Econometric Approaches to Examine the Onset and Duration of Temporal Variations in Pedestrian and Bicyclist Injury Severity Analysis

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Abstract

There is considerable evidence in existing safety literature that the exogenous variable effects are likely to be time-varying in the injury severity analysis. The majority of these earlier studies tested time-varying effects of exogenous variables by crash year. However, there might be variability in the variable effects within a year, while the same effect might carry over in some or all parts of the preceding years. Towards that end, in this study, we propose a flexible framework to identify when the time-varying effect is likely to occur (the onset of temporal variation) and how long such time-varying effect lasts (duration of temporal variation) in the model estimates. In the study design, we assume that the onset of temporal variation can be any quarter of a year under consideration, while the time-varying effect can continue over different quarters after the onset of temporal variation in a variable effect. The injury severity model is estimated by using Correlated Random Parameter Generalized Ordered Logit formulation with piecewise linear functions. The empirical analysis is demonstrated by employing active traveler (pedestrian and bicyclist) crash data from Queensland, Australia for the years 2015 through 2020. The estimation results are further augmented by computing elasticity effects. The results indicate that the time-varying effects are likely to be different across years for several variables, while for other variables, the onset of time-varying effects could be different than the start of a year. Such flexibility in model specification is likely to have significant implications for devising and implementing effective countermeasures since it allows us to understand how road traffic injuries are evolving over time and when a new road safety issue might be arising.

Keywords: *Active travel; Temporal variation; Systematic heterogeneity; Crash; Pedestrian; Bicyclist*

1. Introduction

1.1. Background

The econometric issue relevant to time-varying effects of exogenous variables in crash data analyses (both aggregate level crash risk and disaggregate level injury severity analysis) received significant attention since the publication of a seminal work by Mannering (2018). Crashes are rare and random events. As such, traditionally, crash data analysis by using statistical approaches consider accumulation of crash record over multiple years[1]. However, relationships between exogenous variables and crash risk/severity outcomes might be time-varying resulting in structural changes in the variable effects[2]. The reasons for such temporal variations (also often referred to as temporal instability) in exogenous variable effects can be attributed to improvements in vehicle technology, changes in roadway design, changes in travel behavior, implementation of new laws/regulations and other unobserved factors (see Mannering (2018) for a detailed discussion on the potential sources of time-varying effect in crash data analysis). However, the reasons for such temporal variations in variable effects may or may not be observable to the analysts.

There is considerable evidence in existing safety literature that the exogenous variable effects are likely to be time-varying in the crash risk/severity analysis. For example, Behnood and Mannering (2015) used mixed logit model to examine the time-varying effects of exogenous variables contributing towards driver injury severity outcome for single vehicle crashes by using data for the years 2004 through 2012 from Chicago, Illinois, USA. In this study, time-varying effects of exogenous variables are examined by developing separate models for each crash year (generally known as exogenous segmentation approach[3]). Building on such exogenous segmentation approach by different years, to date, a number of studies in existing safety literature have examined time-varying effects of exogenous variables (Ahmed et al., 2022; Alnawmasi and Mannering, 2023; Alzaffin et al., 2023; Chang et al., 2021; Dzinyela et al., 2024; Hosseini et al., 2022; Li et al., 2021; Pang et al., 2022; Se et al., 2023; Shabab et al., 2024; Song et al., 2023; Wang et al., 2022; Xing et al., 2023; Yan et al., 2023; Yu et al., 2023). In addition, to capture time-varying effects of exogenous variables, researchers have also considered time-elapsed variables derived from the differences between the most recent years and the base year available in the dataset (Chang et al., 2022; Kabli et al., 2023; Marcoux et al., 2018; Phuksuksakul et al., 2023; Shinthia et al., 2023; Yasmin et al., 2022). By quantifying the duration between these time points, this variable provides a systematic approach to capturing time-varying effects, however, such effects are likely to be monotonic in nature. Further, Alnawmasi and Mannering (2023) and Bhowmik et al. (2019) tested for systematic heterogeneity in variable effects by pooling data records and estimating varying effects based on interaction terms. In this approach, the heterogeneity in variable effects across different attributes (such as time periods) are tested based on the data fit measures of the estimated models.

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[1] To be sure, yearly crash records or more disaggregated time points of data records are also considered based on the objective of the relevant study.
[2] Structural change refers to time-varying effects in the parameters of econometric models. Without accommodating for structural changes in econometric models, the model is likely to be error prone and unreliable.
[3] Exogenous segmentation generally refers to consideration of splitting the data sample (data records) by different exogenous attributes (such as year, collision type) and estimation of separate models for each segment.

In addressing the time-varying effects in injury severity analysis, studies adopted several econometric approaches, which include - (1) Random parameter logit model with heterogeneity in means and variances (Alnawmasi and Mannering, 2022, 2023; Alogaili and Mannering, 2022; Behnood and Mannering, 2019; Hosseini et al., 2022; Islam and Mannering, 2020; Li et al., 2021; Mansour et al., 2021; Seraneeprakarn et al., 2017; Song et al., 2023; Zamani et al., 2021), (2) Random parameter multinomial logit model (Behnood and Mannering, 2015, 2016), (3) Random thresholds random parameters hierarchical ordered probit model (Yu et al., 2021), (4) Random thresholds random parameters generalized ordered logit model (Song et al., 2023), (5) Random parameters hazard-based duration model with means and variances heterogeneity (Alzaffin et al., 2023; Pang et al., 2022), (6) Correlated random parameter bivariate tobit model (Ahmed et al., 2022), (7) Latent segmentation based random parameters ordered logit model with time elapsed variables (Chang et al., 2021), (8) Latent class multinomial logit model (Behnood and Mannering, 2016), and (9) Markov switching models (Malyshkina and Mannering (2009) and Xiong et al. (2014)).

The abovementioned studies provided valuable insights and information on the importance of accommodating time-varying effects in analyzing crash data. However, these studies mostly tested time-varying effects of exogenous variables by crash year. Implicitly, these earlier studies assumed that the effects of an exogenous variables remain same within a year[4]. However, there might be variability in the variable effects within a year while the same effect might carry over in some or all parts of the preceding years. For example, in Brisbane, Australia, there are more pedestrian and bicyclist activities during the last quarter of a calendar year due to summer festivities and holiday seasons which continues until February of the next year and wind down in March with the starting of the school and regular working rhythm. Such differences in activities across different parts of the year are likely to contribute towards different crash risk and severity profiles for active traveler crashes. Moreover, after COVID-19 period, there has been significant investment in active traveler infrastructures, which is likely to contribute towards a different safety profile for active travelers. Therefore, in examining time-varying effects of exogenous variables, it is important to allow for such flexibility to identify when the time-varying effect is likely to occur (the onset of temporal variation) and how long such time-varying effect lasts (duration of temporal variation) in the model estimates.

In examining the temporal variations, Markov Switching models might offer a more flexible approach by allowing parameters to transition between distinct states more frequently, such as on a weekly basis. These models can capture the rapid shifts in roadway safety conditions caused by unobserved factors like changes in weather or traffic patterns, which may occur at finer temporal resolutions (see Malyshkina and Mannering (2009) and Xiong et al. (2014) for such examples). Specifically, switching models assume that some observed process in the data is influenced by an unobserved process that switches between different states over time, while each state implies a different probability model. In estimating these models, an analyst generally needs to choose an adequate parametric function for different states a priori. Choosing an adequate parametric family is likely to be challenging since the underlying states of observations are likely to be unknown before a model is fitted. Such restriction in model specification can result in overestimation of the number of states and difficulties in making inferences related to the identified states (Pohle et al., 2017). It is also important to recognize that switching models with parametric

[4] It is worthwhile to mention here that some of the studies accommodated the variations in variable effects within a year by specifying it as random variables (Ahmed et al., 2022; Fountas et al., 2018).

family formulations are numerically more stable, hence, these approaches should be adopted based on the empirical context under scrutiny (Langrock et al., 2017).

As such, it might be advantageous and worthwhile to investigate the time-varying effects of exogenous variables while also examining the onset and duration of such temporal heterogeneity by using a more computationally tractable approach. Towards that end, in this study, we propose a flexible framework for examining the onset and duration of time-varying effects in developing injury severity models[5]. The applications of piecewise polynomials for capturing the time-varying effects or testing for other structural changes are an established approach in econometric texts (Blanchini and Giordano, 2014; De Baets et al., 2011; Goujon et al., 2023; Greene, 2017). In regressing the dependent variable (y) on independent variables $(\boldsymbol{x})$, piecewise polynomial functions allow to examine the possibility of intervals in $(\boldsymbol{x})$ by dividing it into pieces at specific knots, thus, allow for more flexible representations in $f(\boldsymbol{x})$. Piecewise polynomials can be considered as constant, linear, quadratic and/or cubic functions[6] in allowing the flexibility for polynomial representation in specifying $f(\boldsymbol{x})$. In the proposed approach of this study, the structural changes in the variable effects are tested by using piecewise linear functions[7] (*i.e.* interaction terms of a time period and different exogenous variables). A linear approximation of $f(\boldsymbol{x})$. is a worthy initial step as these first order Taylor approximations for specifying temporal variation in independent variables are computationally tractable and easy to interpret without overfitting. In the context of injury severity model estimation, an extension of linear approximation of time-varying effects by considering piecewise quadratic and cubic functions could be an avenue for future research direction.

In this study, the breakpoint (knot) of the piecewise linear function is assumed to be the start of a quarter of year and segment is defined by different quarters of the year under consideration. Thus, we assume that the onset of temporal variation can be any quarter of a year under consideration, while the time-varying effect can continue over different quarters after the onset of temporal variation in a variable effect. In this setting, the duration of time-varying effects of an exogenous variable is empirically tested by combining the quarters following the onset quarter in the model estimates. It is worthwhile to mention here that, in this study, quarter is considered as the highest resolution to allow for sufficient observations (crash records) across different time periods in the piecewise linear function formulation. However, time-varying effects can be tested by using any other resolutions in the available temporal scale (such as day, week, time-of-day).

1.2. Contributions of the current study

The major objective of this study is to examine the time-varying effects of exogenous variables in injury severity analysis while also identifying the onset and duration of such structural changes. Specifically, the injury severity model is estimated by using Correlated Random Parameter Generalized Ordered Logit formulation with piecewise linear functions. Building on Balusu et al. (2018), in this study, we adopt the variance reduction technique by specifying

[5] The proposed flexible approach in capturing the onset and duration of time-varying effects can also be adopted for developing crash risk models.

[6] An analyst is unlikely to go beyond piecewise cubic polynomials unless the goal is to achieve a smooth derivative in optimizing the objective function (Hastie et al., 2009).

[7] Piecewise linear function approach divides the data into a finite number of segments given a pre-defined knot/breakpoint (Malash and El-Khaiary, 2010; Moreno-Carbonell and Sánchez-Úbeda, 2024; PennState, 2024).

correlations across different threshold in developing generalized ordered logit model. The proposed model is demonstrated by developing active traveler (pedestrian and bicyclist) injury severity models based on the data compiled from the State of Queensland in Australia for the years 2015 through 2020. The injury severity models are estimated by considering a comprehensive set of exogenous variables, including active traveler characteristics, motorist characteristics, motor vehicle characteristics, environmental characteristics, and roadway geometric characteristics.

Several studies in existing safety literature examined temporal variability of variable effects in developing active traveler injury severity models (Alnawmasi and Mannering, 2023; Alogaili and Mannering, 2022; Behnood and Mannering, 2016; Hosseini et al., 2022; Li et al., 2021; Phuksuksakul et al., 2023; Song et al., 2020; Zamani et al., 2021). However, these studies examined time-varying effects by years. As such, the current study contributes towards safety literature both methodologically and empirically by proposing a mathematical simpler approach to address time-varying effect of exogenous variables while also identifying the onset and duration of such variations. Methodologically, the empirical formulation proposes in this study addresses three econometric issues, which are – (1) allows additional flexibility in specifying systematic heterogeneity in developing injury severity models, (2) incorporates unobserved heterogeneity through a discrete mixture-of-normals approach, and (3) allows dependence of unobservables between threshold functions in the generalized ordered logit formulation. Empirically, the study contributes towards identifying the critical factors contributing towards active travelers' injury severity outcomes.

The rest of the paper is structured as follows. Section 2 presents the econometrics framework of the proposed model. Section 3 demonstrates data description and empirical design of the study. Section 4 describes the model estimation results. Section 5 summarizes the paper.

2. Econometric framework

The major focus of the study is to examine the onset and duration of temporal variations in exogenous variable effects in developing active traveler injury severity model. Specifically, the temporal variations are examined by employing a correlated random parameter generalized ordered logit model with piecewise linear functions. The econometric formulation for the proposed model is presented in this section.

Let us assume that $i\ (i = 1,2, \dots, I)$ be the index to represent active traveler crash, $j\ (j = 1, 2, \dots, J; J = 4)$ be the index to demonstrate injury severity levels including 'Minor injury $(j = 1)$', 'Moderate injury $(j = 2)$', 'Major injury $(j = 3)$' and 'Fatal injury $(j = 4)$', $m\ (m = 1,2, \dots, M; M = 6)$ be the index to represent years which takes the form of 'year 2015 $(m = 1)$', 'year 2016 $(m = 2)$', 'year 2017 $(m = 3)$', ... , 'year 2020 $(m = 6)$', and $k\ (k = 1,2, \dots, K; K = 4)$ be the index to represent yearly quarters which takes the form of '1st quarter' $(k = 1)$, '2nd quarter $(k = 2)$', '3rd quarter $(k = 3)$', and '4th quarter $(k = 4)$[8]. $h\ (h = 1,2, \dots, H = 2)$ be the index to represent active traveler types which are 'bicyclist $(h = 1)$' and 'pedestrian $(h = 2)$'. Based on these notational indices, the econometric framework employed in this study is presented as follows.

[8] According to the notation, in a single crash year (k), m can be matched with a maximum of 4 quarters i.e.$[m, k] \in \{[1,1], [1,2], [1,3], [1,4], [2,1], [2,2], \dots [6,3], [6,4]\}$ to represent the 1st, 2nd, 3rd,4th quarter of each crash year from 2015 through 2020.

Let y_i be the discrete injury severity levels sustained by active traveler in crash i. y_i is assumed to be associated with an underlying continuous latent variable y_i^* that can be specified as a linear function as follows:

$$y_i^* = (\boldsymbol{\beta} + \boldsymbol{\alpha}_i)\boldsymbol{x}_i + \varepsilon_i \qquad for\ i = 1, 2, 3, \ldots, I \tag{1}$$

where, $\boldsymbol{x}_i$ is a vector of exogenous variables, $\boldsymbol{\beta}$ is a vector of parameters to be estimated (including a scalar constant). $\boldsymbol{\alpha}_i$ is a vector of unobserved variables on the injury severity propensity for active traveler crash i and its associated characteristics (assumed to be independent realizations from normal population distribution: $\boldsymbol{\alpha}_i \sim \mathbb{Q}(0, \lambda^2)$) and, ε_i is the random disturbance term (assumed to be standard logistic that captures the idiosyncratic effect of all omitted variables in injury severity propensity). Let us assume that the unobserved latent variable y_i^* is associated with the observed discrete injury severity levels y_i by the τ_j thresholds ($\tau_0 = -\infty\ and\ \tau_J = +\infty$) which is associated with injury severity level j; then, y_i can be expressed as:

$$y_i = j, \qquad if\ \tau_{j-1} < y_i^* < \tau_j \qquad for\ j = 1, 2, \ldots, J \tag{2}$$

In addressing the constant threshold assumption from traditional ordered models, a generalized ordered formulation with different parametric functions has been proposed and applied in previous studies (Eluru et al., 2008; Eluru and Yasmin, 2015; Maddala, 1983; Srinivasan, 2002). Among different proposed specifications of generalized ordered logit model formulations, in this study, to maintain the ordinality of injury severity levels ($-\infty < \tau_1 < \tau_2 < \cdots < \tau_{j-1} < +\infty$), we adopt the parametric form proposed by Eluru et al. (2008), which can be expressed as:

$$\tau_j = \tau_{j-1} + e^{(\sigma_j + \xi_{ij})\boldsymbol{z}_{ij}} \tag{3}$$

where, $\boldsymbol{z}_{ij}$ is a set of exogenous variables related with j^{th} threshold for each active traveler crash i. $\boldsymbol{\sigma}_j$ is the vector of parameters to be estimated associated with injury severity levels j. $\boldsymbol{\xi}_{ij}$ is demonstrating unobserved variable specific to the associated environment for active traveler crash i in injury level j and assumed to be independent realizations from normal population distribution: $\boldsymbol{\xi}_{ij} \sim \mathbb{Q}(0, \beth^2)$).

The effect of different exogenous variables might vary across different time intervals under consideration. In this study, we assume that the onset of temporal variation can be a quarter (m') of any year (k') which can continue over different quarters ($\mathbb{M}, \mathbb{K} = [m', k'] + \sum[(m > m'), (k > k')]$) after the onset of temporal variation in a variable effect which is empirically tested based on the data fit. Thus, $[m', k']$ represents the onset of temporal variation and $[\mathbb{M}, \mathbb{K}]$ represents the duration of temporal variation specific to an exogenous variable. Further, we assume that the effects of different variables might also vary by active traveler group h. To allow for such heterogenous effect of exogenous variables, $\boldsymbol{\beta}_s$ and $\boldsymbol{\sigma}_j$ in Equations 1 and 3, respectively, are specified as:

$$\boldsymbol{\beta} = \boldsymbol{\gamma} + \boldsymbol{\gamma}_{\mathbb{M},\mathbb{K}} + \boldsymbol{\gamma}_h \tag{4}$$

$$\boldsymbol{\sigma}_j = \boldsymbol{\rho}_j + \boldsymbol{\rho}_{j\mathbb{M},\mathbb{K}} + \boldsymbol{\rho}_{jh} \tag{5}$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\rho}_j$ represent the main effects of exogenous variables in the propensity and threshold functions, respectively. $\boldsymbol{\gamma}_{\mathbb{M},\mathbb{K}}$ and $\boldsymbol{\rho}_{j\mathbb{M},\mathbb{K}}$ represent (spline variables) the time varying relationship of exogenous variables in the propensity and threshold functions, respectively. $\boldsymbol{\gamma}_h$ and $\boldsymbol{\rho}_{jh}$ represent (spline variables) the varying relationship of exogenous variables by active traveler type h in the propensity and threshold functions, respectively.

In the generalized model specification, the higher order threshold includes its preceding threshold to maintain the increasing order in thresholds (Equation 3). Such restrictive specifications can lead to difficulty in random parameter estimates in the higher order thresholds (see Balusu et al. (2018) for a detailed discussion on this). Balusu et al. (2018) proposed the use of negative correlations between random thresholds to relax this restriction and to allow flexibility in random parameter estimates for the higher order thresholds. As such, in this study, in order to explore the correlations between the random parameters in thresholds, $\boldsymbol{\xi}_{ij}$ is assumed to follow a multivariate distribution with mean vector $\beth^2$ and a correlation structure of $\boldsymbol{\Omega}$ as $[0,\ \boldsymbol{\zeta}_{23},\ \pm\boldsymbol{\zeta}_{23}]$ across τ_1, τ_2 and τ_3. A positive (negative) sign for $\boldsymbol{\zeta}_{23}$ indicates that random variables in thresholds are likely to be positively (negatively) correlated, which is empirically tested based on the data fit. Then, the probability expressions for active traveler crash i and alternative j from quarter k in the correlated random parameter generalized ordered logit model with piecewise linear function can be expressed as:

$$\begin{aligned}\boldsymbol{\varphi}_{ij} = \Pr\left(y_i = j\right) & \\ &= \Lambda_j\left[\tau_j + e^{(\sigma_j+\xi_{ij})z_{ij}} - (\boldsymbol{\beta}+\boldsymbol{\alpha}_i)\boldsymbol{x}_i\right] \\ &- \Lambda_j\left[\tau_{j-1} + e^{(\sigma_{j-1}+\xi_{i,j-1})z_{ij}} - (\boldsymbol{\beta}+\boldsymbol{\alpha}_i)\boldsymbol{x}_i\right]\end{aligned} \tag{6}$$

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

The parameters to be estimated in the correlated random parameter generalized ordered logit model with piecewise linear function include $[\boldsymbol{\beta},\boldsymbol{\sigma}_j]$ and the variances of the stochastic component $\left[\boldsymbol{\alpha}_i,\boldsymbol{\xi}_{ij}\right]$. In this study, these stochastic elements are drawn from an independent realization of the normal distribution. Let the stochastic terms are represented by Θ. Therefore, conditional on Θ, the likelihood function can be expressed as:

$$L_i|\Theta = \prod_{i}^{I}\left[\prod_{j=1}^{J}\left(Pr(y_i = j|\Theta)\right)\right] \tag{7}$$

Finally, the log-likelihood function can be expressed as:

$$LL = \sum_{i=1}^{N} ln\left\{\int_{\Xi} (L_i|\Theta)f(\Theta)d(\Theta)\right\} \tag{8}$$

The log-likelihood function in Equation 7 involves the evaluation of a multi-dimensional integral of size equal to the number of rows in Θ. Therefore, to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function, we applied Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence (Bhat, 2001; Yasmin and Eluru, 2013). Specifically, we have applied 200 random draws based on the Scrambled Halton sequence (Bhat, 2003). The likelihood functions are programmed in Gauss matrix programming language (Aptech, 2023).

3. Data description and empirical design

Active traveler (pedestrian and bicyclist) crash data for the current study is sourced from the official crash database of Queensland, Australia for the years 2015 through 2020. The current study is focused on injury severity outcomes sustained by active traveler in crashes with motor vehicle (referred to as active traveler crash hereafter). Between 2015 and 2020, 8,414 active traveler crashes were recorded which includes 3,873 pedestrians and 4,577 bicyclists involved crashes. Crashes involving single active traveler and single motor vehicle are used for further analysis[9]. Crash records with missing information for essential attributes are removed from the current analysis. The final data set has a record of 6,304 active traveler crashes (2,864 pedestrians and 3,440 bicyclists involved crashes). From the final dataset, 5,000 (2,276 pedestrians and 2,724 bicyclists involved crashes) records are randomly selected for model estimation purposes. Further, 1,304 records are selected for validation purposes.

3.1. Dependent variable

In the crash database, injury severity outcomes of active traveler are recorded as four-point ordinal scale variable representing – (1) minor injury, (2) moderate injury, (3) major injury, and (4) fatal injury[10]. Injury severity distributions by years and quarters in the final data sample are presented in Figure 1(a) and 1(b), respectively. From Figure 1(a), it can be observed that the majority of active travelers are recorded to sustain major injury in crashes with motor vehicles indicating their vulnerability as unprotected and unshielded road user groups. From the overall trends in different injury severity outcomes in Figure 1(a), it is alarming to note that the proportion of major and fatal injuries are increasing in recent years. Further, it can be observed from Figure 1(b) that there are significant variations in active traveler injury severity outcome profiles across different quarters of a year. Across six years, the overall proportions of minor, moderate, major, and fatal injuries are 10.30%, 35.57%, 51.56% and 2.58%, respectively. The percentages of fatal injury were found to be higher than average (2.58%) in the 4th quarter/2015 (2.63%), 1st, 3rd, 4th quarter/2016 (5.68%, 3.18%, and 2.84%, respectively), 1st to 4th quarters/2018 (2.63%, 3.69%, 3.86%, and 4.04%, respectively) and 1st to 2nd quarter/2020 (3.31% and 3.70%, respectively). As is evident, the highest proportion of fatal injury was observed for the 1st quarter/2016 and 4th quarter/2018. The percentages of major injuries were found to be significantly higher than average (51.56%) in the 1st quarter/2015 (54.45%), 3rd and 4th quarter/2016 (58.64% and 52.13%, respectively), 2nd quarter/2017 to 2nd quarter/2018 (56.28%, 52.21%, 53.69%, 52.49%, 55.26%, and 57.60%, respectively), and 2nd to 4th quarter/2020 (56.08%, 55.45%, and 58.85%,

[9] Crashes including multiple active travelers or multiple motor vehicles are likely to have different injury severity mechanisms due to the complexity in the crash chaining process. Thus, these crashes are not considered in the current empirical study and could be an avenue for future research.
[10] The crash data recorded in Queensland does not include 'no injury' crashes since 2010. Therefore, the data has records for crashes resulting in casualty only.

respectively). Within a year, the highest variations of major injury severity profiles were observed for the 2nd to 4th quarters/2020 relative to 1st quarter/2020. Hence, it is clear that there are significant temporal variations in active traveler injury severity distributions across different years as well as across different quarters within a year[11].

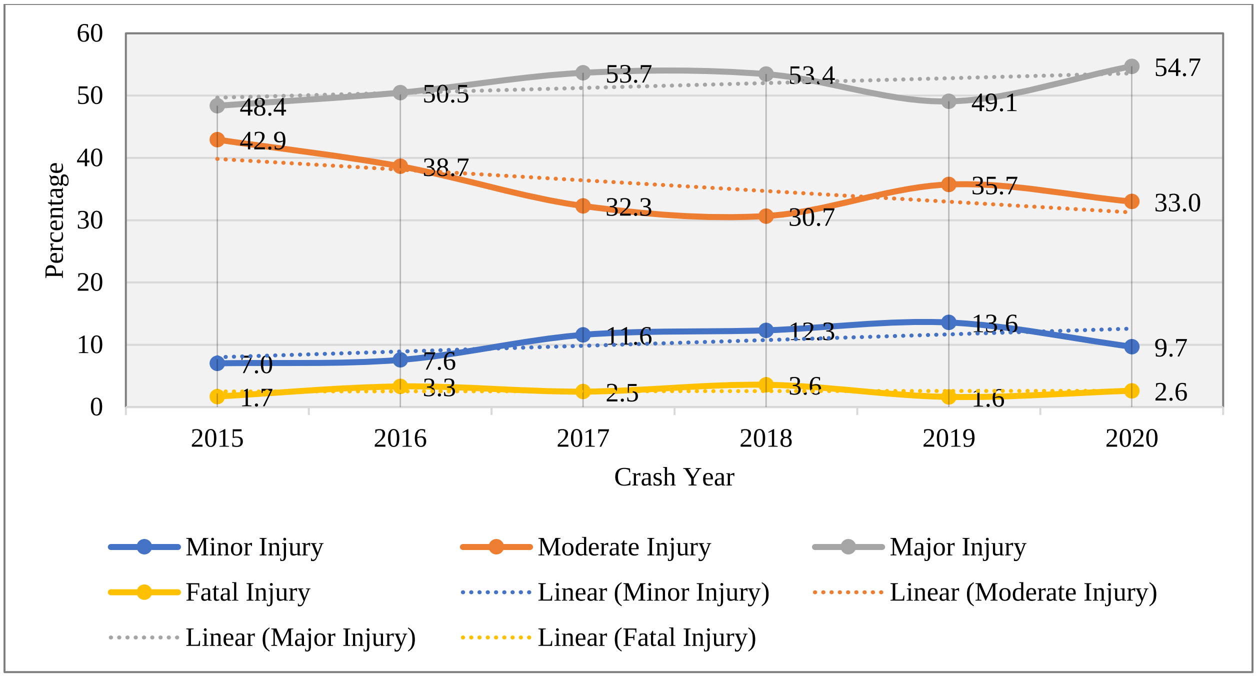


Fig. 1(a). Injury severity distributions (percentage across injury severity within a year) of active traveler crashes by years between 2015 and 2020 *[overall trends across all years are presented by dotted lines]*.

[11] From Figure 1(a) it can be observed that the active traveler crash data under consideration might have long-term trends (*i.e.* steady upward and downward trends) across different injury severity categories. In this study, the major focus is to demonstrate the applications of piecewise linear function in examining the finer resolution of temporal variations (onset and duration of seasonal patterns). The model estimates for temporal variations are likely to be inconsistent if a certain part of seasonality evolves in a similar pattern as in the long-term trend. From Figure 1(b), it could be observed that there are significant variations in the injury severity patterns for a certain quarter across different years. Such variations in injury severity patterns across different quarters do not visually follow the strict upward/downward long-term trend in the data. However, in future, it might be interesting to test such a hypothesis empirically and develop injury severity models by incorporating both long-term trends and seasonal variations of variable effects in the same model.

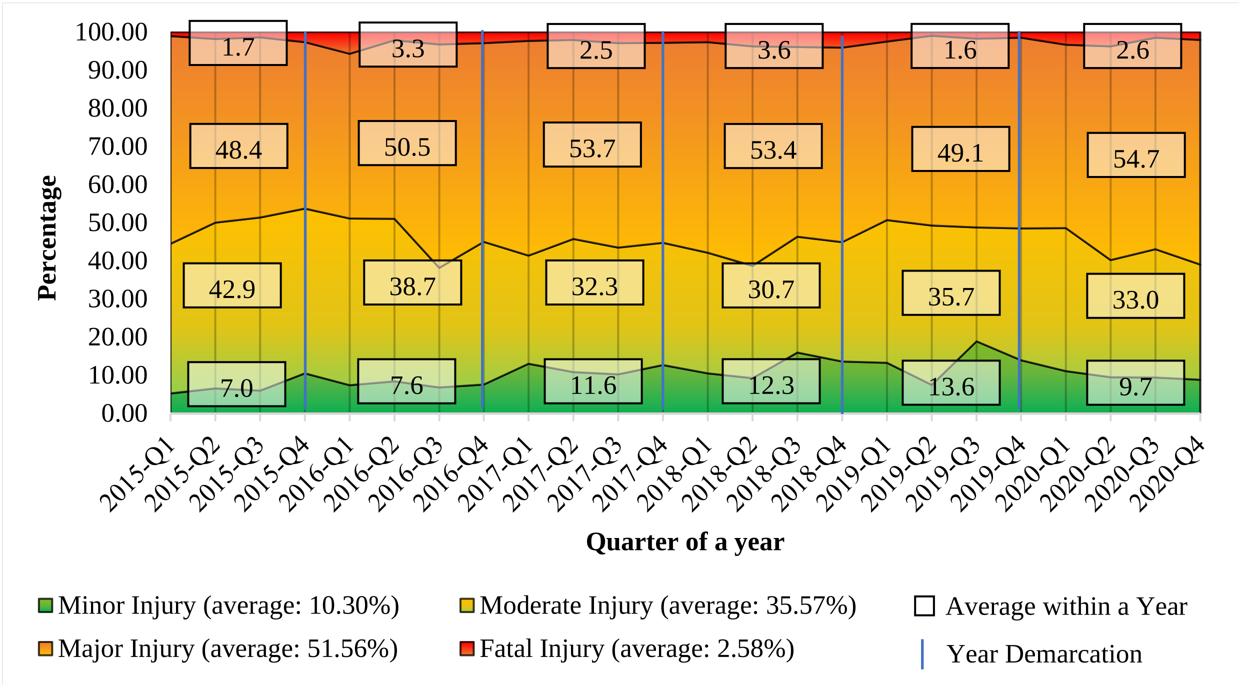


Fig. 2(b). Injury severity distributions of active traveler crashes by quarters (Q)[12,13] from the year 2015 through 2020.

3.2. Independent variables

The independent variables considered in this study can be grouped into five broad categories:

- *Active traveler characteristics* include active traveler's age, gender, active traveler under the influence of alcohol, active traveler intended action, active traveler at-fault.
- *Motorist characteristics* include motorist age, gender, motorist under the influence of alcohol, distracted/unattended motorist, motorist indented action.
- *Motor vehicle characteristics* include vehicle type and vehicle age.
- *Environmental attributes* include time-of-the-year, week, day-of-week, time-of-the-day, and lighting conditions.
- *Roadway characteristics* include posted speed limit, road geometries (horizontal and vertical alignments), road surface condition, weather condition, road region, crash location, and presence of traffic control.

In this study, the possible time-varying effects (onset and duration of time-varying effects) are specified as a piecewise linear function of exogenous variables. Specifically, interaction terms of different quarters (from 1st quarter/2015 through 4th quarter/ 2020) and other exogenous variables

[12] According to Figure 1, the term Q represents the quarter of the year where Q1 is between January-March, Q2 is between April-June, Q3 is between July-November, and Q4 is between October-December, Therefore, each of the year from 2015 through 2020 are recategorized based on quarter of the year (The first quarter through the fourth quarter).

[13] The value as represent in the rectangular boxes represent the average percentage of each injury severity level for each year from 2015 – fatal, major, moderate and minor injuries from the top row to the bottom row.

are generated to accommodate the possible time-varying effects in the model specifications. The interaction terms in the consecutive time points (duration of time-varying effects) are tested for similarities in effects by using the likelihood ratio test (nested models). The final model is developed based on exogenous variables (main effect and interactions) which are statistically significant (at a 90% confidence level) in the propensity and threshold functions. Further, there might be variations in variable effects by different active traveler groups (pedestrian vs. bicyclist). Such variations by active traveler groups are specified as interactions of active traveler group by different exogenous variables. Table 1 provides descriptive statistics for the dependent and all exogenous variables by crash year considered in the current study.

Table 1
Summary Statistics of Injury Severity Distributions and Exogenous Variables.

Injury Severity Distributions	**CRASH COUNTS**					
	Crash Year					
	2015	**2016**	**2017**	**2018**	**2019**	**2020**
Minor injury	58	64	103	100	117	74
Moderate injury	355	327	287	249	308	262
Major injury	400	427	477	434	423	418
Fatal injury	14	28	22	29	14	20
Total	**827**	**846**	**889**	**812**	**862**	**764**
Exogenous Variables	**SAMPLE SHARE (%)***					
	Crash Year					
	2015	**2016**	**2017**	**2018**	**2019**	**2020**
Active Traveler Characteristics						
Active traveler type						
Pedestrian	47.5	48.0	46.5	45.8	43.4	41.6
Bicyclist	52.5	52.0	53.5	54.2	56.6	58.4
Active traveler age						
≤15 years old	16.4	16.8	17.5	18.0	17.4	18.2
16-24 years old	15.6	14.8	16.0	12.8	17.9	13.6
25-39 years old	25.3	22.3	25.9	24.6	22.5	22.8
40-49 years old	15.8	16.7	15.0	14.3	15.3	13.9
50-59 years old	12.7	13.2	12.8	12.2	10.9	14.8
≥60 years old	14.1	16.2	12.8	18.1	16.0	16.8
Active traveler gender						
Male	71.5	68.4	68.7	70.0	69.3	72.4
Female	28.5	31.6	31.3	30.0	30.7	27.6
Under the influence of alcohol						
No	94.6	95.9	95.2	95.0	96.5	95.8
Yes	5.4	4.1	4.8	5.0	3.6	4.2
Active traveler intended action						
Cross carriageway	32.6	31.7	29.6	28.0	29.5	27.0
Remain stationary	5.1	6.4	5.2	5.3	3.9	4.7
Other (e.g. go straight)	62.3	61.9	65.2	66.7	66.6	68.3
Active traveler at-fault						

No	58.2	60.6	57.0	60.0	59.6	61.8
Yes	41.8	39.4	43.0	40.0	40.4	38.2
Motorist Characteristics						
Motorist age						
≤20 years old	6.5	7.7	6.7	7.6	6.8	8.4
21-24 years old	8.6	9.5	8.9	6.7	6.7	6.9
25-39 years old	10.9	9.7	8.8	9.6	11.1	10.6
30-39 years old	22.2	18.3	17.5	16.5	18.9	17.9
40-49 years old	18.7	20.0	19.7	21.2	18.3	21.5
50-59 years old	13.8	14.4	17.0	18.3	18.6	14.5
≥60 years old	19.2	20.4	21.4	20.1	19.5	20.2
Motorist gender						
Male	61.5	59.0	62.1	60.1	60.8	57.7
Female	38.5	41.0	37.9	39.9	39.2	42.3
Under the influence of alcohol						
No	95.6	94.4	94.6	94.7	94.9	94.5
Yes	4.4	5.6	5.4	5.3	5.1	5.5
Distracted/unattended motorist						
No	95.4	94.8	94.5	92.9	94.0	92.5
Yes	4.6	5.2	5.5	7.1	6.0	7.5
Motorist intended action						
Make right turn	19.5	19.6	18.0	15.8	17.5	18.1
Make left turn	16.2	17.1	16.2	17.6	18.3	15.8
Other (e.g., Change lanes, slow/stop)	64.3	63.3	65.8	66.6	64.2	66.1
Motor Vehicle Characteristics						
Vehicle type						
Car/station wagon	74.4	76.2	75.0	74.9	76.7	77.1
Motorcycle and moped	1.7	1.9	1.0	0.6	1.4	1.3
Utility/panel van	18.0	16.1	18.9	20.4	17.7	17.7
Bus and truck	5.9	5.8	5.1	4.1	4.2	3.9
Vehicle age (Crash year – Vehicle manufacturing year)						
0-5 years	38.7	36.6	37.8	34.9	32.9	33.1
6-10 years	30.0	28.6	27.1	27.0	27.5	26.7
11-15 years	18.1	20.7	20.1	24.4	23.9	23.2
16-20 years	8.8	9.3	11.5	9.2	10.7	12.2
>20 years	4.4	4.7	3.5	4.6	5.0	4.8
Environmental Characteristics						
Week						
Weekend	19.8	21.6	23.1	21.7	20.6	22.9
Weekday	80.2	78.4	76.9	78.3	79.4	77.1
Day-of-week						
Monday	15.7	12.1	11.2	16.4	11.5	12.6
Tuesday	17.2	13.7	17.1	17.5	17.6	17.7
Wednesday	16.0	18.6	15.9	15.1	16.2	14.0
Thursday	15.1	17.4	16.6	15.8	15.8	17.7
Friday	16.2	16.7	16.1	13.5	18.2	15.2
Saturday	11.9	11.2	11.4	12.9	11.9	13.2

Sunday	8.0	10.4	11.7	8.7	8.7	9.7
Time-of-the-day						
Morning peak hour (6am-8am)	23.9	25.1	24.2	25.1	23.7	22.5
Morning off-peak (9am-11am)	13.9	14.9	14.8	16.6	14.8	17.1
Afternoon (12am-2pm)	12.9	11.5	13.2	11.7	13.8	11.9
Evening peak hour (3pm-6pm)	31.8	33.3	29.5	30.5	30.2	34.6
Nighttime (7pm-10pm)	8.6	8.9	8.9	8.9	9.0	8.4
Late night until early morning (11pm-5am)	8.8	6.4	9.4	7.1	8.5	5.5
Translink (Public Transport system) peak and off-peak hour						
Off-peak hour (9am-2pm and 7pm-5am)	44.3	41.6	46.3	44.3	46.2	42.9
Peak hour (6am-8am and 3pm-6pm)	55.7	58.4	53.7	55.7	53.8	57.1
Lighting condition						
Darkness-lighted	15.8	15.7	16.8	13.4	17.1	14.4
Darkness-not lighted	2.3	3.7	3.6	4.3	2.2	3.0
Dawn/dusk	10.0	9.0	9.1	8.6	7.0	7.3
Daylight	71.9	71.6	70.5	73.7	73.7	75.3
Roadway Characteristics						
Posted speed limit						
10-30 km/hr	3.4	4.6	2.5	3.4	4.6	3.3
40 km/hr	10.0	10.2	9.6	10.7	10.7	10.1
50 km/hr	27.2	31.4	30.7	32.1	28.2	34.7
60 km/hr	52.8	48.0	51.9	47.4	50.2	45.3
≥70 km/hr	6.5	5.8	5.4	6.3	6.3	6.7
Horizontal alignments						
Curve-open/obstructed view	15.0	15.0	13.7	14.8	14.4	15.6
Straight	85.0	85.0	86.3	85.2	85.6	84.4
Vertical alignments						
Grade	15.1	13.0	14.3	11.5	12.3	11.0
Crest and dip	7.9	7.3	7.3	5.9	7.4	9.7
Level	77.0	79.7	78.4	82.6	80.3	79.3
Roadway surface condition						
Wet road surface	8.2	6.1	6.6	6.9	5.1	7.5
Dry road surface	91.8	93.9	93.4	93.1	94.9	92.5
Weather condition						
Adverse weather (raining/fog/smoke/dust)	5.8	4.1	5.4	4.6	3.2	5.4
Fine weather	94.2	95.9	94.6	95.4	96.8	94.6
Remoteness classification						
Major cities	68.7	70.6	74.0	71.8	70.2	70.2
Inner regional	16.2	14.4	12.6	13.4	16.5	14.0
Outer regional	13.7	14.1	11.7	13.3	12.3	14.4
Remote	1.0	0.7	1.5	1.0	0.9	0.9
Very remote	0.5	0.2	0.2	0.5	0.1	0.5
Crash location						
Cross intersection	16.3	15.1	14.7	13.7	14.0	12.8
Roundabout	8.3	9.9	9.1	10.5	10.4	9.7
T junction	25.0	25.3	26.8	24.0	28.8	28.1
Mid-block	50.4	49.7	49.4	51.8	46.8	49.4

Presence of traffic control						
Operating traffic lights	13.7	13.2	13.5	14.0	15.1	12.6
Stop sign and give way sign	21.0	20.1	18.8	19.1	20.8	21.5
Pedestrian crossing sign and operated lights	5.2	4.4	4.6	4.2	5.5	3.8
Other traffic control (e.g. police)	60.1	62.3	63.1	62.7	58.6	62.1
Column percentage						

4. Results and Discussion

The empirical analysis involves the estimation of a series of injury severity models, which includes (1) Ordered Logit model, (2) Ordered Logit model with piecewise linear functions of temporal heterogeneity, (3) Generalized Ordered Logit model with piecewise linear functions of temporal heterogeneity, (4) Generalized Ordered Logit model with piecewise linear functions of temporal and active traveler group heterogeneity, and (5) Correlated Random Parameters Generalized Ordered Logit model with piecewise linear functions of temporal and active traveler group heterogeneity.

To identify the model with the best data fit in the current empirical context, the data fit measures of different estimated models are compared in this section. All the estimated competitive models are nested versions of each other, and hence, the data fit measures for these models are compared by employing the likelihood ratio test, expressed as:

$$\chi^2 = -2[LL_{Restricted\ model} - LL_{Unrestricted\ model}] \tag{9}$$

where LL is the log-likelihood value at the convergence.

For the empirical context of this study, the log-likelihood at zero (equal share model) and the log-likelihood at constant (market share model) are -6931.472 and -5184.416, respectively. First, a traditional Ordered Logit model is estimated to establish the benchmark for comparison. Log-likelihoods at zero and constant provide a baseline for a clear assessment of how much the inclusion of predictors enhances the model's explanatory power (Cameron and Trivedi, 2005). As is evident, the traditional ordered logit model provides significantly better data fit over equal share and market share models and hence enhances the model explanatory power. The log-likelihood at convergence and number of parameters for different final specified models are presented in Table 2, while the second-row panel of Table 2 presents the results of likelihood ratio tests across different competitive models.

The estimates of the Ordered Logit model are further tested for the onset and duration of temporal variations. The onset of temporal variation in any variable effect is assumed to be a quarter of any year under consideration and are specified as the interactions of quarters and the exogenous variable. In this study, the dataset has 24 quarters over 6 years of crash data. Thus, 23 interaction terms (deviations) can be specified for each exogenous variable (at least one of the quarters needs to serve as the base case) (see Bhowmik et al. (2019) and Phuksuksakul et al. (2024) for further details on such model specification). The statistically significant (at 90% confidence level) deviations are the onset of temporal variations.

In this study, in identifying the duration of the temporal effect, it is further assumed that the temporal variation can continue over different quarters after the onset of temporal variation in a variable effect which is empirically tested based on the data fit. As explained in the econometric framework section, such duration is specified as piecewise linear function of $(\mathbb{M}, \mathbb{K} = [m', k'] + \sum[(m > m'), (k > k')])$, where quarter (m') of year (k') is a significant onset of temporal variation. In identifying the temporal duration, the following quarters (m) of the onset quarter (m') are added to the onset (m') until adding further (m) does not improve the data fit. For example, let us assume that the interaction terms of variable 'x' with quarter 1 of year 2015 (Q1/2015) is found to be statistically significant – Model 1. Thus, Q1/2015 is the onset of a temporal variation episode for 'x'. Once the onset is identified, in the next step, an interaction of the indicator for (Q1+Q2)/2015 with 'x' is specified to test for temporal duration, which is found to be statically significant – Model 2. The likelihood ratio test between Models 1 and 2 shows that Model 2 performs better, signifying that the effects of Q1/2015 and Q2/2015 are the same. Further, Model 3 is estimated by adding Q3/2015 to (Q1+Q2)/ 2015. For the sake of this example, let us assume that the likelihood ratio test demonstrates that Model 3 does not improve the data fit over Model 2. Thus, Model 2 is the best specified model in this example with Q1/2015 as the onset of temporal variation and (Q1+Q2)/2015 as the duration for this episode of temporal variation. Splitting the data across different quarters might result in smaller data records across different injury severity levels, specifically in the fatal injury category. Thus, the proposed study design of identifying the temporal duration over different quarters intrinsically reduces the possibility of estimating a parameter with a very small number of data records across different quarters.

According to Table 2, the results suggest that the model with piecewise linear function of temporal heterogeneity provides better data fit in the current study context (χ^2, dof, p-value: 205.32, 16, p-value <0.01). Therefore, the result supports our hypothesis that the effects of exogenous variables are likely to vary across different timepoints of the year under consideration. Further, it can be observed that the generalized ordered logit model outperforms the ordered logit model in terms of data fit supporting our hypothesis that the effects of exogenous variables are likely to vary across different alternatives of the dependent variable.

Further, we hypothesize that there might be systematic heterogeneity in the effects of variables by active traveler groups; thus, the estimated generalized ordered logit model with piecewise linear function of temporal heterogeneity is augmented by interaction terms of active traveler indicators (GOL-P_{kh}). However, none of the interactions between active traveler group and other exogenous variables is statistically significant in the current study context. The result is perhaps indicating the similarity in injury severity mechanism between pedestrian and bicyclist when crash with motor vehicle as these two are the most vulnerable road users.

As stated in the econometric framework section, the thresholds in the generalized ordered logit formulation might be correlated through unobservables. As such, in this study, the Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity (in both propensity and thresholds) is further tested for the correlations of exogenous variables across different threshold functions (GOLC- P_k). Correlations across different thresholds are examined by using multivariate distribution of normal variables that stitches the thresholds through unobserved error terms. The statistical significance of the correlation terms is empirically tested based on the data fit (at 90% confidence level). However, none of the correlation parameters are found to be significant in the current empirical context. The result is perhaps indicating that the model with structural variations in temporal effects of exogenous variables provide more observed information, and hence, the role of unobserved heterogeneity is likely to become statistically less prominent in developing active traveler injury severity models.

Models GOL-P_{kh} and GOLC- P_k do not have any additional parameters and hence, are reduced to model GOL-P_k. Thus, GOL-P_k is considered the best-specified model and is considered for further analysis. Model GOL-P_k is further tested for unobserved heterogeneity in parameter estimates of the Generalized Ordered Logit formulation, and one of the variables is found to be random. The likelihood ratio test indicates that the model with random parameter outperforms the model without random parameter (χ^2, dof, p-value: 3.46, 1, 0.05 < p-value < 0.1) and hence highlighting the superiority of addressing unobserved heterogeneity in the effect of exogenous variables.

Finally, to further assess the performance of the best-specified model, a validation experiment is also carried out by using 1,304 hold-out samples. For the validation sample, based on the estimates of the Random parameter Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity (RGOL- P_k), the predicted shares (observed shares) across different injury severity categories are: 0.099 (0.098) for minor injury, 0.360 (0.359) for moderate injury, 0.515 (0.516) for major injury and 0.025 (0.025) for fatal injury. The reasonable predicted share shows that the estimated model performs well in the current study context. Moreover, for the hold-out sample, the log-likelihood at converge (number of parameters) for the Ordered Logit and Random parameter Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity are -1273.52 (18) and -1252.40 (41), respectively. The likelihood ratio test indicates that the model with random parameter outperforms the traditional ordered logit model without temporal heterogeneity (χ^2, dof, p-value: 42.24, 23, p-value < 0.01), and hence, highlighting the superiority of addressing temporal heterogeneity in the effect of exogenous variables.

Table 2

Comparison of data fit measures across models.

Model	**Log-Likelihood at Convergence**	**Number of Parameters**
Ordered Logit model (OL)	-4,947.23	18
Ordered Logit model with piecewise linear function of temporal heterogeneity (OL-P_k)	-4,931.03	24
Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity (GOL-P_k)	-4,828.37	40
Random parameter Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity (RGOL- P_k)	-4,826.65	41
Comparison model		
Nested model – Likelihood ratio test	(χ^2, dof) p-value – Best model	
OL/OL-P_k	(32.42, 6) < 0.01 – OL- P_k	
OL-P/ GOL-P_k	(205.32, 16) < 0.01 – GOL- P_k	
GOL- P_k /RGOL- P_k	0.05 < (3.46, 1) < 0.1 – RGOL- P_k	
dof: degree of freedom; NS: Insignificant; --: no presence of statistically significant exogenous variables		

4.1. Model estimation results

In presenting the proposed model estimation results, we will restrict ourselves to the discussion of the best-specified model (as presented in Table 2) that is the ‘Random parameter Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity’ (referred to as generalized ordered model for brevity hereafter). Table 3 presents the results of the model. A positive (negative) coefficient in the propensity corresponds to an increased (decreased) likelihood of serious injury severity outcome. In thresholds, a positive (negative) parameter implies that the threshold is bound to increase (decrease). Since the major focus of this study is to examine the onset and duration of temporal variations in the variable effects, the results of the time-varying effects are presented first. The estimation results are explained by variable groups in the following sections.

Table 3
Estimation results of the Random parameter Generalized Ordered Logit model with piecewise linear function of temporal heterogeneity.

Explanatory variables	**Estimates**		
	Propensity	Threshold between Moderate and Major injury	Threshold between Major and Fatal injury
Constant	-1.716***	0.753***	1.406***
Active Traveler Characteristics			
Active traveler age (Base: Other active traveler age group)			
≤15 years old	0.231***	--	--
≥60 years old	0.534***	--	-0.407***
Active traveler gender (Base: Male)			
Female″	0.585***	0.166***	--
From 2015, Q1 to 2016, Q3‴	-0.237*	--	--
From 2019, Q2 to 2020, Q1	-0.414***	--	--
Under the influence of alcohol (Base: No)			
Yes	0.864***	--	-0.771***
Active traveler intended action (Base: Other, *e.g.* remain stationary)			
Crossing carriageway	0.487***	--	--
From 2015, Q1 to 2016, Q2	-0.247*	--	--
From 2018, Q1 to 2018, Q4	-0.461***	--	--
Active traveler at-fault (Base: No)			
Yes	0.601***	--	0.427*
Standard deviation	--	--	0.485**
From 2016, Q1 to 2016, Q4	--	--	-0.211*
From 2019, Q1 to 2019, Q4	-0.233*	--	--
Motorist Characteristics			
Motorist age (Base: Other motorist age group)			
≤24 years old	0.280***	--	--
25-39 years old	0.195**	--	--
Motorist gender (Base: Male)			
Female	-0.125**	--	--
Under the influence of alcohol (Base: No)			
Yes	0.587***	--	--
Distracted/unattended motorist (Base: No)			
Yes	0.629***	--	--
Motor Vehicle Characteristics			
Vehicle type (Base: Other, e.g. Passenger car)			
Bus and truck	0.302*	--	-0.551***
Vehicle age (Base: Other age groups)			
0-5 years old	--	--	0.129*
Environmental Characteristics			

Time-of-the-day (Base: Other time-of-the-day)			
Nighttime (7pm-10pm)	--	-0.097*	--
Late night until early morning (11pm-5am)	0.319***	--	--
Roadway Geometric Characteristics			
Posted speed limit (Base: 60 km/hr)			
10-40 km/hr	-0.364***	--	0.566***
50 km/hr	-0.375***	-0.127***	0.168**
From 2015, Q1 to 2015, Q4	--	0.135**	--
From 2019, Q1 to 2020, Q2	--	--	0.288*
From 2020, Q1 to 2020, Q4	0.265*	--	--
>70 km/hr	--	-0.351***	--
Presence of traffic control (Base: No traffic control)			
Operating traffic lights	--	--	0.322***
Stop sign and give way sign	--	--	0.763***
Log-likelihood at convergence	-4,826.645		
Number of observations	5,000		

*--: Non statistically significant; *: Statistically significant at 90%, **: Statistically significant at 95% and ***: Statistically significant at 99%; ʺ: Main effect of the variable; ‴: Second order effect (interaction of the variable and the temporal duration)*

4.1.1 Time-varying effects

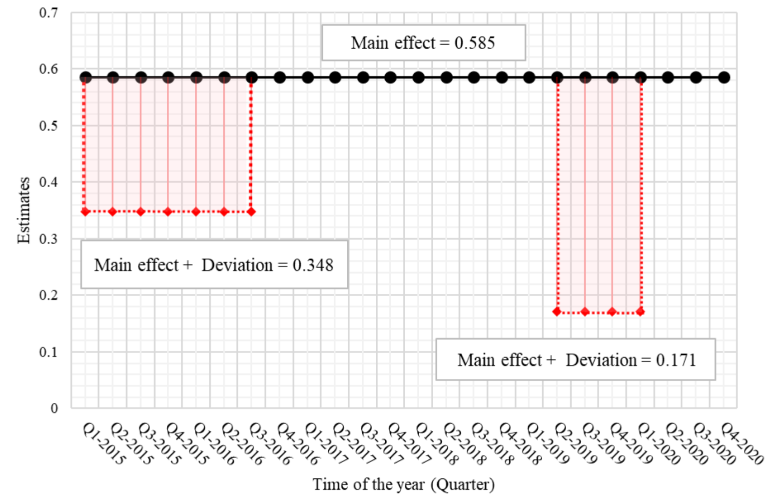
Several exogenous variables are found to be associated with time-varying effects in the propensity and threshold functions. For ease of presentation, the coefficients with the time-varying effects are plotted and presented in Figure 2. The variables with time-varying effects in the propensity functions are – (Figure 2(a)) female active traveler, (Figure 2(b)) active traveler crossing carriageway, (Figure 2(c)) at-fault active traveler, and (Figure 2(e)) posted speed limit of 50 km/hr. The variables with time-varying effects in the threshold functions are – (Figure 2(d)) at-fault active traveler and (Figures 2(f) and 2(g)) posted speed limit of 50 km/hr. In Figure 2, the black line represents the main effect, the breakpoint for the beginning of the blocks represents the onset of time-varying effect, and the block represents the duration of time-varying effect. Thus, the total effect of an exogenous variable can be computed by summing up the main and time-varying effects (deviation). For example, the time-varying effect in Figure 2(a) for female active traveler in the propensity function can be interpreted as:

- The main effect of female active traveler is 0.585.
- There are two episodes of time-varying effects.
- The onset of the first episode of time-varying effect is 1st quarter/2015. The duration of this time-varying episode is from 1st quarter/2015 to 3rd quarter/2016. The overall effect of female active traveler during this first episode is (0.585 - 0.237) = 0.348.
- The onset of the second episode of time-varying effect is 2nd quarter/2019. The duration of this time-varying episode is from 2nd quarter/2019 to 1st quarter/2020. The overall effect of female active traveler during this second episode is (0.585 – 0.414) = 0.171.

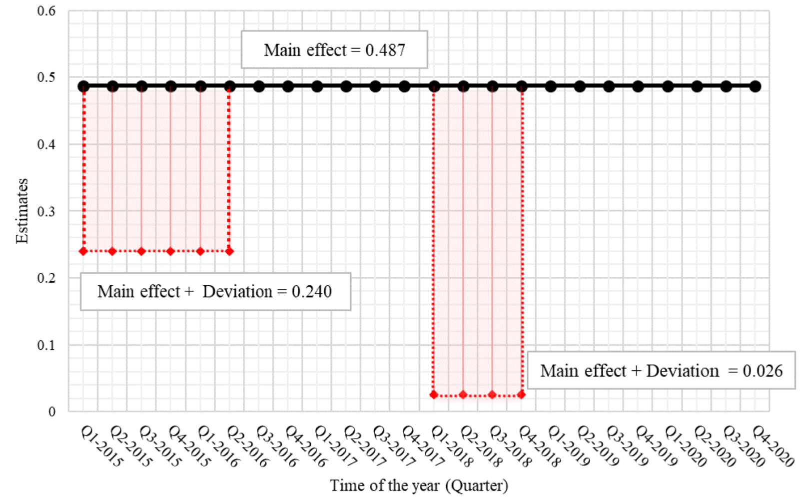
The rest of the variables with time-varying effects can be interpreted in a similar manner. The results support our hypothesis that the effect of an exogenous variable might be different within a year which can be carried over to some part of the next year. On the other hand, some of the years might have the same effect throughout the year. As such, it is important to consider disaggregated time points in examining injury severity mechanism, where feasible. Further, the main effect of at-fault active traveler in the threshold demarcating major and fatal injury is found to be normally distributed. Therefore, in presenting the time-varying effects of “at-fault active traveler” indicator in the threshold functions in Figure 2(d), the black line represents the mean main effect (0.427).

The supporting argument on such time-varying effects are discussed in the following sections along with other variables.

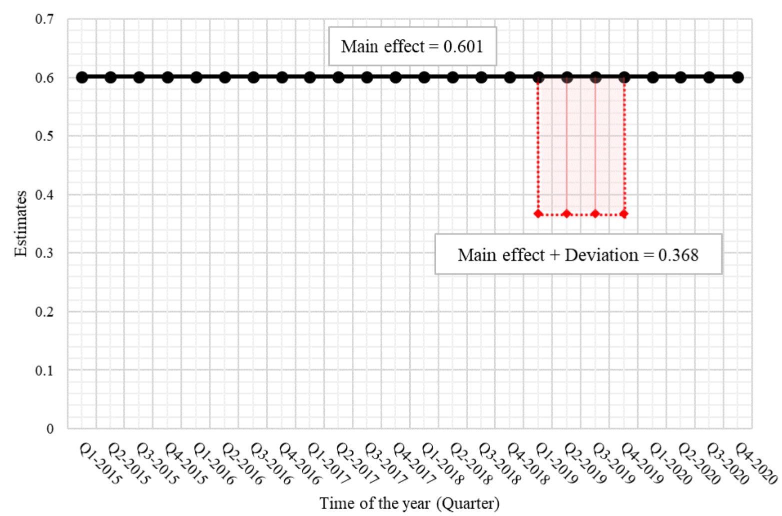
(a) - Time-varying estimate of female active traveler in the propensity function



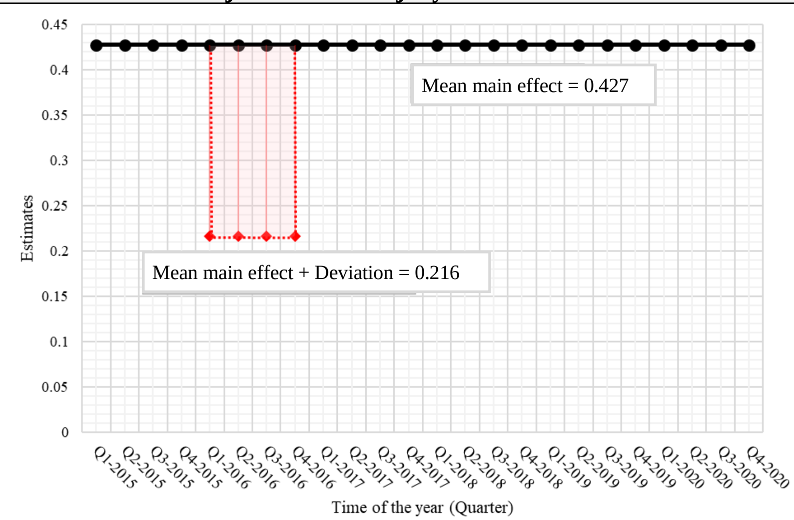
(b) - Time-varying estimate of active traveler action crossing carriageway in the propensity function



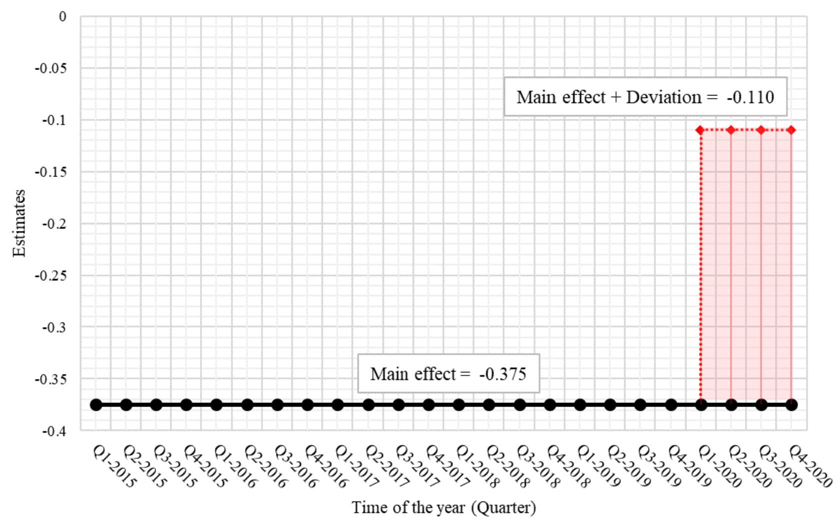
(c) - Time-varying estimate of at-fault active traveler in the propensity function



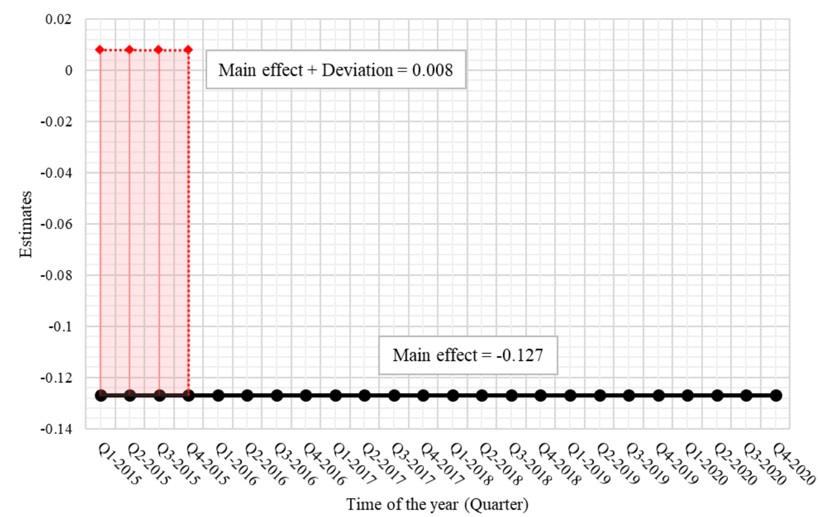
(d) - Time-varying estimate of at-fault active traveler in the threshold function between major and fatal injury



(e) - Time-varying estimate of posted speed limit 50 km/hr in the propensity function



(f) - Time-varying estimate of posted speed limit 50 km/hr in the threshold function between moderate and major injury



(g) - Time-varying estimate of posted speed limit 50 km/hr in the threshold function between major and fatal injury

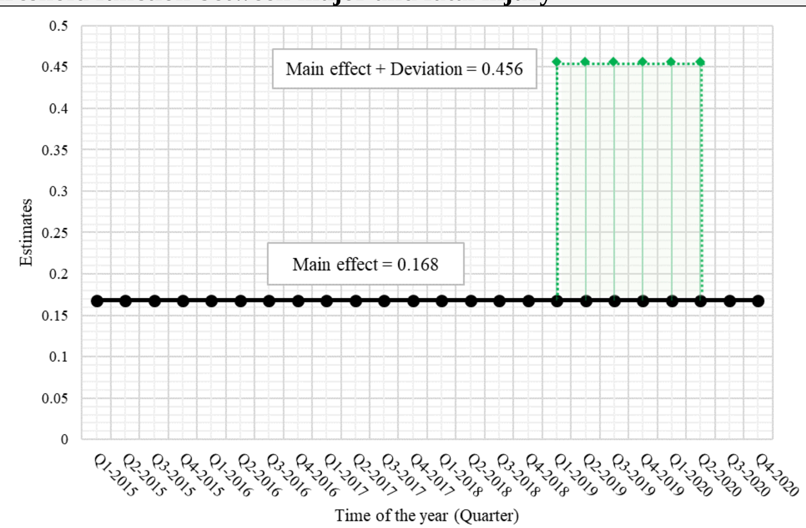


Fig. 3. Effect of exogenous variables with time-varying effects.

4.1.2. Active traveler characteristics

With respect to active traveler characteristics, several exogenous variables are found to be statistically significant. The results highlight that relative to the 16 to 59 years old active traveler group, young (≤15 years old) and elderly (≥60 years old) active travelers are likely to be severely injured in the event of crashes with motor vehicles. Moreover, the indicator representing elderly active traveler is also found to be negative in the threshold demarcating major and fatal injury representing a higher likelihood of fatal injury for this road user group. These results highlight the frailty of young and elderly active travelers relative to their other counterparts (Eluru et al., 2008; Moore et al., 2011).

With regards to active traveler gender, the results indicate that female active traveler is more likely to sustain serious injury with an overall higher likelihood of sustaining moderate injury relative to their male counterpart. The result could be explained by less physiological strength of female to withstand blunt force trauma (Hosseini et al., 2022; Tay et al., 2011). Further, the results also indicate time-varying effects of female active traveler group. The results indicate a decrease in the size of propensity (can be computed as 0.348 = 0.585 – 0.237) between the 1st quarter/2015 to 3rd quarter/2016. Between 4th quarter/2016 and 1st quarter/2019, the overall propensity of injury severity for the female active traveler is 0.578, which decreased to 0.171 (0.585 – 0.414) between 2nd quarter/2019 and 1st quarter/2020. Empirical evidence from Queensland indicates a significant surge in mental and behavioral health issues among females during 2017-2018 period compared to the preceding years (Queensland Government, 2021b). Moreover, females were reported to exhibit higher levels of psychological distress and anxiety, potentially leading to riskier behaviors, particularly on roads. Consequently, this heightened propensity for risk-taking behavior among female active travelers over 2017 and 2018 may have contributed towards greater likelihood of severe injuries for this road user group relative to their male counterpart (Ceccato et al., 2015; Esmaili et al., 2021). The relatively higher injury severity outcome of female active traveler in the last three quarters of 2020 is perhaps reflecting the impact of COVID-19. During this period, higher levels of traffic violations were observed, which contributed to higher crash risk and injury severity outcomes (Hughes et al., 2022; Lee et al., 2023). Thus, the less physiological strength of women and overall increase in risk taking behavior among road users during COVID period perhaps contributed towards higher injury severity outcomes among female active traveler relative to their male counterparts. Overall, the results indicate that female active travelers are likely to sustain higher injury severity in crashes with motor vehicles relative to male active traveler, and the size of effect on severity outcome is time-varying. Thus, the net effect of female active traveler on injury severity outcome can be computed in conjunction with propensity, thresholds, and time-varying effects in the model.

As expected, active travelers under the influence of alcohol are likely to sustain higher injury severity outcomes in the event of crashes with motor vehicles relative to non-alcohol impaired active travelers. A negative sign in the threshold demarcating major and fatal injury indicates a higher likelihood of fatal injury outcome for alcohol impaired active travelers. Alcohol consumption potentially compromises the central nerve system which in turn decreases the decision-making skill, thus, an alcohol impaired active traveler might fail to take effective action in the advent of a crash resulting in higher injury severity outcome (Kweon and Lee, 2010; Lin and Fan, 2021).

We find that the effect of active traveler intended action, crossing carriageway indicator is found to be temporally varying. The results indicate a positive coefficient ($\beta = 0.487$) in the propensity function, which declines to 0.240 ($\beta = 0.487 - 0.247$) between 1st quarter/2015 to 2nd quarter/2016 and reaches to 0.026 ($\beta = 0.487 - 0.461$) during 2018 and increases back to 0.484 in 2019 and 2020. While the effect varies across quarters, the results indicate a higher likelihood of active travelers sustaining severe injury in crashes with motor vehicles while crossing the carriageway. The observed increase in injury severity outcome among active travelers can be attributed to the higher rates of distraction, such as the use of mobile phones while walking or cycling, even during road crossing; moreover, this results could reflect a growing non-compliance issue of road rules among road users in recent years (e.g. jaywalking or red light crossing, or not giving way to pedestrian), particularly during the COVID-19 period resulting in higher severity outcome for active traveler during these years (Arafat et al., 2023; Krizsik and Pauer, 2023; Pešić et al., 2016). Overall, active travelers are likely to sustain serious injury in a crash with motor vehicle while crossing carriageway compared to other actions. While crossing carriageway, active travelers are most exposed to the oncoming traffic. Therefore, while crossing a carriageway, an active traveler is likely to withstanding the direct impact of a motor vehicle resulting in higher severity outcome from a crash (Zajac and Ivan, 2003).

In the official crash database of Queensland, a crash victim is identified as 'at-fault' party if the crash victim is attributed with traffic violations or if the crash victim is identified to be the "most at-fault" by police. The results indicate that the active travelers who are identified as at-fault are likely to be severely injured relative to their not-at-fault counterparts. However, the effects are found to be time-varying while also vary by injury severity alternatives. In 2019, the effect of "at-fault" status is found to be less positive ($\beta = 0.601 - 0.233 = 0.368$) relative to other years. On the other hand, the positive coefficient in the threshold demarcating major and fatal injury indicate lower probability of fatal injury, but the negative coefficient in threshold demarcating major and fatal injury probability of fatal injury is higher in 2016 ($\sigma = 0.427 - 0.211 = 0.216$) relative to other years. In fact, the effect of at-fault active traveler in the threshold demarcating major and fatal injury is found to be normally distributed with a standard deviation of 0.485. However, the mean value of the normally distributed parameter is 0.427 for the years 2015 and 2017-2020, while the mean value is 0.216 for the year 2016. Thus, the normal distribution spread of the indicator for 2016 and other years are different in the current study context. Figure 3 represents the overall distributions of at-fault status in the threshold demarcating major and fatal injury across different years. From Figure 3, it could be observed that over 81% (68%) of at-fault active travelers are likely to sustain fatal injury in crashes with motor vehicles for the years 2015 and 2017-2020 (2016). The lower proportion of fatality among active traveler in 2016 relative to other years are perhaps indicating the positive impacts of "Queensland Police Service" campaign in 2016 to encourage active travelers, specifically pedestrians, to use the road on safe side of the law (QPS, 2016).

The lower propensity in injury severity outcomes of at-fault active travelers in 2019 relative to the preceding years could be attributed to significant investments in safer infrastructure that better caters for active traveler needs in Queensland (TMR (2018). However, in 2020, during the outbreak of COVID-19, there were significant increase in risky behavior among active travelers which perhaps contributed towards higher injury severity outcomes among at-fault active travelers (Inada et al., 2021; Katrakazas et al., 2020; Zafri et al., 2021). In general, the time-varying effect of at-fault active traveler can be attributed to several risky actions such as jay walking, crossing from the wrong side, traveling against traffic flow, or darting across the road. Such risky behaviors could lead to the reduced perception-reaction time or time-to-collision of approaching motor vehicle. In fact, such unexpected situations where at-fault active travelers entering the roadway could lead to unavoidable conflicts and hence active traveler are more likely to receive full crash momentum which in turn increasing the injury severity outcomes of active travelers (Dai, 2012; Haleem et al., 2015; Zhu et al., 2021).

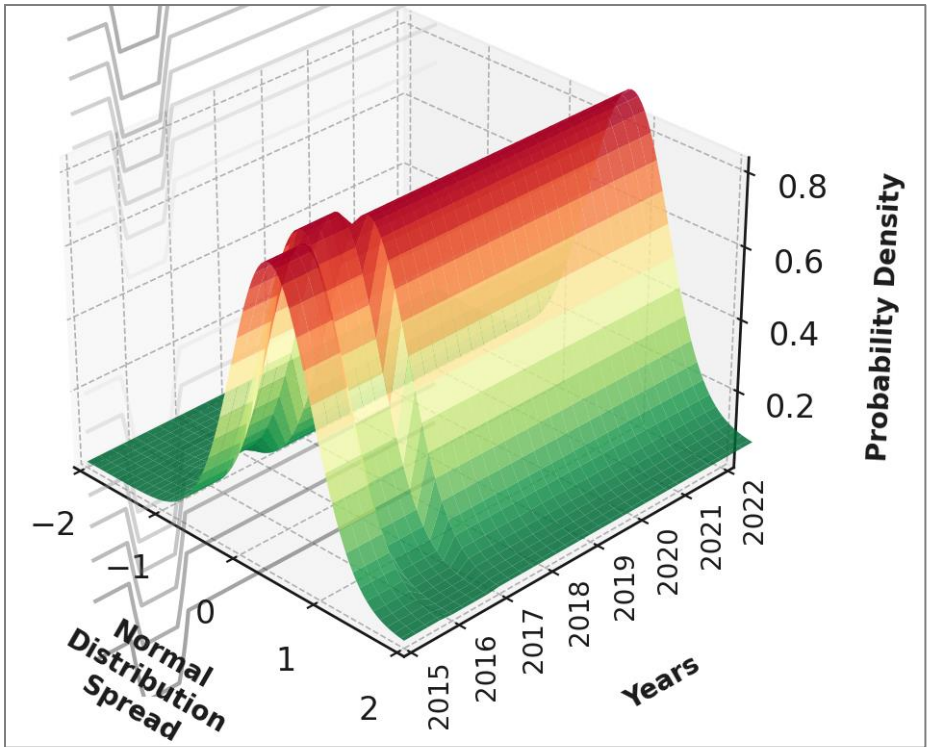


Fig. 3. Distributions of random parameter of at-fault status in the threshold demarcating major and fatal injury across different years

4.1.3. Motorist characteristics

In the current study context, none of the motorist characteristics is found to have time-varying effect on active traveler injury severity outcome. The results highlight that active travelers are more likely to sustain serious injury in crashes with motor vehicles driven by young (age ≤24 years old) and young-adult motorists (25-39 years old) relative to other motorist groups. The results could be explained by less driving experience and driving maneuverability skills of younger motorists (Nishimoto et al., 2019). Moreover, driving with high mean speed and high velocity are found to be dominant among young motorists' cohort (Boyce and Geller, 2002), which in turn can result in more severe outcome for active traveler crashes. Several previous studies found that most of the female motorists are likely to maintain a lower speed profile and are less likely to be engaged in speeding behavior (Roidl et al., 2013; Shinar et al., 2001). Moreover, earlier studies found that female drivers are generally more attentive and engage in less aggressive driving behavior (Kovaceva et al., 2020; Nishimoto et al., 2019). Thus, female motorists are generally involved in less severe active traveler crashes. In this study, we also find that active traveler crashes involving female motorist is likely to be less serious than active traveler crashes involving male motorists.

Alcohol impairment affects driving behavior by compromising cognitive, decision skill and perception-reaction time while also contributing towards high risk-taking behavior. As expected, active traveler crashes involving alcohol impaired motorists are found to be serious relative to active traveler crashes involving sober drivers (see Eluru et al. (2008) and Liu et al.

(2019) for similar findings). With respect to distracted/unattended motorists, the result highlights the possibility of serious injury outcome for active travelers relevant to such risky driving behavior. Distracted/unattended behavior compromises driving performance, resulting in insufficient judgement time when taking effective evasive actions in the presence of an active traveler (Haque and Washington, 2014), resulting in higher injury severity outcomes for active travelers.

4.1.4. Motor vehicle characteristics

Active travelers are more likely to suffer serious injury in the event of crashes with heavy and large vehicles (bus and truck) relative to passenger vehicles. Heavy and large vehicles are likely to produce higher crash momentum due to their weights along with larger impact area resulting in higher crash severity outcomes for active travelers (Marcoux et al., 2018; Yasmin et al., 2014). With regards to vehicle age, the indicator for newer vehicles (0-5 years old vehicle) is insignificant in the propensity function, however, it is found to be significant in the threshold between major and fatal injury. The result indicates that crashes with newer vehicles are likely to be less severe than older vehicles. Newer vehicles are likely to be associated with the improvement in vehicle's design and composited with built-in driving assistant features (such as pedestrian detection and automatic brake) and hence, is likely to mitigate crash outcomes for active travelers (Mahdinia et al., 2022).

4.1.5. Environmental characteristics

Among different environmental characteristics, only time-of-day is found to have significant effect on active traveler injury severity outcomes. The results indicate negative consequences of active traveler crashes during nighttime (7pm-10pm) and late night (11pm-5am). The negative sign in the threshold demarcating minor and major injury of active traveler crash during nighttime indicates higher probability of major injury severity outcome. At the same time, late-night period shows an overall higher probability of serious injury outcome for active traveler crashes. The results can be attributed to the restricted visibility of road users during nighttime (Hezaveh and Cherry, 2018; Nishimoto et al., 2019). Moreover, during nighttime and late-night periods, there might be prevalence of speeding and alcohol impairment deteriorating overall safety conditions for active travelers. The presence of an active traveler on roadway during late night period might be unexpected to a motorist which might contribute towards less efficient reaction to effectively avoid an impending crash, further contributing towards higher active traveler injury severity outcome.

4.1.6. Roadway characteristics

With respect to roadway characteristics, posted speed limit and presence of traffic control devices are found to be significant in the estimated model. With regards to posted speed limit, the results highlight the benefits of low-posted speed limit roadways (10-40 km/hr). Active travelers are likely to be less seriously injured with an overall less likelihood of fatal injury when involved in crashes with motor vehicles on 10-40 km/hr speed limit roadways.

On the other hand, active traveler injury severity outcome is found to be lower on 50 km/hr roadway with an overall higher probability of major injury (negative and positive coefficients in the thresholds indicate a higher probability for major injury category). However, the effects of 50km/hr are time-varying. The effect in the propensity increased by -0.110 ($\beta = -0.375 + 0.265$) unit in 2020 relative to other years. In 2015, 50 km/hr is found to contribute towards lower major injury probability relative to other years. Finally, between 1st quarter/2019 to 2nd quarter

2020, the probability of fatal injury is found to be much lower than other quarters. Thus, it is evident that the overall effect of 50 km/hr can be computed by considering the values in the propensity, and threshold functions while also accommodating for time-varying effects. 50 km/hr posted speed limit is applied in built-up area[14] where there are diversities in road user groups along with activities of commercial and freight vehicles. Such characteristics of 50 km/hr roadway contribute towards higher level of complexity in road usage, specifically, complexity in the right of way for active traveler group which simultaneously increase the perception-reaction time contributing towards higher active traveler injury severity outcomes on 50 km/hr roadways (Hussain et al., 2023). The speed limit in built-up areas in Queensland is 50km/h, and the default speed limit on a road outside a built-up area is 100km/h (unless otherwise indicated by signs) (Queensland Government, 2024). As such, the negative coefficient for threshold demarcating minor and major injury for active traveler from year 2016 could perhaps indicate the inappropriate posted speed limit zone with regards to impendent urbanization trends since there is significant increase in urbanization in Queensland from 2016 (approximately 15% increase in urbanization and about 3 times increase in resident population) (Queensland Government, 2021a). However, there was an initiation of posted speed reduction in areas with high active traveler activity according to the 'Safe System Approach' between the year 2017-2019 (Queensland Government, 2017), and hence resulting in reduced active traveler injury severity outcomes as presented by the positive coefficient of the threshold demarcating major and fatal injury in year 2019. In addition, the result associated with the year 2020 is perhaps highlighting the effect of COVID-19 period on active traveler injury severity outcomes. Motorists were reported to be associated with higher risky driving behavior during COVID-19 (increased driving speed, harsh acceleration, harsh braking event and mobile phone usage while driving) resulting in the lower awareness or intention to yield to active traveler, in turn contributing towards higher injury severity outcome for active traveler in 2020 relative to other years (Inada et al., 2021; Katrakazas et al., 2020; Zafri et al., 2021).

With regards to posted speed limit, although the high posted speed limit indicator (>70 km/hr) is insignificant in the propensity function, it is found to be negative in the threshold between minor and major injury. The result shows a higher probability of major injury for active traveler crashes on >70 km/hr roadways. Overall, the results highlight the negative safety impacts of higher posted speed limits on active traveler injury severity outcomes. On roadways with higher posted speed limit, the right of way is prioritized to motor vehicles in order to maximize vehicle movements. Also, less amount of active traveler facilities could be expected on high posted speed limit roadways. With the less active traveler facilities (proper crosswalk, pedestrian/cyclist signal, proper walkway/cyclist way, and crossing facilities), active traveler is likely to be fully exposed to motor vehicles on high posted speed limit roadway while using these roadways. On the other hand, motor vehicles are expected to travel at higher speed, and hence, it is likely to take longer stopping distance for a motor vehicle to react in time. As such, active traveler injury severity outcome is likely to be higher on high posted speed limit locations resulting from high crash momentum of vehicle mass and impact speed on such roadways (Das, 2021; Eluru et al., 2008; Wahi et al., 2018).

Regarding the presence of traffic control devices, the effects of operating traffic light and stop/giveway signs are statistically significant, with positive coefficients in the threshold demarcating major and fatal injury. The results indicate that active travelers are less likely to sustain fatal injury on roadways with operating traffic lights and stop/giveway signs. The results

[14] Land use with a mix use of residential, industrial and commercial areas (TMR, 2023) is known as the built-up area in Queensland.

highlight the benefits of traffic control devices in mitigating crash outcomes for active travelers. These devices are designed to accommodate mixed traffic environment by managing traffic flows by road user groups from different directions resulting in less possibility of traffic conflicts and hence are likely to result in lower injury severity outcomes for active travelers in the event of crashes with motor vehicles (Liu et al., 2019).

4.2. Elasticity effects and Model implications

The estimated effects of the exogenous variables presented in Table 3 and Figure 2 do not directly describe the magnitude of the effects of exogeneous variables on active traveler injury severity outcomes. Therefore, to identify these effects, aggregate level elasticity effects are computed (see Eluru and Bhat (2007) for methodology and discussions on elasticity effects). For computing aggregate level elasticity effects, the base-probabilities by injury severity categories ($\Pr(y_i = j)_{Base}$) are computed by applying Equation 8. Then, we compute the shift-probability function ($\Pr(y_i = j)_{shift}$) for those exogeneous variable by switching those value of exogeneous variable ($\boldsymbol{z}_{ij}, \boldsymbol{x}_i$) to zero (one) for exogenous variable which takes a value of one (zero). The elasticity effects of exogenous variables by different years are computed as:

$$EE_j = \frac{\sum_{i=1}^{I}\left[\Pr(y_i = j)_{Shift} - \Pr(y_i = j)_{Base}\right]}{\sum_{i=1}^{I}\left[\Pr(y_i = j)_{Base}\right]} \times 100 \times S$$

$$where\ S = \begin{cases} 1 & if\ \boldsymbol{z}_{ij,shift}\ or\ \boldsymbol{x}_{i,shift} = 0 \\ -1 & if\ \boldsymbol{z}_{ij,shift}\ or\ \boldsymbol{x}_{i,shift} = 1 \end{cases} \tag{10}$$

The notations specified in Equation 10 are described in Section 2. The elasticity effects are computed as an average measure across all quarters, which are presented in Table 4. Further, elasticity effects are computed by quarters for variables with time-varying effects, which are presented in Table 5. Further, for ease of representation, the elasticity values in Table 5 are represented by using heat map[15] to show the variations in elasticity values across different time of the year.

Table 4
Average elasticity effect of exogenous variables.

Explanatory variables	Active traveler injury severity outcomes			
	Minor Injury	**Moderate Injury**	**Major Injury**	**Fatal Injury**
Active Traveler Characteristics				
Age ≤15 years old	-12.714	-5.898	5.735	16.454
Age ≥60 years old	-26.931	-15.214	7.770	154.488
Female	-16.562	-0.876	3.444	8.741
Under the influence of alcohol	-51.746	-33.410	2.547	588.890
Intended action Crossing	-18.193	-7.847	8.505	10.022
At-fault	-10.648	-4.756	4.868	10.117

[15] In Table 5, the darker the color of a block, the higher is the value of elasticity effect specific to an exogenous variable.

Motorist Characteristics				
Age ≤24 years old	-15.728	-7.962	7.793	15.773
Age 25-39 years old	-12.809	-6.295	6.240	12.385
Female	2.180	0.989	-0.938	-3.397
Under the influence of alcohol	-37.515	-22.036	20.191	47.076
Distracted/unattended	-38.572	-23.043	20.851	51.756
Motor Vehicle Characteristics				
Bus and truck	-21.549	-11.139	-1.258	253.030
Age 0-5 years old	--	--	0.560	-10.710
Environmental Characteristics				
Nighttime (7pm-10pm)	--	-10.544	6.713	10.549
Late night until early morning (11pm-5am)	-21.460	-11.134	10.945	19.118
Roadway Geometric Characteristics				
Posted speed limit 10-40 km/hr	26.463	9.357	-8.276	-65.813
Posted speed limit 50 km/hr	14.557	-1.080	-1.186	-18.532
Posted speed limit >70 km/hr	--	-34.979	21.726	45.457
Operating traffic lights	--	--	2.066	-39.533
Stop sign and give way sign	--	--	3.910	-74.821

Table 5
Elasticity effects by different quarters for variables with time-varying effects.

Time-of-the-year		**Exogenous variables**							
		Female active traveler				**Active traveler crossing carriageway**			
		Injury severity				**Injury severity**			
Year	**Quarter**	Minor injury	Moderate injury	Major injury	Fatal injury	Minor injury	Moderate injury	Major injury	Fatal injury
2015	1	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
	2	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
	3	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
	4	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
2016	1	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
	2	-2.304	7.419	-4.303	-6.710	-1.822	0.825	0.128	-6.389
	3	-2.304	7.419	-4.303	-6.710	-18.193	-7.847	8.505	10.022
	4	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
2017	1	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	2	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	3	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	4	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
2018	1	-16.562	-0.876	3.444	8.741	17.599	8.711	-8.507	-19.095
	2	-16.562	-0.876	3.444	8.741	17.599	8.711	-8.507	-19.095
	3	-16.562	-0.876	3.444	8.741	17.599	8.711	-8.507	-19.095
	4	-16.562	-0.876	3.444	8.741	17.599	8.711	-8.507	-19.095
2019	1	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	2	13.817	14.160	-11.486	-19.545	-18.193	-7.847	8.505	10.022
	3	13.817	14.160	-11.486	-19.545	-18.193	-7.847	8.505	10.022
	4	13.817	14.160	-11.486	-19.545	-18.193	-7.847	8.505	10.022
2020	1	13.817	14.160	-11.486	-19.545	-18.193	-7.847	8.505	10.022
	2	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	3	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
	4	-16.562	-0.876	3.444	8.741	-18.193	-7.847	8.505	10.022
		Exogenous variables							

Time-of-the-year		At-fault active traveler				Posted speed limit 50 km/hr			
		Injury severity				Injury severity			
Year	**Quarter**	Minor injury	Moderate injury	Major injury	Fatal injury	Minor injury	Moderate injury	Major injury	Fatal injury
2015	1	-10.648	-4.756	4.868	10.117	14.557	15.867	-12.090	-33.298
	2	-10.648	-4.756	4.868	10.117	14.557	15.867	-12.090	-33.298
	3	-10.648	-4.756	4.868	10.117	14.557	15.867	-12.090	-33.298
	4	-10.648	-4.756	4.868	10.117	14.557	15.867	-12.090	-33.298
2016	1	5.748	3.593	-3.390	-4.415	14.557	-1.080	-1.186	-18.532
	2	5.748	3.593	-3.390	-4.415	14.557	-1.080	-1.186	-18.532
	3	5.748	3.593	-3.390	-4.415	14.557	-1.080	-1.186	-18.532
	4	5.748	3.593	-3.390	-4.415	14.557	-1.080	-1.186	-18.532
2017	1	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	2	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	3	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	4	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
2018	1	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	2	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	3	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
	4	-10.648	-4.756	4.868	10.117	14.557	-1.080	-1.186	-18.532
2019	1	-10.648	-4.756	2.628	52.987	14.557	-1.080	0.849	-57.467
	2	-10.648	-4.756	2.628	52.987	14.557	-1.080	0.849	-57.467
	3	-10.648	-4.756	2.628	52.987	14.557	-1.080	0.849	-57.467
	4	-10.648	-4.756	2.628	52.987	14.557	-1.080	0.849	-57.467
2020	1	-10.648	-4.756	4.868	10.117	-7.263	-10.012	10.938	-49.636
	2	-10.648	-4.756	4.868	10.117	-7.263	-10.012	10.938	-49.636
	3	-10.648	-4.756	4.868	10.117	-7.263	-10.012	8.459	-2.196
	4	-10.648	-4.756	4.868	10.117	-7.263	-10.012	8.459	-2.196

Several observations can be made from Table 4. First, the most important variables in terms of increase in fatal injury outcome for active travelers are active travelers under the influence of alcohol, crashes with bus and truck, and elderly active traveler (active traveler age ≥60 years old). Second, the most important variables in terms of decrease in serious injury outcome for active travelers are crashes on posted speed limit of 10-40 km/hr and posted speed limit of 50 km/hr, stop and giveway sign, and operating traffic lights. From Table 5, it can be observed that time-varying effects are likely to be different across quarters for several variables, while for other variables, the onset of time-varying effects could be different than the start of a year. Thus, the results highlight the importance of examining the disaggregated nature of time-varying effects (onset and duration of time-varying effects) in developing injury severity models, where feasible. Such flexibility in model specification is likely to have significant implications for devising and implementing effective countermeasures since it allows us to understand how road safety landscapes are evolving over time and when a new road safety issue is arising. In fact, understanding time-varying effects is crucial for developing dynamic policies that not only enhance road safety but also reduce active traveler injury severity. By analyzing these time-varying effects, policymakers can adjust safety measures across different seasons as needed by using the changes in safety landscape across different parts of the year. For example, stricter speed limits (or adaptive posted speed limit) and increased enforcement can be implemented during specific time-of-the-year according to the traffic activities or weather conditions (e.g. adverse weather or seasons).

5. Conclusion

There is considerable evidence in existing safety literature that the exogenous variable effects are likely to be time-varying in the crash risk/severity analysis. The majority of these earlier studies in existing safety literature tested for such time-varying effects of exogenous variables by crash year. Implicitly, these earlier studies assumed that the effects of exogenous variables remained the same within a year. However, there might be variability in the variable effects within a year, while the same effect might carry over in some or all parts of the preceding years. As such, it might be advantageous and worthwhile to investigate the time-varying effects of exogenous variables while also examining the onset and duration of such temporal heterogeneity. Towards that end, in this study, we proposed a flexible framework for examining the onset and duration of time-varying effects in developing injury severity models. In the proposed approach, we assumed that the onset of temporal variation can be any quarter of a year under consideration, while the time-varying effect can continue over different quarters after the onset of temporal variation in a variable effect. In this setting, the duration of time-varying effects of an exogenous variable was empirically tested by combining the quarters following the onset quarter in the model estimates.

The injury severity model was estimated by using Correlated Random Parameter Generalized Ordered Logit formulation with piecewise linear functions. The empirical analysis was demonstrated by employing active traveler (pedestrian and bicyclist) crash data from Queensland, Australia for the years 2015 through 2020. In the estimated model, several exogenous variables were found to be associated with time-varying effects in the propensity and threshold functions of the generalized ordered logit formulation. In the current study context, these variables (temporal variation - onset; duration) were:

- Female active traveler in the propensity function - (1st quarter 2015; 1st quarter 2015 to 3rd quarter 2016) and (2nd quarter 2019; 2nd quarter 2019 to 1st quarter 2020).
- Active traveler crossing carriageway in the propensity function - (1st quarter 2015; 1st quarter 2015 to 2nd quarter 2016) and (1st quarter 2018; 1st quarter 2018 to 4th quarter 2020).
- Active traveler at-fault in the propensity function - (1st quarter 2019; 1st quarter 2019 to 4th quarter 2019).
- Active traveler at-fault in the threshold function between major and fatal injury - (1st quarter 2016; 1st quarter 2016 to 4th quarter 2016).
- Posted speed limit in the propensity function - (1st quarter 2020; 1st quarter 2020 to 4th quarter 2020).
- Posted speed limit in the threshold function between moderate and major injury - (1st quarter 2015; 1st quarter 2015 to 4th quarter 2015).
- Posted speed limit in the threshold function between major and fatal injury - (1st quarter 2019; 1st quarter 2019 to 2nd quarter 2020).

The results supported our hypothesis that the effect of an exogenous variable might be different within a year, which can be carried over to some part of the next year. On the other hand, some of the years might have the same effect throughout the year. Thus, the results highlighted the importance of examining the disaggregated nature of time-varying effects (onset and duration of time-varying effects) in developing injury severity models, where feasible. Such flexibility in model specification is likely to have significant implications for devising and implementing effective countermeasures since it allows us to understand how road safety landscapes are evolving over time and when a new road safety issue is arising. The model results were further augmented by computing elasticity effects. Elasticity effects showed that the most important variables in terms of increase in fatal injury outcome for active travelers were active travelers under the influence of alcohol, crashes with bus and truck, and elderly active traveler (active traveler age ≥60 years old).

The approach employed in the paper estimates piecewise linear terms to represent the deviations. However, the deviation estimated is reliant on the base variable and the breakpoints are pre-defined. As such, it would be useful to compare the current approach with recently proposed spline approach in Shabab et al. (2024) and Markov Switching approach in Xiong et al. (2014). As demonstrated in this study, capturing finer resolution of temporal variations by quarters can provide detailed insights into the onset and duration of these variations. Future research could consider incorporating seasonal variations (building on the proposed approach in this study) while also isolating long-term trends (adding trend variables, such as linear or quadratic temporal trend variables) from these fluctuations. Further, as the sample share imbalance of the dependent variable across different time periods can result in biased estimates (irrespective of the choice of modeling structure), addressing this could be an avenue for future research. It might be worth examining the performance of ordered and unordered outcome models by using the proposed modeling structure of accommodating for finer resolution of temporal variations (onset and duration of temporal variations).

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