Addressing Endogeneity in modeling Speed Enforcement, Crash Risk and Crash Severity Simultaneously

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ABSTRACT

Speeding is one of the major significant causes of high crash risk and the associated injury severity outcomes. To combat such significant safety concerns, a speed limit enforcement system has been adopted widely around the world. This study aims to present an econometric approach that estimates the casual effect of speed enforcement on safety while addressing the endogeneity issue by employing an instrumental variable approach within a maximum simulated likelihood framework. In our study, safety enforcement is represented as the number of speeding tickets issued from the speed camera systems, while safety profile is presented as two dimensions of interest, including total crash risk and crashes by injury severity levels. The proposed econometric model takes the form of a correlated panel random parameters model with speed enforcement endogeneity. In estimating the joint panel model, speed enforcement and crash severity components are modeled by employing Random Parameters Ordered Logit Fractional Split technique, while crash risk component is modeled by employing Random Parameters Negative Binomial regression technique. In the current study context, the 'operational duration of speed camera' serves as the instrumental variable for controlling the endogeneity between speed enforcement and safety. Further, the analysis is augmented by a detailed policy scenario analysis. The empirical analysis is demonstrated by employing roadway segment-level crash data and speeding tickets data from Queensland, Australia, for the years 2010 through 2013. From the policy analysis, it is found that a stricter speed enforcement for serious level of speeding offenses is likely to have greater safety benefits in reducing crash severity levels. Moreover, a targeted increase in operation duration along with stricter citations for major speeding is likely to have significant safety gain. The outcome of the study will allow the decision-makers to identify a robust resource allocation and speed camera deployment plan.

Keywords: Speeding; Speed Camera; Crash risk; Crash severity; Endogeneity; Policy analysis; Scenario development

1 INTRODUCTION

Speeding – often defined as driving a vehicle with speed over the posted speed limit – is one of the significant causes of high crash risk and the associated injury severity outcomes. Globally, speed contributes towards 30% of fatal crashes in high-income countries, while the contribution is more than 50% towards fatal crashes in low-and-middle-income countries (WHO, 2004). Despite these unfortunate events, there is evidence that drivers still perceive speeding to be socially acceptable, and, hence, are likely to engage in speeding behaviour occasionally (Fleiter et al., 2010). To combat such significant safety concerns, stricter speed limit enforcement systems at the roadway network level have been adopted widely around the world. Such systems include speed camera enforcement (fixed, mobile, covert, point-to-point), automated average speed enforcement, and seamless speed enforcement systems. There is a growing body of existing safety studies focusing on evaluating the effectiveness of such roadway segment level speed enforcement measures on safety performance (Soole et al. 2013; Thomas et al., 2008; Zhou et al., 2020).

The speed enforcement systems are found to have an overall positive effect on reducing speeding behaviour, crash risk and the occurrence of severe crashes (Tay, 2009; Ahmed et al., 2016; Wali et al., 2018; Pantangi et al., 2019; Matsuo et al., 2020; Pineda-Jaramillo et al., 2022). Several studies reported a significant influence of traffic fines on speeding violations (Walter et al., 2011). The positive effects of speed cameras in improving safety are evident from several earlier studies (Jones et al., 2008; Carnis and Blais, 2013; Izadpanah et al., 2015). Other studies found the speed camera enforcement to be effective only within the vicinity of enforcement locations (De Pauw et al., 2014). Li et al. (2020) found that the safety effects of speed cameras are likely to experience a sharp decrease during the medium periods after implementation but recover the trend in safety gain slightly during the late period. Most recently, studies also highlighted the positive influence of the average speed enforcement system on safety (Soole et al., 2013)[1].

Evaluation of speed enforcement programs is of utmost importance for monitoring the program, understanding the effectiveness and future budget allocation decisions. We argue that the impact of speed enforcement in a roadway section would reflect on the safety profile over time, but the impacts are likely to be different across different roadway locations and are likely to vary across different time periods. Moreover, the speed selection behaviour of drivers is likely to be different by different roadway features. Earlier studies found that driving speeds are likely to vary across roadway sections with posted speed limits, horizontal curvature, heavy vehicle proportion, traffic volume and number of lanes (Afghari et al., 2020; Shankar and Maaring, 1998; Kong et al., 2020; Eluru et al., 2013; Bhowmik et al., 2019[2]). Therefore, it is of utmost importance to quantify the relative magnitude of the impact of speed enforcement on safety while controlling for other exogenous variables (such as traffic exposure, roadway geometry, and situational attributes). However, studies examining the causal effect of speed enforcement on safety are far and few between.

In establishing the causal relationship between speed enforcement and safety outcomes based on empirical analysis, it is important to realize that speed enforcement measures are generally implemented at specific locations of the roadway rather than the entire roadway network since these measures are associated with significant economic investments. Therefore, if the analysis of a causal relationship is based on the sample of roadway with the speed enforcement system only, the estimates are likely to be biased if the sampling technique suffers from a self-selection issue. Moreover, the location of speed enforcement on a roadway network

[1] Reviewing all existing studies focusing on the evaluation of different speed enforcement measures are beyond the scope of this study.

[2] See Bhowmik et al. (2019) for a detailed review of these studies.

is generally motivated by its association with higher speeding-related crash records resulting in reverse causality. Thus, it is evident that endogeneity is an inherent issue in establishing the causal relationship between speed enforcement and safety. The current research addresses these gaps and contributes toward existing safety literature by presenting an econometric approach that estimates the causal effect of speed enforcement on safety while also addressing the endogeneity issue of speed enforcement level in the safety components. Guevara (2015) presented a detailed discussion of five different methods to correct for endogeneity bias in discrete choice models. These approaches are – use of proxys; two steps control-function method; simultaneous estimation of the control-function method via maximum-likelihood; multiple indicator solution; and integration of latent-variables. Among these approaches, simultaneous estimation of the control function method via Maximum-Likelihood is likely to provide with an efficient estimator, and it allows for direct estimation of the standard errors. However, it requires an instrumental variable.

In this study, to address speed enforcement endogeneity in the safety analysis[3], we have adopted an instrumental variable approach of control function in conjunction with a maximum simulated likelihood approach. Specifically, we have developed a simultaneous equation system to model speed enforcement, crash risk and crash severity components at the roadway segement level, while considering 'operational duration of speed camera' as an instrumental variable in the endogenous speed enforcement component. In our study, safety enforcement is represented as the number of speeding tickets issued from the speed camera systems, while safety profile is presented as two dimensions of interest, including total crash risk and crashes by injury severity levels. Specifically, in examining the causal effect of speed enforcement on safety, the empirical analysis proposes in this study addresses three different econometric issues, including (1) correcting for speed enforcement endogeneity in crash risk and crash severity, (2) observation level unobserved heterogeneity (sourced from panel structure of dataset) and (3) other unobserved heterogeneity (sourced from unobserved information).

The proposed econometric model takes the form of a joint modeling system of speed enforcement component, crash risk component and crash severity component. The joint model is estimated by employing a correlated panel random parameters model with speed enforcement endogeneity. In estimating the joint panel model, speed enforcement and crash severity components are modeled by employing Random Parameters Ordered Logit Fractional Split technique, while crash risk component is modeled by employing Random Parameters Negative Binomial regression technique. In correcting for endogeneity, the speed enforcement propensity from the speed enforcement component is considered as an exogenous variable in the crash risk and crash severity components while estimating these three dimensions simultaneously. In the current study context, the 'operational duration of speed camera' serves as the instrumental variable for controlling the endogeneity between speed enforcement and safety.

The empirical analysis is demonstrated by employing crash data and speed enforcement data collected in the form of speeding tickets issued identified from speed cameras from Queensland, Australia, for the years 2010 through 2013. The data is drawn from several highways and major arterials in Queensland, Australia. The casual effect is studied by employing a comprehensive set of exogenous variables, including Traffic characteristics, Roadway design and operational characteristics, Temporal and situation characteristics and Speed camera deployment characteristics. Further, the analysis is augmented by a detailed policy analysis. The outcome of the study will allow decision-makers to identify a robust resource allocation and speed camera deployment plan.

[3] See Mannering and Bhat (2014) for a detailed discussion on safety studies addressing endogeneity in crash risk/crash severity analyais.

The rest of the paper is organized as follows. Section 2 presents the data and lays out the empirical design of the study. In Section 3, the econometric framework is presented. Section 4 discusses the empirical results and findings from model illustrations in the forms of elasticity effects and policy scenario analysis. Section 5 concludes the study along with some insights on future research directions.

2 DATA AND EMPIRICAL DESIGN

For the proposed empirical study, the data is drawn from several highways and major arterials, commonly referred to as State Controlled Roads, in Queensland, Australia. Specifically, the extent of the transport network considered in this study covers 1,477 kilometres of State Controlled roadways comprising 521 road segments. For these segments, data were collected and compiled for four years, from 2010 through 2013. These locations and time periods were selected due to the simultaneous availability of speeding tickets, crash, and roadway design attributes[4].

Speed enforcement data was collected in the form of speeding tickets issued per year per segment identified from speed cameras maintained by the Queensland Police Service. The total deployment duration of speed cameras along these 521 segments were 38,656 hrs in 2010, 36,898 hrs in 2011, 37,235 hrs in 2012 and 52,085 hrs in 2013. However, the operational duration was not uniform across all segments for different cameras. Therefore, the speeding ticket data collected per camera per year were normalized as the rate of 1,000 vehicles monitored on these segments per year. Thus, the total number of speeding tickets issued per 1,000 vehicles monitored across segments are 4083, 4386, 3684 and 2879 in 2010, 2011, 2012 and 2013, respectively. The distribution of speeding ticket issues and operational duration for speed cameras across different years are presented in Figure1.

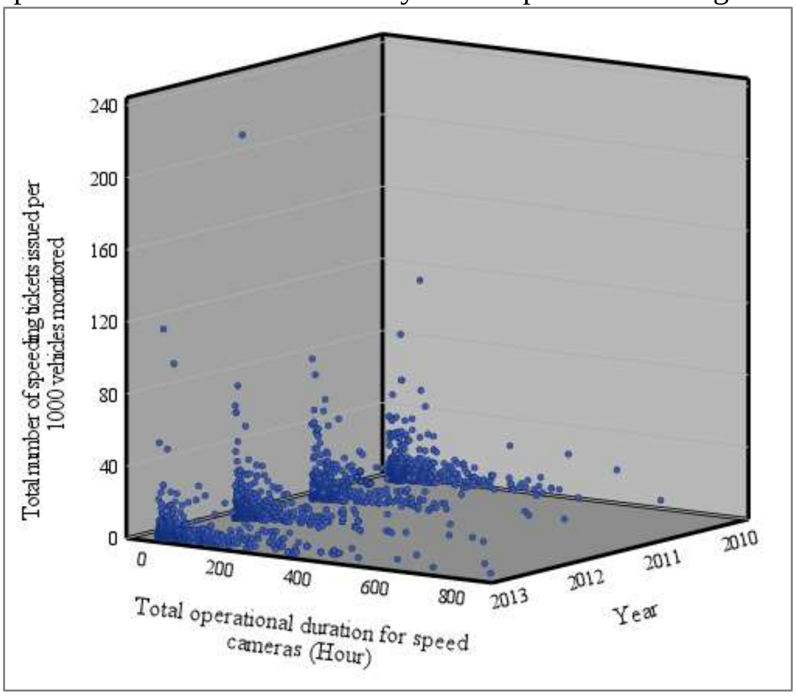

Figure 1: Speeding Ticket Issued vs. Operation Duration for Speed Camera across Different Years

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[4] The proposed framework of the current study is generic and is applicable for analysing most recent data if available.

Crash data for the empirical study is compiled from the Queensland Department of Transport and Main Roads official crash database. The crash data reported in Queensland does not record 'no injury' crashes since 2010. Therefore, the data has injury severity levels information for the crashes resulting in casualty only. The crashes are recorded in the three injury severity categories as (1) minor injury, (2) major/hospitalized injury and (3) fatal injury. The total number of crashes recorded for the selected State Controlled network are 1578, 1503, 1476 and 1575 for the years 2010, 2011, 2012 and 2013, respectively. Finally, roadway design and situational attributes are collected from the Department of Transport and Main Roads, Australian Bureau of Meteorology and Queensland Spatial Catalogue databases. All the databases were integrated together based on spatial coordinates by using the ArcGIS platform.

2.1 Dependent Variables

In estimating the proposed joint panel model, the empirical analysis involves three components of analysis: (1) Speed enforcement component, (2) Crash risk component and (3) Crash severity component. The formation of dependent variables for these three components are presented in this section.

Speed enforcement component: The number of speeding tickets issued was recorded in fixed increment of speeding citation levels above the posted speed limit (PSL) as (1) <13km/h above PSL, (2) 13-20km/h above PSL, (3) 20-30km/h above PSL, (4) 30-40km/h above PSL and (5) >40km/h above the PSL. Analysis of the total number of tickets by speeding level would require having all speeding ticket records for the study locations. However, the records represent only the speeding ticket profile of vehicles for the operational period of speed cameras in these locations. In our empirical study, we assume that the speeding ticket profile remains the same at a segment level in a year irrespective of speed camera operational and non-operational periods. Therefore, as opposed to modeling the absolute number of records by speeding ticket levels, we represent the speed enforcement profile as the contributing number of tickets by speeding levels relative to the total number of speeding tickets issued. Thus, the dependent variable of the speed enforcement component is considered as a fraction, represented as:

$$\left(\frac{\text{Number of speeding tickets issued by speeding level per segment per year}}{\text{Total number of speeding tickets issued per segment per year}}\right)$$

The dependent variable of the speed enforcement component is considered as an ordered variable with tickets issued for three speeding levels including: (1) proportion of minor speeding tickets (<13km/h over PSL), (2) proportion of moderate speeding tickets (13-20 km/h over PSL) and (3) proportion of major speeding tickets (>20km/h over PSL)[5].

Crash risk component: The dependent variable of the crash risk component is the total casualty crash count[6] reported in each segment per year.

Crash severity component: As opposed to modeling the number of crashes by different severity levels, in this study, we consider the proportion of crashes by different severity levels

[5] 20-30km/h above PSL, 30-40km/h above PSL and >40km/h above the PSL speeding citation categories are merged as one category due to small sample shares.
[6] In the following sections, total casualty crash is referred to as total crash for simplicity. As mentioned before, Queensland does not record 'no injury' crashes and hence represents only casualty crashes.

as dependent variables. Thus, the dependent variable of crash severity component is considered as a fraction, represented as:

$$\left(\frac{\text{Number of crashes by injury severity levels per segment per year}}{\text{Total number of crashes per segment per year}}\right)$$

The dependent variable of crash severity component is considered as an ordinal variable with three levels, including (1) proportion of minor injury crashes, (2) proportion of major injury and (3) proportion of fatal injury crashes[7].

The dependent variables for the abovementioned three components are presented in Table 1. From Table 1, we can observe that minor speeding ticket has the lowest fraction. The major injury category has the highest fraction relative to the other two severity categories.

Table 1: Summary Statistics of Dependent Variables

Dependent Variables	Definitions	Mean	Standard Deviation	Minimum	Maximum
Speed Enforcement Component					
Fraction of tickets for minor speeding	Fraction of tickets for minor speeding = (Number of speeding ticket issued per 1000 vehicle for the magnitude of speeding less than 13km/h above posted speed limit per year per segment/Total number of speeding ticket issued per 1,000 vehicles per year per segment)	0.560	0.145	0.000	1.000
Fraction of tickets for moderate speeding	Fraction of tickets for moderate speeding = (Number of speeding ticket issued per 1000 vehicle for the magnitude of speeding between 13-20km/h above posted speed limit per year per segment/Total number of speeding ticket issued per 1,000 vehicles per year per segment)	0.362	0.124	0.000	1.000
Fraction of tickets for major speeding	Fraction of tickets for major speeding = (Number of speeding ticket issued per 1000 vehicle for the magnitude of speeding above 20km/h above posted speed limit per year per segment/Total number of speeding ticket issued per 1,000 vehicles per year per segment)	0.068	0.065	0.000	0.500
Crash Risk Component					
Total number of crashes	Total number of crashes recorded per year per segment	2.942	4.573	0.000	51.000
Crash Severity Component					
Fraction of minor injury crashes	Fraction of minor injury crashes = (Number of minor injury crashes per year per segment/Total number of crashes per year per segment)	0.108	0.225	0.000	1.000
Fraction of major injury crashes	Fraction of major injury = (Number of major injury crashes per year per segment/Total number of crashes per year per segment)	0.561	0.444	0.000	1.000

[7] Several studies in existing safety lietarute have demonstrated the application of Fractional Split approach in modeling crash counts by crash severity levels (Yasmin et al., 2014; Bhowmik et al., 2019 and 2021; Yasmin and Eluru, 2018).

Fraction of fatal injury crashes	Fraction of fatal injury = (Number of fatal injury crashes per year per segment/Total number of crashes per year per segment)	0.012	0.082	0.000	1.000

2.2 Independent Variables

In generating the segment level variables, the explanatory variables considered in the current study are aggregated at each segment level across different years. The explanatory variables considered can be categorized in five broad categories representing: (1) *Traffic characteristics* including annual average daily traffic (AADT) and proportion of heavy vehicles; (2) *Roadway design and operational characteristics* including segment length, number of lanes, lane width, shoulder width, median width, radius of horizontal alignment, degree of horizontal curve, roughness, rutting, functional classification of road, presence of shoulder, shoulder type, posted speed limit, terrain type and pavement seal condition; (3) *Temporal and situation characteristics* including rainfall, rainy days and wind speed; and (4) *Speed camera deployment characteristics* including covert speed cameras, total number of deployed speed camera and operational durational for speed camera. In terms of temporal characteristics, a "time elapsed" variable has been computed as the difference between the most recent years (2011, 2012 and 2013) from the base year (2010) available in the study context. Such lapsed effect of the temporal variable will allow us to forecast for future year scenarios. In the model specification, both linear and square effects of time elapsed variable are considered.

Table 2 offers a summary of the sample characteristics of the exogenous factors in the estimation dataset. The table represents the definition of variables considered for the final model specification along with the minimum, maximum, standard deviation, and mean values. The final specification of the model development was based on removing the statistically insignificant variables in a systematic process based on statistical significance (90% confidence level). The specification process was also guided by prior research and parsimony considerations. In estimating the models, several functional forms and variable specifications were explored. The functional form that provided the best result was used for the final model specifications and, in Table 2, the variable definitions are presented based on these final functional forms.

Table 2: Summary Statistics of Independent Variables

CONTINUOUS/ORDINAL VARIABLES					
Variables	**Variable Descriptions**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Traffic Characteristics					
AADT	ln(Average Annual Daily Traffic (vehicles/day))	9.53	1.17	3.53	13.28
Proportion of heavy vehicle	Number of heavy vehicle traffic/Total number of traffic	0.10	0.09	0.00	0.96
Roadway Design and Operational Characteristics					
Length	Segment length (km)	2.83	3.19	0.08	20.90
Number of lanes	Number of lanes	1.00	8.00	1.00	8.00
Lane width	Lane width (m)	3.07	0.42	2.00	5.00
Shoulder width	Shoulder width (m)	0.91	1.47	0.00	15.00
Median width	Median width (m)	4.00	4.95	0.00	38.00
Radius of horizontal alignment	Radius of horizontal alignment (km)	0.13	41.22	12.10	5.88
Degree of horizontal curve	Degree of horizontal curve (degree)	0.82	1.05	0.05	10.52

Roughness	Roughness (mm/km)	50.49	33.96	0.00	150.00
Rutting		2.81	2.01	0.00	9.60
Temporal and Situational Characteristics					
Rainfall	Average rainfall per year (mm/100)	0.00	1.07	0.34	0.17
Rainy days	Average number of rainy days per year	36.13	11.23	0.00	75.00
Wind speed	Average wind speed per year (km/h)	10.91	5.65	0.00	26.00
Speed Camera Deployment Characteristics					
Covert speed cameras	Proportion of deployed covert speed cameras per year	0.18	0.23	0.00	1.00
Total number of deployed speed cameras	Total number of deployed speed camera per year	22.18	28.73	1.00	328.00
Operational duration for speed camera enforcement	Total operational duration for speed camera per year (hour/100)	0.80	1.02	0.01	8.60
CATEGORICAL VARIABLES					
Variables		**Sample Share (%)**			
Functional classification of road					
Rural road		33			
Urban road		67			
Presence of shoulder					
Yes		61			
No		39			
Shoulder type					
Paved		96			
Unpaved		4			
Posted speed limit					
High speed limit (≥100 km/h)		20			
Medium speed limit (>50 and <100 km/h)		56			
Low speed limit (≤50 km/h)		24			
Terrain type					
Rolling/Mountainous		11			
Flat		89			
Pavement seal condition					
Sealed		76			
Unsealed		24			

3 ECONOMETRIC FRAMEWORK

Let us assume that $i\ (i = 1,2, \dots, I; I = 521)$ be the index to represent roadway segment, $t\ (t = 1,2, \dots, T; T = 4)$ represents different time periods. In this empirical study, t takes the value of '2010 $(t = 1)$', '2011 $(t = 2)$', '2012 $(t = 3)$' and '2013 $(t = 4)$'. $j\ (j = 1,2, \dots, J)$ be the index to represent injury severity categories representing 'minor injury $(j = 1)$', 'major injury $(j = 2)$' and 'fatal injury $(j = 3)$'. Let k be the index for tickets issued by the level of speeding categories. In this study, k is defined as tickets issued for 'minor speeding $(k = 1)$', 'moderate speeding $(k = 2)$' and 'major speeding $(k = 3)$'. By using these notational indices, the econometric framework employed in this study is presented in this section.

3.1 Speed Enforcement Component

In the joint panel model framework, the speed enforcement component is represented by speeding tickets (speeding citations) issued by speeding levels per segment per year. The dependent variable of the speed enforcement component is considered as the proportion of speeding tickets issued by different speeding levels, including (1) proportion of minor speeding tickets, (2) proportion of moderate speeding tickets and (3) proportion of major speeding tickets. The speeding levels considered are ordinal in nature ranging from the least to the highest level of speeding citations. Therefore, modeling of speed enforcement component represented by speeding tickets issued is undertaken by employing Random Parameters Ordered Logit Fractional Split model in accommodating for the ordinal nature of the speeding citation levels and unobserved heterogeneity in parameter estimates. In the ordered outcome framework, the actual speeding ticket proportions (s_{ikt}) are assumed to be associated with an underlying continuous latent variable (s_{it}^*). Thus, the latent propensity equation for speed enforcement component can be written as:

$$s_{it}^* = \{(\boldsymbol{\beta} + \boldsymbol{\alpha}'_{it} + \boldsymbol{\gamma}'_i)\boldsymbol{x}_{it} + (length_i) + \ \varepsilon_{it} + \eta_{it}\},$$
$$s_{ikt} = k_t \ if \ \tau_{(k-1),t} < s_{it}^* < \tau_{kt} \tag{1}$$

The latent propensity s_{it}^* is mapped to the actual speeding levels s_{ikt} by τ_t thresholds ($\tau_{0,\mathrm{t}} = -\infty$ and $\tau_{K,t} = +\infty$) as presented in equation 1. k_t is speeding citation levels specific to year t. $\boldsymbol{x}_{it}$ is a vector of attributes (not including a constant) that influences the propensity associated with the tickets issued by speeding levels. $\boldsymbol{\beta}$ is the corresponding vector of mean effects. $\boldsymbol{\alpha}'_{it}$ is a vector of unobserved factors on the propensity of speeding ticket proportions for segment i and its associated characteristics and is assumed to be independent realizations from normal distribution: $\boldsymbol{\alpha}' \sim N(0, \boldsymbol{\alpha}^2)$. $\boldsymbol{\gamma}'_i$ is a vector of unobserved effects specific to the repetition level i, thus capturing the potential correlation at a segment level across different time points in the speed enforcement component. $\boldsymbol{\gamma}'_i$ is assumed to be independent realizations from normal population distribution: $\boldsymbol{\gamma}' \sim N(0, \boldsymbol{\gamma}^2)$. $(length_i)$ is the length for segment i which is specified as an offset variable in the fractional split model of the speed enforcement component[8]. ε_{it} is an idiosyncratic error term assumed to be identically and independently standard logistic distributed across segment i for different time points t. η_{it} term generates the correlation among three components (speed enforcement, crash risk and crash severity components) in the joint panel system. To estimate the model presented in equation 1, we assume that:

$$\mathbb{E}(s_{ikt}|\boldsymbol{x}_{it}) = \mathbb{H}_{ikt}(\boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \eta_{it}), 0 \leq \mathbb{H}_{ikt} \leq 1, \sum_{k_t=1}^{K_t} \mathbb{H}_{ikt} = 1 \tag{2}$$

$\mathbb{H}_{ikt}$ in our model takes the ordered logistic probability $(\mathcal{P})$ form for the speeding citation level k. Given these relationships across different parameters, the resulting probability $(\mathcal{P})$ for the fractional split model takes the following form:

[8] In the current study, the segment length varies from 0.008km to 20.903km with a mean of 2.834km. Given such wide range of variations in segment lengths, we specify the segment length as an offset variable in order to account for different lengths of segment. The coefficient of the offset variable is restricted to be one in estimating the model to normalize for the recorded events by segment length.

$$\mathcal{P}(s_{ikt} = k_t) = \varphi[\tau_{kt} - \{(\boldsymbol{\beta} + \boldsymbol{\alpha}_{it} + \boldsymbol{\gamma}_i)\boldsymbol{x}_{it} + \varepsilon_{it} + \eta_{it}\}] - \varphi\left[\tau_{(k-1),t} - \{(\boldsymbol{\beta} + \boldsymbol{\alpha}_{it} + \boldsymbol{\gamma}_i)\boldsymbol{x}_{it} + \varepsilon_{it} + \eta_{it}\}\right] \tag{3}$$

where, $\varphi(\cdot)$ is the standard logistic cumulative distribution function.

3.2 Crash Risk Component

In the joint panel model framework, the dependent variable of the crash risk component is the total crash count reported in each segment i across different time points t. Total crash counts aggregated at a segment level at any given time interval are non-negative integer value and hence is modeled by employing Random Parameters Negative Binomial regression model, which accounts for unobserved heterogeneity in parameter estimates as well. For the joint approach, the equation system for the total crash count in the usual negative binomial formulation can be written as:

$$Q(c_{ti}) = \frac{\Gamma\left(c_{it} + \frac{1}{\lambda}\right)}{\Gamma(c_{it} + 1)\Gamma\left(\frac{1}{\lambda}\right)} \left(\frac{1}{1 + \lambda\mu_{it}}\right)^{\frac{1}{\lambda}} \left(1 - \frac{1}{1 + \lambda\mu_{it}}\right)^{c_{it}} \tag{4}$$

where, c_{it} be the index for crashes occurring over a period t in segment i. $Q(c_{it})$ is the probability that segment i has c_{it} number of crashes over time t. $\Gamma(\cdot)$ is the gamma function, λ is NB overdispersion parameter and μ_{it} is the expected number of crashes occurring in segment i over a given time period t. In equation 4, we can express μ_{it} by using a log-link function:

$$\begin{aligned}\mu_{it} &= \mathbb{E}(c_{it}|\boldsymbol{z}_{it}) \\ &= exp\{(\boldsymbol{\delta} + \boldsymbol{\rho}'_{it} + \boldsymbol{\theta}'_i)\boldsymbol{z}_{it} + (length_i) + (\boldsymbol{\omega} * \hbar_{it} + \sigma'_{it} + \Omega'_i)s^*_{it} + \xi_{it} \\ &\quad \pm \eta_{it}\}\end{aligned} \tag{5}$$

where, $\boldsymbol{z}_{it}$ is a vector of explanatory variables associated with segment i for the time period t. $\boldsymbol{\delta}$ is a vector of coefficients to be estimated. $\boldsymbol{\rho}'_{it}$ is a vector of unobserved factors on crash count propensity for segment i for the time period t and is assumed to be independent realizations from normal population distribution: $\boldsymbol{\rho}' \sim N(0, \boldsymbol{\rho}^2)$. $\boldsymbol{\theta}'_i$ is a vector of unobserved effects specific to repetition level i, thus capturing the potential correlation at a segment level across different time points in the crash risk component. $\boldsymbol{\theta}'_i$ is assumed to be independent realizations from normal population distribution: $\boldsymbol{\theta}' \sim N(0, \boldsymbol{\theta}^2)$. $(length_i)$ is the length for segment i which is specified as an offset variable in the NB specification.

$\hbar_{it}$ is a vector of exogenous variables that moderate the effect of speed enforcement propensity on crash risk and $\boldsymbol{\omega}$ is the corresponding vector of coefficient (including a scalar constant). Further, σ'_{it} (specific to segment i and time point t) and Ω'_i (specific to segment i) are the unobserved components influencing the impact of speed enforcement propensity s^*_{it} on crash risk. σ'_{it} and Ω'_i are assumed to be independent realizations from normal population distribution: $\sigma' \sim N(0, \sigma^2)$ and $\Omega' \sim N(0, \Omega^2)$, respectively. ξ_{it} is a gamma distributed error term with mean 1 and variance λ. η_{it} captures unobserved factors that simultaneously impact three components in the joint panel system. The $\pm$ sign in front of η_{it} in equation 5 indicates that the correlation in unobserved individual factors among different components may be positive or negative. To determine the appropriate sign, one can empirically test the models with both $' + '$ and $' - '$ signs independently. The model structure that offers the superior data fit is considered as the final model.

3.3 Crash Severity Component

In the joint model framework, crash severity component is represented as crashes by injury severity levels per segment per year. The dependent variable of the crash severity component is considered as proportion of crashes by different crash severity levels, including (1) proportion of minor injury crashes, (2) proportion of major injury crashes and (3) proportion of fatal injury crashes. The modeling of crash severity component is undertaken by employing Random Parameter Ordered Logit Fractional Split model in accommodating the ordinal nature of injury severity outcomes while accommodating for unobserved heterogeneity in parameter estimates. In the ordered outcome framework, the actual injury severity proportions $\left(y_{ijt}\right)$ are assumed to be associated with an underlying continuous latent variable (y_{it}^{*}). The latent propensity equation is typically specified as the following linear function:

$$
\begin{aligned}
&y_{it}^{*} = \{(\boldsymbol{\vartheta} + \boldsymbol{\pi}_{it}' + \boldsymbol{\varrho}_i')\boldsymbol{\mathcal{L}}_{it} + (length_i) + (\boldsymbol{\ell} * \boldsymbol{g}_{it} + \iota_{it}' + \Lambda_i')s_{it}^{*} + \zeta_i \pm \eta_{it}\},\\
&y_{ijt} = j_t \ if \ \psi_{(j-1),t} < y_{it}^{*} < \psi_{jt}
\end{aligned}
\tag{6}
$$

The latent propensity y_{it}^{*} is mapped to the actual severity proportion categories y_{ijt} by ψ thresholds ($\psi_{0,\mathrm{t}} = -\infty \ and \ \psi_{J,t} = +\infty$) as presented in equation 6. j_t is the severity level specific to year t. $\boldsymbol{\mathcal{L}}_{it}$ is a vector of attributes (not including a constant) that influences the propensity associated with severity proportion categories. $\boldsymbol{\vartheta}$ is the corresponding vector of mean effects. $\boldsymbol{\pi}_{it}'$ is a vector of unobserved factors on the propensity of severity proportion for segment i and its associated characteristics and is assumed to be independent realizations from normal population distribution: $\boldsymbol{\pi}'\sim N(0, \boldsymbol{\pi}^2)$. $\boldsymbol{\varrho}_i'$ is a vector of unobserved effects specific to repetition level i, thus capturing the potential correlation at a segment level across different time points in the crash severity component. $\boldsymbol{\varrho}_i'$ is assumed to be independent realizations from normal population distribution: $\boldsymbol{\varrho}'\sim N(0, \boldsymbol{\varrho}^2)$. $(length_i)$ is the length for segment i which is specified as an offset variable in the ordered fractional split specification for crash severity component.

$\boldsymbol{g}_{it}$ is a vector of exogenous variables that moderate the effect of speed enforcement propensity on severity proportion and $\boldsymbol{\ell}$ is the corresponding vector of coefficient (including a scalar constant). Further, while ι_{it}' (specific to segment i and time point t) and Λ_i' (specific to segment i) are the unobserved components influencing the impact of speed enforcement propensity s_{it}^{*} on crash severity. ι_{it}' and Λ_i' are assumed to be independent realizations from normal population distribution: $\iota'\sim N(0, \iota^2)$ and $\Lambda'\sim N(0, \Lambda^2)$, respectively. ζ_i is an idiosyncratic error term assumed to be identically and independently standard logistic distributed across segment i for the time period t. η_{it} term generates the correlation among three components of interest. Similar to Equation 5, the $\pm$ sign in front of η_i in Equation 6 indicates that the correlation in unobserved individual factors among different components may be positive or negative. To determine the appropriate sign, one can empirically test the models with both $' + '$ and $' - '$ signs independently. The model structure that offers the superior data fit is considered as the final model.

To estimate the model presented in Equation 6, we assume that:

$$\mathbb{E}(y_{ijt}|\boldsymbol{\mathcal{L}}_{it}) = \mathbb{G}_{ijt}(\boldsymbol{\vartheta}, \boldsymbol{\pi}, \boldsymbol{\varrho}, \boldsymbol{\ell}, \iota, \Lambda, \eta_{it}),\ 0 \leq \mathbb{G}_{ijt} \leq 1, \textstyle\sum_{j_t=1}^{J_t} \mathbb{G}_{ijt} = 1 \tag{7}$$

$\mathbb{G}_{ijt}$ in our model takes the ordered logistic probability ($\mathcal{F}$) form for the severity category j for the time period t. Given these relationships across different parameters, the resulting probability ($\mathcal{F}$) for the fractional split model in the crash severity component takes the following form:

$$\begin{aligned} &\mathcal{F}(y_{ijt} = j_t) = \\ &\phi\big[\psi_{jt} - \{(\boldsymbol{\vartheta} + \boldsymbol{\pi}'_{it} + \boldsymbol{\varrho}'_i)\boldsymbol{\mathcal{L}}_{it} + (\boldsymbol{\ell} * \boldsymbol{g}_{it} + \iota'_{it} + \Lambda'_i)s^*_{it} + \zeta_i \pm \eta_{it}\},\big] - \\ &\phi\big[\psi_{(j-1),t} - \{(\boldsymbol{\vartheta} + \boldsymbol{\pi}'_{it} + \boldsymbol{\varrho}'_i)\boldsymbol{\mathcal{L}}_{it} + (\boldsymbol{\ell} * \boldsymbol{g}_{it} + \iota'_{it} + \Lambda'_i)s^*_{it} + \zeta_i \pm \eta_{it}\},\big] \end{aligned} \tag{8}$$

where, $\phi(\cdot)$ is the standard logistic cumulative distribution function.

3.4 Correlation Structure

In estimating the joint panel model, it is important to note here that the unobserved heterogeneity (captured by common unobserved terms η_{it}) among the three components can vary across observations. Therefore, in the current study, the corresponding correlation parameter (η_{it}) is specified as a function of observed attributes as follows:

$$\eta_{it} = (\boldsymbol{r}'_i + \boldsymbol{\varkappa}'_{it})\boldsymbol{\mathcal{H}}_{it} \tag{9}$$

where $\boldsymbol{\mathcal{H}}_{it}$ is a vector of exogenous variables, while $\boldsymbol{r}'_i$ (specific to segment i) and $\boldsymbol{\varkappa}'_{it}$ (specific to segment i and time point t) is a vector of unknown parameters to be estimated. $\boldsymbol{r}'_i$ includes a scalar contant representing the variations at the segment level across all time points under consideration. $\boldsymbol{\varkappa}'_{it}$ also includes a scalar constant representing variations at the segment level within a specific time point t. $\boldsymbol{r}'_i$ and $\boldsymbol{\varkappa}'_{it}$ are assumed to be independent realizations from normal population distributions: $\boldsymbol{r}' \sim N(0, \boldsymbol{r}^2)$ and $\boldsymbol{\varkappa}' \sim N(0, \boldsymbol{\varkappa}^2)$. As indicated by $\pm$ sign in front of η_{it} in Equations 5 and 6, the correlations in unobserved individual factors among the three components could be $'+'$ or $'-'$. Thus, in specifying the joint panel model, the following four correlation structures are specified:

$$\begin{aligned} &[Speed\ enforcement\ (Equation\ 1), Crash\ risk\ (Equation\ 5), \\ &\ Crash\ severity\ (Equation\ 6)] \\ &\sim \\ &[\eta_{it}, \eta_{it}, \eta_{it}];\ [\eta_{it}, \eta_{it}, -\eta_{it}];\ [\eta_{it}, -\eta_{it}, \eta_{it}];\ [\eta_{it}, -\eta_{it}, -\eta_{it}] \end{aligned} \tag{10}$$

A positive sign implies that the segments with greater proportions for tickets with higher speeding levels intrinsically incur higher crash risk and higher proportions for severe crashes. The second correlation structure implies that the segments with greater proportions for tickets with higher speeding levels intrinsically incur higher crash risk but lower proportions for severe crashes. The third correlation structure implies that the segments with greater proportions for tickets with higher speeding levels intrinsically incur lower crash risk but higher proportions for severe crashes. On the other hand, the fourth structure implies that the segments with greater proportions for tickets with higher speeding levels intrinsically incur lower crash risk and lower proportions for severe crashes. To determine the appropriate sign, one can estimate models with $'+'$ and $'-'$ signs independently and then empirically test the models. The model structure that offers the superior data fit is considered as the final model. It is worthwhile to mention here that the correlation structure presented in Equation 10 is generic and can also be employed to capture the correlation between any two sub-set of the three components while restricting $\eta_{it} = 0$ for the respective third component. For example, the correlation structure $[\eta_{it}, \eta_{it}, 0]$ could be implemented to capture the correlation between speed enforcement and crash risk components.

3.5 Model Estimation

The parameters to be estimated in the joint panel model system include $[\boldsymbol{\beta}, \tau, \boldsymbol{\delta}, \boldsymbol{\omega}, \boldsymbol{\vartheta}, \boldsymbol{\ell}, \psi]$ and the variances of the stochastic components $[\boldsymbol{\alpha}'_{it}, \boldsymbol{\gamma}'_{i}, \boldsymbol{\rho}'_{it}, \boldsymbol{\theta}'_{i}, \boldsymbol{\pi}'_{it}, \iota'_{it}, \Lambda'_{i}, \boldsymbol{r}'_{i}\boldsymbol{\varrho}'_{i}, \boldsymbol{\varkappa}'_{it}]$ and in this paper, these elements are drawn from independent realization of normal distribution as: $N{\sim}\{0, (\boldsymbol{\alpha}^2, \boldsymbol{\gamma}^2, \boldsymbol{\rho}^2, \boldsymbol{\theta}^2, \boldsymbol{\pi}^2, \iota^2, \Lambda^2, \boldsymbol{r}^2, \boldsymbol{\varrho}^2, \boldsymbol{\varkappa}^2)\}$. Let the stochastic terms are represented by $\boldsymbol{\Xi}$. Thus, conditional on $\boldsymbol{\Xi}$, the likelihood function for the joint probability can be expressed as:

$$L_i|\Xi = \prod_{t=1}^{T}\left[\prod_{i=1}^{I}\left\{\left(\mathcal{P}(s_{ikt} = k_t)\right)^{a_{it}s_{ikt}} * \mathcal{Q}(c_{ti}) * \left(\mathcal{F}(y_{ijt} = j_t)\right)^{b_{it}y_{ikt}}\right\}\right] \tag{11}$$

a_{it} is 1 if segment i at any time period t has non-zero speeding tickets reported and 0 otherwise. s_{ikt} is the proportion of speeding ticket categories specific to segment i and time period t. b_{it} is 1 if segment i at any time period t has at least one crash recorded and 0 otherwise. y_{ikt} is the proportion of crashes by severity levels specific to segment i and time period t. Finally, the log-likelihood function can be written as:

$$LL = \sum_{i} ln\left\{\int_{\Xi} \left((L_i|\Xi)f(\Xi)\mathrm{d}\Xi\right)\right\} \tag{12}$$

The likelihood function in Equation 11 involves the evaluation of a multi-dimensional integral of size equal to the number of rows in $\boldsymbol{\Xi}$. We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function (See Bhat 2001; Yasmin and Eluru 2013 for more details). The likelihood functions are programmed in Gauss (Aptech 2016).

4 EMPIRICAL ANALYSIS

4.1 Model Specification and Overall Measures of Fit

The major focus of the study is to examine speed enforcement (in the form of speeding ticket issued), crash risk, crash severity simultaneously while also controlling for the endogeneity of speed enforcement in the crash risk and crash severity components. The empirical analysis involves estimation of a series of models, including (1) Independent model without speed enforcement endogeneity, (2) Uncorrelated model with speed enforcement endogeneity, (3) Correlated panel model with speed enforcement endogeneity and (4) Correlated panel random effect model with speed enforcement endogeneity. Independent models without speed enforcement endogeneity involve a simple ordered logit fractional split model for speed enforcement component, a simple negative binomial model for crash risk component and a simple ordered logit fractional split model for crash severity component. In the independent models, the crash risk and crash severity models do not include the speed propensity function identified from the speed enforcement component as exogenous variables. These models serve as the basis for comparisons.

In the second step, an uncorrelated model with speed enforcement endogeneity is estimated by integrating the speed enforcement propensity into the crash risk and crash severity components simultaneously. In this effort, 'operational duration for speed cameras' is considered as an instrumental variable in the speed enforcement component. Based on the result of the uncorrelated model, a correlated model with speed enforcement endogeneity is estimated by stitching the three dimensions of interests through a common unobserved random term while also capturing the panel effect of repeated observations. In estimating the correlated model, we have specified the correlation by using four different correlation structures as presented in Equation 10. The correlation structure that provides the best data fit is further selected for the next step of analysis.

Finally, all the exogenous variables in the correlated model (correlation structure with the best data fit) are tested for random effects while also capturing the panel effect of repeated observations, which is referred to as Correlated panel random effect model with speed enforcement endogeneity. Prior to discussing the estimation results, we compare the performance of different estimated models in this section. We employ Bayesian Information Criteria (BIC) for comparing the models. The BIC can be expressed as:

$$BIC = -2LL + \mathbb{K}ln(\mathbb{Q}) \tag{13}$$

where LL is the log likelihood value at convergence, $\mathbb{K}$ is the number of parameters, and $\mathbb{Q}$ is the number of observations. The model with the lower BIC is the preferred model. The BIC (LL; $\mathbb{K}$) values for the estimated models are –

1) Independent model without speed enforcement endogeneity: 13351.93 (-6557.51, 31)
2) Uncorrelated model with speed enforcement endogeneity: 13303.76 (-6529.61, 32)
3) Correlated panel model with speed enforcement endogeneity and correlation structure $[\eta_{it}, \eta_{it}, \eta_{it}]$: 11762.18 (-5751.17, 34)
4) Correlated panel model with speed enforcement endogeneity and correlation structure $[\eta_{it}, \eta_{it}, -\eta_{it}]$: 11850.95 (-5795.56, 34)
5) Correlated panel model with speed enforcement endogeneity and correlation structure $[\eta_{it}, -\eta_{it}, -\eta_{it}]$: 11742.54 (-5741.36, 34)
6) Correlated panel model with speed enforcement endogeneity and correlation structure $[\eta_{it}, -\eta_{it}, \eta_{it}]$: 11678.40 (-5709.28, 34)
7) Correlated panel random effect model with speed enforcement endogeneity and correlation structure $[\eta_{it}, -\eta_{it}, \eta_{it}]$: 11672.69 (-5706.43, 34)

From the BIC values, it is evident that the uncorrelated model with speed enforcement endogeneity outperforms the independent model without speed enforcement endogeneity supporting our hypothesis that speed enforcement is endogenous to crash risk and crash severity. Further, all the correlated models have superior data fit over the independent and uncorrelated models, supporting our hypothesis that the three dimensions of interest are correlated. Thus, ignoring such correlation is likely to result in biased and inconsistent parameter estimates contributing to inefficient policy implications (Washington et al., 2020). Among different correlation structures, the model with $[\eta_{it}, -\eta_{it}, \eta_{it}]$ in the speed enforcement, crash risk and crash severity components has the lowest BIC value. Thus, we can argue that the correlation structure $[\eta_{it}, -\eta_{it}, \eta_{it}]$ captures the simultaneity among the three dimensions better and provides the best data fit in the current study context. Finally, the correlated model with the correlation structure $[\eta_{it}, -\eta_{it}, \eta_{it}]$ is tested for random coefficients in three dimensions. After capturing for correlation, one of the parameters in the crash risk component is found to be random with improved data fit. Thus, the comparison exercise highlights the superiority of the correlated panel random effect model with speed enforcement endogeneity in terms of the data fit compared to other models.

4.2 Measures of Fit for Instrumental Variable

In this empirical study, 'operation duration of speed camera' is considered as an instrumental variable (IV) of the endogenous regressor (speed enforcement level) in developing the safety models. In econometric analysis, two important characteristics of the IV are – (1) relevance of IV (instrument relevance assumption) and (2) validity of IV (instrument exogeneity assumption). A valid and reliable IV is likely to explain significant variations in the endogenous regressor, and hence can be considered as a strong IV. The analysis results of IV relevance and validity are discussed in the following sub-sections.

4.2.1 Relevance of Instrumental Variable

In econometric analysis, a relevant instrumental variable (IV) is expected to be highly correlated with the endogenous measure of speed enforcement level. Thus, a good IV is expected to remain relevant (significant) in the regression estimation of the endogenous variable even after controlling for other exogenous variables. In empirically testing for the relevance of the IV, at first, an ordered logit fractional split model for speed enforcement is estimated by considering the IV – 'operational duration of speed camera' – as the only exogenous variable. The parameter estimates for the IV is $(estimate, t\text{-}stat) = (-0.154, -5.907)$. Further, the model is augmented with other exogenous variables and the resulted parameter estimates for the IV is $(estimate, t\text{-}stat) = (-0.145, -6.1.89)$ and, hence, remains significant. Thus, we can argue that the considered IV is relevant in the empirical setting of the current study context.

4.2.2 Validity of Instrumental Variable

An Instrumental Variable (IV) can be considered valid if it is uncorrelated with the error term (assumption of instrument exogeneity). To be sure, it is not possible to test for such econometric restriction directly and/or fully, which would require a strong theoretical argument. An alternate approach for examining such IV validity can be performed by employing Overidentifying Restriction test[9]. Examining such instrument validity is econometrically feasible when

$$[No\ of\ endogenous\ regressors < Number\ of\ instrumental\ variables]$$

i.e. coefficients of the instruments on the endogenous regressors has to be overidentified. Therefore, in the current study context, an overidentifying restriction test is employed by adding an additional instrument – 'proportion of covert camera deployed per segment per year'.

[9] Overidentifying restriction test is also known as J-statistic, which examines the hypothesis that all instruments are exogenous.

In empirically testing for the validity of the IV, ordered logit fractional split models for speed enforcement is estimated with and without the additional instrument as exogenous variable. Further, the performance of these models is compared by employing J-statistic as:

$$\begin{aligned} &\mathcal{J} \sim \chi^2_{\oint - r}\ ; \ \ with\ degrees\text{-}of\text{-}freedom = (\oint - r), \\ &\oint = no\ of\ instruments, r = no\ of\ endogenous\ regressors \end{aligned} \tag{14}$$

The computed J-statistic = 17.96 $> \chi^2_{\oint - r} = 6.63$, which favors the validity of 'operational duration of speed camera' as instrument in this study and, hence, is consistent.

4.3 Model Estimation results

In interpreting the effects of exogenous variables, we will restrict ourselves to the discussion of the best specified model –'Correlated panel random effects model with speed enforcement endogeneity', which is referred to as joint panel model in the following sections for simplicity. In the current study context, the correlation structure of the joint model that provides with the best data fit is

$$\big[[Speed\ Enforcement, Crash\ risk, Crash\ severity] \sim [\eta_{it}, -\eta_{it}, \eta_{it}]\big]$$

Table 3 presents the results of the joint panel model with the speed enforcement component results in the 1st row panel, crash risk component results in the 2nd row panel, and crash severity component results in the 3rd row panel. The correlation parameters of the joint panel model are presented in the last row panel of Table 3. For the ease of presentation, the results of different components are discussed separately in the following sections.

Table 3: Model Results for the Correlated Panel Random Parameter Model with Speed Enforcement Endogeneity

SPEED ENFORCEMENT COMPONENT		
Variables	**Estimate**	**t-stat**
Threshold parameters		
Threshold between minor and moderate speeding citations	2.144	6.887
Threshold between moderate and major speeding citations	4.589	14.667
Traffic characteristics		
AADT	0.106	3.544
Proportion of heavy vehicle	1.833	4.670
Roadway design and operational characteristics		
Length (Offset)	1.000	---*
Presence of shoulder		
Yes	0.192	3.547
No	---	---
Posted speed limit		
High speed limit (>100 km/h)	0.491	4.426
Medium speed limit (>50 and <100 km/h)	---	---
Low speed limit (<50 km/h)	---	---
Pavement sealed condition		

Sealed	---	---
Unsealed	-0.769	-9.679
Terrain type		
Rolling/Mountainous	0.195	2.439
Flat	---	---
Speed Camera Deployment Characteristics		
Operational duration for speed cameras	-0.089	-4.015
CRASH RISK COMPONENT		
Variables	**Estimates**	**t-stat**
Constant	-1.449	-2.783
Traffic characteristics		
AADT	0.247	5.184
Roadway design and operational characteristics		
Length (Offset)	1.000	---
Number of lanes	0.156	6.196
Median width	-0.033	-3.747
Radius of horizontal alignment	-0.016	-1.962
Functional classification of road		
Rural road	-0.804	-7.685
Standard deviation of rural road	0.391	5.422
Urban road	---	---
Shoulder width	-0.078	-3.362
Shoulder type		
Paved	---	---
Unpaved	-0.304	-1.999
Rutting	0.102	5.155
Temporal and Situational Characteristics		
Rainfall	-0.380	-1.924
Wind speed	-0.020	-3.650
Speed Camera Deployment Characteristics		
Speed enforcement propensity		
Constant	-0.548	-8.080
Overdispersion parameter	0.017	3.474
CRASH SEVERITY COMPONENT		
Variables	**Estimates**	**t-stat**
Threshold parameters		
Threshold between minor and major injury	-1.931	-5.823
Threshold between major and fatal injury	3.904	10.627
Traffic characteristics		
Proportion of heavy vehicle	1.740	1.854
Roadway design and operational characteristics		
Length (Offset)	1.000	---
Number of lanes	-0.091	-2.425
Posted speed limit		

High speed limit (>100 km/h)	0.858	3.534
Medium speed limit (>50 and <100 km/h)	---	---
Low speed limit (<50 km/h)	---	---
Temporal and Situational Characteristics		
Time elapsed (Linear)	0.180	4.102
Speed Camera Deployment Characteristics		
Speed enforcement propensity		
Constant	-0.868	-8.908
CORRELATION COMPONENT		
Variables	**Estimates**	**t-stat**
Standard deviation of common error among speed enforcement, crash risk and crash severity components (Segment level)	0.427	19.262

**Insignificant at 10% significance level*

4.3.1 Speed Enforcement Component

The estimation results of the speed enforcement component are presented in the first-row panel of Table 3. In the current study, the speed enforcement component is modeled by employing an ordered logit fractional split modeling technique. In the fractional split model, a positive (negative) coefficient corresponds to increased (decreased) proportions for major speeding citations. A positive (negative) threshold implies that it is bound to increase (decrease). In the speed enforcement component, segment length is specified as an offset variable, and the coefficient of the offset variable is restricted to be one to normalize for the recorded events by segment length. The estimation results of the speed enforcement component are discussed below.

In the speed enforcement component of the joint panel system, linear, non-linear (logarithmic) and quadratic (square) functional forms of AADT are considered. In the final model specification of the speed enforcement component, the logarithmic function of AADT is found to be significant with better data fit relative to models with other specifications confirming a non-linear relationship between speed enforcement propensity and AADT. From Table 3, it can be observed that the likelihood of major speeding citations increases with an increasing AADT at a roadway segment level. The higher level of traffic volume is generally associated with less vehicle maneuvering freedom. Hence, the effect of AADT on the speed enforcement propensity apparently may seem to be counterintuitive as one may expect that the chance of speeding is likely to decrease with the increase in traffic volume. Hu et al. (2009), in an experimental study, found that the relationship between speeding rate and traffic volume is rather quadratic with an increasing trend up to the network reaching a certain critical traffic volume level. After the traffic stream reaches the critical volume, the speeding rate is likely to decrease. Be motivated by this finding, initially, we specified AADT as a linear and square functions in the speed enforcement component. The linear form had a significant positive coefficient and the square of AADT had a negative insignificant coefficient, which was in line with the result from Hu et al. (2009). However, the logarithmic function of AADT provide with the best data fit and hence is considered in the final model specification. The positive effect of logarithmic of AADT on speeding citation propensity is perhaps indicating that the drivers tend to engage in a higher level of speeding with the perception of losing time as the traffic gets heavier (see Ambros et al., 2020 for similar results).

The proportion of heavy vehicle in the speed enforcement component reveals that the proportion of major speeding citations is likely to be higher in the roadway segments with a higher proportion of heavy vehicles. The result might be attributable to the significant change in driver behavior in the presence of heavy vehicles in a traffic stream. As is evident from earlier studies (Moridpour et al., 2015), drivers of other vehicles are likely to change their behavior (such as speed choice, headway, lane changing) frequently in the presence of heavy vehicles in the traffic stream. For instance, Kong et al. (2016) found that almost 50% of the drivers reported to change lane immediately when they felt the impact of a truck in a traffic stream. Thus, the higher proportions of major speeding citations may be attributable to speeding related to overtaking heavy vehicles. In an earlier study employing the same speeding citation data, Afghari et al. (2018) reported similar effect while noting that such relations are likely to be prominent on multilane roadways where there are legitimate opportunities for frequent lane changing and overtaking.

The variable indicating the presence of shoulder has a positive coefficient which indicates that the propensity of major speeding citations is likely to be higher on roadway segments with shoulder relative to the roadways without shoulder. The presence of a shoulder is likely to provide with an additional safety margin for driving, and hence the tendency to drive over the posted speed limit in these locations is likely to be higher relative to locations with no shoulder. With regards to posted speed limit, the estimation results from Table 3 reveals that the roadway section with posted speed limit ≥100 kmph are likely to be associated with higher citations of major speed limit violations. The result may appear to be counterintuitive as one may do less speeding on a roadway, which is already catering a higher level of posted speed limit. However, as reported by Haglund and Åberg (2000), the intuition to abide by the posted speed limit are likely to decrease with increasing posted speed limit. In fact, the study found that 56% of the drivers exceeded posted speed limit by 10 km/h on a road with posted speed limit ≥100 km/h. Such outcome might be attributable to higher design standards of these roadways allowing for greater margin to drive over the posted speed limit.

The unsealed pavement condition of a roadway section provides restrictive driving maneuverability, and as expected, the variable indicating unsealed condition is found to have a negative influence on the speeding citation propensity. With regards to other roadway elements, a rolling/mountainous terrain is found to have a positive association with speeding citation propensity.

With regards to the speed camera deployment characteristics, operational duration for speed camera serves as the instrumental variable for endogenous speed enforcement component. From Table 3, we can see that the likelihood of major speeding citations is likely to be lower in the roadway segments with higher operational duration for speed camera enforcement. Over the time, drivers may become more cautious about the presence of speed camera in locations with higher enforcement duration resulting in greater self-awareness and less engagement in speeding violations along these roadway corridors. Moreover, the result might be attributable to the time-halo effect of speed camera operation. The time-halo effect signifies the duration over which the deterrence effects of enforcement are likely to continue after the operation of enforcement ends. For example, Gouda and El-Basyouny (2017) found that a 22 hours of speed camera enforcement operation may extend up to 5 days of time-halo effect, while a drop of 19% speed limit violations could be expected. Thus, it is evident that a longer enforcement duration of speed camera is likely to have a greater added benefit on deterrence effect from higher cumulative time-halo effect. In fact, creating time-halo effect of speed camera operation is one of the major focuses in achieving a widespread general deterrence effect in speeding behavior (Champness et al., 2005). Therefore, examining such causal effect of speed camera enforcement duration on speeding violation has greater importance in identifying the optimal resource allocation in achieving greater safety benefits of speed camera enforcement.

4.3.2 Crash Risk Component

The second-row panel of Table 3 presents the estimation results of the crash risk component of the joint panel modeling system. In the current study, the crash risk component is modeled by employing the negative binomial regression technique. A positive (negative) sign for a coefficient in the crash risk component indicates that an increase in the magnitude of the variable is likely to results in higher (lower) crash risk. In the crash risk component, segment length is specified as an offset variable, and the coefficient of the offset variable is restricted to be one to normalize for the recorded events by segment length. In the subsequent sections, detailed discussions of the model results for the crash risk component are provided.

In developing the crash-causal relationship, AADT is often deemed to be one of the most important exogenous variables controlling for exposure (Papadimitriou et al., 2019). As such, with respect to traffic characteristics, AADT is considered as a measure of exposure. In the crash risk component, a linear, non-linear (logarithmic) and quadratic (square) function of AADT is considered. In the final model specification, the logarithmic function of AADT is found to be significant, confirming the non-linear relationship between crash risk and AADT in the current study context. The positive coefficient of the logarithmic of AADT clearly underscores that the likelihood of crash risk increases with increased exposure to crashes. The result is in line with previous studies (Afghari et al., 2020; Wen et al., 2018).

The positive parameter of number of lanes indicates that a higher number of traffic lanes contribute towards a higher likelihood of crash risk. The result might be attributable to greater chances of lane-changing behavior in the roadway segments with more lanes resulting in higher lane-changing related crash risks (Venkataraman et al., 2014; Afghari et al., 2020). As found in previous studies (Yu and Abdel-Aty, 2013; Farid et al., 2018), median width is found to have a negative association with crash risk. A wider median reflects an extra margin of safety for vehicle maneuvering and hence is likely to provide a higher level of safety margins for evasive actions in case of an impending crash (Saeed et al., 2019). Therefore, the crash risk on roadway segments with a wider median is likely to be lower.

The road section with a larger horizontal curve is likely to impose less navigating complexity and hence are likely to be safer than a road section with tight horizontal curvature (Li et al., 2014; Rusli et al., 2017). Analogous to such findings, in the current study, it is found that a larger horizontal radius is likely to contribute towards lower crash risk. As expected, the results in Table 3 reveal a reduced crash risk on rural roadways relative to urban roadways, presumably due to the lower exposure to traffic in a rural environment. In addition, the indicator for rural roads is found to have random parameters, and the result indicates that the crash is more likely to be lower (higher) in more than 98% (less than 2%) of the cases on rural roads. Among other roadway cross-sectional elements, in the crash risk component, should width is found to be one of the significant contributors of crash risk. An increasing shoulder width is found to be associated with a lower likelihood of crash risk (see Anastasopoulos and Mannering, 2009 for similar result).

With regards to shoulder type, the coefficient corresponding to unpaved shoulder type indicates that roadway with unpaved shoulder is likely to have reduced crash risk relative to segments with paved shoulder. In the crash risk component, the result specific to rutting indicates that the likelihood of crash risk increases with increasing rutting (see Hou et al., 2018 for similar result).

The average climate condition is often considered in developing crash prediction models to capture the situational condition of the roadway environment. Among different climate conditions, the findings from the existing studies for the effect of average rainfall on crash risks are rather multifaceted. Some of the studies found the relationship to be positive (Yu et al., 2015), while other studies reported this to be negative (Jung et al., 2014). From Table 3, it can be observed that average rainfall per year has a negative impact on crash risk, presumably reflecting the risk compensation behavior of the drivers. Among other meteorological variables, wind speed is found to be significant with a negative impact on crash risk. Afghari et al. (2018) found a similar impact in a study employing the crash data from Queensland, Australia.

The effect of speeding ticket propensity, which addresses the effect of speed enforcement endogeneity in crash risk, is found to have a significant effect on the crash risk component. In the final model, the speed propensity is specified as a scalar constant (other exogenous variables and unobserved effects are not found to be significant). The effect of speeding ticket propensity is negative, which indicates that the likelihood of total crash risk decreases with an increase in the latent propensity of major speeding citations. Given a legal sanction like speeding tickets, one of the major focuses of law enforcement is to increase the certainty of deterrence and comprehension (Tay, 2005), which may result in greater levels of enforcement in the form of more speeding tickets in locations with speed enforcement. The roadways under examination in this study are the major arterial corridors of Queensland, which are most likely to be used by regular commuters throughout the year. For these regular commuters, the information set of a higher level of major speeding citations along these corridors may instigate higher levels of perceived apprehension resulting in more cautious driving behavior. For example, Li et al. (2011) reported that the drivers ticketed for speeding are likely to be associated with a lower level of subsequent speeding citations. Therefore, the result associated with speeding ticket propensity on crash risk is perhaps an indication that stringent enforcement of posted speed limit is highly likely to improve the overall safety in these locations.

4.3.3 Crash Severity Component

The estimation results of the crash severity component of the joint panel modeling system are presented in the third-row panel of Table 3. In the current study, the crash severity component is estimated by employing an ordered logit fractional split modeling technique. In the fractional split model, a positive (negative) coefficient corresponds to increased (decreased) proportions for severe injury outcomes. A positive (negative) threshold implies that it is bound to increase (decrease). In the crash severity component, segment length is specified as an offset variable, and the coefficient of the offset variable is restricted to be one to normalize for the recorded events by segment length. The estimation results of the crash severity component are discussed below.

The estimation result for heavy vehicle proportion has a positive coefficient in the crash severity component, suggesting that higher volumes of heavy vehicles in a traffic stream are likely to incur a higher fraction of severe crashes. Number of lanes has an opposing impact in the crash severity component than in the crash risk component. The variable has a negative impact on the proportion of crash severity outcomes, implying a lower likelihood of severe crashes on roadway segments with more lanes.

Relative to roadway segments with posted speed limit<100 km/h, the posted speed limit≥100 km/h is associated with a higher proportion of severe crashes. The result could be attributed to the higher energy of collision on a higher posted speed limit location (Farmer, 2017). The time elapsed variable (linear form) is found to be significant in the crash severity component only of the joint panel system. Over the last decade, there was a significant decline in road fatalities in Australia, but the trend in hospitalized/serious injury has increased since 2013 (BITRE, 2020). The positive effect of the time elapsed variable in the crash severity component is perhaps picking up such an increasing trend of serious injury crashes.

The effect of speeding ticket propensity, which addresses the effect of speed enforcement endogeneity in crash severity, is found to have a significant effect on the crash severity component. In the final model, the speed propensity is specified as a scalar constant, while other exogenous variables and unobserved effects are found to be insignificant. The effect of speeding ticket propensity is negative, which indicates that the likelihood of severe crashes decreases with an increased propensity of major speeding citations. As explained in the crash risk component, a higher level of enforcement is likely to result in a greater probability of perceived apprehension among drivers. Thus, a general deterrent impact of speed enforcement is the reduction in speeding behavior. On the other hand, speeding is a major contributor to fatal crashes, and in fact, speeding is one of the 'fatal five' behavior of road trauma in Queensland (Salmon et al., 2016). Therefore, we can argue that a higher level of speed enforcement is likely to contribute towards less speeding behavior, which in turn is likely to result in lower incidences of serious crash events.

4.3.4 Correlation Component

The last row panel of Table 3 represents the correlation component of the joint panel model system. In the model, we consider different levels of (segment and observation) correlation effects across three dimensions. Further, we have also considered different levels of correlations between two sub-set dimensions at different levels (segment and observation). Moreover, the correlation structure is parameterized as a function of other exogenous variables (as discussed in Section 3.4). In the final specified model, the correlation structure, represented as a scalar constant term, at the roadway segment panel level is found to be significant. Further, as discussed in the methodology section, the correlation among the three components could be either positive or negative. The correlation structure that provides the best data fit is

$$\left[[Speed\ Enforcement, Crash\ risk, Crash\ severity] \sim [\eta_{it}, -\eta_{it}, \eta_{it}]\right]$$

The correlation structure implies that the unobserved factors resulting in greater proportions of major speeding citations intrinsically incur lower crash risk but intrinsically incur higher proportions for severe crashes. In this study context, the associations among speed enforcement, crash risk and crash severity are examined at a roadway network level without consideration of specific driver-level traits. Thus, the absence of driver behavior data may be a significant source of unobserved heterogeneity in this empirical analysis. In the correlation component, the negative association between speed enforcement and crash risk is perhaps indicating that the majority of the drivers are compliant with the posted speed limit due to the higher level of perceived apprehension on the roadways with stricter enforcement levels. On the other hand, a portion of high-risk taking drivers are less likely to be compliant to traffic rules irrespective of the level of enforcement. High-risk takers (attributed to speeding, drink-driving and/or disobeying traffic rules) are likely to be involved in more severe crashes (Gebers and Peck, 2033). In fact, Factor (2014) found a strong positive correlation between the number of tickets drivers receive and their subsequent involvement in severe crashes. Thus, in this study, the positive correlation between speed enforcement and crash severity components is perhaps indicating the unobserved effects of risky driving behavior and the consequent crash severity outcomes irrespective of high enforcement levels.

None of the other specifications in the correlation component are found to be significant. Other exogenous variables are also found to be insignificant in the correlation component. Overall, the results clearly highlight the importance of accommodating the common unobserved factors influencing speed enforcement and safety.

4.4 Model Implications

4.4.1 Elasticity Effects

To quantify the effects of parameter estimates of the joint model (presented in Section 4.3), we have computed aggregate level "elasticity effects" of variables in the speed enforcement, crash risk and crash severity components (see Eluru and Bhat (2007) for a detailed discussion of methodology for computing elasticities). The elasticity effects are computed by changing the value of indicator variables from zero (one) to one (zero), by considering 10% increase in continuous variables or by one unit increase for ordinal variables. The elasticities are computed for the three components simultaneously considering 300 realizations of parameters (mean and the associated standard deviation) employing normal distributions, and the values are presented as the average measure of elasticities in Figure 2. In speed enforcement and crash severity components, the elasticity effects can be interpreted as the percentage change in the probabilities of dependent variable alternatives due to the changes in an exogenous variable (other characteristics being equal). In the crash risk component, elasticity effects can be interpreted as the percentage change in expected number of crashes due to a change in an exogenous variable (other characteristics being equal).

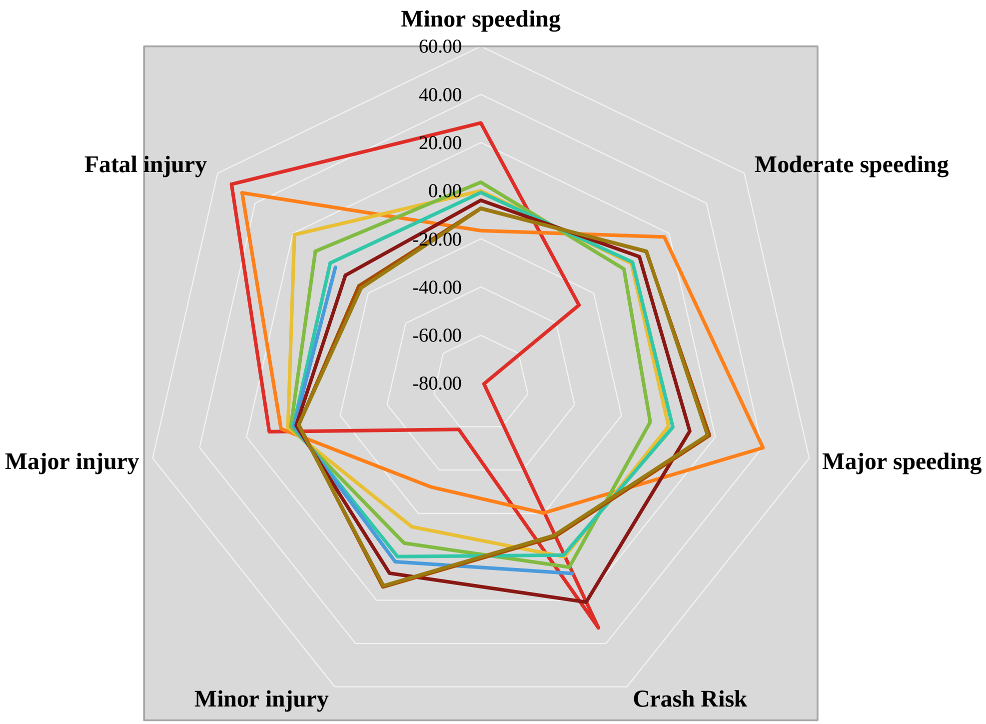
Several important observations can be made from the elasticity estimates presented in Figure 2. With regards to the speed enforcement component, the most important factors associated with major speeding citations are the high posted speed limit, rolling/mountainous terrain, and presence of shoulder. On the other hand, unsealed pavement condition and operation duration of speed camera are the two major factors associated with less serious speeding citations. In the crash risk component, roadway segment with unsealed condition and AADT have higher elasticities indicating 32.76% and 20.86% increase in expected number of crashes, respectively. With respect to crash severity component, the elasticity effects for unsealed pavement condition and high posted speed limit show 52.67% and 47.04% increase in fatal crash risk proportions. Rolling/mountainous terrain and the presence of shoulder are the most important variables associated with the reduction in fatal crash proportions.

It is important to mention here that the exogenous variables in the speed enforcement component have indirect effects[10] (also referred to as mediating effect) on crash risk and crash severity components through the latent propensity function of speed enforcement components. The independent model ignores such common causes, which may result in spurious effect of mediator on the associated dependent variable. The exogenous variables in the safety components which are not mediated by speed enforcement propensity can be referred to as direct effect. Thus, the total effect of a variable sums up to direct and indirect effects. The type of mediating effects of exogenous variables in the safety components is presented in Figure 2, along with the elasticity effects.

In the safety components, high posted speed limit (≥100 km/h), rolling/mountainous terrain, presence of shoulder, AADT, proportion of heavy vehicle, operational duration for speed camera and unsealed pavement condition have indirect effects. Among the variables, AADT is likely to lead to higher crash risk and higher citations of major speeding events. Such a common cause could be attributed to drivers' perception of loosing time in heavier traffic which may lead to higher speeding behavior resulting in higher crash risk. On the other hand, the high posted speed limit indicator is likely to lead to higher citations of major speeding events while also contributing towards an increase in the proportions of both fatal and major injury crashes. The potential common cause for such outcome could be attributed to longer duration of speeding events on higher functional class of roads with a high posted speed limit. As argued in Kong et al. (2020), the speeding behavior of drivers tends to last longer in roadways with higher functional class. The higher construction and operational standards of

[10] According to Sobel (1990), an indirect effect represents a causal hypothesis whereby an independent variable causes a mediating variable, which, in turn, causes a dependent (response/outcome) variable.

these roads might provide drivers with a false sense of safety, which in turn may result in longer duration speeding events. Such unsafe behavior may contribute towards serious speeding events resulting in serious crash outcomes.



Variables (Legends)	Mediating Effects in Safety Components	
	Crash Risk	Crash Severity
Unsealed pavement condition	I	I
High posted speed limit (≥100 km/h)	I	D & I
Time elapsed (Linear)	N	D
Operational duration for speed camera	I	I
Proportion of heavy vehicle	I	D & I
Number of lanes	D	D
AADT	D & I	I
Rolling/Mountainous terrain type	I	I
Presence of shoulder - Yes	I	I
Rural road	D	N
Unpaved shoulder type	D	N
Median width	D	N
Radius of horizontal alignment	D	N
Rainfall	D	N
Shoulder width	D	N
Wind speed	D	N
Rutting	D	N

Figure 2: Elasticity effects and Type of Mediating Effects *(I=Indirect Effect; D=Direct Effect; N= No Effect)*

4.4.2 Policy Scenario Analysis

From the parameter estimates presented in Section 4.3, it is evident that speed enforcement has a causal effect on safety. To illustrate the implications of such intricate results, we employ the estimates from the best-specified model (presented in Table 3) to generate hypothetical scenarios with different speed enforcement levels (while other characteristics remain equal) and compute the associated elasticity effects for the safety components. In doing so, it is important to realize that in the joint modeling system, the speed enforcement levels are represented by the latent propensity function (s_{it}^*) in the safety components (in Equations 5 and 6). Therefore, to impose a change in the speed enforcement level, we rescale the latent propensity of the speed enforcement component (s_{it}^* in Equation 1, 5 and 6) following Jackman (2000) as:

$$\mathbb{S}_{it}^* = \mathscr{m} * s_{it}^* + \mathfrak{g} \tag{15}$$

Where $\mathbb{S}_{it}^*$ is the rescaled latent propensity function of speed enforcement, $\mathscr{m}$ is the rescaling constant and $\mathfrak{g}$ is the location shift[11]. Finally, with rescaled $\mathbb{S}_{it}^*$, the elasticities (percentage changes) in speed enforcement levels, crash risk and crash severity levels can be computed as:

$$Elasticities\ for\ speeding\ levels = \left[\frac{\hat{\mathcal{P}}(k_t|\boldsymbol{x}_{it}, \mathbb{S}_{it}^*) - \mathcal{P}(k_t|\boldsymbol{x}_{it}, s_{it}^*)}{\mathcal{P}(k_t|\boldsymbol{x}_{it}, s_{it}^*)}\right] * 100$$

$$Elasticities\ for\ crash\ risk = \left[\frac{\{\hat{\mu}_{it} = \mathbb{E}(c_{it}|\boldsymbol{z}_{it}, \mathbb{S}_{it}^*)\} - \{\mu_{it} = \mathbb{E}(c_{it}|\boldsymbol{z}_{it}, s_{it}^*)\}}{\{\mu_{it} = \mathbb{E}(c_{it}|\boldsymbol{z}_{it}, s_{it}^*)\}}\right] * 100 \tag{16}$$

$$Elasticities\ for\ crash\ severity\ levels = \left[\frac{\hat{\mathcal{F}}(j_t|\boldsymbol{\mathcal{L}}_{it}, \mathbb{S}_{it}^*) - \mathcal{F}(j_t|\boldsymbol{\mathcal{L}}_{it}, s_{it}^*)}{(j_t|\boldsymbol{\mathcal{L}}_{it}, s_{it}^*)}\right] * 100$$

where s_{it}^* and $\mathbb{S}_{it}^*$ are the original and rescaled latent propensity function for speed enforcement component. $\mathcal{P}$ and $\hat{\mathcal{P}}$ are probabilities for speeding citation level k specific to s_{it}^* and $\mathbb{S}_{it}^*$, respectively. μ and $\hat{\mu}$ are expected crash count specific to s_{it}^* and $\mathbb{S}_{it}^*$, respectively. $\mathcal{F}$ and $\hat{\mathcal{F}}$ are probabilities for severity j specific to s_{it}^* and $\mathbb{S}_{it}^*$, respectively. The rest of the terms are defined in Section 2. In generating the hypothetical scenarios, we have considered changes in speed enforcement levels with respect to 'changes in proportion of speeding citations' and changes in 'operation duration for speed camera'[12]. Specifically, the hypothetical scenarios considered are:

[11] As argued in Jackson (2000), "It is sometimes possible to re-define the latent variable as substantively meaningful quantity" leveraging different identification constraints imposed in estimating ordered models. Thus, in this study, we have redefined the speeding enforcement propensity in generating a different levels of speeding proportions relative to observed ones.

[12] Operational duration for speed camera has indirect effect on safety components through the latent propensity function of speed enforcement and hence are likely to generate different safety profile with different operational duration.

Scenario 1: $m = 0.5, \mathrm{g} = -0.05$[13], $\mathbb{OD}$
Scenario 2: $m = 1.15, \mathrm{g} = 0.01, \mathbb{OD}$
Scenario 3: $m = 1.25, \mathrm{g} = 0.02, \mathbb{OD}$
Scenario 4: $\mathbb{OD}$ +100 hour for all i
Scenario 5: $m = 1.25, \mathrm{g} = 0.02$, $\mathbb{OD}$ +100 hour for all i
Scenario 6: $m = 1.25, \mathrm{g} = 0.02, \mathbb{OD}$ +100 hour for randomly selected 266 (out of 521) i
Scenario 7: $m = 1.25, \mathrm{g} = 0.02,$ [($\mathbb{OD}$ +200 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) > $2\}$] + [($\mathbb{OD}$ +100 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) = 1 or $2\}$] + [($\mathbb{OD}$ +0 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) ≤ $0\}$]
Scenario 8: $m = 1.25, \mathrm{g} = 0.02,$ [($\mathbb{OD}$ +200 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) > $2\}$] + [($\mathbb{OD}$ +100 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) = 1 or $2\}$] + [($\mathbb{OD}$ * 0.5) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) ≤ $0\}$]
Scenario 9: $m = 1.25, \mathrm{g} = 0.02,$ [($\mathbb{OD}$ +400 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) > $2\}$] + [($\mathbb{OD}$ +200 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) = 1 or $2\}$] + [($\mathbb{OD}$ * 0.5) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) ≤ $0\}$]
Scenario 10: $m = 1.30, \mathrm{g} = 0.02,$ [($\mathbb{OD}$ +200 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) > $2\}$] + [($\mathbb{OD}$ +100 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) = 1 or $2\}$] + [($\mathbb{OD}$ * 0.5) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) ≤ $0\}$]
Scenario 11: $m = 1.30, \mathrm{g} = 0.02,$ [($\mathbb{OD}$ +400 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) > $2\}$] + [($\mathbb{OD}$ +200 hour) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) = 1 or $2\}$] + [($\mathbb{OD}$ * 0.5) if $\{(c_{i2} + c_{i3}$ in 2013) $- (c_{i2} + c_{i3}$ in 2010) ≤ $0\}$]

where m is the rescaling constant and g is the location shift in Equation 15, $\mathbb{OD}$ is the operational duration for speed cameras, i is roadway segment, c_{i2} is the number of major injury crashes for segment i and c_{i3} is the number of fatal injury crashes for segment i. The computed elasticities (following Equation 16) in speeding and safety levels for the considered scenarios are presented in Figure 3.

For the policy scenario illustration, at first, we have imposed changes in speeding citations by rescaling the latent propensity of the speed enforcement component (Scenarios 1 through 3). From these scenarios, we can observe that changes in the proportion of speeding citations have a greater impact on the changes in the proportion of fatal injury crashes. An increase in minor speeding citations is likely to contribute towards an increase in crash risk and an increase in the proportion of serious injury categories. However, a higher level of major speeding citations is likely to contribute towards reduction in crash risk, major and fatal injury proportions. As is evident from Figure 3, about a 55% increase in the proportion of major speeding citations is likely to contribute towards more than 9% reduction in crash risk and more than 33% reduction in fatal crash proportion. The amount of kinetic energy produced by a crash is directly proportionate to speed, thus a higher speeding level is likely to result in serious crash outcomes. As such, stricter enforcement of major speeding violations is likely to contribute towards a greater reduction in crash severity than to the total number of crashes (as also argued in Elvik, 2012).

The second attribute of the speed enforcement measure is 'operation duration for speed camera'. In Scenario 4, we have considered an increase in operation duration across all roadway segments. From this scenario, we can observe that an increase in operation duration without imposing a stricter level of speed enforcement might not be effective in achieving

[13] Our major focus is on understanding the trade-off between changes in speeding ticket levels and safety levels. Therefore, in this study, we have chosen arbitrary numbers for m and c to generate different speed enforcement levels. To be sure, such exercise could be demonstrated for any defined levels of speed enforcement.

safety gain. Therefore, in the third step of policy analysis, we have imposed changes in the operation duration of speed cameras along with changes in speeding citations by rescaling the latent propensity (Scenarios 5 through 9). In these scenarios, the same rescaling parameters as in Scenario 3 are considered, and hence, Scenario 3 serves as the base case for comparison. From these scenarios, we can observe that imposing both speed enforcement measures is likely to have an overall safety gain. However, the safety gain is relatively lower in these scenarios compared to the base case scenario. This is expected as an increase in operation duration is likely to decrease the serious speeding citations relative to the base condition. Hence, the level of safety gains in fatal and major injury categories are also likely to be lower in these scenarios relative to the base case scenario (Scenario 3).

It is worthwhile to notice that an improved safety gain is possible by increasing the operation duration of speed cameras where safety situation got worse over time. From Scenarios 7 and 8, we can see that if we decrease the operation duration of speed camera for the locations with unchanged/improved safety situation by 50%, keeping the same level of operation duration for locations with worsening safety conditions, we are likely to have approximately 2% safety gain in crash risk and fatal injury proportions. On the contrary, from Scenarios 7 and 9, we can see that if we decrease the operation duration of speed cameras for the locations with unchanged/improved safety situation by 50% while increasing the operation duration for locations with worsening safety situation, we are likely to have approximately 2% safety loss in crash risk and fatal injury proportions. To delve into this further, in Scenarios 10 and 11, we have rescaled the speeding citation propensity with different parameters to achieve a higher proportion of major speeding tickets keeping the operation duration of the speed camera at the same level as in Scenarios 8 and 9, respectively. From Scenarios 10 and 11, we can observe that stricter enforcement of serious speeding offences has greater safety gain in reducing crash risk and crash severity levels; however, the maximum safety gain might be possible for an optimal operation duration of speed camera balanced across targeted locations[14].

From the policy scenario analysis, we can argue that stricter speed enforcement for serious level of speeding offenses is likely to have greater safety benefits in reducing crash severity levels. However, the effect is not as pronounced for reducing the overall crash risk. However, such stricter measures could be imposed by increasing the operation duration of speed cameras as it would allow citing of more offenders over a longer time. In doing so, a targeted increase in operation duration along with stricter citations for major speeding is likely to have significant safety gain. Moreover, there are trade-offs in safety gains due to the changes in speed enforcement levels (changes in the proportion of speeding citations and changes in operational duration for speed cameras). Thus, we can argue that identification of optimal operational duration of speed camera and enforcement levels are imperative in achieving targeted safety benefits.

[14] The analysis for the identification of optimal operational duration of speed camera in achieving the targeted safety gain is beyond the scope of this study. Our major focus of this study is to identify the causal relationship of speed camera enforcement with safety. Such extension could be an avenue for future research while considering the outcome of this study as a base case condition.

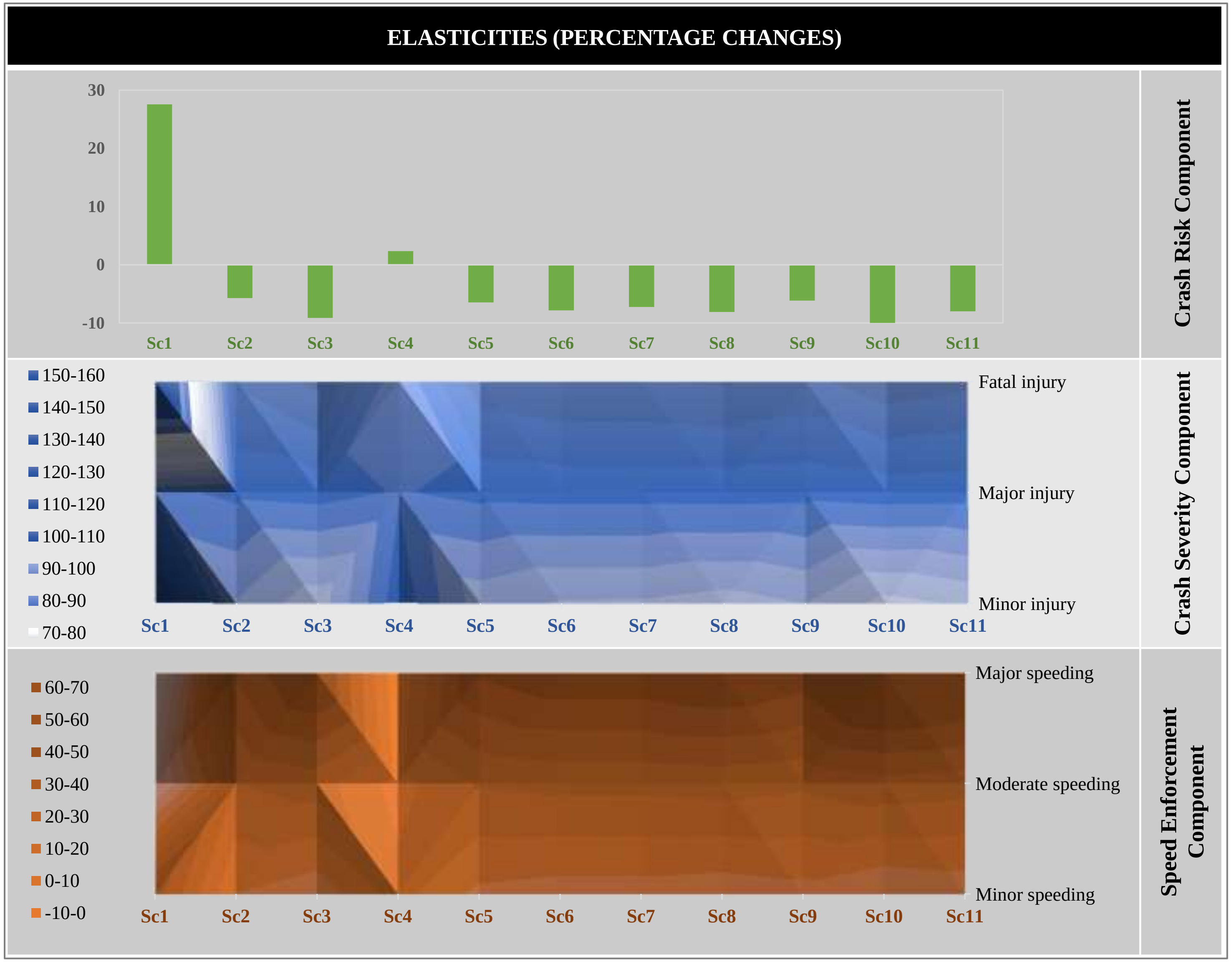


Figure 3: Policy Scenario Analysis Illustration ***(Sc= Scenario, scenarios are described in Section 4.4.2)***

5 CONCLUSION

Speeding is one of the fatal five characteristics (speeding, drink driving, fatigue, no restraints and distraction) of road traffic crashes. It significantly contributes towards the increase in crash risk and crash severity outcomes. Different speed enforcement measures are devised and implemented all around the world in dealing with these serious safety concerns. In order to devise an optimal solution to combat speeding, it is of utmost importance to quantify the relative magnitude of the impact of speed enforcement on safety while controlling for other exogenous variables (such as traffic exposure, roadway geometry, and situational attributes). As such, the current study contributes towards existing safety literature by presenting an econometric approach that estimates the causal effect of speed enforcement on safety while also addressing the endogeneity issue by employing an instrumental variable approach in conjunction with a maximum simulated likelihood approach. In our study, safety enforcement was represented as the number of speeding tickets issued from the speed camera systems, while safety profile was presented as two dimensions of interest, including total crash risk and crashes by injury severity levels. The study employed crash data and speed enforcement data from Queensland, Australia, for the years 2010 through 2013. The joint model was estimated by employing a correlated panel random parameters model with speed enforcement endogeneity. In estimating the causal effect of speed enforcement on safety, the empirical analysis proposed in this study addressed three different econometric issues, including (1) correcting for speed enforcement endogeneity in crash risk and crash severity, (2) observation level unobserved heterogeneity (sourced from panel structure of dataset), and (3) other unobserved heterogeneity (sourced from missing information).

From the empirical analysis, it was found that the effect of speeding ticket propensity was endogenous in both crash risk and crash severity components. The effect of speed enforcement propensity was found to be negative in crash risk and crash severity components which indicated that the likelihoods of total crash risk and higher severity outcomes decrease with an increase in the latent propensity of speeding citations. The result could be an indication that stringent enforcement of posted speed limits is highly likely to improve overall safety in these locations. The study highlighted the importance of incorporating the effect of endogeneity in establishing the causal relationship between speed enforcement and safety.

From elasticity effects computation, it was observed that the most important factors associated with major speeding citations were the high posted speed limit, rolling/mountainous terrain, and presence of shoulder. On the other hand, unsealed pavement condition and operation duration of speed camera were the two major factors associated with less serious speeding citations. In the crash risk component, roadway segment with unsealed condition and AADT had higher elasticities, respectively. With respect to crash severity component, the elasticity effects for unsealed pavement condition and high posted speed limit were associated with greater increase in fatal crash risk proportions. Rolling/mountainous terrain and the presence of shoulder were the most important variables associated with the reduction in fatal crash proportions.

From the policy scenario analysis, we found that stricter speed enforcement for serious level of speeding offenses is likely to have greater safety benefits in reducing crash severity levels. Such stricter measures could be imposed by increasing the operation duration of speed cameras as it would allow citing of more offenders over a longer time. In doing so, a targeted increase in operation duration along with stricter citations for major speeding is likely to have significant safety gain. Moreover, there were trade-offs in safety gains due to the changes in speed enforcement levels (changes in the proportion of speeding citations and changes in operational duration for speed cameras). Thus, we argued that identification of optimal operational duration of speed camera and enforcement levels are imperative in achieving targeted safety benefits. The outcome of the study will allow the decision-makers to identify a robust resource allocation and speed camera deployment plan. The study is not without limitations. In the current study, the models were estimated without considering the effect of spatial heterogeneity, which could an avenue for future research.

AUTHOR CONTRIBUTION STATEMENT

All authors reviewed the results and approved the final version of the manuscript.

Authors	Study conception and design	Data collection	Model estimation	Analysis and interpretation of results	Draft manuscript preparation
Shamsunnahar Yasmin					
Naveen Eluru					
Mazharul Haque					

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