Accident Analysis and Prevention 124 (2019) 151–162

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Crash severity effects of adaptive signal control technology: An empirical assessment with insights from Pennsylvania and Virginia

Zulqarnain H. Khattak[a,*], Michael D. Fontaine[b], Brian L. Smith[a], Jiaqi Ma[c]

[a] Department of Engineering Systems and Environment, University of Virginia, Charlottesville, VA 22904, United States
[b] Virginia Transportation Research Council, Charlottesville, VA 22903, United States
[c] Department of Civil, and Architectural Engineering and Construction Management, University of Cincinnati, Cincinnati, OH 45221, United States

ARTICLE INFO

Keywords:
Adaptive signal control technology crashes
Injury severity
Intelligent transportation systems
Safety
Spatial transferability
Random parameters ordered probit models

ABSTRACT

Adaptive signal control technology (ASCT) is an intelligent transportation systems (ITS) technology that optimizes signal timings in real time to improve corridor flow. While a few past studies have examined the impact of ASCT on crash frequency, little is known about its effect on injury severity outcomes. Similarly, the impact of different types of ASCTs deployed across different states is also uncertain. This paper therefore, used ordered probit models with random parameters to estimate the injury severity outcomes resulting from ASCT deployment across Pennsylvania and Virginia. Two disparate systems deployed across the two different states were analyzed to assess whether they had similar impacts on injury severity, although signal timings are optimized using different algorithms by both systems. The estimation results revealed that both ASCT systems were associated with reductions in injury severity levels. Marginal effects showed that Type A ASCT systems reduced the propensity of severe plus moderate and minor injury crashes by 11.70% and 10.36% while type B ASCT reduced the propensity of severe plus moderate and minor injury crashes by 4.39% and 6.92%. Similarly, the ASCTs deployed across the two states were also observed to reduce injury severities. The combined best fit model also revealed a similar trend towards reductions in severe plus moderate and minor injury crashes by 5.24% and 9.91%. This model performed well on validation data with a low forecast error of 0.301 and was also observed to be spatially transferable. These results encourage the consideration of ASCT deployments at intersections with high crash severities and have practical implications for aiding agencies in making future deployment decisions about ASCT.

1. Introduction

According to the American Association of State Highway and Transportation Officials (AASHTO), on average there are five crashes at intersections every minute, and one person dies every hour of every day at an intersection somewhere in the United States (AASHTO, 2005). Similarly, according to United States Department of Transportation (USDOT, 2017), an average of one-quarter of traffic fatalities and roughly half of all traffic injuries in the United States are attributed to intersections. Given these issues, agencies are constantly seeking new approaches to mitigate safety issues at intersections.

Adaptive Signal Control Technology (ASCT) is a signalized intersection control technology that seeks to optimize cycle lengths, green times, and/or phasing sequences for traffic signals based on real-time traffic volumes collected from advanced detectors (Sussman, 2008). ASCT has historically been deployed to reduce traffic congestion, particularly during highly variable traffic conditions since ASCT optimizes signal timing plans in real time. Prior to the development of ASCT, traffic engineers frequently used time-of-day (TOD) timing plans that ran on a specified schedule for multiple hour time periods during specific days of the week. Since these predetermined TOD timing plans cannot dynamically accommodate variable traffic demands within those particular time periods, delays created by the traffic signal might become unnecessarily long when traffic volumes deviate from the conditions originally used to develop the timing plan. ASCT, on the other hand, adjusts signal timings and phasing scenarios in real time which allows the signal to better adjust the changes in demand created by incidents, special events, seasonal variation, or traffic growth over time. Recent studies have revealed that operational improvements created by ASCT can also create secondary safety benefits (Khattak,

* Corresponding author.
E-mail addresses: zk6cq@virginia.edu (Z.H. Khattak), Michael.Fontaine@VDOT.Virginia.gov (M.D. Fontaine), briansmith@virginia.edu (B.L. Smith), jiaqi.ma@uc.edu (J. Ma).

https://doi.org/10.1016/j.aap.2019.01.008
Received 9 May 2018; Received in revised form 4 January 2019; Accepted 6 January 2019
Available online 11 January 2019

2016; Khattak et al., 2017a; Ma et al., 2016, 2015).

While the aforementioned studies have identified the safety benefits of ASCT in terms of crash reduction, it is still unclear how ASCT affects injury severity outcomes relative to signals running TOD plans. This paper addresses whether ASCT has significant effects on injury severity outcomes, and whether those effects are consistent across different systems and deployments across different states.

2. Literature review

Although the safety effects of traffic signal installation are well-established in the literature (Sacchi et al., 2016), the impact of signal operations on injury severity has not been thoroughly studied. Previous studies have analyzed ASCTs for various factors contributing to operational and safety benefits, but little literature is available on the injury severity outcomes that may result from such deployments. Various studies on ASCTs and crash severity modeling are summarized below.

2.1. Simulation studies of the safety effect of ASCT

A few studies (Kergaye and Haigwood, 2011; Sabra et al., 2013, 2010; Shahdah et al., 2015) used simulation techniques to assess safety benefits of ASCT and signalized intersections. Kergaye and Haigwood, (2011) compared safety surrogate measures from microsimulation and real-world data from two sites in Utah to assess safety effects of ASCT. They concluded that ASCT generated fewer rear end and total conflicts than traditional signalized traffic control. Sabra et al., (2010) and Sabra et al., (2013) also developed a crash prediction method using field data from ASCT and actuated signal deployments. After training the network with around 150 signal timing scenarios, the crash prediction method produced an average conflict prediction error of 17%. The comparison of adaptive vs. actuated models showed either no improvement in safety or an increase in total number of conflicts for adaptive signals. For example, one comparison on a grid network showed that adaptive signals increased conflicts from 1009 to 1126 as compared to actuated signals.

2.2. Field studies of the safety effects of ASCT

Relatively few studies (Clark, 2010; Khattak, 2016; Khattak et al., 2017a; Lodes and Benekohal, 2013; Ma et al., 2016, 2015) have analyzed the safety effects of ASCTs using field data. Lodes and Benekohal, (2013) used one year of crash data from three intersections to conduct a cost benefit analysis and found that crashes reduced from 79 to 71 after ASCT deployment within a one-year period. However, the change was not statistically significant. Clark, (2010) examined safety of the InSync adaptive signal system on five different corridors using a simple observational before and after crash data analysis. In one case, a 30% reduction in crashes was observed on Highway 71 in Arkansas using a one year naive before and after data evaluation. Ma et al., (2016) analyzed 47 intersections deployed with the InSync ASCT in the state of Virginia using an empirical Bayes (E-B) before-after analysis. That study found a reduction in both total and fatal and injury crashes, with crash modification factors (CMFs) of 0.83 and 0.92 for the two crash categories, respectively. More recently, another study (Khattak et al., 2017a) analyzed 41 urban/suburban intersections in Pennsylvania equipped with two different types of ASCT (SURTRAC and InSync) systems. Their E-B analysis concluded that both systems showed safety benefits, with average CMF values of 0.87 and 0.64 for total and fatal + injury crashes, respectively.

2.3. Injury severity

Only two studies (Dutta et al., 2010; Fink et al., 2016) have evaluated the impact of ASCT on injury severities. Dutta et al., (2010) analyzed the impact of the Sydney Coordinated Adaptive Traffic System (SCATS) ASCT system on intersection and segment crash data using a simple before and after crash data analysis. 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 differences at a 95% confidence level. Fink et al., (2016) studied the safety benefits of the SCATS system in Oakland County, Michigan using a cross sectional analysis due to limited availability of after deployment data. Multinomial logit models of injury severity showed that SCATS created a statistically significant increase in non-serious injuries and no significant reduction in incapacitating injuries or fatal crashes. However, the study found that impacts on injury severity were inconclusive overall.

2.4. Crash severity modeling

A variety of modeling approaches have been used in the literature to model crash severity outcomes depending on the individual dataset under evaluation and the expected outcomes. Since crash severities are ordinal in nature, ordered logit or ordered probit models are commonly used when developing crash severity models for various types of countermeasures and crash evaluations (Haleem et al., 2015; Liu et al., 2015; Obeng, 2011; Robartes and Chen, 2017; Zhao and Khattak, 2015). In some cases, the ordinal nature is neglected and injury severities are treated as discrete outcomes. For such cases, multinomial logit models are sometimes estimated (Fan and Hale, 2014; Fink et al., 2016; Zhao and Khattak, 2015). Similarly, Hu et al., (2010) have used generalized logit models, Zhao and Khattak, (2015) have used random parameters logit models, and Eluru et al., (2012) have used latent segmentation based ordered logit models. In cases where discrete outcomes are expected to be highly correlated, nested logit models (Hu and Donnell, 2010; Mehta and Lou, 2013) have also been used to address unobserved heterogeneity effects across severity levels.

Ye and Lord, (2014) analyzed the three commonly used models (ordered probit (OP), multinomial logit (ML) and random parameter logit (RPL)) by using observed and simulated data through Monte Carlo simulation. The authors concluded that each model performs the best under certain, specific conditions and these models have increasing sample size requirements as you move from OP to ML and then RPL.

2.5. Summary of literature

Although two studies related to injury severity outcomes of ASCT were identified in the literature, both had inconclusive results and suffered from limited data collected using a single ASCT system. Hence, there is a need to analyze the injury severity outcomes expected from multiple ASCT deployments across different states to have a clear and transferable perspective regarding the effects of this technology. This paper fills this gap in the literature by developing injury severity models using up to eleven years of crash data from two different states. Furthermore, the presence of two different ASCT systems was analyzed to determine the degree to which individual technologies affect results. These systems will be referred to generically as systems A and B in this paper so as not to provide any implied endorsement of an individual vendor.

3. Purpose and scope

The purpose of this study was to evaluate the impact of ASCT on crash severity using a large amount of after deployment data. A before-after methodology was used to develop models for injury severity outcomes expected from deployment of ASCT. This study contributes to the existing literature by answering the following questions:

1) How did the presence of ASCT affect injury severity outcomes?
2) Are there additional factors along with the presence of ASCT that

contribute significantly to the injury severities?
3) Do deployments across different states show similar effects?
4) Are ASCT injury severity models spatially transferable?

ASCT safety effects were evaluated by developing various injury severity models. Two different types of ASCT systems were analyzed to assess whether they had similar impact on injury severity, although signal timings are optimized using different algorithms by both systems. Knowledge of the degree of similarity in safety impact between disparate systems deployed across different states could be beneficial to agencies seeking to invest in ASCT.

4. Data description

This study used a before-after evaluation since data from both periods were available across all study sites. It should be noted that before-after in this paper refers to the use of sites with long term before and after deployment of ASCT data availability for crash severity modeling. This approach offers a number of benefits over using a comparison group approach. Although crash data for a large number of non-ASCT sites can be collected with comparison groups, those comparison sites may not be representative of the characteristics at the ASCT sites, which could lead to biased results. The limitations of comparison group approach have also been noted by past studies (Fink et al., 2016; Sacchi et al., 2016) and the use of before-after approach has been suggested. The use of before-after with comparison group may account for unobserved confounding factors, however this approach was not used to avoid accounting for confounding effects twice (Elvik, 2002) since AADT, geometrics and driver behavior characteristics were used as confounding factors during modeling. ASCT deployments provided by the Pennsylvania Department of Transportation (PennDOT) and Virginia Department of Transportation (VDOT) were both used in this paper. The authors initially received lists of sites from PennDOT and VDOT that underwent different treatments and geometric changes during the study period. The initial lists had far more intersections compared to the selected study sites from Pennsylvania and Virginia. The sites that underwent multiple treatments apart from ASCT deployment, had varied characteristics or missing data elements were removed from the analysis. Furthermore, different roadway features such as AADT on major and minor roads, speed limits, number of lanes and intersection type were used as confounding factors in the analysis to account for any variation from year to year. The authors additionally calibrated models with limited years of data before and after ASCT installation (6 years for VA and 4 years for PA) to assess whether long-term trends in safety due to unobserved factors (e.g., changes in vehicle design, driver behavior) might be influencing the longer duration results. The results from that shorter duration analysis were consistent with those observed from the longer period. The sites selected for analysis had to have at least three years of before and after period data available, and also occurred on routes with similar AADTs and speed limits to ensure comparability across states. The analyzed data consisted of crash records from Pennsylvania and Virginia between the years 2007–2014 and 2006–2016, respectively. The crash data for Pennsylvania was collected from PennDOT for the before and after deployment period with two different ASCT systems (denoted as type A and type B). Type A ASCT uses a schedule driven approach to individually optimize signal timings second by second at each intersection in real time. The data is mainly collected using radar and video cameras along with inductive loop detectors, typically placed at the stop bars and as advance detectors on intersection. The system seeks to minimize waiting time, travel time, and environmental pollution (Smith et al., 2013). The type B ASCT on the other hand, uses four video detection cameras to collect real time data on each approach of the intersection. The signalization parameters such as state, sequence, and amount of green time are selected based on the collected data to best service the prevailing conditions second by second. Optimization is based on minimizing the overall delay and reducing stops (Engineering, 2017). Since the optimization approach differs, it is uncertain whether the different systems produce differing safety impacts. Furthermore, the study analyzed ASCT systems deployed across two different states to provide guidance on whether deployments across different states have similar effects.

Crashes within 350 ft of the midpoint of the intersection were regarded as intersection crashes. It should be noted that the commonly used buffer is 250 ft. However, an ASCT field study (Khattak et al., 2018) identified that ASCT affected driver behavior beyond the conventional 250 ft. Thus, crashes within 350 ft of the intersection were considered to be affected by ASCT installed at the intersections. These crash reports contained information on crash characteristics, vehicle characteristics, environmental conditions, crash contributing factors, and intersection type.

Additional data on the average annual daily traffic (AADT), speeds, and number of lanes on the major and minor roads were also collected. Data on speed limits and number of lanes were collected from roadway inventory files for both states and through visual observation using Google Earth. AADTs for Pennsylvania sites were collected from PennDOT's Internet Traffic Management System (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 FHWA website. A challenge here 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 using PennDOT established 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 AADT information for Virginia sites, on the other hand, was collected directly from the VDOT Traffic Monitoring System. The VDOT system had data for both before and after deployment period on major and minor roads.

The emphasis of this research was to study the impact of the presence of ASCT on the level of overall injury sustained in a crash (based on the worst injury sustained), hence interpretation of injury severity outcomes from the two states is provided. The injury outcomes are categorized in Pennsylvania police reports as fatal, major, moderate, minor and no injury. Virginia records severities slight differently as fatal, serious injury (in place of major injury), possible injury (in place of moderate injury), no apparent injury (in place of minor injury), and no injury. Both of these categories correlate to the KABCO scale. A fatality is reported when a person dies as a result of injuries sustained. Incapacitating injuries are categorized as major and serious injuries include laceration, broken bones, and bleeding wounds. Non-incapacitating injuries categorized as moderate or possible injury include those requiring some form of medical treatment such as bruises or swellings. Minor or no apparent injury includes cases when no injury is visible but there is a complaint of pain. The final category includes property damage only crashes.

Table 1 show the corridors from both states selected for the study along with the crashes observed. In total, 4557 crashes were analyzed in this study after data cleaning. Out of these, 722 crashes occurred in Pennsylvania, while 3836 crashes occurred in Virginia. Further, in PA data- the before period consisted of 381 crashes and the after period consisted of 340 crashes while in the VA data, the before period consisted of 2425 crashes and the after period consisted of 1411 crashes. The before deployment period for Pennsylvania and Virginia consisted of data between 2007–2010 and 2006–2011, respectively. Similarly, the after-deployment period for Pennsylvania and Virginia ranged from 2011 to 2014 and 2012–2016, respectively. However, six months of post deployment data were removed from the analysis to reduce the

Table 1
Description of Corridors and Sites.

State	Corridor Name	County/City	District	Intersections with ASCT	# of Crashes
Virginia	**Winchester US 11**	Frederick County	Staunton	5	338
	SR 7	City of Winchester	Staunton	6	345
	SR 277	Fredrick County, Stephens City	Staunton	7	277
	US 250 Staunton Route	Augusta County/City of Staunton	Staunton	3	239
	US 17 York City Route	York County	Hampton Roads	11	895
	SR 419 in Salem (Electric Rd)	Roanoke County	Salem	5	836
	US 50 (Northwestern Pike) in Winchester	Frederick	Staunton	2	56
	Warrenton US 29	Fauquier County	Culpeper	4	354
	US 250 Pantops	Albemarle County/Charlottesville	Culpeper	6	496
Pennsylvania	**East Liberty Corridor**	Allegheny	Engineering district 11, Pittsburgh	9	127
	Delaware Valley Corridor	Montgomery	Engineering district 6	21	441
	Upper Merion Corridor	Montgomery	Engineering district 6	12	153

Table 2
Descriptive Statistics of the Pennsylvania and Virginia Dataset.

Deployment Period	Continuous Variables	Mean		S.D		Min		Max	
		PA	VA	PA	VA	PA	VA	PA	VA
Before Period	*Speed limit on major road*	41.6	41.9	5.36	6.30	25	25	45	55
	Speed limit on minor road	34.5	32.3	7.83	8.75	15	15	45	55
	Number of lanes on major road	2.97	3.48	.547	.739	1	2	4	4
	Number of lanes on minor road	2.51	2.47	.736	.834	1	1	4	4
After Period	*Speed limit on major road*	38.8	40.6	8.16	6.58	25	25	45	55
	Speed limit on minor road	31.2	31.8	8.13	8.31	15	15	45	55
	Number of lanes on major road	2.78	3.45	.721	.730	1	2	4	4
	Number of lanes on minor road	2.26	2.28	.726	.735	1	1	4	4

Note: PA = Pennsylvania data, VA = Virginia data.

potential influence of deployment activities and to account for the initial driver adjustment to the treatment. The descriptive statistics for both states' datasets are shown in Tables 2–3. It should be noted that ASCT was often installed on a number of other intersections in each corridor, but intersections were omitted from the analysis if they were missing information on minor road traffic volumes or the site underwent multiple treatments.

5. Methodology

Ordered probit, multinomial logit, and random parameter logit models were considered using the specifications for sample size and other restrictions mentioned in (Ye and Lord, 2014) and (Abdel-Aty, 2003). The random parameter logit model required a sample size of 5000 crashes and was thus abandoned from further consideration. The ordered probit model was preferred because it provided a better fit with significant parameters while keeping the ordinal nature of the crash severities intact. Hence, the model estimation methodology and results for only best fit ordered probit models with and without random parameters are presented here.

The response variable in this study was the injury severity outcome of the crashes resulting from the presence of ASCT. The PA crash data did not have any reported fatalities and the VA data only had 6 reported fatalities. Hence, these fatalities were removed to have consistency across the two datasets. Furthermore, there were relatively fewer crashes reported for the serious category, hence this category was combined with moderate injuries to achieve significant threshold points μ for the models. The threshold points are benchmark values used to define the different categories of severity. The severities were thus coded in three categories: (1) severe plus moderate injury, (2) minor or apparent injury, and (3) no injury. The other data elements including information on crash characteristics, vehicle characteristics, environmental conditions, driver distraction, and intersection type were included as independent variables in the model. Considering the injury severities as discrete ordinal choices (such as the three severities *1-3*), injury severity of the ordered probit model is calculated by estimating a variable y^* as a function of crash characteristics given in Eq. (1) (Ben-Akiva and Lerman, 1985; Washington et al., 2011).

$$y^* = \beta X_n + \varepsilon_n \tag{1}$$

Where βX_n represents a systematic component (e.g. β is the coefficient of the explanatory variable X_n, which could be any of the crash characteristic such as environmental condition or AADT) and ε_n represents a random component accounting for unobserved impacts such as characteristics of crash or driver and follows standard normal distribution. Then the value of injury severity of the dependent variable y^* is given by the following (Greene, 2008).

$$Y1 = 1 \; if \; y^* \le \mu_0 \tag{2}$$

$$Y2 = 2 \; if \; \mu_0 \le y^* \le \mu_1 \tag{3}$$

$$Y3 = 3 \; if \; y^* \ge \mu_1 \tag{4}$$

Where μ_i represents the thresholds or bounds for the defined categories of injury severity. It should be noted that the threshold μ_0 for the first injury severity outcome was specified as zero, without loss of generality (Washington et al., 2011). This means that only k-2 thresholds are estimated, where k represent the total number of outcomes. The propensity of a crash falling into a particular category is calculated as follow (represents standard normal distribution) (Greene, 2008).

$$P_n(Y1 = 1|x) = \phi(-\beta X_n) \tag{5}$$

$$P_n(Y2 = 2|x) = \phi(\mu_1 - \beta X_n) - \phi(-\beta X_n) \tag{6}$$

$$P_n(Y3 = 3|x) = 1 - \phi(\mu_1 - \beta X_n) \tag{7}$$

One basic limitation in ordered probit model is that the interpretation of intermediate outcomes of injury severity are not clear and one is unable to distinguish the effect of a positive or negative coefficient on intermediate severities. This limitation is countered through the use of marginal elasticities, which show the probability change of the

Table 3
Descriptive Statistics for Response and Indicator Variables.

Category	Variables	Level	Before Deployment Period				After Deployment Period			
			Frequency		Percent		Frequency		Percent	
			PA	VA	PA	VA	PA	VA	PA	VA
Response Variable	Injury Severity	Severe + Moderate	83	386	22.9	16.4	36	167	9.97	11.1
		Minor	137	486	36.0	20.0	114	252	33.4	17.8
		No injury	161	1553	43.4	66.2	190	992	54	66
Driver Characteristics	*Careless Driving*	Yes	120	250	31.5	10.3	171	121	50.1	8.6
		No	261	2175	68.5	89.7	170	1290	49.9	91.4
	Distracted Driving	Yes	54	301	14.3	12.4	32	140	9.4	9.9
		No	327	2124	85.7	87.6	309	1271	90.6	90.1
ASCT Presence	*Type A*	NA	NA	NA	NA	NA	89	0	26.2	0
	Type B	NA	NA	NA	NA	NA	251	1411	73.7	100
Roadway Characteristics	*Intersection* Type	4-legged	316	2236	83	92.2	284	1348	83.4	95.5
		3-legged	65	189	17	7.8	57	63	16.6	4.5
	Average Annual Daily Traffic on major road	Btw 20K-50K	299	1981	78.4	81.7	253	1098	74.3	77.8
		Below 20K	82	441	21.5	18.2	87	312	25.6	22.1
	Average Annual Daily Traffic on minor road (1 if below 2000)	Yes	265	550	69.5	22.7	265	450	77.7	31.9
		No	116	1875	30.5	77.3	76	961	22.3	68.1
Crash Type	*Angle (1 if angle)*	Yes	192	740	50.4	30.5	139	387	40.7	27.4
		No	189	1685	49.6	69.5	202	1024	59.3	72.6
	Rear end (1 if rear end)	Yes	149	1341	39	55.3	112	741	32.7	52.5
		No	232	1084	61	44.7	229	670	67.3	47.5
Pavement Condition	*Wet/Icy (1 if wet or icy)*	Wet	64	364	16.9	15	70	212	20.5	15
		Not Wet	317	2061	83.1	85	271	1199	79.5	85
Weather Conditions	*Rain (1 if rain)*	Rain	53	293	14	12.1	53	178	15.4	12.6
		No rain	328	2132	86	87.9	288	1233	84.6	87.4
	Snow (1 if snowing)	Snow	47	238	12.4	9.8	39	126	11.5	8.9
		No snow	334	2187	87.6	90.2	302	1285	88.5	91.1
Crash Characteristics	*Three or more vehicles (1 if three or more involved)*	Yes	77	344	20.2	14.2	44	183	12.8	13
		No	304	2081	79.8	85.8	297	1228	87.2	87
	Two vehicles (1 if two involved)	Yes	265	1950	69.5	80.4	263	1150	77.2	81.5
		No	116	475	30.5	19.6	78	261	22.8	18.5
	Urban intersection (1 *if urban, 0-suburban)*	Urban	27	0	7	0	89	0	26.2	0
		Suburban	354	2425	93	100	252	1411	73.8	100
	Heavy vehicle (1 if heavy vehicle is involved)	Heavy Veh	34	10	8.8	0.4	44	14	12.9	1
		No HeavyVeh	347	2415	91.2	99.6	297	1397	87.1	99
	Pedestrian (1 if pedestrian is involved)	Ped	15	133	3.9	5.5	10	4	2.8	0.3
		No Ped	366	2292	96.1	94.5	331	1407	97.2	99.7
	Night and dark conditions with lighting (1 if dark or night)	Dark	101	594	26.6	24.5	112	333	32.7	23.6
		Not Dark	280	1831	73.4	75.5	229	1078	67.3	76.4
	SUV(1 if SUV was involved in a crash)	SUV	89	0	23.4	0	83	7	24.2	0.5
		No SUV	292	2425	76.6	100	258	1404	75.8	99.5

Note: PA = Pennsylvania Data, VA = Virginia Data.

intermediate severity outcomes with (1) a unit change from the zero (base condition) to one specified for dummy variables or (2) a one standard deviation change specified from the mean for continuous variables. According to Greene, (2008), the marginal effects for the three severity levels are computed as follows.

$$\frac{\partial P_n(Y1 = 1|x)}{\partial x} = -\phi(-\beta X_n)\beta \tag{8}$$

$$\frac{\partial P_n(Y2 = 2|x)}{\partial x} = \phi(-\beta X_n)\beta - \phi(\mu_1 - \beta X_n)\beta \tag{9}$$

$$\frac{\partial P_n(Y3 = 3|x)}{\partial x} = \phi(\mu_1 - \beta X_n)\beta \tag{10}$$

Although the ordered probit model can account for ordinal discrete choices, a potential concern is that effects of certain parameters may vary across observations due to unobserved heterogeneity. Thus, constraining the parameters to be constant across observations may lead to inconsistent and biased estimates (Washington et al., 2011). To address this issue, random parameters can be estimated by allowing parameters to vary across observations (Eluru et al., 2008; Fountas and Anastasopoulos, 2017; Russo et al., 2014). Two hundred Holton draws of simulations were used for this purpose which is in line with the past studies (Halton, 1960; Train, 2003) (Washington et al., 2011). According to (Greene, 2008), such variability can be incorporated as:

$$\beta_i = \beta + \mu_i \tag{11}$$

where β_i represents vector of specific parameter related to driver or other crash characteristics and μ_i represents randomly distributed term having a mean of zero and variance σ. Different distributions (normal, lognormal, triangular and uniform) were tested for random parameters however, normal disttribution was finally selected since it provided a better fit.

The actual implementation of Eqs. (1)–(11) was conducted using the N-Logit 4.0 software package. The data were formatted for the software package and cleaned using SAS and R. Variables having correlation above 0.90 were removed from the analysis since highly correlated variables are not desirable (Fink et al., 2016; Khattak et al., 2017b; Washington et al., 2011). In the Pennsylvania data set, the variables urban and speed limit on minor road had a high correlation coefficient of -0.92 while rain or snow and wet or icy pavement had a correlation coefficient of 0.96. Similarly, in the Virginia data set, the highest correlations of 0.87 and 0.82 were observed between variables of rain or snow and wet or icy pavement, and variables of three or more vehicles and two vehicles involved in a crash.

The best fit models were selected based on two criterions. First, significant parameters were examined to determine whether signs and magnitudes were reasonable and showed intuitive trends. Next, the Akaike Information Criteria (AIC) was compared, and the likelihood ratio test was applied to ensure the selected model provided value over rejected models. An overall, best fit model was calibrated based on splitting the data into two sets; 80% of the data points were used to calibrate the model while the remaining 20% data points were used to validate the model. Furthermore, separate models were also calibrated for the two different ASCT system. For brevity, the results for only final selected best fit models are presented in this paper.

6. Model estimation results and discussion

Initially, a combined model was estimated for both data sets to find the overall impact of ASCT presence and other contributing factors on injury severity outcomes at signalized intersections. Later, separate models were estimated for the presence of the two ASCT systems (labeled Type A and B) and deployments across the two states. Data from 2006 to 2016 were used for these model estimations. It should be noted that the S.D. of the parameter distribution are provided only for the parameters defined as random for the random parameter ordered probit models. The results[1] are provided in the subsequent sections.

6.1. Combined best fit model

This section presents the final combined best fit model using both types of ASCTs that was calibrated using 80% (3646) of the data points. The remaining 20% data points were later used in validation. The validation dataset was randomly sampled, however the authors ensured that both datasets had similar percentages of data by category and variable characteristics. The final model for ASCT deployment had eight statistically significant explanatory variables beyond the ASCT variable. Both fixed and random parameter ordered probit (FPOP and RPOP) were estimated for the ASCT effects. Although both models provided parameter estimates that showed a similar direction, the random parameter model explained the variability in parameter effects across individual observations and provided highly significant parameters. Additionally, the likelihood ratio test revealed that RPOP provided improved fit compared to FPOP model. Additional explanatory variables were also explored for their impact. Only statistically significant variables are included in the models with p-values < 0.005 and p-values < .01. Additionally, individual models were also calibrated for the deployments across the two states to analyze how close or different the results were.

Table 4 reveals that sites with ASCT deployments shows a potential indication that drivers are less prone to sustaining more severe category (severe plus moderate and minor) crashes compared to the case when normal time of day signal timing plans are deployed. The marginal effects in Table 5 clearly reveals the impact on each severity level. Table 5 shows that the presence of ASCT changes the risk of sustaining severe plus moderate, minor, and no injury crashes by -5.24%, -9.91% and 15.15%, respectively. These findings suggest that ASCT deployment increases the propensity of no injury crashes compared to other classes. This finding is consistent with the individual ASCT models presented later and can be attributed to the ASCT's algorithm, which handles conflicting movements at intersections in real time. The reduced stops with ASCT present could be responsible for lower rear end crashes that could lead to changes in potential severities. These findings are also consistent with previous published results for crash modification factors of the ASCT systems (Khattak et al., 2017a), which showed a 40% reduction in fatal and injury crash frequency. To further explore the differences in terms of the impact of ASCTs deployed across the two states, individual models were calibrated for PA and VA datasets shown in Table 6. The results reveal that ASCT deployments across PA leads to a slightly higher reduction in the propensity of more severe category crashes. Marginal effects from Table 7 shows that PA deployments reduces the propensity of severe plus moderate and minor injury crashes

Table 4
Combined Best Fit Model.

Variable	Fixed Parameters		Random Parameters	
	Coef	p-values	Coef	p-values
Presence of Adaptive Control-ASCT (1 if present)	.2997	< .001	.629	< .001
Indictor Variable for State (1 if PA,0 if VA)	.348	< .001	.439	< .001
Driver Characteristics				
Driver distraction (1 if ditracted)	−.413	.001	−1.11	< .001
Careless driving (1 if careless)	−.448	< .001	−1.132	< .001
(Standard deviation of parameter distribution)			(.595)	(< .001)
Crash Type				
Angle crashes (1 if rear end)	−.245	< .001	−.560	< .001
Rear end crashes (1 if rear end)	−.1925	.002	−.356	< .001
Roadway Characteristics				
Speed limit on minor road	−.096	< .001	−.084	< .001
(Standard deviation of parameter distribution)			(.075)	(< .001)
AADT on minor road (1 if AADT is < 20 K)	.001	.89	−.104	.02
Crash Characteristics				
Vehicles involved (1 if 3 or more vehichles)	−.324	< .001	−.810	< .001
Presence of Pedestrians (1 if pedestrians are present)	−1.243	< .001	−2.98	< .001
(Standard deviation of parameter distribution)			(.138)	(< .001)
μ_1	.6765	< .001	1.815	< .001
No. Of Observations	3646		3646	
Loglikelihood at Convergence	−3261.75		−3101.96	
Likelihood ratio chi-square	319.58			
χ^2cri(0.01)	11.35			

Table 5
Marginal Effects for Combined best fit RPOP model.

Variable	Marginal Effects		
	Severe + moderate	Minor	No-injury
Presence of Adaptive Control-ASCT (1 if present)	−.0524	−.0991	.1515
Indictor Variable for State (1 if PA, 0 if VA)	−.0122	−.0231	.0353
Driver Characteristics			
Driver distraction (1 if ditracted)	.1194	.0518	−.1712
Careless driving (1 if careless)	.1308	.0565	−.1873
Crash Type			
Angle crashes (1 if rear end)	.0600	.0349	−.0948
Rear end crashes (1 if rear end)	.0420	.0269	−.0689
Roadway Characteristics			
Speed limit on minor road	.0044	.0028	−.0072
AADT on minor road (1 if AADT is < 20 K)	.0209	.0130	−.0339
Crash Characteristics			
Vehicles involved (1 if 3 or more vehichles)	.0816	.0416	−.1232
Presence of Pedestrians (1 if pedestrians are present)	.4446	.0235	−.4681

[1] It should be noted that the coefficients of the original models do not reveal the impact of the individual variables on the levels of injury severity. This effect is shown through marginal effects. A positive sign of the original model coefficient provides a potential indication of decrease in propensity of more severe category crashes (y_1=severe plus moderate and y_2=minor crashes) while increase in propensity of no injury category crashes (y_3=no injury). Similarly, a negative coefficient provides a potential indication of increase in propensity of more severe category (severe plus moderate and minor) crashes while decrease in propensity of no injury category crashes.

Table 6
Ordered probit model with random parameters for PA and VA.

Variable	Random Parameters Model PA		Random Parameters Model VA	
	Coef	p-values	Coef	p-values
Presence of Adaptive Control-ASCT (1 if present)	.5313	< 0.001	.2461	.0004
Driver Characteristics				
Driver distraction (1 if dsitracted)	−.3314	0.037	−.4279	0.027
Careless driving (1 if careless)	−.5263	< 0.001	−.7713	< 0.001
(Standard deviation of parameter distribution)	.0019	< 0.001	.0037	< 0.001
Crash Type				
Angle crashes (1 if angle)	–	–	−.3114	< 0.001
Rear end crashes (1 if rear end)	−.2465	0.021	−.1766	.0013
Roadway Characteristics				
Speed limit on minor road	–	–	−.0189	< 0.001
(Standard deviation of parameter distribution)			.0013	< 0.001
Speed limit on major road	−.0431	0.047	–	–
(Standard deviation of parameter distribution)	.0047	< 0.001		
AADT on major road (1 if AADT is between 20 K and 50 K)	−.1435	0.214	–	–
(Standard deviation of parameter distribution)	.0044	< 0.001		
AADT on minor road (1 if AADT is < 2000)	–	–	−.1132	0.018
(Standard deviation of parameter distribution)			0.016	< 0.001
Urban intersection (1 if intersection is urban)	.7543	0.005	–	–
Intersection type (1 if 4 legs)	–	–	.3465	< 0.001
Crash Characteristics				
Vehicles involved (1 if 3 or more vehichles)	–	–	−.310	< 0.001
Presence of Pedestrians (1 if pedestrians are present)	−1.643	< 0.001	−1.320	< 0.001
μ_1	.3143	< 0.001	−.8643	< 0.001
Number of Observations	577		3069	
Loglikelihood at Convergence	−501.32		−2663.12	

Table 7
Marginal Effects for PA and VA ordered probit models with random parameters.

Variable	Marginal Effects for PA model			Marginal Effets for VA model		
	Severe + moderate	Minor	No-injury	Severe + moderate	Minor	No-injury
Presence of ASCT (1 if present)	−.0742		.1273	−.0485	−.0363	.0848
Driver Characteristics						
Driver distraction (1 if distracted)	.0897	.0312	−.1209	.1151	.0544	−.1695
Careless driving (1 if careless)	.1428	.0614	−.2042	.2262	.0699	−.2961
Crash Type						
Angle crashes (1 if rear end)	–	–	–	.0677	.0436	−.1113
Rear end crashes (1 if angle)	.0620	.0288	−.0908	.0396	.0288	−.0684
Roadway Characteristics						
Speed limit on major road	.0085	.0043	−.0128	–	–	–
Speed limit on minor road	–	–	–	.0044	.0031	−.0075
AADT on major road (1 if AADT is between 20 K and 50 K)	.0291	.0161	−.0452	–	–	–
AADT on minor road (1 if AADT is < 2000)	–	–	–	.0237	.0164	−.0401
Intersection type (1 if 4 legged)	–	–	–	−.0809	−.0447	.1256
Crash Characteristics						
Vehicles involved (1 if 3 or more vehichles)	–	–	–	.0785	.0455	−.1240
Presence of Pedestrians (1 if pedestrians are present)	.5679	−.1250	−.4429	.3645	.0556	−.4202
Urban intersection (1 if intersection is urban)	−.1698	−.1548	.3246	–	–	–

by 7.31% and 5.31% while the deployments across VA lead to a reduction in propensity of the two categories by 4.85% and 3.63%. However, these differences are negligible and may be attributed to improved operations over specific corridors and thus, should not be generalized.

Exploring other contributing factors revealed that driver characteristics such as distraction or careless driving increase the risk of being involved in more severe category crashes. Marginal effects show that distracted driving was associated with an increase in propensity of severe plus moderate and minor crashes by 11.94% and 5.18%, respectively, while there was a decrease of 17.12% in no injury crashes. Similarly, careless driving was observed to be associated with increased propensity of more severe crashes by 13.08% and 5.65% for severe plus moderate and minor injury crashes, respectively, while producing a decrease in propensity of 18.73% in no injury crashes.

The negative coefficient for rear end and angle crashes in Table 4 indicates that drivers are more likely to sustain crashes in a more severe category as opposed to no injury category crashes for those crash types. The finding for angle crashes is intuitive, however the increased severity for rear end crashes is counterintuitive. This may be attributed to higher speeds created by improved flow causing more severe conflicts between stopped and moving vehicles leading to whiplash (Jonsson et al., 2013). Past studies (Chen et al., 2016; Khattak, 2001; Qi et al., 2013) have also identified higher speed differential, poor lighting, improper head restraints, and weight and age of colliding vehicles as major factors leading to increased severity during rear end crashes.

Roadway characteristics such as the AADT on the minor road and the speed limit on the minor road were also found to have a significant impact on crash severity. Table 4 reveals that when the AADT along the minor road was less than 20,000 vehicles per day, the crashes experienced were in more severe crash categories. The marginal effects show an increase in propensity of 2.09% and 1.30% for severe plus moderate and minor crashes while there was a decrease in the propensity of 3.39% for no injury crashes. These results are intuitive since roadway traffic plays a significant role in crash occurrence at signalized intersections. The ASCT systems however, can help to counter this issue and reduce such severities by harmonizing the flow of heavy traffic. Another significant influencing factor was speed limit on the minor road. Marginal effects from Table 5 reveal that increases in speed limit lead to a higher propensity of sustaining more severe category crashes as opposed to no injury category crashes. These findings are also consistent with past studies (Haleem and Abdel-Aty, 2010; Milton et al., 2008).

Furthermore, crash characteristics such as number of vehicles involved in a crash and presence of pedestrians were also found to have significant impact on crash severity. Table 4 reveals that involvement of three or more vehicles in a crash is associated with increased propensity of more severe category crashes as compared to no injury category crashes. The presence of pedestrians was also observed to contribute to more severe crashes. This finding is intuitive since pedestrian are vulnerable road users and expected to experience more severe crashes.

6.2. Models for presence of type a and type B ASCT

The individual ASCT systems were also analyzed separately to determine their impact on signalized intersection crashes. The results are shown in Tables 8 and 9. The RPOP was again observed to provide improved fit as compared to the FPOP model. Marginal effects were estimated to properly interpret the impact of individual variables on each severity level, as shown in Table 10. For this purpose, the variables other than the ones under prediction were held constant at their mean or base values.

The model in Table 8 reveals that the presence of Type A ASCT reduces the propensity of sustaining more severe category crashes as compared to the case when the normal time of day signals are deployed.

Table 8
Model for Type A ASCT Deployment.

Variable	Fixed Parameters		Random Parameters	
	Coef	p-values	Coef	p-vales
Presence of Type A ASCT (1 if present)	.538	.044	.569	.033
Driver Characteristics				
Driver distraction (1 if distracted)	−.317	.027	−.340	.017
Careless driving (1 if careless)	−.452	< .001	−.477	< 0.001
(Standard deviation of parameter distribution)			(.021)	(< .001)
Crash Type				
Rear end crashes (1 if rear end)	−.214	.037	−.220	.034
Roadway Characteristics				
Presence of Pedestrians (1 if pedestrians are present)	−1.482	< 0.001	−1.55	< 0.001
AADT on major road (1 if AADT is between 20 K and 50 K)	−.087	< 0.001	−.075	< 0.001
(Standard deviation of parameter distribution)			(.014)	(< 0.001)
Speed limit on major road	−.028	< 0.001	−.029	< 0.001
(Standard deviation of parameter distribution)			(.005)	(< .001)
Urban intersection (1 if intersection is urban)	.538	.021	.642	.001
μ_1	.928	17.27	1.02	19.40
No. Of Observations	721		721	
Loglikelihood at Convergence	−747.96		−716.97	
Likelihood ratio chi-square	61.98			
χ2 cri(0.01)	11.35			

Table 9
Model for Type B ASCT Deployment.

Variable	Fixed Parameters		Random Parameters	
	Coef	p-values	Coef	p-values
Presence of Type B ASCT (1 if present)	.309	< 0.001	.493	< 0.001
Driver Characteristics				
Driver distraction (1 if dsitracted)	−.389	< 0.001	−.773	< 0.001
Careless driving (1 if careless)	−.426	< 0.001	−.843	< 0.001
(Standard deviation of parameter distribution)			(.412)	(< 0.001)
Crash Type				
Angle crashes (1 if angle)	−.184	< 0.001	−.200	< 0.001
Rear end crashes (1 if rear end)	−.190	< 0.001	−.385	< 0.001
Roadway Characteristics				
Speed limit on minor road	.00009	.289	−.067	< 0.001
(Standard deviation of parameter distribution)			(.110)	(< 0.001)
AADT on minor road (1 if AADT is < 2000)	−.080	0.04	−.213	< 0.001
Intersection type (1 if 4 legs)	.786	< 0.001	1.24	< 0.001
Crash Characteristics				
Vehicles involved (1 if 3 or more vehichles)	−.253	< 0.001	−.885	< 0.001
Pedestrians (1 if pedestrians are present)	−.758	< 0.001	−2.88	< 0.001
μ_1	.666	.001	1.89	< 0.001
Number of Observations	4557		4557	
Loglikelihood at Convergence	−4126.18		−4041.06	
Likelihood ratio chi-square	170.24			
χ2 cri(0.01)	9.21			

Relative comparisons in various categories through marginal effects show that with the deployment of Type A ASCT, the risk of sustaining severe plus moderate, minor and no injury crashes change by -11.70%, -10.36% and 22.06%. This means that under the deployment of Type A ASCT, drivers are more likely to sustain only no injury crashes compared to any other classes. Similarly, type B model reduces the risk of sustaining severe plus moderate and minor injury crashes by 4.39% and 6.92%. These are very intuitive finding and can be explained by the fact that ASCT may be leading to reduced crashes due to the way in which its algorithm handles conflicting movements at intersections in real time. Thus, with reduced stops and wait times at intersections, there may be less chance of rear end collisions that could potentially lead to severe injuries.

Other important contributory factors were related to driver characteristics such as distraction or careless driving. It is commonly observed that distraction or careless driving increases the risk of being involved in crashes. Similarly, Tables 8 and 9 revealed that careless and distracted driving leads to higher propensity of being involved in more severe crash categories that could lead to possible injuries. However, distraction was found to be associated with relatively higher propensity of severe crashes as compared to carelessness. Table 10 reveals that careless driving as opposed to normal driving is associated with an increase in propensity of severe plus moderate and minor crashes by 9.76% and 3.59%, respectively, while producing a decrease of 13.35% in no injury crashes. Similarly, distracted driving is associated with an increase in propensity of more severe crash category by 12.70% and 6.10% for severe plus moderate and minor injury crashes, respectively. It also produces a decrease in no injury crashes by 18.80%. Table 10 also reveals a similar effect for the Type B model. These are intuitive findings since distracted and careless drivers are prone to more severe crashes due to their inability to manage the traffic situation at hand properly.

Crash type is also an important factor in analyzing severity of signalized intersection crashes since various type of crashes can have different impacts on severities. Similar to the combined model, the negative coefficient for rear end crashes in Tables 8 and 9 indicates that

Table 10
Marginal Effects for Random Parameter Ordered Probit Models.

Variable	Marginal Effects for ASCT Type A model			Marginal Effets for ASCT Type B model		
	Severe + moderate	Minor	No-injury	Severe + moderate	Minor	No-injury
Presence of ASCT (1 if present)	−.1170	−.1036	.2206	−.0439	−.0692	.1131
Driver Characteristics						
Driver distraction (1 if distracted)	.0976	.0359	−.1335	.1130	.0523	−.1653
Careless driving (1 if careless)	.1270	.0610	−.1880	.1215	.0566	−.1781
Rear end crashes (1 if rear end)	.0581	.0296	−.0877	.0579	.0373	−.0953
Angle crashes (1 if angle)	–	–	–	.0272	.0305	−.0577
Speed limit on major road	.0247	.0129	−.0376	–	–	–
Speed limit on minor road	–	–	–	.0069	.0030	−.0099
AADT on major road (1 if AADT is between 20 K and 50 K)	.0189	.0111	−.0300	–	–	–
AADT on minor road (1 if AADT is < 2000)	–	–	–	.0148	.0151	−.0299
Intersection type (1 if 4 legged)	–	–	–	−.0510	−.0303	.0813
Vehicles involved (1 if 3 or more vehichles)	–	–	–	.0690	.1262	−.1952
Presence of Pedestrians (1 if pedestrians are present)	.5532	−.1130	−.4402	.4281	.0353	−.4634
Urban intersection (1 if intersection is urban)	−.1169	−.0984	.2153	–	–	–

drivers have higher probability of sustaining crashes in a more severe category as compared to the no injury category. The ASCT type A model shows that rear end crashes as opposed to other type of crashes lead to an increase in propensity of severe plus moderate and minor crashes by 5.81% and 2.96%, respectively, while producing a decrease in the propensity of no injury crashes by 8.77%.

Similarly, the ASCT type B model shows that rear end crashes are associated with increase in propensity of severe plus moderate and minor injury crashes by 5.79% and 3.73%, respectively, while producing a decrease in the propensity of no injury crashes by 9.53%. This finding is somewhat counterintuitive, but could again be attributed to whiplash crashes (Jonsson et al., 2013) where the energy of impact from the colliding bumpers is transferred to the back and neck of drivers, which may lead to severe neck and back injuries in such cases. However, this finding needs further investigation.

The presence of pedestrians also has a significant impact on crash severity. The marginal effects for the ASCT type A model in Table 10 reveal that involvement of one or more pedestrians is associated with increasing the propensity of severe plus moderate crashes by 55.32% while decreasing the propensity of minor and no injury crashes by 11.30% and 44.02%, respectively. The marginal effects for the ASCT type B model in Table 10 shows an increasing propensity for severe plus moderate and minor crashes by 42.81% and 3.53%, respectively, while producing a decrease in the propensity of no injury crashes by 46.34%. These results are not surprising since pedestrians are vulnerable road users and are expected to experience severe crashes.

Other contributing factors include AADT and speed limit on major and minor road, and whether an intersection was in an urban area. The ASCT type A model in Table 8 reveals that higher major road AADTs between 20,000 and 50,000 are associated with an increasing propensity for more severe category crashes involving injuries. The increases in propensity are 1.89% and 1.11% for severe plus moderate and minor crashes, respectively, with a decrease in propensity of 3.00% for no injury crashes. The ASCT type B model in Table 10 reveals a slightly lower propensity of increase in severity by 1.84% and 1.51% for severe plus moderate and minor injury crashes, respectively, compared to the ASCT type A model when the AADT on the minor road is less than 2000. These results are intuitive since in general- both major and minor road traffic contributes to intersection crashes, so higher traffic on any approach may lead to increased conflicts if timing plans are not properly updated. The ASCT systems can therefore, help to counter this issue and reduce the negative impact of AADT on severity outcomes. Speed limit on the major road was also found to influence the severity of crashes at signalized intersections. Both models revealed that higher speed limits were associated with an increased propensity of more severe category crashes as opposed to no injury category crashes. The type B model however, revealed relatively lower propensities of severe plus moderate and minor injury crashes by 0.69% and 0.30%, respectively, for a unit increase in speed limit on minor road as compared to 2.47% and 1.29% for a unit increase in speed limit on major road with type A model. These findings are also consistent with past studies (Haleem and Abdel-Aty, 2010; Milton et al., 2008). Another important factor was whether the location of the intersection was urban or suburban since both are associated with some degree of variability in driver behavior and traffic characteristics. The model from Table 10 revealed that urban intersections are more likely to experience no injury crashes as opposed to other crash categories when compared to suburban intersections. This shows that urban locations as opposed to suburban are associated with a decrease in propensity of severe plus moderate and minor injury crashes and a relative increase in propensity of no injury crashes. This finding may be attributed to higher speed limits observed over the suburban settings. Thus, the reduced speed limit of urban intersections may have led to reduced propensity of severe crashes and generally drivers are more cautious in dense urban settings. Furthermore, increased deployment of ASCTs may reduce this problem by harmonizing the flow of traffic.

6.3. Validation and transferability of best fit model

The practical value of a model depends on its forecast accuracy; however, econometric models have rarely been validated for their forecast accuracy. Although, some recent studies (Anastasopoulos and Mannering, 2011; Fountas and Anastasopoulos, 2017) have considered forecast accuracy using the same dataset that is used to calibrate the model but an important question of testing a model's performance on a different dataset than the one used to calibrate the original model is usually left unanswered. More specifically, it is important to see how a model performs on a separate validation dataset rather than the one used to calibrate the mode (i.e. training data). Hence, the authors used a separate randomly sampled validation dataset (i.e. 20% of the data points, 911 data points) that were not used in calibration for testing the forecast accuracy of the combined best fit model. Table 11 shows observed and predicted outcomes along with correct predictions for both training and validation dataset. It is observed that the model performs equally well on a separate validation dataset. However, it should be noted that prediction power for severe plus moderate category is lower due to the lower number of observations in this category, but the overall prediction power is more important. In reality, it is impossible to achieve a 100% accurate prediction (James et al., 2017) for any category with a disaggregate analysis and the fact that lower observation in any category (minor and severe injury are always lower relative to no injury) leads to lower prediction accuracy has also been identified by previous studies (Chen et al., 2016; Zhao and Khattak, 2015; Fountas and Anastasopoulos, 2017). The authors also estimated the prediction

Table 11
Observed and Model Predicted Outcomes for Combined Best Fit Model.

Outcomes	Observed		Calibrated Model Predictions		% Correct Predictions	
	Training data	Validation data	Training data	Validation data	Training data	Validation data
No injury	2349	547	2704	675	92.4%	89.7%
Minor	731	258	597	165	47.2%	45%
Severe + moderate	566	106	345	71	34.5%	34%
Overall	3646	911	3646	911	74.3%	69.8%

Table 12
Observed and Model Predicted Outcomes for Individual VA and PA Models.

Model	Outcomes	Observed		Calibrated Model Predictions		% Correct Predictions	
		Training data	Validation data	Training data	Validation data	Training data	Validation data
VA Model	No injury	2064	481	2385	535	93.1%	91.5%
	Minor	536	202	370	167	59.5%	58%
	Severe + moderate	469	84	320	60	53.4%	51.1%
	Overall	3069	767	3075	762	84.8%	81.9%
PA Model	No injury	288	63	310	96	85.1%	83.6%
	Minor	196	55	201	39	32.1%	29.7%
	Severe + moderate	93	26	61	14	22.7%	19.8%
	Overall	577	144	572	149	64%	61.3%

power for individual PA and VA fitted models separately, as shown in Table 12. It can be observed that the prediction power shows similar trends based on the relative number of observations in each category. The prediction power of the VA model is higher than the PA model, which is consistent with the fact that PA model has a relatively smaller sample. Thus, there is a tradeoff between retaining slightly higher prediction accuracy for the individual VA model or using a combined model with disparate datasets for assessing the effects of ASCTs across the two states. Additional factors such as variation in trends in police crash reporting, speeds observed over urban/suburban corridors, weather, or other localized factors across the two states may also be responsible for the lower prediction accuracy with the combined model. The authors additionally tested the prediction accuracy of random parameters logit model to observe whether it could yield a higher prediction power at the cost neglecting the ordinal nature of injury severities. The model provided a slight increase in prediction power for the minor injury category, but it reduced the prediction power of no injury category. The authors therefore, preferred using random parameters ordered probit models for this study.

The forecast accuracy was further assessed by statistical measures of mean absolute deviation, mean squared error and root mean squared error using observed and predicted severity outcomes shown in Table 13. These provide the average magnitude of error by measuring the difference between the observed and predicted outcome. This relative difference was individually calculated for each observation. For example, using both training and validation data points, the severity outcome predicted by the model was separately estimated and its relative difference compared to the observed outcome was calculated. Such differences over all observations were summed up and divided by the total number of observations to come up with the forecast error. Since a well calibrated model is expected to perform better on its training data, it was more relevant to see how it performs on a different data set that has not been used to build the model. Table 13 provides forecast errors for the final best fit model using both training and validation data. It was observed that the model provided a relatively low error for the validation data and performed similarly to the training data for all metrics. Lower values close to zero suggest good prediction with accurate forecasts.

Table 13
Forecast Error for Best Fit Model (Combined PA and VA).

Statistical Measure	Forecast Error of Best Fit Model	
	Training data	Validation data
Mean absolute deviation [*,**] $MAD = \frac{\sum_{i=1}^{n} \mid \varepsilon_i}{n}$	0.274	0.301
Mean squared error [*,**] $MAD = \frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}$	0.287	0.313
Root mean squared error [*,**] $RMSE = \sqrt{\frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}}$	0.535	0.559

* $\varepsilon_i = Observed\ Outcome - Predicted\ Outcome$.
** f $n = Number\ of\ Observations$.

Furthermore, the spatial transferability of the model was also tested as specified in (Washington et al., 2011). Separate models were estimated for Pennsylvania and Virginia datasets based on the 80% calibration data shown in Table 14 and likelihood ratio test was conducted as:

$$\chi 2 = -2[LL(\beta_{comb}) - LL(\beta_{PA}) - LL(\beta_{VA}) \quad (12)$$

where LL (β_{comb}) is the log-likelihood of combined best fit model, LL (β_{PA}) is the loglikelihood of Pennsylvania model and LL (β_{VA}) is the log-likelihood of Virginia model based on similar parameter specification. The degrees of freedom (DOF) is equal to the difference of DOF between

Table 14
Spatial Transferability test.

Spatial Transferability test	Observations [a,b]	Log-Likelihood
Pennsylvania Model	577	−573.41
Virginia Model	3069	−2521.20
Combined Model	3646	−3103.84
Likelihood ratio χ^2	−2(-3103.84 + 573.41 + 2521.20) = 18.46	
χ^2 crit(0.01)	29.14	

[a] Considering 80% of the data for all cases.
[b] All models for this assessment were estimated using similar parameters.

the sum of individual and combined model. The results specify that the model is spatially stable and parameters estimated are widely transferable across regions.

7. Study limitations

The findings of this study are based on police reported crash data which have inherent limitations. Thus, the injury severity scales reported may have errors due to the nature of the police reporting mechanism. It is therefore, possible that several categories may be misclassified or underreported. Due to the limitations of crash reporting, several important characteristics associated with the injury severities of adaptive signal control technology may also be under-reported or misclassified. For instance, driver behavior characteristics such as careless and distracted driving are not easily detectable in the field from a police officers' perspective and may be misclassified. Such instances with distracted drivers may be much higher in reality than reported. Furthermore, the difference in crash reporting mechanisms and trends across the two states (Pennsylvania and Virginia) may also lead to under/over reporting of crashes and specific injury severity categories. Since the findings in this study are heavily dependent on the accuracy of reported crashes and severity levels, any inaccuracy in these reports may lead to bias in results.

From a methodological standpoint, this study used ordered probit model with random parameters to estimate the injury severity outcomes resulting from ASCT deployment and their associated factors. The model accounts for the ordinal nature of severity outcomes and unobserved heterogeneity by allowing the parameters to vary across observations. The model performs well on both training and test data overall, but the prediction power for the severe plus moderate category was lower, mainly due to the lower number of observations in this category. Additionally, the disparate data reporting mechanisms and trends in driver behavior and seasonal variation across the two states may also contribute to this lower prediction accuracy with the combined data. In order to improve prediction accuracy for this category, the authors recommend identifying data from additional states with a similar crash reporting mechanism and general crash trends. Furthermore, the use of random parameter logit model with heterogeneity in means and variance may help in improving the prediction power of the severe plus moderate injury category at the cost of neglecting the ordinal nature of severities. It may also make sense to try machine learning algorithms such (K-Nearest Neighbor Classifier and Random Forest) instead of discrete choice models, which could yield better prediction power for disaggregate severity levels since they don't rely on making assumptions about the functional form of the data and require fewer parameters to tune.

8. Conclusions and future research

This study explicitly analyzed the impact of adaptive signal control technology on crash injury severity. The study used comprehensive datasets from two different states to calibrate and validate the final combined injury severity model. Thus, the results presented are not limited to a single region but are broadly transferrable.

The study results reveal that ASCT generally leads to a lower propensity for severe injury crashes. More specifically, ASCT in general and both types of ASCTs explored in this study (type A and type B) were found to be associated with less severe crashes. Furthermore, ASCT systems from both the states (PA and VA) were also found to reveal similar results and thus, the combined model also showed a similar trend for crash severities, pointing towards reduction in propensity of severe plus moderate and minor injury crashes by 6.52% and 3.52%. These results are also of national interest since two different ASCT systems have been analyzed using data from two different states.

Furthermore, additional explanatory variables related to driver, roadway and crash characteristics were also explored and found to increase the propensity of severe and minor injury crashes compared to no injury crashes. Most of these crashes and their severity levels can also be reduced by deploying ASCT as explained in the discussion. In terms of forecast accuracy, the best fit model performs well on the validation data and produces low forecast error of 0.301 expressed by MAD.

Since the main objective of this paper was to perform exploratory analysis of ASCT's impact on signalized intersection crash severity, crash frequency and individual crash type models were not considered in this research. Another reason was that the authors have already developed crash modification factors for ASCT (Khattak et al., 2017a) and considered those to be more useful to both practitioners and researchers. However, an interesting future research direction would be to examine how the results of crash frequency and individual crash type models compare with the crash severities presented in this paper and the CMFs developed by the authors. The optimization algorithms vary across the ASCT systems and may provide differing benefits thus, future studies could also look at crash severity effects of other ASCT systems as opposed to the two systems analyzed in this research and draw a comparison. Likewise, the emergence of automated traffic signal performance measurement systems provides an additional technology that could be compared against ASCT. With the development of connected and automated vehicles (CAV), CAV-enabled signal controls may also be analyzed in the future to see whether they provide any additional safety benefits compared to the ASCT systems analyzed in this research. Since crash trends vary across states, data from additional states across the United States can also provide significant insights about the crash severity effects of ASCTs. Another promising research direction could be to analyze the different econometric models and machine learning algorithms in order to see which modeling approach could provide better prediction accuracy with the severe plus moderate injury category, since that category had the lowest number of observations.

9. Practical implications

These research findings have several practical implications. This research enhances the understanding of injury severity outcomes resulting from ASCT deployment and contributes to the future improvement of intersection safety. Additionally, this research could serve as guidance useful resource for state and local agencies in prioritizing their road safety projects. For example, this information could be used by agencies to help quantify the safety benefits of ASCT, and help economically justify future projects. These findings from injury severity models can also be useful for practitioners and planners as they quantify the impact of ASCT on levels of injury severity. This information about reduction in crash severity is also relevant to Crash Modification Factors used in the Highway Safety Manual. For example, Khattak et al., (2017a) shows that ASCT deployment is associated with 40% reduction in the number fatal and injury crashes. These results further complement the CMF results by providing information useful in quantifying the changes in injury severity distribution expected after deployment of ASCTs. The results also reveal the impact of additional influencing factors such as driver, roadway and crash characteristics on intersection safety. For example, increase in traffic and driver related characteristics such as distraction were observed to increase injury crashes. These findings necessitate the emphasis on policies for improvement of driver behavior and educational campaigns. Since a recent study (Khattak et al., 2018) has also shown ASCT to harmonize traffic and improve driver behavior thus, these results could serve the basis for triggering ASCT deployments at locations where improvement in driver behavior and harmonization of traffic is needed to reduce such crashes.

Acknowledgement

The authors would like to thank PennDOT and VDOT for providing the data used in this manuscript. The authors would also like to thank the two anonymous reviewers; whose valuable comments have improved the manuscript significantly.

References

AASHTO, 2005. Strategic Highway Safety Plan 5800 202.
Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J. Safety Res. 34 (5), 597–603. https://doi.org/10.1016/j.jsr.2003.05.009.
Anastasopoulos, P.C., Mannering, F., 2011. An empirical assessment of fixed and random parameter logit models using crash- and non-crash-specific injury data. Accid. Anal. Prev.
Ben-Akiva, M., Lerman, S.R., 1985. Discrete Choice Analysis. MIT Press.
Chen, C., Zhang, G., Yang, J., Milton, J.C., Dely, A., 2016. An explanatory analysis of driver injury severity in rear-end crashes using a decision table / Naïve Bayes (DTNB) hybrid classifier. Accid. Anal. Prev. 90, 95–107. https://doi.org/10.1016/j.aap.2016.02.002.
Clark, J., 2010. InSync Adaptive Traffic Control Shows Initial Safety Benefits. [WWW Document]. URL. https://www.westernite.org/annualmeetings/14_Rapid_City/Presentations/4C-Gannaway.pdf.
Dutta, U., Bodke, S., Dara, B., Lynch, J., 2010. Safety Evaluation of SCATS Control System. Rep. No. MIOH UTC TS22p1-2 2010-Final. Michigan-Ohio Univ. Transp. Center, Michigan Dept. Transp., Lansing, MI.
Eluru, N., Bhat, C., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accid. Anal. Prev. 40, 3.
Eluru, N., Bagheri, M., Miranda-Moreno, L.F., Fu, L., 2012. A latent class modeling approach for identifying vehicle driver injury severity factors at highway-railway crossings. Accid. Anal. Prev. 47, 119–127. https://doi.org/10.1016/j.aap.2012.01.027.
Elvik, R., 2002. The importance of confounding in observational before-and-after studies of road safety measures. Accid. Anal. Prev. 34, 631–635.
Engineering, R., 2017. How InSync Adaptive Signal Control Technology works? [WWW Document]. URL. http://rhythmtraffic.com/how-insync-works/.
Fan, W., Hale, E., 2014. Analysis of severity of vehicle crashes at highway-rail grade crossings:multinomial logit modeling. Transp. Res. Board 93rd Annu. Meet.
Fink, J., Kwigizile, V., Oh, J.S., 2016. Quantifying the impact of adaptive traffic control systems on crash frequency and severity: evidence from Oakland County. Michigan. J. Safety Res. 57, 1–7. https://doi.org/10.1016/j.jsr.2016.01.001.
Fountas, G., Anastasopoulos, P.C., 2017. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. Anal. Methods Accid. Res. 15, 1–16. https://doi.org/10.1016/j.amar.2017.03.002.
Greene, W., 2008. Econometric Analysis. Pearson Prentice Hall, Up. Saddle River,New Jersy.
Haleem, K., Abdel-Aty, M., 2010. Examining traffic crash injury severity at unsignalized intersections. J. Safety Res. 41 (4), 347–357. https://doi.org/10.1016/j.jsr.2010.04.006.
Haleem, K., Alluri, P., Gan, A., 2015. Analyzing pedestrian crash injury severity at signalized and non-signalized locations. Accid. Anal. Prev. 81, 14–23. https://doi.org/10.1016/j.aap.2015.04.025.
Halton, J., 1960. On the efficiency of evaluating certain quasi-random sequences of points in evaluating multi-dimensional integrals. Numer. Math 2, 84–90.
Hu, W., Donnell, E.T., 2010. Median barrier crash severity: some new insights. Accid. Anal. Prev. 42 (6), 1697–1704. https://doi.org/10.1016/j.aap.2010.04.009.
Hu, S.R., Li, C.S., Lee, C.K., 2010. Investigation of key factors for accident severity at railroad grade crossings by using a logit model. Saf. Sci. 48 (2), 186–194. https://doi.org/10.1016/j.ssci.2009.07.010.
James, G., Witten, D., Hastie, T., Tibshirani, R., 2017. An Introduction to Statistical Learning. Springer, Newyork, NY.
Jonsson, B., Tingvall, C., Krafft, M., Bjornstig, U., 2013. The risk of whiplash-induced medical impairment in rear-end impacts for males and females in driver seat compared to front passenger seat. IATSS Res. 37 (1), 8–11. https://doi.org/10.1016/j.iatssr.2013.04.001.
Kergaye, C., Haigwood, J., 2011. Assessment of surrogate safety benefits of an Adaptive traffic control system. Proc.,3rd Int. Conf. Road Saf. Simulation, Sept. 14-16, 2011 1–21.
Khattak, A.J., 2001. Injury severity in multivehicle rear-end crashes. Transp. Res. Rec. J. Transp. Res. Board 1746. https://doi.org/10.3141/1746-08.
Khattak, Z.H., 2016. Evaluating the Operational & Safety Aspects of Adaptive Traffic Control Systems in Pennsylvania. Univ. Pittsburgh Thesis. .
Khattak, Z.H., Magalotti, M.J., Fontaine, M.D., 2017a. Estimating safety effects of adaptive signal control technology using the empirical bayes method. J. Safety Res. https://doi.org/10.1016/j.jsr.2017.12.016.
Khattak, Z.H., Magalotti, M.J., Miller, J.S., Fontaine, M.D., 2017b. Using New mode choice model nesting structures to address emerging policy questions: a case study of the Pittsburgh Central Business District. Sustainability. https://doi.org/10.3390/su9112120.
Khattak, Z.H., Fontaine, M.D., Boateng, R.A., 2018. Evaluating the impact of adaptive signal control technology on driver stress and behavior using real-world experimental data. Transp. Res. Part F Traffic Psychol. Behav. 58, 133–144. https://doi.org/10.1016/j.trf.2018.06.006.
Liu, J., Khattak, A.J., Richards, S.H., Nambisan, S., 2015. What are the differences in driver injury outcomes at highway-rail grade crossings? Untangling the role of pre-crash behaviors. Accid. Anal. Prev. 85, 157–169. https://doi.org/10.1016/j.aap.2015.09.004.
Lodes, M., Benekohal, R.F., 2013. “Safety Benefits of Implementing Adaptive Signal Control Technology”: FHWA-ICT-12- 020. Fed. Highw. Adm., Washington, DC, pp. 12.
Ma, J., Fontaine, M.D., Zhou, F., Hale, D.K., Clements, M.O., 2015. Estimation of the safety effects of an adaptive traffic Signal control system. Transp. Res. Board 94th Annu. Meet.
Ma, J., Fontaine, M.D., Zhou, F., Hu, J., Hale, D.K., Clements, M.O., 2016. Estimation of crash modification factors for an adaptive traffic-signal control system. ASE J. Transp. Eng 1–10. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000890.
Mehta, G., Lou, Y., 2013. Modeling school bus seat belt usage: nested and mixed logit approaches. Accid. Anal. Prev. 51, 56–67. https://doi.org/10.1016/j.aap.2012.10.008.
Milton, J.C., Shankar, V.N., Mannering, F.L., 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accid. Anal. Prev. 40 (1), 260–266. https://doi.org/10.1016/j.aap.2007.06.006.
Obeng, K., 2011. Gender differences in injury severity risks in crashes at signalized intersections. Accid. Anal. Prev. 43 (4), 1521–1531. https://doi.org/10.1016/j.aap.2011.03.004.
Qi, Y., Srinivasan, R., Teng, H., Baker, R., Qi, Y.I., Srinivasan, R., Teng, H., Baker, R., 2013. Analysis of the Frequency and Severity of Rear-End Crashes in Work Zones Analysis of the Frequency and Severity of Rear-End Crashes in Work Zones 9588. doi:10.1080/15389588.2012.675109.
Robartes, E., Chen, T.D., 2017. The effect of crash characteristics on cyclist injuries: an analysis of Virginia automobile-bicycle crash data. Accid. Anal. Prev. 104, 165–173. https://doi.org/10.1016/j.aap.2017.04.020.
Russo, B.J., Savolainen, P.T., Schneider IV, W.H., Anastasopoulos, P.C., 2014. Comparison of factors affecting injury severity in angle collisions by fault status using a random parameters bivariate ordered probit model. Anal. Methods Accid. Res. 2, 21–29. https://doi.org/10.1016/j.amar.2014.03.001.
Sabra, Z.A., Gettman, D., Henry, R.D., Nallamothu, V., 2010. Balancing Safety and Capacity in an Adaptive Signal Control System—Phase 1. Rep. No. HRT-10-038. Fed. Highw. Adm., Washington, DC.
Sabra, Z.A., Gettman, D., Henry, R.D., Nallamothu, V., 2013. Enhancing Safety and Capacity in an Adaptive Signal Control System—Phase 2. Rep. No. FHWA-PROJ-10-0037. Fed. Highw. Adm., Washington, DC.
Sacchi, E., Sayed, T., El-Basyouny, K., 2016. A full Bayes before-after study accounting for temporal and spatial effects: evaluating the safety impact of new signal installations. Accid. Anal. Prev. 94, 52–58. https://doi.org/10.1016/j.aap.2016.05.015.
Shahdah, U., Saccomanno, F., Persaud, B., 2015. Application of traffic microsimulation for evaluating safety performance of urban signalized intersections. Transp. Res. Part C Emerg. Technol. 60, 96–104. https://doi.org/10.1016/j.trc.2015.06.010.
Smith, S., Barlow, G., Xie, X.-F., Rubinstein, Z.B., 2013. SURTRAC: scalable Urban traffic control. Transp. Res. Board Annu. Meet. pp. 15.
Sussman, J.S., 2008. Perspectives on Intelligent Transportation Systems (ITS). Springer Science & Business Media.
Train, K., 2003. Discrete Choice Methods With Simulation, first. ed. Cambridge University Press, Cambridge, United Kingdom.
USDOT, 2017. Traffic Signals [WWW Document]. Br. Issue Safe Roads. URL. Safety Issue Brief 5.pdf (accessed 8.23.17). https://safety.fhwa.dot.gov/intersection/other_topics/fhwasa09027/resources/Intersection.
Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2011. Statistical and Econometric Methods for Transportation Data Analysis. CRC Press Taylor and Francis Grouphttps://doi.org/10.1198/tech.2004.s238.
Ye, F., Lord, D., 2014. Comparing three commonly used crash severity models on sample size requirements: multinomial logit, ordered probit and mixed logit models. Anal. Methods Accid. Res. 1, 72–85. https://doi.org/10.1016/j.amar.2013.03.001.
Zhao, S., Khattak, A., 2015. Motor vehicle drivers' injuries in train-motor vehicle crashes. Accid. Anal. Prev. 74, 162–168. https://doi.org/10.1016/j.aap.2014.10.022.