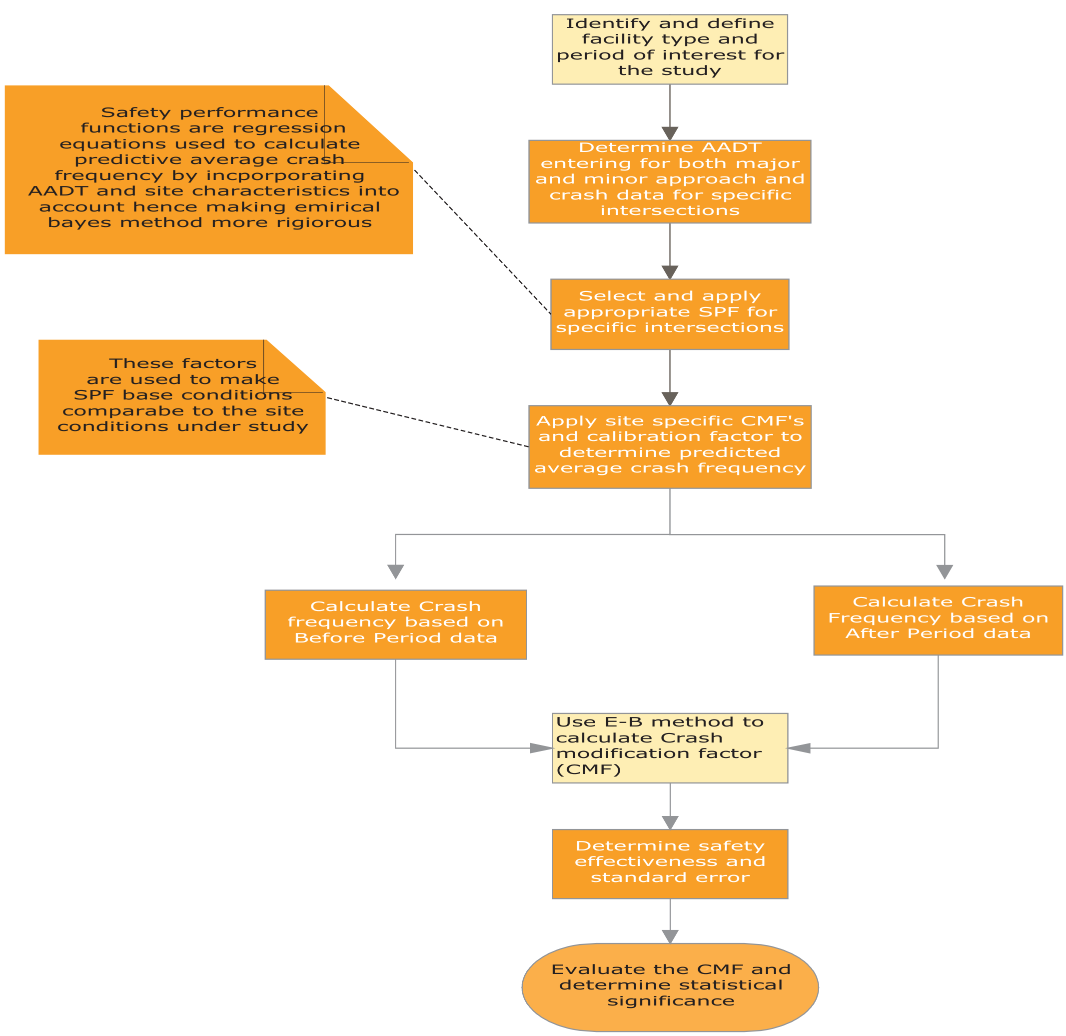

Fig. 4. Flow chart for Empirical Bayes method to determine CMF for ASCT.

Table 2
National safety performance functions for multivehicle crashes at urban/suburban intersections from Highway Safety Manual (AASHTO, 2010).

Type of intersection	Crash severity	Safety performance functions (SPF)	Over-dispersion parameter (k)
4-Legged signalized	Total	$\exp(-10.99 + 1.07 * \ln(AADT_{maj}) + 0.23 * \ln(AADT_{min}))$	0.39
	Fatal + injury	$\exp(-13.14 + 1.18 * \ln(AADT_{maj}) + 0.22 * \ln(AADT_{min}))$	0.33
3-Legged signalized	Total	$\exp(-12.13 + 1.11 * \ln(AADT_{maj}) + 0.26 * \ln(AADT_{min}))$	0.33
	Fatal + injury	$\exp(-11.58 + 1.02 * \ln(AADT_{maj}) + 0.17 * \ln(AADT_{min}))$	0.30

Bayes before and after evaluation was used by Høye (2015) and Ahmed and Abdel-Aty (2015) for estimating the safety benefits of fixed speed and red light running cameras and found statistically significant reduction in crashes. Similarly, Wood, Donnell, and Porter (2015) compared CMF's for total crashes and run off the road crashes using Empirical Bayes before/after, cross sectional and propensity scores potential outcomes and found that all three methods yielded the similar results, with E-B providing results having lowest standard errors hence, suggesting that E-B should be used as a preferred method of analysis when it is both possible and practically feasible. The three basic assumptions of Empirical Bayes method include (Hauer, 1997): (a) the number of crashes at any site follows the Poisson distribution, (b) the mean of a population can be approximated by a gamma distribution, (c) changes from year to year unaccounted for factors are similar for all reference sites. All the above-mentioned assumptions and data requirements were satisfied. The procedure used to conduct the E-B analysis is shown in Fig. 4.

After collecting relevant data and classifying the study intersections as urban/suburban, the predicted average crash frequencies for both before and after period were estimated using Safety Performance Functions (SPF); which are negative binomial regression models developed using sites with pre-defined base conditions. The SPFs for Pennsylvania were still in developmental stages during this research, so national SPFs from the Highway Safety Manual were utilized and calibrations and adjustment factors were applied to make the conditions of study intersections comparable to the base conditions used for developing national SPFs. The general SPF equation is given by Eq. (1), while the national SPFs used are shown in Table 2. In this study, only SPFs for multivehicle crashes were examined since the crash counts for single vehicle and pedestrian crashes were much smaller to generate significant CMFs. As a result, those crashes were removed from the data set.

$$N_{spf} = \exp(a + b * \ln(AADT_{maj}) + c * \ln(AADT_{min})) \quad (1)$$

$AADT_{maj}$ and $AADT_{min}$ refer to major and minor street AADT. The equations in Table 2 were calculated annually using the appropriate major and minor road AADT at each site. Once the SPFs for specific intersections were selected, they were adjusted for deviation of HSM base conditions using the CMFs from Highway Safety Manual and calibrated to achieve the most reliable estimates shown in Eq. (2). The readers interested in more detailed explanation of the methodology are encouraged to refer to AASHTO (2010) and Khattak (2016).

$$N_{predicted(b)} = N_{spf} * (CMF_{1x} * CMF_{2x} * \ldots\ldots * CMF_{yx}) * C_x \quad (2)$$

where N_{spf} is the SPF equation, CMF_{yx} represents the crash modification factors used from the HSM to adjust for deviations from base conditions.

Table 3
CMFs for presence of left and right turn lanes.

Type of turn lanes	# of legs	Number of approaches with right or left turn lanes			
		One	Two	Three	Four
Right turn	3	0.96	0.92	–	–
	4	0.96	0.92	0.88	0.85
Left turn	3	0.93	0.86	0.80	–
	4	0.90	0.81	0.73	0.63

The base conditions established by the HSM include absence of left and right turn lanes, right turn on red permitted on all approaches, absence of lighting, and permitted left turn phasing. CMFs were multiplied with predicted crash frequency N_{spf} obtained from SPFs. The values for CMFs were taken from HSM Tables 12–24 to 12–26 and are shown in Tables 3 and 4 and Eqs. (3) and (4) below.

The number of approaches with left or right turn lanes at a particular intersection were checked using Google Earth, and the applicable CMF for 3-leggged or 4-legged intersection was applied from Table 3 (HSM Table 12–24 and 12–26).

Similarly, the CMF for left turn phasing was selected from Table 4 (HSM Table 12–25) according to the type of turn phasing provided at each intersection. The base condition is permissive left turn phasing with CMF = 1.

The CMF for right turn on red prohibition was calculated using Eq. (3), where n_{proh} stands for number of approaches on which right turn on red was prohibited. The base condition here refers to permitted right turn on red on all approaches of a signalized intersection.

$$CMF_{right\ turn} = CMF = 0.98^{n_{proh}} \quad (3)$$

Similarly, the CMF for the effect of presence of lighting on roadway was calculated using Eq. (4). p_{night} stands for proportion of night time crashes at each intersection, which was calculated using the number of night time crashes in the observed crash data. The base condition is the absence of lighting.

$$CMF_{lighting} = 1 - 0.38 * p_{night} \quad (4)$$

Similarly, C_x in Eq. (2) represents a calibration factor for the national HSM SPF calculated using Eq. (5). The recommendation from the HSM part 2 appendix A-4 and section A1.1.3 specifies that calibration factor should be calculated for the same time period over which analysis is being performed. The calibration factor serves to correct for systematic trends in crash frequencies over time, as well as differences in crash relationships between a jurisdiction and the national HSM models. The calibration factor values ranged from 0.96 to 1.1 for before period and 0.6 to 0.7 for after period. The after-period calibration factors reflect a general trend towards reduced crash frequency nationally, and serves to better isolate the effects of the ASCT from broader systemic trends in safety due to vehicle design, changes in driver behavior, etc. These calibration factors were developed using thousands of sites from the state of Pennsylvania and tested with additional 20 sites from the study region.

$$Cx = \frac{\sum Observed\ Crash\ Frequency}{\sum Predicted\ Average\ Crash\ Frequency} \quad (5)$$

After calculating the predicted average crash frequencies, the E-B correction was applied by weighting observed and predicted crash

Table 4
CMFs for type of left turn phasing.

Type of turn phasing	CMF
Permissive	1.00
Protected/permissive	0.99
Protected	0.94

frequencies to calculate an expected average crash frequency in the before period using Eq. (6).

$$N_{expected,B} = w_{i,B} * N_{predicted} + (1-w_{i,B}) * N_{observed,B} \quad (6)$$

where $W_{i,\,B}$ represent the weighted adjustment, and is calculated using Eq. (7).

$$W_{i,B} = \frac{1}{1 + k\sum N_{predicted}} \quad (7)$$

It is worth noting that Eq. (6) represents the crash estimates in terms of expected average crash frequency in the before period and the E-B method also requires crash estimates for after deployment period hence an adjustment is made using Eq. (8) to account for differences between the before and after periods of crash data in the duration, number of years, and traffic volumes.

$$r_i = \frac{\sum N_{predicted,A}}{\sum N_{predicted,B}} \quad (8)$$

Finally, the expected crash frequency in the after-deployment period was calculated which is given by:

$$N_{expected,A} = N_{expected,B} * r_i \quad (9)$$

The overall effectiveness of the treatment in terms of index of effectiveness was calculated by:

$$OR' = \frac{\sum_{All\ sites} N_{observed,A}}{\sum_{All\ sites} N_{expected,A}} \quad (10)$$

The crash modification factor that indicates the safety benefit in terms of relative change in crash frequency due to a change in specific road condition (traffic control in our case) was calculated by:

$$CMF = \frac{OR'}{1 + \frac{Var(\sum_{All\ sites} N_{expected,A})}{(\sum_{All\ sites} N_{expected,A})^2}} \quad (11)$$

Based on Hauer (1997):

$$Var[\sum_{All\ sites} N_{expected,A}] = \sum_{All\ sites}\left[(r_i)^2 * N_{expected,B} * (1-w_{i,B})\right] \quad (12)$$

While CMF is a point estimate for safety benefit, the safety effectiveness in terms of percentage was calculated by:

$$Safety\ Effectiveness = (1-CMF) * 100 \quad (13)$$

The standard error of overall effectiveness using information on variance of crashes is given by:

$$\sigma' = \sqrt{\frac{(OR')^2\left[\frac{1}{N_{observed,A}} + \frac{Var(\sum_{All\ sites} N_{expected,A})}{(\sum_{All\ sites} N_{expected,A})^2}\right]}{1 + \frac{Var(\sum_{All\ sites} N_{expected,A})}{(\sum_{All\ sites} N_{expected,A})^2}}} \quad (14)$$

The standard error was used to assess whether any changes in crash frequency after ASCT installation were significant.

6. Results and discussion

6.1. Empirical Bayes (E-B) before & after safety evaluation

The E-B before-after method of safety analysis was conducted on 41 intersections deployed with two different types of adaptive signal control systems (InSync and SURTRAC) to evaluate the safety effects of the systems. The two systems were first evaluated as one aggregate system (Table 5) and then evaluated separately to determine if there were any variations in safety benefits based on system type (Table 6). Safety effects were also examined based on intersection configuration (Table 7).

Table 5 shows the aggregate safety effect of ASCT on all intersections studied. For total crashes, the CMF is 0.87, indicating a 13% reduction in total crashes, which was statistically significant. Similarly, fatal and injury crashes had a CMF value of 0.64, indicating a 36% reduction in those crash types. This was again statistically significant. Thus, across both systems benefits were attained in terms of reductions in both the number of total and fatal and injury multivehicle crashes at the intersection following ASCT deployment.

Table 6 shows the CMFs when the results are broken up by system. Table 6 shows that both systems generally produced similar safety ef-

Table 5
Multivehicle crash modification factors, all intersections.

Crash severity	Crash modification factor	Std. error	Safety effectiveness
Total	0.87[a]	0.058	13%
Fatal + injury	0.64[a]	0.063	36%

[a] Significant at 95% confidence level.

Table 6
Multivehicle crash modification factor results for SURTRAC and InSync.

ASCT type	Crash severity	Crash modification factor	Std. error	Safety effectiveness
SURTRAC	Total	0.89	0.10	11%
	Fatal + injury	0.60[a]	0.13	40%
InSync	Total	0.86[a]	0.06	14%
	Fatal + injury	0.66[a]	0.05	34%

[a] Significant at 95% confidence level.

Table 7
Multivehicle crash modification factor results for 4 and 3 legged intersections.

# of legs	Crash severity	Crash modification factor	Std. error	Safety effectiveness
4	Total	0.77[a]	0.057	23%
	Fatal + injury	0.60[a]	0.056	40%
3	Total	0.78[a]	0.107	22%
	Fatal + injury	0.45[a]	0.035	55%

[a] Significant at 95% confidence level.

Table 8
Multivehicle crash modification factor results by system type and intersection configuration.

ASCT type	# of legs	Crash severity	# of sites	Crash modification factor	Std. error	Safety effectiveness
SURTRAC	4	Total	6	0.67[a]	0.11	33%
		Fatal + injury	6	0.50[a]	0.09	50%
	3	Total	3	1.04	0.20	−4%
		Fatal + injury	3	0.60[b]	0.21	40%
InSync	4	Total	23	0.79[a]	0.09	21%
		Fatal + injury	23	0.82[a]	0.08	18%
	3	Total	9	0.20[a]	0.107	80%
		Fatal + injury	9	0.22[a]	0.107	78%

[a] Significant at 95% confidence level.
[b] Significant at 90% confidence level.

fects. The CMFs for total and fatal/injury crashes were within 6% of one another. Although total crash CMFs were similar between systems, the CMF for total crashes for SURTRAC was not statistically significant at the 95th percentile confidence level. The lack of significance is likely partially attributable to the lower sample size of SURTRAC intersections (9 sites) versus InSync (32 sites). The fatal and injury CMFs were not significantly different between the two systems.

Table 7 shows how safety effectiveness varies as a function of intersection type, aggregated across both systems. CMFs for total crashes were generally consistent for 3 and 4 leg intersections, but fatal/injury crash CMFs were larger for 3-leg intersections.

Table 8 shows the variation in safety effectiveness by both system type and severity. All CMFs were statistically significant at 95% confidence level except for the 3-leg SURTRAC CMFs, which were limited by a very small sample size. Confidence intervals for the 4-leg total crash CMFs overlap for SURTRAC and InSync, indicating that type of system does not create a significant difference in CMFs between the two. The CMF for 4-leg fatal and injury crashes is significantly lower for SURTRAC than InSync, indicating that it produced larger reductions in severe crashes. That analysis is limited by small sample size as well, however, and needs further research to confirm whether that trend is sustainable.

6.2. Crash type distribution

The previous analysis proved the potential of ASCT to improve safety and reduce crashes at intersections, but whether certain type of crashes were more or less affected was still unclear. Hence, the crash types were analyzed to see any significant differences in crash proportions as shown in Table 9.

The results from Table 9 show that the proportion of rear end crashes was reduced as expected, but the decrease in the proportion of rear end crashes was offset by an increase in the proportion of angle crashes. These changes were evaluated using a Z-test of proportionality to find whether the observed changes were statistically significant or not. Minitab was used to perform Z-test for 2 proportions with a null hypothesis that the sample proportions for before and after period crashes were the same. The results of the proportionality test are provided in Table 10. The proportionality test reveals that none of the observed differences in crash type proportions are statistically significant except for head-on crashes. As a result, there is no statistically significant evidence that rear end crashes were disproportionately affected by the ASCT installation.

The crash proportions were also analyzed based on the two types of systems (Table 11) and intersection configuration (Table 12). The test of crash proportions generally revealed that the proportions did not change significantly before and after deployment of the ASCT system, with the exception of InSync total head on crashes and fatal and injury angle crashes. SURTRAC did not experience any significant changes in proportions.

Table 12 shows the test of crash proportions by intersection configuration, across both systems combined. Again, there was generally no significant change in crash proportions, with the exception of 3-leg head on total crashes.

The crash type analysis was somewhat surprising. The initial hypothesis was that installation of ASCT would produce reductions in rear end collisions due to improved operations on the corridor, however no statistically significant reductions in rear end crash proportions were observed. Instead, it seems that safety improvements generally accrued more or less evenly across all major crash types at the intersections.

Table 9
Crash type analysis for aggregate systems.

Crash type	Total crashes		Fatal and injury crashes	
	Before	After	Before	After
Rear end	145 (43%)	115 (40.9%)	83 (50%)	51 (45.13%)
Angle	166 (49%)	155 (55.5%)	80 (47.9%)	60 (53.09%)
Sideswipe	13 (3.56%)	5 (1.8%)	3 (1.5%)	2 (1.7%)
Head on	16 (4.44%)	5 (1.8%)	1 (0.6%)	0 (0%)
Total	340 (100%)	280 (100%)	167 (100%)	113 (100%)

Table 10
2-Proportions Z-test for crash types.

Crash type	Change in total crash proportions (Before-After)	p-Value	Change in fatal + injury crash proportions (Before-After)	p-Value
Rear end	1.57%	0.69	4.56%	0.45
Angle	−6.5%	0.10	−5.1%	0.39
Side-swipe	2%	0.13	0.02%	0.98
Head on	2.9%	0.04[a]	0.59%	0.41

[a] Significant at 95% confidence level.

Table 11
Crash proportions analysis based on type of system.

Crash type	Change in total crash proportions (Before-After)		p-Value		Change in fatal + injury crash proportions (Before-After)		p-Value	
	SURTRAC	InSync	SURTRAC	InSync	SURTRAC	InSync	SURTRAC	InSync
Rear End	0.55%	1.05%	0.94	0.81	3.75%	6.65%	0.79	0.29
Angle	−9.70%	−5.1%	0.20	0.24	−3.75%	−14.4%	0.79	0.02[a]
Sideswipe	8.19%	1.03%	0.10	0.42	0.00%	2.02%	1.00	0.14
Head On	2.08%	3.00%	0.33	0.07[b]	0.00%	0.67%	1.00	0.40

[a] Significant at 95% confidence level.
[b] Significant at 90% confidence level.

Table 12
Crash proportions based on intersection configuration.

Crash type	Change in total crash proportions (Before-After)		p-Value		Change in Fatal + injury crash proportions (Before-After)		p-Value	
	4-Leg	3-Leg	4-Leg	3-Leg	4-Leg	3-Leg	4-Leg	3-Leg
Rear end	2.03%	−0.70%	0.63	0.94	6.40%	−2.00%	0.35	0.87
Angle	−5.09%	−13.8%	0.25	0.15	−7.20%	2.00%	0.29	0.87
Sideswipe	2.18%	0.00%	0.18	1.00	0.00%	0.00%	1.00	1.00
Head on	0.82%	14.5%	0.57	0.002[a]	0.00%	0.00%	1.00	1.00

[a] Significant at 95% confidence level.

7. Conclusions and recommendations

This paper examined the safety benefits of ASCT using a rigorous Empirical Bayes Safety Evaluation method along with a crash type analysis. The safety benefits of adaptive signal control technology are explored since a safety evaluation of multiple ASCT systems does not currently exist.

The results from this study indicate that deployment of ASCT at urban/suburban intersections leads to improved safety effectiveness. The results also indicate that both SURTRAC and InSync have similar safety benefits associated with them, although the smaller sample size of SURTRAC systems limits the confidence in those results. An aggregate ASCT CMF value of 0.87 for total crashes and 0.64 for fatal and injury crashes was observed, translating into a 13% and 36% reduction in crash frequencies, respectively. The lower CMF value for 3 legged intersections indicated variation of safety benefits from one site to another. The analysis revealed that the proportion of crashes by type did not change significantly after the ASCT was installed.

Based on the results of this research, the authors recommend that ASCT projects should consider its safety benefits along with operational benefits. The authors also recommend that crash modification factor for ASCT should be incorporated into the Highway Safety Manual, which would provide a tool for planners and researchers to evaluate the safety impact of ASCT at intersections before deployment. Although, this research has proved the fact that ASCT have safety benefits, researchers should also consider other type of ASCTs present in the market to get a more holistic view of the technology and its safety benefits. Since safety effects between the two ASCT systems were relatively similar, this may imply that the speed limit had a minor effect on the analysis. Additional examination of systems across a range of roadway conditions would help determine this conclusively, however. It would also be interesting to see whether the systems analyzed in this research show any variation in safety benefits if deployed under different conditions, such as deploying SURTRAC at a suburban location and InSync at an urban location. Only multivehicle crashes were analyzed in this research since sample sizes prohibited examination of pedestrian and single vehicle crashes. If more data were collected, CMFs for those crash types could also be investigated. The research used a limited sample size for 3 legged SURTRAC intersections, so future research could determine whether the data from this limited sample represents a broader safety effect of the system. Future research could also focus on the impact of ASCT on human behavior (i.e. driver stress and fatigue). A human factors study would also provide a better perspective of how drivers respond to these changes in timing plans created by ASCT.

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Zulqarnain H. Khattak, MSCE: Mr. Zulqarnain is a doctoral candidate at Center for Transportation Studies in the Department of Civil and Environmental Engineering at University of Virginia (UVA). He is working as a research assistant on projects related to cybersecurity and safety, intelligent transportation systems and connected and automated vehicles. He attended University of Pittsburgh and University at Buffalo prior to joining UVA.

Mark J. Magalotti P.E., Ph.D: Dr. Magalotti is a professor of practice at Department of Civil and Environmental Engineering at University of Pittsburgh and the director of Center for Sustainable Transportation Infrastructure, where he guides transportation research. His research interests include traffic operations, safety and multimodal transportation. He is also the founder of Trans Associates, a firm working towards the solution of complex Traffic Engineering and Transportation issues since 1989.

Michael D. Fontaine P.E., Ph.D: Dr. Fontaine is an associate director for safety, operations and traffic engineering at the Virginia Transportation Research Council and a lecturer at the University of Virginia. His research interests include intelligent transportation systems, transportation operations, and highway safety. Prior to joining VTRC, Dr. Fontaine has also worked at the Texas A&M Transportation Institute, Old Dominion University, and as a municipal traffic engineer.