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A SYSTEMATIC UNIFIED APPROACH FOR ADDRESSING TEMPORAL INSTABILITY IN ROAD SAFETY ANALYSIS

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ABSTRACT
Multivariate models are widely employed for crash frequency analysis in traffic safety literature. In the context of analyzing data for multiple instances (such as years), it becomes essential to evaluate the stability of parameters over time. The current research proposes a novel approach, labelled the mixed spline indicator pooled model, that offers significant enhancement relative to current approaches employed for capturing temporal instability. The proposed approach entails carefully creating independent variables that allow us to measure parameter slope changes over time and can be easily integrated into existing methodological frameworks. The current research effort compares four multivariate model systems: year specific negative binomial model, year indicator pooled model, spline indicator pooled model, and mixed spline indicator pooled model. The model performance is compared using log-likelihood and Bayesian Information Criterion. The empirical analysis is conducted using the Traffic Analysis Zone (TAZ) level crash severity records from Central Florida for the years from 2011 to 2019. The comparison results indicate that the proposed mixed spline indicator pooled model outperforms the other models providing superior data fit while optimizing the number of parameters. The proposed mixed spline model can allow a piece-wise linear functional form for the parameter and is suitable to forecast crashes for future years as illustrated in our predictive performance analysis.

Keyword: Crash severity, Crash frequency, Temporal instability, Unobserved effects, Mixed Spline Pooled Negative Binomial Model.

1. BACKGROUND

1.1 Motivation

Crash frequency models are employed in road safety literature to identify the factors affecting crash occurrence. These frequency models are developed either at the microscopic level (such as intersection and segment) or the macroscopic level (such as county and Traffic Analysis Zone (TAZ)). Earlier research efforts focused on employing a single dependent variable – total number of crashes – to study crash occurrence using univariate count regression models such as Poisson, Negative Binomial, and Poisson Log-Normal models (Anastasopoulos & Mannering, 2009; Barua et al., 2014; Bhowmik et al., 2018; Cai et al., 2018; Chiou et al., 2014; Lord & Mannering, 2010; Yasmin & Eluru, 2018). The univariate model systems were enhanced by incorporating the influence of unobserved factors on crash frequency via different random parameter univariate models (Huo et al., 2020; Z. Li et al., 2019; Venkataraman et al., 2013). In recent years, there is growing recognition that focusing on a single dependent variable can potentially mask the variation in the crash frequency variable due to different attributes such as severity, crash type, and crash location. The recognition has resulted in the consideration of crash frequency by attribute levels – resulting in multiple crash frequency variables. While separate univariate models can be employed to study these crash frequency variables, it is more appropriate to develop a multivariate model that recognizes that the different crash frequency variables for an observation are likely to be closely affected by several common unobserved attributes (Behnood & Mannering, 2015; Bhowmik et al., 2022; Malyshkina & Mannering, 2009; Mannering et al., 2016; Yasmin et al., 2014; Yasmin & Eluru, 2013). The different frameworks employed for modeling multiple crash frequency variables in a joint framework include multivariate Poisson, multivariate Negative Binomial model, multivariate Poisson Log-Normal model, joint crash frequency and fractional split model systems (Negative Binomial Ordered Fractional Split model and Negative Binomial Multinomial Fractional Split model) (Bhowmik et al., 2018; Lee et al., 2014; Yasmin & Eluru, 2018; Ye et al., 2013). The aforementioned multivariate frameworks are well equipped to address the impact of observed and unobserved factors across the multiple dependent variables for a single instance of data (such as a single year). With increasing availability of data for multiple instances (such as multiple years), there are emerging challenges to employ these multivariate frameworks. As discussed in Mannering, 2018, traditional approaches to safety implicitly assume that the impact of independent variables are stable over time in crash frequency and severity models. However, driver behavior changes influenced by cognitive biases, attitudes and personal experience over time might contribute to a changing crash frequency and severity profiles (Mannering, 2018). Thus, when data for multiple instances is available, it would be important to evaluate if parameters are stable over time and identify procedures that can pinpoint the variation (if any). As the dimensions of the dependent variables increase substantially (with data instances >3), accommodating for the potential parameter space of common unobserved factors is far from straight forward.

The existing solutions employed to tackle these challenges associated with data from multiple instances in safety literature can be organized into two categories (see (Kabli et al., 2023) for a brief discussion on this categorization). *In the first category*, studies employ a pooled model assuming temporal stability across all instances and then compare the pooled model's fit with instance-specific models' fit using an appropriate likelihood-ratio test (see (Alogaili & Mannering, 2022; Islam et al., 2020; Islam & Mannering, 2021; Se et al., 2021a, 2022; Song et al., 2020; Tamakloe et al., 2020; C. Wang et al., 2022b; Zamani et al., 2021)). This approach circumvents the dimensionality challenges by estimating models at the extremes of the temporal spectrum. The pooled model treats the data as being generated in a single instance while the instance specific model avoids any need for interaction across instances. However, the instance specific model results in the highest numbers of parameters as every parameter is implicitly assumed to be temporally unstable. The comparison in this approach simply tests if temporal stability exists or not; the approach cannot identify which parameters exhibit a statistically discernible difference over time.

A second approach employs a "pairwise" test to investigate the temporal instability between any two years by examining whether the parameters estimated from one subgroup are statistically different from another (see Al-Bdairi et al., 2020; Alnawmasi & Mannering, 2019; Behnood & Mannering, 2019, 2015; Dabbour, 2017; Hou et al., 2020, 2022; Hu et al., 2013; Islam et al., 2020; Y. Li et al., 2021; Meng et al., 2021; Pang et al., 2022a, 2022b; Ren & Xu, 2023; Se et al., 2021b; Tamakloe et al., 2021; Tirtha et al., 2020; C. Wang et al., 2022a; K. Wang et al., 2019; Yan et al., 2021c, 2021a, 2021b, 2022, 2023a, 2023b; Yu et al., 2021; Zubaidi et al., 2021). The approach relative to the first category of studies offers additional information on which of the instance pairs exhibit stability in terms of parameters. However, even in this approach, the stability is compared for the entire set of variables. Thus, there is no information available on specific parameter stability. Thus, while instance specific models from these two approaches accommodate for temporal instability accurately, they do not identify variables that are temporally unstable and fail to provide a process for employing these models into the future.

Recently, Alnawmasi and Mannering, 2023 and Dzinyela et al., 2024 have proposed approaches to address this limitation. In these studies, the authors employ approaches to compare three variants of the models: (a) unconstrained models, (b) constrained models, and (c) partially constrained models. The approach compares two models using the log-likelihood ratio test to identify the more suited form of temporal stability based on data fit. The approach, while very easy to implement, requires the estimation of separate models and pair-wise test statistics for each individual temporal parameter variation possibility. The number of possible models to be estimated can become very large in scenarios with several temporal instances (>4) and independent variables (>5). For example, to test for all possible temporal variations for a single independent variable with 10 years of data, the full set of models to be developed will be of the order of 2^{10} (see explanation note in the Appendix). When we need to do this simultaneously for several independent variables, the number can be even larger. To be sure, estimating these models is not complicated. It simply would require us to develop an algorithmic approach to carefully test each possibility for temporal variation prior to concluding that an exhaustive test has been conducted. A for loop-based routine in Python or R should be able to generate all the requisite test scores for analysis given adequate time is invested.

1.2 Study in Context

In recent research efforts by Eluru and colleagues, a framework has been proposed to assess the stability of each parameter across temporal periods – labelled year interaction pooled model. This approach involves pooling the data into a unified data frame, selecting a base year as reference, and estimating deviations across multiple time periods. By incorporating this base and deviation approach into the equations, researchers can assess the significance of the deviation for each parameter. If the deviation is found to be statistically significant, it indicates that the variable has a distinct effect in the corresponding year relative to the base year. By analyzing the significance of deviations, researchers can determine when and how certain variables exhibit temporal variability. In the worst-case scenario, the number of parameters required will remain the same as the traditional approach while in the best-case scenario, the proposed framework can significantly reduce the number of parameters (D*X). The approach has been employed in several research efforts and has shown significant reduction in parameters needed relative to single year-based models (see (Kabli et al., 2023; Marcoux et al., 2018; Tirtha et al., 2020)).

However, the pooled approach employed so far has one significant limitation. In the approach, the deviations in parameter impacts are compared with the reference year. However, this does not provide an easy way to examine if year specific deviations across years might be significantly different relative to the base year but yet not different among themselves. For example, the impact of AADT might be different for 2014 and 2015 relative to 2009. However, the approach does not allow us to easily evaluate if we can employ a single parameter to represent the difference from 2014 and 2015. A statistical test will need to be added to test this accurately. The testing of such effects across several pairs (or multiples) will be tedious and resource intensive.

Year	AADT	$Year_1$	$Year_2$	$Year_3$	$Year_4$	$Year_1$* AADT	$Year_2$* AADT	$Year_3$* AADT	$Year_4$* AADT
2018	200	1	0	0	0	200	0	0	0
2019	325	2	1	0	0	650	325	0	0
2020	150	3	2	1	0	450	300	150	0
2021	330	4	3	2	1	1320	990	660	330

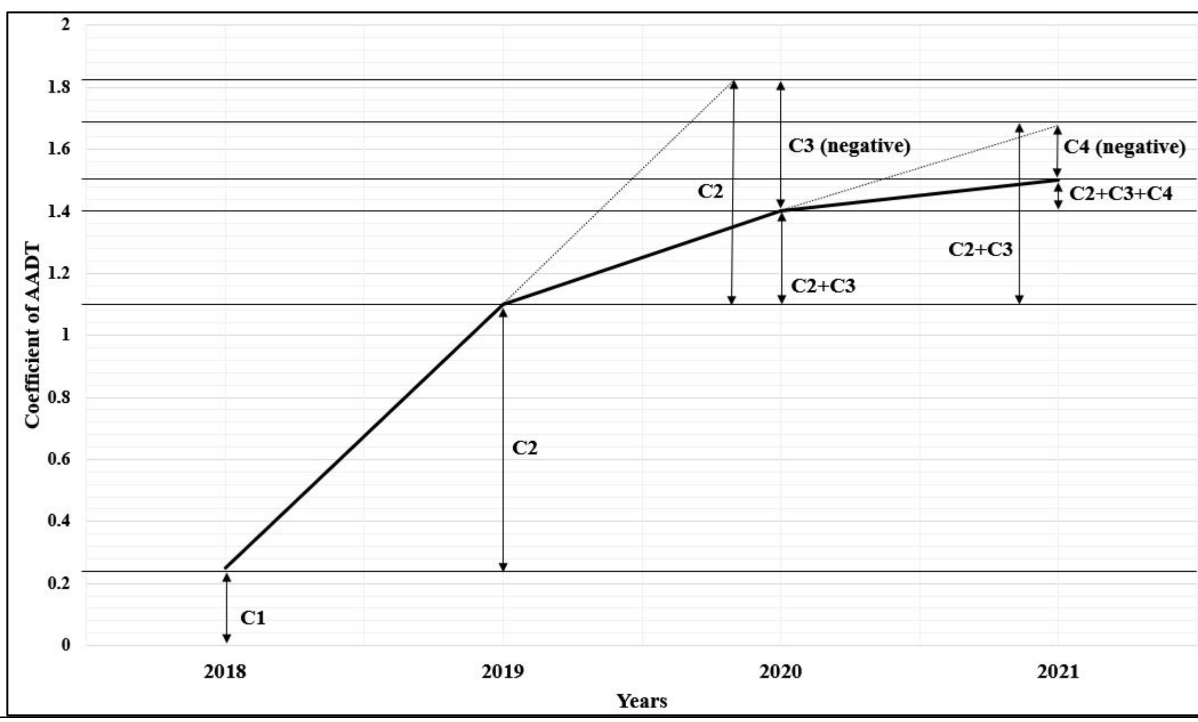


Figure 1. Year Specific Variable Creation and Spline Formulation Method

In our research, we propose a novel approach that builds on the pooled data approach while also making it easier to evaluate differences across parameters. The new approach labelled the spline indicator pooled model, utilizes the same pooling approach discussed earlier, but instead of creating year-specific dummies, we adopt the spline approach to creating temporal variations. In this approach, as opposed to creating year specific dummy variables, we create time variables using the following approach:

$Year_1 = Max(Year_{record} – Year_{base}, 0);$

$Year_2 = Max(Year_{record} – Year_{base} -1,0);$

…

$Year_N = Max(Year_{record} – Year_{base} –(N-1),0)$

where $Year_{record}$ corresponds to year of the observation, and $Year_{base}$ corresponds to the year of data prior to the first year used for analysis. The approach will yield the same number of variables as the year dummy approach (N variables). In the model estimation effort, the independent variable is interacted with the newly created year variables to estimate temporal effects. The proposed approach effectively serves as a piecewise linear formulation for each parameter over the years.

The spline variables allow for easy identification of the real changes in slope over time for the different variables. These variables are used directly to get year specific variations. These variables can be interacted with any independent variable to test the temporal stability of that variable. The advantage of these variables is illustrated in Figure 1 (see (Eluru & Gayah, 2022) for another example). Figure *1* presents an example with four time periods (2018, 2019, 2020 and 2021). $Year_{base}$ in the example will be 2017. The Year specific variables created are shown on the top and their impact on propensity are presented on the bottom of Figure *1*. We can see that the four years provide four degrees of freedom for estimation represented as C1, C2, C3 and C4. C1 serves as the base variable impact and the spline variables provide the year specific deviations as 2019 – C2, 2020 – C3 and 2021 – C4. If any of the year specific parameters are insignificant then the deviation for that year is 0. The approach is quite straightforward to implement and only requires the creation of additional independent variables.

Further, the proposed approach allows us to generate a relationship of how parameters vary over time. This linearized relationship will allow us to generate potential values of the parameters for future years. Thus, the proposed model system enables us to develop future forecasts while allowing temporal variation. The current approaches are geared toward estimating the temporal variation without offering any information on future parameter variation. The methodological frameworks currently employed in research or practice can easily incorporate these variables. The current research effort compares four model multivariate model systems: (a) year specific negative binomial (YSNB), (b) year indicator pooled model and (c) spline indicator pooled model and (d) mixed spline indicator pooled model. The model performance is compared using log-likelihood and Bayesian Information Criterion. The modeling exercise is conducted using the Traffic Analysis Zone (TAZ) level crash records from four counties of Central Florida for the years 2011 to 2019 considering a comprehensive set of exogenous variables.

The remainder of the paper is structured as follows: The methodological framework used in the study is presented in the second section, and the dataset is thoroughly described in the third section. The fourth section covers the interpretation of the model results, and the last section contains some concluding remarks.

2 ECONOMETRIC FRAMEWORK

We consider four injury severity categories (no injury, minor injury, non-incapacitating injury, and serious injury crashes). Thus, in estimating Multivariate Panel Mixed NB model, we examine four different Panel NB models considering 9 years of crash data for four different injury severity types simultaneously. In this section, we briefly provide details of the model frameworks employed in our study.

Let's assume i $(i = 1,2,3, \ldots N, N = 1,200)$ be an index to represent observation unit (TAZs); j j $(j = 1,2,3, \ldots J, J = 4)$ be an index for different crash severity levels and t $(t = 1,2,3, \ldots T, T = 9)$ 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. Using these notations, the equation system for modeling crash count across crash severities j and different years t in the usual NB formulation can be written in equation 1 as:

$$P(c_{ij,t}) = \frac{\Gamma\left(c_{ij,t} + \frac{1}{\alpha_{j,t}}\right)}{\Gamma(c_{ij,t}+1)\Gamma\left(\frac{1}{\alpha_{j,t}}\right)} \left(\frac{1}{1+\alpha_{j,t}\mu_{ij,t}}\right)^{\frac{1}{\alpha_{j,t}}} \left(1 - \frac{1}{1+\alpha_{j,t}\mu_{ij,t}}\right)^{c_{ij,t}} \tag{1}$$

where, $c_{ij,t}$ be the index for crash counts specific crash severity level j and year t occurring over a period of time in TAZ i. $P(c_{ij,t})$ is the probability that TAZ i has $c_{ij,t}$ number of crashes specific to crash severity j for year t. $\Gamma(\cdot)$ is the gamma function, $\alpha_{j,t}$ is NB over dispersion parameter for the corresponding severity level j and year t . $\mu_{ij,t}$ is the expected number of crashes for crash severity level j occurring in TAZ i over a given time period for year t. We can express $\mu_{ij,t}$ as a function of explanatory variables by using a log-link function as follows in equation 2:

$$\mu_{ij,t} = E(c_{ij,t}|z_{ij,t}) = exp((\delta_{j,t} + \zeta_{ij,t})z_{i,t} + ln(SG\_length_{i,t}) + \eta_{it} + \phi_{ij} + \varepsilon_{ij,t}) \tag{2}$$

where, $z_{i,t}$ is a vector of explanatory variables associated with TAZ i for the year t. $SG\_length_{i,t}$ 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 NB model specification. $\delta_{j,t}$ is a vector of coefficients to be estimated for each severity level across each year. $\zeta_{ij,t}$ is a vector of unobserved factors on crash count propensity associated with injury severity type j for TAZ i and its associated zonal characteristics, assumed to be a realization from standard normal distribution: $\zeta_{ij,t} \sim N(0, \pi^2)$. In our current analysis, there are two levels of unobserved factors that can simultaneously impact the number of crashes for different severity levels over the nine years period: 1) within TAZ i and year t, crashes of different severity levels could be correlated; η_{it} captures such correlations and 2) for same severity level j, crashes can be correlated across the years as same TAZ i is repeated 9 times (9 years); ϕ_{ij}captures such correlations. Finally, $\varepsilon_{ij,t}$ is a gamma distributed error term with mean 1 and variance $\alpha_{j,t}$.

Here, it is important to note that the two unobserved heterogeneities that impact different crash levels (over the severities and over the years) can vary across TAZs. Therefore, in the current study, the correlation parameters η_{it} and ϕ_{ij} are parametrized as a function of observed attributes as follows in equation 3 and equation 4 respectively:

$$\eta_{it} = \gamma_{i,t} s_{i,t} \tag{3}$$

$$\phi_{ij} = \text{þ}_{i,j} q_{i,t} \tag{4}$$

where, $s_{i,t}$ and $q_{i,t}$ are vector of exogenous variables, $\gamma_{i,t}$ and $\text{þ}_{i,j}$ are a vector of unknown parameters to be estimated (including a constant). In examining the model structure of crash count across different injury severity types over the years, it is necessary to specify the structure for the unobserved vectors $\zeta, \gamma\ and\ \text{þ}$ represented by Ω. In this paper, it is assumed that these elements are drawn from independent normal distributions: $\Omega \sim N(0, (\pi^2, \sigma^2, \psi^2))$. Thus, conditional on Ω, the likelihood function for the joint probability can be expressed in equation 5 as:

$$L_i = \int_{\Omega} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(P\left(c_{ij,t}\right) \right) f(\Omega) d\Omega \tag{5}$$

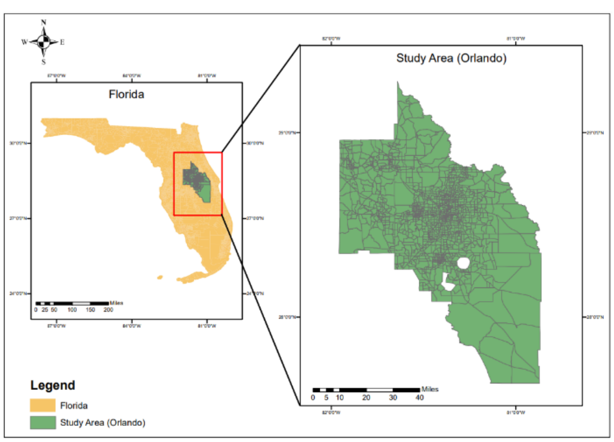
Finally, the log-likelihood function is as follows in equation 6:

$$LL = \sum_i Ln(L_{i,t}) \tag{6}$$

All the parameters in the model are estimated by maximizing the logarithmic function LL presented in equation 6using routines coded in GAUSS Matrix Programming software (Aptech, 2015).

3 DATA DESCRIPTION

The analysis was conducted using crash data from 2011 to 2019 obtained from Signal Four Analytics (S4A) database for the Greater Orlando Region with 1611 Traffic Analysis Zones (TAZs). We used four injury severity categories: no injury, minor injury, non-incapacitating injury, and serious injury (incapacitating injury and fatal injury were combined) as dependent variables for this study. A summary of how crash frequency mean varies by severity and year is provided in Figure *2*. The results indicate an overall increase in mean crash frequency across all severity levels (relative to 2011). While the first three injury severity levels exhibit a monotonic increase in the tie period of analysis, we notice an up and down trend for the serious injury category.



Year	No Injury	Minor Injury	Non-Incapacitating	Serious Injury
2011	17.56	4.10	3.52	0.87
2012	22.53	5.03	3.33	0.92
2013	27.12	5.98	3.61	1.20
2014	29.90	6.52	3.67	1.69
2015	32.46	7.12	3.88	1.97
2016	31.83	7.50	4.06	1.70
2017	34.63	7.93	4.17	1.54
2018	36.00	8.69	4.44	1.36
2019	36.49	9.02	4.77	1.28

Figure 2. Study Area Map and Yearly Crash Mean by Severity Type for 1611 TAZ's

In this study, we consider a wide range of independent variables, such as sociodemographic, land use, and transportation infrastructure characteristics. Sociodemographic variables are sourced from American Community Survey (ACS) data. Transportation infrastructure variables are processed in ArcGIS using roadway shapefiles hosted by the Florida Department of Transportation (FDOT). Land use variables are processed from high-resolution parcel data provided by Florida Department of Revenue (FDOR). The independent variables considered in our analysis are summarized in Table 1.

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

Variable Names (N=1611)	**Description**	**Min**	**Max**	**Mean**	**Standard Deviation**
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
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 Road Length in TAZ	0.000	1.000	0.196	0.324
Intersection Density	Ln (Traffic Intersection Number in TAZ)	0.000	4.234	2.010	1.063
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
Proportion of agricultural land	Agricultural land area in TAZ/Total land area in TAZ	0.000	1.000	0.109	0.219
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 other land	Others land area in TAZ /Total land area in TAZ	0.000	1.000	0.059	0.101
Proportion of public land	Public land area in TAZ /Total land area in TAZ	0.000	1.000	0.066	0.133
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
Proportion of vacant land	Vacant land area in TAZ /Total land area in TAZ	0.000	1.000	0.191	0.188
Proportion of waterbody	Water land area in TAZ /Total land area in TAZ	0.000	1.000	0.009	0.042
Land use mix	Land use mix = $\left[\frac{-\sum_k(p_k(lnp_k))}{lnN}\right]$, 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
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
Average Income	TAZ Average Income/TAZ Employment Number	1.564	6.826	3.179	0.700

Proportion of non-motorized commuter	Proportion of non-motorized commuter in TAZ	0.000	13.242	0.424	0.823
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

The reader would note that the variation over time in independent variables for crash frequency datasets at the macrolevel are likely to be smaller than the variation over time in independent variables for crash severity datasets. In our research analysis, we consider a larger time horizon (10 years) and thus we observed more variability in independent variables (relative to temporal studies with smaller time horizons). In the interest of space, we briefly discuss variations for a subset of the independent variables. The reader will note that the mean and standard deviation values vary differently for different variables over time. For example, for population density, the variable mean varies from 3.01 in 2011 to 3.49 in 2019. Thus, we observe there is substantial variation - 16% over 10 years - in our analysis. We can see similar trends for multiple variables including employment density (a variation of 11%), percentage of heavy vehicles (19%), and proportion of residential land (17%). The reader will also note that some variables in the dataset show smaller variations (less than ±5%). Overall, it is beneficial to examine variations in independent variables prior to developing models.

4 EMPIRICAL ANALYSIS

4.1 Model specification and overall measure of fit

The dimensionality of the dependent variables in our study is 36 (4 severity levels and 9 years). The empirical study involves a series of model estimation from three approaches: 1) traditional model framework where individual Year Specific Negative Binomial model (YSNB) and 2) year indicator pooled negative binomial model (YIPNB), and 3) spline indicator pooled negative binomial model (SIPNB). The three model systems are evaluated based on Bayesian Information Criterion (BIC). BIC (log-likelihood at convergence) values for the three models are: (a.) YSNB model (356 parameters) is 232723.58, (b.) YIPNB model (152 parameters) is 230470.03, and (c.) SIPNB model (122 parameters) is 230406.68. The comparison exercise highlights two important aspects. First, the number of parameters required in pooled models are significantly lower than the year specific models. The difference clearly highlights the parsimonious nature of pooled frameworks employed in our study. Second, the pooled models provide a significantly improved data fit relative to their traditional counterparts (year specific NB models) as indicated by their lower BIC values. Second, within the pooled approaches, the SIPNB model shows considerable improvement in data fit compared to the YIPNB model. Finally, the results highlight how the additional flexibility from the spline model reduces the number of parameters from the year indicator model without a significant drop in data fit.

For the best performing spline model incorporates unobserved heterogeneity along two dimensions: *i)* severity level correlation across each year and *ii)* temporal correlations across severity levels. The BIC (log-likelihood at convergence) for the spline model with unobserved heterogeneity with 131 parameters is 219819.44 (-109301.40). The BIC value is significantly better than the simple spline model. The improvement in model fit highlights the contribution of severity and temporal factor specific unobserved heterogeneity.

4.2 Model Estimation Results

We describe the results of the spline model with unobserved heterogeneity effects. The spline indicator variable introduces several parameter specific deviations over time. Thus, we present our findings through two comprehensive tables each offering valuable insights into the temporal fluctuations as well as the overall effect of the variables on the crash severity components.

In the first table (Table 2), we conduct a comprehensive examination of the temporal fluctuations of each variable's impact on crash severity. For the base year (e.g., 2011), we provide the slopes (coefficient) representing the variable's effect on the corresponding crash severity level. Then, we calculate the deviations in these slopes for each subsequent year (e.g., 2012 compared to 2011, 2013 compared to 2012, and so forth). These deviations allow us to determine whether the influence of each variable varies significantly over time or remains relatively stable. When the deviations are statistically significant, they indicate variations in the variable's effect across different years. For example, consider the effect of proportion of arterial roads estimated in the no injury crash count components over the years. In 2011, we observed a positive impact indicating a rise in no injury crash counts with increased proportion of arterial roads. However, the effect significantly changed over the next three years as indicated by the significant variation in slope for 2012, 2013 and 2014 in Table 2 (a downward shift in 2012 compared to 2011; an upward shift in 2013 compared to 2012 and an again downward shift in 2014 compared to 2013). Interestingly, after 2014, the effect remained remarkably stable, showing no significant fluctuation (2014 to 2019).

The second table (
Table 3) presents the net effect of the variables on different severity components across the years. A positive (negative) sign for a variable in

Table 3 signifies that an increase in the respective variable is likely to result in more (less) motor vehicle crashes for the corresponding crash severity level, specific to that year. For instance, with respect to proportion of arterial roads effect on no injury crash counts, the slope was found to be 0.37 for year 2011 (as presented in Table 2) and hence the overall impact is simply 0.37 for the year 2011. In 2012, the deviation was found to be -0.561 compared to 2011 (Table 2) and therefore, the net effect for 2012 would be: 0.37*2+(-0.561)*1 = 0.179 (please see

Table 3). For 2013, we found another significant deviation of 0.311 relative to year 2012 as indicated in Table 2. So, the net effect of the variable in 2013 would be: 0.370*3+(-0.561)*2+0.311 = 0.299 (see

Table 3). Finally, in 2014, we observed additional deviation from 2013 and hence, the net effect in 2014 would be: 0.370*4+(-0.561)*3+0.311*2-0.139 = 0.288.We did not find any other significant deviation after 2014 and hence, the slopes remained the same as in 2014 for all the other years from 2015. For example, the net effect of the proportion of arterial roads on no injury crash counts in the year 2017 would be: is 0.370*7+(-0. 561)*6+0.311*5-0.139*4 = 0.222.

Table 2: Mixed Spline Indicator Pooled Negative Binomial Model (MSIPNB) Results with Base and Deviation Effect of Each Exogenous Variable

Definition	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant									
No Injury	0.383	-0.555	0.250						

<table>
<tr><td>Minor Injury</td><td>-1.181</td><td>1.204</td><td colspan="7">0.060</td></tr>
<tr><td>Non-Incapacitating</td><td>-0.841</td><td colspan="8">0.880</td></tr>
<tr><td>Serious Injury</td><td>-2.194</td><td>2.132</td><td colspan="3">0.302</td><td colspan="4">-0.398</td></tr>
<tr><td colspan="10">Roadway Characteristics</td></tr>
<tr><td colspan="10">Proportion of arterial road</td></tr>
<tr><td>No Injury</td><td>0.370</td><td>-0.561</td><td>0.311</td><td colspan="6">-0.139</td></tr>
<tr><td>Minor Injury</td><td>0.326</td><td>-0.517</td><td>0.326</td><td colspan="3">-0.175</td><td colspan="3">0.071</td></tr>
<tr><td>Non-Incapacitating</td><td>0.413</td><td>-0.600</td><td colspan="7">0.192</td></tr>
<tr><td>Serious Injury</td><td>0.332</td><td>-0.587</td><td>0.655</td><td colspan="2">-0.404</td><td colspan="3">-0.140</td><td>0.276</td></tr>
<tr><td colspan="10">Proportion of divided road</td></tr>
<tr><td>No Injury</td><td>0.343</td><td colspan="2">-0.399</td><td colspan="6">0.058</td></tr>
<tr><td>Minor Injury</td><td colspan="2">0.234</td><td>-0.538</td><td colspan="6">0.320</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Intersection density</td></tr>
<tr><td>No Injury</td><td>--</td><td>-0.056</td><td colspan="3">0.062</td><td>-0.071</td><td colspan="3">0.060</td></tr>
<tr><td>Minor Injury</td><td>0.033</td><td>-0.085</td><td colspan="7">0.036</td></tr>
<tr><td>Non-Incapacitating</td><td colspan="9">-0.014</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Average speed</td></tr>
<tr><td>No Injury</td><td colspan="5">-0.032</td><td colspan="2">0.031</td><td colspan="2">-0.020</td></tr>
<tr><td>Minor Injury</td><td>--</td><td>--</td><td>-0.110</td><td colspan="6">0.105</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Traffic Characteristics</td></tr>
<tr><td colspan="10">AADT</td></tr>
<tr><td>No Injury</td><td colspan="2">0.081</td><td colspan="7">-0.076</td></tr>
<tr><td>Minor Injury</td><td colspan="3">0.049</td><td colspan="6">-0.047</td></tr>
<tr><td>Non-Incapacitating</td><td>0.046</td><td>0.060</td><td colspan="2">-0.103</td><td colspan="5">-0.003</td></tr>
<tr><td>Serious Injury</td><td colspan="2">0.035</td><td>-0.075</td><td>0.074</td><td colspan="3">-0.047</td><td colspan="2">0.036</td></tr>
<tr><td colspan="10">Percentage of heavy vehicles</td></tr>
<tr><td>No Injury</td><td>-0.036</td><td colspan="8">0.039</td></tr>
<tr><td>Minor Injury</td><td>-0.019</td><td colspan="3">0.020</td><td>0.006</td><td colspan="4">-0.004</td></tr>
<tr><td>Non-Incapacitating</td><td colspan="4">-0.007</td><td colspan="5">0.010</td></tr>
<tr><td>Serious Injury</td><td colspan="2">-0.002</td><td>0.015</td><td>-0.044</td><td colspan="2">0.028</td><td>0.048</td><td colspan="2">-0.058</td></tr>
<tr><td colspan="10">Land Use Attributes</td></tr>
<tr><td colspan="10">Proportion of retail area</td></tr>
<tr><td>No Injury</td><td>1.623</td><td>-1.123</td><td colspan="7">-0.518</td></tr>
<tr><td>Minor Injury</td><td>1.709</td><td colspan="8">-1.709</td></tr>
<tr><td>Non-Incapacitating</td><td>1.294</td><td colspan="8">-1.267</td></tr>
<tr><td>Serious Injury</td><td colspan="2">0.584</td><td colspan="7">-0.651</td></tr>
</table>

<table>
<tr><td colspan="10">Proportion of residential area</td></tr>
<tr><td>No Injury</td><td colspan="5">0.107</td><td colspan="4">-0.102</td></tr>
<tr><td>Minor Injury</td><td colspan="9">0.053</td></tr>
<tr><td>Non-Incapacitating</td><td>0.196</td><td colspan="8">-0.169</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Proportion of institutional area</td></tr>
<tr><td>No Injury</td><td>-0.472</td><td colspan="8">0.722</td></tr>
<tr><td>Minor Injury</td><td>--</td><td colspan="2">0.359</td><td colspan="6">-0.335</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Sociodemographic Characteristics</td></tr>
<tr><td colspan="10">TAZ population density</td></tr>
<tr><td>No Injury</td><td>0.104</td><td colspan="8">-0.109</td></tr>
<tr><td>Minor Injury</td><td>0.122</td><td>-0.163</td><td colspan="2">0.053</td><td colspan="5">-0.022</td></tr>
<tr><td>Non-Incapacitating</td><td>0.074</td><td colspan="8">-0.075</td></tr>
<tr><td>Serious Injury</td><td>0.088</td><td>-0.119</td><td colspan="2">0.044</td><td colspan="5">-0.026</td></tr>
<tr><td colspan="10">Proportion of NMT</td></tr>
<tr><td>No Injury</td><td>0.064</td><td colspan="8">-0.061</td></tr>
<tr><td>Minor Injury</td><td>0.056</td><td colspan="3">-0.067</td><td colspan="5">0.021</td></tr>
<tr><td>Non-Incapacitating</td><td>0.046</td><td colspan="8">-0.045</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Overdispersion Parameter</td></tr>
<tr><td>No Injury</td><td>0.960</td><td>-1.161</td><td colspan="7">0.200</td></tr>
<tr><td>Minor Injury</td><td>0.574</td><td colspan="8">-0.582</td></tr>
<tr><td>Non-Incapacitating</td><td>0.477</td><td colspan="8">-0.480</td></tr>
<tr><td>Serious Injury</td><td>0.699</td><td colspan="8">-0.699</td></tr>
<tr><td colspan="10">Unobserved Heterogeneity</td></tr>
<tr><td>Severity specific correlations</td><td colspan="4">0.475</td><td colspan="4">0.583</td><td>0.442</td></tr>
<tr><td colspan="10">Temporal Interactions</td></tr>
<tr><td>Non-Incapacitating</td><td colspan="9">0.419</td></tr>
<tr><td>Serious Injury</td><td colspan="9">0.357</td></tr>
</table>

Table 3: MSIPNB Model Results with Net Effect of Each Exogenous Variable

Definition	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Constant									
No Injury	0.383	0.211	0.288	0.366	0.443	0.521	0.598	0.676	0.753
Minor Injury	-1.181	-1.159	-1.076	-0.994	-0.912	-0.829	-0.747	-0.665	-0.583
Non-Incapacitating	-0.841	-0.803	-0.764	-0.726	-0.687	-0.648	-0.610	-0.571	-0.533
Serious Injury	-2.194	-2.256	-2.016	-1.776	-1.537	-1.695	-1.854	-2.013	-2.172
Roadway Characteristics									

The proportion of arterial road									
No Injury	0.370	0.179	0.299	0.280	0.261	0.241	0.222	0.203	0.183
Minor Injury	0.326	0.134	0.269	0.229	0.189	0.149	0.180	0.211	0.242
Non-Incapacitating	0.413	0.225	0.230	0.234	0.238	0.242	0.247	0.251	0.255
Serious Injury	0.332	0.077	0.477	0.473	0.469	0.324	0.180	0.035	0.167
The proportion of divided road									
No Injury	0.343	0.287	0.231	0.233	0.236	0.238	0.240	0.242	0.244
Minor Injury	0.234	0.469	0.166	0.182	0.198	0.215	0.231	0.248	0.264
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Intersection density									
No Injury	--	-0.056	-0.051	-0.046	-0.041	-0.107	-0.113	-0.118	-0.124
Minor Injury	0.033	-0.019	-0.036	-0.052	-0.069	-0.085	-0.102	-0.118	-0.135
Non-Incapacitating	-0.014	-0.028	-0.042	-0.056	-0.070	-0.083	-0.097	-0.111	-0.125
Serious Injury	--	--	--	--	--	--	--	--	--
Average speed									
No Injury	-0.032	-0.063	-0.095	-0.126	-0.158	-0.158	-0.159	-0.179	-0.200
Minor Injury	--	--	-0.110	-0.116	-0.122	-0.127	-0.133	-0.138	-0.144
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Traffic Characteristics									
AADT									
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								

4.2.1 <u>Roadway Characteristics</u>

With respect to roadway characteristics, our analysis revealed a consistent positive impact (as indicated in

Table 3) associated with the proportion of arterial road variables, indicating a higher risk of crashes in zones with an increased proportion of arterial roads, across all severity levels (Bhowmik et al., 2021a). Further, the model results also highlight the significant fluctuation of the effect across the years, particularly for minor and serious injury counts, indicative of the varying effects of arterials roads on the corresponding crash severity risks. Interestingly, for the other two injury severity levels, we observe some variability in arterial roads effect until 2014 after which the impact becomes relatively stable. This is an example of how the proposed framework allows us to obtain a parsimonious specification. Traditional approaches in frequency modeling would have estimated nine separate parameters over the 9 years period for each severity level, thus resulting in a total of 36 parameters. In other words, traditional approaches would strictly assume that the effect will change across every year. In contrast, the proposed model allowed us to reflect variation and stability with fewer number of parameters (18 for arterial roads) compared to traditional system.

The parameters specific to divided roads indicate that zones with higher proportion of divided roads is more likely to experience increased incidence of property damage and minor injury crashes. Divided roadways provide barriers from opposing traffic flows and thus allow for fast moving traffic. Further, it is common for divided roads to have a complex intersection design with extra turning lanes and complex traffic signal design and hence the positive effect is intuitive (see (Stigson, 2009) for similar results). In terms of temporal variation, we found the impact of the variable significantly varies for both severity levels untill 2014 followed by consistent effect in the subsequent years. As is evident from

Table 3, we observe that intersection density in a zone is negatively associated with less severe crashes (proporerty damage, minor and non-incapaciating injuris) indicating a lower likelihood of these crashes in an area with higher number of intersections. It appreas that the impact might not be severity specific, rather it is perhaps indicatve of the reduction in overall crashes in intersection-rich zones. Advanced traffic signals, visible traffic signs, and dedicated turning lanes are some of the possible factors resulting in a safer environment (Retting et al., 2011). Further, we also found temporal variation in the impact over the years for each severity level. Intersitngly, we found no significant fluctuation in the impact of intersection density on non-incapacitating crashes over the years. Finally, the parameter associated with average speed limit exhibits a negative impact on crash frequency for both property damage and minor injury. At first glance, the effect might seem unintuitive, but it could be attributed to better roadway facility conditions and design for high-speed facilities (Milton & Mannering, 1998). Regarding temporal variation, the results reveal three distinct levels of fluctuation in no injury crash counts. On the other hand, for minor injury counts, the effect displays variation from the years 2013 to 2014, followed by a stable trend in subsequent years.

4.2.2 Traffic Characteristics

Among the several traffic characteristics considered in the model estimation process only Average Annual Daily Traffic (AADT) and heavy vehicle percentage in a zone are found to influence zonal level crash risks. Over the 9-year period analyzed in

Table 3, the model findings highlight a significant positive relationship between AADT and crash occurrence across all four severity levels (Satria et al., 2021; Veeramisti et al., 2021). As for temporal variations, the results show two levels of fluctuations for less severe crashes while for severe crashes, we observe several levels of significant variations for the effect over time. Improvements/upgrades in road infrastructure, changes in driving behavior and land use changes are some of the possible factors leading to such varying impact of AADT. The results regarding heavy vehicle percentage are quite interesting, revealing multiple fluctuations over the years across all for crash severity levels. Notably, for serious crashes, we found six distinct variations in the effect of heavy vehicles as evidenced in Table 2. In terms of actual impact, our analysis consistently demonstrates a negative relationship between heavy vehicle percentage and the crash risk across all four severity levels (see

Table 3). However, an interesting observation arises when we focus on serious crashes. In certain instances, we observed a positive association between heavy vehicles and serious crash incidences. The result might seem counterintuitive at first. However, heavy vehicles are usually dangerous due to their size and weight while at the same time, their presence on the road might promote cautious behavior among drivers, hence the varying impacts is intuitive.

4.2.3 Land Use Attributes

With respect to land use attributes, we found that TAZ with high retail and residential area will likely experience increased incidence of crashes across all severity levels, as indicated by the positive impact of these variables in

Table 3 (Parsa et al., 2020). Regarding temporal variations, both these variables showed a small number of fluctuations in the 9-year period analyzed in the study. Proportion of institutional area in a zone is also found to have a significant impact on crash occurrences, particularly for less severe crashes (no injury and minor injury). While the impact varies slightly for both severity levels over the years (only two times), an intriguing trend is observed focusing on the net impact of the variable presented in

Table 3. In general, the impact is positive indicating a higher likelihood of crashes for the corresponding severity with an increased proportion of institutional area in a zone (Bhowmik et al., 2019). However, a negative coefficient is observed for no injury crash counts highlighting the varying trends of the effect of institutional area in zonal level property damage crashes. Several factors like traffic volumes during peak hours, parking and drop-off activities, pedestrian movements might explain such two directional impact (Pulugurtha et al., 2013).

4.2.4 Sociodemographic Characteristics

In terms of sociodemographic characteristics, population density and proportion of non-motorists in a zone are found to be positively associated with crash frequency across different crash severity levels. Similar results were also found in earlier studies (Cai et al., 2016; Chen & Zhou, 2016). Interestingly, starting from 2012, the variable associated with population density remained temporally stable for property damage and non-incapacitating injury crashes. However, for minor injury and serious injury crashes, we observed notable fluctuations in the impact of population density over the years. Similarly, the impact of non-motorists also shows no variation after 2012, particularly for property damage and non-incapacitating injury crashes while an additional variation is observed in minor crashes from 2015.

4.2.5 Unobserved Heterogeneity

The final set of variables in both Table 2 and

Table 3 correspond to the correlation matrix (unobserved heterogeneity) in the spline indicator model with unobserved heterogeneity. As discussed earlier, in the current research effort, two types of correlations are tested including: 1) severity specific correlation: common unobserved factors affecting the crash severity components within the same year and 2) temporal correlation: common unobserved factors affecting over the 9 years period analyzed in the study across different severity levels. Both these factors are found to be significant in our analysis (see Table 2) and these factors further demonstrate how our proposed unified model provides a parsimonious system with reduced complexity. For instance, traditional modeling system could be employed in two ways: The first modeling algorithm could be estimated while developing multivariate approaches considering four different severity levels models for each year, thus resulting in 9 different severity specific correlations while ignoring the temporal correlations. The second modeling approach could be employed considering 9 years of data for each severity level, thus proving 4 temporal correlations while ignoring the severity correlations. To that extent, our approach is advantageous in two ways: 1) it allows us to capture both severity specific and temporal correlations thus offering a more accurate and unbiased parameter estimates; 2) it allows us to identify the number of severity specific correlations over the years. For example, in our analysis, we found three distinct levels of severity correlations over the 9-year period highlighting that correlation itself might not differ in subsequent years. Further, with respect to temporal correlations, the results show two significant correlation parameters particular for non-incapacitating and serious crashes.

4.3 Predictive Performance Evaluation

To demonstrate the applicability of our proposed approach, we conducted a comparison exercise by evaluating the prediction performances of the models. Specifically, we evaluated the performance of four models: year specific model, year indicator pooled model, spline indicator pooled model, and spline indicator pooled model with unobserved heterogeneity by employing mean absolute percentage error (MAPE) and root mean square values (RMSE) (Bhowmik et al., 2018, 2019) for all four severity levels over the 9-year period on a holdout sample (sample size = 3699 TAZs). A lower MAPE/RMSE indicates better predictive performance, as it represents the model's ability to closely approximate the observed data. Table 4 and Table 5 provide the results of the MAPE and RMSE measures. The MAPE and RMSE tables also include two composite indicators. The first indicator counts the instances in which a model system offers improved results across the years. The second indicator presents the average error across the years.

The MAPE table highlights that our proposed model significantly outperforms the other comparable models as illustrated by comparison across the years and the values from count and average values. For the MAPE measure, the proposed spline indicator pooled models (with and without heterogeneity) outperform the other models. The spline indicator pooled model with unobserved heterogeneity provides a superior fit in all 36 possible cases. In the RMSE comparison, the proposed spline model with unobserved heterogeneity does not offer as clear an improvement as was the case in the MAPE comparison. However, across the different injury severities, spline models (with and without unobserved heterogeneity) offer an improved fit 23 times out of 36 possible cases. We can observe that spline models offer improvement in less severe injury categories while performing slightly worse in more severe categories. The reader would note that the increase in error is small and is achieved with a substantially lower number of parameters.

Table 4: Prediction Comparison of Models (MAPE)

Injury Severity	Years	2011	2012	2013	2014	2015	2016	2017	2018	2019	Count (# of times a model offered best fit across the years)	Average across years
No Injury	YSNB	1.46	1.35	1.23	1.28	1.29	1.26	1.30	1.36	1.16	0	1.30
	YIPNB	1.47	1.41	1.28	1.28	1.26	1.28	1.29	1.33	1.14	0	1.30
	SIPNB	1.40	1.35	1.31	1.30	1.22	1.29	1.29	1.36	1.16	0	1.30
	MSIPNB	1.18	1.26	1.14	1.15	1.16	1.10	1.12	1.18	1.04	9	1.15
Minor Injury	YSNB	0.82	1.06	0.84	0.87	1.02	1.00	0.96	1.05	1.00	0	0.96
	YIPNB	0.82	1.07	0.84	0.89	1.03	1.04	0.98	1.07	0.95	0	0.97
	SIPNB	0.70	0.96	0.80	0.95	1.03	1.09	0.99	0.90	0.84	0	0.92
	MSIPNB	0.68	0.91	0.72	0.78	0.87	0.83	0.82	0.87	0.82	9	0.81
Non-Incapacitating Injury	YSNB	0.85	0.76	0.70	0.73	0.75	0.82	0.82	0.84	0.90	0	0.80
	YIPNB	0.84	0.76	0.71	0.72	0.80	0.80	0.81	0.83	0.93	0	0.80
	SIPNB	0.77	0.72	0.70	0.78	0.76	0.80	0.83	0.84	0.91	1	0.79
	MSIPNB	0.76	0.72	0.66	0.67	0.68	0.75	0.73	0.75	0.80	9	0.72
Serious Injury	YSNB	0.48	0.51	0.59	0.73	0.73	0.78	0.70	0.63	0.59	0	0.64
	YIPNB	0.48	0.52	0.60	0.71	0.75	0.75	0.72	0.63	0.59	0	0.64
	SIPNB	0.48	0.62	0.59	0.72	0.76	0.76	0.63	0.57	0.58	0	0.63
	MSIPNB	0.41	0.46	0.51	0.61	0.60	0.62	0.60	0.55	0.51	9	0.54

Table 5: Prediction Comparison of Models (RMSE)

Injury Severity	Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	Count (# of times a model offered best fit across the years)	Average across years
No Injury	YSNB	23.20	25.80	26.70	30.38	30.52	28.75	31.62	33.51	33.86	0	29.37
	YIPNB	23.02	24.45	26.72	28.21	30.14	28.71	33.17	34.87	33.68	1	29.22
	SIPNB	22.92	26.18	27.23	28.48	30.06	29.40	31.98	33.31	33.51	1	29.23
	MSIPNB	23.17	24.64	25.81	27.48	29.01	28.29	30.48	32.29	32.40	7	28.17
Minor Injury	YSNB	4.63	5.87	5.62	6.34	6.74	6.83	7.25	7.90	8.39	2	6.62
	YIPNB	4.60	5.45	5.68	6.31	6.67	6.88	7.19	8.01	8.41	3	6.58
	SIPNB	4.82	5.49	5.75	6.13	6.81	6.88	7.17	7.77	8.32	3	6.57
	MSIPNB	4.75	5.60	6.06	6.31	6.89	6.96	7.21	7.80	8.16	1	6.64
Non-Incapacitating Injury	YSNB	3.66	3.28	3.37	3.51	3.78	3.93	3.80	4.18	4.54	3	3.78
	YIPNB	3.70	3.25	3.37	3.50	3.80	3.97	3.84	4.22	4.47	1	3.79
	SIPNB	3.68	3.24	3.36	3.52	3.75	3.96	3.84	4.19	4.49	2	3.78
	MSIPNB	3.79	3.23	3.43	3.57	3.75	3.99	3.83	4.14	4.46	4	3.80
Serious Injury	YSNB	1.15	1.32	1.63	2.43	2.73	2.27	1.99	1.75	1.58	5	1.87
	YIPNB	1.15	1.33	1.63	2.43	2.71	2.27	1.96	1.76	1.58	6	1.87
	SIPNB	1.15	1.33	1.63	2.42	2.74	2.27	1.98	1.74	1.59	5	1.87
	MSIPNB	1.21	1.37	1.73	2.54	2.93	2.35	2.00	1.78	1.61	0	1.95

Finally, incorporating unobserved heterogeneity within spline model improves the prediction further, particularly for property damage and minor injury crashes while the prediction performance dropped slightly for non-incapacitating injury and serious injury crashes. The reader would note that this small drop in prediction performance is not unexpected. In multivariate model development, in the presence of a very small number of variables, adding an independent variable might improve the model for all dependent variables. However, adding a small number of unobserved heterogeneity variables (3-4) in a model with over 100 variables, it is not surprising that there are some trade-offs in predictive performance across dependent variables

The traditional year specific framework (YSNB) and the spline model with unobserved effects are also compared by conducting a correct classification analysis. Using observed crash counts for each severity level, the holdout sample zones (3699) were divided into four quartiles based on the crash numbers. Similarly, using the predicted counts from the YSNB and MSIPNB models, we created the four quartiles again, and the percentage of correctly classified TAZs within each group was calculated. The error margin for prediction window is extended to 20% of the mean. Suppose if the range is [20-30], we use the 20% of the mean value (5) and build a corresponding crash bin as [15-35]. If prediction from the model for [20-30] falls within [15-35] we label it as correct and false otherwise.

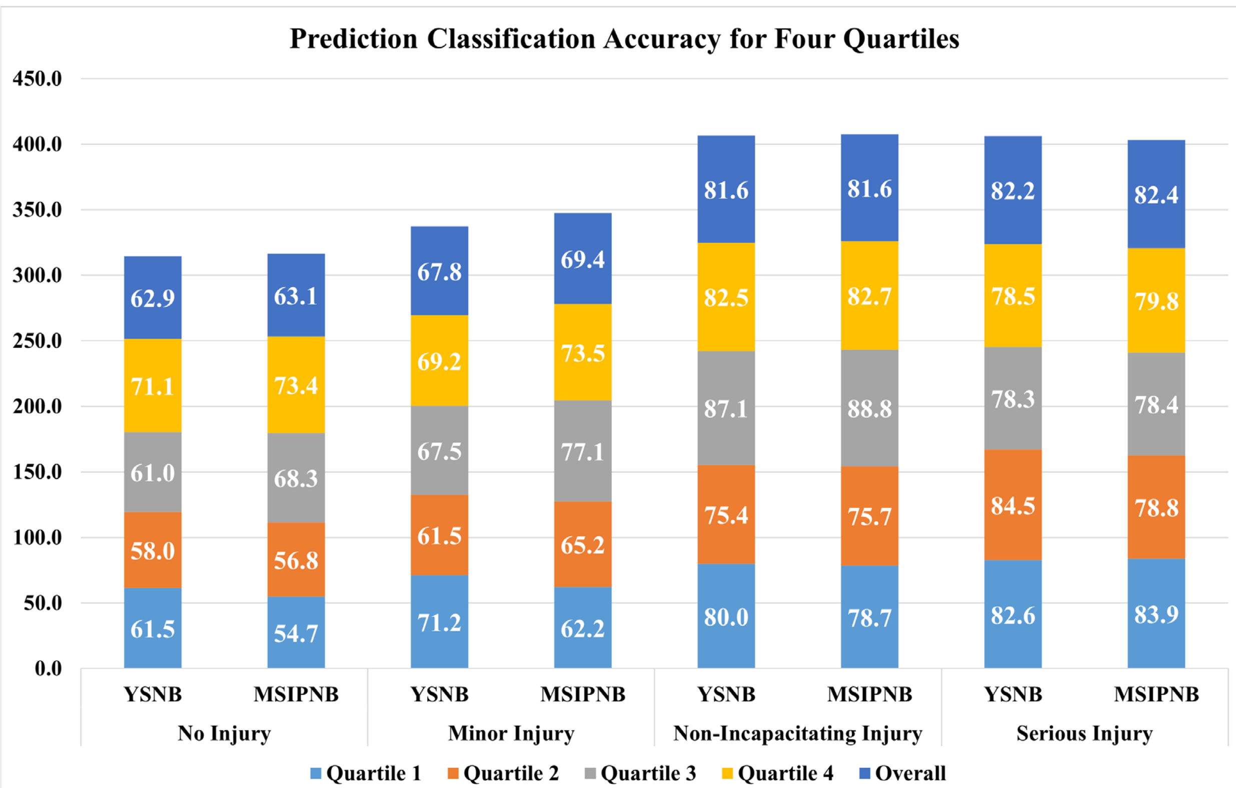


Figure 3. Classification Comparison for Two Models (YSNB and MSIPNB)

It is evident from Figure 3 that the proposed framework outperformed the traditional model in 15 out of 20 instances. Further, as the parameter variation trends are estimated, the proposed spline model has the potential to forecast crashes for future years. We tested the model for predicting crash frequencies across the different severity levels for the year 2021. The spline model with unobserved heterogeneity was able to predict crash frequency class around 55-78% on average across different severity levels of crashes.

5 CONCLUSION

Multivariate frameworks effectively handle the influence of observed and unobserved factors across multiple dependent variables for a single instance of data. However, the recent pooled multivariate crash severity prediction models are unable to identify specific parameters exhibiting statistically discernible differences over time and lack a process for future model application. The current research proposed a novel approach, labelled the mixed spline indicator pooled model, that offered a significant enhancement of current approaches to capture temporal instability. The proposed entails carefully creating additional independent variables that allow us to measure parameter slope changes over time and can be easily integrated into existing methodological frameworks. The modeling exercise is conducted using the Traffic Analysis Zone (TAZ) level crash records from Central Florida for the years 2011 to 2019 considering a comprehensive set of exogenous variables.

In the empirical analysis, we estimated a series of models including the Year Specific Negative Binomial model (YSNB), the year indicator pooled negative binomial model (YIPNB), and the spline indicator pooled negative binomial model (SIPNB), to address the dimensionality challenges of 36 dependent variables representing different severity levels over nine years. The comparison exercise revealed the superior performance of the pooled models, which demonstrated significantly lower Bayesian Information Criterion (BIC) values compared to the traditional year specific NB models. Among the pooled approaches, the SIPNB model exhibited considerable enhancement in data fit relative to the YIPNB model, highlighting the benefits of the additional flexibility introduced by the spline framework. Notably, the best-performing spline model incorporated unobserved heterogeneity along two dimensions: severity level correlation across each year and temporal correlations across severity levels. The prediction performances of four models were also assessed. The results demonstrated that the proposed spline model consistently outperformed its counterparts in terms of predictive accuracy across all dimensions. Moreover, a correct classification analysis revealed that the proposed framework consistently outperformed the traditional year specific model in the majority of the instances. The findings support the applicability and potential of the spline model in forecasting crashes for future years, with the model achieving an average prediction accuracy of around 55-78% across different severity levels of crashes in the year 2021. Overall, our research highlights the effectiveness of the mixed spline indicator pooled model in providing a parsimonious specification with improved data fit. By addressing the limitations of previous approaches, our proposed model holds promise for advancing the analysis of data from multiple instances, identifying variation in parameter effects and improving the accuracy of temporal predictions.

To be sure, the study is not without limitations. In our analysis, we considered all motorized vehicle crashes in the study region and classified them by severity level. The approach implicitly ignores the impact of crash type on crash frequency and severity. It might be interesting to consider an approach that accommodates for crash type within the modeling framework (see an example model system from Bhowmik et al., 2021b). Of course, such a consideration would rapidly increase the number of dependent variables (from 36 in our study to 36 * # of crash types) and would be significantly more challenging.

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Appendix

Table A1: Year Specific Negative Binomial Model (YSNB) Results

Definition	2011	2012	2013	2014	2015	2016	2017	2018	2019
Constant									
No Injury	0.404	0.400	0.388	0.542	0.566	0.759	0.786	0.823	0.949
Minor Injury	-1.200	-1.260	-1.362	-1.089	-0.819	-0.924	-0.767	-0.619	-0.643
Non-Incapacitating	-0.716	-1.111	-1.343	-1.323	-0.887	-0.949	-0.883	-1.255	-0.906
Serious Injury	-2.181	-2.337	-2.338	-1.993	-1.817	-1.572	-1.802	-2.237	-2.391
Roadway Characteristics									
The proportion of arterial road									
No Injury	0.494	0.160	0.503	0.389	0.353	0.162	0.169	0.216	0.237
Minor Injury	0.423	0.186	0.474	0.305	0.303	0.251	0.190	0.243	0.279
Non-Incapacitating	0.540	0.160	0.412	0.363	0.460	0.267	0.238	0.215	0.207
Serious Injury	0.555	--	0.722	0.546	0.625	0.385	0.237	0.165	0.280
The proportion of divided road									
No Injury	0.338	0.463	--	--	--	0.344	0.337	0.306	0.277
Minor Injury	0.427	0.545	--	0.183	0.182	--	0.254	0.357	0.348
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Intersection density									
No Injury	--	--	-0.094	-0.079	-0.102	-0.168	-0.177	-0.145	-0.133
Minor Injury	--	--	-0.094	-0.071	-0.131	-0.176	-0.168	-0.173	-0.139
Non-Incapacitating	--	--	-0.068	-0.079	-0.074	-0.127	-0.131	-0.102	-0.111
Serious Injury	--	--	--	--	--	--	--	--	--
Average speed									
No Injury	--	--	-0.124	-0.150	-0.213	-0.152	-0.196	-0.168	-0.209
Minor Injury	--	--	-0.130	-0.107	-0.244	-0.137	-0.221	-0.251	-0.204
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Traffic Characteristics									
AADT									
No Injury	0.089	0.112	0.203	0.210	0.221	0.197	0.212	0.188	0.186
Minor Injury	0.089	0.123	0.240	0.210	0.224	0.233	0.229	0.220	0.200
Non-Incapacitating	0.066	0.133	0.171	0.197	0.135	0.177	0.158	0.162	0.155
Serious Injury	0.068	0.136	0.109	0.122	0.124	0.101	0.094	0.122	0.142
Percentage of heavy vehicles									
No Injury	-0.042	-0.037	-0.044	-0.045	-0.032	-0.039	-0.022	-0.014	-0.011
Minor Injury	-0.038	-0.022	-0.047	-0.049	-0.022	-0.036	-0.013	--	--
Non-Incapacitating	-0.019	-0.025	-0.03	-0.042	-0.033	-0.044	-0.024	--	-0.017

Serious Injury	-0.016	-0.039	-0.018	-0.049	-0.054	-0.047	--	--	-0.015
Land Use Attributes									
The proportion of retail area									
No Injury	1.657	2.134	2.038	1.969	2.224	2.010	1.926	1.931	2.015
Minor Injury	1.505	1.729	1.602	1.568	1.779	1.782	1.587	1.592	1.617
Non-Incapacitating	0.985	1.418	1.371	1.122	1.359	1.164	1.223	1.412	1.247
Serious Injury	0.544	0.955	1.079	0.984	0.980	0.756	0.743	0.972	0.690
The proportion of residential area									
No Injury	--	--	0.274	--	0.518	0.528	0.446	0.392	0.494
Minor Injury	0.268	--	0.348	--	0.345	0.459	0.315	0.298	0.312
Non-Incapacitating	--	0.250	0.222	--	0.279	0.212	0.252	0.377	--
Serious Injury	--	--	--	--	--	--	--	--	--
The proportion of institutional area									
No Injury	--	--	--	--	0.926	1.084	1.034	0.989	1.132
Minor Injury	--	--	0.951	--	1.146	1.119	0.746	0.788	1.115
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Sociodemographic Characteristics									
TAZ population density									
No Injury	0.117	0.096	0.101	0.124	0.088	0.064	0.072	0.070	0.056
Minor Injury	0.117	0.091	0.083	0.120	0.085	0.078	0.085	0.075	0.067
Non-Incapacitating	0.097	0.059	0.077	0.092	0.075	0.068	0.072	0.058	0.082
Serious Injury	0.102	0.063	0.064	0.098	0.077	0.069	0.051	0.047	0.043
Proportion of NMT									
No Injury	0.079	0.078	0.075	0.045	0.075	0.094	0.104	0.124	0.142
Minor Injury	0.080	0.067	0.067	--	0.065	0.070	0.105	0.111	0.138
Non-Incapacitating	0.055	0.046	--	--	0.064	0.062	--	0.091	0.066
Serious Injury	--	--	--	--	--	--	--	--	--
Overdispersion Parameter									
No Injury	0.960	0.755	0.737	0.742	0.760	0.737	0.753	0.790	0.743
Minor Injury	0.555	0.646	0.493	0.516	0.563	0.549	0.485	0.526	0.516
Non-Incapacitating	0.486	0.481	0.460	0.497	0.543	0.520	0.465	0.465	0.464
Serious Injury	0.332	0.585	0.632	0.900	0.933	0.896	0.671	0.559	0.483

Table A2: Year Indicator Pooled Negative Binomial Model (YIPNB) Results

<table>
<tr><th>Definition</th><th>2011</th><th>2012</th><th>2013</th><th>2014</th><th>2015</th><th>2016</th><th>2017</th><th>2018</th><th>2019</th></tr>
<tr><td colspan="10">Constant</td></tr>
<tr><td>No Injury</td><td>0.606</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Minor Injury</td><td>-1.314</td><td>--</td><td>--</td><td>--</td><td colspan="3">0.595</td><td colspan="2">0.627</td></tr>
<tr><td>Non-Incapacitating</td><td>-1.003</td><td>-0.659</td><td>-0.907</td><td>-1.286</td><td>--</td><td>-0.783</td><td>-0.478</td><td>-0.620</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>-2.254</td><td>--</td><td>--</td><td>--</td><td>--</td><td colspan="2">0.799</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Roadway Characteristics</td></tr>
<tr><td colspan="10">The proportion of arterial road</td></tr>
<tr><td>No Injury</td><td>0.417</td><td>-0.301</td><td>--</td><td>--</td><td>-0.172</td><td colspan="2">-0.239</td><td colspan="2">-0.196</td></tr>
<tr><td>Minor Injury</td><td>0.329</td><td>-0.151</td><td>--</td><td>--</td><td>--</td><td>-0.209</td><td>-0.157</td><td>--</td><td>--</td></tr>
<tr><td>Non-Incapacitating</td><td>0.289</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>0.533</td><td>-0.401</td><td>0.210</td><td>--</td><td>--</td><td>--</td><td colspan="3">-0.314</td></tr>
<tr><td colspan="10">The proportion of divided road</td></tr>
<tr><td>No Injury</td><td>0.280</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Minor Injury</td><td>0.363</td><td>--</td><td colspan="3">-0.196</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Intersection density</td></tr>
<tr><td>No Injury</td><td>--</td><td colspan="4">-0.074</td><td colspan="2">-0.169</td><td colspan="2">-0.132</td></tr>
<tr><td>Minor Injury</td><td>0.054</td><td colspan="3">-0.139</td><td colspan="5">-0.202</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>-0.064</td><td colspan="2">-0.098</td><td>-0.143</td><td>-0.124</td><td>-0.097</td><td>-0.137</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Average speed</td></tr>
<tr><td>No Injury</td><td>-0.110</td><td>--</td><td>--</td><td>--</td><td>-0.084</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Minor Injury</td><td>--</td><td>--</td><td>--</td><td>-0.110</td><td>-0.197</td><td>-0.180</td><td colspan="3">-0.221</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Traffic Characteristics</td></tr>
<tr><td colspan="10">AADT</td></tr>
<tr><td>No Injury</td><td>0.108</td><td colspan="3">0.052</td><td>0.101</td><td colspan="2">0.091</td><td colspan="2">0.074</td></tr>
<tr><td>Minor Injury</td><td>0.088</td><td>0.075</td><td>0.099</td><td colspan="6">0.124</td></tr>
<tr><td>Non-Incapacitating</td><td>0.097</td><td>0.064</td><td>0.099</td><td>0.145</td><td>0.018</td><td>0.110</td><td colspan="2">0.078</td><td>0.044</td></tr>
<tr><td>Serious Injury</td><td>0.075</td><td>0.049</td><td>0.026</td><td>0.074</td><td>0.086</td><td>--</td><td>--</td><td colspan="2">0.053</td></tr>
<tr><td colspan="10">Percentage of heavy vehicles</td></tr>
<tr><td>No Injury</td><td>-0.040</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>0.017</td><td colspan="2">0.028</td></tr>
<tr><td>Minor Injury</td><td>-0.033</td><td>--</td><td>-0.019</td><td>--</td><td>--</td><td>--</td><td colspan="3">-0.019</td></tr>
<tr><td>Non-Incapacitating</td><td>-0.028</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>0.017</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>-0.015</td><td>-0.025</td><td>--</td><td colspan="3">-0.028</td><td>--</td><td>0.012</td><td>--</td></tr>
</table>

Land Use Attributes									
The proportion of retail area									
No Injury	2.043	--	--	--	--	--	--	--	--
Minor Injury	1.663	--	--	--	--	--	--	--	--
Non-Incapacitating	1.375	--	--	--	--	--	--	--	--
Serious Injury	0.858	--	--	--	--	--	--	--	--
The proportion of residential area									
No Injury	0.329	--	--	--	--	0.241	--	--	0.221
Minor Injury	0.315	--	--	--	--	--	--	--	--
Non-Incapacitating	0.287	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
The proportion of institutional area									
No Injury	-0.427	--	--	0.961	1.240	1.570	1.367		1.665
Minor Injury	--	--	0.952	--	1.102		0.692		1.193
Non-Incapacitating	--	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Sociodemographic Characteristics									
TAZ population density									
No Injury	0.088	--	--	--	--	-0.021	--	--	-0.023
Minor Injury	0.114	-0.038		--	-0.037				
Non-Incapacitating	0.078	-0.022	--	--	--	--	--	--	--
Serious Injury	0.096	-0.033		--	--	-0.022	-0.053		
Proportion of NMT									
No Injury	0.089	--	--	--	--	--	--	--	--
Minor Injury	0.087	--	--	-0.055	--	--	--	--	--
Non-Incapacitating	0.057	--	--	--	--	--	--	--	--
Serious Injury	--	--	--	--	--	--	--	--	--
Overdispersion Parameter									
No Injury	0.970	-0.173	-0.220					-0.176	-0.221
Minor Injury	0.527	0.124	--	--	--	--	--	--	--
Non-Incapacitating	0.468	--	--	--	--	--	--	--	--
Serious Injury	0.339	0.276		0.572			0.341	0.219	0.150

Table A3: Spline Indicator Pooled Negative Binomial Model (SIPNB) Results

<table>
<tr><th>Definition</th><th>2011</th><th>2012</th><th>2013</th><th>2014</th><th>2015</th><th>2016</th><th>2017</th><th>2018</th><th>2019</th></tr>
<tr><td colspan="10">Constant</td></tr>
<tr><td>No Injury</td><td>0.486</td><td>-0.740</td><td colspan="7">0.363</td></tr>
<tr><td>Minor Injury</td><td>-1.213</td><td>1.111</td><td colspan="7">0.209</td></tr>
<tr><td>Non-Incapacitating</td><td>-0.911</td><td colspan="8">0.965</td></tr>
<tr><td>Serious Injury</td><td>-2.199</td><td>1.886</td><td colspan="3">0.538</td><td colspan="4">-0.463</td></tr>
<tr><td colspan="10">Roadway Characteristics</td></tr>
<tr><td colspan="10">The proportion of arterial road</td></tr>
<tr><td>No Injury</td><td>0.469</td><td>-0.784</td><td>0.547</td><td colspan="6">-0.269</td></tr>
<tr><td>Minor Injury</td><td>0.489</td><td>-0.791</td><td>0.510</td><td colspan="3">-0.272</td><td colspan="3">0.081</td></tr>
<tr><td>Non-Incapacitating</td><td>0.548</td><td>-0.825</td><td colspan="7">0.272</td></tr>
<tr><td>Serious Injury</td><td>0.537</td><td>-0.914</td><td>0.845</td><td colspan="2">-0.477</td><td colspan="3">-0.154</td><td>0.288</td></tr>
<tr><td colspan="10">The proportion of divided road</td></tr>
<tr><td>No Injury</td><td>0.428</td><td colspan="2">-0.539</td><td colspan="6">0.130</td></tr>
<tr><td>Minor Injury</td><td colspan="2">0.302</td><td>-0.793</td><td colspan="6">0.532</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Intersection density</td></tr>
<tr><td>No Injury</td><td>--</td><td>-0.083</td><td colspan="3">0.085</td><td>-0.067</td><td colspan="3">0.058</td></tr>
<tr><td>Minor Injury</td><td>0.055</td><td>-0.172</td><td colspan="7">0.099</td></tr>
<tr><td>Non-Incapacitating</td><td colspan="9">-0.017</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Average speed</td></tr>
<tr><td>No Injury</td><td colspan="5">-0.033</td><td colspan="2">0.032</td><td colspan="2">-0.028</td></tr>
<tr><td>Minor Injury</td><td>--</td><td>--</td><td>-0.155</td><td colspan="6">0.144</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">Traffic Characteristics</td></tr>
<tr><td colspan="10">AADT</td></tr>
<tr><td>No Injury</td><td colspan="2">0.089</td><td colspan="7">-0.086</td></tr>
<tr><td>Minor Injury</td><td colspan="3">0.076</td><td colspan="6">-0.079</td></tr>
<tr><td>Non-Incapacitating</td><td>0.068</td><td>0.042</td><td colspan="2">-0.104</td><td colspan="5">-0.009</td></tr>
<tr><td>Serious Injury</td><td colspan="2">0.072</td><td>-0.110</td><td>0.065</td><td colspan="3">-0.041</td><td colspan="2">0.036</td></tr>
<tr><td colspan="10">Percentage of heavy vehicles</td></tr>
<tr><td>No Injury</td><td>-0.044</td><td colspan="8">0.048</td></tr>
<tr><td>Minor Injury</td><td>-0.031</td><td colspan="3">0.027</td><td>0.020</td><td colspan="4">-0.011</td></tr>
<tr><td>Non-Incapacitating</td><td colspan="4">-0.011</td><td colspan="5">0.017</td></tr>
<tr><td>Serious Injury</td><td colspan="2">-0.018</td><td>0.035</td><td>-0.050</td><td colspan="2">0.033</td><td>0.051</td><td colspan="2">-0.059</td></tr>
</table>

<table>
<tr><th colspan="10">Land Use Attributes</th></tr>
<tr><td colspan="10">The proportion of retail area</td></tr>
<tr><td>No Injury</td><td>1.677</td><td>-1.104</td><td colspan="7">-0.621</td></tr>
<tr><td>Minor Injury</td><td>1.590</td><td colspan="8">-1.580</td></tr>
<tr><td>Non-Incapacitating</td><td>1.300</td><td colspan="8">-1.281</td></tr>
<tr><td>Serious Injury</td><td colspan="2">0.513</td><td colspan="7">-0.552</td></tr>
<tr><td colspan="10">The proportion of residential area</td></tr>
<tr><td>No Injury</td><td colspan="5">0.097</td><td colspan="4">-0.112</td></tr>
<tr><td>Minor Injury</td><td colspan="9">0.048</td></tr>
<tr><td>Non-Incapacitating</td><td>0.252</td><td colspan="8">-0.245</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td colspan="10">The proportion of institutional area</td></tr>
<tr><td>No Injury</td><td>-0.564</td><td colspan="8">0.828</td></tr>
<tr><td>Minor Injury</td><td>--</td><td colspan="2">0.379</td><td colspan="6">-0.340</td></tr>
<tr><td>Non-Incapacitating</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><th colspan="10">Sociodemographic Characteristics</th></tr>
<tr><td colspan="10">TAZ population density</td></tr>
<tr><td>No Injury</td><td>0.108</td><td colspan="8">-0.114</td></tr>
<tr><td>Minor Injury</td><td>0.131</td><td>-0.185</td><td colspan="2">0.069</td><td colspan="5">-0.025</td></tr>
<tr><td>Non-Incapacitating</td><td>0.075</td><td colspan="8">-0.075</td></tr>
<tr><td>Serious Injury</td><td>0.102</td><td>-0.147</td><td colspan="2">0.060</td><td colspan="5">-0.026</td></tr>
<tr><td colspan="10">Proportion of NMT</td></tr>
<tr><td>No Injury</td><td>0.060</td><td colspan="8">-0.053</td></tr>
<tr><td>Minor Injury</td><td>0.085</td><td colspan="3">-0.100</td><td colspan="5">0.034</td></tr>
<tr><td>Non-Incapacitating</td><td>0.051</td><td colspan="8">-0.049</td></tr>
<tr><td>Serious Injury</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><th colspan="10">Overdispersion Parameter</th></tr>
<tr><td>No Injury</td><td>0.960</td><td>-1.161</td><td colspan="7">0.200</td></tr>
<tr><td>Minor Injury</td><td>0.574</td><td colspan="8">-0.582</td></tr>
<tr><td>Non-Incapacitating</td><td>0.477</td><td colspan="8">-0.480</td></tr>
<tr><td>Serious Injury</td><td>0.699</td><td colspan="8">-0.699</td></tr>
</table>

Note summarizing the number of model estimations

In this section, we briefly summarize the number of model estimations and corresponding pair-wise tests required in the Alnawmasi and Mannering, 2023 and Dzinyela et al., 2024 approach for temporal stability analysis.

Consider data is compiled for N years. For each variable, across the years, the number of variable impacts is anywhere between 0 (insignificant) and N (significant for every year). models. For example, for variable AADT the number of models to be tested for each dependent variable are as follows:

AADT has no impact across all years and/or AADT different across all years (N) [unconstrained models by year] ${}^{N}C_1$

AADT – different for N-2 years and same for two years [the two common years can be anywhere] ${}^{N}C_2$

AADT – different for N-3 years and same for three years ${}^{N}C_3$

…

AADT - same across all years – 1 model [Constrained model] ${}^{N}C_N$

So, the total number of models to be estimated is ${}^{N}C_1 + {}^{N}C_2 \ \ldots\ {}^{N}C_N = 2^N - 1$

If N = 10; the number of model estimations for one independent variable is 1023. Now, one could argue that, with multiple independent variables and dependent variables (4 in our case), the number will definitely be higher.