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Analysis of injury severity of work zone crashes on rural and urban work zones: Accounting for out-of-sample prediction and temporal instability

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ABSTRACT

This research utilizes data collected in Florida to examine the differentials in injury severities among single-vehicle drivers involved in work zone-related incidents, specifically focusing on the distinctions between rural and urban areas. The study encompasses a four-year period (2016–2019) of crash dataset. A likelihood ratio test was performed to examine model estimate's temporal consistency in datasets from rural and urban areas across several time periods throughout the year. Separate statistical models were estimated for both rural and urban datasets to understand different driver injury severity outcomes (no injury, minor injury, and severe injury) using a mixed logit approach with possible heterogeneity in mean and variance of random parameters. Out-of-sample simulations were conducted to see the effect of different parameter changes on injury severity probabilities in rural and urban work zone crashes. Over multiple years, various years in both rural and urban models have generated statistically significant random factors that effectively capture the presence of heterogeneity in means, accounting for unobservable variations within the data. Clear evidence of factors such as speed limits, work zone type, and traffic volume affecting the work zone injury severities were found to vary significantly between rural and urban work zone areas. However, despite this difference, rural and urban work zones share common safety problems and countermeasures such as driver education, improved signage, and appropriate traffic controls; combining ITS technologies and enhanced law enforcement can help mitigate crash severity in urban and rural work zone areas.

1. Introduction

The US Department of Transportation (DOT) has expressed significant concerns with the escalating number of work zone fatalities. The time frame of the work zone can vary from a few days to several years and encompasses lane closures, detours, the movement of equipment, and regular maintenance activities, which include vehicles and workers. Since 2010, work zone deaths have increased by 63 %, and the largest increase in fatalities in work zone crashes was observed in the year 2019, with 845 deaths ("The National Safety Council," 2023). Florida, one of the states with the most worker deaths in work zone safety, experienced 272 total fatal crashes between the years 2016 and 2019 in the work zone-related crashes (AASHTO/ARTBA, 2023).

Many research efforts related to work zones have focused on potential solutions for improving work zone safety. For example, Mohammed et al. (2023) focused on finding factors associated with work zone crashes that would help make policies. Osman et al., (2018) studied passenger-car injury severity specific to work zone configurations where a crash occurred. Islam (2022) analyzed driver injury severities in work and non-work zone crashes involving large single-vehicle trucks. Prior studies have found major differences between single-vehicle and multi-vehicle crashes when compared (Dong et al., 2018; Martensen and Dupont, 2013; Ulfarsson and Mannering, 2004; Wang and Feng, 2019; Wu et al., 2016, 2014). Studies such as Ulfarsson and Mannering (2004) found single and multi-vehicle crashes could not be modeled together as a substantial difference between these severities could not be accurately captured in one model. Hence, it is important to study single and multi-vehicle work zone crashes separately, and this research focuses on studying single-vehicle work zone-related crashes.

Most crash studies related to work zones need to differentiate between incidents occurring in rural and urban areas. However, due to fundamental differences in travel patterns, road network density, and

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land use, the characteristics of work zone crashes may differ between rural and urban areas. Previous crash injury severity studies have found significant differences between rural and urban areas concerning various contributing factors (Chen and Fan, 2019; Hao and Kamga, 2017; Leff et al., 2003; Saleem et al., 2020; Wu et al., 2016; Yu et al., 2022; Zwerling et al., 2001). Yu et al. (2022) employed mixed logit and partial proportional odds logit models to compare the severity of injuries resulting from truck-related crashes occurring on rural and urban routes. They identified significant differences between crashes in rural and urban work zones. According to the study conducted by Wu et al. (2016), the utilization of nested and mixed logit models revealed notable disparities in the parameters influencing driver injury severity in single-vehicle crashes between rural and urban regions. In terms of methodology, several discrete choice models have been developed in previous studies to investigate work zone-related crashes (Ahmed et al., 2023; Ghasemzadeh and Ahmed, 2019; Hasan et al., 2022; Islam et al., 2020; Islam, 2022; Khattak and Targa, 2004; Madarshahian et al., 2023; Mohammed et al., 2023; Mokhtarimousavi et al., 2021; Osman et al., 2016, 2018; Sze and Song, 2019; Wei et al., 2017; Yu et al., 2020; Zhang, 2019; Zhang and Hassan, 2019a). The mixed logit and multinominal logit models were the most common methodology for analyzing the work zone crash data. Sze and Song (2019) employed a multinomial logistic regression model to determine the correlation between the severity of crashes and the factors contributing to those crashes' severity. Madarshahian et al. (2023) studied the injury severity of work zone trucks involved using a mixed logit model. Contributing factors to the severity of injuries were identified, including lighting conditions and driving at excessive speeds relative to roadway conditions. Islam et al., (2020a) found temporal instability in analyzing work zone crash severities using a mixed logit model accounting for heterogeneity in mean and variance. Rangaswamy et al. (2023) found a wide range of improper pre-crash actions affecting crash occurrence and outcomes in single-vehicle work zone crashes. These comprehensive previous studies are necessary to understand contributing factors of driver injury severities in work zone crashes.

The researchers of this study observed an absence of research initiatives that have specifically examined the differentiation between urban and rural work zone locations in the context of investigating crashes and their severities. This research intends to understand the factors affecting the injury severity of single-vehicle crashes occurring in work zones and whether and how rural and urban work zones could differ. In order to achieve the objectives, this study used mixed logit with partially constrained temporal modeling approach to identify significant factors involving driver, vehicle, environmental features, etc., and quantify their contribution to driver injury severities in rural and urban work zone areas. Temporal instability tests were conducted to understand the statistically significant differences in each injury severity data year. Furthermore, an out-of-sample prediction simulation has been used to compare predictions and analyze the significant fluctuations in the predicted probabilities of each injury over time.

2. Literature review

Work zone, vehicle, driver, environment, and temporal factors are the general categories into which the factors influencing work zone crashes can be classified. Many studies have used the historical data discussed in the previous section to explore the factors influencing the crash and injury risks in work zones. Yu et al. (2022) compared truck-involved crashes in work zones on rural and urban highways and found that the injury severity levels of work zone crashes on rural and urban highways are significantly different. A study by Islam (2022) showed that the likelihood of large truck driver injury severity was found to be fourteen times higher in rural and six times higher in urban interstates. Variables such as male, alcohol involved, dawn, ongoing activity, asphalt pavement, restraints used, and ongoing activity were found to have significant injury severity both in rural and urban work zone models (Yu et al., 2022). In the following studies, rural area was found to be a significant factor influencing the work zone injury severity (Ghasemzadeh and Ahmed, 2019; Islam et al., 2020; Mohammed et al., 2023; Osman et al., 2016, 2018; Yu et al., 2020; Zhang and Hassan, 2019b, 2019a), and Ghasemzadeh and Ahmed (2019b) and Se et al., (2022) found urban areas to be a significant factor influencing the injury severity in work zone crashes.

In a work zone area, a vehicle can be involved in a crash in two basic ways. First is a single vehicle (SV) crash where a driver in the work zone loses control and collides with a fixed object/pedestrian/worker/bicyclist, including a passenger. Second, a multi-vehicle (MV) crash is where there are multiple collisions involving multi-vehicle in a crash. In crash injury studies, few researchers have tried to understand the difference between single and multi-vehicle crashes. Martensen and Dupont (2013) found that the most important variables to differentiate between single and multi-vehicle crashes were the presence of junctions, the physical division between carriageways, and traffic flow. Wang and Feng (2019) emphasize the significance of identifying between single-vehicle (SV) and multiple-vehicle (MV) crashes. They explore the research of freeway safety and discover that some traffic operation features, which strongly influence MV crashes, do not have a significant relationship with SV crash occurrence. Dong et al., (2018) found that speed gap, length of segment, and wet road surfaces were significant for both SV and MV accidents. While investigating the driver injury severities on rural two-lane highways, Wu et al. (2014) found a significant difference between casual attributes determining driver injury severities with MV crashes having more severe and fatal crashes when motorcycles or trucks were involved. With these studies, we can understand that it is important to differentiate SV and MV crashes while performing injury severity analysis. This research study focuses on single-vehicle work zone-related crashes as single-vehicle crashes tend to surpass multi-vehicle collisions in the occurrence of crash-related fatalities across both rural and urban areas (IIHS, 2023). Moreover, many similar studies have been conducted focusing on single-vehicle crashes to investigate driver injury severities in work zone-related crashes (Ahmed et al., 2023; Islam, 2022; Islam et al., 2020; Madarshahian et al., 2023; Mokhtarimousavi et al., 2021; Rangaswamy et al., 2023; Wei et al., 2017).

Previous studies show that the presence of work zones can significantly increase crash severity and injury rate. For example, Islam (2022) found that driver characteristics such as careless driving have a higher probability of increasing severe injury in work zones compared to non-work zone areas. Yu et al. (2022) found that young drivers (<25) increasing the likelihood of possible injury (Ahmed et al., 2023; Islam et al., 2020; Yu et al., 2020; Zhang and Hassan, 2019b, 2019a) similarly, found young drivers to have an influence on crash injury severities in their research, about environmental characteristics. Wei et al. (2017) found work zones under dark-lighting conditions injury rate to be higher than day-lighting conditions; however, previous (Mohammed et al., 2023) research shows work zone crashes were higher during daylight than night conditions. Work zone characteristics such as before-work area, after-work area, and types of work zones were found to affect rare-end work zone crash injury severity (Yu et al., 2020). Work zone with ongoing activity was found to have a lower probability of injury, according to (Yu et al., 2022). Islam et al., (2020a) found absence of law enforcement tends to increase minor injury severity in single-vehicle work zone crashes. Rangaswamy et al. (2023) studied the influence of contributing factors on the likelihood of pre-crash actions in single-vehicle work zone accidents. They discovered a range of variables affecting these actions, including driver and weather conditions, work-zone type, and lighting characteristics. Temporal characteristics, like weekends, increased the likelihood of higher injury severity across all work zone configurations compared to weekday travel (Ahmed et al., 2023; Osman et al., 2018). Additionally, road user attributes, such as motorcyclists, cyclists, and pedestrians, increased the likelihood of various injury severities in work zone crashes (Sze and Song, 2019).

Table 1
Proportion of total single-vehicle work zone crashes in urban and rural areas by year.

Crash year	2016			2017			2018			2019		
Injury level	*No Injury*	*Minor Injury*	*Severe Injury*	*No Injury*	*Minor Injury*	*Severe Injury*	*No Injury*	*Minor Injury*	*Severe Injury*	*No Injury*	*Minor Injury*	*Severe Injury*
Urban	0.75	0.19	0.06	0.79	0.14	0.04	0.86	0.12	0.02	0.81	0.16	0.03
Rural	0.82	0.14	0.04	0.84	0.11	0.04	0.84	0.11	0.05	0.81	0.14	0.05

In order to investigate injury severity in work zone-related crashes, various methodologies have been employed, as detailed in the introduction section. The method includes but is not limited to regression modeling, classification tree modeling, hierarchical modeling, probit classification tree, mixed generalized ordered probit modeling, multinomial logistic regression, and many more. Previous studies (Islam, 2022; Islam et al., 2020) to study crash data from driver injury severities in single-large truck crashes in work-zone and non-work-zone areas used random parameters logit models that allow for possible heterogeneity of parameter estimates. Similarly, Yu et al. (2020a) investigated factors affecting the injury severity of rear-end crashes in WZ using a random parameters logit approach with heterogeneity in means and variances. Studies such as (Alnawmasi and Mannering, 2022; Alogaili and Mannering, 2022; Hou et al., 2022; Rangaswamy et al., 2023; Se et al., 2022; Xu et al., 2021) conducted a full simulation of random parameters for out-of-sample injury level predictions to assess the accuracy of the estimated models in the recent crash injury studies. This study uses a mixed logit model with heterogeneity in means and variances to understand the single-vehicle injury severity of work zone crashes in rural and urban areas. Then, the predictions of injury severities based on the full simulation of random parameters are provided, and the predictive performance of estimated models is assessed. Finally, the testing methods for temporal instability are evaluated, and a summary and concluding remarks are provided.

3. Data description

The work zone crash data over four years (2016–2019)[1] was obtained from Signal Four Analytics. The database contains data on various aspects of crashes, such as the time of occurrence, location, environmental conditions, geometric factors, vehicles involved, and individuals affected. The present study selected 2,886 single-vehicle incidents from a dataset focused on work zone crashes. Among these, 1,429 crashes were shown to be associated with rural locations, while 1,457 crashes were associated with urban areas. The data element is based on the police report uploaded to Signal Four Analytics and the injury severity proportion of total single-vehicle work zone crashes in urban and rural areas by year is presented in Table 1. Table 2 shows a statistical description of the variables used in the upcoming four-year estimations.

4. Methodology

This research paper uses mixed logit models to identify the variables that impact the severity of driver injuries categorized as No injury (no injury), Minor injury (possible injury and non-capacitating injury), and severe injury (fatal or incapacitating injury) during work zone-related collisions in both urban and rural areas. Prior studies have demonstrated that this methodological approach is highly adaptable in modeling discrete outcomes, as it effectively accounts for unobserved variability (Islam, 2022; Mannering et al., 2016; Osman et al., 2016; Rangaswamy et al., 2023; Yu et al., 2022).

In order to measure the influence of various factors on the outcomes of driver injuries, a propensity function is established, as described by (Washington et al., 2020)

$$S_{yn} = \boldsymbol{\beta}_y \boldsymbol{X}_{yn} + \varepsilon_{yn} \tag{1}$$

S_{yn} represents the vector of explanatory variables that impact the severity of injuries in single-vehicle work zone–related crashes of type y. The error term is ε_{yn}, while $\mathbf{X}_{yn}$ is a vector in inquiry incorporating explanatory factors that influence the degree of damage for type y. $\boldsymbol{\beta}_y$ is a vector of estimable parameters. The usual multinomial logit model is obtained when the generalized extreme value distribution is specified for this error factor (McFadden, 1981)

$$P_i(n) = \frac{EXP[\boldsymbol{\beta}_n \boldsymbol{X}_{ni}]}{\sum_{\forall n} EXP[\boldsymbol{\beta}_k \boldsymbol{X}_{ni}]} \tag{2}$$

$P_i(n)$ is the likelihood that an injury severity outcome type n will result from a work zone–related collision i where i is the set of the three injury severities. In order to incorporate the potential variation of one or more parameter estimates in the vector $\boldsymbol{\beta}_n$ among crash observations, Equation (2) can be rewritten as follows (Train, 2009)

$$P_i(n) = \int \frac{EXP(\boldsymbol{\beta}_n \boldsymbol{X}_{ni})}{\sum_{\forall n} EXP(\boldsymbol{\beta}_n \boldsymbol{X}_{ni})} f(\boldsymbol{\beta}_n | \boldsymbol{\varphi}_n) d\boldsymbol{\beta}_n \tag{3}$$

where $f(\boldsymbol{\beta}_n|\boldsymbol{\varphi}_n)$ is the density function of $\boldsymbol{\beta}_n$ and $\boldsymbol{\varphi}_n$ is the vector of parameters characterizing the density function, including the mean and variance, which is consistent with the previously established definitions of all other words.

In order to incorporate the potential for variation in the means and variances of parameters that fluctuate with observations, define $\boldsymbol{\beta}_{ni}$ as a vector of estimable parameters that undergoes variation across the defined crashes (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019, 2017, 2016; Seraneeprakarn et al., 2017; Waseem et al., 2019; Washington et al., 2020)

$$\boldsymbol{\beta}_{\mathrm{ni}} = \boldsymbol{\beta}_n + \Theta_{ni} \boldsymbol{Z}_{\mathrm{ni}} + \sigma_{ni} EXP(\Psi_{ni} \boldsymbol{W}_{ni}) \nu_{ni} \tag{4}$$

In the given context, β_n represents the mean parameter estimate for all crashes, $\mathbf{Z}_{ni}$ signifies a vector of crash-specific explanatory variables that accounts for variability in the mean of the specified injury severity type n, $\boldsymbol{\Theta}_{ni}$ signifies a vector of estimable parameters that correspond to the corresponding $\mathbf{Z}_{ni}$, $\mathbf{W}_{ni}$ signifies a vector of crash-specific explanatory variables that accounts for variability in the standard deviation σ_{ni} with the corresponding Ψ_{ni} parameter vector, and ν_{ni} denotes a disturbance term.

Numerous density functions were empirically evaluated for $f(\boldsymbol{\beta}_n|\boldsymbol{\varphi}_n)$ during model estimation. All model estimations utilized the normal distribution as none of the alternatives demonstrated statistical superiority. This choice aligns with previous empirical research conducted in the sector (Behnood and Mannering, 2016). The model estimations using a simulated maximum likelihood approach, with 1,000 Halton draws (Bhat, 2001; McFadden and Train, 2000; Rangaswamy et al., 2023; Train, 2009; Washington et al., 2020). In order to discover the influence of independent factors on the outcome, marginal effects were calculated for crash injury severity type probabilities. The concept of

[1] These years were chosen due to data availability, and we acknowledge that obtaining more recent data would enhance the understating of drivers' behaviors in work zone locations that might be affected by the COVID-19 pandemic.

Table 2
Statistical description of variables found to be statistically significant.

Variables	RURAL				URBAN			
	2016	2017	2018	2019	2016	2017	2018	2019
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Roadway and traffic characteristics								
Road alignment (straight)	0.890	0.908	0.843	0.899	0.879	0.863	0.863	0.878
	(0.312)	(0.288)	(0.363)	(0.300)	(0.325)	(0.343)	(0.343)	(0.327)
Road alignment (curve)	0.107	0.091	0.153	0.100	0.112	0.129	0.133	0.115
	(0.310)	(0.288)	(0.360)	(0.300)	(0.316)	(0.336)	(0.339)	(0.319)
Road alignment (curve left)	0.059	0.047	0.084	0.044	0.060	0.058	0.077	0.068
	(0.496)	(0.211)	(0.278)	(0.206)	(0.237)	(0.234)	(0.268)	(0.253)
Interstate	0.560	0.432	0.285	0.260	0.324	0.348	0.376	0.315
	(0.496)	(0.495)	(0.451)	(0.439)	(0.468)	(0.476)	(0.484)	(0.465)
Posted speed (25–50 mph)	0.211	0.264	0.347	0.368	0.442	0.427	0.399	0.450
	(0.408)	(0.411)	(0.476)	(0.482)	(0.496)	(0.494)	(0.490)	(0.497)
Posted speed (51–60 mph)	0.299	0.288	0.175	0.219	0.136	0.147	0.172	0.209
	(0.458)	(0.453)	(0.380)	(0.414)	(0.343)	(0.354)	(0.377)	(0.407)
Posted speed (60 + mph)	0.441	0.361	0.746	0.330	0.248	0.241	0.279	0.181
	(0.496)	(0.480)	(0.435)	(0.470)	(0.432)	(0.428)	(0.448)	(0.385)
Two-way undivided	0.133	0.179	0.714	0.237	0.274	0.284	0.259	0.303
	(0.340)	(0.383)	(0.451)	(0.426)	(0.446)	(0.451)	(0.448)	(0.459)
Two-way divided	0.804	0.738	0.043	0.721	0.573	0.583	0.584	0.596
	(0.396)	(0.439)	(0.204)	(0.448)	(0.494)	(0.493)	(0.493)	(0.490)
Shoulder (paved)	0.662	0.717	0.028	0.676	0.591	0.586	0.597	0.631
	(0.472)	(0.450)	(0.164)	(0.468)	(0.491)	(0.272)	(0.438)	(0.482)
Signs	0.558	0.064	0.833	0.055	0.054	0.080	0.048	0.065
	(0.229)	(0.246)	(0.372)	(0.229)	(0.228)	(0.499)	(0.215)	(0.247)
Signals	0.037	0.038	0.407	0.044	0.099	0.091	0.077	0.078
	(0.191)	(0.191)	(0.491)	(0.206)	(0.299)	(0.288)	(0.268)	(0.268)
No controls	0.832	0.811	0.594	0.817	0.738	0.727	0.779	0.784
	(0.373)	(0.391)	(0.491)	(0.382)	(0.439)	(0.445)	(0.414)	(0.411)
No. lanes (4–5)	0.481	0.376	0.150	0.412	0.277	0.302	0.285	0.346
	(0.499)	(0.484)	(0.357)	(0.429)	(0.447)	(0.459)	(0.451)	(0.476)
Crash characteristics								
Vehicle impact (front)	0.534	0.555	0.250	0.587	0.164	0.577	0.587	0.581
	(0.498)	(0.497)	(0.433)	(0.492)	(0.371)	(0.494)	(0.438)	(0.493)
Vehicle impact (rear)	0.147	0.194	0.326	0.189	0.178	0.183	0.188	0.212
	(0.354)	(0.395)	(0.468)	(0.392)	(0.382)	(0.387)	(0.391)	(0.409)
Driving speed (25–50 mph)	0.175	0.252	0.253	0.301	0.138	0.286	0.298	0.318
	(0.380)	(0.434)	(0.435)	(0.459)	(0.345)	(0.452)	(0.457)	(0.466)
Driving speed (50–60 mph)	0.534	0.264	0.166	0.260	0.382	0.158	0.198	0.200
	(0.498)	(0.441)	(0.372)	(0.439)	(0.486)	(0.365)	(0.398)	(0.400)
Driving speed (60 + mph)	0.313	0.294	0.379	0.252	0.403	0.183	0.191	0.125
	(0.464)	(0.455)	(0.485)	(0.434)	(0.490)	(0.387)	(0.393)	(0.330)
Environmental conditions								
Weather (cloudy)	0.185	0.155	0.451	0.122	0.052	0.170	0.146	0.103
	(0.388)	(0.362)	(0.497)	(0.328)	(0.222)	(0.375)	(0.353)	(0.304)
Lighting condition (dark)	0.353	0.402	0.056	0.438	0.410	0.380	0.418	0.412
	(0.478)	(0.490)	(0.230)	(0.496)	(0.492)	(0.485)	(0.493)	(0.495)
Night	0.405	0.438	0.442	0.475	0.403	0.727	0.451	0.446
	(0.491)	(0.496)	(0.496)	(0.499)	(0.490)	(0.445)	(0.497)	(0.497)
Driver and passenger characteristics								
Driver age (15–19)	0.055	0.050	0.084	0.022	0.052	0.302	0.045	0.046
	(0.229)	(0.218)	(0.278)	(0.147)	(0.222)	(0.459)	(0.208)	(0.211)
Driver age (25–45)	0.407	0.438	0.442	0.423	0.410	0.577	0.464	0.450
	(0.491)	(0.496)	(0.084)	(0.494)	(0.492)	(0.494)	(0.498)	(0.497)
Driver age (65–80)	0.0638	0.067	0.084	0.078	0.073	0.183	0.064	0.078
	(0.244)	(0.251)	(0.278)	(0.268)	(0.260)	(0.387)	(0.246)	(0.268)
Driver action (careless)	0.197	0.241	0.266	0.230	0.196	0.286	0.172	0.159
	(0.398)	(0.428)	(0.442)	(0.421)	(0.397)	(0.452)	(0.377)	(0.366)
Driver action (no action)	0.487	0.482	0.523	0.535	0.497	0.158	0.535	0.437
	(0.499)	(0.499)	(0.499)	(0.499)	(0.500)	(0.365)	(0.498)	(0.496)
Gender (male)	0.640	0.664	0.667	0.665	0.641	0.183	0.633	0.628
	(0.479)	(0.472)	(0.471)	(0.472)	(0.479)	(0.387)	(0.482)	(0.483)
Alcohol (no)	0.978	0.952	0.962	0.936	0.937	0.286	0.967	0.950
	(0.146)	(0.211)	(0.190)	(0.243)	(0.242)	(0.452)	(0.177)	(0218)
Vehicle characteristics								
Vehicle defect (yes)	0.095	0.067	0.081	0.070	0.068	0.158	0.077	0.062
	(0.294)	(0.251)	(0.273)	(0.256)	(0.251)	(0.365)	(0.268)	(0.242)
Vehicle defect (no)	0.904	0.911	0.902	0.929	0.929	0.183	0.896	0.934
	(0.294)	(0.283)	(0.296)	(0.256)	(256)	(0.987)	(0.305)	(0.247)
Passenger car	0.572	0.505	0.573	0.542	0.554	0.170	0.896	0.606
	(0.494)	(0.500)	(0.494)	(0.498)	(0.497)	(0.375)	(0.305)	(0.488)

(continued on next page)

Table 2 (*continued*)

Variables	RURAL				URBAN			
	2016	2017	2018	2019	2016	2017	2018	2019
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Vehicle built (1965–2000)	0.079 (0.271)	0.094 (0.292)	0.075 (0.263)	0.070 (0.256)	0.130 (0.337)	0.078 (0.268)	0.564 (0.496)	0.606 (0.488)
Vehicle built (2010 +)	0.449 (0.497)	0.500 (0.500)	0.554 (0.497)	0.624 (0.484)	0.418 (0.493)	0.496 (0.500)	0.068 (0.252)	0.043 (0.204)
Registered outside FL	0.103 (0.305)	0.126 (0.332)	0.119 (0.324)	0.066 (0.250)	0.068 (0.251)	0.069 (0.254)	0.581 (0.493)	0.615 (0.486)
Registered in FL	0.894 (0.307)	0.861 (0.345)	0.871 (0.334)	0.933 (0.250)	0.926 (0.260)	0.908 (0.288)	0.071 (0.257)	0.109 (0.312)
Work zone characteristics								
WZ type (lane closure)	0.169 (0.375)	0.264 (0.441)	0.203 (0.403)	0.286 (0.452)	0.222 (0.416)	0.228 (0.419)	0.237 (0.425)	0.884 (0.319)
WZ type (lane shift)	0.103 (0.305)	0.064 (0.246)	0.100 (0.300)	0.063 (0.243)	0.073 (0.260)	0.089 (0.285)	0.116 (0.321)	0.193 (0.395)
Worker's present (no)	0.540 (0.498)	0.544 (0.498)	0.467 (0.499)	0.457 (0.498)	0.403 (0.490)	0.476 (0.499)	0.480 (0.499)	0.546 (0.498)
Worker's present (yes)	0.365 (0.481)	0.394 (0.488)	0.420 (0.493)	0.460 (0.498)	0.479 (0.499)	0.378 (0.485)	0.389 (0.487)	0.350 (0.477)
Law enforcement present (yes)	0.842 (0.364)	0.850 (0.357)	0.783 (0.411)	0.765 (0.423)	0.806 (0.395)	0.803 (0.397)	0.766 (0.423)	0.103 (0.304)
WZ location (advance warning area)	0.101 (0.302)	0.097 (0.296)	0.078 (0.268)	0.118 (0.323)	0.078 (0.269)	0.087 (0.282)	0.116 (0.321)	0.056 (0.230)
WZ type (intermittent)	0.055 (0.229)	0.055 (0.229)	0.056 (0.230)	0.081 (0.274)	0.0523 (0.222)	0.046 (0.211)	0.048 (0.215)	0.259 (0.438)
Temporal characteristics								
Winter	0.209 (0.407)	0.220 (0.414)	0.163 (0.369)	0.267 (0.443)	0.232 (0.422)	0.187 (0.390)	0.155 (0.362)	0.259 (0.438)
Spring	0.267 (0.442)	0.252 (0.434)	0.244 (0.430)	0.260 (0.439)	0.321 (0.467)	0.277 (0.447)	0.262 (0.440)	0.271 (0.445)
Other variables								
East	0.159 (0.366)	0.179 (0.383)	0.194 (0.395)	0.193 (0.395)	0.180 (0.384)	0.187 (0.390)	0.172 (0.377)	0.228 (0.419)
North	0.373 (0.483)	0.335 (0.472)	0.285 (0.451)	0.368 (0.482)	0.301 (0.458)	0.270 (0.444)	0.279 (0.448)	0.315 (0.465)
South	0.339 (0.473)	0.320 (0.466)	0.344 (0.475)	0.219 (0.414)	0.282 (0.450)	0.328 (0.469)	0.282 (0.450)	0.253 (0.435)

Table 3
Likelihood ratio test results between rural and urban (in parentheses) for different years [refer Eq. (5)].

Time	X^2	Percent Confidence Level	Degree of Freedom
2016	45.32 (19.48)	99.99 (85.52)	12 (14)
2017	31.28 (31.18)	99.99 (99.89)	12 (11)
2018	24.92 (39.24)	99.99 (99.99)	9 (10)
2019	12.32 (28.24)	73.57 (99.99)	10 (11)

marginal effect suggests that a single-unit increase in an explanatory variable is associated with changes in the probability of crash-type injury severity. The average marginal effect of overall crash observations is presented in future tables for potential concerns connected with marginal effects computations in the context of random parameters models (Hou et al., 2022).

5. Temporal stability test

In evaluating whether there are statistically significant differences in driver injury severity models between urban and rural work zone areas for the years 2016–2019, likelihood ratio tests were performed for each year using a $\chi 2$ distributed test statistic (where the degree of freedom corresponds to the number of estimated parameters) (Washington et al., 2020)

$$X^2 = -2[LL(\boldsymbol{\beta}_{RU}) - LL(\boldsymbol{\beta}_R)] \tag{5}$$

Where $LL(\boldsymbol{\beta}_{RU})$ is the log-likelihood at the convergence of a model (for a given year) having converged parameters from rural work zone (wz) on urban wz data (restricting the parameters to be rural estimated parameters) from the year, $LL(\boldsymbol{\beta}_R)$ is the log-likelihood at the convergence of the model using the urban wz data. Reversing rural and urban for this test was also performed each year. The value X^2, which follows a $\chi 2$ distribution, can be utilized to assess if it is possible to reject the null

Table 4
Comparing the outcomes of likelihood ratio tests conducted in rural and urban work zones using a single vehicle throughout the years. Shown are the confidence levels in percentage and (degrees of freedom in parentheses) and [x^2 in brackets] {refer Eq. (6)}.

Rural	p_2			
p_1	2016	2017	2018	2019
2016	–	212.92 (12) [>99.99 %]	231.42 (9) [>99.99 %]	259.98 (10) [>99.99 %]
2017	156.24 (12) [>99.99 %]	–	39.58 (9) [>99.99 %]	57.44 (10) [>99.99 %]
2018	123.71 (12) [>99.99 %]	21.52 (12) [>94.96 %]	–	37.10 (10) [>99.99 %]
2019	191.96 (12) [>99.99 %]	13.91 (12) [>69.28 %]	18.34 (9) [>96.85 %]	–
Urban	p_2			
p_1	2016	2017	2018	2019
2016	–	19.23 (11) [>94.29 %]	285.80 (10) [>99.99 %]	192.90 (11) [>99.99 %]
2017	51.58 (14) [>99.99 %]	–	302.60 (10) [>99.99 %]	208.14 (11) [>99.99 %]
2018	206.81 (14) [>99.99 %]	224.82 (11) [>99.99 %]	–	66.58 (11) [>99.99 %]
2019	130.01 (14) [>99.99 %]	156.18 (11) [>99.99 %]	112.42 (10) [>99.99 %]	–

Table 5
Partially temporally constrained random parameters logit with heterogeneity in means and variances results for single-vehicle urban work-zone crashes in Florida (parameters defined for: [NI] No injury; [MI] Minor injury; [SI] Severe injury; years [2016], [2017], [2018],[2019].

Variable Description	Estimated Parameter	t-stat	Marginal effects		
			No injury	Minor injury	Severe injury
Constant [NI] [2017]	2.9018	9.37			
Constant [NI] [2018]	4.0499	4.24			
Constant [MI] [2016]	−1.4831	−5.18			
Constant [MI] [2017]	2.1802	6.66			
Constant [MI] [2018]	5.7166	3.85			
Constant [MI] [2019]	−0.9866	−4.15			
Constant [SI] [2019]	−3.3134	−2.55			
Random parameter (normally distributed)					
Mid-age 1 indicator (1 if driver age is between 25 and 45; 0 otherwise) [NI] [2016]	2.7815	1.71	0.0016	−0.0014	−0.0003
Standard deviation of no action indicator	1.7340	1.43			
Newer vehicle indicator (1 if the vehicle build is 2010+; 0 otherwise) [NI] [2018]	3.1701	1.91	−0.008	0.002	0.006
Standard deviation of no action indicator	1.4499	1.12			
Heterogeneity in the mean of the random parameters					
No action indicator (1 if driver's first action is no contributing action; 0 otherwise) [NI] [2018]	3.5823	2.08			
Curve left indicator (1 if road alignment is curve left; 0 otherwise) [NI] [2016]	3.4083	1.57			
Roadway and traffic characteristics					
Straight indicator (1 if road alignment is straight; 0 otherwise) [SI] [2019]	−3.0921	−2.64	0.0067	0.0012	−0.0079
Posted speed 60 plus indicator (1 if the posted speed is 60 plus mph; 0 otherwise) [SI] [2019]	4.0806	2.56	−0.0037	−0.0006	0.0041
Posted speed 50–60 indicator (1 if the posted speed is between 50 and 60 mph; 0 otherwise) [MI] [2016]	1.2446	2.94	−0.0061	0.0071	−0.0009
Curve left indicator (1 if road alignment is curve left; 0 otherwise) [NI] [2016]	−1.7777	−2.84	−0.0040	0.0032	0.0008
Four-five lane indicator (1 if 4–5 lanes; 0 otherwise) [SI] [2019]	−4.1044	−2.19	0.0019	0.0004	−0.0023
Two-way indicator (1 if the roadway has two-way divided traffic; 0 otherwise) [MI] [2016]	0.9517	2.04	−0.0046	−0.0025	0.0072
Signals indicator (1 if signals present; 0 otherwise) [MI] [2017]	1.2187	2.01	−0.0011	−0.0004	0.0015
Sign indicator (1 if signs present; 0 otherwise) [MI] [2019]	0.9478	1.73	−0.0026	0.0026	0.0001
No controls indicator (1 if there are no traffic controls; 0 otherwise) [NI] [2018]	1.6436	3.04	0.0159	−0.0133	−0.0025
Crash characteristics					
Vehicle front impact indicator (1 if vehicle principal impact was on front; 0 otherwise) [NI] [2018]	−1.8912	−2.80	−0.0212	0.0173	0.0039
Vehicle front impact indicator (1 if vehicle principal impact was on front; 0 otherwise) [SI] [2019]	−4.1828	−2.93	0.0033	0.0007	−0.0041
Vehicle rear impact indicator (1 if vehicle principal impact was on the rear; 0 otherwise) [MI] [2017]	−0.7212	−1.67	0.0028	−0.0030	0.0002
Environmental conditions					
Dark indicator (1 if the lighting condition is dark; 0 otherwise) [SI] [2019]	1.7468	1.70	−0.0034	−0.0006	0.0041
Night indicator (1 if the crash occurred in nighttime; 0 otherwise) [MI] [2018]	1.6226	3.00	0.0094	−0.0104	0.0010
Driver and passenger characteristics					
No action indicator (1 if driver's first action is no contributing action; 0 otherwise) [NI] [2017] [2019]	0.7714	3.76	0.0201	−0.0170	−0.0031
No action indicator (1 if driver's first action is no contributing action; 0 otherwise) [MI] [2016]	−1.6203	−2.39	0.0022	0.0012	−0.0033
Speed 26–49 mph indicator (1 if the vehicle speed is between 26–49 mph; 0 otherwise) [NI] [2017]	−0.5223	−2.00	−0.0083	0.0067	0.0017
Speed 26–49 mph indicator (1 if the vehicle speed is between 26–49 mph; 0 otherwise) [MI] [2016]	0.7887	2.34	−0.0071	0.0082	−0.0011
Speed 50–60 mph indicator (1 if the vehicle speed is between 50–60 mph; 0 otherwise) [MI] [2018]	−21661	−2.58	0.0028	−0.0033	0.0004
Male indicator (1 if driver gender is male; 0 otherwise) [MI] [2018]	−1.4611	−2.58	0.0094	−0.0104	0.0010
No alcohol indicator (1 if driver not impaired by alcohol; 0 otherwise) [MI] [2016]	−2.6931	−5.49	0.0162	0.0084	−0.0246
Vehicle characteristics					
Defect indicator (1 if the vehicle has a defect; 0 otherwise) [MI] [2017]	0.7651	1.81	−0.0032	0.0034	−0.002
Passenger car indicator (1 if the vehicle is a passenger car; 0 otherwise) [NI] [2016] [2018]	1.3509	4.91	0.0301	−0.0242	−0.0059
Newer vehicle indicator (1 if vehicle built is 2010+; 0 otherwise) [MI] [2019]	−0.5666	−1.79	0.0083	−0.0085	0.0002
Registered in state indicator (1 if the vehicle is registered in Florida) [MI] [2018]	−2.7803	−2.48	0.0287	−0.0313	0.0026
Registered out-of-state indicator (1 if the vehicle is registered outside Florida) [MI] [2019]	−1.1053	−1.69	0.0019	−0.0020	0.0001
Registered out-of-state indicator (1 if the vehicle is registered outside Florida) [NI] [2017]	2.5163	2.43	0.0016	−0.0014	−0.0003
Work zone characteristics					
Advance warning indicator (1 if the location is an advance warning area; 0 otherwise) [SI] [2019]	3.6835	3.00	−0.0043	−0.0008	0.0051
Advance warning indicator (1 if the location is an advance warning area; 0 otherwise) [MI] [2017]	−1.9243	−2.52	0.0023	−0.0024	0.0001
Intermittent indicator (1 if work zone type is intermittent; 0 otherwise) [SI] [2016]	1.2055	1.52	−0.0011	−0.0004	0.0015
Law enforcement present indicator (1 if law enforcement is present in the work zone; 0 otherwise) [NI] [2017]	1.4911	1.96	0.0019	−0.0014	−0.0005
No workers indicator (1 if no workers are present in the work zone; 0 otherwise) [MI] [2016]	0.9070	2.81	−0.0118	0.0137	−0.0018
Worker's present indicator (1 if workers present in the work zone; 0 otherwise) [MI] [2017]	−0.8648	−2.65	0.0073	−0.0077	0.0004
Temporal characteristics					
Winter indicator (1 if the crash occurred between the months of December–February; 0 otherwise) [MI] [2017]	−0.6461	−1.68	0.0033	−0.0036	0.0002
Spring indicator (1 if the crash occurred between the months March-May; 0 otherwise) [SI] [2018]	2.1337	2.25	−0.0034	−0.0013	0.0048
Other variables					
South indicator (1 if the crash direction is south; 0 otherwise) [MI] [2016]	1.0846	2.12	−0.0034	−0.0016	0.0050
No. of observations	1457				
LL at zero	−865.05				
LL at convergence	−724.13				

hypothesis that the parameters are the same throughout all four periods. As shown in Table 3, this test clearly shows that the null hypothesis that rural and urban injury severity models are the same can be rejected with high confidence levels for each of the four years.

In addition to assessing the temporal stability of the factors that influence the severity of driver injuries in work-related crashes throughout the study period, a set of likelihood ratio tests was performed to compare models developed annually. These tests aimed to determine whether the estimated parameters remain constant over time. The test statistic is expressed as follows: $\chi 2$ distribution, where degrees of freedom correspond to the number of calculated parameters.

$$X^2 = -2\left[LL(\beta_{p_2p_1}) - LL(\beta_{p_1})\right] \quad (6)$$

In this context, the log-likelihood at convergence of a model with converged parameters derived from time-period p_2's data and data from time-period t_1 is denoted by $LL(\beta_{p_2p_1})$ and $LL(\beta_{p_1})$ represent the log-likelihood at convergence of the model utilizing time-period t_1's data, without being limited to time-period p_2's converged parameters, as is the case with $LL(\beta_{p_2p_1})$. Additionally, this examination was conducted in reverse, so that time period p_2 became subset p_1 and time period t_1 was converted to time period p_2 (thus giving two test results for each model comparison). The value X^2, which follows a $\chi 2$ distribution, can be utilized to assess if it is possible to reject the null hypothesis that the parameters are identical during the two periods. As shown in Table 4, the null hypothesis that rural and urban model estimates are the same from one year to the next can be rejected with over 99 % confidence.

6. Partially temporally constrained modeling

The issue of small sample size is a critical consideration, as discussed in previous studies (de Jong et al., 2019; Ye and Lord, 2014), when crash severity models have a small sample size, they can give unpredictable results. This limits their ability to accurately estimate the real factors and can lead to inaccurate predictions about how likely different levels of severity are. De Jong et al. (2019) conducted a simulation study on the effects of the number of multinomial events per variable (EPV_m), highlighting the importance of sample size, where predictive performance improves with an increasing EPV_m ratio. Models with $EPV_m < 10$ were recommended to be interpreted cautiously, and the use of penalized methods was suggested for better predictive performance. Ye and Lord (2014) focused on crash severity models, emphasizing the significant impact of small sample sizes on model development. Their study used Monte-Carlo simulation and revealed that the mixed logit model requires the largest sample size, the ordered probit requires the lowest, and the multinomial logit model falls in between.

This study utilized a technique known as the partially constrained temporal modeling approach, as demonstrated in Table 5 and Table 6, to tackle potential sample size challenges within the dataset. This approach utilizes all available data, defining parameters for each time period and conducting statistical tests, such as the likelihood ratio test, to determine if individual parameters from different time periods can be combined. This method is equivalent to estimating separate models for each time period. The partially temporally constrained model provides a comprehensive analysis of temporal variations in variable impacts on crash severity, offering a robust solution to mitigate the impact of potential sample size limitations as mentioned in previous studies (de Jong et al., 2019; Ye and Lord, 2014). Partially temporally constrained method, as discussed in a prior study by (Alnawmasi and Mannering, 2023), allows for detailed modeling, accommodating variable effects that may change over time while maintaining consistency in others. Careful consideration of these approaches is crucial to enhance predictive accuracy and avoid potential modeling errors.

To construct the partially temporally constrained model, all available years of data are utilized, with specific indicators defined for each year. For instance, in the context of a four-year period, indicators for a four-lane closure work zone type are established: 1 if a lane closure and the crash occurred in 2016, 0 otherwise; 1 if a lane closure and the crash occurred in 2017, 0 otherwise; 1 if a lane closure and the crash occurred in 2018, and 1 if a lane closure and the crash occurred in 2019, 0 otherwise. The main emphasis of this paper lies in the results of partially temporally constrained parameter estimation, as showcased in Table 5 (urban work zones) and Table 6 (rural work zones). It's important to note that these results are statistically identical to those obtained from the unconstrained models (Alnawmasi and Mannering, 2023).

6.1. Variables producing random parameters

Table 5 and Table 6 present results for single-vehicle urban and rural work-zone crashes in Florida for the years between 2016–2019, respectively. As shown in Table 5, mid-age 1 (age between 25–45) indicator in 2016 and newer vehicle (built in 2010 or later) indicator in 2018 were found to be statistically significant random parameters with the higher likelihood of having no injury severity. Similarly, Table 6 highlights random parameters, such as the paved indicator in 2016 and 2017 and the straight indicator in 2018 to be statistically significant random parameters with the higher likelihood of having minor injury.

Variables such as the no action (driver pre-crash action before getting into crash) indicator (in 2018) and curve left indicator (in 2016) for no injury in the impact of road alignment on injury probabilities showcase heterogeneity in their means for the significant random parameters for urban dataset. For rural dataset, as shown in Table 6 demonstrates instances of mean parameter heterogeneity, the combined effect of other pre-crash driver actions (such as engaging in unpredictable, dangerous, or aggressive driving behaviors, such as operating a motor vehicle, over-correcting/over-steering, running off the roadway, running red lights or stop signs, swerving or avoiding, driving on the wrong side or wrong way, disregarding road markings or traffic signs, exceeding posted speed limits, failing to yield right-of-way, following too closely, improper backing, improper passing, and improper turns) for no injury in 2016. Overall, the significance of these random parameters with or without heterogeneity in their mean and variance shows that specific factors influence work zone crashes in rural and urban settings.

7. Model estimation results

In both urban (Table 5) and rural (Table 6) work zone crash models, the straight indicator significantly impacts injury probabilities. For instance, in the rural work zone areas (2018), a straight road alignment is associated with a decrease in the likelihood of severe injury, as indicated by the negative marginal effects of −0.0091. Similarly, in the urban work zone areas (2019), the same straight indicator demonstrates a positive impact on severe injury probabilities, with a marginal effect of 0.0041, and these results are consistent with previous studies (Ahmed et al., 2023; Al-Bdairi, 2020; Osman et al., 2018; Zhang, 2019; Zhang and Hassan, 2019b). The no action (driver pre-crash action) indicator consistently influences the probabilities of no injury in urban (2018) and rural (2017) work zones, with marginal effects of 0.0287 and 0.0201, respectively, suggesting an increased likelihood of avoiding injuries when the driver's first action does not contribute to the crash. The posted speed (1 if the posted speed is 60 + mph; 0 otherwise) indicator was found to increase the probability of severe injury in rural (2019) and urban (2019) work zones. The dark lighting condition indicator, shared in both rural (2018) and urban (2019) work zones, increased the likelihood of severe injury; similar results have been found in previous studies (Al-Bdairi, 2020; Ghasemzadeh and Ahmed, 2019; Islam et al., 2020; Li and Bai, 2009; Madarshahian et al., 2023; Wei et al., 2017; Yu et al., 2022).

Work zones with four to five lanes were found to increase the likelihood of severe injury in 2019 in urban work zones. On the other hand, the interstate indicator in 2016 was found to increase the likelihood of minor injury. The presence of signals in urban work zones (in 2017) is linked to a higher probability of severe injury. Based on the findings of the urban Table 5 and rural Table 6 models, a work zone featuring two-way divided traffic may generate more complicated traffic patterns and interactions, hence increasing the probability of minor injuries, as shown by an average marginal effect of 0.0072 in 2016 urban work zones [Table 5]. However, in the 2017 rural work zone [Table 6], two-way undivided traffic increased the likelihood of no injury with a marginal effect of 0.0031. If the vehicle's principal impact was front, lower probabilities of severe injury were observed specific to urban work zones

Table 6
Partially temporally constrained random parameters logit with heterogeneity in means and variances results for single-vehicle rural work-zone crashes in Florida (parameters defined for: [NI] No injury; [MI] Minor injury; [SI] Severe injury; years [2016], [2017], [2018],[2019].

Variable Description	Estimated parameter	t-stat	Marginal effects		
			No injury	Minor injury	Severe injury
Constant [MI] [2016]	−1.6666	−4.87			
Constant [MI] [2017]	−1.1429	−3.51			
Constant [MI] [2018]	−2.1703	−4.35			
Constant [MI] [2019]	−1.8387	−4.97			
Constant [SI] [2016]	−2.6084	−6.09			
Constant [SI] [2017]	−2.3864	−2.93			
Constant [SI] [2018]	−4.2978	−5.27			
Constant [SI] [2019]	−4.5641	−5.60			
Random parameter (normally distributed)					
Paved indicator (1 if paved shoulder; 0 otherwise) [MI] [2016] [2017]	1.6534	1.86	−0.0061	0.0062	−0.0001
Standard deviation of no action indicator	−1.3177	−1.64			
Straight indicator (1 if road alignment is straight; 0 otherwise) [MI] [2018]	2.7382	1.61	−0.0012	0.0013	−0.0001
Standard deviation of no action indicator	−2.7761	−1.48			
Heterogeneity in the mean of the random parameters					
Other action indicator (1 if the first harmful event is other actions; 0 otherwise) [NI] [2016]	1.1163	2.04			
Roadway and traffic characteristics					
Straight indicator (1 if road alignment is straight; 0 otherwise) [SI] [2017]	−1.2775	−1.95	0.0080	0.0011	−0.0091
Curve indicator (1 if road alignment is curved; 0 otherwise) [MI] [2016]	1.0499	2.20	−0.0054	0.0056	−0.0003
Interstate indicator (1 if the road is interstate; 0 otherwise) [NI] [2016]	0.9643	2.81	0.0178	−0.0119	−0.0059
Posted speed 25–50 indicator (1 if the posted speed is between 25 and 50 mph; 0 otherwise) [SI] [2017]	1.2900	1.80	−0.0041	−0.0007	0.0048
Posted speed 60 plus indicator (1 if the posted speed is 60 plus mph; 0 otherwise) [SI] [2016]	1.0054	1.88	−0.0057	−0.0006	0.0038
Two-way indicator (1 if the roadway has two-way undivided traffic; 0 otherwise) [NI] [2017]	0.9137	1.75	0.0031	−0.0022	−0.0009
Crash characteristics					
Vehicle front impact indicator (1 if vehicle principal impact was on front; 0 otherwise) [NI] [2016]	−0.6707	−2.23	−0.0161	0.0116	0.0045
Environmental conditions					
Cloudy indicator (1 if the weather condition is cloudy; 0 otherwise) [SI] [2016]	0.9293	1.82	−0.0032	−0.0005	0.0038
Dark indicator (1 if the lighting condition is dark; 0 otherwise) [SI] [2018]	1.0190	1.81	−0.0047	−0.0006	0.0053
Driver and passenger characteristics					
Very young indicator (1 if driver age is between 15 and 19; 0 otherwise) [MI] [2017]	1.0544	1.73	−0.0064	0.0070	−0.0006
Mid-age 1 indicator (1 if driver age is between 25 and 45; 0 otherwise) [MI] [2016]	−0.7007	−1.94	0.0065	−0.0069	0.0003
Old indicator (1 if driver age is between 65 and 80; 0 otherwise) [SI] [2016] [2019]	1.0306	2.70	−0.0051	−0.0008	0.0059
Carless action indicator (1 if the driver's first action is operated vehicle careless or negligent; 0 otherwise) [MI] [2019]	0.9386	3.54	−0.0142	0.0151	−0.0009
No action indicator (1 if driver's first action is no contributing action; 0 otherwise) [NI] [2017]	1.0974	2.77	0.0085	−0.0061	−0.0025
Speed 60 + indicator (1 if the vehicle speed is between 60 + mph; 0 otherwise) [SI] [2017]	1.3802	1.98	−0.0052	−0.0006	0.0058
Male indicator (1 if driver gender is male; 0 otherwise) [SI] [2018] [2019]	1.8739	2.51	−0.0260	−0.0039	0.0299
Vehicle characteristics					
Defect indicator (1 if the vehicle has a defect; 0 otherwise) [MI] [2016]	0.9326	1.82	−0.0036	0.0038	−0.0002
Defect indicator (1 if the vehicle has a defect; 0 otherwise) [MI] [2018]	2.6272	2.78	−0.0050	0.0056	−0.0006
Passenger car indicator (1 if the vehicle is a passenger car; 0 otherwise) [SI] [2016] [2019]	−1.2481	−3.04	0.0065	0.0009	−0.0074
Very old vehicle indicator (1 if the vehicle built is 1965–2000; 0 otherwise) [MI] [2017]	1.0544	1.73	−0.0027	0.0030	−0.0002
Newer vehicle indicator (1 if vehicle built is 2010+; 0 otherwise) [MI] [2019]	−1.0356	−2.74	0.0086	−0.0092	0.0006
Newer vehicle indicator (1 if vehicle built is 2010+; 0 otherwise) [SI] [2016] [2018]	−2.2071	−4.05	0.0055	0.0005	−0.0060
Work zone characteristics					
Lane closure indicator (1 if work type is lane closure; 0 otherwise) [MI] [2017] [2019]	−1.2099	−2.93	0.0061	−0.0065	0.0004
Lane shift indicator (1 if work zone type is lane shift; 0 otherwise) [MI] [2018]	1.7623	2.34	−0.0041	0.0045	−0.0004
No workers indicator (1 if no workers are present in the work zone area; 0 otherwise) [NI] [2019]	−0.6390	−1.89	−0.0097	0.0073	0.0024
Temporal characteristics					
Winter indicator (1 if the crash occurred between the months of December–February; 0 otherwise) [MI] [2019]	0.7887	2.02	−0.0054	0.0058	−0.0004
Other variables					
East indicator (1 if the crash direction is east; 0 otherwise) [SI] [2019]	1.1791	1.96	−0.0030	−0.0006	0.0037
North indicator (1 if the crash direction is north; 0 otherwise) [MI] [2016]	−0.6849	−1.80	0.0055	−0.0058	−0.0003
No. of observations	1429				
LL at zero	−793.56				
LL at convergence	−689.63				

in 2019 with a marginal effect of −0.0041 [Table 5]. Conversely, Table 6 shows an increased likelihood of no injury in rural areas with a front impact (in 2016) with a marginal effect of 0.6707. This might be due to the presence of lower traffic volumes and open roads in rural areas resulting in different crash dynamics compared to urban areas with higher traffic and complex road layouts.

Urban work zones during nighttime are found to increase the probability of severe injury at night, with a marginal effect of 0.0094. In rural work zones, cloudy weather conditions show an increased likelihood of severe injury, with a marginal effect of 0.0032.

Male indicators have a stronger influence on both urban and urban work zone crashes, with a lower probability of having a minor injury in urban work zones (in 2018) and a higher probability of having a severe injury in rural work zones (in 2019). Drivers with no influence of alcohol were found to have less likelihood of having a minor injury in the urban 2016 model. Previous studies (Al-Bdairi, 2020; Wei et al., 2017; Yu et al., 2022, 2020) have found similar results in work zone-related crashes with an increase in severe injury severity if influenced by alcohol or a decrease in injury severity if not influenced by alcohol.

Conversely, very young indicators (drivers aged 15–19) and old indicators (drivers aged 65–80) show a more pronounced effect on rural work zone crashes with a higher likelihood of having severe injury (2016 and 2019 model) and minor injury (2017 model), and these findings align with other previous studies (Al-Bdairi, 2020; Islam et al., 2020; Yu et al., 2020; Zhang, 2019). Previous studies (Ghasemzadeh, 2019; Islam et al., 2020; Li and Bai, 2009; Zhang, 2018) have found driver pre-crash action to influence crash injury severity significantly. In this research, drivers with no contributing pre-crash action were significant in urban (2017 and 2019), significantly increasing the likelihood of having no injury and in 2016 decreasing the likelihood of minor injury, whereas in rural work zones, in 2017, the likelihood of having no

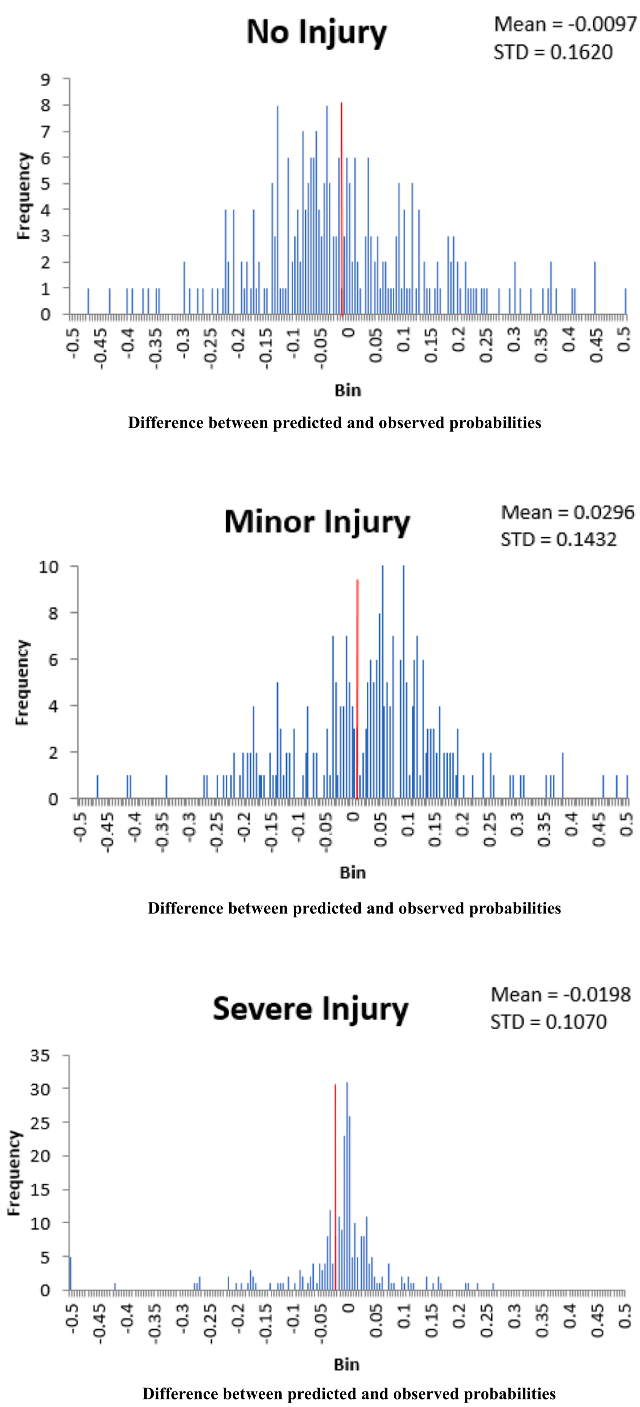

Fig. 1. Difference between 2016-rural model predicted probabilities in 2019-rural data and 2019-rural "observed probabilities."

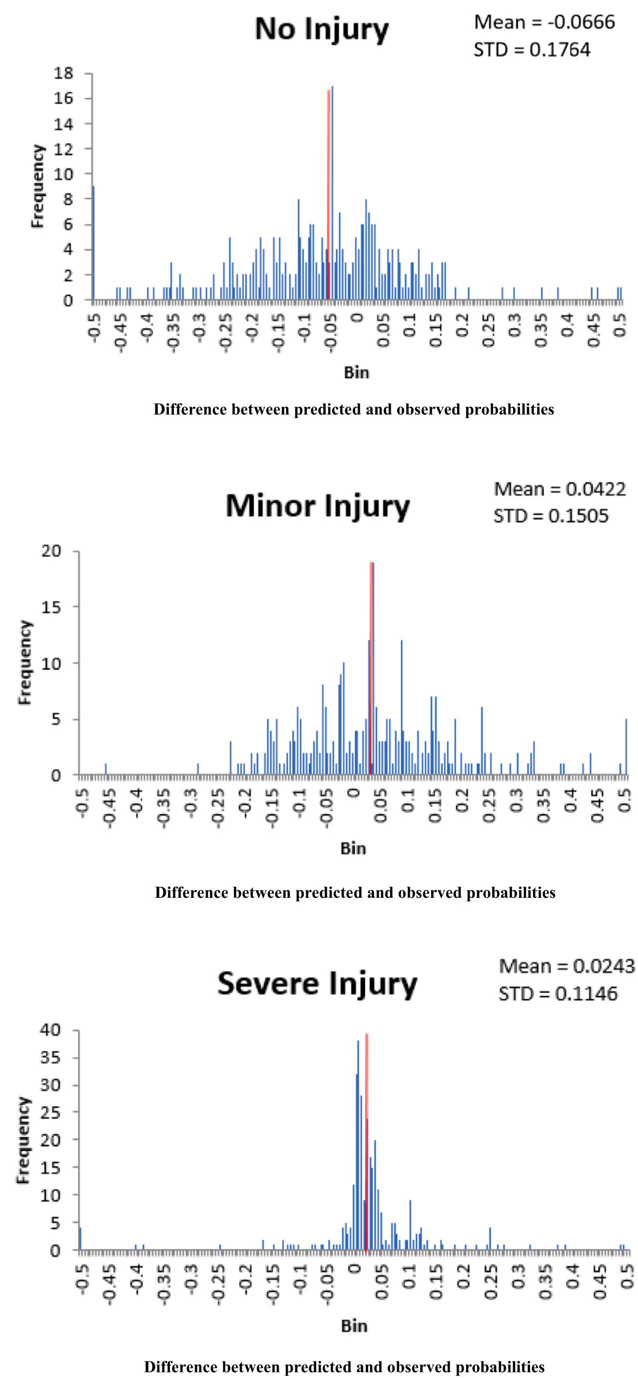

Fig. 2. Difference between 2016-urban model predicted probabilities in 2019-urban data and 2019-urban "observed probabilities."

injury was found to be increasing.

In rural areas [Table 6], vehicle defects (2012 model) and vehicles built between 1965–2000 (2016 and 2018) significantly increased the likelihood of minor injury, and in urban areas [Table 5] in the year 2017. In urban work zones, vehicles registered in the state were found to decrease the likelihood of minor injury (2018), and vehicles not registered in Florida tend to decrease the likelihood of minor injury (2016) and increase the likelihood of no injury (2017). Passenger cars had a higher probability of having no injury (2016 and 2018) in urban work zones, whereas in rural work zones, the passenger car indicator increased the probability of having severe injury (2016 and 2019). Previous studies (Al-Bdairi, 2020; Islam et al., 2020; Osman et al., 2018;

Yu et al., 2022; Zhang and Hassan, 2019b) have also found similar results wherein passenger vehicles have influenced work zone crash injury severities. Additionally, new vehicle indicators (vehicles built in 2010 or later) have varying effects on rural and urban work zone crashes, significantly decreasing the likelihood of having minor and severe injury, further emphasizing the importance of considering vehicle characteristics in a location-specific context.

Work zone characteristics are crucial in influencing crash likelihood in both rural and urban areas. In rural work [Table 6] zones, lane shift (2018) indicator with a decreasing probability of minor injury and lane closure (2017 and 2019) indicators have with increasing probability of minor injury, while advance warning indicators have a significant likelihood of increasing the severe injury (2019) and decreasing the likelihood of minor injury (2017) in urban work zones [Table 5]. These differences underscore the varying nature of work zone-related risks in different locations, and similar findings have been found in previous studies (Ahmed et al., 2023; Islam et al., 2020; Osman et al., 2018; Wong et al., 2011). Crashes occurring between December to February [Winter indicator] in both urban (2017) and rural (2019)areas were found to have a greater likelihood of minor injury. Zhang (2019) found similar results where winter indicators influence work zone crash severity. Vehicles traveling in the east and north directions in rural work zone areas (2019 and 2016, respectively) and urban work zone areas traveling in the south direction (2016) influenced the likelihood of crash injury severities. In Florida, east and south directions often correspond to major transportation corridors with higher traffic volumes and speed limits. Over the past couple of years, these corridors have been congested with active work zones, and the combination of these factors has influenced work zone crash severity.

8. Predictive comparison

In order to understand how temporal shifts impact the likelihood of crash injury severity in rural and urban work zone crashes, this study conducted out-of-sample predictions using a simulation approach. Previous studies such as (Alogaili and Mannering, 2022; Rangaswamy et al., 2023) have used similar approaches to analyze injury severity probabilities and pre-crash action.

The probabilities of single-vehicle driver injury severities for observed individual crashes in both rural and urban areas in 2019 were compared. This comparison was made between the 'predicted' values, calculated using the 2016 rural and urban models, and the 'observed' values calculated by the 2019 rural and urban models.

The mean and standard deviation of the differences between the two probabilities are shown in Fig. 1 (for the rural model) and Fig. 2 (for the urban model). The mean at the injury severity levels for rural shows that using 2016 model parameters, no injury and severe injury by 0.0097 and 0.0198, respectively, and overestimates minor injury by 0.0296. In urban areas, the mean at the injury severity levels shows minor injury and severe injury being overestimated by 0.0422 and 0.0243, respectively, and underestimates no injury by 0.0666. This indicated that if the explanatory were the same in each crash in rural and urban work zones in 2019, the 2016 estimated parameter would predict fewer no injuries and severe injuries in rural and no injuries in urban work zone crashes than were observed.

9. Discussion

The research objective of this study is to determine whether there is a difference in contributing factors for crashes in rural and urban work zones. Consistent with previous studies, the results indicated the factors are different. For instance, indicators such as roadway alignment, driver pre-crash actions, and vehicle characteristics exhibited varying degrees of influence on injury severity outcomes, depending on whether the crash occurred in a rural or urban setting. In rural work zones, factors such as lane shift and lane closure were found to have contrasting effects on injury probabilities, underscoring the importance of considering specific work zone characteristics. Similarly, the direction of travel and seasonal variations emerged as significant predictors of injury severity, highlighting the need for actions required to address the specific challenges of each location.

Our predictive comparison using out-of-sample simulations shows how injuries changed over time in the study. By comparing predicted values based on the 2016 models with observed values from 2019, we found potential differences in injury predictions, particularly in minor and severe injury categories. These findings underscore the dynamic nature of work zone safety and the importance of regularly updating predictive models to account for evolving risk factors. By examining rural and urban work zones separately, we provide valuable insights that can inform targeted strategies aimed at improving work zone safety and mitigating injury risks for single-vehicle drivers. Overall, our findings contribute valuable insights to inform targeted strategies for improving work zone safety and mitigating injury risks for drivers in both rural and urban environments.

10. Conclusions

Work zone crashes are relatively common and pose a significant safety concern for drivers and workers in the work zone area. Reduced visibility, changing road conditions, reduced maneuverability, and hazards within the construction areas contribute to increasing work zone fatalities in the United States. Data from single-vehicle work zone-related collisions in Florida spanning the years 2016 to 2019 were utilized in this research. To verify the correlation between the severity of work zone accidents in rural and urban locations throughout the year, a series of random parametric logit models that exhibit heterogeneity in both the mean and variance were computed.

Over the study years, many statistically significant variables affected the work zone-related severity in rural and urban areas. Both urban [Table 5] and rural [Table 6] models across different years produced statistically significant random parameters with heterogeneity in mean capturing unobserved heterogeneity in the data. Some variables, such as the posted speed 60 plus indicator and dark lighting condition indicator, significantly increased the severe injury severity in rural and urban areas. However, variable such as straight road alignment was found to decrease the probability of severe injury in rural and urban areas.

Indicators such as the male driver indicator were more likely to have a severe injury in rural work zones and less likely to have a minor injury in urban work zones. In comparison, the advance warning sign indicator was unstable as it increased the likelihood of severe injury in 2019 and decreased the likelihood of minor injury in 2017 in urban work zones. Other indicators such as cloudy weather conditions, very young drivers, older drivers, lane closure, lane shift, east, north, and carless action were all found to be statistically significant in rural areas only. Nighttime indicators, south, vehicle registered, drivers not impaired by alcohol, number of lanes, and no traffic controls were found to be statistically significant in urban areas only.

The partially constrained approach using data from all the years in the estimation provides not only the ability to use a large number of observations by combining multiple years of data but also provides a convenient way to statistically determine if the parameters of specific variables changed over time. Empirical works that split the data by time periods (Rangaswamy et al., 2023) could only make a qualitative assessment of how parameters have shifted over time. The result of this approach shows clear evidence that the factors affecting the work zone injury severities vary significantly between rural and urban work zones as factors such as speed limits, work zone layout, and traffic volumes vary across these work zone areas. Despite this difference, rural and urban work zones share common safety challenges. Countermeasures such as driver education, improved signage, and appropriate traffic controls with the combination of ITS technologies such as AWAD (Lin et al., 2023), Dynamic speed back signs (Rangaswamy et al., 2022), and enhanced law enforcement (Lin et al., 2021) can help mitigate crash severity in all work zone areas.

CRediT authorship contribution statement

Rakesh Rangaswamy: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Nawaf Alnawmasi:** Writing – review & editing, Supervision. **Yu Zhang:** Writing – review & editing, Supervision.

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.

Data availability

The authors do not have permission to share data.

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