Clemson University

TigerPrints

Publications

Glenn Department of Civil Engineering

9-2020

Investigating Hierarchical Effects of Adaptive Signal Control System on Crash Severity using Random-parameter Ordered Regression Models Incorporating Observed Heterogeneity

Weimin Jin

Clemson University, weiminj@g.clemson.edu

Mashrur Chowdhury

Clemson University, mac@clemson.edu

M. Sabbir Salek

Clemson University, msalek@clemson.edu

Sakib Mahmud Khan

University of California - Berkeley, sakibk@berkeley.edu

Patrick Gerard

Clemson University, pgerard@clemson.edu

Follow this and additional works at: https://tigerprints.clemson.edu/civileng_pubs

Part of the [Civil and Environmental Engineering Commons](#)

Recommended Citation

Please use the publisher's recommended citation. <https://www.sciencedirect.com/science/article/pii/S0001457520303183>

This Article is brought to you for free and open access by the Glenn Department of Civil Engineering at TigerPrints. It has been accepted for inclusion in Publications by an authorized administrator of TigerPrints. For more information, please contact kokeefe@clemson.edu.

**Investigating Hierarchical Effects of Adaptive Signal Control System on Crash Severity
using Random-parameter Ordered Regression Models Incorporating Observed
Heterogeneity**

Weimin Jin^{1*}, Mashrur Chowdhury², M Sabbir Salek³, Sakib Mahmud Khan⁴, and Patrick Gerard⁵

¹Glenn Department of Civil Engineering, Clemson University, Clemson, SC, 29634, USA;
email: weiminj@g.clemson.edu

²Ph.D., Professor, Glenn Department of Civil Engineering, Clemson University, Clemson, SC,
29634, USA; email: mac@clemson.edu

³Glenn Department of Civil Engineering, Clemson University, Clemson, SC, 29634, USA;
email: msalek@clemson.edu

⁴Ph.D., Postdoctoral Scholar, Institute of Transportation Studies, U.C. Berkeley 94720, USA;
email: sakibk@berkeley.edu

⁵Ph.D., Professor, School of Mathematical and Statistical Sciences, Clemson University,
Clemson, SC, 29634, USA; email: pgerard@clemson.edu

*Corresponding author.

ABSTRACT

By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, the Adaptive Signal Control System (ASCS) can potentially improve the operation and safety of signalized intersections on a corridor. This study identifies the hierarchical effects of ASCS on the crash severity by exploring the heterogeneous effect of ASCS on the crash severity. Four different random-parameter ordered regression models (two ordered probit models, and two ordered logit models) are developed and compared. The analysis reveals that the random-parameter ordered probit and logit models (ROP and ROL) with observed heterogeneity perform better than the random-parameter ordered probit and logit models (RP and RL) without observed heterogeneity in terms of the Akaike information criteria and the goodness of fit of the model. The ROP model performs better than the ROL model in terms of classification model performance measures. The ROP model enables parameters (i.e., the coefficients of the explanatory variables) to vary as a function of explanatory variables as well as across observations, thus accounting for both observed (captured by available explanatory variables) and unobserved (not captured by available explanatory variables) heterogeneity. The analysis reveals that the presence of ASCS is associated with lower crash severity. In this study, observed heterogeneity of ASCS effects on the crash severity is captured by variables related to the intersection and corridor features. Other contributing factors besides ASCS, such as annual average daily traffic, speed limit, lighting, peak period, crash type (rear-end, angle), and pedestrian involvements, are also associated with the probability of crash severity. Unobserved heterogeneity of the effect of angle crash type on the crash severity is found to exist across the observations. The findings of this research have practical implications

for establishing ASCS implementation guidelines in lowering the probability of higher crash severity.

Keywords: Adaptive Signal Control System, Safety, Crash Severity, Ordered Regression Model, Unobserved and Observed Heterogeneity

1 Introduction

According to the American Association of State Highway and Transportation Officials (AASHTO) Strategic Highway Safety Plan (Antonucci et al., 2004), intersection-related crashes make up about 23 percent of all fatal crashes. Improving safety at intersections has become one of 22 key areas of focus in this plan. Through traffic control and operational improvement strategies, this plan aims at lowering crash severity and decreasing crash frequency at signalized intersections. Transportation agencies have been seeking new insights and approaches to improve safety at signalized intersections.

Adaptive Signal Control System (ASCS) is an advanced signal control system deployed at intersections. Although each type of ASCS is unique, all types of ASCS use a similar framework to meet fluctuating real-time traffic demand. ASCS usually includes algorithms that optimize and update parameters (i.e., cycle length, offsets, phase splits, and phase sequence) of traffic signals in real-time (Gartner et al., 2002; Lowrie, 1990). ASCS requires detectors such as loop detectors and video detectors, and a communication network enabling the central and/or local controllers to communicate with such detectors. Prior to the deployment of ASCS, conventional signal systems (i.e., pre-timed or actuated signal control) based on Time of Day (TOD) are typically

used at signalized intersections. These TOD based signal systems with pre-set signal plans usually updated every two to three years cannot handle highly variable traffic demand. However, ASCS can better accommodate fluctuating traffic demand or extreme traffic conditions. Previous studies suggest that ASCS has produced significant operational improvements on corridors and at intersections (Eghtedari, 2006; Elkins and Niehus, 2012; Fontaine et al., 2015; Kergaye et al., 2009; Khattak, 2016; Khattak et al., 2019b; So et al., 2014). By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, ASCS can smooth traffic flow and reduce traffic congestion, thus potentially yielding safety benefits for signalized intersections (Dutta et al., 2010; Fink et al., 2016; Jin et al., 2019; Khattak et al., 2018; Ma et al., 2016). These studies related to the safety effects of ASCS have emphasized the impact of ASCS on the crash frequency but not its effect on the outcomes of crash severity (i.e., non-injury, possible injury, non-incapacitating injury, incapacitating injury, or fatal).

Only a few previous studies have examined ASCS effects on crash severity outcomes. Out of those studies, two studies (Dutta et al., 2010; Fink et al., 2016) assume that the ASCS effects on crash severity are fixed in all signalized intersections for a certain type of ASCS. One recent study (Khattak et al., 2019a) has identified the disparity of ASCS effects on crash severity with two different types of ASCS and the difference of ASCS effects on crash severity between two states- Pennsylvania and Virginia. However, previous studies typically assume that ASCS effects on crash severity outcomes do not vary across observations (i.e., crashes).

Crash severity outcomes could be associated with a series of variables related to the corridor, intersection, and crash features. A multilevel structure (i.e., hierarchical structure) inherent in the

crash data will be overlooked if all the variables are viewed at one level. Hierarchical modeling is used to represent the multilevel-structure of the crash data. The hierarchical effect on crash estimation has been explored in previous studies (Chen and Persaud, 2014; Huang et al., 2008; Khazraee et al., 2018; Krishnan et al., 2013; Xie et al., 2013). In this study, ASCS is usually deployed at several signalized intersections on corridors; thus, the hierarchical structure exists inherently in the crash data. The crash data structure can be viewed as a two-level hierarchy with Level 1 being an individual crash, and Level 2 being the intersection and corridor (i.e., one individual crash can be associated with one specific intersection and corridor). The ASCS effect on the crash severity that exists in the hierarchical structure can be estimated by implementing hierarchical models. A random-parameter ordered regression model integrating observed heterogeneity (also known as a hierarchical model) allows the ASCS parameter to vary both as a function of explanatory variables related to the intersection and corridor features, and across crashes. This kind of ASCS effect that exists in the hierarchical structure is referred to as “Hierarchical Effects of ASCS on the Crash Severity” in this paper.

In previous studies related to crash severity outcome modeling, random-parameter ordered regression models have been implemented, but they have not been integrated with observed heterogeneity. This study contributes to the literature related to ASCS effects on crash severity by developing random-parameter ordered regression models with observed heterogeneity. Our model is capable of accounting for both observed (i.e., changes in the effect of predictors across the observations that are known and could be captured by available explanatory variables) and unobserved (i.e., changes in the effect of predictors across the observations that are unknown and could not be captured by available explanatory variables) heterogeneity. The objective of this

paper is to determine the hierarchical effects of ASCS on the crash severity. Through accounting for the observed heterogeneity in random-parameter ordered regression models using crash data from six ASCS corridors with 65 signalized intersections, the hierarchical effects of ASCS on the crash severity are identified. The identification of the hierarchical effects of ASCS on the crash severity provides several practical implications on ASCS implementations at the standpoint of safety. The same ASCS type has been deployed at the intersections considered in this study. So, the algorithms of this particular type of ASCS are the same for all the intersections considered in this study. ASCS optimizes the cycle length, phase splits, and offsets in real-time based on current traffic conditions to minimize overall traffic delays at the intersections while guaranteeing a reasonable coordination between the intersections on a corridor. Our study focuses on investigating the effects of a particular ASCS type (which this paper refers to as “ASCS”) on the cash severity without considering the variations between multiple ASCS types as it is not within the scope of this study.

The remainder of the paper is organized as follows: literature review, research method, data description, results and analysis, and conclusions. The literature review section entails the safety effects of the ASCS on the crash frequency, the crash severity outcomes associated with ASCS, and models developed for the crash severity outcomes. A discussion of the ordered regression models and model implementation are included in the research method section. The data description details the description of variables contributing to the crash severity. The model comparison and estimation results on the association between contributing factors and crash severity are detailed in the results and analysis section. Finally, the summary findings and practical implications are detailed in the conclusions section.

2 Literature review

2.1 Safety effects of adaptive signal control systems on crash frequency

As ASCS uses real-time traffic data to maximize vehicle progression and reduce vehicle stops, it is expected to improve safety by reducing rear-end crash probability compared to pre-timed or actuated signal control systems. Based on multiple evaluations across the nation, ASCS has been found to improve intersection safety, with a few exceptions. In one study conducted in Virginia, Fontaine et al. (Fontaine et al., 2015) note that a 17 % reduction in the total number of crashes is associated with ASCS using the Empirical Bayes (EB) method. In Pennsylvania, Khattak (Khattak, 2016) notes that 34 % and 45 % reductions in the total number of crashes and fatal and injury crashes are associated with ASCS, respectively. Based on the analysis of ten years of crash data (1999 - 2008) in Michigan, ASCS is found to reduce the total crash rate by 6% (Dutta et al., 2010). Fink et al. (Fink et al., 2016) have examined the safety effects of signalized intersections with Sydney Coordinated Adaptive Traffic System (SCATS), an ASCS type, in Michigan. Fink et al. (Fink et al., 2016) have implemented a cross-sectional method by using 498 signalized intersections and found that a 19.3% reduction in angle crashes is associated with SCATS.

2.2 Safety effects of adaptive signal control systems on crash severity outcomes

Evaluation of the impact of ASCS deployment on crash severity outcomes is predominantly absent from the literature. Only a few studies related to crash severity effects of ASCS are identified. Dutta et al. (Dutta et al., 2010) have used before period (1999 - 2001) and after period (2003 - 2008) crash data from one corridor with SCATS and another with the pre-timed signal. They perform a *t*-test analysis and find that a definite change in severity from incapacitating

injury and non-incapacitating injury to possible injury. But, the t -test fails to prove the superiority of SCATS over the pre-timed signal control system in lowering the crash severity at a 0.05 significance level.

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

Similarly, in the examination of the effect of ASCS on the crash severity, Khattak et al. (Khattak et al., 2019a) have identified the disparity between two different types of ASCS and between two states- Pennsylvania and Virginia. They have found that both types of ASCS are associated with lower crash severity, and ASCS implemented in these two states are also associated with lower crash severity.

2.3 Modeling of crash severity outcomes

Of the various modeling approaches developed for modeling the crash severity outcomes, the most widely used models are ordered regression models (i.e., ordered probit and logit models), which account for the ordinal nature reflected in crash severity levels.

Khattak and Tung (Khattak and Tung, 2015) have used an ordered probit model to quantify the impact of various contributing factors (e.g., train speed, weather condition, area types, etc.) on three different severity levels (i.e., no injury, injury, and fatal) of pedestrian injuries. Zhao and Khattak (Zhao and Khattak, 2015) have used an ordered probit model to investigate contributing

factors (e.g., the involvement of freight trains, older drivers, high train speeds, high vehicle speeds, and female drivers) correlated with crash severity levels of motorists in the case of the train-vehicle crashes. Eluru et al. (Eluru et al., 2012) have used a latent segmentation based ordered logit model to identify the contributing factors (e.g., time of the collision, motorist age, snow and/or rain condition, the presence of a vehicle struck by a train, and driver operation in the pre-crash) that influence injury severity of vehicle drivers in train-motor crashes at highway-railway grade crossings. In some studies, researchers have not considered crash severity levels as ordinal outcomes and therefore used multinomial logit models (Fan et al., 2015; Fink et al., 2016). Based on a comparative analysis of the three most common models (i.e., ordered probit, mixed logit model, and multinomial logit), Ye, and Lord (Ye and Lord, 2014) have concluded that each can be the best choice based on the sample size requirement. Among the three models, the mixed logit model requires the largest sample size, and the multinomial logit model requires the second-largest sample size. In contrast, the ordered probit model requires the smallest sample size. The minimum sample size recommended by (Ye and Lord, 2014) for the mixed logit model, multinomial logit model, and ordered probit models is 5000, 2000, and 1000, respectively.

3 Research method

Ordered regression models (i.e., ordered probit and logit models) are implemented to account for the ordinal nature (e.g., ranging from non-injury to possible injury, to non-incapacitating injury, to incapacitating injury, to fatal) of crash severity. The ordered regression models have been widely used to consider the ordinal nature of crash data mainly. However, an underlying assumption of ordered regression models is that the estimated parameters across crash severity

levels are constant. This assumption is referred to as “the proportional odds or parallel regression” assumption. In this study, the authors initially fit ordered regression models and test this possible assumption by using the Brant test (Brant, 1990). It is found that the variable associated with the presence of ASCS does not violate the assumption. However, ordered regression models cannot capture unobserved heterogeneity across observations. Thus, the models may result in incorrect estimates (Washington et al., 2020). The random-parameter ordered regression model enables the parameters to vary across observations and has been explored by previous studies (Dabbour et al., 2017; Jalayer et al., 2018; Khattak et al., 2019a). However, in previous studies related to crash severity outcome modeling, random-parameter ordered regression models have not been integrated with observed heterogeneity.

3.1 Random-parameter ordered regression model

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

$$y_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_i, \quad i = 1, \dots, n \quad (1)$$

$$\boldsymbol{\beta}_i \sim g(\boldsymbol{\beta}_i | \boldsymbol{\theta}) \quad (2)$$

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

225 In Eq. (1) and (2), β_i is allowed to be different for each observation i rather than fixed for all
 226 observations. The distribution $g(\beta_i | \theta)$ is specified to enable β_i vary across observations, where
 227 θ is a vector of the mean and variance of the random distribution.

228

229 β_i can be written as $\beta_i = \beta + L\omega_i$, where β is the vector of the mean of the coefficients. Each
 230 coefficient β_{ki} can be expressed as $\beta_{ki} = \beta_k + \sigma_k \omega_{ki}$. β_{ki} is the k^{th} element in β_i . ω_i is a vector
 231 of random variables that follow a random distribution. ω_{ki} is the k^{th} element in ω_i . ω_{ki} has a
 232 specific random distribution such as normal distribution and uniform distribution. L is a diagonal
 233 matrix of the standard deviations of the coefficients, σ_k . The unobserved heterogeneity is
 234 represented by σ_k . β_{ki} has a specific random distribution such as normal distribution and
 235 uniform distribution. For example, β_{ki} follows a normal distribution with a mean of β_k and a
 236 variance of σ_k^2 when $\omega_i \sim N(0,1)$.

237

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

$$239 \quad p(y_i = j) = P(\mu_{j-1} < y_i^* \leq \mu_j) = F(\mu_j - \mathbf{X}_i \beta_i) - F(\mu_{j-1} - \mathbf{X}_i \beta_i) \quad (3)$$

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

243

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

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

$$y_i = 0 \text{ if } y_i^* \leq \mu_0 \quad (4)$$

$$y_i = 1 \text{ if } \mu_0 < y_i^* \leq \mu_1 \quad (5)$$

$$y_i = 2 \text{ if } y_i^* > \mu_1 \quad (6)$$

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

3.2 Random-parameter ordered regression model with observed heterogeneity

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

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

Figure 1 Hierarchical Structure of Crash Data

283

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

$$286 \quad y_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_i, \quad i = 1, \dots, n \quad (7)$$

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

289

290 In the intersection/corridor level (Level 2 in the hierarchical model), $\boldsymbol{\beta}_i$ is specified by Eq. (8).
291 The specification of Eq. (8) allows the coefficients to vary with different intersections and
292 corridors.

$$293 \quad \boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Pi} \mathbf{s}_i + \mathbf{L} \boldsymbol{\omega}_i \quad (8)$$

294 where, $\boldsymbol{\beta}$ is a vector of the mean of coefficients; $\boldsymbol{\omega}_i$ is a vector of random variables that follow
295 random distributions; $\mathbf{L}$ is a diagonal matrix of the standard deviations of the coefficients; $\mathbf{s}_i$ is a
296 vector of intersection/corridor-level explanatory variables; $\boldsymbol{\Pi}$ is a matrix of coefficients of the
297 intersection and corridor related variables. Then, the expectation of coefficients is
298 $E(\boldsymbol{\beta}_i) = \boldsymbol{\beta} + \boldsymbol{\Pi} \mathbf{s}_i$. The expectation of coefficients is a function of the intersection/corridor-level
299 variables, $\mathbf{s}_i$.

300

301 More specifically, in Eq. (8), two components, $\boldsymbol{\Pi} \mathbf{s}_i$ and $\mathbf{L} \boldsymbol{\omega}_i$ are introduced to allow the
302 coefficients to vary with different levels. First, $\boldsymbol{\Pi} \mathbf{s}_i$ is a linear function depending on the
303 intersection/corridor related variables, $\mathbf{s}_i$. The primary purpose of using $\boldsymbol{\Pi} \mathbf{s}_i$ is to capture the

observed heterogeneity across different intersections and corridors. It is expected that the varying intersections and corridor features (e.g., number of legs at an intersection, number of through/left/right lanes at an intersection, speed limit difference between a major street and a minor street at an intersection, and signalized intersection distance on a corridor) may lead to different crash severity. This specification of Πs_i is the same as reported in (Huang et al., 2008). Second, $L\omega_i$ represents random effects, which capture both the intersection/corridor-level variability (Level 2) and the crash-level variability (Level 1). The primary purpose of using $L\omega_i$ is to capture the unobserved heterogeneity in the crash data. These random effects are assumed not only to vary across various intersection/corridors (Level 2) but also to vary for the crashes (Level 1) within the same intersection/corridor. This specification of random effects is different from the (Huang et al., 2008) study, in which it is assumed that the random effects only vary across different crashes (Level 2 in the model of the (Huang et al., 2008) study), whereas they are kept the same for all the driver-vehicle units (Level 1 in the model of the (Huang et al., 2008) study) within the same crash.

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

$$\hat{E}(\beta_i | \text{data}_i) = \sum_{r=1}^R \left(\frac{\hat{P}(\mathbf{y}_i | \mathbf{X}_i, \beta_{ir})}{\sum_{r=1}^R \hat{P}(\mathbf{y}_i | \mathbf{X}_i, \beta_{ir})} \right) \hat{\beta}_{ir} \quad (9)$$

where, $\hat{\beta}_{ir} = \hat{\beta} + \hat{\Pi} s_i + \hat{L} \omega_{ir}$; $\hat{P}(\mathbf{y}_i | \mathbf{X}_i, \beta_{ir})$ is the estimated simulated probability for a crash i evaluated at the r^{th} draw of β_i ; data_i represents the explanatory variables; R is the total number

of draws in the SML procedure. The random draws are generated by a Halton random number generator with a standard uniform distribution, $U(0,1)$. Detail Halton draws procedure can be found in (Sarrias, 2016).

3.3 Model implementation and estimation

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

To evaluate the effect of the explanatory variables on the probability of crash severity, especially on the intermediate level (i.e., C), marginal effects for the three crash severity levels (i.e., O, C, and KAB) are computed. The marginal effect of explanatory variables indicates the change of the probability of crash severity associated with a one-unit change in the continuous variables or change from “0” to “1” in the indicator variables. It should also be noted that marginal effects are estimated at the sample mean of the explanatory variables using the expectation of

parameters when computed for random parameters. Marginal effects for the three crash severity levels are computed (Greene, 2003; Washington et al., 2020) as follows:

$$\frac{\partial p(y_i = 0)}{\partial x} = -\varphi(-\mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \quad (10)$$

$$\frac{\partial p(y_i = 1)}{\partial x} = \varphi(-\mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} - \varphi(\mu_1 - \mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \quad (11)$$

$$\frac{\partial p(y_i = 2)}{\partial x} = \varphi(\mu_1 - \mathbf{X}\boldsymbol{\beta})\boldsymbol{\beta} \quad (12)$$

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

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

the model is developed using the training dataset, and then the model is evaluated using the test dataset. The accuracy, precision, and recall are computed for the test dataset using Eq. (13) to Eq. (15) (Sammut Claude and Webb, 2010; Ting, 2010).

$$\text{Accuracy} = CT / N \quad (13)$$

$$\text{Precision} = TP_t / (TP_t + FP_t) \quad (14)$$

$$\text{Recall} = TP_t / (TP_t + FN_t) \quad (15)$$

where, CT is the total number of correctly classified instances for all classes; N is the total number of instances for all classes; t is the class label (i.e., O, C, or KAB); TP_t is true positive for the class label t ; FP_t is false positive for the class label t ; FN_t is false negative for the class label t .

Overall precision and recall are evaluated by computing the micro-average values of precision and recall (Van Asch, 2013), which are derived by Eq. (16) and Eq. (17).

$$\text{Precision}_{\text{Micro-average}} = \sum_{t=1}^T TP_t / (\sum_{t=1}^T TP_t + \sum_{t=1}^T FP_t) \quad (16)$$

$$\text{Recall}_{\text{Micro-average}} = \sum_{t=1}^T TP_t / (\sum_{t=1}^T TP_t + \sum_{t=1}^T FN_t) \quad (17)$$

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

4 Data description

Initially, the authors obtained crash data from 13 corridors that have installed ASCS. Original crash data have before period and after period data. The authors only include corridors that have

at least a two-year after period crash data for this study. As listed in **Table 1**, there is a total of six corridors (one in Lexington, one in Greenville, two in Charleston, one in Pawleys Island, and one in Summerville) with a total of 65 intersections where ASCS has been deployed. In total, 6,570 crashes are analyzed in this study. Only one type of ASCS is investigated in this study. For this specific type of ASCS, there are three main components, including server, local traffic controller, and vehicle detection. The server is responsible for processing data and calculating updated signal timings. The local traffic controller is responsible for gathering detection data and executing the commands received from the server. The interaction between the server and the local traffic controller is performed every few seconds to ensure signal timings are always up-to-date. The primary objective of the algorithm of this type of ASCS is to minimize traffic delays at the intersections while ensuring reasonable progression bandwidth of the corridor. This type of ASCS optimizes the cycle length, splits, and offsets based on real-time traffic conditions. By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, ASCS can smooth traffic flow and reduce traffic congestion, thus potentially yielding safety benefits for signalized intersections.

Table 1 Corridor Information

Location	Corridor Name	Number of Signals	Installation Date	Number of Crashes at Intersections
Greenville	Roper Mt Rd/ Garlington Rd	5	November 2016	193
Charleston	SC 642	18	June 2015	931

Location	Corridor Name	Number of Signals	Installation Date	Number of Crashes at Intersections
Charleston	US 52	17	October 2016	2387
Lexington	N Lake Drive	7	December 2015	502
Pawleys Island	US 17	6	February 2016	552
Summerville	US 17A	12	June 2015	2005

406

407 According to SCDOT, the intersection-related crashes are those that occurred within 0.05 miles
408 of the center of the intersection. Using the threshold of 0.05 miles, the intersection-related
409 crashes are identified. Crash data are collected for all study corridors from 2011 to 2018. Crash
410 data of six months after the installation of ASCS are removed from the analysis, which
411 eliminates the effect of acclimation to ASCS of drivers. As shown in **Table 2**, around 79 % of
412 the crashes are O (i.e., no injury), and a small proportion (around 6 %) of the crash is KAB (i.e.,
413 fatal, incapacitating injury, and non-incapacitating injury combined).

414

415 **Table 2 Frequency (and percentage) of Crash Severity**

Crash Severity Outcome	Frequency (Percentage)
O*	5182 (78.9 %)
C*	1005(15.3 %)
KAB*	383 (5.8 %)

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

In order to properly analyze the crash data, the authors collect information from SCDOT regarding whether any other possible safety improvements, in addition to the ASCS, have been implemented at intersections. Flashing Yellow Arrow (FYA) was installed on some signalized intersections before or after the ASCS was installed. Although only 3.9 % (256 out of 6,570) of the observations have FYA, FYA may affect the crash severity outcome. Therefore, the authors initially consider FYA as one of the explanatory variables of the model. A categorical variable is considered to distinguish the effects of different numbers of FYA at the intersections on the crash severity outcomes. It is found that the categorical variable is not significant and adding the categorical variable increases AIC of the model. Thus, the FYA variable is taken out of the model since it cannot provide useful information. Left-turn lanes were modified at one intersection in one of study corridors after the ASCS was installed. To exclude the effect of such improvements that may impact safety, the crashes that occurred at this intersection are not included in the analysis. An additional signal phase was added to one signal after the ASCS was installed; thus, the crashes located at this intersection are not included in the analysis as well.

Table 3 shows a summary of descriptive statistics of the geometric features of intersections and speed limit data. The difference in the geometric features of intersections and speed limit between before period and after period is very small.

Table 3 Descriptive Statistics of Geometric Features of Intersections and Speed Limit Data

Variables	Before Period				After Period			
	Mean	S.D. ^a	Min	Max	Mean	S.D. ^a	Min	Max

Variables	Before Period				After Period			
	Mean	S.D. ^a	Min	Max	Mean	S.D. ^a	Min	Max
Number of legs at intersections	3.82	0.38	3	4	3.80	0.40	3	4
Number of through lane(s) on major roads	5.37	1.44	2	8	5.29	1.28	2	8
Number of the exclusive right-turn lane(s) on major roads	1.20	0.80	0	2	1.16	0.84	0	2
Number of the exclusive left-turn lane(s) on major roads	2.28	0.91	0	4	2.22	0.89	0	4
Number of through lane(s) on minor roads	2.16	1.21	0	5	2.14	1.19	0	5
Number of the exclusive right-turn lane(s) on minor roads	1.02	0.70	0	2	0.87	0.75	0	2
Number of the exclusive left-turn lane(s) on minor roads	1.81	0.89	0	4	1.89	0.89	0	4
Number of access points on major roads	3.03	1.75	0	7	3.27	1.80	0	7
Number of access points on minor roads	2.38	1.92	0	7	2.39	1.88	0	7
Speed limit on major roads (mph)	42.64	5.00	25	55	41.47	5.53	25	55
Speed limit on minor roads (mph)	32.15	4.89	25	50	31.78	4.71	25	50

^a S.D.-Standard deviation

The following crash attributes are provided by SCDOT: collision time, crash severity, Annual Average Daily Traffic (AADT), light condition, road surface condition, crash type, weather condition, work zone, first harmful event, and probable cause. The purpose of the inclusion of the first harmful event is to determine the involvement of pedestrians. The purpose of the inclusion of probable cause is to identify the careless (distracted) or aggressive drivers (i.e., aggressive operation of the vehicle or at excessive speed). The light (dawn, daylight, dusk or dark), and weather conditions (rain or not) are accounted for because those attributes may impact

crash severity. Peak periods for each corridor analyzed in this study are identified by analyzing hourly average travel time data provided by the Iteris ClearGuide system (Iteris, 2020). The peak periods only exist on weekdays for the study corridors, and we found that the hourly average travel time does not vary much over the 24 h during weekends on our study corridors. That is why only weekday peak periods are considered in this paper, as shown in **Table 4**. Crash data available for South Carolina and provided by the SCDOT do not map crashes to traffic signal status (green, yellow, or red) (SCDOT, 2020a). Consequently, each crash cannot be associated with a specific signal phase from the available data. Due to this limitation, signal related parameters, such as signal status (green, yellow or red) and green/yellow/red time, could not be introduced into the model.

Table 4 Peak Periods for the Study Corridors

Location	Corridor Name	Peak Period
Greenville	Roper Mt Rd/ Garlington Rd	7:00 - 10:00
		16:00 - 19:00
Charleston	SC 642	6:00 - 9:00
		15:30 - 18:30
Charleston	US 52	7:00 - 10:00
		14:00 - 18:00
Lexington	N Lake Drive	7:00 - 10:00
		15:00 - 19:00
Pawleys Island	US 17	11:00 - 15:00
Summerville	US 17A	11:00 - 14:00

Location	Corridor Name	Peak Period
		16:00 -19:00

460

461 The attributes from the crash database are converted to the response and explanatory variables.

462 The response variable includes three crash severity levels- O, C, and KAB. The explanatory

463 variables include light condition, ASCS presence, FYA presence, peak period, crash type (rear-

464 end or angle), weather condition, careless driving, aggressive driving, the presence of

465 pedestrians, and AADT. Also, the authors have collected area type (urban or not) and speed limit

466 data from the SCDOT website (SCDOT, 2020b), and corridor geometric features (i.e., the

467 average distance between signalized intersections) from Google Earth. The descriptive statistics

468 for the response and the significant explanatory variables for both before period and after period

469 are shown in **Table 5**. A Pearson correlation test between AADT and the peak period is

470 conducted, and it is found that there is no correlation between AADT and the peak period in our

471 study. A high traffic volume may be associated with a higher crash severity. An AADT threshold

472 of 30,000 is used to identify relatively high traffic volume in this study based on a previous study

473 (Fink et al., 2016). A threshold of 10 mph speed difference between a major road and a minor

474 road at an intersection is used to divide the observations into two groups (one group for which

475 the speed limit difference between a major road and a minor road is equal to or greater than 10

476 mph; another group for which the speed limit difference between a major road and a minor road

477 is less than 10 mph) because, based on our analysis, the median speed limit difference between a

478 major road and a minor road in the sample is about 10 mph. In this study, all explanatory

479 variables are tested in terms of MC. It is found that the maximum value of VIF is 2.37. Thus, the

480 MC issue should not be of concern for the variables considered in this study. The authors

481 initially include the interaction variables into the model to account for the interaction between

ASCS and angle crash and the interaction between ASCS and rear-end crash in the model. However, the interaction variables are not significant and adding these interaction variables increases the AIC of the model. Therefore, the interaction variables are later excluded from the model.

Table 5 Summary of Descriptive Statistics of Response Variables and Significant Explanatory Variables

Variable	Definition	Level/Data Type	Before Period Frequency (Percentage)	After Period Frequency (Percentage)
<i>Crash_Severity</i>	Crash severity outcome	0 - O	3093 (77.7 %)	2089 (80.6 %)
		1 - C	631 (15.9 %)	374 (14.4 %)
		2 - KAB	255 (6.4 %)	128 (4.9 %)
<i>Light</i>	Dark (1 if dark, otherwise 0)	1	912 (22.9 %)	579(22.3%)
		0	3067 (77.1 %)	2012 (77.7 %)
<i>ASCS</i>	The presence of ASCS (1 if Yes, otherwise 0)	1	-	2591 (39.4 %)
		0	3979 (60.6 %)	-
<i>Peak</i>	Peak period (1 if peak period, otherwise 0)	1	1075 (27.0 %)	698 (26.9 %)
		0	2904 (73.0 %)	1893 (73.1 %)
<i>Rear_end</i>	Rear-end (1 if rear-end, otherwise 0)	1	2140 (53.8 %)	1335(51.5 %)
		0	1839 (46.2 %)	1256 (48.5 %)
<i>Angle</i>	Angle (1 if angle, otherwise 0)	1	1073 (27 %)	672(25.9 %)
		0	2906 (73 %)	1919 (74.1 %)
<i>Pedestrian</i>	The presence of pedestrian (1 if pedestrian-involved, otherwise 0)	1	21 (0.5 %)	12 (0.5 %)
		0	3958 (99.5 %)	2579 (99.5 %)

Variable	Definition	Level/Data Type	Before Period Frequency (Percentage)	After Period Frequency (Percentage)
<i>AADT_over_30k</i>	AADT at a road on which a crash occurred (1 if greater than 30k, otherwise 0)	1	3256 (81.8 %)	2272 (87.7 %)
		0	723 (18.2 %)	319 (12.3 %)
<i>S_Difover10</i>	Speed limit difference between major roads and minor roads at an intersection (1 if equal to or greater than 10 mph, otherwise 0)	1	2894 (72.7 %)	1882 (70.3 %)
		0	1085 (27.3 %)	769 (29.7 %)
			<i>Mean (S.D^a)</i>	<i>Mean (S.D^a)</i>
<i>Speed_Limit</i>	Speed limit (mph)	<i>Numeric</i>	40.71 (6.20)	39.83 (6.33)
<i>Signal Distance</i>	Average signal distance on a corridor (miles)	<i>Numeric</i>	0.38 (0.12)	0.36 (0.12)

^a S.D.-Standard deviation

5 Results and analysis

Four random-parameter ordered regression models are firstly compared. The model estimation results on the association between the presence of ASCS and the crash severity and the relationship between other contributing factors and the crash severity are then presented.

5.1 Comparison of random-parameter ordered regression models

The following four models are estimated and compared:

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

- Random-parameter ordered probit model (RP)
- Random-parameter ordered logit model (RL)

In the model estimation results in **Table 6**, a positive sign of the coefficient of predictors is associated with higher crash severity, while a negative sign of the coefficient is associated with lower crash severity. From the negative sign of the coefficient (i.e., -0.113 for the RP model and -0.205 for the RL model) of the ASCS variable in **Table 6**, it shows that the presence of ASCS is associated with lower crash severity. Since the standard deviation associated with ASCS is found to be statistically insignificant in the RP, RL, ROP, and ROL models, ASCS is not considered as a random parameter for these models. Instead, ASCS is considered as a fixed parameter for the RP and RL models, and a varying parameter depending on intersection/corridor-level variables (i.e., S_Difover10 and Signal Distance) for the ROP and ROL models. Only the angle variable is considered as a random parameter with the mean (i.e., mean.Angle) and the standard deviation (i.e., S.D. Angle) in these models.

Table 6 Model Estimation Results

	ROP ^a		ROL ^a		RP ^a		RL ^a	
Coefficients	Est.	p-value	Est.	p-value	Est.	p-value	Est.	p-value
Threshold, μ_1^b	0.858	< 0.001	1.675	< 0.001	0.855	< 0.001	1.671	< 0.001
Constant	-1.554	< 0.001	-2.822	< 0.001	-1.618	< 0.001	-2.947	< 0.001
Pedestrian	2.078	< 0.001	3.711	< 0.001	2.061	< 0.001	3.660	< 0.001
AADT_over_30k	0.235	< 0.001	0.425	< 0.001	0.225	< 0.001	0.405	< 0.001
Speed_Limit	0.009	0.008	0.019	< 0.001	0.011	0.001	0.022	< 0.001
Light	0.324	< 0.001	0.553	< 0.001	0.321	< 0.001	0.543	< 0.001

Rear_end	0.133	0.006	0.319	< 0.001	0.134	0.005	0.318	< 0.001
Peak	-0.090	0.037	-0.178	0.027	-0.093	0.031	-0.183	0.023
ASCS	-	-	-	-	-0.113	0.002	-0.205	0.003
mean.ASCS ^c	-0.443	< 0.001	-0.799	< 0.001	-	-	-	-
mean.Angle ^c	0.330	< 0.001	0.416	0.016	0.331	< 0.001	0.501	< 0.001
S_Difover10 ^d	0.127	0.071	0.256	0.055	-	-	-	-
Signal Distance ^d	0.637	0.007	1.081	0.013	-	-	-	-
S.D.Angle ^e	1.030	< 0.001	2.532	< 0.001	1.018	< 0.001	1.369	< 0.001
Log-Likelihood	-4024		-4025		-4030		-4031	
Number of observations	6570		6570		6570		6570	
AIC	8076.28		8078.20		8082.41		8084.15	

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

b: estimated threshold in Eq. (5) – (6)

c: mean of the coefficient

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

e: standard deviation of the coefficient

As indicated in the previous studies, the AIC difference between two competing models that is greater than 2 (Burnham and Anderson, 2004) or 2.5 (Hilbe, 2011) could be used as a threshold to distinguish different models. Based on the recommendation of these studies, the difference of AIC between two models greater than 2.5 is considered as the threshold to select the preferred models in this study. As indicated in **Table 7**, the ROP and ROL models are better than the RP and RL models in terms of AIC. As indicated in **Table 7** (in the last two columns), in terms of AIC, there are no significant differences between the ROP and ROL models, as well as between the RP and RL models.

Table 7 Model Comparison based on AIC Difference

Model Comparisons

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

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

In addition to using AIC, a likelihood ratio test (Washington et al., 2020) for comparing nested models (e.g., RL VS. ROL, RP VS. ROP, RL VS. ROP, RP VS. ROL) is conducted in this study to identify a superior model with better goodness of fit of the model, as shown in **Table 8**. The likelihood ratio Chi-squared statistics are statistically significant at a 0.05 significance level, suggesting that the ROP and ROL models are better than the RP and RL models in terms of the goodness of fit of the model. The likelihood ratio tests are not conducted for comparing non-nested models (e.g., ROP VS. ROL, RP VS. RL) as the likelihood ratio test does not apply to compare non-nested models. Based on both AIC (**Table 7**) and the likelihood ratio test (**Table 8**) findings, the ROP and ROL models are better than the RP and RL models in terms of both the AIC and goodness of fit of the model.

Table 8 Likelihood Ratio Test Results for Nested Models

	Model comparison			
	RL VS. ROL ^a	RP VS. ROP ^a	RL VS. ROP ^a	RP VS. ROL ^a
Difference of degrees of freedom between two	3	3	3	3

Model comparison				
	RL VS. ROL ^a	RP VS. ROP ^a	RL VS. ROP ^a	RP VS. ROL ^a
competing models				
Likelihood ratio Chi-squared				
statistic	12.28	12.44	14.78	9.94
p-value	0.006 ^b	0.006 ^b	0.002 ^b	0.02 ^b
Superior model (with better goodness of fit of the model)	ROL	ROP	ROP	ROL

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

b statistically significant at a 0.05 significance level.

Since the ROL and ROP models are compared as non-nested models, the likelihood ratio test (Washington et al., 2020) does not apply to the comparison of the ROL and ROP models. Alternatively, three metrics: precision, recall, and accuracy, which are widely used for evaluating a classification model, are used for evaluating the performance of the ROP and ROL models. A training dataset with 80 % of the sample and a test dataset with 20 % of the sample are obtained. The training dataset and test dataset are randomly sampled. During the sampling, both datasets are ensured to have similar percentages of data points by category (i.e., by crash severity outcomes). The sampling procedure is repeated 30 times (Rahman et al., 2019; Xie et al., 2019). For each time, the model is developed using the training dataset, and then the model is evaluated using the test dataset. The three metrics are evaluated for 30 times, and the results are averaged and presented in **Table 9**. The precision and recall are evaluated for each crash severity level (i.e., O, C, or KAB). Also, the overall precision and recall are evaluated by computing the micro-average values of the precision and recall, and the results are shown in **Table 9**. A *t*-test is

conducted to determine if the means of evaluated metrics for the ROP and ROL models are significantly different from each other. In terms of accuracy, overall precision, and overall recall, the ROP model outperforms the ROL model. The results of accuracy, overall precision, and overall recall for the ROP and ROL models are significantly different from each other at a 0.05 significance level.

Table 9 Classification Model Performance Metrics

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

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

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

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

5.2 ASCS effects on crash severity

Since the ROP model is deemed as best based on the discussion in Subsection 5.1, only ROP model estimation results are discussed here. As shown in **Table 6**, observed heterogeneity of ASCS is estimated by two intersection/corridor-level variables (i.e., S_Difover10 and Signal Distance). Other variables related to intersection features such as the number of legs at an intersection and the number of through/left/right lanes at an intersection are attempted in the model, but these variables are not significant. Other variables related to corridor features such as average AADT on a corridor are tried in the model, but they are not significant.

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

$$\beta_{ASCS,i} = -0.443 + 0.127(x_{S_Difover10,i}) + 0.637(x_{Signal\ Distance,i}) \quad (18)$$

where, i is an observation ID (i.e., a specific crash). $x_{S_Difover10,i}$ is 1 if the speed limit difference between a major street and a minor street at an intersection is equal to or greater than 10 mph and otherwise is 0. $x_{Signal\ Distance,i}$ is the average signal distance on a corridor.

Figures 2 to 4 show observed heterogeneity in terms of coefficient of the ASCS variable estimated by the ROP model, which represents hierarchical effects of ASCS on the crash severity. The hierarchical effects of ASCS on the crash severity represent the ASCS effect varied by intersection and corridor features. Based on Eq. (18), two linear functions are plotted in **Figure 2**. In **Figure 2**, a negative coefficient in the y-axis indicates that the presence of ASCS is associated with lower crash severity, whereas a positive coefficient indicates that the presence of ASCS is associated with higher crash severity. The following observations are derived from **Figure 2**:

- In Case 1, where speed limit difference between a major street and a minor street at an intersection (intersection feature) is equal to or greater than 10 mph, the coefficient of ASCS increases as the average signal distance on a corridor increases. When the average signal distance on a corridor (corridor feature) exceeds the threshold of 0.49 miles for

Case 1, the coefficient of ASCS becomes positive, suggesting that the presence of ASCS is associated with higher crash severity.

- In Case 2, where speed limit difference between a major street and a minor street at an intersection is less than 10 mph, the coefficient of ASCS increases as the average signal distance on a corridor increases. When the average signal distance on a corridor exceeds the threshold of 0.69 miles for Case 2, the coefficient of ASCS becomes positive, suggesting that the presence of ASCS is associated with higher crash severity.
- The threshold of average signal distance, as discussed earlier, for Case 2 is larger than that for Case 1, indicating that when the speed limit difference between a major street and a minor street at an intersection (i.e., less than 10 mph) is less likely to increase the crash severity, the larger signal distance on a corridor can be accepted to deploy the ASCS without increasing the probability of higher crash severity.

Figure 2 Coefficient of ASCS VS. Average signal distance

622

623 **Figure 3** shows the kernel density of conditional means of the coefficient of the ASCS variable.

624 The conditional means of the coefficient of the ASCS variable is calculated by using Eq. (9). It

625 turns out that the majority (78 %) of the conditional means (the unshaded portion in the figure)

626 has negative signs, suggesting that the presence of ASCS is associated with lower crash severity

627 for most of the observations. It is concluded that the presence of ASCS is associated with lower

628 crash severity.

629

630 **Figure 3 Kernel density of the conditional means for the coefficient of ASCS variable**

631

632 **Figure 4** shows 95% confidence intervals for the conditional means of the coefficient of the

633 ASCS variable in the ROP model for observation IDs from 2600 to 2800 (total number of

634 observations in the sample is 6,570 in this study). The ASCS effect on crash severity varies

635 across different intersections and corridors. In contrast, some crashes have the same ASCS effect

since they occurred at a similar intersection (same speed limit difference category) on the same corridor.

Figure 4: 95% confidence intervals for the conditional means of the coefficient of the ASCS variable in the ROP model for observation IDs from 2600 to 2800

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

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

The marginal effects for the three crash severity levels are computed, as shown in **Table 10**. A positive sign of the value in the marginal effects table indicates an increase in the probability of a severity level for the ASCS variable, meaning that such a level is indeed likely to increase due to ASCS. However, a negative sign of the value in the marginal effects table indicates a decrease in

the probability of the severity level for the ASCS variable, meaning that such a level is likely to decrease due to ASCS.

The marginal effects in **Table 10** show that ASCS can reduce the probability of C and KAB for the majority of intersections and corridors except for the N Lake Dr, SC 642, and US 17 with speed limit difference between major roads and minor roads equal to or greater than 10 mph. The marginal effects of ASCS vary in terms of intersection and corridor features. For example, for US 17A with speed limit difference between major roads and minor roads less than 10 mph, ASCS reduces the probability of C and KAB by 4.76 % and 2.13 %, respectively, while increasing the probability of O by 6.89 %. Although the absolute value of the ASCS effect on the KAB seems to be small, for the case of the small proportion of KAB (average is around 6 %) in the studied intersections, ASCS is quite effective in reducing the probability of KAB for crashes that occurred at intersections. The effectiveness of reducing KAB (marginal effect for KAB divided by the proportion of KAB for the corresponding intersections) is computed in the last column in **Table 10**. For example, the highest benefit is achieved for Garlinton Rd by $1.76\% / 1.55\% = 113.23\%$.

Table 10 Marginal Effects of ASCS on Crash Severity Levels

Corridor or Intersection Feature	Corridor Feature	Marginal Effect for	Marginal Effect for	Marginal Effect for	Proportion of KAB	Effectiveness of
---	---------------------	------------------------	------------------------	------------------------	----------------------	------------------

	Speed Limit Difference Equal to or greater than 10 mph?	Average Signal Distance (miles)	O Level	C Level	KAB Level	Level	reducing KAB Level
US17A	No	0.27	6.89%	-4.76%	-2.13%	4.17%	51.12%
	Yes	0.27	3.87%	-2.61%	-1.25%	4.29%	29.11%
Garlinto n Rd	No	0.36	5.58%	-3.82%	-1.76%	1.55%	113.23%
N Lake	No	0.55	2.38%	-1.59%	-0.79%	5.43%	14.54%
Dr	Yes	0.55	-1.01%	0.66%	0.35%	4.40%	-7.95%
SC 642	No	0.52	3.05%	-2.05%	-1.00%	6.40%	15.62%
	Yes	0.52	-0.45%	0.30%	0.16%	7.13%	-2.24%
US 52	No	0.31	6.31%	-4.35%	-1.97%	5.61%	35.09%
	Yes	0.31	3.22%	-2.16%	-1.05%	6.47%	16.23%
US 17	Yes	0.61	-2.15%	1.39%	0.77%	9.96%	-7.73%

669

670 5.3 Effects of other contributing factors on crash severity

671 Note that, the coefficient of the angle variable is a random parameter that follows a random
672 distribution. As shown in **Table 6**, the mean of the coefficient (mean.Angle) associated with
673 angle is found to be positive and statistically significant in the ROP model. Its standard deviation
674 (S.D.Angle) is also found to be statistically significant, implying the existence of unobserved
675 heterogeneity across observations. The coefficient of the angle variable is estimated to follow a
676 uniform distribution with a mean of 0.330 and a standard deviation of 1.030. It is found that all

observations have a positive coefficient associated with the angle crashes, suggesting an association between angle crashes and higher crash severity.

As depicted by the marginal effects in **Table 11**, other contributing factors except for the peak period are associated with higher crash severity levels (i.e., C and KAB) while less likely to be a lower crash severity (i.e., O). Crashes involving pedestrians will lead to higher crash severity levels and increase the probability of KAB by 57.69%. The presence of AADT over 30,000 vehicles/day results in a corresponding increase in the likelihood of C and KAB given the critical role of high traffic volume in overall crashes at the signalized intersections. Not surprisingly, an increase in the posted speed limit is associated with a greater likelihood of C and KAB. The higher speed limit naturally results in a higher vehicle operational speed, with an increase in the severity of crashes. The bad light condition (i.e., dark) of roadways is associated with a higher likelihood of C and KAB. The peak period leads to lower crash severity (i.e., O). During peak periods, the traffic volume is relatively higher compared to off-peak periods, which would contribute to lower average speeds of the vehicles during peak periods, thus resulting in reduced crash severity. The crash, which is either rear-end or angle crash, is associated with higher probability of C and KAB.

Table 11 Marginal Effects of other Contributing Factors

Other Contributing Factors	Marginal Effect for O	Marginal Effect for C	Marginal Effect for KAB
Pedestrian	-69.83 %	12.14 %	57.69 %
AADT_over_30k	-5.92 %	4.11 %	1.81 %

Other Contributing Factors	Marginal Effect for O	Marginal Effect for C	Marginal Effect for KAB
Speed_Limit	-0.24 %	0.16 %	0.07 %
Light	-9.14 %	6.01 %	3.13 %
Peak	2.30 %	-1.59 %	-0.71 %
Rear_end	-3.47 %	2.38 %	1.09 %
Angle	-9.21 %	6.09 %	3.12 %

696

697 6 Conclusions

698 This study has investigated the hierarchical effects of ASCS on the crash severity by developing
699 random-parameter ordered regression models with observed heterogeneity, which accounts for
700 both observed and unobserved heterogeneity. Crash data from six ASCS corridors with 65
701 signalized intersections are used to develop the models. Four different random-parameter ordered
702 regression models (two ordered probit models, and two ordered logit models) are established and
703 compared. It is found that the ROP and ROL models perform better than the RP and RL models
704 in terms of the AIC and the goodness of fit of the model. The ROP model outperforms the ROL
705 model in terms of classification model performance measures: accuracy, overall precision, and
706 overall recall. This study is unique as it demonstrates the existence of the hierarchical effects of
707 ASCS on the crash severity. The analyses reveal that the presence of ASCS is associated with
708 lower crash severity. Speed limit difference between major streets and minor streets at an
709 intersection (intersection feature) and average signal distance on a corridor (corridor feature) are
710 found to be capable of capturing the hierarchical effects of ASCS on the crash severity. Other

variables related to intersection features such as the number of legs at an intersection and number of through/left/right lanes at an intersection and corridor features such as average AADT on a corridor are attempted in the model, but these variables are not statistically significant. Thus, these variables are not able to capture the hierarchical effects of ASCS on the crash severity in this study. In the future, variables related to zonal features such as population densities could be accounted for to capture the hierarchical effects of ASCS on the crash severity. Other contributing factors, such as annual average daily traffic, speed limit, lighting, crash type (rear-end, angle), pedestrian involvements, are associated with higher crash severity. The peak period leads to lower crash severity. Unobserved heterogeneity of the effect of angle crashes on crash severity is found to exist across the observations by using the uniform distribution to explicitly account for crash-specific variations in the effects of angle crashes.

To evaluate the performance of the ROP model on the high proportion of severe crash severity, further studies on investigating the applicability of the model in the case of the high proportion of severe crash severity may be carried out once a suitable case study is available.

Identifying the hierarchical effects of ASCS on the crash severity could help transportation agencies achieve higher safety benefits by selecting ASCS deployment sites by considering specific intersection and corridor features. The findings of this study have several practical implications for establishing ASCS implementation guidelines from the standpoint of safety. Two useful metrics, speed limit difference between a major street and a minor street at an intersection (intersection feature) and average signal distance on a corridor (corridor feature), could help transportation agencies to deploy ASCS appropriately. Two practical implications are

found: 1) when speed limit difference between major streets and minor streets at an intersection is equal to or greater than 10 mph, and the average signal distance on a corridor is less than the threshold of 0.49 miles, the ASCS is more likely associated with lower crash severity; and 2) when speed limit difference between major streets and minor streets at an intersection is less than 10 mph, and the average signal distance on a corridor is less than the threshold of 0.69 miles, the ASCS is associated with lower crash severity. This finding is related to the particular type of ASCS, and future studies may be conducted to include multiple types of ASCS.

Declarations of Interest: None.

Acknowledgments

The authors acknowledge the South Carolina Department of Transportation (SCDOT), which provided funding (SCDOT Research Project: SPR 737) for this research. The authors also sincerely acknowledge SCDOT SPR 737 Steering Committee for providing valuable guidance to the authors. The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the presented data. The contents do not reflect the official views of SCDOT or FHWA. This paper does not constitute a standard, specification, or regulation.

REFERENCE

Antonucci, N.D., Hardy, K.K., Slack, K.L., Pfefer, R., Neuman, T.R., 2004. Guidance for implementation of the AASHTO strategic highway safety plan. Volume 12: A Guide for Reducing Collisions at Signalized Intersections, Transportation Research Board of the National Academies, Washington, DC.

755 Brant, R., 1990. Assessing proportionality in the proportional odds model for ordinal logistic
756 regression. *Biometrics* 46 4 , 1171. doi:10.2307/2532457

757 Burnham, K.P., Anderson, D.R., 2004. Multimodel inference. *Sociol. Methods Res.* 33 2 , 261–
758 304. doi:10.1177/0049124104268644

759 Chen, Y., Persaud, B., 2014. Methodology to develop crash modification functions for road
760 safety treatments with fully specified and hierarchical models. *Accid. Anal. Prev.* 70, 131–
761 139. doi:10.1016/j.aap.2014.03.012Dabbour, E., Easa, S., Haider, M., 2017. Using fixed-
762 parameter and random-parameter ordered regression models to identify significant factors
763 that affect the severity of drivers' injuries in vehicle-train collisions. *Accid. Anal. Prev.* 107,
764 20–30. doi:10.1016/j.aap.2017.07.017

765 Dutta, U., Lynch, J., Dara, B., Bodke S., 2010, Safety evaluation of the SCATS control system,
766 Rep. No. MIOH UTC TS22p1-2 2010-Final, Michigan Ohio University Transportation
767 Center.

768 Eghtedari, A.G., 2006. Measuring benefits of adaptive traffic signal control: case study of Mill
769 Plain Boulevard, Vancouver, Washington. *Transp. Res. Board* 85th Annu. Meet.

770 Elkins, S., Niehus, G., 2012. InSync adaptive traffic control system for the Veterans Memorial
771 Hwy Corridor on Long Island, NY. New York State Dept. of Transportation.Eluru, N.,
772 Bagheri, M., Miranda-Moreno, L.F., Fu, L., 2012. A latent class modeling approach for
773 identifying vehicle driver injury severity factors at highway-railway crossings. *Accid. Anal.*
774 *Prev.* 47, 119–127. doi:10.1016/j.aap.2012.01.027

775 Fan, W., Kane, M.R., Haile, E., 2015. Analyzing severity of vehicle crashes at highway-rail
776 grade crossings: multinomial logit modeling. *J. Transp. Res. Forum.*
777 <https://doi.org/10.22004/ag.econ.241825>

778 Fink, J., Kwigizile, V., Oh, J.-S., 2016. Quantifying the impact of adaptive traffic control
779 systems on crash frequency and severity: Evidence from Oakland County, Michigan. *J.*
780 *Safety Res.* 57, 1–7. doi:10.1016/j.jsr.2016.01.001

781 Fontaine, M.D., Ma, J., Hu, J., 2015, Evaluation of the Virginia Department of Transportation
782 adaptive signal control technology pilot project. Report. No. VCTIR 15-R24, Virginia
783 Center for Transportation Innovation and Research.

784 Gartner, N.H., Pooran, F.J., Andrews, C.M., 2002. Optimized policies for adaptive control
785 strategy in real-time traffic adaptive control systems: implementation and field testing.
786 *Transp. Res. Rec. J. Transp. Res. Board* 1811 1 , 148–156. doi:10.3141/1811-18

787 Greene, W.H., 2003. *Econometric Analysis*. Pearson Education India.

788 Greene, W.H., Hensher, D.A., 2010. *Modeling Ordered Choices: A primer*. Cambridge
789 University Press.

790 Hilbe, J.M., 2011. *Negative Binomial Regression*. Cambridge University Press.

791 Huang, H., Chin, H.C., Haque, M.M., 2008. Severity of driver injury and vehicle damage in
792 traffic crashes at intersections: a Bayesian hierarchical analysis. *Accid. Anal. Prev.* 40 1 ,
793 45–54. doi:10.1016/j.aap.2007.04.002

794 Iteris, 2020. Iteris ClearGuide [WWW Document]. URL <https://scdot.iteris-clearguide.com/>
795 (accessed 4.3.20).

796 Jalayer, M., Shabanpour, R., Pour-Rouholamin, M., Golshani, N., Zhou, H., 2018. Wrong-way
797 driving crashes: a random-parameters ordered probit analysis of injury severity. *Accid.*
798 *Anal. Prev.* 117, 128–135. doi:10.1016/j.aap.2018.04.019

799 Jin, W., Khan, S.M., Chowdhury, M., 2019. Exploring the safety effects of adaptive signal
800 control systems, in: *International Conference on Transportation and Development 2019*.

801 American Society of Civil Engineers. doi:10.1061/9780784482575.002

802 Kergaye, C., Stevanovic, A., Martin, P., 2009. Comparison of before-after versus off-on adaptive
803 traffic control evaluations. *Transp. Res. Rec. J. Transp. Res. Board* 2128, 192–201.
804 doi:10.3141/2128-20

805 Khattak, Z.H., 2016. Evaluating the Operational and Safety Aspects of Adaptive Traffic Control
806 Systems in Pennsylvania. Univ. Pittsburgh Thesis.

807 Khattak, A., Tung, L.-W., 2015. Severity of pedestrian crashes at highway-rail grade crossings.
808 *J. Transp. Res. Forum*. <https://doi.org/10.22004/ag.econ.241830>

809 Khattak, Z.H., Fontaine, M.D., Smith, B.L., Ma, J., 2019a. Crash severity effects of adaptive
810 signal control technology: an empirical assessment with insights from Pennsylvania and
811 Virginia. *Accid. Anal. Prev.* 124, 151–162. doi:10.1016/j.aap.2019.01.008

812 Khattak, Z.H., Magalotti, M.J., Fontaine, M.D., 2019b. Operational performance evaluation of
813 adaptive traffic control systems: a Bayesian modeling approach using real-world {GPS} and
814 private sector {PROBE} data. *J. Intell. Transp. Syst.* 24 2 , 156–170.
815 doi:10.1080/15472450.2019.1614445

816 Khattak, Z.H., Magalotti, M.J., Fontaine, M.D., 2018. Estimating safety effects of adaptive
817 signal control technology using the Empirical Bayes method. *J. Safety Res.* 64, 121–128.
818 doi:10.1016/j.jsr.2017.12.016

819 Khazraee, S.H., Johnson, V., Lord, D., 2018. Bayesian Poisson hierarchical models for crash
820 data analysis: investigating the impact of model choice on site-specific predictions. *Accid.*
821 *Anal. Prev.* 117, 181–195. doi:10.1016/j.aap.2018.04.016

822 Krishnan, M.J., Anjana, S., Anjaneyulu, M.V.L.R., 2013. Development of hierarchical safety
823 performance functions for urban mid-blocks. *Procedia - Soc. Behav. Sci.* 104, 1078–1087.

doi:10.1016/j.sbspro.2013.11.203

Lowrie, P.R., 1990. Scats, sydney co-ordinated adaptive traffic system: A traffic responsive method of controlling urban traffic.

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. *J. Transp. Eng.* 142 12 , 4016061. doi:10.1061/(asce)te.1943-5436.0000890

National Research Council (US)., 2010. Highway Safety Manual. AASHTO.

O'brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. *Qual. Quant.* 41 5 , 673–690. doi:10.1007/s11135-006-9018-6

Rahman, M.S., Abdel-Aty, M., Lee, J., Rahman, M.H., 2019. Safety benefits of arterials' crash risk under connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* 100, 354–371. doi:10.1016/j.trc.2019.01.029

Sammur Claude and Webb, G.I. (Ed.), 2010. Accuracy, in: *Encyclopedia of Machine Learning*. Springer US, Boston, MA, pp. 9–10. doi:10.1007/978-0-387-30164-8_3

Sarrias, M., 2016. Discrete choice models with random parameters in R: The Rchoice Package. *J. Stat. Softw.* 74 10 . doi:10.18637/jss.v074.i10

SCDOT, 2020a. South Carolina Traffic Collision Report Form (TR-310) and Supplement Truck and Bus Report Form Instruction Manual [WWW Document]. URL [https://scdps.sc.gov/sites/default/files/Documents/forms/TR-310 Report Manual Revised May 2019.pdf](https://scdps.sc.gov/sites/default/files/Documents/forms/TR-310%20Report%20Manual%20Revised%20May%202019.pdf) (accessed 4.17.20).

SCDOT, 2020b. GIS/Mapping [WWW Document]. URL <https://www.scdot.org/travel/travel-mappinggis.aspx> (accessed 2.17.20).

So, J., Stevanovic, A., Posadas, E., Awwad, R., 2014. Field evaluation of a SynchroGreen

847 adaptive signal system, in: T&DI Congress 2014. American Society of Civil
 848 Engineers, Reston, VA, pp. 388–399. doi:10.1061/9780784413586.037
 849 Ting, K.M., 2010. Precision and recall, in: Sammut Claude and Webb, G.I. (Ed.),
 850 Encyclopedia of Machine Learning. Springer US, Boston, MA, p. 781. doi:10.1007/978-0-
 851 387-30164-8_652
 852 Van Asch, V., 2013. Macro-and micro-averaged evaluation measures [[basic draft]]. Belgium:
 853 CLiPS 49.
 854 Washington, S., Karlaftis, M.G., Mannering, F., Anastasopoulos, P., 2020. Statistical and
 855 Econometric Methods for Transportation Data Analysis. CRC press.
 856 Xie, K., Wang, X., Huang, H., Chen, X., 2013. Corridor-level signalized intersection safety
 857 analysis in Shanghai, China using Bayesian hierarchical models. *Accid. Anal. Prev.* 50, 25–
 858 33. doi:10.1016/j.aap.2012.10.003
 859 Xie, K., Yang, D., Ozbay, K., Yang, H., 2019. Use of real-world connected vehicle data in
 860 identifying high-risk locations based on a new surrogate safety measure. *Accid. Anal. Prev.*
 861 125, 311–319. doi:10.1016/j.aap.2018.07.002
 862 Ye, F., Lord, D., 2014. Comparing three commonly used crash severity models on sample size
 863 requirements: multinomial logit, ordered probit and mixed logit models. *Anal. Methods*
 864 *Accid. Res.* 1, 72–85. doi:10.1016/j.amar.2013.03.001
 865 Zhao, S., Khattak, A., 2015. Motor vehicle drivers' injuries in train-motor vehicle crashes.
 866 *Accid. Anal. Prev.* 74, 162–168. doi:10.1016/j.aap.2014.10.022
 867