

**A Joint Count and Generalized Ordered Fractional Split Approach for
Addressing Temporal Instability in Road Safety Analysis**

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ABSTRACT

This study addresses temporal instability in multivariate crash frequency models using data from the Greater Orlando Region (2011-2019). We compare the performance of the Joint Negative Binomial-Generalized Ordered Probit Fractional Split (NB-GOPFS) Model with the performance of the Multivariate Mixed Negative Binomial Model with a specific emphasis on parameter temporal variability. The dataset includes four injury severity categories: no injury, minor injury, non-incapacitating injury, and serious injury. The independent variables considered include sociodemographic, land use, and transportation infrastructure variables. Performance assessments using root mean square error (RMSE) values show that the NB-GOPFS model consistently outperforms the Multivariate Mixed Negative Binomial model in accuracy and parsimony. The NB-GOPFS approach enhances prediction accuracy and model simplicity, making it effective for crash frequency modeling with temporal instability in exogenous variables. This study supports the integration of advanced multivariate models in transportation safety analysis to improve intervention strategies and policymaking.

Keywords: Crash severity, Crash frequency, Temporal instability, Unobserved effects, Negative Binomial Generalized Ordered Probit Fractional Split Model.

ACRONYMS

NB – Negative Binomial

GOPFS – Generalized Ordered Probit Fractional Split

NB-GOPFS – Negative Binomial-Generalized Ordered Probit Fractional Split

MNB – Multivariate Negative Binomial

RMSE – Root Mean Square Error

TAZ – Traffic Analysis Zone

AADT – Average Annual Daily Traffic

NMT – Non-Motorized Traffic

FDOT – Florida Department of Transportation

1. INTRODUCTION

1.1 Background and Motivation

Understanding and mitigating road crashes is a priority across transportation safety research. Modeling crash frequency and severity plays a foundational role in identifying key crash contributing factors. To achieve this, researchers have increasingly relied on statistical, econometric, and emerging data driven analytical approaches. These models can assist road safety engineers, public health professionals and policymakers in identifying and implementing interventions that can contribute to minimizing the impact of road crashes. Further, insights acquired from these models have helped create proactive, medium to long-term policy-based actions as well as decision-support systems that address critical safety implications (Yasmin and Eluru, 2018). As these modeling practices have evolved over time, there is growing emphasis on capturing crash outcomes at the finest resolution possible in recent years recognizing that aggregated models may miss important trends. For example, instead of modeling total crash counts, researchers now focus on modeling multiple crash frequency outcomes such as by crash type or severity level to gain more granular insights (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2015, 2019; Bhowmik et al., 2018; Jonathan et al., 2016; Wang et al., 2019). Similarly, within the severity realm, there is growing interest regarding the severity at the body region resolution as opposed to one single severity level for an individual (Kabli et al., 2020, 2023). However, this shift towards greater resolution also introduces a range of methodological, specification and estimation challenges. In particular, considering multiple crash frequency/severity variables for an observation unit increases model complexity, as the number of dependent variables grows with the attributes dimension selected for analysis (such as crash type, severity level, road user group, or vehicle type). A common and straightforward approach to address this is to estimate separate models for each attribute level. In the field of transportation safety, numerous studies have adopted this approach identifying a single count variable for different crash attributes, within a specific spatial unit to investigate the effects of independent variables (Huang et al., 2016; Roshandeh et al., 2016; Shin et al., 2012; Abdel-Aty et al., 2011; Dong et al., 2017; Lee and Mannering, 2002; Lord and Mannering, 2010).

However, these separate model systems ignore that multiple dependent variables for the same observational unit are likely to be correlated (Alogaili and Mannering, 2022; Islam et al., 2020; Mannering et al., 2016). Hence, it is necessary to consider frameworks that can accommodate the presence of common unobserved factors affecting the different dependent variables. In recent years, with advances in modeling and computation, exploring such interrelationships among multiple dependent variables has become more practical and common (Bhowmik et al., 2021; Anastasopoulos and Mannering, 2009; Barua et al., 2014; Lord and Mannering, 2010). Several research efforts examined different crash count factors using multivariate econometric frameworks. These frameworks offer a reliable method for examining the joint dynamics of the linked crash variables (Li et al., 2019; Mannering et al., 2016). These models employ separate propensity equations stitched together through unobserved factors to estimate frequency models (see (Yasmin and Eluru, 2018)). Numerous studies have adopted this approach across different spatial resolutions, with micro level applications focusing on smaller entities such as segments, junctions, or traffic intersections (Aguero-Valverde and Jovanis, 2009; Hosseinpour et al., 2022; Park and Lord, 2007; Roshandeh et al., 2016; Xiong et al., 2014; Ye et al., 2009), and macro-level resolution analyzing larger geographic areas such as districts, census tracts, and traffic analysis zones (TAZs) (Nashad et al., 2016; Song et al., 2006; Zhan et al., 2015). Several techniques including Poisson regression, Negative Binomial, Poisson lognormal models,

conditional autoregressive models, copula-based models, and random parameters zero-inflated negative binomial models have been utilized in these studies to account for both observed and unobserved heterogeneity. Building on these traditional multivariate frameworks, recent studies have also examined alternative approaches that jointly model multiple crash outcomes. One such approach is the use of joint count and fractional split models, where an independent variable can simultaneously influence the propensity of all attribute levels. These frameworks capture interactions across dependent variables through both observed and unobserved factors, offering greater modeling flexibility compared to traditional multivariate systems (Afghari et al., 2020; Bhowmik et al., 2018, 2019; Wang et al., 2021; Yasmin and Eluru, 2018).

While these approaches (both multivariate and joint count-fractional split) effectively address cross-sectional heterogeneity, the increasing availability of multi-year datasets introduces additional modeling challenges. Specifically, they raise concerns about the temporal stability of model parameters, an issue that traditional safety modeling often overlooks. As discussed by Mannering (Mannering, 2018), many conventional models assume that the effect of explanatory variables remains constant over time. However, several factors including changes in driver behavior, roadway characteristics, and technology adoption (e.g., advanced traffic control systems or vehicle automation) can lead to significant shifts in crash frequency and severity profiles. Hence, when multiple instances of data are available, it becomes crucial to assess parameter stability over time and identify any variations (Kabli et al., 2023; Marcoux et al., 2018). When only a limited number of time points are available (like three years), these variations can be tested with manageable complexity. However, as the number of years increases, capturing and characterizing temporal heterogeneity within multivariate models quickly becomes computationally intensive. As a result, recent studies have broadly approached this issue using two strategies: (a) temporal instability identification and (b) temporal instability characterization (see (Shabab et al., 2024) and (Kabli et al., 2023) offer a brief discussion about this categorization).

In the temporal identification category, studies examine if and when temporal stability is violated. This literature is built around comparisons among two types of model specifications: fully constrained models, where parameters are fixed (assumed to be stable) across all time periods; and fully unconstrained models, where parameters are allowed to vary freely by each time period. Specifically, a pooled model assuming temporal stability across all time periods is first estimated (fully constrained) and then the model is compared with a set of time-specific (fully unconstrained) models using a global likelihood-ratio test. If the likelihood-ratio test is not statistically significant, temporal stability is supported and the fully constrained model is retained. If the test is statistically significant, temporal stability is rejected, indicating that at least some parameters vary over time. (see (Alogaili and Mannering, 2022; Islam et al., 2020; Islam and Mannering, 2021; Se et al., 2021, 2022; Song et al., 2020; Tamakloe et al., 2020; Wang et al., 2022b; Zamani et al., 2021)). While the global test indicates whether temporal instability exists overall, it does not identify between which specific time periods the instability occurs. To address this limitation, several studies employed a *pairwise* likelihood-ratio testing approach to examine temporal instability between any two years by testing whether parameters estimated for one period differ statistically from those of another (see (Al-Bdairi et al., 2020; Alnawmasi and Mannering, 2019; Behnood and Mannering, 2015b, 2019; Dabbour, 2017; Hou et al., 2020, 2022; Hu et al., 2013; Islam et al., 2020; Li et al., 2021; Meng et al., 2021; Pang et al., 2022; Ren and Xu, 2023; Se et al., 2021; Tamakloe et al., 2021; Tirtha et al., 2020; Wang et al., 2019, 2022a; Yan et al., 2021a, 2021b, 2021c, 2022, 2023; Zubaidi et al., 2021)). The approach allows the analyst to determine which of the instance pairs exhibit stability in the set of parameter estimates by time

instance. However, these studies do not offer any details on specific parameter stability. It is quite possible that temporal instability is not uniform across all variables. In practice, some parameters may remain stable over time while others vary. For example, an independent variable impact across multiple time instances (say 5) may vary in many ways. The impact could remain the same for years 1, 2 and 3 and change for years 4 and 5. The partially constrained approach allows the analyst to test all these possibilities by estimating separate models with the relationship embedded.

Recently, a number of studies compared these three model variants (fully constrained, fully unconstrained and partially constrained) and found that partially constrained models tend to outperform the other specifications in most cases. This highlights that not all parameters exhibit the same temporal behavior, with some remaining stable over time while others vary. However, identifying these patterns using the partially constrained approach requires estimating multiple separate models and conducting pairwise likelihood-ratio tests for each possible temporal variation, which can quickly become burdensome as the number of time periods (>4) and independent variables increases (>5) (see (Shabab et al., 2024) for more details).

In the *temporal instability characterization* category, the emphasis goes beyond temporal instability identification. The focus is on parametrically characterizing this instability (*i.e.*, identifying how the parameter varies over time). The approach relies on developing pooled models with carefully crafted interaction variables. Earlier attempts employ the year interaction pooled model where a base year is selected as a reference parameter category and time-period-specific deviations are estimated (Bhowmik et al., 2018, 2022; Yasmin and Eluru, 2013, 2018). Potential variations across years relative to the base can be determined based on t-statistics of the estimated parameters. Because the deviations in parameter impacts are compared with the reference year estimate, the framework does not offer a mechanism to examine whether year-specific deviations, while different relative to the base year are significantly different among themselves (Kabli et al., 2023; Marcoux et al., 2018; Tirtha et al., 2020). Building on this approach, authors (Shabab et al., 2024) proposed the “spline indicator pooled model” that simplified parameterizing temporal instability. Instead of using year-specific dummy variables, spline variables based on the difference between the observation year and a base year are generated to produce a piecewise linear representation over time. By interrelating independent variables with these spline variables, the model captures year-specific deviations in parameter effects. This method facilitates the identification of significant changes in slopes over time, offering a straightforward implementation that enhances the analysis of temporal stability in parameters. The effectiveness of the approach is demonstrated in our recent work (Shabab et al., 2024).

1.2 Study in Context

In this study, we develop a comprehensive and efficient framework for capturing dependencies across multiple dependent variables while accommodating temporal variation in parameter impacts. The traditional multivariate negative binomial models can only accommodate interactions across dependent variables through unobserved factors. The overreliance on unobserved factors is exacerbated in the presence of multiple instances of data. Towards addressing this limitation, we combine two elements from earlier research. We hypothesize that fractional split model systems due to their flexibility in addressing interactions across the dependent variables through observed and unobserved factors are likely to offer significant benefits in temporal stability analysis. Thus, drawing on our earlier work (Shabab et al., 2024; Bhowmik et al., 2021), we incorporate the spline indicator pooled models proposed for temporal stability analysis within a joint count and fractional split model system to build an efficient framework for addressing the impact of observed factors,

unobserved factors and temporal variability. A comprehensive performance comparison between two multivariate models: (a) joint Negative Binomial Ordered Probit Fractional Split model (NB-GOPFS) and (b) multivariate negative binomial model (MNB) - is conducted in the context of temporal instability. The two model systems arise from different mathematical structures. Hence, while we cannot compare them directly through log-likelihood metrics, the two model systems offer the same prediction outcomes. Hence, we can compare model performance using predictive measures such as root mean square error (RMSE). The comparison exercise also accounts for the difference in parameters estimated in each model to evaluate how model performance (i.e., RMSE) varies based on number of parameters. The analysis is conducted using data from the Greater Orlando Region, covering 1,611 Traffic Analysis Zones (TAZs) from 2011 to 2019. These 1,611 TAZs were partitioned into 1,200 TAZs for model estimation and 411 TAZs reserved for validation purposes.

The rest of the paper is organized as follows: The next section provides a detailed description of the dataset while the methodological framework adopted in the analysis is presented in section 3. Model findings are discussed in the fourth section followed by the prediction performance evaluation and the policy implications of the proposed model. Finally, the concluding remarks are summarized in the last section.

2. DATA DESCRIPTION

The analysis utilized crash data from 2011 to 2019, sourced from the Signal Four Analytics (S4A) database, covering 1,611 Traffic Analysis Zones (TAZs) in the Greater Orlando Region. Four categories of injury severity were analyzed: no injury, minor injury, non-incapacitating injury, and serious injury (combining incapacitating and fatal injuries). These categories serve as the dependent variables in the study. **Figure 1** presents a summary of how the mean crash frequency varies by severity and year. The findings show a general increase in mean crash frequency across all severity levels compared to 2011. The first three severity levels show a consistent upward trend throughout the analysis period, while the serious injury category exhibits a fluctuating pattern. The sample of 1,611 TAZs was separated into an estimation sample with 1,200 TAZs and a validation sample of 411 TAZs.

The study examines a broad range of independent variables, including sociodemographic, land use, traffic characteristics and transportation infrastructure characteristics. Sociodemographic data were obtained from the American Community Survey (ACS). Transportation infrastructure variables were processed in ArcGIS using roadway shapefiles from the Florida Department of Transportation (FDOT), and land use variables were derived from high-resolution parcel data provided by the Florida Department of Revenue (FDOR). The independent variables considered in our analysis are summarized in **Table 1**. It is worth noting that the same dataset has also been used in (Shabab et al., 2024); however, the present study differs substantially in both its modeling framework and research objectives.

The reader should note that, due to differences in data collection frequency, not all independent variables are available on an annual basis. As a result, some variables remain constant over the study period. While it would be ideal to compile all variables annually, the focus of temporal instability analysis is on the variation of parameter estimates rather than the variation of the independent variables themselves. Therefore, the lack of temporal variability in some explanatory variables does not affect the validity of the proposed methodology. In fact, examining temporal instability for variables that remain constant over time can provide additional insight into

how their effects evolve due to unobserved factors. The current limitation in data variability can be readily addressed in future applications as more frequent data updates become available.

3. SPLINE APPROACH AND COMPARISON WITH EXISTING METHODS

In this section, we provide a detailed presentation of the proposed spline-based approach for capturing temporal instability. We first lay out the methodological framework adopted in this study, followed by a comparison with existing approaches to highlight the advantages of the proposed method.

3.1 Econometric Framework

We developed a joint Negative Binomial - Generalized Ordered Probit Fractional Split (Bhowmik et al., 2021) while considering four injury severity categories accommodating 9 years of crash data simultaneously. In the following sections, we will provide details of each model component starting with the count model structure (Negative Binomial framework) followed by the fractional split model (Generalized Ordered Probit Fractional Split framework).

Let's assume i ($i = 1, 2, 3, \dots, N$, $N=1,200$) to be the index for the observation unit (TAZs), j ($j = 1, 2, 3, \dots, J$, $J=4$) to be the index for the injury severity category, and t ($t = 1, 2, 3, \dots, T$, $T = 9$) be the index to represent different years of crash data at observation unit i . In this empirical study, the index j may take the values of no injury ($j = 1$), minor injury ($j = 2$), non-incapacitating injury ($j = 3$), and serious injury ($j = 4$) crashes. The equation system for modeling total crash count in the usual NB formulation can be written as:

$$P(c_{i,t}) = \frac{\Gamma(c_{i,t} + \frac{1}{\alpha_t})}{\Gamma(c_{i,t} + 1) \Gamma(\frac{1}{\alpha_t})} \left(\frac{1}{1 + \alpha_t \mu_{i,t}} \right)^{\frac{1}{\alpha_t}} \left(1 - \frac{1}{1 + \alpha_t \mu_{i,t}} \right)^{c_{i,t}} \quad (1)$$

where $c_{i,j,t}$ represents the total crash counts at year t in TAZ i . $P(c_{i,j,t})$ is the probability that TAZ i has $c_{i,j,t}$ number of crashes for year t . $\Gamma(\cdot)$ is the gamma function, α_t is NB over dispersion parameter for the corresponding year t . $\mu_{i,t}$ is the expected number of crashes occurring in TAZ i over a time period for year t . We can express $\mu_{i,t}$ as a function of explanatory variables by using a log-link function as follows in equation:

$$\mu_{i,t} = E(c_{i,t} | x_{i,t}) = \exp((\beta_t + \zeta_{i,t})x_{i,t} + \ln(SG_length_{i,t}) + \eta_{i,t} + \phi_i + \varepsilon_{i,t}) \quad (2)$$

where $x_{i,t}$ is a vector of independent variables associated with TAZ i and year t ; and β_t is a vector of coefficients to be estimated across each year. $\zeta_{i,t}$ is a vector of unobserved factors on crash count propensity associated with total crash counts for TAZ i across year t and its associated zonal characteristics, assumed to be a realization from standard normal distribution: $\zeta_{i,t} \sim N(0, \pi^2)$. $SG_length_{i,t}$ is the total segment length (in mile) in TAZ i for each year t and this variable is used as an offset variable in the Negative Binomial model specification. In our analysis, we explored two levels of unobserved correlation that can simultaneously affect the crash outcomes: first, within each year, the total crash counts and the corresponding crash severities can be correlated which is represented by the term $\eta_{i,t}$; and second, total crash counts across the years can be correlated as same TAZ i is repeated 9 times (9 years), ϕ_i captures such correlations. It is important to note that the $\eta_{i,t}$ can vary across TAZs and hence, the correlation parameter is parameterized as a function of observed attributes as follows:

$$\eta_{i,t} = k_{i,t} s_{i,t} \quad (3)$$

where, $s_{i,t}$ is vector of exogenous variables, and $k_{i,t}$ is a vector of unknown parameters to be estimated (including a constant). Finally, $\varepsilon_{i,t}$ is a random term which follows a gamma distribution with mean 1 and variance σ_t .

In the joint model framework, the modeling of crash proportions by severity levels across different crash types is undertaken using the Generalized Ordered Probit Fractional Split (GOPFS) model. Let's define the $p_{ij,t}$ be the actual proportion of crash severity j at TAZ i across year t which is assumed to be associated with a latent variable $p_{i,t}^*$. The latent variable can be specified as (Yasmin and Eluru, 2018):

$$p_{i,t}^* = (\gamma_t + \rho_{i,t} + \delta_{i,t})z_{i,t} + \eta_{i,t} + \varsigma_i, \quad p_{i,j,t} = j_t \text{ if } \psi_{i,j-1,t} < p_{i,t}^* < \psi_{i,j,t} \quad (4)$$

This latent propensity $p_{i,t}^*$ is mapped to the actual severity proportion categories $p_{i,j,t}$ by the ψ thresholds ($\psi_{i,0,t} = -\infty$ and $\psi_{i,j,t} = \infty$). $z_{i,t}$ is a vector of attributes that influences the propensity associated with crash severity proportions at year t . γ_t is a corresponding vector of mean effects across year t , and $\rho_{i,t}$ is a vector of unobserved factors on severity proportion propensity for site i over year t and its associated characteristics assumed to be a realization from standard normal distribution: $\rho_t \sim N(0, k_t^2)$. $\delta_{i,t}$ is an idiosyncratic random error term assumed to be identically and independently standard normal distributed across observational unit i over year t . $\eta_{i,t}$ generates the correlation between equations for total number of crashes and crash proportions by severity levels for the corresponding year t and TAZ i . Finally, the ς_i represents vector of unobserved effects which will be same across severity proportions in any TAZs over the time period t , thus captures the temporal correlations across the severity proportions.

The basic idea of the GOPFS is to represent the threshold parameters as a linear function of exogenous variables to account for the heterogeneity. Thus, the thresholds are expressed as:

$$\psi_{i,j,t} = fn(v_{i,t}) \quad (5)$$

where, $v_{i,t}$ is a set of exogenous variables (including a constant) associated with j^{th} threshold across year t . Further, to ensure the accepted ordering of observed severity proportions ($-\infty < \psi_{i,1,t} < \psi_{i,2,t} < \dots < \psi_{i,j-1,t} < +\infty$), we use the following parametric form as employed by (Eluru et al., 2008):

$$\psi_{i,j,t} = \psi_{i,j-1,t} + exp((\tau_{j,t} + \theta_{i,j,t}) d_{i,t} + \eta_{i,t} + \varepsilon_i) \quad (6)$$

where, $\tau_{j,t}$ is a vector of parameters to be estimated across year t . $\theta_{i,j,t}$ is another vector of unobserved factors moderating the influence of attributes in $d_{i,t}$ on the severity proportions for TAZ i across year t and injury severity category j . ε_i is a vector of unobserved effects which will be same across the threshold parameters (upper severity categories) in any TAZ over the 9 years period and thus the unobserved heterogeneity across the threshold parameters will be captured. It is noted from equation 4 that $p_{i,j,t}$ is the actual proportion of crash severity j , which is different from the traditional generalized ordered Probit model framework where the dependent variable is an indicator of crash severity level. In order to estimate the generalized order Probit framework with a continuous dependent variable, let's assume (Yasmin and Eluru, 2018):

$$E(p_{i,j,t} | z_{i,t}) = H_{i,j,t}(\gamma_t, \psi_{i,j,t}, \zeta_{i,t}, \eta_{i,t}, \phi_i, \theta_{i,j,t}, \varepsilon_{ij}), \quad 0 \leq H_{i,j,t} \leq 1, \sum_{j=1}^J H_{i,j,t} = 1 \quad (7)$$

Where $H_{i,j,t}$ accounts for the ordered Probit probability ($P_{i,j,t}$) form for the crash severity level j over year t , and it is defined as:

$$P_{i,j,t} = G\{\psi_{i,j,t} - [(\gamma_t + \rho_{i,t} + \delta_{i,t})z_{i,t} + \eta_{i,j,t} + \varsigma_i]\} - G\{\psi_{i,j-1,t} - [(\gamma_t + \rho_{i,t} + \delta_{i,t})z_{i,t} + \eta_{i,j,t} + \varsigma_i]\} \quad (8)$$

where $G(\bullet)$ is the cumulative standard normal distribution. To jointly estimate the Negative Binomial probability function (see equation 1) for total crash counts and the GOPFS probability function (see equation 7), let's define a structure Ω for all vectors (*i.e.* $\zeta, \eta, \phi, \delta, \varsigma, \theta$, and $\mathbf{E}$) that account for unobserved heterogeneity, either in Negative Binomial (NB) or Generalized Ordered Probit Fractional Split (GOPFS) model framework, and $\Omega \sim N(0, (\pi^2, k^2, m^2, n^2, w^2, q^2 \text{ and } r^2))$. The likelihood function of the Joint NB-GOPFS model can be written as:

$$L_i = \int_{\Omega} \prod_{t=1}^T \left[P(c_{i,t}) \right] \times \prod_{j=1}^J (P_{i,j,t})^{\omega_{i,t} p_{i,j,t}} d\Omega \quad (9)$$

where $\omega_{i,t}$ is a dummy indicator where $\omega_{i,t} = 1$ represents TAZ i across year t has at least one crash, otherwise $\omega_{i,t} = 0$. Finally, the log-likelihood function can then be written as:

$$LL = \sum_i \ln(L_{i,t}) \quad (10)$$

All the parameters in the model are estimated by maximizing the logarithmic function LL presented in equation 10. The parameters to be estimated in the model are: $\beta, \zeta, \eta, \phi, k, \gamma, \delta, \varsigma, \tau, \theta$, and $\mathbf{E}$. The Quasi-Monte Carlo simulation approach based on the scrambled Halton sequence is applied to estimate the log-likelihood function, using the GAUSS Matrix Programming Software (Aptech, 2015).

3.2 Comparison with Current Approaches

A key point in understanding the proposed spline-based approach is its interpretation in representing temporal variation. Conceptually, temporal variation can be viewed as a sequence of parameter values observed over time. A simple linear approximation may capture the general trend using a single parameter but cannot fully represent variation across all time points. In contrast, a piecewise representation allows each transition between the time periods to be captured explicitly through incremental changes. This formulation does not approximate the temporal pattern but instead reconstructs it exactly through cumulative deviations. As a result, the spline-based approach subsumes the unconstrained, partially constrained, and fully constrained systems within a unified specification. The system is designed to do this through a structured set of operations on the independent variables. Therefore, this method reflects the full distribution of temporal effects in a computationally efficient manner and provides a systematic way to represent parameter values across time periods without imposing any predetermined functional form.

To illustrate this in a step-by-step process, we conducted a simple empirical demonstration using our dataset. For this exercise, we focused on three years of data and analyzed total crashes using a constant term and a single explanatory variable AADT. With this set up, we estimate the fully unconstrained model and our spline model. For the ‘‘Fully unconstrained model’’, coefficients of the constant and AADT were allowed to vary freely across each year. Next, a ‘‘Spline model’’ was estimated where the constant and AADT were interacted with the three cumulative spline indicators. The spline indicators and their formulation used in this example are shown in Table 2, while the comparison between the fully unconstrained and spline model specifications is presented in Table 3. The second row in Table 3 presents the results for the fully unconstrained model, while the third row presents the results from the spline model, partitioned into two sub-rows. As expected, for the fully unconstrained model, we obtain three constant parameters and three AADT parameters for the three years of data. The spline model achieves the same representation using three indicators for both the constant and AADT. Importantly, both models yield identical log-likelihood (LL) values, demonstrating that the spline formulation is an alternative parameterization of the fully unconstrained model. Now, because the variables differ across the two specifications,

the raw spline parameter estimates do not directly match those of the unconstrained model. However, when the implied year-specific effects are computed, the spline model produces estimates that exactly match the fully unconstrained model parameters for each year. This confirms that the proposed spline framework does not approximate the temporal pattern or impose restrictive assumptions, but instead fully reproduces the unconstrained specification.

While replicating the unconstrained model system, the spline model offers substantial advantages. The spline model identifies through a simple t-statistic which temporal variation parameters are significant. If a particular indicator is insignificant, we can drop this variable easily and re-run the model. As a result, the spline approach avoids the need to estimate a large number of partially constrained model specifications, which is typically required in traditional partially constrained approaches. Specifically, the spline framework identifies the appropriate temporal structure by systematically eliminating insignificant deviation parameters within a single estimation framework. Therefore, the effort required for this process does not increase with the number of years or variables, whereas partially constrained approaches become increasingly complex as these dimensions grow. This computational burden is one reason why many existing studies limit their analysis to a small number of time periods. In contrast, the proposed approach enables the estimation of temporally rich models with multiple variables and extended time horizons. The only additional requirement is the construction of the spline indicator variables prior to model estimation.

Now let us illustrate this flexibility in our example data. The spline deviation parameter associated with the Year 2 AADT specification is statistically insignificant at the 95% confidence level. This immediately indicates that the slope of AADT does not change between Years 1 and 2. In contrast, identifying this same pattern under the partially constrained framework would require conducting multiple parameter equality tests across years. For example, with three years of data, the possible constraint combinations for a variable include $\beta_1 = \beta_2$, $\beta_1 = \beta_3$, $\beta_2 = \beta_3$, and $\beta_1 = \beta_2 = \beta_3$, in addition to the fully unconstrained specification (while assuming the other variables are not altering). Thus, even for a single variable, five alternative specifications would need to be estimated and compared using likelihood-ratio tests. When multiple variables exhibit variation over time, the number of possible combinations increases rapidly because each variable can independently follow any of these temporal structures. In the present illustration, the model contains two parameters that vary across time (the constant and AADT). In principle, both parameters could follow any of the five temporal patterns described above, resulting in up to 25 possible model configurations that may need to be examined to identify the most appropriate specification.

For simplicity and clarity in this demonstration, we keep the constant and over-dispersion term fully unconstrained across years and focus only on testing the possible constraint structures for the AADT coefficient. The results are summarized in Table 4, where log-likelihood (LL) values and corresponding likelihood-ratio (LR) test statistics are reported for each specification. The likelihood-ratio tests show that all partially constrained specifications are statistically worse than the fully unconstrained model at the 95% confidence level. In contrast, the spline framework produces a parsimonious specification by dropping the Year 2 deviation parameter, while still maintaining a model fit that is statistically equivalent to the fully unconstrained model. The procedure described here clearly highlights the superior ability of the spline model system in detecting the deviations over time. Also, the reader will note that the deviation parameter insignificance does not suggest that AADT variable is insignificant, it simply highlights that there

is no additional deviation for AADT variable in Year 2. The coefficient still has a net effect through the base parameter and the cumulative spline structure.

In short, the spline-based method provides an efficient and effective improvement over the traditional partially constrained approach because the temporal evolution of parameters can be evaluated directly through the statistical significance of the deviation parameters within a single model estimation. This avoids the need to estimate and compare multiple equality-constrained models; in fact, all possible combinations are rarely tested due to the associated computational burden. Overall, the spline-based framework offers a flexible and scalable approach for temporal instability analysis and can serve as a practical alternative to both unconstrained and partially constrained models.

4 EMPIRICAL ANALYSIS

As discussed earlier, we estimated two model systems: (a) joint Negative Binomial-Generalized Ordered Probit Fractional Split model (NB-GOPFS) and (b) Multivariate Negative Binomial model (MNB). For ease of presentation, we will only focus on NB-GOPFS model results (see Appendix Table A1 for the result of MNB model). Multiple parameter-specific deviations are gradually introduced using the spline indicator variable. The results are discussed by each component, starting with the crash count component, followed by the severity proportion component.

4.1 Crash Count Component

Table 5 presents the temporal variation of the exogenous variable's impact on the total crash likelihood (NB component of the NB-GOPFS model). In the context of a base year (e.g., 2011), we established slopes representing the impact of a particular variable on total crash propensity. Subsequently, we calculated the change in slopes for the successive year (e.g., comparing 2016 to 2015, 2017 to 2016, and so on). These variations in slopes help identify whether the influence of the variable fluctuates significantly over time or remains relatively consistent. Statistically significant variations suggest temporal variation of the variable's impact across different years. For example, Average Annual Daily Traffic (AADT) had a positive effect on crash occurrence in 2011 and remained stable until 2012. In 2013, there was a significant downward shift in AADT effect on total crash likelihood, thus highlighting the temporal fluctuation, which remained stable throughout the subsequent years (2013 to 2019, **Table 5**). Using these base-deviations, we can estimate the net effect of each variable across the years. For AADT the slope in 2011 was found to be 0.0835 and, hence, the impact would be 0.0835 in 2011. In 2012, there was no deviation found relative to 2011 and therefore, the net effect of AADT on total crash counts in 2012 would be $0.0835 \times 2 = 0.167$. Now, a negative deviation (-0.0868) was found for AADT effect in 2013 and hence, the net effect would be: $0.0835 \times 3 - 0.0868 \times 1 = 0.1637$. There is no significant temporal effect found after 2013; therefore, the calculations will be similar to 2013 for the subsequent years. For example, in 2014, the net effect of AADT would be $0.0835 \times 4 - 0.0868 \times 2 = 0.1604$, while in 2019, the net effect would be $0.0835 \times 9 - 0.0868 \times 7 = 0.1439$. The net effect of all the significant variables for the model was calculated using the abovementioned approach. **Table 6** represents the net effect of estimation results throughout the years for the NB component of the NB-GOPFS model. For the ease of presentation, the estimation results for the count component are discussed by variable groups in the subsequent sections.

4.1.1 Roadway Characteristics

The parameter associated with arterial and divided roads offers a positive impact on crash count propensity indicating an increased incidence of traffic crashes in zones with higher proportion of arterial and divided roads (Bhowmik et al., 2021). Additionally, the results show significant variation in the effects over the years as indicated in **Table 5**. The impact of arterial roads fluctuated significantly until 2014, after which the effect becomes relatively stable. For divided roads, the results show three variations for the effect over the study period. Further, the estimated results show that higher number of intersections in a zone results in higher likelihood of traffic crashes, an expected result as intersections typically increase the potential for vehicle conflicts due to the high frequency of turning movements (Retting et al., 2011). Interestingly, we found no temporal variability in the impact of intersections on total crash propensity over the years.

4.1.2 Traffic Characteristics

The coefficients associated with traffic characteristics offer expected results. Zonal AADT is positively associated with traffic crashes, indicating a higher likelihood of crashes in zones with increased AADT (Satria et al., 2021; Veeramisti et al., 2021). On the other hand, zones with increased exposure to truck volume are likely to experience reduced risk of traffic crashes. Although this result might seem counterintuitive at first glance, the presence of more trucks on the road may promote more cautious behavior among drivers, making the effect understandable. In terms of temporal variations, both these variables show two fluctuations during the study period.

4.1.3 Land-Use Characteristics

With respect to land-use attributes, several factors significantly influence the crash count component. Specifically, the findings indicate that a higher proportion of residential and office areas within a zone correlates with an increased likelihood of traffic crashes (Parsa et al., 2020). Further, from **Table 5**, we observe that the parameter related to residential areas remains consistent over the years, while the impact of office areas shows minor fluctuations throughout the study period. However, an interesting observation arises when we focus on the results regarding the proportion of institutional areas. The trend indicates that for the first two years of the study, the impact of institutional areas on crash count propensity is negative, while from 2013 onwards, a positive association is observed (Wang et al., 2019). This shift can be attributed to changes in urban development and infrastructure that initially decreased crashes but later resulted in higher crash incidence as the factors evolved.

4.1.4 Sociodemographic Characteristics

Among the sociodemographic characteristics, proportion of non-motorists and population density in a zone are found to be strongly associated with increased traffic crash frequencies. In terms of temporal stability, the effect of non-motorists shows no variations over the years, while the variable related to population density shows only one fluctuation in 2012 (Cai et al., 2016).

4.2 Severity Proportion Component

Similar to the count component, we provided two tables representing the base-deviation and the overall net effects of the variables in the severity proportion component (GOPFS model) in **Table 7** and **Table 8** respectively. The results are discussed in the following sections by variable groups.

4.2.1 Roadway Characteristics

The variable specific to arterial road does not show any significant influence on the likelihood of severe crashes until 2013, after which a negative association is observed indicating a reduced likelihood of severe crashes in zones with higher share of arterial roads. In terms of temporal variation, we found the impact of the variable significantly varies till 2016 followed by consistent effect in the subsequent years. Further, we found an effect of arterial road on the threshold value indicating heterogeneity in thresholds across observations. The negative coefficient of this variable on the threshold value underscores the increased proportion of serious (non-incapacitating) injury crashes as the proportion of arterial roads increases (Wang et al., 2019). Additionally, we also found variation of the effect on the threshold value over the years, as indicated in **Table 7**. Similar to arterial roads, the proportion of divided roads is also found to be positively associated with crash severity proportions from 2014 onwards, with two temporal variations observed.

The results regarding the number of intersections offer intriguing trends. In some instances, we observe a positive association suggesting an increased proportion of severe crashes with higher number of intersections while in other years, a negative trend is found indicating a reduced likelihood of severe crashes with more intersections in a zone. The results seem counterintuitive at first glance. However, intersections are inherently risky due to increased conflict points and complex traffic movements, which explains the positive impact on severe crashes. Conversely, a higher number of intersections may also indicate a congested environment with more stops, leading to lower operating speeds and, consequently, reduced crash severities. Further, speed limit (serves as a proxy for vehicular speed) is one of the most crucial variables and consistent with previous research, we also found a positive association between average speed limit in a zone and the proportion of severe crashes. The negative impact of the variable on the threshold value further reflects the higher propensity for increased severe crash proportion with increased average speed limit in a zone (Milton and Mannering, 1998). In terms of temporal variation, we observe two fluctuations for the speed limit variable while no variation is found for the variable on the threshold value.

4.2.2 Traffic Characteristics

With respect to traffic characteristics, AADT in a zone is found to have a negative impact on crash severity outcome suggesting a reduced likelihood of severe crash proportions in zones with increased traffic volume. Interestingly, we found four distinct variations in the impact of AADT variables over the study period, as evidenced in **Table 7**. In addition to AADT, proportion of heavy vehicles is also found to significantly influence the zonal level crash severity proportions with a fluctuating (6 variations) positive impact over the years. This is likely due to the greater mass and momentum of heavy vehicles, which can lead to more serious consequences in the event of a crash. We also found a positive impact of the variable on the threshold value demarcating the possible and non-incapacitating injury proportion suggesting a higher probability of non-incapacitating injuries with increased share of heavy vehicles in the zone (Veeramisti et al., 2021).

4.2.3 Land Use Attributes

The findings regarding the land use related variables show that crash severity proportions are negatively associated with increased share of office and institutional areas. While the parameter specific to institutional areas remains consistent throughout the years, only one variation is observed in the impact of the office area variable. The stable effect of office area on the threshold values further indicates the lower likelihood of severe crashes in zones with higher office areas.

4.2.4 Sociodemographic Characteristics

With respect to socio-demographic characteristics, several variables are considered among which only number of non-motorists and population density have significant impact on the crash severity outcome. Both these variables reveal a negative association with crash severity proportions, with only one variation in their effects observed over the years (see **Table 7**). Finally, we found a consistent positive impact of population density on the threshold value between non-incapacitating and severe injury indicating a further lower probability of severe crashes in zones with higher population density, a result also observed in earlier studies (Cai et al., 2016; Chen and Zhou, 2016).

4.2.5 Unobserved Heterogeneity

As previously discussed, the study considered two levels of correlations: (1) common unobserved factors influencing total crash counts and the corresponding crash severity proportions simultaneously in any given year, and (2) common unobserved factors affecting over the study period analyzed in the study for both count and severity components. For the first level, we found a significant and consistent correlation between the count and severity components during the first three years, and this correlation indicates a persistent relationship between the total number of crashes and their severity proportions in these initial years. With respect to temporal correlation, the results show one correlation parameter particularly for the no injury crash proportions.

4.3 Predictive Performance Evaluation

The number of parameters in the NB-GOPFS model is 69 while the number of parameters in the final MNB models is 129. It is not surprising that NB-GOPFS model has fewer parameters (it has been documented in other studies (see for example Yasmin et al., 2016)). To illustrate the comparison between NB-GOPFS and MNB models, we evaluate the predictive performance of the models by calculating the root mean square error (RMSE) values (see (Bhowmik et al., 2019b)). RMSE metric quantifies the error associated with model predictions and the model with lower RMSE values represents a model's ability to closely match the observed data. The comparison was made for all four severity levels and the total number of crashes over a 9-year period. This assessment was conducted on both the estimation sample consisting of 10,800 records from 1,200 TAZs ($1,200 \times 9 \text{ years} = 10,800$) and the holdout sample comprising 3,699 records from 411 TAZs ($411 \times 9 \text{ years} = 3,699$ records). **Figure 2** and **Figure 3** present the RMSE comparison results of the NB-GOPFS and MNB models for estimation and validation sample respectively, by severity level. As is evident from the figures, we can observe that the NB-GOPFS model outperforms the traditional MNB models across most of the measures computed (67 out of 72). A similar trend is also observed for the total number of crashes, which is presented in the appendix (Figure A1). The results clearly highlight the superior performance of the NB-GOPFS model with improved prediction accuracy for temporal datasets. The results are particularly impressive given the difference in the number of parameters across the two systems.

A further examination of model performance was conducted by evaluating how well the models perform across various population sub-groups. This analysis specifically focused on different attribute levels including income, land use mix, proportion of divided roads, proportion of urban areas, heavy vehicle percentage, proportion of non-motorized vehicles, population density, and traffic signal density. For these variables, the performance of the models (RMSE comparison) was compared for two specific crash severities: No Injury and Serious Injury crashes. **Figure 4** provides a detailed comparison of the predicted performance between the MNB and NB-

GOPFS models for two severity levels across the different subgroups (low, medium, and high) considered. For these subgroups, we calculate a relative ratio by comparing the RMSE value of the proposed NB-GOPFS model to that the RMSE value of the MNB model. This ratio serves as an indicator of model accuracy, with the benchmark threshold set at 1. A ratio above the benchmark indicates the inferior performance of the NB-GOPFS model, while a ratio below the benchmark indicates superior performance of the NB-GOPFS model. A ratio close to 1 will indicate that the two models offer similar predictive accuracy.

Two important observations can be made from the figure. First, for No Injury crashes, the NB-GOPFS model consistently demonstrates superior predictive performance across all subgroups, as indicated by ratios under 1 in **Figure 4**. Specifically, out of 24 measures, only four exceed 0.9, with none surpassing 0.95, reaffirming the model's robustness in this category. Second, the trend is quite similar for serious Injury crashes as well, with the NB-GOPFS model generally showing superior performance. While the ratios are slightly higher compared to no injury crashes (eight exceeding 0.9 and one close to 1), none surpasses the benchmark, further reinforcing the model predictive capability. In summary, out of 48 measures, the proposed NB-GOPFS model provides better predictive performance in 98% of cases (47 measures), showcasing its reliability and superiority over the traditional MNB model in accurately predicting crash severities across diverse population subgroups.

4.4 Policy and Behavioral Implications

The findings of this study have important implications for both safety policy and behavioral interventions. The results demonstrate that temporal instability is not uniform across variables, with some factors exhibiting stable effects over time while others show meaningful temporal variation. This indicates that changes in crash outcomes are not always driven by changes in infrastructure or exposure alone, but may also reflect evolving driver behavior, enforcement practices, or other unobserved factors. For example, the number of intersections in a zone may remain the same in two consecutive years, and overall traffic exposure may also be similar. However, crash frequency and severity can still differ across those years due to changes in features available across the vehicle fleet. In one year, access to better vehicle features may reduce risky movements at intersections compared to vehicle movements in the previous year and contribute to fewer crashes at the same locations. Such vehicle or other behavioral factors, however, are typically not directly observed or available to the analyst. So, in this case, the infrastructure does not change, but its safety impact does change over time, due to the unobserved factors.

From a policy perspective, this distinction is very critical. For variables with stable effects, policymakers can be more confident that traditional countermeasures will continue to perform as expected over time. For variables with temporally varying effects, the results signal that static, one-size-fits-all interventions may be insufficient. Instead, agencies may need to complement infrastructure-based solutions with adaptive strategies such as changes in signal timing, enforcement practices, speed management, or targeted safety campaigns that respond to evolving conditions. By distinguishing between stable and time-varying effects, the proposed modeling framework provides actionable insights to better align safety interventions with changing conditions.

5 CONCLUSION

This study develops a comprehensive and efficient econometric framework tailored for the analysis of crash data with multiple dependent variables over time by combining two elements

from prior research. First, we employ the Joint Negative Binomial-Generalized Ordered Probit Fractional Split (NB-GOPFS) to study multiple dependent variables. The framework enhances traditional multivariate approaches for multiple dependent variables by allowing for observed and unobserved interactions across dependent variables. Second, we draw on the spline pooled modeling approach to quantitatively characterize the nature of temporal variation in independent variable effects. We compare the performance of our proposed NB-GOPFS model with spline variables with the Multivariate Negative Binomial (MNB) model with spline variables. The analysis is conducted utilizing crash data from the Greater Orlando Region between 2011 and 2019 for four injury severity categories while considering a comprehensive set of exogenous variables including roadway, traffic, land-use and sociodemographic characteristics.

The model estimation results reveal different temporal variability trends across various independent variables. We observe that some variables exhibit multiple fluctuations over the analysis period while others show little to no variation at all over the study period. The results clearly highlight the effectiveness of the proposed model system in addressing temporal variability comprehensively and efficiently. As opposed to testing a large number of model systems, the proposed approach characterizes temporal heterogeneity in an efficient and parsimonious manner. The superior model performance was also confirmed through a predictive exercise comparing RMSE values for the proposed model and the MNB model. The comparative analysis is further augmented by evaluating the models' effectiveness across a range of demographic and geographic sub-groups, income levels, land use mix, the proportion of divided roads, urban area coverage, heavy vehicle traffic, non-motorized vehicle presence, population density, and traffic signal density. The estimated results further reinforce the improved performance of the NB-GOPFS model over the MNB model in our empirical context. It is particularly noteworthy that the proposed model system outperforms the traditional multivariate approach with significantly fewer parameters highlighting that the proposed model is potentially reflecting the multivariate data generation process more closely.

In conclusion, this study underscores the necessity of considering temporal instability in crash frequency models and demonstrates the practical benefits of using the NB-GOPFS model with spline variables for more precise and actionable insights in transportation safety. Future research should continue to refine these models and explore their applications in various geographic and temporal contexts to further advance the field of traffic safety analysis. At the same time, it is important to interpret the observed temporal variations with appropriate caution, particularly when drawing variable-specific policy implications. In our model development process, every effort was made to explore the impact of different observed and unobserved factors on the dependent variable. However, the reader would note that it is not possible to eliminate the impact of unobserved or omitted variables on the various estimated model parameters. Hence, it is always prudent to consider the temporal variability from this perspective. While these variations are observed specific to an independent variable, it is possible that they serve as proxy variables to different unobserved/omitted variables in the model. Addressing this challenge is far from straightforward in empirical datasets. There might be some possible approaches to address this using simulated crash data in future research.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Naveen Eluru, Tanmoy Bhowmik, Kazi Redwan Shabab; data collection: Kazi Redwan Shabab, Tanmoy Bhowmik; model estimation and validation: Kazi Redwan Shabab, Tanmoy Bhowmik, Naveen Eluru; analysis and interpretation of results: Kazi Redwan Shabab, Tanmoy Bhowmik, Naveen Eluru, Mohamed H. Zaki; draft manuscript preparation: Kazi Redwan Shabab, Tanmoy Bhowmik, Naveen Eluru, Mohamed H. Zaki. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION of COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DECLARATION OF GENERATIVE AI in SCIENTIFIC WRITING

The authors declare that they have not used generative AI while writing this paper.

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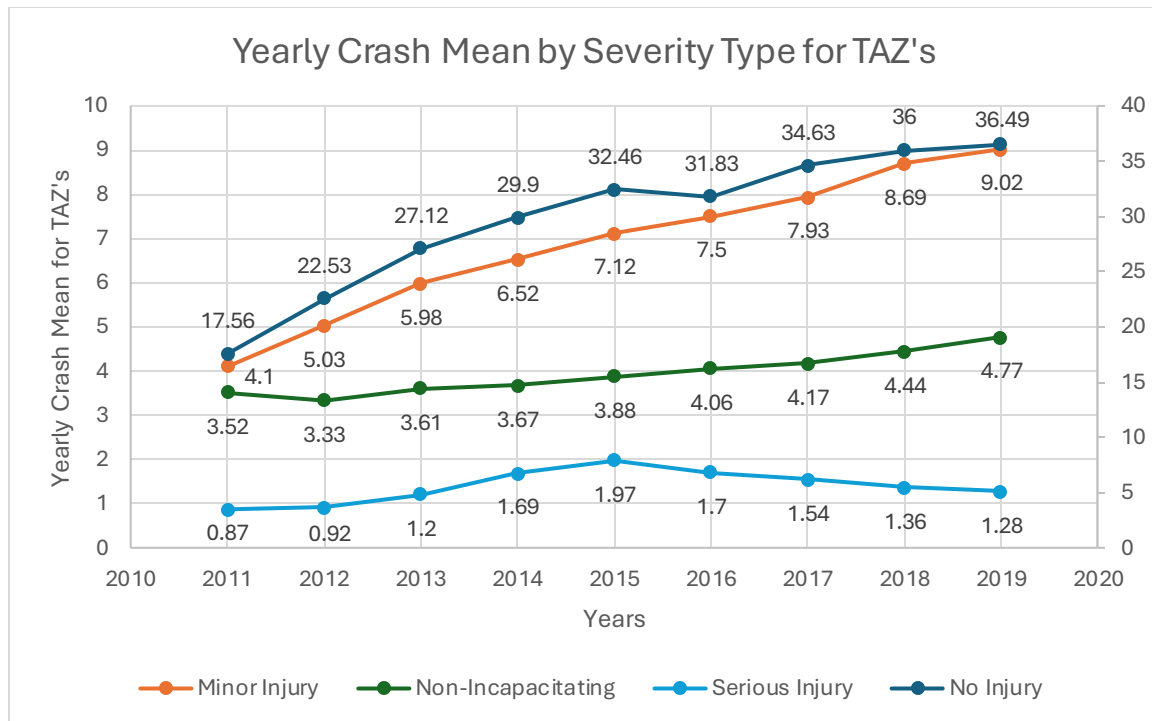


Figure 1: Yearly Crash Mean by Severity Type for 1,611 TAZs

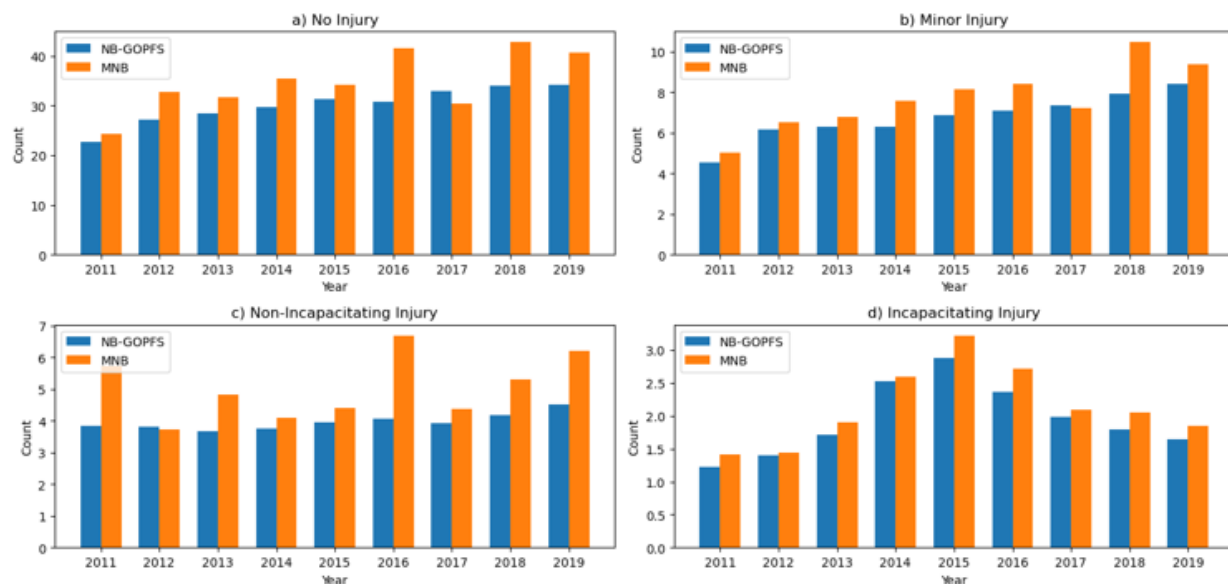


Figure 2: Prediction Comparison of NB-GOPFS and MNB Models (Estimation Sample)

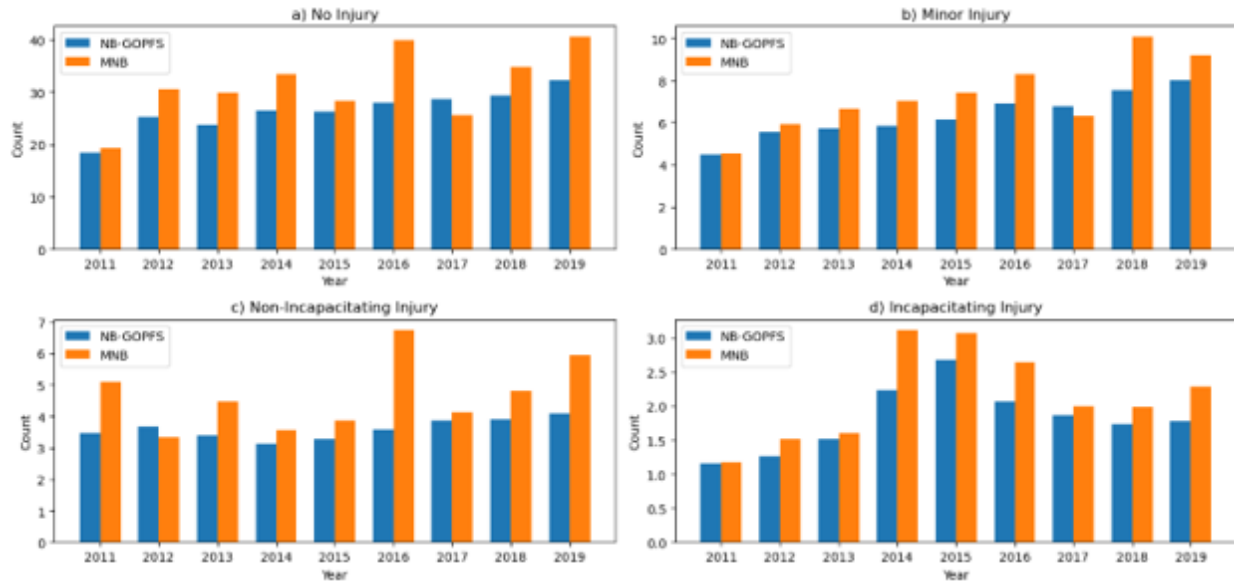


Figure 3: Prediction Comparison of NB-GOPFS and MNB Models (Validation Sample)

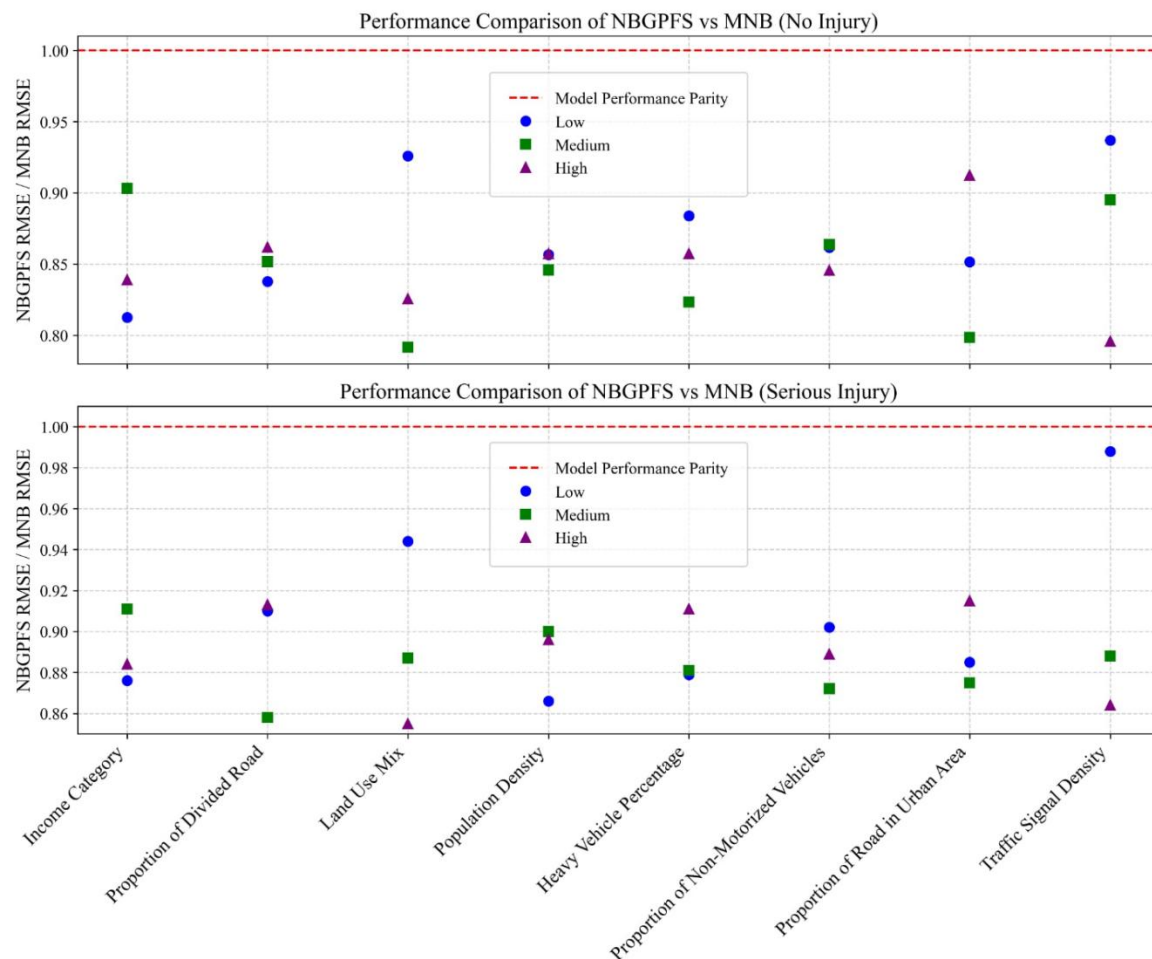


Figure 4: Root Mean Square Error (RMSE) ratio between NB-GOPFS and MNB for no injury and serious injury crashes

Table 1: Summary Statistics of Exogenous Variables (Zonal Level)

Variable Names (N=1,611)	Description	Min	Max	Mean	Standard Deviation
Segment Length	TAZ Segment Length in Miles	0.011	3.8427	0.8711	0.5430
Roadway Characteristics (<i>Source: Florida Department of Transportation</i>)					
Proportion of urban road	Urban Road Length in TAZ/Total Road Length in TAZ	0.000	1.000	0.092	0.272
Proportion of rural road	Rural Road Length in TAZ / Total Road Length in TAZ	0.000	1.000	0.867	0.326
Proportion of arterial road	Arterial Road Length in TAZ / Total Road Length in TAZ	0.000	1.000	0.385	0.376
Proportion of collector road	Collector Road Length in TAZ /Total Road Length in TAZ	0.000	1.000	0.455	0.383
Proportion of Freeway	Freeway Length in TAZ / Total Road Length in TAZ	0.000	1.000	0.088	0.214
Proportion of local road	Local Road Length in TAZ / Total Road Length in TAZ	0.000	1.000	0.030	0.119
Proportion of divided road	Ln (Divided Road Length in TAZ)	0.000	1.000	0.483	0.350
Intersection Density	Ln (Traffic Intersection Number in TAZ)	0.000	4.234	2.010	1.063
Average speed	Ln (Average Speed of major roads in TAZ)	0.000	4.248	3.487	0.968
Speed greater than 55 mph	Road Length with Speed>55 mph in TAZ /Total TAZ Road length	0.000	1.000	0.196	0.324
Signal Density	Ln (Traffic Signal Number in TAZ)	0.000	2.079	0.155	0.382
Proportion of poor pavement	Poor Pavement Length in TAZ /Total Pavement Length in TAZ	0.000	1.000	0.066	0.200
Traffic Characteristics (<i>Source: the Florida Department of Transportation</i>)					
Average annual daily traffic	Ln (AADT)	0.000	12.859	8.559	2.820
Percentage of heavy vehicle	(Truck AADT/AADT) * 100	0.000	40.197	7.539	5.340
Land Use Attributes (<i>Source: Florida Department of Revenue</i>)					
Proportion of industrial land	Industrial land area in TAZ /Total land area in TAZ	0.000	0.928	0.037	0.103
Proportion of institutional land	Institutional land area in TAZ /Total land area in TAZ	0.000	0.754	0.027	0.059
Proportion of recreational land	Recreational land area in TAZ /Total land area in TAZ	0.000	0.992	0.013	0.064
Proportion of residential land	Residential land area in TAZ /Total land area in TAZ	0.000	1.000	0.362	0.281
Proportion of retail land	Retail land area in TAZ /Total land area in TAZ	0.000	1.000	0.128	0.198
Land use mix	Land use mix = $\left[\frac{-\sum_k (p_k \ln p_k)}{\ln N} \right]$, where k is the category of land-use, p is the proportion of the developed land area for specific land-use, N is the number of land-use categories	0.000	0.900	0.366	0.152

Sociodemographic Characteristics (<i>Source: American Community Survey</i>)*					
Population density	TAZ Population Count/ Total area of TAZ in acre	0.009	24.637	3.210	2.785
Employment density	Total Employed Count in TAZ/Total area of TAZ in acre	0.004	13.599	1.720	1.594
Income	Ln (Average TAZ income)	4.098	11.859	8.770	1.262
Non-motorized commuter	Proportion of non-motorized commuter in TAZ	0.000	13.242	0.424	0.823

*Note: Sociodemographic variables were obtained from ACS 5-year Census tract estimates. For each analysis year, the corresponding ACS 5-year estimate available for that year was used and joined to the crash data. We have added this clarification as a note in Table 1.

Table 2: Construction of Cumulative Spline Indicators for Temporal Modeling

<i>Year</i>	<i>Indicator 1</i>	<i>Indicator 2</i>	<i>Indicator 3</i>
Year 1	1	0	0
Year 2	2	1	0
Year 3	3	2	1

Table 3: Comparison of Fully Unconstrained and Full Spline Model Specifications

Model		Constant			AADT			Log-Likelihood
		Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	
<i>Fully unconstrained model</i>		2.345	1.508	1.226	0.122	0.215	0.255	-15651.96
<i>Spline model (full specification)</i>	Raw Parameter	2.345	-3.182	0.555	0.122	-0.029	-0.053	-15651.96
	Implied Year-Specific Effects	2.345	$2.345*2 - 3.182 = 1.508$	$2.345*3 - 3.182*2 + 0.555 = 1.226$	0.122	0.215	0.255	

Table 4: Comparison of Partially Constrained Models and Final Spline Specification

Model	Condition	Log-Likelihood	LL ratio value (decision)
Partially Constrained Model	All AADT effect are different (unconstrained model)	-15651.96 (9 parameters)	Base Model
	AADT effect in year 1 and 2 is equal, year 3 is different	-15655.87(8 parameters)	7.82 (Reject)
	AADT effect in year 1 and 3 is equal, year 2 is different	-15700.93(8 parameters)	97.94 (Reject)
	AADT effect in year 2 and 3 is equal, year 1 is different	-15681.55(8 parameters)	59.18 (Reject)
	All AADT effect are equal	-15714.49 (7 parameters)	125.06 (Reject)
Final Spline model	Year 2 AADT effect is insignificant, so dropped it	-15653.452 (8 parameters)	2.984 (accept)

Table 5: NB-GOPFS Model Results with Base Effect of Propensity of Exogenous Variables (Negative Binomial Component)

Variable Descriptions	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant	0.8344**	-1.3193**	0.5893***						
Roadway Characteristics									
Proportion of arterial road	0.4802**	-0.8297**	0.6232**	-0.3120**					
Proportion of divided road	0.4444**	-0.5745***		0.1395**					
ln(Intersection)	0.0184**								
Traffic Characteristics									
ln(AADT)	0.0835**		-0.0868**						
Proportion of Truck AADT	-0.0398**	0.0428**							
Land Use Characteristics									
Proportion of residential area	0.0627**								
Proportion of office area	1.0924***		-1.1241**						
Proportion of institutional area	-0.7181**	1.1790***				-0.5469**			
Socio-Demographic Characteristics									
Proportion of NMT	0.0169**								
Population density	0.1153**	-0.1224**							
Overdispersion Parameter	0.3520**			-0.4588**					

Notes: * indicates 90% confidence, ** 95% confidence, and *** 99% confidence.

Table 6: NB-GOPFS Model Results with Net Effect of Propensity of Exogenous Variables (Negative Binomial Component)

Variable Descriptions	2011	2012	2013	2014	2015	2016	2017	2018	2019
Segment Length	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Constant	0.834	0.350	0.454	0.558	0.663	0.767	0.872	0.976	1.080
Roadway Characteristics									
Proportion of arterial road	0.480	0.131	0.404	0.366	0.328	0.290	0.251	0.213	0.175
Proportion of divided road	0.444	0.314	0.324	0.333	0.343	0.352	0.361	0.371	0.380
ln(Intersection)	-0.018	-0.037	-0.055	-0.074	-0.092	-0.110	-0.129	-0.147	-0.166
Traffic Characteristics									
ln(AADT)	0.084	0.167	0.164	0.160	0.157	0.154	0.151	0.147	0.144
Proportion of Truck AADT	-0.040	-0.037	-0.034	-0.031	-0.028	-0.025	-0.022	-0.019	-0.016
Land-Use Characteristics									
Proportion of residential area	0.063	0.125	0.188	0.251	0.314	0.376	0.439	0.502	0.564
Proportion of office area	1.092	2.185	2.153	2.121	2.090	2.058	2.026	1.995	1.963
Proportion of institutional area	-0.718	-0.257	0.204	0.665	1.126	1.040	0.954	0.868	0.782
Socio-Demographic Characteristics									
Proportion of NMT	0.017	0.034	0.051	0.068	0.085	0.101	0.118	0.135	0.152
Population density	0.115	0.108	0.101	0.094	0.087	0.080	0.073	0.066	0.059
Overdispersion Parameter	0.352	0.704	1.056	0.949	0.842	0.736	0.629	0.522	0.415

Table 7: NB-GOPFS Model Results with Base and Deviation Effect (Generalized Ordered Probit Fractional Split Component)

Variable Descriptions	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant									
Threshold 1	0.3915**	-0.2787***		-0.1142**					
Threshold 2	-0.6452*	0.6419**							
Threshold 3	--	-0.2043**			0.1593**				
Roadway Characteristics									
Proportion of arterial road	--	--		-0.0488**	0.0984**	-0.0628***			
Possible and non-incapacitating injury	--	--		-0.0492*		0.0986**			
Proportion of divided road	--	--		-0.0184**					0.0894*
ln(Intersection)	0.0344*	-0.0462***				0.0183**			
ln(Average Speed)	0.0353**			-0.0390***					
Non-incapacitating and severe injury	-0.0263**		0.0265						
Traffic Characteristics									
ln(AADT)	-0.0281*	0.0319***					-0.0157**	0.0135**	
Proportion of heavy vehicle	0.0167*	-0.0285**		0.0124**		-0.0078***	0.0170**	-0.0134**	
Possible and non-incapacitating injury	-0.0108**	0.0125**							
Land Use Attributes									
Proportion of office area	-0.0579**					0.0785***			
Possible and non-incapacitating injury	0.0162***								
Proportion of Institutional Area	--	-0.0607**							
Sociodemographic Characteristics									
Proportion of non-motorized traffic	-0.0174**	0.0190**							
Population Density	--	-0.0175***		0.0185**					
Non-incapacitating and severe injury	--	0.0022**							
Unobserved Heterogeneity									
Count and severity correlation	0.2732**			--					
Temporal Correlation	0.0563**								

Notes: * indicates 90% confidence, ** 95% confidence, and *** 99% confidence.

Table 8: NB-GOPFS Model Results with Net Effect (Generalized Ordered Probit Fractional Split Component)

Definition	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant									
Threshold 1	0.392	0.504	0.503	0.502	0.500	0.499	0.497	0.496	0.495
Threshold 2	-0.645	-0.649	-0.652	-0.655	-0.658	-0.662	-0.665	-0.668	-0.672
Threshold 3	0.000	-0.204	-0.409	-0.454	-0.499	-0.544	-0.589	-0.634	-0.679
Roadway Characteristics									
Proportion of arterial road	0.000	0.000	-0.049	0.001	-0.012	-0.026	-0.039	-0.052	-0.065
Possible and non-incapacitating injury	0.000	0.000	0.000	-0.049	-0.098	-0.049	0.000	0.050	0.099
Proportion of divided road	0.000	0.000	-0.034	-0.068	-0.102	-0.069	-0.037	-0.004	0.029
ln(Intersection)	0.034	0.023	0.011	-0.001	-0.013	-0.006	0.000	0.007	0.013
ln(Average Speed)	0.035	0.071	0.067	0.063	0.060	0.056	0.052	0.048	0.045
Non-incapacitating and severe injury	-0.026	-0.053	-0.052	-0.052	-0.052	-0.052	-0.052	-0.051	-0.051
Traffic Characteristics									
ln(AADT)	-0.028	-0.024	-0.021	-0.017	-0.013	-0.009	-0.021	-0.019	-0.018
Proportion of heavy vehicle	0.017	0.005	0.006	0.006	0.007	-0.001	0.009	0.006	0.002
Possible and non-incapacitating injury	-0.011	-0.009	-0.007	-0.006	-0.004	-0.002	-0.001	0.001	0.003
Land Use Attributes									
Proportion of office area	-0.058	-0.116	-0.174	-0.232	-0.290	-0.269	-0.248	-0.228	-0.207
Possible and non-incapacitating injury	0.016	0.032	0.049	0.065	0.081	0.097	0.113	0.130	0.146
Proportion of Institutional Area	0.000	-0.061	-0.121	-0.182	-0.243	-0.304	-0.364	-0.425	-0.486
Sociodemographic Characteristics									
Proportion of non-motorized traffic	-0.017	-0.016	-0.014	-0.013	-0.011	-0.009	-0.008	-0.006	-0.005
Population Density	0.000	-0.018	-0.017	-0.016	-0.015	-0.014	-0.013	-0.012	-0.011
Non-incapacitating and severe injury	0.000	0.002	0.004	0.007	0.009	0.011	0.013	0.015	0.018
Unobserved Heterogeneity									
Count and severity correlation	0.273			--					
Temporal Correlation	0.056								

Appendix**Table A1: Multivariate Negative Binomial (MNB) Model Results with Base and Deviation Effect**

Definition	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant									
No Injury	0.383**	-0.555*	0.250**						
Minor Injury	-1.181**	1.204*	0.060***						
Non-Incapacitating	-0.841**	0.880**							
Serious Injury	-2.194*	2.132**	0.302*			-0.398**			
Roadway Characteristics									
Proportion of arterial road									
No Injury	0.370**	-0.561**	0.311**	-0.139***					
Minor Injury	0.326**	-0.517**	0.326**	-0.175**			0.071**		
Non-Incapacitating	0.413**	-0.600**	0.192***						
Serious Injury	0.332**	-0.587*	0.655**	-0.404***		-0.140**			0.276*
Proportion of divided road									
No Injury	0.343**	-0.399**		0.058***					
Minor Injury	0.234**		-0.538*	0.320**					
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Intersection density									
No Injury	--	-0.056*	0.062**			-0.071*	0.060**		
Minor Injury	0.033**	-0.085*	0.036**						
Non-Incapacitating	-0.014								
Serious Injury	--	--	--	--	--	--	--	--	--
Average speed									
No Injury	-0.032**					0.031*		-0.020**	
Minor Injury	--	--	-0.110**	0.105**					
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Traffic Characteristics									

Average Annual Daily Traffic									
No Injury	0.081*			-0.076**					
Minor Injury	0.049**				-0.047***				
Non-Incapacitating	0.046**	0.060**	-0.103***			-0.003**			
Serious Injury	0.035**		-0.075**	0.074*	-0.047**			0.036**	
Percentage of heavy vehicles									
No Injury	-0.036*	0.039**							
Minor Injury	-0.019**	0.020**			0.006*	-0.004**			
Non-Incapacitating	-0.007**				0.010**				
Serious Injury	-0.002**		0.015**	-0.044*	0.028**		0.048**	-0.058**	
Land Use Attributes									
Proportion of retail area									
No Injury	1.623**	-1.123*	-0.518**						
Minor Injury	1.709*	-1.709**							
Non-Incapacitating	1.294**	-1.267**							
Serious Injury	0.584**		-0.651**						
Proportion of residential area									
No Injury	0.107**					-0.102*			
Minor Injury	0.053**								
Non-Incapacitating	0.196**	-0.169**							
Serious Injury	--	--	--	--	--	--	--	--	--
Proportion of institutional area									
No Injury	-0.472**	0.722**							
Minor Injury	--	0.359**			-0.335***				
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Sociodemographic Characteristics									
TAZ population density									
No Injury	0.104**	-0.109***							
Minor Injury	0.122**	-0.163*	0.053**		-0.022**				

Non-Incapacitating	0.074**	-0.075***							
Serious Injury	0.088**	-0.119*	0.044**			-0.026**			
Proportion of NMT									
No Injury	0.064**	-0.061**							
Minor Injury	0.056*	-0.067**				0.021**			
Non-Incapacitating	0.046**	-0.045**							
Serious Injury	--	--	--	--	--	--	--	--	--
Overdispersion Parameter									
No Injury	0.960*	-1.161*	0.200**						
Minor Injury	0.574*	-0.582**							
Non-Incapacitating	0.477**	-0.480**							
Serious Injury	0.699**	-0.699**							
Unobserved Heterogeneity									
Severity specific correlations	0.475**				0.583*				0.442**
Temporal Interactions									
Non-Incapacitating	0.419**								
Serious Injury	0.357**								

Notes: * indicates 90% confidence, ** 95% confidence, and *** 99% confidence

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Average Annual Daily Traffic									
No Injury	0.081	0.161	0.166	0.171	0.176	0.181	0.186	0.190	0.195
Minor Injury	0.049	0.098	0.147	0.149	0.151	0.154	0.156	0.158	0.160
Non-Incapacitating	0.046	0.151	0.154	0.156	0.156	0.155	0.155	0.155	0.155
Serious Injury	0.035	0.069	0.029	0.063	0.049	0.036	0.022	0.045	0.067
Percentage of heavy vehicles									
No Injury	-0.036	-0.034	-0.031	-0.029	-0.026	-0.024	-0.021	-0.019	-0.016
Minor Injury	-0.019	-0.019	-0.019	-0.019	-0.013	-0.011	-0.010	-0.008	-0.007
Non-Incapacitating	-0.007	-0.015	-0.022	-0.030	-0.027	-0.024	-0.022	-0.019	-0.017
Serious Injury	-0.002	-0.004	0.009	-0.022	-0.025	-0.028	0.017	0.003	-0.010
Land Use Attributes									
The proportion of retail area									
No Injury	1.623	2.124	2.107	2.090	2.072	2.055	2.038	2.020	2.003
Minor Injury	1.709	1.709	1.709	1.709	1.709	1.709	1.709	1.709	1.709
Non-Incapacitating	1.294	1.322	1.349	1.377	1.404	1.432	1.459	1.487	1.514
Serious Injury	0.584	1.167	1.099	1.031	0.963	0.895	0.828	0.760	0.692
The proportion of residential area									
No Injury	0.107	0.214	0.322	0.429	0.536	0.541	0.547	0.552	0.558
Minor Injury	0.053	0.105	0.158	0.210	0.263	0.315	0.368	0.420	0.473
Non-Incapacitating	0.196	0.224	0.252	0.280	0.308	0.335	0.363	0.391	0.419
Serious Injury	--	--	--	--	--	--	--	--	--
The proportion of institutional area									
No Injury	-0.472	-0.222	0.029	0.279	0.529	0.779	1.030	1.280	1.530
Minor Injury	--	0.359	0.718	0.743	0.768	0.793	0.817	0.842	0.867
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Sociodemographic Characteristics									
TAZ population density									
No Injury	0.104	0.098	0.093	0.088	0.082	0.077	0.071	0.066	0.061
Minor Injury	0.122	0.082	0.095	0.107	0.098	0.088	0.078	0.069	0.059

Non-Incapacitating	0.074	0.073	0.073	0.072	0.071	0.071	0.070	0.069	0.068
Serious Injury	0.088	0.056	0.069	0.081	0.069	0.056	0.043	0.030	0.017
Proportion of NMT									
No Injury	0.064	0.068	0.071	0.074	0.078	0.081	0.085	0.088	0.091
Minor Injury	0.056	0.044	0.033	0.021	0.030	0.039	0.048	0.057	0.066
Non-Incapacitating	0.046	0.046	0.046	0.047	0.047	0.047	0.047	0.048	0.048
Serious Injury	--	--	--	--	--	--	--	--	--
Overdispersion Parameter									
No Injury	0.960	0.759	0.759	0.759	0.758	0.758	0.758	0.757	0.757
Minor Injury	0.574	0.566	0.557	0.549	0.541	0.532	0.524	0.516	0.507
Non-Incapacitating	0.477	0.475	0.473	0.470	0.468	0.466	0.464	0.461	0.459
Serious Injury	0.699	0.700	0.700	0.701	0.701	0.702	0.702	0.703	0.703
Unobserved Heterogeneity									
Severity specific correlations	0.475				0.583				0.442
Temporal Correlations									
Non-Incapacitating	0.419								
Serious Injury	0.357								

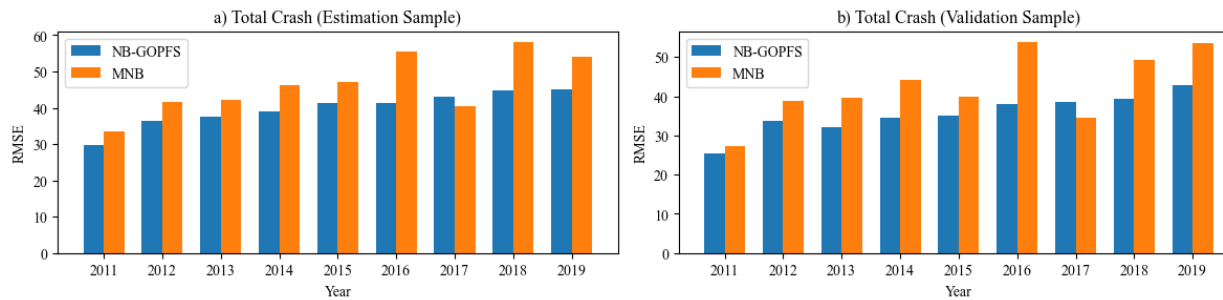


Figure A1: Prediction Comparison of NB-GOPFS and MNB Models (Total Crash)